Four Essays on Linear and Extreme Dependences in Credit Derivatives and Equity Markets

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vorgelegt von

Hendrik Supper

Master of Science

aus Kamen

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Chapter 1

Introduction

Linear and extreme dependences are ubiquitous in financial markets. While linear correlations and covariances have been well investigated in the literature and established as a critical input in financial management, the notion of extreme dependences between financial variables has mainly been fostered during the recent financial crisis. Extreme dependences capture the behavior of variables during tail events and their neglection is thought to be one of the main reasons for the severity of the financial crisis. The dissertation investigates the linear and extreme dependence structures in credit derivatives and equity markets and studies their possible implications for asset pricing and portfolio management.

Linear dependences in the form of correlations and covariances between the returns on financial assets have been a recurring topic in both research and practical applications. The consideration and the reliable estimation of correlations and covariances play a crucial role in asset pricing, portfolio selection, and risk management. For example, most asset pricing theories rely on the assumption that the risk premium of an asset is determined by the covariance between the future return on the asset and one or more benchmark portfolios. The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) predicts that expected excess returns on an asset are proportional to the covariance of the asset returns with the returns on a portfolio composed of all available assets in the market. Similarly, the asset pricing studies in Fama and French (1993) and Carhart

(1997) show that the risk premium of an asset depends on the covariance between the asset returns and the returns on several benchmark portfolios accounting for market returns, size effects, differences in book-to-market equity, and momentum in stock returns. More recently, Acharya and Pedersen (2005) extend the CAPM to the inclusion of liquidity risk and document return premia due to the covariance between individual and market-wide liquidity, individual stock returns and market-wide liquidity, and between individual liquidity and market returns. Moreover, portfolio selection and asset allocation are widely based on the mean-variance approach proposed by Markowitz (1959) and, hence, rely on the estimation of the potentially large number of correlations between the returns on the underlying assets. More precisely, deriving the optimal portfolio in the Markowitz (1959) framework requires a forecast of the covariance matrix of the asset returns to obtain the corresponding portfolio variances that are used to identify the mean-variance combination which maximizes the investor's utility. Furthermore, linear dependences are essential in risk management applications such as, e.g., the calculation of portfolio Value-at-Risk and Expected Shortfall as well as the computation of optimal hedge ratios. While the former requires the estimation of the correlation between the risk factors of the portfolio, the latter relies on the covariance between the returns of the assets in the hedge. More recently, linear dependences are found to be of prime importance in the measurement of systemic risk. In this context, Acharya et al. (2010) define the marginal expected shortfall (MES) as the average return of a particular firm during the 5% worst days for the market and show that MES predicts systemic risk. Brownlees and Engle (2012) build on this idea and propose an econometric approach for the estimation of MES that explicitly models the correlation between firm and market returns.

The statistical properties of correlations have been extensively studied in the econometrics literature. It has now become common knowledge that correlations change through time and are asymmetric in the sense that the correlation between asset returns tends to be greater during market downturns than during market upturns. While the first evidence on time-varying variances and covariances dates back to the seminal studies of Mandelbrot (1963) and Fama (1965), it was not until the work of Bollerslev et al. (1988)

that researchers started to explicitly model time-variation in correlations. Several extensions have been developed since then (see, e.g., Engle and Kroner, 1995; Tse and Tsui, 2002). Engle (2002) proposes dynamic conditional correlation estimators that remain tractable in high dimensions. The notion of asymmetries in correlations, on the other hand, has been widely supported in the financial economics literature. Erb et al. (1994) study cross-country correlations and find correlations to be higher during recessions than during growth periods, while Longin and Solnik (2001) focus on extreme correlations between international equity markets and document that correlation increases in bear markets, but not in bull markets. Further, Ang and Bekaert (2002) develop a regime-switching dynamic asset allocation model to quantify the effect of asymmetric correlations on optimal portfolio choice, and Ang et al. (2006a) compute CAPM betas conditional on market up- and downturns and show that investors demand compensation for holding stocks with high covariation conditional on downward movements of the market. Patton (2006) documents asymmetric correlations between exchange rates, and Christoffersen et al. (2012) find asymmetric correlations between equity returns of developed and emerging markets.

Asymmetries in the correlation structure of asset returns imply deviations from multivariate normality. Another source of multivariate non-normality is constituted by the existence of extreme dependences which are also in the focus of the dissertation.[1] Extreme dependence captures the behavior of economic variables during tail events and is a source of risk to investors. Informally, it denotes the probability of one variable being in its extremes, given that the other variable also takes on extreme values. Ignoring extreme dependence can be costly, as documented by the recent financial crisis.

Starting in 2007, the financial crisis arose from the combination of a credit boom and a housing bubble. The resulting collapse of the financial system was essentially driven by the securitization of mortgages that was conducted by financial institutions to evade regulatory capital requirements. Substantial increases in mortgage financing and house prices encouraged banks to enhance yields by securitizing subprime mortgages, which led to a dramatic growth in the market for credit risk transfer instruments, enabling investors to

[1] Extreme dependence is also referred to as tail dependence in the following.

price, repackage, and disperse credit risk throughout the financial system. Large banks and other complex financial institutions, however, used credit risk transfer products such as collateralized debt obligations (CDOs) to repackage subprime mortgages into opaquely structured securitized mortgages which were erroneously triple-A rated by rating agencies due to modeling failures and conflicts of interest. Instead of transferring the associated credit risks of the subprime mortgages to other investors and completely removing the large risk concentrations from their balance sheets, most of these financial institutions invested in triple-A rated tranches of subprime CDOs, betting against the event that a large number of subprime mortgages defaulted at once. But, as is well known, their bets turned out to be wrong and the housing bubble burst, resulting in rapidly falling house prices and a huge number of mortgage delinquencies. In a couple of months, the market of structured credit risk transfer instruments declined seriously and the liquidity of mortgage-backed securities dried up, causing many financial institutions to suffer profound liquidity problems and severe losses. Consequently, a lot of distressed banks were bailed out and even more banks received financial aids from governments, leading to worldwide collapses in the financial system.[2]

It is the neglection of extreme dependence that critically added to the severity of the financial crisis. The underestimation of the probability for the contemporaneous default of many mortgages was a consequence of modeling failures that resulted from using correlation-based and tail-independent pricing models. More precisely, when pricing the credit risk for a portfolio of defaultable entities, the modeling of joint default probabilities is essential. Li (2000) suggests to model the default correlations between the survival times of the defaultable entities and proposes corresponding pricing formulas for credit transfer products based on a Gaussian copula framework. The Gaussian copula is, however, asymptotically independent in the tails and assumes that tail events occur independently in each margin. That is, Li's (2000) pricing framework is based on the simplifying assumption that mortgages default independently of each other, thereby assigning zero probability to tail events such as joint defaults of many mortgages. Despite

[2]See Acharya and Richardson (2009) for a critical discussion on the causes of the financial crisis.

these limitations, the simplicity and tractability of Li's (2000) pricing approach attracted worldwide attention and was adopted by the vast majority of investors, financial institutions, rating agencies, and regulators, leading to an overly optimistic assessment of credit risks and, in the sequel, to a mispricing of credit transfer products. The resulting distortion of corresponding risk-return profiles spurred a dramatic surge in the issuance and trading volume of these products, which finally resulted in worldwide bankruptcies and financial collapses after the burst of the housing bubble. Hence, extreme dependence contains valuable information and ignoring this information has potentially serious and costly economic consequences.

Empirical evidence of extreme dependences has been found long before the financial crisis hit. Starting with Longin and Solnik (2001) who apply extreme value theory to derive the distribution of extreme correlations and find evidence for extreme dependences in the negative tail of multivariate equity return distributions, the seminal work of Poon et al. (2004) provides a general framework for the identification and modeling of extreme dependences based on techniques from multivariate extreme value theory. The latter find supportive evidence for the results in Longin and Solnik (2001) and document that stock returns exhibit considerable left-tail dependence which is much stronger than right-tail dependence. Eventually, the onset of the financial crisis has given tail risks a renewed salience and spurred a surge in empirical studies on extreme dependences in the financial economics literature. For example, a new strand in the literature has given rise to studies focusing on the possible implications of tail risks and extreme dependences on asset pricing. Recently, Bollerslev and Todorov (2011) analyze the time-variation and the pricing of tail risk in aggregate stock returns and show that the compensation for rare events accounts for a large fraction of the average equity and variance risk premia. In a related study, Kelly and Jiang (2013) isolate a common tail risk factor in the cross-section of individual stocks and find this factor to be a strong predictor for aggregate market returns. Kole and Verbeek (2006) and Ruenzi and Weigert (2013), on the other hand, document a similar result for the cross-section of stock returns using lower tail dependence coefficients as a proxy for equity tail risk. However, the notion that the assumption of multivariate Gaussianity is inadequate when modeling dependences between financial variables has prompted researchers to revisit classical problems not only in asset pricing but also in various other fields of financial economics like, e.g., financial intermediation (Oh and Patton, 2013), portfolio management (Christoffersen et al., 2012), and credit risk (Christoffersen et al., 2012; Oh and Patton, 2012).

Apart from the introduction, the dissertation is composed of four self-contained chapters, which can be read independently of each other and examine different facets of the linear and extreme dependences in credit derivatives and equity markets. Credit derivatives are financial instruments which derive their value from the credit risk of the underlying asset (e.g., defaultable bonds). Here, we are especially interested in credit default swaps (CDS) which are widely used to transfer credit risks among economic agents and attracted worldwide attention during the recent financial crisis. A credit default swap is essentially an insurance contract that provides protection against credit loss due to default. The buyer of a CDS contract makes periodic payments (referred to as premiums) to the seller of the contract and, in exchange, receives a payoff from the seller if the reference entity defaults on a loan or a bond prior to the maturity date of the contract. The periodic amount that the protection buyer pays the protection seller is quoted in terms of a spread. There now exists a substantial body of literature on CDS contracts. The interest in credit default swaps is largely driven by the close relation between CDS spreads and the market perception of default probabilities. For instance, CDS spreads are higher for entities which the market perceives to have higher default probabilities or higher losses given default (see Creal et al., 2012; Oh and Patton, 2013).

Credit default swaps are focused on in Chapters two and three of the dissertation. The second chapter deals with extreme dependences between the CDS spreads of major European banks and shows that the propensity of a bank to experience extreme co-movements in its CDS premia together with the market is priced in the bank's default swap spread during the recent financial crisis. The aversion of investors to the risk of joint extreme co-movements in default probabilities is measured by estimating the upper tail dependence in the CDS spreads of individual banks with respect to a CDS sector index and this is referred to as the bank's CDS tail beta. From a theoretical point of view, there exist two potential channels for tail risk being priced in CDS premia. First, tail risk could be priced in CDS premia due to time-varying recovery rates and, second, due to counterparty credit risk. The empirical pricing study documents that CDS tail beta is a significant determinant of the CDS premia of banks. Banks with higher CDS tail betas exhibit significantly higher CDS spreads. This effect is economically large as banks in the upper quintile of CDS tail betas have an average CDS spread that is 140 basis points higher than the average spread of banks in the lower quintile of CDS tail betas. The regression analyses show that the risk premium protection sellers receive for bearing the risk of a surge in CDS spreads complements the traditional determinants of CDS premia like, e.g., leverage and volatility. Moreover, these findings are robust to the additional inclusion of several alternative measures of linear co-movement in CDS and equity markets. Finally, sub-sample analyses show that the correlation between banks' CDS premia and CDS tail betas is limited to the crisis years of 2007 to 2010. The third chapter studies linear dependence structures in the liquidity of CDS contracts and investigates the impact of commonality in CDS liquidity on the pricing of credit default swaps. The chapter analyzes commonality in CDS liquidity as a different facet of liquidity risk and proposes a novel approach of measuring commonality in the liquidity of CDS contracts. More precisely, liquidity commonality is measured by the R^2 of regressions of individual liquidity on market-wide liquidity. Theoretically, since CDS markets are in zero net supply, credit default swaps should only carry a premium for expected illiquidity but not for liquidity risk. The empirical pricing study, however, shows that the proposed measure of commonality in CDS liquidity is priced in both the cross-section and time series of credit default swap premia. CDS spreads include a statistically significant discount for liquidity risk in the form of liquidity commonality. The effect is also economically meaningful as an increase in CDS liquidity commonality by about 10.7% decreases the CDS spread by approximately 11 bps. Further, the pricing of commonality in CDS liquidity is different for calm and crisis periods as liquidity risk is found to be a priced factor in CDS spreads only during the recent financial crisis. Finally, the chapter documents that liquidity seems to be more important for the pricing of CDS than fundamentals from structural models of default risk. The fourth chapter extends the scope of the dissertation and additionally studies the dependence structures in equity markets as well as cross-dependences between credit derivatives and equity markets. To be precise, Chapter four analyzes the linear and extreme dependences between stock prices, stock liquidity, and credit risk and proposes an econometric approach to dynamically model their joint distribution. Stock liquidity is proxied by the corresponding bid-ask spreads and credit risk is measured by the default probabilities extracted from credit default swaps. The chapter proposes a dynamic vine copula model that captures the dependence between a stock's return and its liquidity, a stock's return and the default intensity of the underlying firm, stock liquidity and the default intensity of a given firm, and all relevant cross-dependences (e.g., between a stock's return and the liquidity of another stock). The empirical study first documents the existence of significant time-varying tail dependence between the stock returns, stock liquidity, and the respective firm's default intensities and then proposes a liquidity- and credit-adjusted Value-at-Risk that enables risk managers to reliably forecast the total risk exposure of a stock investment. The proposed dynamic vine copula model is found to capture time-varying tail dependence significantly better than static copula or dynamic correlation-based models. Finally, Chapter five investigates whether the choice of extreme dependence estimator affects the assessment of tail risks and has a significant impact on the validity and economic significance of key results from recent studies in the financial economics literature. As stated above, the recent financial crisis has renewed interest in the exploration of tail risks and prompted researchers to substitute linear correlations by measures of extreme dependence in classical studies on asset pricing, portfolio selection, and risk management. The consensus underlying these studies is that joint extreme co-movements in equity prices, default intensities, and liquidity are not adequately captured by correlation but should rather be modeled using estimates of tail dependence. The empirical finance literature, however, is far from agreeing on the question how extreme dependence should be measured. Thus, the fifth chapter reviews various commonly used techniques for estimating the tail dependence of a joint distribution in a given data sample. Starting with a comprehensive Monte-Carlo simulation study, the chapter first shows that especially static estimators produce severely biased estimates of tail dependence when applied to samples with time-varying extreme dependence. The empirical study then documents that the choice of estimator significantly affects the importance of tail dependence in asset pricing. Contrary to earlier findings in the literature, the economic significance of the crash-sensitivity of stocks as a priced factor in the cross-section of stock returns is found to be small and to critically depend on the choice of extreme dependence estimator.

Chapter 2

Is Tail Risk Priced in Credit Default Swap Premia?

2.1 Introduction

Do spreads of single-name credit default swaps (CDS) written on bank names reflect a risk premium for extreme financial disasters? There is increasing empirical evidence that stock market investors receive compensation for bearing the risk of extreme tail events in the financial market (see Bollerslev and Todorov, 2011). Consequently, investors agreeing to sell protection via a credit default swap could just the same receive a premium for bearing the risk of the swap being triggered during periods of financial turmoil. If tail risk is indeed priced in a firm's credit default swap premia,[1] this effect should be particularly pronounced for banks. Although macroeconomic shocks should indubitably affect all industry sectors, concerns about the financial strength of a bank could induce a bank run by depositors (see Diamond and Dybvig, 1983) and creditors (see Duffie, 2010; Gorton and Metrick, 2012), likewise. This in turn could lead to an additional increase in the bank's default probability. In this paper, we estimate a bank's upper tail dependence between the log differences of its CDS and a relevant CDS market index (referred to as the *CDS tail beta*) to investigate whether the propensity of an individual bank to jointly

[1]Throughout this paper, we use the terms "CDS premia" and "CDS spreads" synonymously.

surge with the banking sector is priced in the bank's CDS premia. We find that it is: the propensity of a bank's CDS to experience extreme upward co-movements with a CDS index for the financial market is a significant determinant of the bank's CDS premia.

Many analyses in option pricing have emphasized the finding that investors are crash-averse. As deep out-of-the-money index puts have often been found to have a high implied volatility, investors appear to insure themselves against extreme downward movements of the market when investing in equity markets (see Jackwerth and Rubinstein, 1996; Aït-Sahalia and Lo, 2000; Garleanu et al., 2009). Empirical support for this hypothesis of investors demanding compensation for bearing crash risk is given by Ruenzi and Weigert (2013), who find that a stock's lower tail dependence with respect to the market portfolio is a priced factor in the cross-section of stock returns. Surprisingly, the literature on credit risk still lacks an investigation into the question whether investors selling protection in a CDS contract receive a comparable premium for bearing the risk of the reference firm defaulting when default probabilities experience a market-wide increase.

Predictions from theoretical models of CDS premia on the question why sellers of CDS contracts should be compensated for tail risk are inconclusive. The majority of pricing models for CDS contracts are based on the framework of Duffie and Singleton (1997, 1999). In their model, two possible channels exist for tail risk being priced in CDS premia. First, tail risk could be priced in CDS premia due to time-varying recovery rates. Shleifer and Vishny (1992) show in their model that asset values at liquidation, i.e., the recovery rates in the models of Duffie and Singleton (1997, 1999), are low for firms that default when other firms in their industry are experiencing cash flow problems or when macroeconomic conditions are poor. This, in turn, should lead a rational protection seller to ask to be compensated for the risk that the CDS will trigger in times of financial distress. If the reference firm defaults when other firms in the same industry are also in trouble, this lowers the recovery rate received by the protection seller.[2] Everything else remaining constant, protection sellers will require a higher premium for selling CDS contracts on firms that tend to default when instances of default increase in their industry

[2]Acharya et al. (2007) show empirically that creditors of defaulted firms recover significantly lower amounts in present-value terms when the industry of defaulted firms is in distress.

(or in the overall economy). Second, tail risk could also be priced in CDS premia due to counterparty credit risk. However, counterparty credit risk should primarily affect the buyer of the CDS contract leading to a lower price at which the buyer is willing to purchase protection due to the fact that CDS transactions are required to be marked-to-market daily and to be over-collateralized in favor of the large dealer banks that usually sell CDS contracts. Empirically, however, the effect of counterparty credit risk on CDS premia has been shown to be vanishingly small (see Arora et al., 2012). Consequently, theory implies that tail risk should be priced in CDS premia although the expected direction of this effect is unclear. While we expect time-varying recovery rates (implying a positive relation between tail risk and CDS premia) to dominate the effect of counterparty risk (implying lower premia for firms with higher tail risk), the questions whether and how tail risk affects CDS premia ultimately require an empirical analysis.

There now exists a substantial body of literature on the determinants of credit spreads. Collin-Dufresne et al. (2001) examine the drivers of corporate bond yield spreads and find that most drivers proposed in theory have little to none explanatory power in regressions of corporate credit spreads. Closely related, Campbell and Taksler (2003) and Cremers et al. (2008) find that idiosyncratic volatility is an economically significant determinant of levels of corporate credit spreads. The analysis of corporate bond yields, however, only offers a distorted picture of a firm's credit risk. As noted by Blanco et al. (2005) and Ericsson et al. (2009), new information is incorporated faster and more accurately into credit default swap premia than into corporate bond yields. Moreover, the latter include further nondefault components (like, e.g., liquidity risk and taxes) and require the specification of a risk-free yield curve model to calculate spreads from bond yields (Duffie and Liu, 2001; Longstaff et al., 2005; Ericsson and Renault, 2006). Yet, we still know relatively little about the fundamental factors driving CDS premia. While studies on the determinants of credit spreads question the explanatory power of observable covariates, Ericsson et al. (2009) show that equity volatility and firm leverage suffice to explain most of the variation in CDS premia over time and across firms.[3] The theo-

[3]Using a discrete time no-arbitrage model with observable covariates, Doshi et al. (2013) show that four (observable) covariates extracted from the riskless term structure, the firm's distance-to-default computed

retical basis for most of these hypothesized determinants is given in the structural model of Merton (1974). In his model, a firm's default probability (and consequently, the value of a corresponding CDS), are influenced by the firm's leverage, equity volatility and the level of the risk-free rate. Especially during times of financial crisis, however, CDS premia could additionally be driven by risk preferences of protection sellers.[4]. If investors were averse to downside risk (see, e.g. Roy, 1952; Kahneman and Tversky, 1979), CDS protection sellers should require a premium for bearing the risk of negative externalities spilling over from other financial institutions to the reference bank.[5] Anecdotal evidence from the recent financial crisis strongly supports this notion as banks experienced extreme co-movements in their CDS premia following the collapse of Lehman Brothers. In this paper, after carefully controlling for the temporal variation in the tail dependence of CDS spreads, we test and confirm the hypothesis that CDS protection sellers are compensated for the risk of a joint crash in the CDS market.

We measure the aversion of investors to the risk of joint extreme co-movements in default probabilities by estimating the upper tail dependence in the CDS spreads of individual banks with respect to a CDS sector index and refer to this as the bank's *CDS tail beta*. In essence, the upper tail dependence between two random variables measures the probability of both variables to experience co-movements in their upper right tail. As linear correlations cannot fully describe the complete dependence structure in a joint return distribution in a non-gaussian framework, a growing body of literature has employed methods from extreme value theory and copula theory to study non-linear dependence in asset returns (see, e.g., Longin and Solnik, 2001; Poon et al., 2004; Ruenzi and Weigert, 2013). In this paper, we build on these recent results from the literature and employ the Dynamic Asymmetric Copula (DAC) model of Christoffersen et al. (2012) to estimate the upper tail dependence between the log differences of an individual bank's CDS spreads and the log differences of a CDS bank sector index. We then follow in the

using option-implied volatility, and the VIX suffice to explain CDS spreads.

[4]As noted by Christie (1982) and Collin-Dufresne et al. (2001), however, market value leverage can also increase due to negative stock returns. There is thus a direct link between the pricing of CDS contracts via the model of Merton (1974) and extreme crash risk in equity prices

[5]Recent studies in the literature that incorporate (crash) risk averse investors into standard asset pricing models include, e.g., Shumway (1997); Ang et al. (2006a); Ruenzi and Weigert (2013).

footsteps of Collin-Dufresne et al. (2001); Campbell and Taksler (2003); Cremers et al. (2008); Zhang et al. (2009) and Ericsson et al. (2009) and estimate time-series and panel regressions of CDS premia with bank fixed effects on known drivers of credit risk as well as on CDS tail beta.

We find that CDS tail beta is a significant determinant of the CDS premia of banks. Banks with higher CDS tail betas exhibit significantly higher CDS spreads. This effect is economically large as banks in the upper quintile of CDS tail betas have an average CDS spread that is 140 basis points higher than the average spread of banks in the lower quintile of CDS tail betas. In our regression analyses, we show that the risk premium protection sellers receive for bearing the risk of a surge in CDS spreads complements the traditional determinants of CDS premia like, e.g., leverage and volatility. Moreover, our findings are robust to the additional inclusion of several alternative measures of linear co-movement in CDS and equity markets. In our sub-sample analysis, we show that the correlation between banks' CDS premia and CDS tail betas that we find is limited to the crisis years of 2007 to 2010.

Our paper is related to several recent investigations into the pricing of equity and credit derivatives. Most notably, our investigation draws inspiration from the study of Ruenzi and Weigert (2013) who document a crash risk premium in equity prices. While their study is concerned with the correlation between lower tail dependence and equity prices, our analysis investigates the determinants of CDS premia.[6] Moreover, in contrast to their work, we account for time variation in the dependence structure of individual and sector-wide CDS premia. Our work is also related to the studies by Ericsson et al. (2009) and Doshi et al. (2013), but we additionally consider a premium for crash risk in the CDS market as an additional explanatory factor in our empirical analysis of CDS premia. Nevertheless, our results do not refute but rather complement the findings by Ericsson et al. (2009) as their results remain valid in our sample period. Investors thus seem to demand a risk premium for CDS tail beta when it is needed the most: during a tail event. Finally, our paper is also related to the contemporaneous studies by Oh and Patton (2013) and

[6] The link between a firm's stock returns and its credit risk is analyzed in detail by Friewald et al. (2014). Their study, however, is not concerned with the determinants of CDS spreads per se.

Christoffersen et al. (2013). Both studies, however, do not consider the determinants of CDS premia.

The rest of this paper is organized as follows. Section 2.2 describes the data and the econometric models we use for estimating CDS tail betas. In Section 2.3, we present and discuss the results of our analysis on the determinants of CDS premia. Section 2.4 concludes.

2.2 Modeling extreme CDS spread co-movements

The purpose of this section is to present the data and outline the econometric framework for modeling log differences of CDS spreads as well as their dynamic multivariate dependence structure. We start with a description of the data and a brief study on the stylized facts of log differences of CDS spreads to identify the correct model specifications.

2.2.1 CDS data and stylized facts of CDS spreads

To investigate the economic importance of CDS tail beta for the European banking sector, we construct a sample of more than 54,000 daily CDS mid-quotes between January 2004 and September 2010. The data on CDS quotes are retrieved from *Credit Market Analysis (CMA)* via *Thomson Reuters Financial Datastream*. For all available major European banks, we also collect daily bid and ask quotes. To ensure accuracy and data consistency, we apply several filtering criteria to our data. The considered CDS series are exclusively written on single-name entities and are denoted in Euro. We further include only those contracts in our final sample that refer to senior debt issues and discard the class of subordinated debt. Additionally, we restrict our analysis solely to contracts exhibiting a five-year term structure, since these are the most frequently traded terms and therefore unlikely to be distorted from low levels of liquidity. Moreover, for a bank to be included in the our sample, we require the bank to be listed on a major stock exchange and have stock price data readily available in *Datastream*.[7] Finally, on the individual bank level we

[7]Note that the subsequent empirical analysis requires CDS as well as stock market quotations. See Section 2.3 for details.

exclude all time series with missing values after observing the first quote. Starting with a universe of all European bank names covered by *CMA*, we identify a remaining total of 35 banks matching the above mentioned filtering criteria.[8] Note that the overall sample size is solely restricted by data availability of both CDS and stock market quotes. To estimate the CDS tail betas of the banks in our sample, we later employ log differences of an index of CDS spreads that is constructed as the log differences of an equally-weighted average of individual CDS spreads across all sample banks. For increased transparency, Table A.1 in Appendix A provides an overview of the bank names as well as corresponding ticker symbols.

Table 2.1 reports summary statistics of daily CDS spreads. Whereas the mean sample spread is at a comparatively modest level of 91.94 bps, the minimum and maximum premia range from 1 bp (EBKOF) up to 1327.86 bps (BILMI), indicating fundamental changes in investors' risk perception during the sample period. In addition, an average standard deviation of more than 100 bps reflects a significant level of volatility in observed CDS spreads. Furthermore, an analysis of the CDS spreads' percentiles and skewness indicates that a great portion of daily spread quotations can be found in the lower tail of the distribution. We find average CDS spreads to be positively skewed suggesting that the pre-crisis period is characterized by lower credit spreads and hence, lower CDS-implied default risk. This is confirmed by the evolution of average spreads over time depicted in Panel (a) of Figure 2.1. As can be seen from Figure 2.1, daily CDS spreads remain on low levels between January 2004 until mid-2007. With the commencement of the sub-prime crisis however, a fundamental re-valuation of credit risk took place resulting in highly elevated CDS levels after mid-2007. Additionally, we report the evolution of daily minimum and maximum spread quotations illustrated by the shaded gray area. We find the cross-sectional variation to be rather low in the pre-crisis period but find a substantial widening after mid-2007, suggesting not only a system-wide increase of CDS-implied default risk but also an asymmetric assessment of banks' credit risk during the crisis.

[8] A comprehensive overview of bank-specific CDS data available in *CMA* can also be found in Annaert et al. (2013).

Table 2.1: Descriptive statistics of CDS spreads.

The table presents descriptive statistics on daily CDS spreads of the 35 sample banks for the period from January 2004 to October 2010. We report the number of observations, minimum and maximum values, percentiles and moments as well as first order autocorrelations (in %, denoted as AC(1)), where the minimum and maximum of each column is printed in bold type. Except for the number of observations, skewness, (excess) kurtosis, and AC(1), all entries are denominated in basis points (bps). Company names are abbreviated by their corresponding Bloomberg ticker symbols listed in Table A.1 in Appendix A.

			Percentiles							Moments				
	Obs	Min	1st	5th	20th	80th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.	AC(1)
ACA	1760	5.50	6.00	6.20	7.80	90.52	132.08	173.73	237.81	47.04	46.87	0.87	-0.27	99.43
AIBSF	1761	5.70	6.20	6.60	8.20	233.95	457.51	616.88	646.72	115.94	152.07	1.49	1.45	99.45
ALPHA	1761	10.80	16.50	18.50	25.47	**37.00**	716.90	938.96	1048.80	109.79	209.75	**2.77**	**6.84**	99.42
BBPI	1761	10.50	11.50	13.50	17.50	104.95	357.53	437.19	507.20	70.63	95.30	2.65	6.81	99.25
BBVA	1761	7.10	8.00	8.60	9.40	95.41	185.57	249.67	295.16	54.27	58.86	1.42	1.59	99.34
BCPSF	1761	13.00	13.50	14.50	22.50	325.00	485.00	579.50	579.50	134.44	171.49	1.20	-0.02	99.73
BILMI	870	**65.70**	**72.50**	**100.00**	**152.30**	**560.94**	**1087.12**	**1271.10**	**1327.86**	**390.53**	**315.66**	1.38	0.81	99.35
BKESF	1761	8.20	9.00	9.90	13.00	124.50	378.53	515.37	635.58	82.12	110.31	2.44	6.20	99.34
BKT	1358	10.50	10.77	11.31	14.72	219.70	294.02	321.26	356.00	98.44	108.54	0.71	**-1.14**	99.59
BMDPF	1761	6.00	6.16	7.20	14.00	87.50	159.08	206.68	228.63	52.26	48.99	1.32	1.16	99.24
BNP	1761	5.00	5.50	6.00	7.50	68.80	**105.33**	**127.21**	**155.38**	**36.69**	**34.60**	0.91	-0.26	99.34
BPCGF	1761	8.00	8.70	9.20	12.00	104.50	356.67	451.08	572.28	72.72	98.50	2.47	6.08	99.24
BPESF	1761	7.50	8.34	9.00	10.50	200.00	301.88	344.01	437.70	86.16	108.48	1.04	-0.44	99.63
BPI	1756	9.80	11.02	13.60	31.00	122.60	214.25	363.63	439.99	84.82	68.46	1.69	3.86	99.50
BPMLF	1761	11.40	11.70	13.00	17.80	81.80	140.70	156.65	185.00	50.34	41.67	1.14	0.13	99.47
CBK	1761	7.40	8.16	9.00	14.00	85.40	123.86	145.00	170.52	49.23	38.93	0.75	-0.57	99.27
CRIH	1761	7.00	8.00	10.00	12.00	103.20	155.07	215.00	278.74	54.63	53.47	1.13	0.57	99.40
DBK	1761	8.70	9.40	10.80	13.50	98.70	140.00	165.00	187.95	52.33	45.98	0.80	-0.65	99.44
DEXB	1761	2.50	3.00	**4.50**	8.00	222.09	335.00	433.68	550.00	103.25	124.56	1.00	-0.22	99.72
EBKOF	1761	**1.00**	**1.00**	11.95	15.00	152.68	240.00	397.30	487.13	80.77	89.51	1.53	2.59	99.16
EFG	1289	12.22	12.71	14.58	14.79	165.60	757.24	983.56	1236.70	124.28	241.02	2.30	4.20	99.23
FSVVF	1761	5.80	6.00	6.50	14.50	113.30	281.61	386.96	415.00	68.61	80.88	2.13	4.66	99.21
GLE	1761	5.70	6.00	6.40	8.00	94.82	125.82	153.71	208.55	46.81	45.32	0.74	-0.80	99.46
IITSF	1761	5.40	5.80	7.00	12.50	73.52	131.20	164.76	200.00	43.80	40.94	1.27	0.81	99.33
IKB	1761	**1.00**	**1.00**	12.50	16.00	387.54	965.44	1008.40	1109.86	220.85	285.59	1.41	1.07	99.63
ILB	1761	12.22	12.45	12.64	19.89	230.00	369.09	545.00	584.50	116.50	129.06	1.24	0.93	99.40
ING	1761	4.00	4.30	5.00	**7.00**	89.57	130.00	160.00	188.30	45.72	45.60	0.85	-0.56	99.50
IRLBF	1752	5.00	6.00	6.80	8.42	232.49	379.51	620.11	670.28	113.65	143.55	1.41	1.52	99.48
KBC	1759	6.90	7.20	7.50	9.50	137.21	253.92	308.67	343.30	75.49	83.61	1.16	0.39	99.60
KN	1761	6.30	7.00	7.50	9.20	151.50	276.01	325.00	390.18	81.85	93.52	1.09	0.02	99.57
MDIBF	1761	6.50	7.00	7.40	13.30	82.02	143.33	165.50	175.00	47.41	44.83	1.14	0.11	99.50
SAB	850	19.60	21.00	27.40	126.00	287.51	336.52	362.54	383.55	197.09	91.29	**-0.15**	-0.91	99.14
SAN	1761	7.00	8.00	8.80	10.00	95.73	161.70	202.15	260.51	52.77	52.83	1.09	0.31	99.32
UBI	1718	6.50	12.50	13.00	16.00	87.03	159.22	182.46	223.56	52.53	48.96	1.19	0.35	99.42
UNBLF	1552	22.00	23.30	25.00	31.42	153.24	375.00	543.63	601.30	104.16	113.42	2.21	4.72	99.81
Average	1676	9.64	10.72	13.18	21.22	157.15	320.33	406.32	466.24	91.94	101.78	1.37	1.47	99.43

Figure 2.1: Time evolution of CDS spreads, log differences of CDS spreads, and equity returns.

The panels of this figure show, respectively, the time evolution of CDS spreads, log differences of CDS spreads, and equity log returns over the sample period from January 2004 to October 2010. In each of the panels, the black line refers to the average across all 35 sample banks, whereas the shaded area represents the span between maximum and minimum spread/return values and shows the range of values that is covered for each day of the sample. To facilitate visual inspection, we smooth the shaded area by applying moving averages to the maximum and minimum spread/return series. Equity returns and log differences of CDS spreads are measured in %, CDS spreads are denominated in basis points (bps).

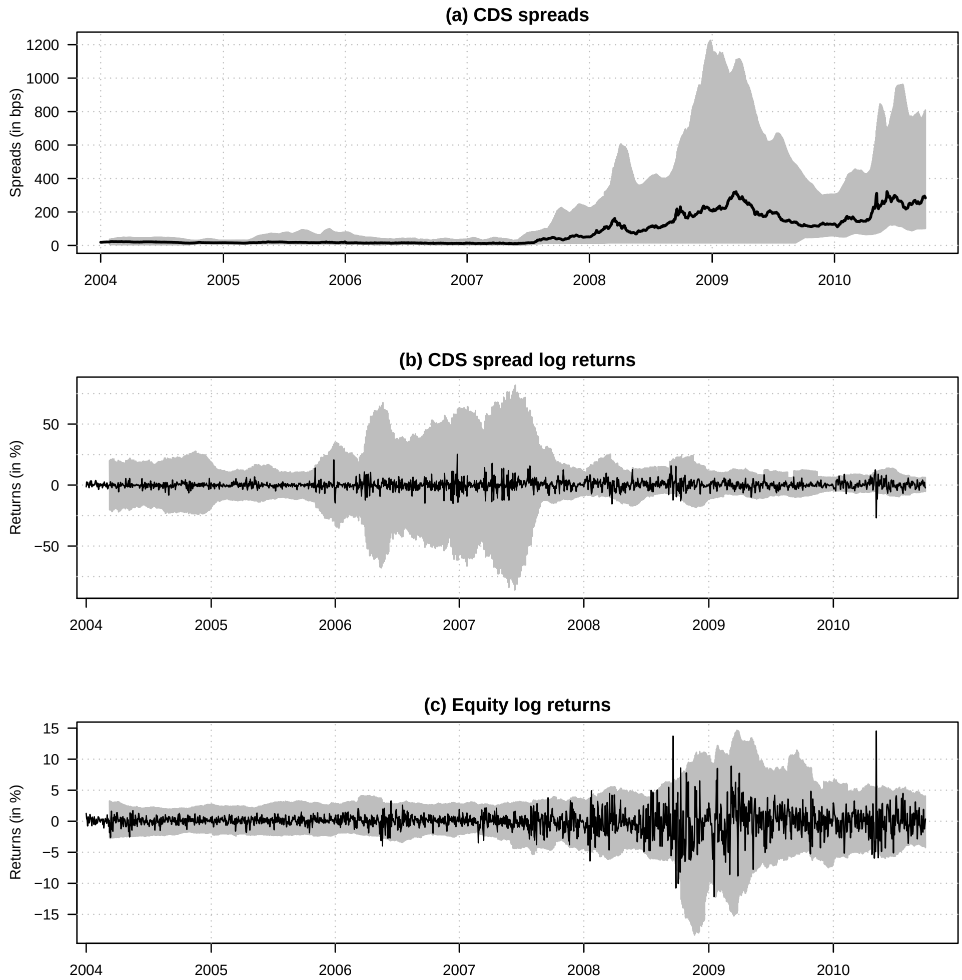


Table 2.2 presents descriptive statistics on the log differences of CDS spreads. The log differences range from -77.67% to 106.63% on average, reflecting both substantial upward and downward movements in CDS spreads. As we can see from the results on the moments, the log differences are characterized by a negligible mean (0.15% on average) and a significant standard deviation ranging from 4.51% (UNBLF) to 51.25% (EBKOF). Additionally, the log differences are positively skewed (2.75 on average) and exhibit tail risk, as indicated by a pronounced excess kurtosis. The first-order autocorrelations are negative for most sample banks and -8.02% on average. The time evolution of the log differences of CDS spreads is illustrated in Panel (b) of Figure 2.1. The plot shows that in the beginning of the sample period the average log differences vary between -10% and 15%, whereas the shaded area between maximum and minimum observations stays relatively tight around the average differences. As of 2006 (observation 530), the magnitude and volatility of average log differences increase and the shaded area raises gradually indicating growing cross-sectional variation in the log differences of CDS spreads. After the onset of the financial crisis, the shaded area tightens sharply around the average log differences in October 2007, whereas the magnitude and volatility of the average log differences remain in approximately the same range.

Complementing the analysis of CDS spreads, we also shortly comment on some descriptive statistics of the banks' equity (log) returns presented in Table A.2.[9] Not surprisingly, returns vary across a wide range of values and, according to the results on percentiles and moments, the stocks possess the usual stylized characteristics of negligible mean log returns (-0.04% on average) and non-normally distributed returns with a slight skewness of, on average, -0.43. The evolution of daily log returns over time is shown in Panel (c) of Figure 2.1. Underlining our previous findings, the graph exhibits a pattern that is commonly associated with equity return series.

[9]To preserve space, the summary statistics for equity returns are shown in Table A.2 in Appendix A.

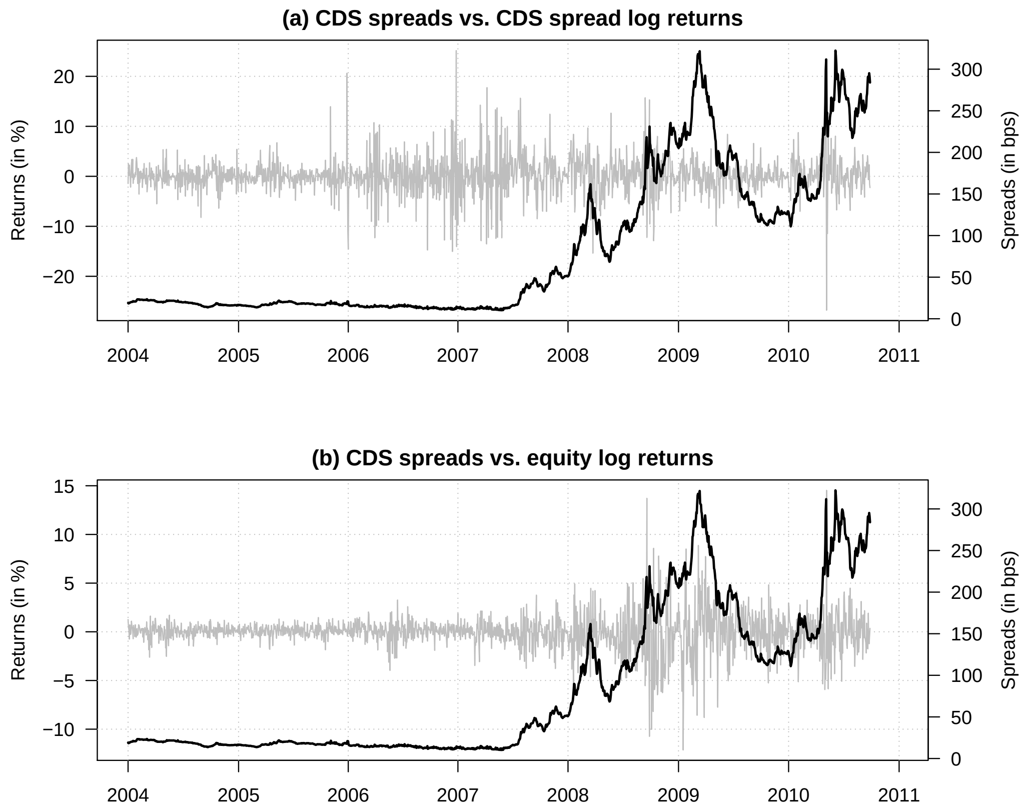
Table 2.2: Descriptive statistics of log differences of CDS spreads.

The table presents descriptive statistics on daily log differences of CDS spreads of the 35 sample banks for the period from January 2004 to October 2010. We report the number of observations, minimum and maximum values, percentiles and moments as well as first order autocorrelations (denoted as AC(1)), where the minimum and maximum of each column is printed in bold type. Except for the number of observations, skewness and (excess) kurtosis, all entries are denominated in %. Company names are abbreviated by their corresponding Bloomberg ticker symbols listed in Table A.1 in Appendix A.

			Percentiles							Moments				
	Obs	Min	1st	5th	20th	80th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.	AC(1)
ACA	1759	-43.97	-17.70	-8.84	-3.05	3.55	9.27	16.31	36.51	0.14	5.76	-0.19	5.85	-6.32
AIBSF	1760	-91.06	-21.90	-10.34	-2.85	3.45	11.59	22.95	52.68	0.21	7.39	-0.79	18.82	-17.07
ALPHA	1760	-87.75	-18.93	-2.94	**-0.20**	**0.00**	3.36	21.45	209.20	0.19	7.54	11.66	356.77	-14.74
BBPI	1760	-84.07	-58.23	-5.15	-0.54	0.24	5.46	59.05	148.23	0.16	13.43	0.82	28.89	-28.23
BBVA	1760	-39.32	-15.73	-8.54	-3.11	3.40	8.70	17.54	**31.54**	0.17	5.70	0.03	**5.56**	2.26
BCPSF	1760	-75.81	**-7.08**	**-2.51**	-0.50	0.42	**2.82**	10.03	216.54	0.14	8.85	8.52	237.28	-3.54
BILMI	869	-31.28	-18.97	-7.73	-2.69	2.69	8.06	21.86	66.78	0.11	6.40	2.03	22.64	-10.96
BKESF	1760	-39.65	-14.10	-7.51	-2.69	3.10	7.80	15.52	37.57	0.18	5.15	-0.09	8.63	**8.11**
BKT	1357	-30.16	-8.23	-3.10	-0.80	0.56	3.08	**8.91**	278.70	0.18	8.24	**28.62**	**963.92**	0.74
BMDPF	1760	-41.23	-15.06	-8.37	-2.90	3.19	8.71	15.17	52.24	0.13	5.54	0.46	9.89	6.78
BNP	1760	-36.05	-17.88	-10.21	**-3.60**	3.68	10.54	18.68	62.68	0.13	6.54	0.54	8.39	-10.23
BPCGF	1760	-35.42	-14.90	-7.41	-2.68	3.14	8.34	14.73	40.68	0.18	5.22	0.22	7.88	5.00
BPESF	1760	-120.02	-16.09	-5.89	-0.72	1.08	5.96	16.04	217.39	0.19	8.10	10.68	339.73	-6.85
BPI	1755	-32.20	-16.60	-8.29	-2.70	2.99	8.38	16.54	76.04	0.11	5.81	1.90	24.68	-0.15
BPMLF	1760	-62.73	-15.12	-7.60	-2.43	2.70	8.12	13.60	38.72	0.09	5.49	-1.19	22.84	-9.84
CBK	1760	-46.39	-15.42	-8.43	-3.01	3.32	8.35	16.04	59.86	0.08	6.00	0.67	16.80	3.45
CRIH	1760	-40.80	-15.92	-7.70	-2.96	3.36	8.24	15.35	54.04	0.14	5.68	0.42	13.04	1.10
DBK	1760	-47.63	-16.91	-8.64	-3.28	3.51	8.71	17.24	53.66	0.11	6.02	0.22	10.37	-0.01
DEXB	1760	-95.55	-37.40	-10.54	-2.41	2.62	11.12	47.00	98.08	0.22	11.77	0.93	23.36	-28.91
EBKOF	1760	**-424.49**	**-162.31**	-18.77	-1.22	1.45	23.72	**162.62**	**424.49**	0.13	**51.25**	-0.16	38.12	**-44.63**
EFG	1288	-72.91	-25.84	-2.59	-0.26	0.01	3.54	26.77	249.93	0.27	9.67	13.48	353.22	-7.76
FSVVF	1760	-94.91	-15.29	-6.90	-1.46	1.32	6.90	18.05	83.10	0.09	6.75	1.12	64.71	-6.61
GLE	1760	-41.59	-15.72	-8.85	-3.20	3.58	9.27	17.07	38.00	0.14	5.77	0.15	5.84	-5.11
IITSF	1760	-37.87	-17.12	-8.73	-3.08	3.28	8.86	16.61	75.38	0.11	6.00	1.16	19.34	6.39
IKB	1760	-400.81	-140.63	**-32.21**	-2.49	2.33	**36.59**	128.85	304.84	0.15	39.26	-0.61	32.61	-33.28
ILB	1760	-59.78	-13.35	-4.49	-0.91	0.98	5.41	14.54	134.06	0.19	6.13	6.54	174.79	-2.65
ING	1760	-33.90	-19.60	-9.53	-3.46	3.72	9.98	20.83	43.14	0.12	6.49	0.23	5.76	-15.51
IRLBF	1751	-86.91	-17.22	-7.93	-2.41	2.96	9.27	18.46	37.47	0.21	6.17	**-1.62**	28.97	-14.05
KBC	1758	-69.49	-14.49	-6.07	-1.40	1.83	6.77	13.89	82.73	0.13	5.61	1.97	63.74	-7.08
KN	1760	-50.93	-18.18	-7.91	-2.35	2.58	8.01	18.02	77.42	0.14	5.98	0.85	27.55	-21.59
MDIBF	1760	-35.92	-13.83	-7.41	-2.47	2.48	7.56	15.00	91.63	0.11	5.66	3.22	52.81	-9.76
SAB	849	**-21.13**	-13.75	-6.04	-2.22	2.64	7.79	15.42	55.02	**0.30**	5.06	2.08	21.35	0.09
SAN	1760	-45.72	-16.26	-8.97	-3.37	**3.82**	8.91	17.02	32.54	0.15	5.82	-0.18	5.92	2.57
UBI	1717	-136.69	-24.75	-6.00	-1.17	1.21	7.28	22.12	137.50	0.12	8.85	1.82	103.17	-8.05
UNBLF	1551	-24.16	-13.47	-6.22	-1.80	1.68	7.30	14.69	33.54	**0.07**	**4.51**	0.65	8.98	-4.41
Average	1675	-77.67	-25.83	-8.24	-2.18	2.37	8.96	26.40	106.63	0.15	8.96	2.75	89.49	-8.02

Figure 2.2: CDS spreads versus log differences of CDS spreads and equity returns.

The panels of this figure compare the time evolution of CDS spreads to the time evolution of log differences of CDS spreads and equity log returns, respectively, over the sample period from January 2004 to October 2010. The black line refers to the average CDS spread across all 35 banks and is scaled according to the right-hand y-axis, whereas the gray lines show the average equity log returns/log differences of CDS spreads and are scaled according to the y-axis on the left-hand side. Equity returns and log differences of CDS spreads are measured in %, CDS spreads are denominated in basis points (bps).



The panels of Figure 2.2 compare the time evolution of spreads to that of the log differences of CDS spreads and equity returns. The plot given in Panel (a) of Figure 2.2 does not show any evidence of an increase in the volatility of CDS spreads during the crisis at first glance. However, the volatility of log-differenced CDS spreads was extremely high before the crisis with spreads remaining on a very low level. When excluding the pre-crisis period, key events of the financial crisis (like, e.g., the collapse of Lehman Brothers) coincided with significant spikes in CDS spreads and increased volatility of the log differences. The plot given in Panel (b) further underlines the finding that the average CDS spread and equity return volatility of banks comoved during the financial crisis with both series increasing steeply between 2007 and 2009. CDS spreads decreased after 2009 but started to increase again with the onset of the sovereign debt crisis.

Due to modeling purposes, we will use daily log differences of CDS spreads to estimate our models and to calculate joint extreme crash risk. Since the time series properties of the log differences of CDS spreads are a rather unexplored field in the econometric literature, we will conduct a brief study on the stylized facts of log differences of CDS spreads in the following.[10]

The results of the time series analysis of the log differences of CDS spreads are reported in Table 2.3. In a first step, we check for stationarity of the log differences. To this purpose, we employ the augmented Dickey-Fuller (ADF) test using the general regression equation with a constant and a linear time trend.[11] The corresponding p-values in column 3 of Table 2.3 show that the null of a unit root is rejected and all time series of log-differenced CDS spreads are stationary. Unreported results on additionally conducted PP and KPSS tests support these findings. In the next step, we check for linear serial dependence and employ the Ljung-Box (LB) test with the number of lags equal to 20. The LB test is not rejected for 40% (31%, 23%) of the sample banks at the 1% (5%, 10%) significance level (see column 5 of Table 2.3). Hence, most time series are characterized by significant linear serial dependence. Moreover, we perform Engle's (1982) lagrange multiplier (LM) test to check for ARCH effects. To control for linear serial dependence, we firstly estimate an AR model for each time series.[12] Then, we regress the squared AR residuals on their own history and test the null that all coefficients are equal to zero (no ARCH effects).[13]

[10]Cont and Kan (2011) undertake a similar study on log-differenced CDS spreads for a different set of CDS spreads.

[11]The number of lags included in the regression of the test is chosen to be the upper bound on the rate at which the number of lags grows with the sample size (see Said and Dickey, 1984, for details).

[12]The order of the AR model is chosen such that the null of the LB(20) test cannot be rejected at the 10% significance level.

[13]More precisely, we use five lagged values of the squared residuals.

Table 2.3: Time-series analysis of log differences of CDS spreads.

The table contains the results on the time-series analysis of log differences of CDS spreads. We conduct the augmented Dickey-Fuller (ADF) test of stationarity, the Ljung-Box (LB) test of linear serial dependence (including 20 lags), Engle's (1982) lm test of ARCH effects (ARCH LM) and the Jarque-Bera (JB) test of normality. Further, we calculate upper and lower tail indices using the Hill estimator. The bias test refers to the jointly conducted Sign Bias Test, Negative Size Bias Test as well as Positive Size Bias Test as proposed by Engle and Ng (1993), which test for asymmetries in conditional volatility. The last row presents the numbers of banks for which the null hypothesis of the corresponding test is rejected at the 1%, 5%, and 10% significance level, respectively. Company names are abbreviated by their corresponding Bloomberg ticker symbols listed in Table A.1 in Appendix A.

	ADF test		LB test		ARCH LM test		JB test		Tail indices		Bias test	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value	Upper	Lower	Statistic	p-value
ACA	-10.05	<0.01	22.57	0.31	105.91	<0.01	>10	<0.01	3.35	4.07	4.92	0.18
AIBSF	-11.45	<0.01	79.95	<0.01	37.72	<0.01	>10	<0.01	3.49	2.76	3.43	0.33
ALPHA	-12.39	<0.01	86.01	<0.01	2.54	0.77	>10	<0.01	2.02	0.99	5.62	0.13
BBPI	-13.20	<0.01	267.11	<0.01	96.14	<0.01	>10	<0.01	2.20	5.74	0.44	0.93
BBVA	-11.57	<0.01	24.75	0.21	149.91	<0.01	>10	<0.01	2.45	3.76	1.34	0.72
BCPSF	-12.08	<0.01	29.53	0.08	0.17	0.99	>10	<0.01	**1.09**	**0.89**	0.26	0.97
BILMI	-9.04	<0.01	38.15	<0.01	0.44	0.99	>10	<0.01	1.63	1.82	1.95	0.58
BKESF	-10.61	<0.01	33.52	0.03	127.28	<0.01	>10	<0.01	2.82	2.47	0.71	0.87
BKT	-10.79	<0.01	9.94	0.97	0.01	0.99	>10	<0.01	1.17	1.72	0.46	0.93
BMDPF	-11.39	<0.01	34.58	0.02	169.76	<0.01	>10	<0.01	2.84	3.15	2.83	0.42
BNP	-11.07	<0.01	46.56	<0.01	64.27	<0.01	>10	<0.01	2.72	3.20	0.41	0.94
BPCGF	-10.30	<0.01	27.63	0.12	155.62	<0.01	>10	<0.01	2.70	2.52	0.19	0.98
BPESF	-11.57	<0.01	37.37	0.01	0.05	0.99	>10	<0.01	1.51	2.29	0.90	0.83
BPI	-10.56	<0.01	23.93	0.25	13.27	0.02	>10	<0.01	2.18	3.69	0.83	0.84
BPMLF	-12.32	<0.01	39.40	<0.01	0.35	0.99	>10	<0.01	2.79	2.20	0.34	0.95
CBK	-10.85	<0.01	50.69	<0.01	274.83	<0.01	>10	<0.01	2.51	2.32	2.62	0.45
CRIH	-11.21	<0.01	40.95	<0.01	171.20	<0.01	>10	<0.01	2.43	2.61	1.73	0.63
DBK	-11.63	<0.01	29.13	0.09	131.35	<0.01	>10	<0.01	2.35	3.94	1.25	0.74
DEXB	-11.79	<0.01	197.89	<0.01	196.55	<0.01	>10	<0.01	1.20	6.83	0.39	0.94
EBKOF	-16.89	<0.01	542.72	<0.01	287.80	<0.01	>10	<0.01	1.44	1.62	0.13	0.99
EFG	-12.01	<0.01	23.48	0.27	0.06	0.99	>10	<0.01	1.47	0.90	0.02	0.99
FSVVF	-10.04	<0.01	44.02	<0.01	4.46	0.49	>10	<0.01	1.57	1.90	0.33	0.95
GLE	-10.83	<0.01	40.15	<0.01	129.10	<0.01	>10	<0.01	2.84	3.36	2.98	0.39
IITSF	-11.58	<0.01	46.27	<0.01	153.05	<0.01	>10	<0.01	2.44	2.71	1.61	0.66
IKB	-16.49	<0.01	367.36	<0.01	459.43	<0.01	>10	<0.01	1.57	6.85	0.95	0.81
ILB	-11.88	<0.01	23.39	0.27	0.53	0.99	>10	<0.01	1.61	1.51	0.57	0.90
ING	-9.56	<0.01	84.79	<0.01	161.16	<0.01	>10	<0.01	2.43	**7.99**	2.72	0.44
IRLBF	-10.83	<0.01	75.29	<0.01	27.70	<0.01	>10	<0.01	3.47	3.02	5.35	0.15
KBC	-9.89	<0.01	40.37	<0.01	12.33	0.03	>10	<0.01	1.85	2.04	0.03	0.99
KN	-9.70	<0.01	102.22	<0.01	52.72	<0.01	>10	<0.01	2.31	2.32	0.52	0.92
MDIBF	-11.21	<0.01	43.53	<0.01	1.46	0.92	>10	<0.01	2.00	2.58	1.49	0.69
SAB	-8.96	<0.01	24.48	0.22	1.55	0.91	>10	<0.01	2.27	2.10	1.17	0.76
SAN	-12.14	<0.01	29.87	0.07	161.07	<0.01	>10	<0.01	**4.10**	2.93	2.52	0.47
UBI	-12.68	<0.01	91.21	<0.01	6.20	0.29	>10	<0.01	1.41	1.30	0.81	0.85
UNBLF	-8.36	<0.01	51.33	<0.01	38.84	<0.01	>10	<0.01	2.91	5.45	3.60	0.31
Rej. 1/5/10%		35/35/35		21/24/27		21/23/23		35/35/35		-		0/0/0

The p-values in column 7 of Table 2.3 show that most time series exhibit ARCH effects: the null of no ARCH effects is rejected for 60% (66%) of the sample banks at the 1% (5%, 10%) significance level.

Further, we examine the unconditional distribution of the log differences of the CDS spreads and check for non-normality and heavy tails. Results on Jarque-Bera (JB) tests are listed in columns 8 and 9 of Table 2.3 and show that the null of normally distributed log differences is rejected in all cases. Unreported results on Kolmogorov-Smirnov and Shapiro-Wilk tests confirm this finding. To check for heavy tails, we compute tail indices and study quantile plots. We use the well-investigated Hill estimator for the computation of lower and upper tail indices (see Hill, 1975, for details), and present the estimates in columns 10 and 11 of Table 2.3.[14] The tail indices vary considerably across the sample banks, where the mean upper and lower tail indices are respectively given by 2.3 and 3.0, indicating that the unconditional distribution of the log differences of the CDS spreads is heavy-tailed with heavier left tails on average. An analysis of unreported quantile plots confirms these findings.

As stated by Bera and Higgins (1993) as well as by Bollerslev et al. (1994), fat tailedness in unconditional distributions might be caused by ARCH effects. To check for fat tailedness in the conditional distributions, we compute tail indices for the AR-GARCH residuals of the time series. The unreported results show that, after accounting for ARCH effects, the tail indices remain in the same range and fluctuate around approximately the same means. Hence, the log differences of the spreads of the average sample bank exhibit a heavy-tailed conditional distribution with heavier left tails.

Finally, we check for asymmetries in conditional volatility and jointly conduct the Sign Bias Test, the Negative Size Bias Test as well as the Positive Size Bias Test as proposed by Engle and Ng (1993). More precisely, we test the null that the squared AR-GARCH residuals of the time series cannot be predicted by the sign and the magnitude of shocks in log-differenced CDS spreads. As can be seen from column 13 of Table 2.3,

[14] When applying the Hill estimator, one difficulty is given by the appropriate choice of the threshold k. Here, we follow Guillou and Hall (2001) and apply their diagnostic procedure with parameters $p = 1$ and $c_{\text{crit}} = 1.25$ to compute k.

the p-values of the test are quite large for all series, indicating that there is no predictive power in the shocks with regard to the squared AR-GARCH residuals. Hence, we find no evidence of asymmetric conditional volatility in any of the time series.

2.2.2 Univariate modeling of CDS spreads

We now discuss the marginal models for the log differences of CDS spreads. According to the previous section, the time series of the log-differenced CDS spreads are stationary, autocorrelated and conditionally heteroskedastic. We therefore use an AR(m)-GARCH(p,q) model to account for these time series properties, where $m, p, q \in \mathbb{N}$ denote the number of lags considered in the AR and GARCH equations. To additionally account for skewness and fat tails in the conditional distribution, we assume the conditional distributions of the innovations to follow the skewed t distribution of Hansen (1994). In formal terms, our univariate model approach can be described as follows: with $CDS_{i,t}$ denoting the CDS spread of bank i at time t ($i = 1, ..., N$, $t = 1, ..., T$), the log differences of CDS spreads are given by

$$R_{i,t} = \log(\text{CDS}_{i,t}) - \log(\text{CDS}_{i,t-1}). \tag{2.1}$$

As mentioned above, the CDS spread index, $\text{CDS}_{m,t}$, is calculated as an equally-weighted average of individual CDS spreads across all sample banks. Hence, the log differences of the spread index at time t, $R_{m,t}$, are given by

$$R_{m,t} = \log(\text{CDS}_{m,t}) - \log(\text{CDS}_{m,t-1}), \quad \text{CDS}_{m,t} = \frac{1}{N}\sum_{i=1}^{N} \text{CDS}_{i,t}. \tag{2.2}$$

Further, let $\tilde{t}_{\nu,\lambda}$ denote Hansen's (1994) skewed t distribution with ν degrees of freedom and skewness parameter λ, and let $\mathcal{F}_{i,t}$ be the information available on the time series of the log-differenced CDS spreads of bank i up to and including time t. Assuming an AR(m)-GARCH(p,q) model, the log difference of the CDS spread of bank i at time t

follows the dynamic

$$R_{i,t} = \mu_{i,t} + \varepsilon_{i,t} = \mu_{i,t} + \sqrt{h_{i,t}}z_{i,t}, \quad z_{i,t}|\mathcal{F}_{i,t-1} \sim \tilde{t}_{\nu_i,\lambda_i}, \tag{2.3}$$

$$\mu_{i,t} = \phi_{0,i} + \sum\nolimits_{j=1}^{m} \phi_{j,i}R_{i,t-j}, \tag{2.4}$$

$$h_{i,t} = \omega_i + \sum\nolimits_{k=1}^{p} \alpha_{k,i}\varepsilon^2_{i,t-k} + \sum\nolimits_{l=1}^{q} \beta_{l,i}h_{i,t-l}, \tag{2.5}$$

where the parameters in the conditional mean and variance equation are restricted to be positive, $2 < \nu_i < \infty$ and $-1 < \lambda_i < 1$ for all $i = 1, ..., N$.[15]

Estimation is conducted in two steps: first, we estimate the AR component using conditional least squares and then estimate the GARCH model on the basis of the AR residuals straightforwardly by maximum likelihood. The log likelihood of the GARCH component for bank i is given by

$$\mathcal{L}(\epsilon_i;\theta_i) = \sum_{t=1}^{T}\left[\log(b_ic_i) - \frac{1}{2}\log(h_i) - \frac{\nu_i+1}{2}\log\left(1+\frac{1}{\nu_i-2}\left(\frac{b_i\epsilon_{i,t}h_i^{-\frac{1}{2}}+a_i}{1+\text{sgn}(d_i)\lambda_i}\right)^2\right)\right] \tag{2.6}$$

where $\epsilon_i := (\hat{\varepsilon}_{i,1}, ..., \hat{\varepsilon}_{i,T})^\top$ denotes the vector of AR residuals, θ_i is the $(4+m+p+q)\times 1$ vector containing the model parameters (for bank i), and

$$a_i = 4\lambda_i c_i \frac{\nu_i - 2}{\nu_i - 1}, \quad b_i = \sqrt{1+3\lambda_i^2 - a_i^2}, \quad c_i = \frac{\Gamma\left(\frac{\nu_i+1}{2}\right)}{\sqrt{\pi(\nu_i-2)}\Gamma\left(\frac{\nu_i}{2}\right)}, \quad d_i = \frac{\epsilon_{i,t}}{\sqrt{h_i}} + \frac{a_i}{b_i}. \tag{2.7}$$

2.2.3 Joint modeling of CDS spreads with the DAC model

We now turn to the task of modeling the joint distribution of log differences of CDS spreads and the CDS spread index. Since we are especially interested in joint extreme movements in individual spreads and the spread index as a potential determinant of individual spreads, we rely on a copula model that allows for tail dependence. Naturally,

[15] Note that the distribution of shocks in log-differenced CDS spreads differs across banks, but is constant over time, whereas the distributions of the log differences have time varying conditional means and variances.

the multivariate dependence structure changes through time and might be characterized by strong asymmetries in the sense of asymmetric threshold correlations.[16] To flexibly model the dependence between spreads and our spread index and account for underlying time dynamics as well as multivariate asymmetries, we follow in the footsteps of Christoffersen et al. (2012) by applying their so-called Dynamic Asymmetric Copula (DAC) model to the AR-GARCH filtered spread and index log differences.[17]

The DAC model is based on the skewed t copula discussed in Demarta and McNeil (2004), which is parameterized by the correlation matrix of the copula shocks, an asymmetry parameter and a degree of freedom parameter. The correlation matrix of the copula shocks is then modeled by means of a modified version of Engle's (2002) DCC model, which augments the DCC model by a time-varying matrix capturing time trends and other explanatory variables. In this way, the DAC model accounts for tail dependence, asymmetries and time dynamics in multivariate distributions.

The model takes the following form: let $R_{i,t}$ and $R_{m,t}$ be the log differences of the CDS spread of bank i and the spread index at time t, respectively, and let $\hat{z}_{i,t}$ and $\hat{z}_{m,t}$ denote the AR-GARCH residuals, with $u_{i,t} := F_{i,t}(\hat{z}_{i,t})$ and $u_{m,t} := F_{m,t}(\hat{z}_{m,t})$ being the corresponding ranks. Then, the skewed t copula, C_t, is defined by

$$C_t(u_{1,t}, ..., u_{N,t}; P_t, \gamma, \eta) = t_{P_t,\gamma,\eta}(t^{-1}_{\gamma,\eta}(u_{1,t}), ..., t^{-1}_{\gamma,\eta}(u_{N,t})) \tag{2.8}$$

where γ and η denote the asymmetry and degrees of freedom parameters, respectively, and $t_{P_t,\gamma,\eta}$ and $t^{-1}_{\gamma,\eta}$ are the multivariate cdf and the univariate inverse cdf of the skewed

[16]In a recent study, Christoffersen et al. (2013) show that the dependence in CDS spreads is highly time-varying, persistent, and increased significantly in the financial crisis. Multivariate asymmetries in CDS spreads appear to be less important than asymmetries in equity returns but should nevertheless be accounted for in econometric models of spreads. Note that their study differs significantly from ours due to the fact that their work is only concerned about the documentation of time-varying non-linearities in the dependence structure of CDS spreads and equity returns. Moreover, their work studies the dependence structure between individual firm pairs, while we study the significance of the dependence between a firm's CDS and a CDS index as a priced factor in CDS spreads.

[17]The dependence structure in CDS spreads is also studied with the use of copula models in the recent work of Oh and Patton (2013). In the context of measuring systemic risks, they propose a new class of copula-based dynamic models for high-dimensional conditional distributions of bank CDS premia. In contrast to our work, however, their study centers around the estimation of the probability of the banks' joint distress rather than using the information on dependence in CDS spreads in an asset pricing study.

t distribution discussed in Demarta and McNeil (2004).[18] P_t is the correlation matrix containing the correlations between the copula shocks $z_{i,t}^c := t_{\gamma,\eta}^{-1}(u_{i,t})$, and follows the dynamic

$$P_t = (1 - \psi_1 - \psi_2)\left[(1-\kappa)Q + \kappa D_t\right] + \psi_2 P_{t-1} + \psi_1 \tilde{z}_{t-1}^c \tilde{z}_{t-1}^{c\top} \tag{2.9}$$

where ψ_1, ψ_2 and κ are non-negative parameters, and $\tilde{z}_t^c := (\tilde{z}_{1,t}^c, ..., \tilde{z}_{N,t}^c)^\top$ with $\tilde{z}_{i,t}^c$ given by $z_{i,t}^c \sqrt{P_{ii,t}}$ (see Aielli, 2009, for details). Further, Q is a constant copula correlation matrix calculated as

$$Q = \frac{T^{-1}\sum_{t=1}^{T} \tilde{z}_t^c \tilde{z}_t^{c\top} - \kappa T^{-1}\sum_{t=1}^{T} D_t}{1-\kappa}, \tag{2.10}$$

and D_t is a time trend correlation matrix with trend parameter δ, where the off-diagonal elements are equal to

$$\frac{\delta^2 t^2}{1+\delta^2 t^2}, \quad t = 1, ..., T. \tag{2.11}$$

We refer to Christoffersen et al. (2012) for details on the matrices Q and D_t. Note, however, that setting $\kappa = 0$ yields Engle's (2002) DCC model as applied to copula correlations.

Finally, to ensure that P_t remains in the -1 to 1 interval, we normalize P_t and use the matrix $\tilde{P}_t$ that is defined by

$$\tilde{P}_{ij,t} = \frac{P_{ij,t}}{\sqrt{P_{ii,t}P_{jj,t}}}, \quad i, j = 1, ..., N. \tag{2.12}$$

The DAC model is estimated straightforwardly by maximum likelihood in our bivariate case. Details of the DAC model can be found in Christoffersen et al. (2012).

Note that it could be argued that rather than using a bivariate model for the CDS spreads of individual banks and a sector index, the dependence structure in the CDS

[18] See Demarta and McNeil (2004) for details on the skewed t distribution and the skewed t copula. Note, however, that Hansen's (1994) skewed t distribution (used for the marginals) is different from that discussed in Demarta and McNeil (2004) (used for the joint distribution).

spreads should rather be modeled using a multivariate model like the one, e.g., proposed by Oh and Patton (2012). However, we believe that our bivariate model possesses two main advantages over such a multivariate approach. First, our economic motivation for the bivariate model is the notion that the default risk of individual banks is sensitive to extreme spikes in the default risk of the whole banking sector (proxied by the index) rather than a subset of banks or other individual banks. Second, and more importantly, our bivariate estimation setup ensures that our CDS tail beta is directly comparable to alternative measures of downside and tail risk which are all estimated from bivariate rather than multivariate models (beta, downside beta, equity tail beta, MES) and that are tested later in our robustness checks.

2.2.4 Estimation results

We first summarize the estimation results for the univariate AR(m)-GARCH(p,q) models. We individually choose the AR lag m for each time series such that the LB(20) test cannot be rejected at the 10% significance level. According to (unreported) preliminary tests, setting the GARCH lags p and q to 1 is sufficient to adequately account for ARCH effects in the AR residuals. The estimation results for the AR-GARCH models are reported in columns 2 to 6 of Table 2.4.[19] The parameters governing the conditional volatility are given by ω, α and β. The ω parameter is close to zero (0.0002 for the average sample bank) and not listed in the table. The α parameter quantifies the effect of lagged shocks on current volatility and varies from 0.1377 (EFG) to 0.6600 (MDIBF) (0.3142 on average). Interestingly, volatility in the log differences of CDS spreads seems to be affected to a greater extent by news arrival than volatility in stock price returns.[20] The autoregressive variance parameter, β, is however dominating in most cases and varies from 0.3286 (MDIBF) to 0.8623 (EFG) (0.6751 for the average sample bank).

[19]Note that the results on the AR processes are fairly standard and, therefore, have been omitted to preserve space.

[20]Typically, α is between 0.01 and 0.2 for stock price returns (see, e.g., Christoffersen et al., 2012; Engle, 2002; Kang et al., 2010).

Table 2.4: Parameter estimates for marginal and DAC models.

The table reports the estimation results for the parameters of the univariate AR-GARCH and the bivariate Dynamic Asymmetric Copula (DAC) models. The univariate models are estimated for the log differences of CDS spreads of 35 European banks as well as for the log differences on a CDS spread index, which is calculated as an equally-weighted average of the log differences of individual CDS spreads across all sample banks. The DAC models are estimated on the basis of the AR-GARCH filtered time series of log-differenced CDS spreads, where each model estimation employs the filtered log differences on the corresponding bank's spread and the spread index. The estimation period contains daily observations of the log differences of CDS spreads for the period from January 2004 to October 2010. Company names are abbreviated by their corresponding Bloomberg ticker symbols listed in Table A.1 in Appendix A.

	Marginal models					DAC model					
	α	β	Vol. Pers.	ν	λ	ψ_1	ψ_2	Dep. Pers.	κD_T	η	γ
ACA	0.2069	0.7666	0.9735	3.6469	**-0.0101**	0.0229	0.9744	0.9973	0.5291	8.5491	-0.0369
AIBSF	0.2941	0.6968	0.9909	2.9629	0.0721	0.0140	0.9836	0.9977	**0.6930**	7.5691	0.0384
ALPHA	0.2769	0.7214	0.9984	2.2702	0.5488	0.0252	0.9507	0.9759	**0.0114**	19.8142	-0.0816
BBPI	0.3762	0.6227	0.9989	2.8229	0.3890	0.0395	0.9442	0.9837	0.3272	12.1625	0.1301
BBVA	0.2471	0.7422	0.9893	3.8943	0.0074	0.0246	0.9625	0.9870	0.1679	6.7369	-0.0704
BCPSF	0.6477	0.3511	0.9988	2.6674	0.3557	0.0238	0.9621	0.9859	0.0463	27.0842	-0.0417
BILMI	0.5289	0.4635	0.9924	**2.1820**	0.0622	0.0303	0.7675	**0.7978**	0.2821	10.8310	0.1668
BKESF	0.2474	0.7271	0.9746	3.8432	0.0062	0.0213	0.9685	0.9898	0.0507	7.7725	-0.0608
BKT	0.3971	0.6028	0.9998	3.4692	0.6522	0.0254	0.9685	0.9939	0.5703	40.0387	-0.0632
BMDPF	0.2153	0.7611	0.9763	3.5651	0.0184	0.0175	0.9819	0.9995	0.4144	7.3930	-0.0739
BNP	0.2359	0.7564	0.9922	3.4535	0.0229	0.0301	0.9662	0.9963	0.4395	10.8584	-0.0505
BPCGF	0.2171	0.7677	0.9848	3.2963	0.0209	0.0161	0.9772	0.9934	0.4197	**6.3547**	-0.0378
BPESF	0.4099	0.5900	**0.9999**	2.5593	0.2215	0.0233	0.9682	0.9915	0.4345	18.2846	-0.0237
BPI	0.2083	0.7838	0.9921	2.5184	0.0259	0.0198	0.9750	0.9948	0.4800	7.6221	-0.0240
BPMLF	0.3559	0.6391	0.9951	2.6323	0.0275	0.0329	0.9324	0.9653	0.1310	8.5463	-0.1648
CBK	0.1658	0.8100	0.9759	3.4318	0.0285	0.0163	0.9781	0.9944	0.1340	7.1854	-0.0686
CRIH	0.2663	0.7027	**0.9690**	4.3997	0.0409	0.0549	0.9116	0.9665	0.3243	8.5105	-0.0845
DBK	0.2485	0.7261	0.9745	3.6673	0.0061	0.0210	0.9738	0.9948	0.3511	7.9692	0.0029
DEXB	0.3626	0.6348	0.9974	2.8269	0.0650	0.0106	0.9833	0.9940	0.6609	13.4871	0.1107
EBKOF	0.3565	0.6430	0.9995	4.0014	0.5384	0.0415	0.8679	0.9094	0.2662	35.7974	0.1141
EFG	**0.1377**	**0.8623**	**0.9999**	26.0850	**0.6854**	0.0219	0.9241	0.9460	0.2663	8.0972	**-0.1871**
FSVVF	0.3597	0.6341	0.9938	2.5206	0.0917	0.0211	0.9628	0.9839	0.1997	21.6306	-0.1760
GLE	0.2963	0.6922	0.9884	3.7181	0.0104	0.0134	0.9817	0.9951	0.5660	6.5029	-0.0566
IITSF	0.2336	0.7569	0.9905	3.2646	0.0299	0.0168	0.9829	**0.9996**	0.4555	7.8506	-0.1227
IKB	0.2978	0.7017	0.9995	3.5624	0.2423	**0.0849**	**0.7587**	0.8436	0.1271	16.1319	0.1415
ILB	0.4444	0.5477	0.9921	2.9080	0.2991	0.0155	0.9699	0.9854	0.0229	9.3784	-0.1179
ING	0.2814	0.6933	0.9747	3.7465	0.0290	0.0324	0.9609	0.9933	0.1212	12.4257	0.0436
IRLBF	0.3882	0.5958	0.9840	2.7789	0.0574	0.0636	0.8492	0.9128	0.3106	7.5032	0.0122
KBC	0.3037	0.6912	0.9949	2.9082	0.0785	0.0420	0.9165	0.9585	0.3798	14.5729	-0.0407
KN	0.3926	0.6002	0.9928	3.0278	0.0581	0.0399	0.8804	0.9203	0.3682	12.1134	-0.1591
MDIBF	**0.6600**	**0.3286**	0.9886	2.5534	0.0303	0.0310	0.9611	0.9921	0.3241	**56.5642**	0.0670
SAB	0.3589	0.6337	0.9926	2.9243	0.1002	0.0275	0.8309	0.8583	0.5086	6.8406	**0.1857**
SAN	0.2605	0.7275	0.9880	4.1337	-0.0034	0.0173	0.9747	0.9919	0.5778	7.7209	-0.0595
UBI	0.1386	0.8614	**0.9999**	**58.1108**	0.1549	0.0299	0.9557	0.9855	0.1724	10.5766	0.0118
UNBLF	0.3180	0.6561	0.9741	2.4128	0.0125	**0.0101**	**0.9887**	0.9988	0.3490	10.0678	-0.0952
Index	0.1746	0.8113	0.9859	4.2450	0.0805	-	-	-	-	-	-
Average	0.3142	0.6751	0.9893	5.3614	0.1405	0.0279	0.9399	0.9678	0.3281	13.7298	-0.0249

As indicated by the fourth column, volatility is highly persistent for all time series of log-differenced CDS spreads. The parameter estimates for the conditional distribution of the innovations show that the skewed t GARCH model fully accounts for the evidenced fat tailedness (as indicated by the degrees of freedom parameter being equal to 5.36 on average) and picks up much of the skewness found in Table 2.2.

The (unreported) results on the LB(20) tests confirm the good fit of the marginal models and indicate that there is no autocorrelation left in the AR-GARCH residuals (with the p-value being equal to 0.5816 on average). Further, we conduct LB(20) tests on the absolute residuals as well as Engle's (1982) ARCH LM test to evaluate the performance of the GARCH component. The average p-values of the two tests are 0.6451 as well as 0.8951, respectively, indicating that the AR-GARCH models pick up the persistence in absolute log differences of CDS spreads and adequately account for ARCH effects. Hence, the marginal models generate white-noise residuals so that the theoretical requirements for the application of the DAC model are met.

The parameter estimates for the DAC model are reported in columns 7 to 12 of Table 2.4. The first four columns of the DAC estimates refer to the parameters characterizing the conditional correlation dynamics of the copula shocks. The conditional correlation matrix mean-reverts at time t to a slowly varying component, $(1-\kappa)Q + \kappa D_t$, which is a weighted average of the constant matrix Q (containing average copula correlations) and the time-varying matrix D_t (accommodating for time trends in copula correlations). The ψ_2 and ψ_1 parameters capture the impact of lagged copula correlations as well as the cross-product of lagged copula shocks on current copula correlations, respectively, where $\psi_1 + \psi_2$ yields the persistence in dependence and $1 - \psi_1 - \psi_2$ governs the speed of mean-reversion. As we can see from the estimates, the autoregressive parameter, ψ_2, ranges from 0.7587 (IKB) to 0.9887 (UNBLF) and is 0.9399 on average, dominating the ψ_1 parameter for all banks in the sample. As indicated by the third column of the DAC estimates, the persistence in the dependence structure is high in all models, implying slow mean-reversion in copula correlations. The next column refers to the long-run copula correlations and reports the parameter estimates characterizing the matrix D_t. To identify the portion of the increase in long-run correlations that is due to the time trend component, we follow Christoffersen et al. (2012) and report $\kappa D_{12,T}$.[21] The increases are positive for all banks in the sample and are 0.3281 on average, indicating that our sample period is characterized by a strong upward trend in copula correlations. This is confirmed by Panels (a) and (b) of Figure 2.3. Panel (a) plots average daily dynamic copula correlations (solid line) along with the range between the smoothed series of minimum and maximum correlations (shaded area) as well as the average constant correlations (dashed line). As we can see from the panels, the dynamic correlations are close to the constant correlations in the beginning of the sample and have been on a slight downward trend as of mid-2005, falling below the constant correlations prior to the financial crisis. With the onset of the financial crisis in 2007, however, the copula correlations have been trending upwards, increasing considerably from 20% in 2007 to 60% in 2010. Hence, the average dynamic correlations are below the constant correlations in the pre-crisis period, and are higher in the end of our sample period, reflecting the importance of considering the evolution and time trends of the general dependence level in the DAC framework.

In our empirical study, we investigate whether the propensity of an individual bank to jointly crash with the banking sector is priced in the bank's CDS premia. To this purpose, we introduce the upper tail dependence between individual log differences of CDS spreads and the log differences of the spread index as a potential determinant of individual spreads and call this determinant CDS tail beta. In our DAC model framework, bank's i CDS tail beta at time t can be measured via the probability limit

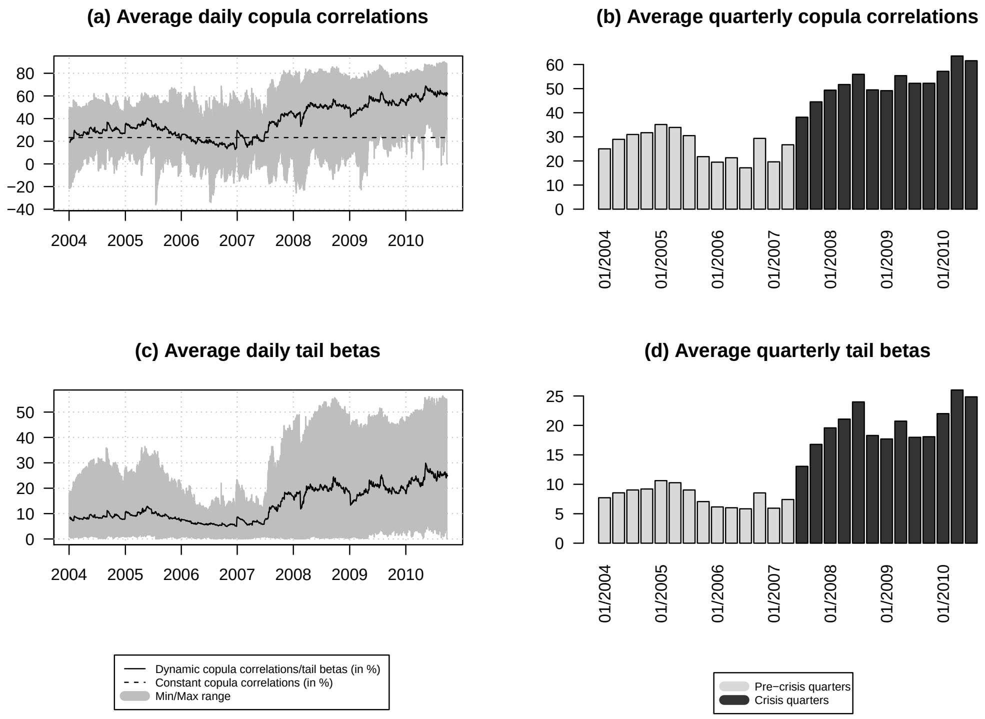
$$\text{CDS tail beta}_{i,t} := \lim_{\xi \to 1} \mathbb{P}\left(u_{i,t} \geqslant \xi | u_{m,t} \geqslant \xi\right) = \lim_{\xi \to 1} \frac{1 - 2\xi + C_t(\xi, \xi; P_t, \gamma, \eta)}{1 - \xi}. \quad (2.13)$$

Panels (c) and (d) of Figure 2.3 show the time evolution of the average daily and quarterly tail betas for our sample period, respectively, where the average is taken across the individual tail betas of the 35 sample banks.

[21]Note that the increase due to the time trend component can be calculated as $\kappa D_{12,t}|_{t=T} - \kappa D_{12,t}|_{t=0} = \kappa D_{12,T} = \kappa\delta^2 T^2/(1 + \delta^2 T^2)$, see Christoffersen et al. (2012).

Figure 2.3: Copula correlations and CDS tail betas.

The panels of this figure show the time evolution of average daily/quarterly dynamic copula correlations and CDS tail betas (denominated in %). The sample period contains daily data from January 2004 to October 2010 and the average is taken across all 35 sample banks. The daily panels show the average daily dynamic (solid line) and constant (dashed line) copula correlations, the average daily CDS tail betas (solid line) as well as the minimum/maximum range for correlations and tail betas, smoothed by a moving average (gray area). The quarterly panels show the average quarterly copula correlations and tail betas, where each quarter in the sample period is represented by a bar. (Pre-)crisis quarters are colored in (light) gray. Copula correlations and CDS tail betas are estimated from the Dynamic Asymmetric Copula (DAC) model, where the tail betas are approximated by numerical integration using $\xi = 0.001$ (see Christoffersen et al., 2012, for details).



As we can see from the panels, the time evolution and trend patterns of tail betas are similar to those of copula correlations. Since the beginning of the sample in 2004, tail betas have been on a slight downward trend, reaching its minimum of 5% in mid-2007. With the onset of the financial crisis, the downward trend abruptly turns into a strong upward trend, and tail betas increase dramatically up to 25%. As can be seen from the quarterly tail betas in Panel (d), the downward trend comes to a halt in the second quarter of 2007. Further, much of the following sharp upward trend is captured in the last two quarters in 2007 and the first three quarters in 2008. In the sequel, the trend corrects and returns to its 2008 levels in the second quarter of 2010.

For increased transparency, Figure 2.4 depicts the time evolution of daily single-bank CDS tail beta estimates for all banks in our sample. As can be seen from the panels, the general pattern in the evolution of tail betas is quite similar across the sample banks. Staying at rather moderate levels in the pre-crisis period, tail betas experience a strong upward trend during the financial crisis as of mid-2007. While this pattern can be found for most of our sample banks (see, e.g., BNP Paribas, Crédit Agricole, and Deutsche Bank), there are, however, some banks for which this pattern is somewhat less pronounced (see, e.g., Alpha Bank and IKB).

Figure 2.4: Single-bank CDS tail beta estimates.

The figure shows the time evolution of daily single-bank CDS tail beta estimates (denominated in %). The sample period contains daily data from January 2004 to October 2010 and the sample banks comprise the 35 European banks listed in Table A.1 in Appendix A. The panels show raw tail beta estimates (gray line) as well as smoothed tail beta estimates (black line) resulting from applying moving averages to the raw estimates. CDS tail betas are estimated from the Dynamic Asymmetric Copula (DAC) model, where the tail betas are approximated by numerical integration using $\xi = 0.001$ (see Christoffersen et al., 2012, for details).

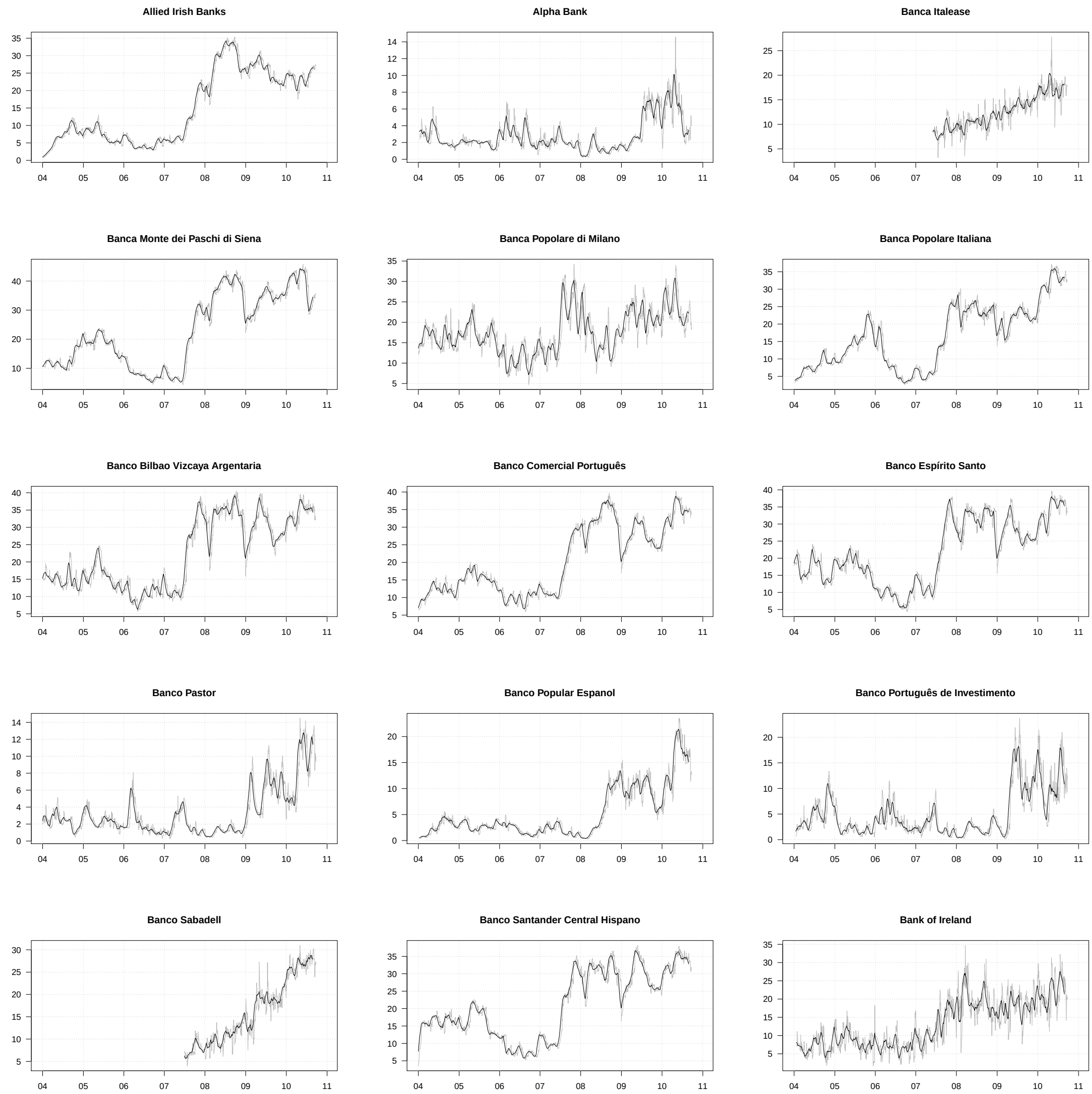
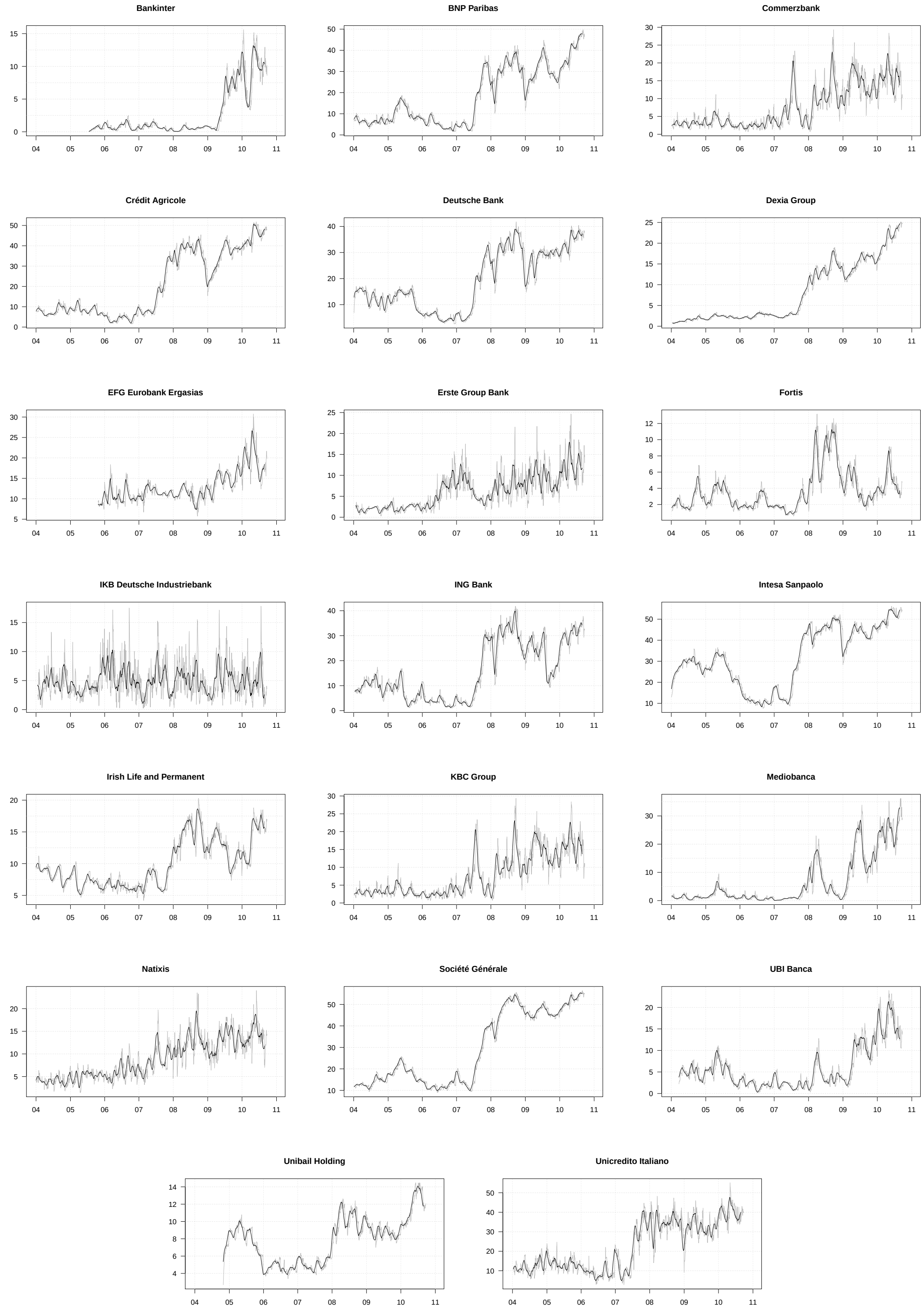


Figure 2.4: Single-bank CDS tail beta estimates (continued).



2.3 Empirical analysis

We aim to answer the question to what extent, if any, tail risk is a priced factor in bank-specific CDS contracts. This section briefly outlines the empirical model and presents our main results. Robustness checks are given at the end of this section.

2.3.1 Main dependent and independent variables

We begin our analysis by briefly reviewing the theoretical determinants of default risk and CDS spreads that are frequently stated in the literature. All variable definitions and data sources are provided in Table A.3 in Appendix A.

In the seminal framework of Merton (1974), a firm's default probability is determined by the firm's leverage (or its value), its asset volatility and the risk-free rate. An increase in the firm's leverage (and conversely, a decrease in firm value) is associated with higher default risk and thus higher CDS spreads. Due to limited balance sheet data, the leverage ratio cannot be measured directly. Moreover, especially off-balance sheet items may not be captured by conventional balance sheet-based proxies of leverage. For this reason, we follow Christie (1982) and Collin-Dufresne et al. (2001) and proxy a bank's change in firm value by using quarterly arithmetic stock returns. Data on daily equity prices are obtained from *Datastream* for all 35 banks in our sample and we expect our variable *Firm value* to be negatively correlated with CDS spreads.

As a second measure of leverage, we also compute the banks' market-based leverage ratios as proposed in Acharya et al. (2010). Their measure of leverage is defined as the ratio of the quasi-market value of assets (defined as the book value of assets minus book value of equity plus the market value of equity) over the market value of equity.

Next, we turn to the expected causal relation between asset volatility and CDS spreads. In theory, higher levels of asset volatility should be associated with higher default probabilities. As a consequence, we expect asset volatility and CDS spreads to be positively correlated. In line with Alexander and Kaeck (2008), we use the variable *Volatility* defined as end-of-quarter values of the VSTOXX implied volatility index to proxy for unobservable asset volatility.[22] The VSTOXX index is inferred from EURO STOXX 50 realtime option prices and mirrors expectations of market participants with respect to future levels of volatility.

Turning to the risk-free rate, increases in the risk-free rate should theoretically lead to lower CDS spreads, since the asset value process recedes from the default barrier. We employ a short-term 1-year Euro swap rate as our variable *Risk-free interest rate* as, e.g., Longstaff et al. (2005) argue that swap rates represent adequate marked-based estimates of the risk-free rate. Nevertheless, we are aware of the fact that short-term interest rates may also reflect the stance of monetary policy and may therefore affect bank business models. Accordingly, we expect the sign of the coefficient on the risk-free rate to be unrestricted. Both the VSTOXX volatility index and short-term swap rates are retrieved from *Datastream*.

Complementing the factors proposed in Merton's model, several further factors have been suggested in the recent literature as potential drivers of default risk and CDS spreads. First, the theoretical and empirical results of Bongaerts et al. (2011) predict and confirm that CDS spreads contain a premium for the contract's marketability. Similar to the results of Campbell and Taksler (2003) and Longstaff et al. (2005) for credit spreads, CDS spreads should thus in part be driven by their illiquidity (see also Annaert et al., 2013). To account for liquidity effects, we additionally collect end-of-quarter bid and ask quotes (in basis points) from *Datastream* and follow Ericsson et al. (2009) in that bid and ask quotes are treated separately in our regression models.

Additionally, CDS spreads could also be driven by the business climate of the bank's home country. There is ample evidence in the empirical literature (see Longstaff et al., 2005; Zhang et al., 2009) that credit risk premia are sensitive to changes in the business climate in which a firm operates. We thus include end-of-quarter values of the S&P 500 index as our variable *Business climate* in our regressions to account for general stock market momentum. Positive index changes are associated with declining default proba-

[22] Benkert (2004) provides evidence in favor of option-implied volatilities over historic volatility measures as option-implied volatilities explain a greater amount of variation in CDS spreads than there empirical counterparts.

bilities and increasing recovery rates, and should therefore be negatively correlated with CDS spreads. Another factor that could affect the pricing of credit protection is the overall stance of the economy as proxied by the growth of the economy. In the context of our analysis, *GDP growth* is a relevant control variable because recent studies like, e.g., the one by the Committee on the Global Financial System (2011) suggest that banks are particularly exposed to their home sovereign as well as to domestic credit markets. At the country level, GDP growth is likely to be accompanied with increasing borrowers' solvency and a lower overall risk exposure of financial institutions to their domestic market. Consequently, we associate increasing growth rates with declining bank-specific default risk premia. Data on quarterly GDP growth rates are obtained from the OECD.

Finally, we also employ the slope of the yield curve as a further explanatory variable in our regression analyses. Here, we use the yield curve slope as an indicator for the country-wide future economic activity of a bank's home country. Our variable *Slope* is defined as a country's respective 10-year minus 2-year government bond benchmark yields. Data on government bond yields are taken from *Datastream*. In theory, spot rates converge to their long-term counterparts, thereby increasing the risk-neutral drift of the asset value process making default less likely to occur (see Longstaff et al., 2005). Nevertheless, also monetary policy measures may be reflected in the slope coefficient. Hence, we expect the direction of the effect of the yield curve slope on CDS spreads to be unrestricted.

Table 2.5 reports sample summary statistics. Mean CDS spreads and log differences of CDS spreads across our full sample are 93.89 bps and -1%, respectively. Estimates for the banks' CDS tail betas vary between 0.07 and 0.55 with the mean CDS tail beta being around 0.14. Log returns on the banks' stocks in our sample exhibit the usual stylized facts. Similar to CDS tail beta, equity tail betas also vary considerably around the mean of 0.33 with a minimum value of zero and a maximum of 0.96. Our proxy for the change in a bank's firm value is zero on average with values ranging from -79% to 230%. Finally, we follow Acharya et al. (2010) and estimate their measure of systemic relevance, the MES.

Table 2.5: Descriptive statistics.

The table shows descriptive statistics on quarterly sampled CDS spreads, log differences of CDS spreads, and equity log returns for the 35 sample banks over: Q1:2004 to Q3:2010. Additionally, we report descriptive statistics for all explanatory variables used in our regression models, sampled quarterly. We report the number of observations, minimum and maximum values, percentiles and moments. All *Merton-type* and *Alternative risk measure* variables are denoted in %. All variables and data sources are defined in Table A.3 in Appendix A.

			Percentiles							Moments			
	Obs	Min	1st	5th	20th	80th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.
CDS/Equity variables													
- CDS spread	903	1.00	6.02	8.42	12.50	145.00	369.14	698.23	1048.80	93.89	141.03	3.29	17.43
- Log difference CDS spread	929	-4.01	-0.19	-0.07	-0.02	0.02	0.07	0.12	1.38	-0.01	0.16	-17.53	469.02
- CDS tail beta	900	0.00	0.00	0.01	0.04	0.24	0.37	0.49	0.55	0.14	0.12	1.11	3.51
- Equity log return	938	-0.13	-0.05	-0.02	-0.01	0.01	0.04	0.09	0.31	0.00	0.03	3.63	35.16
- Equity tail beta	937	0.00	0.00	0.07	0.13	0.51	0.67	0.85	0.96	0.33	0.20	0.48	-0.42
Merton variables													
- GDP growth	945	-4.08	-3.63	-1.63	-0.29	0.87	1.37	2.93	5.45	0.26	1.02	-0.60	7.73
- Interest	945	0.87	0.87	0.94	1.19	4.43	4.74	5.29	5.29	2.82	1.38	0.16	1.71
- Firm value	939	-78.89	-58.15	-34.09	-14.62	11.86	31.70	88.08	229.64	0.10	25.84	2.77	24.09
- S&P 500	945	797.87	797.87	903.25	1114.58	1335.85	1503.35	1526.75	1526.75	1206.82	175.44	-0.21	2.84
- Slope	945	-0.87	0.00	0.09	0.33	1.98	2.51	2.92	3.73	1.11	0.82	0.44	2.22
- Volatility	945	12.38	12.38	13.24	14.56	27.31	42.41	43.87	43.87	22.33	8.92	1.11	3.23
- Leverage	937	1.51	1.72	2.79	9.40	41.37	104.36	426.58	744.12	35.86	63.39	6.16	50.22
Alternative risk measures													
- Beta	862	-0.59	-0.10	0.00	0.09	1.33	2.04	6.96	18.82	0.91	1.45	6.87	66.56
- Coskewness	803	-47.13	-40.26	-31.88	-10.22	6.34	18.03	30.69	87.74	-1.66	13.97	0.10	7.64
- Upside beta (median)	862	-1.51	-0.52	-0.15	0.04	1.25	2.45	9.82	17.59	0.86	1.54	5.62	45.36
- Upside beta (80%)	863	-9.63	-1.51	-0.63	-0.03	1.20	3.02	10.19	23.64	0.78	1.94	4.77	41.60
- Upside beta (90%)	863	-11.69	-3.29	-1.65	-0.31	1.46	3.73	12.02	29.39	0.74	6.22	4.14	37.08
- Upside beta (95%)	864	-70.11	-12.94	-3.00	-0.76	2.06	4.99	15.10	34.56	0.51	5.24	-4.89	72.43
Systemic risk measures													
- Static MES	903	-0.81	-0.27	0.41	1.15	4.78	9.45	13.84	19.05	3.30	2.81	1.87	7.63

As far as the exposure to system-wide tail events is concerned, our results suggest a certain amount of heterogeneity across the 35 banks included in our sample. The 5th percentile of the static MES estimates is at 0.41%, the higher percentiles range up to almost 14%. According to the MES, our sample of European banks thus seems to include both systemically less relevant banks as well as institutions with high exposures to systemic crashes.

2.3.2 Is tail risk priced in CDS contracts?

We are interested in analyzing the casual relation between *CDS tail beta* and both the time-series and the cross-section of banks' CDS spreads. Consequently, in a first step, we explain the time-series of credit risk by performing time-series regressions for each sample bank. In a second step, we estimate a fixed effects panel data model where we account for both time-series as well as cross-sectional effects.

2.3.2.1 Times-series regressions

We follow Collin-Dufresne et al. (2001) and Ericsson et al. (2009) and begin our empirical analysis by explaining the correlations over time between quarterly sampled CDS spreads and *CDS tail beta* as well as further control variables. In principle, the regression analyses could be carried out in levels or differences. In our case, the decision is based on a statistical reasoning. Since we find evidence for nonstationarity in our CDS time series in levels, we perform all regressions in first differences.

For each bank over Q1:2004 to Q3:2010 we estimate a time-series regression model and report all time-series regression coefficients as cross-sectional averages for the full sample and separated by quintiles of CDS tail beta in Table 2.6 and 2.7, respectively.[23] Note that we also estimate all our regression specifications separately for bid- and ask-quotes to control for potential liquidity effects. Nevertheless, we obtain very similar results for the liquidity-adjusted regressions.

[23]That is, we first compute average values of CDS tail beta and then assign each bank to a quintile based on its average CDS tail beta.

Table 2.6: Baseline time-series regressions.

The table reports coefficient estimates and corresponding t-statistics from time-series regressions in differences of quarterly sampled CDS mid-spreads on variables suggested by theory (Panel A) and the variable of interest, *CDS tail beta*, in Panel B. For each bank i over Q1:2004 to Q3:2010 we estimate the following regression model:

$$\Delta\text{CDS}_t^i = \alpha + \beta_1 \cdot \Delta\text{Firm value}_t^i + \beta_2 \cdot \Delta\text{Interest rate}_t^i + \beta_3 \cdot \Delta\text{Volatility}_t^i + \beta_4 \cdot \Delta\text{CDS tail beta}_t^i + \epsilon_t^i.$$

Variable definitions and sources can be found in Table A.3 in Appendix A. For all regressions, we present results on the full sample as well as separated by quintiles of *CDS tail beta*. Coefficients and t-statistics are calculated as outlined in Collin-Dufresne et al. (2001) and Ericsson et al. (2009). ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

		CDS tail beta quintile portfolios				
	Full sample	Q1	Q2	Q3	Q4	Q5
Panel A: Merton-type regressions						
ΔFirm value	-0.086	0.160	-0.148	-0.389	0.041	-0.091
	(0.862)	(0.490)	(0.967)	(1.166)	(0.868)	(1.033)
ΔInterest rate	0.611	13.206	-5.845	-14.555	3.077	7.171
	(0.109)	(0.714)	(0.4847)	(0.860)	(0.745)	(1.764)*
ΔVolatility	6.627	10.751	6.209	8.013	4.039	4.121
	(9.525)***	(5.517)***	(5.625)***	(5.114)***	(9.195)***	(4.921)***
Constant	9.104	13.198	4.231	15.275	6.040	6.775
	(5.194)***	(4.287)***	(2.591)***	(2.100)**	(3.398)***	(3.751)***
Adj. R^2	0.39	0.35	0.42	0.27	0.44	0.45
Avg. obs	25	25	26	21	26	26
Panel B: Baseline regressions						
ΔFirm value	-0.120	0.025	-0.210	-0.395	0.056	-0.074
	(1.203)	(0.077)	(1.403)	(1.155)	(1.107)	(0.710)
ΔInterest rate	-3.007	8.328	-9.122	-22.519	1.783	6.493
	(0.504)	(0.452)	(0.771)	(1.136)	(0.482)	(1.739)*
ΔVolatility	6.353	9.645	5.873	8.133	4.003	4.112
	(9.582)***	(5.194)***	(5.025)***	(5.027)***	(9.495)***	(4.856)***
ΔCDS tail beta	3.424	6.653	0.897	8.647	0.474	0.449
	(3.370)***	(3.444)***	(0.688)	(2.377)**	(1.108)	(1.278)
Constant	6.945	11.903	3.702	7.197	5.570	6.352
	(3.225)***	(3.628)***	(2.091)**	(0.699)	(3.555)***	(3.909)***
Adj. R^2	0.39	0.35	0.44	0.30	0.43	0.44
Avg. obs	25	25	25	21	26	26

Table 2.7: Time-series regressions with additional controls.

The table reports coefficient estimates and corresponding t-statistics from time-series regressions in differences of quarterly sampled CDS mid-spreads on variables suggested by theory, the variable of interest, *CDS tail beta*, and further controls. For each bank i over Q1:2004 to Q3:2010 we estimate the following regression model:

$$\Delta \text{CDS}_t^i = \alpha + \beta_1 \cdot \Delta \text{Firm value}_t^i + \beta_2 \cdot \Delta \text{Interest rate}_t^i + \beta_3 \cdot \Delta \text{Volatility}_t^i + \beta_4 \cdot \Delta \text{CDS tail beta}_t^i + \gamma \cdot \Delta \text{X}_t^i + \epsilon_t^i$$

where X_t^i denotes the following additional control variables: *Business Climate*, *GDP growth*, and the *slope of the yield curve*. Variable definitions and sources can be found in Table A.3 in Appendix A. For all regressions, we present results on the full sample as well as separated by quintiles of *CDS tail beta*. Coefficients and t-statistics are calculated as outlined in Collin-Dufresne et al. (2001) and Ericsson et al. (2009). ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

		CDS tail beta quintile portfolios				
	Full sample	Q1	Q2	Q3	Q4	Q5
ΔFirm value	-0.087	0.336	-0.257	-0.502	0.036	-0.049
	(0.725)	(0.987)	(2.397)**	(1.116)	(0.546)	(0.492)
ΔInterest rate	8.518	1.400	8.061	9.590	11.179	12.362
	(1.078)	(0.057)	(0.323)	(0.440)	(2.768)***	(2.204)**
ΔVolatility	4.748	8.877	4.369	3.997	2.978	3.521
	(6.476)***	(3.379)***	(5.064)***	(2.437)**	(6.384)***	(3.618)***
ΔCDS tail beta	2.019	7.067	0.864	1.058	0.698	0.409
	(1.823)*	(2.907)***	(1.124)	(0.222)	(2.181)**	(1.202)
ΔBusiness climate	-0.118	-0.040	-0.111	-0.352	-0.061	-0.027
	(2.415)**	(0.430)	(1.633)	(1.718)*	(2.755)***	(1.840)*
ΔGDP growth	-7.254	-25.196	-8.617	2.476	-2.950	-1.983
	(2.384)**	(2.677)***	(1.576)	(0.476)	(0.500)	(0.921)
ΔSlope	5.556	-30.915	29.066	2.424	14.518	12.689
	(0.463)	(0.915)	(0.768)	(0.077)	(1.500)	(1.349)
Constant	7.665	9.162	4.469	12.080	5.910	6.704
	(5.398)***	(4.717)***	(2.121)**	(1.941)**	(4.274)***	(4.442)***
Adj. R^2	0.45	0.42	0.58	0.35	0.46	0.44
Avg. obs	25	25	25	21	26	26

Hence, to preserve space, we only report the results for regressions on CDS mid-quotes. All additional regression results are available upon request.

In Panel A of Table 2.6 we first test empirically the determinants of CDS spreads suggested by theory: Firm value, the risk-free interest rate and implied volatility. For the full sample, we find that all variables enter the regression with the expected sign. Coefficients on the risk-free rate and volatility are positive whereas firm value enters with a negative coefficient. However, only changes in volatility are significantly correlated with changes in CDS spreads. The analysis of the quintile portfolios reveals mixed evidence. Although t-statistics indicate some explanatory power of changes in the interest rate in the upper quintile of CDS tail beta, again, only changes in volatility are associated with significantly positive changes in CDS spreads throughout all quintile portfolios. The average adjusted R^2 is around 39% and thus at a comparable yet slightly higher level as compared to Ericsson et al. (2009).

In Panel B of Table 2.6, we directly test the explanatory power of CDS tail beta on the time-series variation of CDS spreads. Our baseline specification shows that adding the variable of interest has almost no effect on the coefficient signs of the variables suggested by theory. The estimated sign on CDS tail beta is positive throughout all regression specifications suggesting that an increase in tail beta is associated with higher CDS spreads. Nevertheless, the coefficient is only statistically significant for the full sample as well as for the lowest and median quintile portfolio.

Complementing our baseline regressions, we also provide regression results in Table 2.7 in which we include further covariates as suggested in Section 2.3.1. The estimated coefficient sign on CDS tail beta remains positive throughout all specifications and is significantly different from zero at the 10% level for the full sample as well as for the first and fourth quintlie specification at significance levels of 1% and 5%, respectively. Changes in volatility increases CDS spreads whereas changes in the business climate and GDP growth are negatively correlated with changes in CDS spreads. The average adjusted R^2 is 45% and considerably higher as compared to the baseline regressions.

The results so far suggest that changes CDS tail beta is a relevant determinant in the time-series variation of bank-specific CDS spreads. The discussion in Section 2.1 suggests two potential channels how CDS tail beta might affect CDS spreads. In our time-series regressions, we find first evidence that tail risk is priced in CDS spreads via the supply-side, as the coefficient is consistently positively estimated. That is, concerns regarding the time variation of recovery rates might dominate potential demand side-driven concerns regarding counterparty risk. Nevertheless, we further need to mitigate concerns that unobservable individual bank characteristics affect our results. We address this issue in the subsequent section and present evidence from a panel data regression model in which we investigate the cross-sectional explanatory power of CDS tail beta for

CDS spreads.

2.3.2.2 Panel regressions - Full sample

This section presents results from panel regressions. All regressions use our full sample of 35 bank names and include bank-fixed effects to account for bank-specific heterogeneity. Corresponding to the time-series regression specifications above, we again use differences instead of levels since we obtain evidence of nonstationarity in our sample banks' CDS. Further, and consistent with our previous analyses, we also estimate all regression models separately for bid- and ask-quotes to control for the potential influence of liquidity.

Table 2.8 reports the results from our benchmark bank-fixed effects regressions.[24] The results presented in Column (1) verify that, consistent with our expectations, firm value and implied volatility are significant drivers of CDS spreads and enter the regression at the 10% and 1% level, respectively. The effect of changes in the interest rate is insignificant and positive.

In the second specification, we investigate the isolated effect of our variable of interest, CDS tail beta, on changes in CDS spreads. In Column (2) we present evidence that CDS tail beta significantly covaries with CDS spreads and is indeed a priced factor in CDS contracts. Sellers of credit protection are concerned about bank names that are more likely to fail, given an extreme market-wide increase in default probabilities. The estimated coefficient is statistically highly significant and large in magnitude.

These results are confirmed by univariate sorts based on CDS tail beta. For each bank in the sample, we first rank the time series of CDS spread observations into quintiles with respect to CDS tail beta, and then compute the average CDS spread for each tail beta quintile. Table 2.9 reports the results and shows that, for most banks, CDS spreads are monotonically increasing in CDS tail beta. The last column contains the difference between high and low tail beta quintile spreads and shows that spreads in high tail beta quintiles are, for the most part, considerably higher than spreads in low tail beta quintiles.

[24]Note that results from the Hausman test indicate that a fixed effects model should be preferred to a random effects model.

Table 2.8: Panel benchmark regressions.

The table reports results from bank-fixed effects regressions in first differences of quarterly CDS mid-spreads on CDS tail beta and further control variables. We estimate the following regression model:

$$\Delta \text{CDS}_{i,t} = \alpha + \beta_1 \cdot \Delta \text{Firm value}_{i,t} + \beta_2 \cdot \Delta \text{Interest rate}_{i,t} + \beta_3 \cdot \Delta \text{Volatility}_{i,t} + \gamma \cdot \Delta \text{CDS tail beta}_{i,t} + \delta \cdot \Delta X_{i,t} + \epsilon_{i,t}$$

where $X_{i,t}$ denotes the set of further control variables: *Business climate*, *GDP growth*, and the *slope of the yield curve*. Column (1) reports results for the regression using the variables suggested by theory. In Column (2), we assess the isolated explanatory power of the coefficient on CDS tail beta. Column (3) denotes our baseline regression. Columns (4) to (6) report estimation results when including further relevant controls. Bank-fixed effects are included in all regressions. Corresponding t-statistics are reported in parentheses. Standard errors are clustered at the bank level and adjusted for heteroskedasticity. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. All variables and data sources are defined in Table A.3 in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔFirm value	-0.13		-0.141	-0.123	-0.122	-0.104
	(1.77)*		(1.88)*	(1.67)	(1.67)	(1.33)
ΔInterest rate	0.683		-0.866	9.681	9.98	7.448
	(0.13)		(0.16)	(2.15)**	(2.17)**	(0.93)
ΔVolatility	6.587		6.503	5.26	5.259	5.258
	(9.01)***		(9.14)***	(7.13)***	(7.17)***	(7.20)***
ΔCDS tail beta		1.587	1.378	1.2	1.146	1.167
		(2.89)***	(3.81)***	(3.33)***	(3.17)***	(3.14)***
ΔBusiness climate				-0.138	-0.144	-0.143
				(3.51)***	(3.43)***	(3.37)***
ΔGDP growth					1.74	1.548
					(0.98)	(0.85)
ΔSlope						-6.95
						(0.41)
Constant	9.351	9.165	8.132	8.861	8.932	8.813
	(31.71)***	(23.25)***	(19.20)***	(21.59)***	(20.36)***	(15.81)***
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.24	0.01	0.25	0.26	0.26	0.26
Obs	868	865	865	865	865	865

Table 2.9: Univariate sorts.

This table reports average daily CDS spreads sorted by CDS tail beta. For each bank in the sample, we rank the time series of CDS spread observations into quintiles (1-5) with respect to realized CDS tail beta and compute the average spread for each tail beta quintile. CDS tail betas are simulated from the DAC model, where the tail betas are approximated by numerical integration using $\xi = 0.001$ (see Christoffersen et al., 2012, for details). To account for daily fluctuations, the univariate CDS spread sortings are based on a smoothed version of the CDS tail beta estimates, which is calculated by applying a simple moving average filter with a lag of 20 trading days to the original tail beta estimates. The last column of the table reports the difference between the average CDS spread of the fifth and the first tail beta quintile, whereas the last column calculates the average spread for each tail beta quintile across all 35 sample banks, with the t-statistic of the t-test on the average high-low difference in parantheses and with significance at the 1%, 5% and 10% being indicated by ***, **, and *, respectively. The sample period contains daily data from January 2004 to October 2010 for 35 European banks. Company names are abbreviated by their corresponding Bloomberg ticker symbols listed in Table A.1 in Appendix A.

	Average quintile spreads					
	1 Low tail beta	2	3	4	5 High tail beta	High - Low
ACA	8.10	9.58	29.53	85.54	104.77	96.67
AIBSF	9.29	10.07	41.22	260.54	265.37	256.07
ALPHA	27.11	27.13	26.38	143.27	331.72	304.61
BBPI	50.43	38.50	40.92	44.58	182.23	131.80
BBVA	9.50	11.32	44.46	93.15	115.70	106.20
BCPSF	78.27	81.92	52.23	141.96	324.26	245.99
BILMI	312.38	465.43	779.18	256.45	183.39	-128.99
BKESF	11.42	17.79	51.63	137.07	196.52	185.10
BKT	39.17	80.76	69.83	88.37	220.39	181.21
BMDPF	10.66	19.81	42.21	91.01	99.49	88.84
BNP	7.21	9.90	28.33	64.36	75.50	68.29
BPCGF	13.45	14.96	40.62	107.34	190.44	177.00
BPESF	13.08	21.51	19.54	143.35	240.03	226.95
BPI	24.21	37.34	110.85	118.93	135.71	111.50
BPMLF	26.56	27.74	47.62	70.22	80.96	54.40
CBK	11.60	20.36	44.93	85.18	85.75	74.15
CRIH	12.56	13.85	42.64	93.98	113.26	100.70
DBK	11.72	15.94	42.47	91.77	102.31	90.59
DEXB	7.10	9.82	27.00	241.54	239.64	232.54
EBKOF	17.85	20.93	87.54	126.76	157.36	139.51
EFG	19.25	17.16	18.38	117.63	459.07	439.82
FSVVF	19.39	25.33	52.11	78.86	170.01	150.62
GLE	9.49	9.27	25.63	87.92	104.33	94.84
IITSF	9.74	17.46	37.13	63.72	92.32	82.58
IKB	293.67	181.26	188.57	232.92	227.83	-65.84
ILB	26.26	24.00	40.71	208.45	289.49	263.23
ING	6.40	10.71	28.01	93.79	92.39	85.99
IRLBF	9.81	9.81	75.70	229.95	250.91	241.10
KBC	17.49	17.09	39.60	141.48	166.01	148.53
KN	11.68	10.01	64.98	153.82	173.20	161.52
MDIBF	21.24	20.85	40.40	65.71	90.72	69.48
SAB	93.98	188.35	259.49	196.83	271.35	177.37
SAN	10.38	12.70	39.62	96.34	107.26	96.88
UBI	26.09	40.88	55.55	37.52	105.94	79.85
UNBLF	32.64	40.90	130.13	158.22	165.31	132.67
Average	37.41	45.16	79.00	127.10	177.46	140.05
						(8.15)***

The average difference is equal to 140.05 bps and significantly different from zero at the 1% level.

In Column (3) of Table 2.8, we turn to our baseline model. When additionally controlling for the variables motivated by Merton's model, see Column (1), we obtain similarly convincing results. Although the coefficient on CDS tail beta decreases slightly, the correlation between tail risk and CDS spreads is still economically and statistically highly significant.

We also test whether the market-based leverage ratio is a more adequate proxy for a bank's default risk than the changes in firm value. Our (unreported) results show that this is not the case. While CDS tail beta remains significant throughout all regression specifications, the coefficient on the market-based measure of leverage is positive yet without any explanatory power. Furthermore, most banks experienced substantial equity losses during the crisis. As a consequence, market-based leverage ratios might be distorted due to the frequent occurrence of outliers. We address this concern and also estimate additional regressions in which we winsorize the explanatory variables at the 1% and 99% quantile, respectively. However, the explanatory power of the leverage variable remains marginal.

To eliminate as many confounding factors as possible, specifications (4) to (6) include several controls suggested in the previous section. In Column (4), we test the robustness of the found correlation between CDS tail beta and CDS spreads to the additional inclusions of changes in the business climate. Our variable business climate aiming to proxy for changes in the state of the economy enters the regression significantly negatively and indicates that improvements in the business climate are associated with potentially lower default probabilities (and higher recovery rates) and consequently lower CDS spreads.

Further controlling for the GDP growth rate and the yield curve slope in Columns (5) and (6), we find that both variables are insignificant. Nevertheless, including further covariates does not change our main findings although the coefficient on CDS tail beta slightly decreases in magnitude compared to the baseline model in Column (3).

As mentioned above, we carry out all of our regression specifications separated by bid- and ask-spreads. Our estimates show highly comparable results for each of the six regression specifications and are reported in Tables A.4 and A.5 in Appendix A, respectively. Based on the results from the bid- and ask-quote regressions, we conclude that contract-specific liquidity does not distort our findings.

Overall, the regression results provide strong support for the hypothesis that CDS investors are indeed crash-averse and hence, demand a risk premium-type markup for bank names with a large exposure to the market during extreme events.

2.3.2.3 Panel regressions - Sub-sample

Is the pricing of tail risk in CDS spreads crisis-dependent? The analyses we have conducted so far present strong empirical evidence that CDS tail beta explains a significant part of the variation in CDS spreads that is not captured by other, previously identified determinants of CDS spreads. Next, we test whether the explanatory power of CDS tail beta changes under economic regimes.

We consider two regimes: the pre-crisis and the crisis regime. Intuitively one would expect the awareness of CDS investors and buyers of extreme market-wide distress to be far less pronounced under the pre-crisis regime. This assumption can be motivated as follows. On the supply side, during economic booms CDS investors may not fear deteriorating recovery values underlying their CDS contracts. On the demand side, counterparty credit risk might also be negligible during the pre-crisis period. However, the beginning of the financial crisis coincided with a significant build-up of systemic risks in the global financial sector (see IMF, 2010) and increased uncertainty among investors concerning the financial health of global banks. As a result, we expect the sensitivity of both buyers and seller of credit protection to market-wide distress to be higher after mid-2007 and particularly pronounced after the failure of Lehman Brothers in September 2008.[25]

[25] This view is underlined, e.g., by the IMF (2009) which argued that the events at Lehman Brothers and AIG increased system-wide conditional risk.

Table 2.10: Sub-sample analysis: Crisis vs. pre-crisis period.

The table reports results from a sub-sample analysis where we regress differences in quarterly sampled CDS mid-spreads on CDS tail beta and on further control variables:

$$\Delta\text{CDS}_{i,t} = \alpha + \beta_1 \Delta\cdot\text{Firm value}_{i,t} + \beta_2 \Delta\cdot\text{Interest rate}_{i,t} + \beta_3 \cdot \Delta\text{Volatility}_{i,t} + \gamma \cdot \Delta\text{CDS tail beta}_{i,t} + \delta \cdot \Delta X_{i,t} + \epsilon_{i,t}$$

where $X_{i,t}$ denotes a set of further control variables: *Business climate*, *GDP growth*, and the *slope of the yield curve*. Column (1) repeats our benchmark regression from Column (6) of Tabel 2.8 for the pre-crisis period: Q1:2004 to Q2:2007. The onset of the crisis is fixed to Q3:2007. Column (2) reports estimation results from the crisis period: Q3:2007 to Q3:2010. Bank-fixed effects are included in all regressions. Corresponding t-statistics are reported in parentheses. Standard errors are clustered at the bank level and adjusted for heteroskedasticity. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. All variables and data sources are defined in Table A.3 in Appendix A.

	Pre-crisis	Crisis
ΔFirm value	-0.08	-0.134
	(2.72)**	(1.45)
ΔInterest rate	-2.589	16.054
	(2.20)**	(1.54)
ΔVolatility	0.119	5.365
	(0.96)	(6.33)***
ΔCDS tail beta	0.031	0.983
	(0.18)	(1.85)*
ΔBusiness climate	0.022	-0.185
	(3.13)***	(2.82)***
ΔGDP growth	0.207	3.949
	(0.94)	(1.05)
ΔSlope	0.498	-7.128
	(0.5)	(0.35)
Constant	-0.705	15.181
	(3.45)***	(5.47)***
Bank-fixed effects	Yes	Yes
Clustered SE	Yes	Yes
Adj. R^2	0.02	0.27
Obs	412	453

To test the the impact of CDS tail beta under the two regimes, we perform a sub-sample analysis. We split the sample in Q3:2007. A comparison of the two estimated regressions presented in Table 2.10 supports the hypothesis that CDS tail risk is only a relevant factor during the crisis period. When estimated on the pre-crisis sub-sample, the coefficient on CDS tail beta has no explanatory power, see Column (1). However, CDS tail beta is significant at the 10% level for the crisis sub-sample in Column (2).

One further observation from the sub-sample analysis is worth mentioning. The overall explanatory power increases sharply when turning from pre-crisis to crisis period as evidenced by the sharp increase in the adjusted R^2.

The strong co-movement in CDS tail beta and CDS premia lends some support to the notion that market participants contemporaneously adjust their individual risk assignments with respect to system-wide risk.

2.3.3 Robustness checks

This section presents several robustness checks complementing the analyses presented in Section 2.3.2. In particular, we test the hypothesis that CDS tail beta complements rather than substitutes other measures of CDS co-movement risk.

2.3.3.1 Is CDS tail beta different from upside risk aversion?

Thus far, we have demonstrated that CDS tail beta is a priced factor in the time-series as well as in the cross-section of CDS spreads. However, these results rely on the assumption that investors' crash aversion, measured by CDS tail beta, is different from general, linear upside risk aversion. Indeed, we find strong evidence for linear co-movement between CDS tail beta and CDS spreads, potentially raising concerns to what extent our results are specific to the chosen measure of tail risk. We address this issue in the following.

In a first step and in the spirit of Ruenzi and Weigert (2013), we disentangle the impact of CDS tail beta on banks' CDS spreads from that of linear comovment risk. To this purpose, we compute measures capturing linear co-movement risk: regular beta, upside beta (see Ang et al., 2006a), and coskewness (see Kraus and Litzenberger, 1976; Harvey and Siddique, 2000). All measures are estimated on each bank's log-differenced CDS spreads with respect to the CDS index over a rolling window of 100 observations. The two CDS beta factors are defined as follows. Regular beta (or simply beta) is the CAPM-type beta factor, upside beta, however, is defined as beta, conditional on the log-difference of the CDS index being above its median. In addition, we consider further definitions of upside beta, conditional on the log-difference of the CDS index being above its 80%, 90%, and 95% quantile, respectively.[26] Coskewness is defined in Table A.3 in Appendix A.

Estimation results are presented in Figure 2.5. The panels on the left-hand side show cross-sectional averages (indicated by the solid line) of all linear measures of comovment risk and how they evolve over time. The right-hand side, however, contrasts CDS tail beta with the respective linear counterparts on a unified scale. Negative deviations between CDS tail beta and the respective measure of linear co-movement are indicated by the light-gray areas, positive deviations, however, by the dark-gray areas.

As can be seen from the right-hand side panels, average beta and upside beta evolve rather smoothly over time, whereas CDS tail beta appears highly sensitive to the series of events during the financial crisis. In the pre-crisis period, beta as well as upside beta 50% and 80% (Panels b, d, f) overestimate extreme co-movement risk, while the opposite is true during the crisis period (Q3:2007 - Q3:2010). Upside beta 90% and 95% (Panels h, j) show even greater deviations from CDS tail beta. While upside beta 90% strongly overestimating extreme spread co-movements almost over the entire sample period, upside beta 95% is shown to underestimate extreme spread co-movements during the crisis. Finally, average coskewness appears to systematically underestimate extreme co-movement risk during the entire sample period.

Although the results from Figure 2.5 suggest that CDS tail beta and measures associated with linear co-movement risk in CDS spreads are governed by different dynamics, we further empirically test their impact on banks' CDS spreads.

[26]Note that this approach is in line with Ruenzi and Weigert (2013) who, in contrast, calculate different specifications of downside beta on the basis of quantiles in the left tail of the market return distribution.

Figure 2.5: Alternative risk measures and CDS tail beta.

The panels of the figure depict the time evolution of average realized alternative risk measures and compare it to the time evolution of average realized CDS tail beta. The alternative risk measures considered in our study are regular beta, different specifications of upside beta as well as coskewness. More precisely, upside betas are calculated as betas conditional on the log difference of the CDS index being above its median and its 80%, 90% and 95% quantile. The realized alternative risk measures are computed from rolling windows of 100 data points using the definitions listed in Table A.3 in Appendix A, where the sample period contains daily data from January 2004 to October 2010 and the average is taken across all banks in the sample. The panels on the left-hand side show the time evolution of average realized alternative risk measures (black lines) as well as the range between their 10th and 90th percentiles (shaded areas). The right-hand side panels compare this time evolution to that of average realized CDS tail betas in terms of risk measure and tail beta indices calculated by expressing each observation in a specific time series as a percentage of the first observation in that time series. The black lines refer to the time series of the corresponding risk measure index, where the light-gray shaded areas refer to upside deviations from the tail beta index, and the dark-gray shaded areas depict downside deviations. CDS tail betas are simulated from the DAC model, where the tail betas are approximated by numerical integration using $\xi = 0.001$ (see Christoffersen et al., 2012, for details).

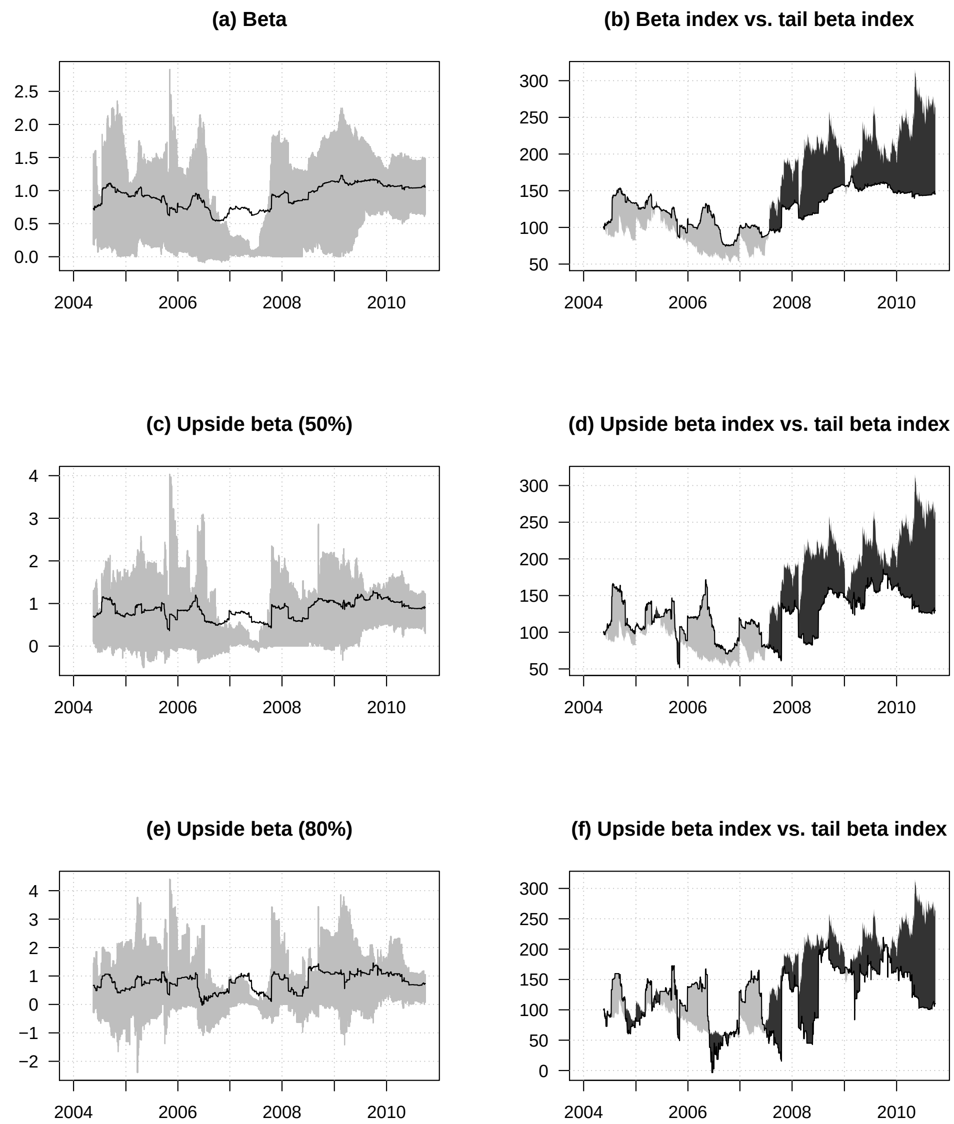
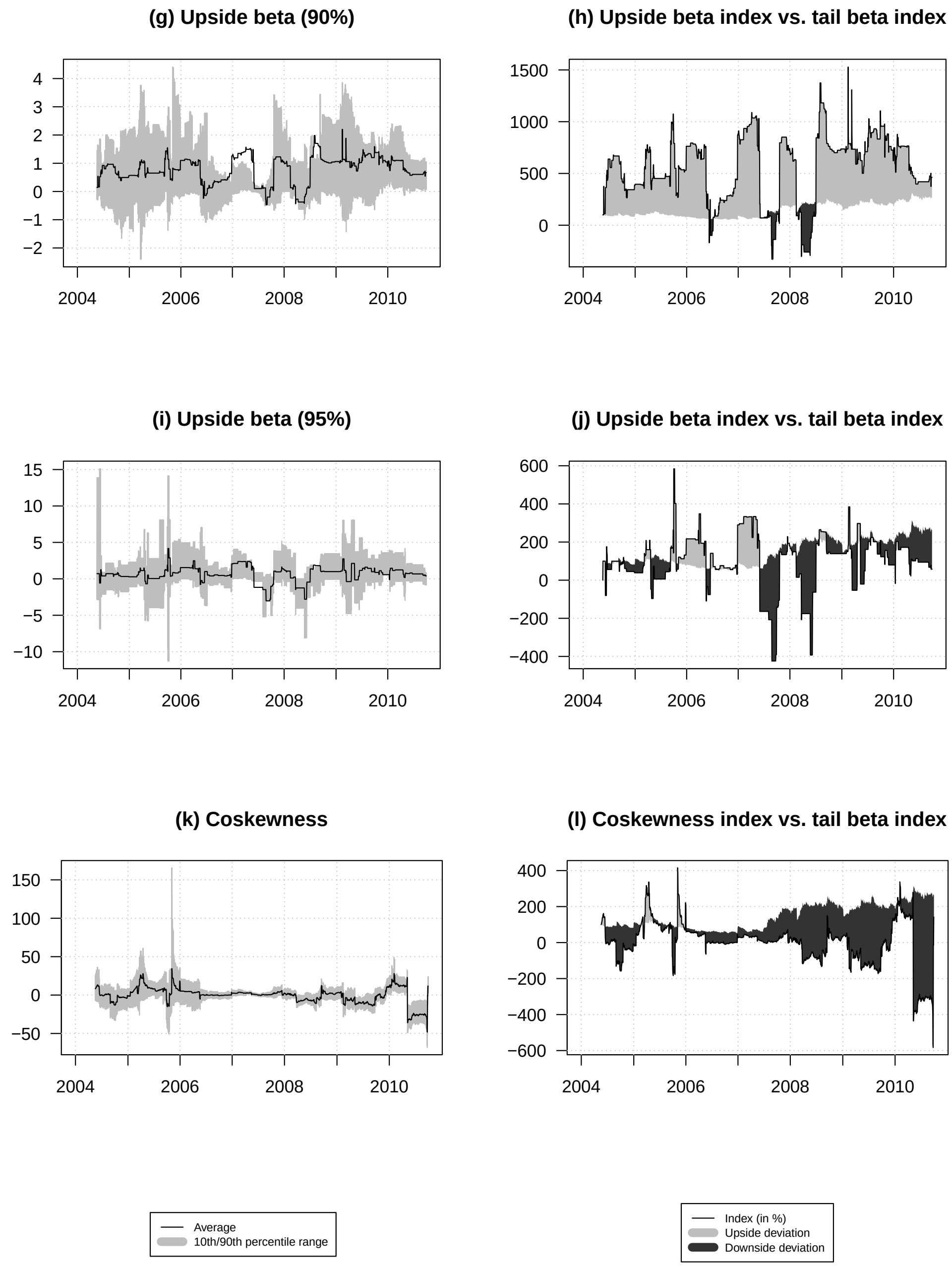


Figure 2.5: Alternative risk measures (continued).



In a first step, we conduct double-sorts in which we analyze the impact of CDS tail beta on CDS spreads after controlling for alternative risk measures. The results of the double-sorts are available upon request and indicate that the impact of CDS tail beta on CDS spreads is different from the impact of alternative, linear risk measures. Nevertheless, double-sorts can only control for one alternative measure of general upside risk aversion on CDS spreads at a time. Hence, it could be argued that our results are biased due to omitted variables. Next, we present results from additional panel regressions. We run our regressions from Table 2.8 while including linear measures of co-movement risk as further controls. Results are presented in Table 2.11. In regression specification (1), we introduce regular beta as a further control, whereas in regressions (2) to (5) we include the different specifications of upside beta. Finally, in regression (6), we consider coskewness in addition to CDS tail beta. As can be seen from specification (1) to (5), all coefficients on the alternative, beta-type risk measures are statistically insignificant when estimated together with CDS tail beta. At the same time, CDS tail beta remains positive and varies only slightly in magnitude as compared to our benchmark model from Table 2.8. Furthermore, the coefficient on CDS tail beta is significantly different from zero at the 1% level throughout all regression specifications. The remaining control variables merely differ slightly across the different regression specifications and are not reported to preserve space. Finally, Column (6) reports results for the coskewness regression. As expected, coskewness enters the regression with a negative but insignificant coefficient.

Overall, including alternative, linear measures of co-movement risk in our regression model does not change our main results. The impact of linear, correlation-based risk measures on CDS spreads is shown to be insignificant. Moreover, it could be argued that the differences between our CDS tail beta and the alternative measures of tail risk are simply an empirical phenomenon. To further illustrate the conceptual differences between these measures, we perform an in-depth comparison of the measures based on Monte-Carlo simulation techniques in Section A.2 in Appendix A.

Table 2.11: Robustness checks using alternative risk measures.

The table reports results from bank-fixed effects regressions of differences in quarterly sampled CDS mid-spreads on CDS tail beta, further control variables, and an alternative set of co-movement risk indicators (CRI). We estimate the following regression model:

$$\Delta\text{CDS}_{i,t} = \alpha + \beta_1 \cdot \Delta\text{Merton-type}_{i,t} + \gamma \cdot \Delta\text{CDS tail beta}_{i,t} + \delta \cdot \Delta\ \text{X}_{i,t} + \theta \cdot \Delta\text{CRI}_{i,t} + \epsilon_{i,t}$$

where $X_{i,t}$ denotes a set of further control variables: *Business climate*, *GDP growth*, and the *slope of the yield curve*. $CRI_{i,t}$ denotes a vector of alternative measures of co-movement risk calculated from each bank's CDS time series with respect to the CDS index: Beta, upside beta (50%, 80%, 90%, 95%), and coskewness. MES is the marginal expected shortfall as proposed by Acharya et al. (2010) and calculated from the respective equity time series with respect to the stock price index. Details on the calculation of the alternative co-movement risk indicators can be found in Table A.3 in Appendix A. Corresponding t-statistics are reported in parentheses. Bank-fixed effects are included in all regressions. Standard errors are clustered at the bank level and adjusted for heteroskedasticity. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. All variables and data sources are defined in Table A.3 in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔCDS tail beta	1.154	1.113	1.14	1.175	1.221	1.06	1.274
	(3.03)***	(2.79)***	(2.93)***	(3.09)***	(3.14)***	(3.08)***	(3.29)***
ΔBeta	0.877						
	(0.78)						
ΔUpside beta 50%		2.468					
		(1.09)					
ΔUpside beta 80%			1.426				
			(0.92)				
ΔUpside beta 90%				0.885			
				(0.96)			
ΔUpside beta 95%					-0.386		
					(0.95)		
ΔCoskewness						-0.2	
						(1.33)	
ΔMES							-2.444
							(1.08)
Constant	8.615	8.648	8.629	8.603	8.519	8.523	8.525
	(11.97)***	(11.71)***	(11.92)***	(12.03)***	(11.90)***	(11.90)***	(11.49)***
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.26	0.26	0.26	0.26	0.26	0.28	0.26
Obs	827	827	828	828	829	756	834

2.3.3.2 Is CDS tail beta simply another proxy for systemic risk exposure?

Acharya et al. (2010) find that a bank's systemic relevance to the financial sector is reflected in CDS spreads during the recent financial crisis. More precisely, they show that a bank's Marginal Expected Shortfall (defined as the conditional mean equity return of the bank when the market is plummeting) is a significant determinant of financial institutions' crisis CDS spreads.

Consequently, it could be argued that CDS tail beta is simply another proxy for a bank's exposure to systemic risk.[27] In the following robustness check we test whether CDS tail beta and MES are distinguishable from each other with respect to their impact on banks' CDS spreads.

We estimate the MES in three specifications, all based on log equity returns. Fist, we estimate the static MES according to Acharya et al. (2010) based on a rolling windows of 100 observations. Second, we follow Brownlees and Engle (2012) and compute dynamic MES models including the VCT model, the Dynamic Conditional Beta model as well as the Dynamic Conditional Copula model based on Patton's (2006) dynamic t-copula.[28]

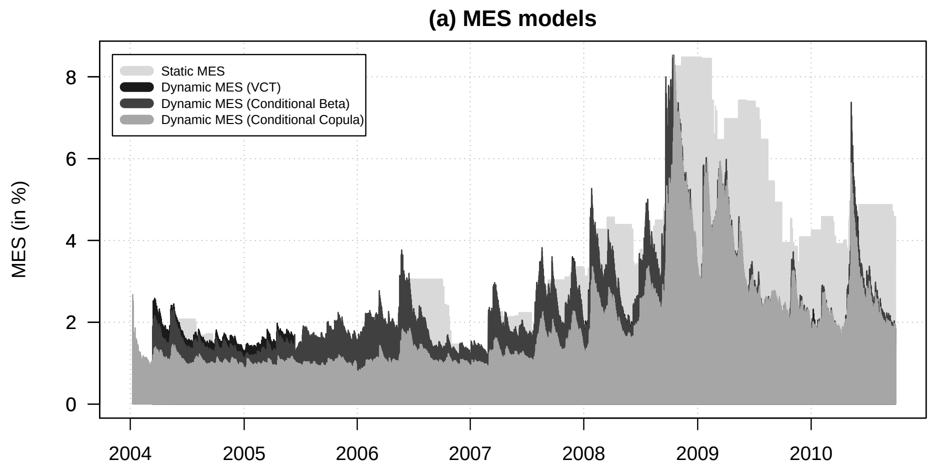
Estimation results for the different MES specifications are shown in Figure 2.6. Panel (a) combines the time-series profiles of all four MES specifications. It is evident that all measures of systemic risk evolve similarly during the sample period. With the onset of the subprime crisis in mid-2007 to 2009, all specifications show a significant surge in the average exposure of banks to systemic tail events. The sharp increase is then followed by a strong downward trend. While the dynamically specified MESs fall to their pre-crisis levels, the static MES remains elevated as compared to the pre-crisis period.

[27] There now exists a vast number of studies in the financial economics literature on the measurement of systemic risks. Further examples for such measures apart from those used in this study are due to De Jonghe (2010); Adrian and Brunnermeier (2011); Huang et al. (2011); Schwaab et al. (2011); Hautsch et al. (2014); Hovakimian et al. (2012) and White et al. (2012). Comprehensive comparisons of different systemic risk measures are due to Bisias et al. (2012) and Benoit et al. (2013).

[28] Further details and a formal description of the different MES models can be found in Acharya et al. (2010) and Brownlees and Engle (2012).

Figure 2.6: MES models and CDS tail beta.

The panels of the figure show the time evolution of average Marginal Expected Shortfall (MES) and compare it to the time evolution of average CDS tail beta. Average MES is calculated from alternative models including the static MES according to Acharya et al. (2010) as well as various dynamic model specifications proposed in Brownlees and Engle (2012). Static MES is computed non-parametrically from rolling windows of 100 data points, and the dynamic MES models include the VCT model, the Dynamic Conditional Beta model as well as the Dynamic Conditional Copula model that is based on Patton's (2006) dynamic t-copula (see Brownlees and Engle, 2012, for details). The sample period contains daily data from January 2004 to October 2010 and the average is taken across all banks in the sample. The first panel depicts the time evolution of the different MES specifications, whereas the following panels compare this time evolution to that of CDS tail beta, with the light-gray shaded areas showing the MES range between the 10th and 90th percentile and with the dark-gray coloured lines referring to CDS tail beta. CDS tail betas are simulated from the DAC model, where the tail betas are approximated by numerical integration using $\xi = 0.001$ (see Christoffersen et al., 2012, for details).



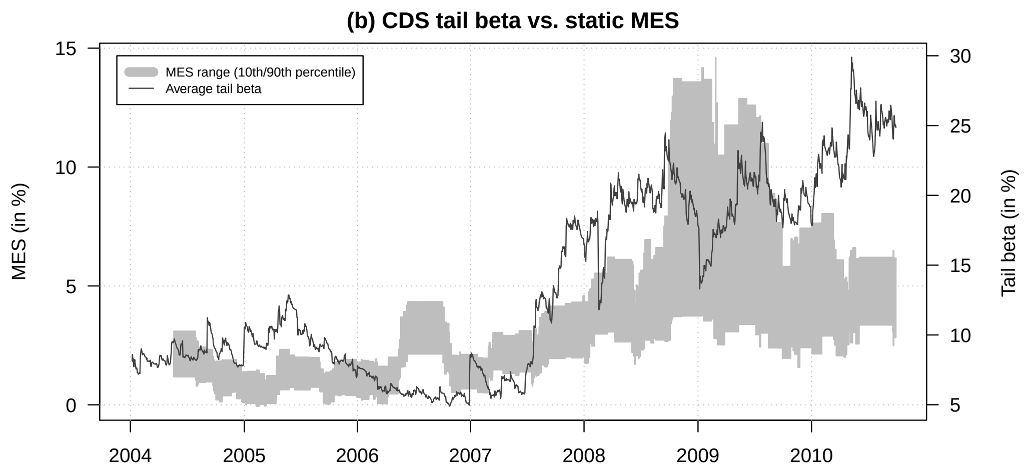
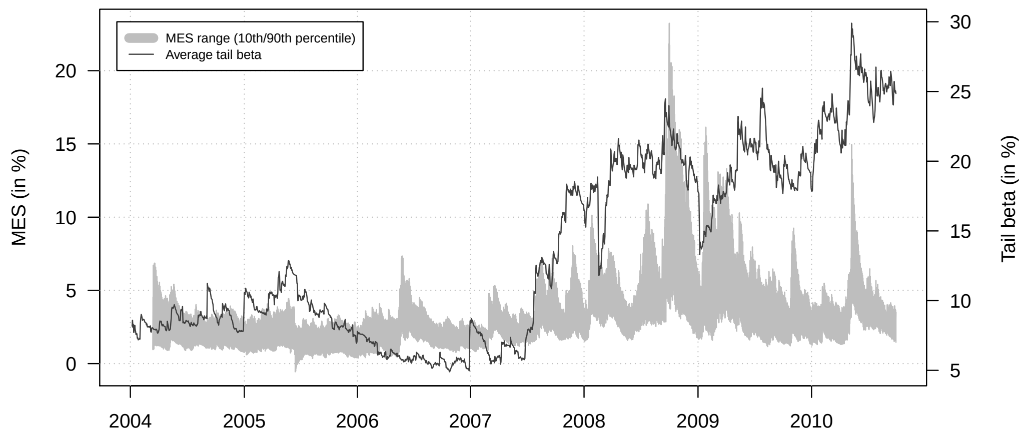
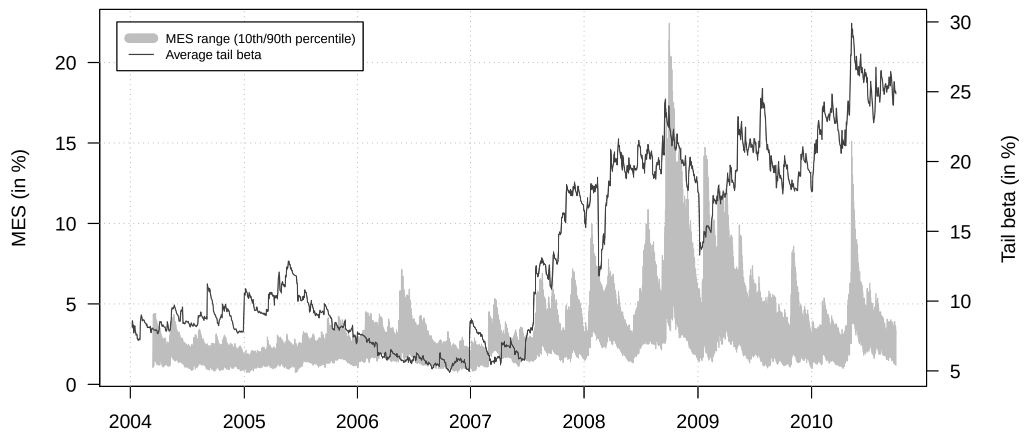


Figure 2.6: MES models and CDS tail beta (continued).

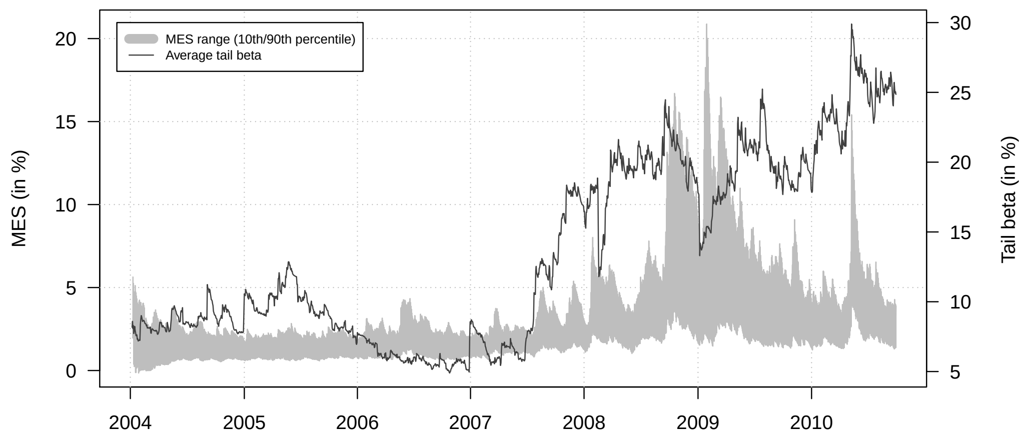
(c) CDS tail beta vs. dynamic MES (VCT)



(d) CDS tail beta vs. dynamic MES (Conditional Beta)



(e) CDS tail beta vs. dynamic MES (Conditional Copula)



Panels (b) to (e) compare the respective MES specifications with our measure of tail risk, CDS tail beta. Whereas the MES is characterized by a sharp increase with the onset of the crisis in 2007, a similarly sharp decline after 2009 and a spike in 2010, CDS tail beta evolves differently. In contrast to MES, CDS tail beta experienced a strong upward trend rather than a temporary surge beginning in mid-2007. We also perform double-sorts with respect to different MES specifications and make the results available upon request. Results across the different MES specifications are qualitatively and quantitatively rather similar and indicate that systemic risk is different from extreme co-movement risk as measured by CDS tail beta.

Finally, we report corresponding regression results in specification (7) of Table 2.11. When estimated together with CDS tail beta and relevant controls, the coefficient on the static MES is negative but insignificant. Although Acharya et al. (2010) find evidence that MES is a significant driver of CDS spreads, we find evidence that it cannot explain the variation in CDS spread changes when estimated together with CDS tail beta. MES cannot capture the dynamics of CDS tail beta which is still significant at the 1% level. Note that we obtain similar results when including the dynamic specification of MES.

In summary, including MES in our multivariate panel regressions re-confirms our findings from the double-sorts. Further, we shows that the impact of CDS tail beta on CDS spreads is different from the impact of MES. Hence, extreme co-movement risk is a complement and not a substitute to measures of systemic risk.

2.3.3.3 Addressing a potential look-ahead bias

Thus far, we have presented evidence for a time-trend in copula correlations between a bank's CDS spread and a CDS index. To this purpose, the copula model is estimated on the entire data set ranging from Q1:2004 to Q3:2010. Since our measure of co-movement risk is also used in the regression models over the same time period, one potential concern might be that this creates a look-ahead bias in the sense that, for a given point in time (except for the last quarter), the full set of information would not have been available to CDS investors and protection buyers. As a consequence, it would not have been possible to neither investors nor protection buyers to adequately price such risk into CDS contracts.

Addressing this issue, we estimate an additional dynamic copula model that is not based on a generic trend component over the entire estimation period. Instead, we successively extend the estimation period quarter by quarter such that the obtained tail dependence coefficients only reflect the set of information available up to the end of the estimation period. Hence, we construct a real time measure of CDS tail beta that would have been available to all market participants. To facilitate the estimation of a dynamic copula model even for shorter time series, we follow Patton (2006) and estimate a conditional t-copula model to infer dynamic tail probabilities. For a detailed discussion on the estimation of conditional copula models we refer to Patton (2006).[29]

Finally, in unreported results we repeat our benchmark regressions from Table 2.8, this time using the real time measures of CDS tail beta, and find its impact on banks' credit spreads to remain statistically and economically unchanged.

2.3.3.4 Measuring tail risk with an alternative benchmark index

Another concern might be the definition of the benchmark index. So far, we have constructed an equally-weighted CDS benchmark index by simply averaging over the individual banks' CDS spreads. Nevertheless, it could be argued that this approach leads, by construction, to mechanical correlations between a bank's CDS spread and the market index. Furthermore, depending on the structure of the index, the price of credit protection for such an index may not necessarily coincide with a representative basket index. In choosing a different benchmark index, the Thomson Reuters EU Banks Sector CDS Index 5Y, we control for the potential influence of mechanical correlations in banks' and the market's CDS spreads. Figure 2.7 shows the average daily CDS tail beta as well as the respective daily minimum and maximum value, estimated from the DAC model.

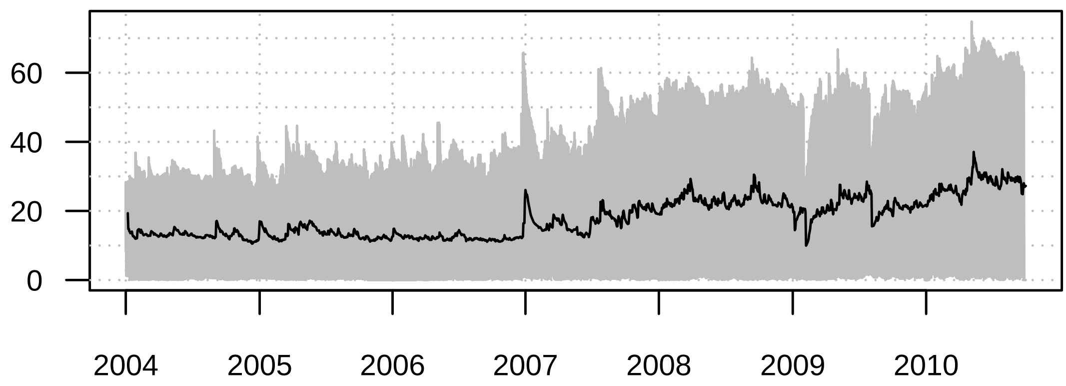
In summary, we find that absolute levels of both the self-constructed as well as a relevant benchmark index are very comparable. Further, we identify a linear correlation between the two time series of around 92.5%.

[29] For the t-copula model, we assume the same correlation dynamics as Patton (2006) proposes for the normal copula.

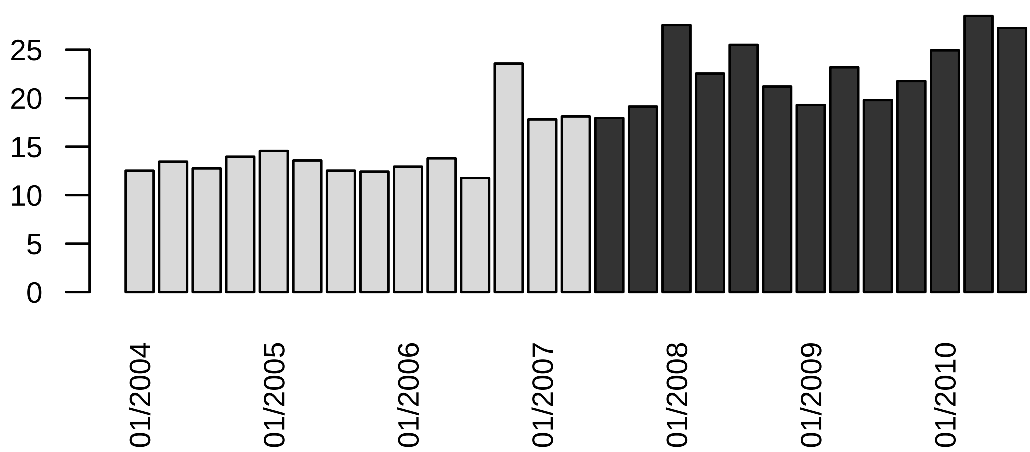
Figure 2.7: Tail risk with an alternative index.

The figure shows estimation results for daily *CDS tail beta*, this time estimated with respect to an alternative market index: the *Thomson Reuters EU Banks Sector CDS Index 5Y*. All previous results are based on tail beta coefficients estimated with respect to a self-constructed, equally-weighted CDS index. Nevertheless, choosing an alternative index does hardly change our main results since we find linear co-movement in the two time series, with a correlation of 92.5%, to be almost identical.

(a) Average daily tail betas (alternative index)



(b) Average quarterly tail betas (alternative index)



The results suggest that the influence of potential mechanical correlation is, if having any relevance at all, only very small. Hence, we conclude that our results are robust to the choice of the benchmark index.

2.4 Conclusion

We find that during the recent financial crisis, credit default swap spreads of European banks included a premium for the bank's CDS tail beta as measured by the upper tail dependence between the spreads of default swaps written on individual bank names and an equally-weighted index of bank CDS. Investors selling protection against the default of a bank receive a premium if the swap's reference entity possesses a higher sensitivity to sector-wide increases in average CDS spreads. This effect is economically large and its direction is in line with our economic intuition. Banks in the upper quintile of CDS tail beta have spreads that are on average 140 basis points higher than those of banks in the lower CDS tail beta quintile. The high CDS spreads of banks possessing high CDS tail betas can neither be explained by traditional factors from Merton's model nor by alternative measures of systematic, tail or systemic risk. Consequently, our study contributes significantly to the open question on which factors can explain the large fraction of variation in spread differences that is not captured by traditional determinants of credit default. However, the explanatory power of CDS tail beta is restricted to our sub-sample of bank-quarters during the financial crisis. Thus, investors appear to be sensitive to crash risk when already facing a sector-wide crisis.

Our results confirm and extend previous findings from the empirical literature on the determinants of CDS spreads. While we confirm the results of Ericsson et al. (2009) on the explanatory power of the Merton factors, our new CDS tail beta factor has high explanatory power increasing the adjusted R^2 in our regressions of CDS spreads from 24% to 32%. Furthermore, our results are also consistent with the findings of Acharya et al. (2010) that CDS spreads of banks are driven by measures of systemic risk exposure. However, our new measure of CDS tail beta complements rather than substitutes other measures of moderate or extreme tail risk. Finally, extending the results of Ruenzi and Weigert (2013), we also document a strong positive correlation between equity tail beta and CDS spreads.

This study focuses solely on the pricing of CDS tail beta in the CDS spreads of banks. A natural extension of our study would include an analysis of non-financial firms before and during the financial crisis. Theory predicts that the correlation between CDS tail risk and CDS spreads is particularly strong for banks as they are more vulnerable to runs of creditors and depositors during financial crises. Yet, non-financial firms should just the same be sensitive to turmoil in the overall CDS market and we would expect CDS tail beta to be priced in non-financial firms' CDS spreads as well. Furthermore, a natural extension of our initial question is whether CDS premia are also correlated with the propensity of the CDS premia to surge together with the CDS spread of sovereign bonds. We leave this question for future work.

Chapter 3

Do CDS spreads move with commonality in liquidity?

3.1 Introduction

Several recent studies in the financial economics literature have focused on the relation of liquidity and asset prices. In particular, the dry-up of liquidity in various asset markets during the financial crisis has amplified interest in the questions how liquidity and liquidity risk drive asset prices in the cross-section and the time series. In the Liquidity Capital Asset Pricing Model (CAPM) of Acharya and Pedersen (2005), illiquidity should always be priced in markets with positive net supply. Similarly, several studies starting with Amihud (2002); Pastor and Stambaugh (2003); Bekaert et al. (2007) and Ruenzi et al. (2013) have shown that equity returns reflect a premium for systematic linear and extreme liquidity risk. For derivatives markets, however, predictions about the pricing of both illiquidity and liquidity risk are much more difficult. In their extension of the liquidity-CAPM, Bongaerts et al. (2011) show for markets with zero net supply that asset prices should only carry a premium for expected illiquidity but not for liquidity risk. They also find empirical support for their theoretical predictions in an analysis of the credit default swaps (CDS) market. However, using a different notion of liquidity risk, Junge and Trolle (2014) show in a related study that liquidity risk is indeed priced in the cross-section of single-name CDS contracts.

In this paper, we analyze commonality in CDS liquidity as a different facet of liquidity risk and show that it is indeed priced in both the cross-section and time series of CDS spreads. We propose a novel approach to measure commonality in the liquidity of single-name CDS contracts by applying the commonality measure suggested in Chordia et al. (2000) and Karolyi et al. (2012) for equity markets to individual and market-wide CDS liquidity proxies. As our main finding, we show that CDS spreads include a statistically significant discount for liquidity risk in the form of liquidity commonality. The results suggest that buyers of credit protection may demand compensation for impaired hedging opportunities. Alternatively, speculators in CDS markets may also require compensation due to potentially lower returns from speculative activities when settlement is costly. The effect is also economically meaningful as an increase in CDS liquidity commonality by about 10.7% (one standard deviation) decreases the CDS spread by approximately 11 bps. In calm periods, however, this effect vanishes. One explanation might be that only when demand for credit protection spikes in times of financial distress, correlated trading behavior in CDS markets increases and drives up commonality in liquidity.

Furthermore, we confirm earlier results of Corò et al. (2013) and Tang and Yan (2013) that illiquidity in CDS markets plays a far more important role for the pricing of credit derivatives than fundamentals from the structural model of Merton (1974). In line with Tang and Yan (2013), we find that a substantial part of the variation in CDS spreads can be attributed to changes in contract-specific liquidity. In our sample, changes in the quoted bid-ask spread alone explain, on average, 39% of the time-series variation in CDS mid-quotes. Adding alternative measures of liquidity to our regression specification increases the adjusted R^2 even further.

As evidenced during the financial crisis, liquidity and liquidity risk appear to play a significant role in credit derivatives markets, even though predictions from financial theory on the effect of liquidity on derivatives' prices are far less obvious than in equity and bond markets (see, e.g., Lin et al., 2011; Bongaerts et al., 2011, 2012).[1] Surprisingly,

[1] Anecdotal evidence for the importance of liquidity in CDS markets is also given by the 2012 trading loss at JP Morgan estimated at 2 billion USD that was caused by the excessive accumulation of outsized

only few empirical papers in the literature have focused on the impact of liquidity risk on CDS spreads so far. Starting with the study of Tang and Yan (2008), there now exists a consensus in the literature that the illiquidity of CDS contracts is reflected in CDS spreads and expected CDS returns. This finding has since been supported in recent studies, like e.g., the works of Tang and Yan (2013), and Junge and Trolle (2014) who all underline the necessity to account for liquidity effects in asset pricing studies of CDS spreads. Despite this recent evidence that suggests that liquidity is an important determinant in the cross-section of CDS spreads (see Lesplingart et al., 2012; Corò et al., 2013), comprehensive time-series evidence on the effect of liquidity on CDS spread movements is rather scarce in the literature. For example, Ericsson et al. (2009) account for liquidity effects in their asset pricing study but do not directly test to what extent CDS spread co-move with changes in the level of liquidity.

Additionally, the empirical evidence on the pricing of liquidity risk in CDS spreads is ambiguous at best. Building on the theoretical framework of Acharya and Pedersen (2005), Tang and Yan (2008) find that CDS spreads are significantly positively related to the sensitivity of individual liquidity shocks to market-wide liquidity shocks. Conversely, they also show that CDS spreads appear to be lower if the sensitivity of shocks to individual CDS spreads to market-wide liquidity shocks is higher. The opposite empirical evidence is found by Bongaerts et al. (2011) in their empirical test of the theoretical extension of the model of Acharya and Pedersen (2005) to markets with liquidity risk and short-selling. They document in their study on 595 CDS contracts between 2004 and 2008 that liquidity risk caused by transaction costs that may increase when systematic default risk increases is not priced in CDS returns. More recent empirical findings by Junge and Trolle (2014), however, underline the notion that liquidity risk does indeed play an economically important role in the pricing of CDS contracts. Focusing on liquidity risk that arises from widening CDS spreads when aggregate liquidity deteriorates, they show that wealth constrained protection sellers require a liquidity risk premium when entering a CDS.

CDS positions through their London branch.

Our analysis on the pricing of liquidity risk in CDS spreads extends several recent studies in the literature. To start with, our paper is closely related to the recent asset pricing studies of Ericsson et al. (2009) and Meine et al. (2013). While the former concentrates on the importance of the variables from Merton's model for CDS prices, the latter finds CDS tail risk to be a significant determinant of the CDS spreads of European banks. Extending their work, our study additionally considers commonality in CDS liquidity as an economically important priced factor. Next, our analysis is also related to the empirical analyses of Bongaerts et al. (2011) and Junge and Trolle (2014). By focusing on the commonality in CDS liquidity and on CDS spreads between 2004 and 2010, however, we extend their work and find new evidence that CDS spreads during the financial crisis included a discount for bearing the risk of comovements in CDS liquidity. Most importantly, liquidity risk only seems to be priced in CDS contracts when comovements in illiquidity increase as a result of an economic crisis. Finally, our study is also related to the works of Corò et al. (2013) and Mayordomo et al. (2014b) who document in their respective studies the existence of significant commonality in the liquidity of CDS contracts. In contrast to our study, however, they do not analyze the implications of this finding for the pricing of CDS.

The rest of this paper is organized as follows. In Section 3.2, we present our data and discuss some descriptive statistics of our sample. Section 3.3 presents the design and the results of our empirical study on the pricing of the commonality in liquidity in CDS spreads. The robustness of our main findings is tested and confirmed in Section 3.4. Section 3.5 concludes.

3.2 Data

This section presents the data used in our empirical study and describes the data sources and screening procedures applied to the data. Further, we define our main independent variables and provide detailed summary statistics.

3.2.1 CDS data

We construct our data set from all available single-name CDS time series for U.S. companies with traded CDS contracts on their debt. Our sample comprises data of 228 financial and non-financial companies for the period from January 2004 to September 2010. CDS data are collected from *Credit Market Analysis (CMA)* and are downloaded via *Thomson Reuters' Datastream*, where we consider only CDS names for which daily mid, bid, and ask quotes are available.

Using data from *CMA* has several advantages. First, *CMA* is a reliable database. Mayordomo et al. (2014a) show that *CMA* data are superior to those provided by other commonly used databases (such as *Markit*) in terms of the price discovery process. Second, *CMA* only reports CDS quotes if a sufficient number of quotes is available, so that quotes are unlikely to be distorted from low levels of liquidity. Since contract-specific liquidity is highest among CDS with a maturity of five years, we restrict our analysis to these contracts. Additionally, we only consider CDS contracts that refer to senior-debt issues and are denominated in U.S. dollar (USD).

We apply the following screening procedures to our data. Starting with a universe of all U.S. companies with traded CDS contracts, we first delete all CDS time series that refer to U.S. sovereign debt issues. Further, we are only interested in companies with a stock market listing and, consequently, delete all unlisted companies from the sample. Next, to uniquely identify the associated equity time series from *Thomson Reuters'* CDS symbols, we first decompose each CDS symbol to construct the corresponding equity symbol. More precisely, we extract the string that refers to the company name from each CDS symbol and add a prefix to determine the market.[2] For example, *3M Company* has the CDS symbol MMM..S5 in *Datastream*. We use the first three digits (MMM) and the market specification (U) to obtain the corresponding equity code (U:MMM). We then screen all matches manually and discard all ambiguous matches from our sample.

[2]Note that CDS symbols (Mnemonics) in *Datastream* are constructed from two strings. The first string refers to the company's name and consists of no more than five digits. The second string specifies the seniority and maturity of the debt. In our case, the second string is 'S5' and denotes CDS contracts that refer to senior-debt issues with a maturity of five years.

Finally, we exclude all companies with an insufficient amount of variation in their CDS time series.[3] Having applied these filtering criteria, our final sample encompasses a total of 228 financial and non-financial companies.

Based on the equity symbols of the companies, we additionally download Industry Classification Benchmark (ICB) Level 3 Supersector Codes from *Datastream* and assign each company to one of the 19 different industrial sectors.

3.2.2 Measures of credit risk

To control for the impact of firm-specific credit risk in our empirical study, we include three credit risk variables that are motivated by theory (see Merton, 1974). In line with Collin-Dufresne et al. (2001), we use a firm's stock return to proxy for changes in the firm value. An increase in the firm value should decrease default risk and, hence, we expect a negative sign for the coefficient of firm value. Further, as a proxy for the volatility of the underlying asset value process, we use equity volatility which is defined as the annualized quarterly stock return volatility. Higher volatility is associated with higher default risk and should therefore be positively correlated with CDS spread changes. As a proxy for the interest rate, we use the *Datastream* two-year U.S. Treasury benchmark yield. From a theoretical perspective, an increase in the drift rate of the asset value process should lower default risk and, consequently, decrease CDS spreads. Nevertheless, it could also be argued that the drift rate captures other macroeconomic factors that are positively correlated with default risk.

Furthermore, we consider additional control variables. We include the option-implied volatility index (VIX), where higher index values are associated with higher default risk and, therefore, higher CDS spreads. Moreover, to account for some of the heterogeneity across firms, we include a size dummy that is defined as the logarithm of quarterly total assets. Additionally, existing studies in the empirical literature find evidence that CDS spreads are sensitive to changes in the business climate in which a firm operates (see, e.g.,

[3]For instance, the CDS time series of *General Electric* exhibits no variation after June 2007 and is therefore deleted from the final sample.

Zhang et al., 2009; Longstaff et al., 2005). Therefore, we include quarterly values of the S&P500 index to proxy for the business climate and expect that changes in the index are negatively correlated with CDS spread changes.[4] Finally, we include book leverage as an additional control variable since it could be argued that our proxy for firm value does not fully reflect the default-related information incorporated in measures of the leverage ratio. Book leverage is calculated as total debt over the sum of total debt and market capitalization.

All variables are retrieved from *Thomson Reuters' Datastream*. Variable definitions, information on data sources, and descriptive statistics are provided in Tables B.1 and B.2 in Appendix B, respectively.

3.2.3 Liquidity variables

We now turn to the liquidity variables included in our empirical study. In addition to three different measures of CDS liquidity, we also propose a novel approach of measuring commonality in CDS liquidity by applying the commonality measure suggested in Karolyi et al. (2012) to individual and market-wide CDS liquidity proxies.

3.2.3.1 Measures of CDS liquidity

To control for the general level of contract-specific liquidity, we include the following liquidity variables. On the company level, we employ absolute and relative bid-ask spreads as well as the updating frequency to account for the impact of liquidity on CDS mid quotes. Bid-ask spreads capture the costs of immediate trading and embody several components such as adverse selection, inventory carrying, and order-processing costs that directly affect liquidity. Bid-ask spreads have been widely used in recent studies on the liquidity in CDS markets (see, e.g., Bongaerts et al., 2011; Tang and Yan, 2013; Junge and Trolle, 2014). The absolute bid-ask spread (BAS_{abs}) is computed as the difference between daily ask and bid quotes and a widening of BAS_{abs} is associated with

[4]Note that positive changes in the S&P500 index are associated with declining default probabilities and increasing recovery rates.

higher trading costs and, consequently, lower levels of liquidity.[5] To avoid potential distortions from artificial level effects, we follow Tang and Yan (2013) and Mayordomo et al. (2014b) and additionally employ the relative bid-ask spread as a control variable. The relative bid-ask spread (denoted as BAS_{rel}) results from dividing the absolute bid-ask spread by the corresponding CDS mid quote.[6]

In the spirit of Pu (2009), we include a liquidity variable that is based on the equity liquidity measure proposed by Lesmond et al. (1999), who employ the incidence of zero equity returns to estimate transaction costs and proxy liquidity in equity markets. Accordingly, we consider the quarterly updating frequency (denoted as UDF) that is calculated as the ratio of zero CDS spread changes to the number of reported bid-ask quotes within a quarter. Consequently, a UDF equal to zero indicates a perfectly liquid market in the sense that new CDS quotes arrive on a daily basis. Conversely, a ratio equal to one indicates zero updates within a quarter and, hence, extremely low levels of liquidity.

Theoretically, since CDS contracts are in zero net-supply, there is no unambiguous prediction on the impact of illiquidity on CDS prices. That is, the effect of illiquidity can either be zero, positive, or negative, depending on whether marginal CDS investors are net short or net long. If marginal investors are net short, the resulting illiquidity premia will be earned by the protection sellers, so that higher levels of illiquidity imply increasing CDS spreads. On the other hand, if marginal investors are net long, protection buyers will demand lower prices, resulting in a negative relation between illiquidity and CDS spreads. Bongaerts et al. (2011) propose a derivative pricing model with liquidity risk and find a positive and highly significant effect of illiquidity on CDS prices in their empirical study. Their results have been confirmed by various empirical studies in the literature (see, e.g., Tang and Yan, 2008; Lesplingart et al., 2012; Corò et al., 2013; Junge and Trolle, 2014). Thus, we expect a positive impact of bid-ask spreads and updating frequencies on CDS prices. Note, however, that existing studies find a reversed time-series pattern in relative bid-ask spreads. More precisely, due to the dramatic increase in CDS prices during

[5]Note that, in fact, the bid-ask spread is a measure of illiquidity rather than a liquidity proxy.

[6]Note that normalizing bid-ask spreads does not alter the economic interpretation. That is, higher values of BAS_{rel} imply lower liquidity and vice versa.

the recent financial crisis, relative bid-ask spreads are generally found to have decreased substantially over the last years.[7] Consequently, empirical studies such as Tang and Yan (2008) and Tang and Yan (2013) find that relative bid-ask spreads are negatively correlated with CDS spreads, so that we expect a negative impact of BAS_{rel} on CDS mid quotes.

Corò et al. (2013) and Arakelyan et al. (2013) argue that, in addition to contract-specific liquidity, industry- and market-wide levels of liquidity are also important drivers of firms' CDS spreads. In the spirit of these two studies, we compute proxies for market-wide and industry-specific liquidity and investigate their explanatory power with regard to CDS price variability. More precisely, we proxy market-wide liquidity by calculating equally weighted cross-sectional averages over the bid-ask spreads on a given day. In our empirical CDS pricing study, we compute market-wide liquidity separately for each firm i in our sample, where we exclude firm i from the calculation of the average bid-ask spreads to avoid mechanical correlations. We calculate market-wide liquidity on the basis of absolute and relative bid-ask spreads and refer to the resulting liquidity measures as $\text{BAS}^{\text{M}}_{\text{abs}}$ and $\text{BAS}^{\text{M}}_{\text{rel}}$, respectively. Based on our ICB industrial sector specifications, we also include industry-specific liquidity measures, which are computed as equally weighted cross-sectional averages over the absolute and relative bid-ask spreads of the firms in a specific industry sector on a given day. The corresponding liquidity measures are denoted as $\text{BAS}^{\text{I}}_{\text{abs}}$ and $\text{BAS}^{\text{I}}_{\text{rel}}$, respectively.[8]

The evidence presented in Corò et al. (2013) and Arakelyan et al. (2013) suggests a positive correlation between $\text{BAS}^{\text{M}}_{\text{abs}}$ and CDS spreads as well as between $\text{BAS}^{\text{I}}_{\text{abs}}$ and CDS spreads, so that we expect positive coefficients on $\text{BAS}^{\text{M}}_{\text{abs}}$ and $\text{BAS}^{\text{I}}_{\text{abs}}$. Concerning $\text{BAS}^{\text{M}}_{\text{rel}}$ and $\text{BAS}^{\text{I}}_{\text{rel}}$, we expect a negative impact on CDS prices due to the reversed time-series patterns in relative bid-ask spreads.

[7]See Section 3.2.4 for a detailed discussion.

[8]Again, we calculate industry-specific liquidity measures separately for each firm in a given industry sector due to endogeneity concerns and mechanical correlations.

3.2.3.2 Measuring commonality in CDS liquidity

Various methods have been applied in the empirical literature to capture commonality in CDS liquidity. For example, Corò et al. (2013) proxy commonality in liquidity by industry-specific average bid-ask spreads as well as asymmetric information measures at the industry level. Others, such as Pu (2009) and Bongaerts et al. (2011), employ principal component analyses and retrieve measures of commonality in liquidity via factor decompositions. More recently, Mayordomo et al. (2014b) and Mayordomo and Peña (2014) use the methodology proposed in Chordia et al. (2000) to define commonality in CDS liquidity. More precisely, they extract commonality measures from simple market model time-series regressions, where percentage changes in individual liquidity variables are regressed on market measures of liquidity.

In contrast to existing studies, we propose a novel approach of measuring commonality in CDS liquidity by applying the commonality measure suggested in Karolyi et al. (2012). They use the R^2 of regressions of individual liquidity on market-wide liquidity as a proxy for commonality in liquidity. Following their approach, we first apply autoregressive filtering regressions to the measures of contract-specific and market-wide CDS liquidity and extract the corresponding innovations in liquidity. In this way, we focus on the part of liquidity that cannot be explained by the generally high level of persistence. Consequently, we define commonality in CDS liquidity as the amount of firm-specific liquidity innovations that can be explained by market-wide innovations in liquidity.

Innovations in liquidity are obtained from first-order autoregressive processes. Formally, we estimate

$$\mathrm{liq}_{i,t}^{\mathrm{CDS}} = \mathrm{liq}_{i,t-1}^{\mathrm{CDS}} + \omega_{i,t}^{\mathrm{CDS}} \tag{3.1}$$

where $\mathrm{liq}_{i,t}^{\mathrm{CDS}}$ denotes the measure of firm-specific liquidity for company i on day t. Next, as suggested in Karolyi et al. (2012), we regress the firm-specific innovations in liquidity on the respective lagged, current, and lead market-wide liquidity innovations.[9] We

[9]See Chordia et al. (2000) and Karolyi et al. (2012) for details.

estimate

$$\hat{\omega}_{i,t}^{\text{CDS}} = \alpha_{i,t} + \sum_{j=-1}^{1} \beta_{i,t,j} \hat{\omega}_{m,t+j}^{\text{CDS}} + \varepsilon_{i,t} \tag{3.2}$$

where $\hat{\omega}_{m,t}^{CDS}$ is the innovation in market-wide liquidity at time t.

In our empirical study in Section 3.3, we estimate commonality in liquidity on the basis of (absolute) bid-ask spreads. Market-wide liquidity is computed as outlined in Section 3.2.3.1. We are aware of the fact that studies on liquidity in equity markets commonly employ value-weighted averages to construct measures of market liquidity. In the case of CDS, however, it is well established to use equally weighted averages (see Junge and Trolle, 2014). We estimate equation 3.2 for each quarter and each company in our sample based on the daily innovations in CDS liquidity and take the respective R^2 as the measure of commonality in CDS liquidity. We denote our measure of commonality in CDS liquidity as $\mathrm{R}^2_{\text{liq}}$ and follow Karolyi et al. (2012) in that we require at least 15 observations per quarter to estimate $\mathrm{R}^2_{\text{liq}}$.

3.2.4 Descriptive statistics

We now turn to the descriptive statistics on CDS mid quotes and our liquidity variables. Table 3.1 documents the variation in CDS mid quotes, liquidity measures, and commonality in liquidity over time. Our sample encompasses the period from January 2004 to September 2010 and, thus, comprises the main part of the recent financial crisis. Turning to CDS mid quotes, we can see that average prices for CDS contracts reached their minimum of 63.7 basis points (bps hereafter) during the pre-crisis period in 2006 and amounted to a maximum of more than 300.6 bps at the peak of the crisis in 2009. This pattern is also reflected by the variation in mid quotes as measured by the standard deviation. As outlined in Section 3.2.3.1, we proxy CDS liquidity by the absolute and relative bid-ask spreads as well as by the UDF. Descriptive statistics on absolute bid-ask spreads are reported in columns four to six of Table 3.1.

Table 3.1: Temporal variation in CDS mid quotes, liquidity measures, and commonality in liquidity.

The table reports summary statistics sorted by year for CDS mid quotes, the measures of contract-specific liquidity, and commonality in CDS liquidity. We use the absolute and relative bid-ask spreads as well as the updating frequency as proxies for liquidity. Absolute bid-ask spreads are calculated as the difference between ask and bid prices, while relative bid-ask spreads result from dividing the absolute bid-ask spreads by the corresponding CDS mid quotes. The updating frequency is computed as the ratio of zero CDS spread changes to the number of reported bid-ask quotes within a quarter. Increasing values of our contract-specific liquidity measures correspond to decreasing levels of liquidity. Commonality in liquidity is calculated as suggested in Karolyi et al. (2012) and defined as the R^2 of the regression of innovations in individual bid-ask spreads on innovations in market-wide bid-ask spreads. Details on the computation of commonality in CDS liquidity can be found in Section 3.2.3.2. CDS mid quotes and absolute bid-ask spreads are measured in basis points (bps), while the remaining variables are denominated in %. Corresponding variable definitions can be found in Table B.1 in Appendix B. Our sample encompasses 228 financial and non-financial companies for the period from January 2004 to September 2010.

Year	CDS mid quotes			Absolute bid-ask spreads			Relative bid-ask spreads			Updating frequency			CDS liquidity commonality		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
2004	78.7	135.7	912	7.3	8.7	912	15.5	14.7	912	17.2	17.9	912	6.0	5.6	905
2005	73.0	101.7	912	7.2	6.2	912	15.4	10.6	912	22.5	17.3	912	5.8	4.9	908
2006	63.7	96.5	912	5.5	4.5	912	16.2	13.3	912	23.6	15.2	912	5.6	4.7	909
2007	88.2	147.4	912	7.1	8.8	912	13.9	9.1	912	18.4	22.2	912	6.0	4.8	890
2008	286.0	455.0	912	21.3	46.3	912	8.3	3.9	912	12.0	19.5	912	9.5	9.8	889
2009	300.6	571.9	912	18.5	25.3	912	9.4	4.9	912	5.6	13.4	912	6.2	5.0	900
2010	186.8	199.0	684	10.4	8.3	684	7.4	3.5	684	2.2	6.0	684	11.9	13.3	683
Total	152.7	319.1	6156	11.1	22.0	6156	12.5	10.3	6156	15.0	18.4	6156	7.1	7.5	6084

An examination of the corresponding means reveals low trading costs during the pre-crisis period, reflecting the fact that trading activity (and, hence, the liquidity) in CDS contracts experienced a strong surge prior to the onset of the financial crisis. The crisis period as of 2007, however, is characterized by a sharp decline in CDS liquidity as indicated by the dramatic increase of bid-ask spreads to more than 20 bps during the market turmoil that followed the collapse of Lehman Brothers. Subsequently, liquidity restored in 2010 and bid-ask spreads declined to pre-crisis levels of about 10 bps. As mentioned in Section 3.2.3.1, relative bid-ask spreads show a somewhat counter-intuitive and reversed pattern, with relative bid-ask spreads being high in the pre-crisis period (around 15% on average) and decreasing substantially in the crisis period (approximately 8% on average), which is a consequence of the sharp increases in CDS mid quotes following the onset of the financial crisis. Surprisingly, we find the same pattern in the time-series variation of the UDF. To be precise, Table 3.1 shows that the UDF increased from 17.2% to 23.6% in the pre-crisis period and sharply declined from 18.4% to 2.2% during the crisis, indicating that trading costs (liquidity) were significantly higher (lower) in the pre-crisis period. Turning to the commonality in CDS liquidity, we find that liquidity commonalities stayed at comparatively modest levels of around 6% in the pre-crisis period and experienced a surge in 2008 (increasing to 9.5%). Interestingly, liquidity commonalities decreased to pre-crisis levels of about 6% in 2009 and, again, increased sharply to nearly 12% in 2010. That is, the amount of firm-specific shocks to liquidity that is due to shocks to market-wide liquidity appears to be greater in times of market turmoil. Put another way, in times of financial markets turbulences, firm-specific liquidity innovations seem to be more sensitive to market-wide liquidity innovations than during calm periods.

Figures 3.1 and 3.2 confirm these findings and depict the time-series variation in CDS mid quotes, the three liquidity measures, and liquidity commonalities. Panel (a) of Figure 3.1 shows corresponding averages and the range between the 5th and 95th percentile. Conforming to Table 3.1, CDS mid quotes and absolute bid-ask spreads stayed flat in the pre-crisis period and surged strongly during the crisis period as of 2007.

Figure 3.1: CDS mid quotes and bid-ask spreads.

The figure depicts the time-series variation in daily CDS mid quotes and absolute as well as relative bid-ask spreads. The first panel plots equally weighted cross-sectional averages (black line) and the range between the (cross-sectional) 5th and 95th percentiles (shaded area), while the second panel compares the time evolution of (average) mid quotes and bid-ask spreads. Absolute bid-ask spreads are computed as the difference between ask and bid prices, while relative bid-ask spreads result from dividing absolute bid-ask spreads by the corresponding CDS mid quotes. CDS mid quotes and absolute bid-ask spreads are measured in basis points (bps), relative bid-ask spreads are denominated in %. Our sample encompasses 228 financial and non-financial companies for the period from January 2004 to September 2010.

(a) Time−series variation in CDS mid quotes and bid−ask spreads

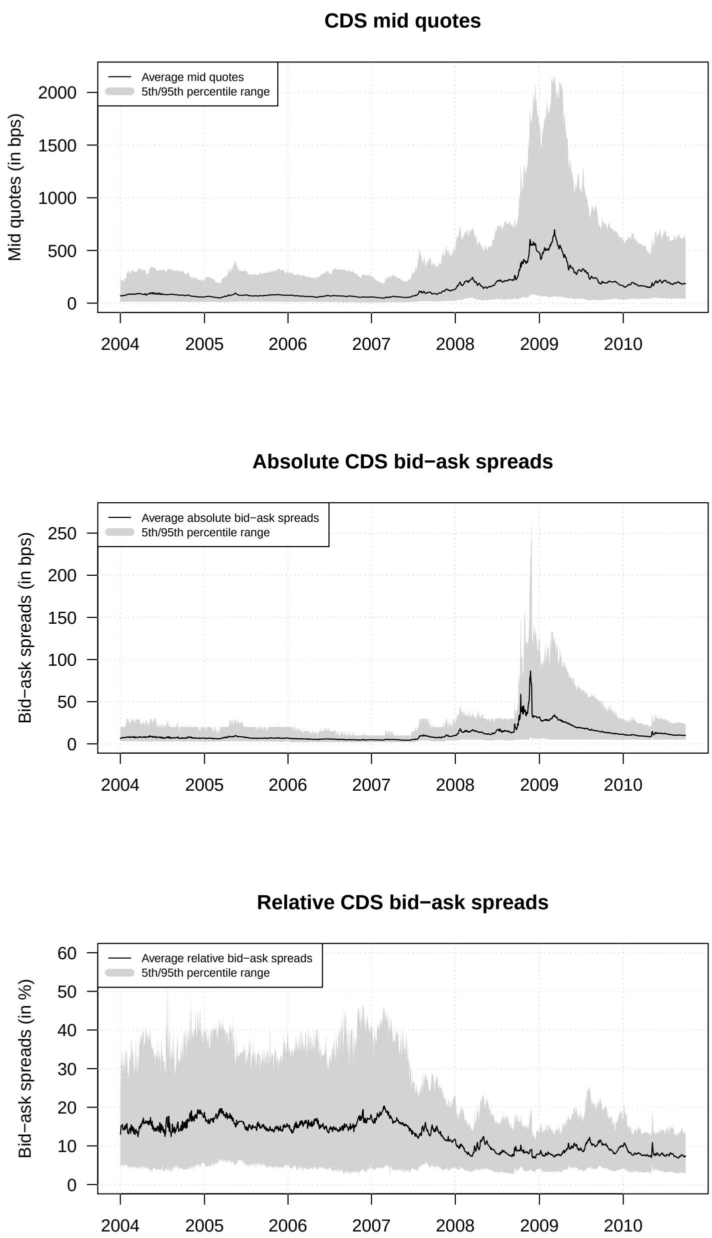


Figure 3.1: CDS mid quotes and bid-ask spreads (continued).

(b) Comparison of CDS mid quotes and bid−ask spreads

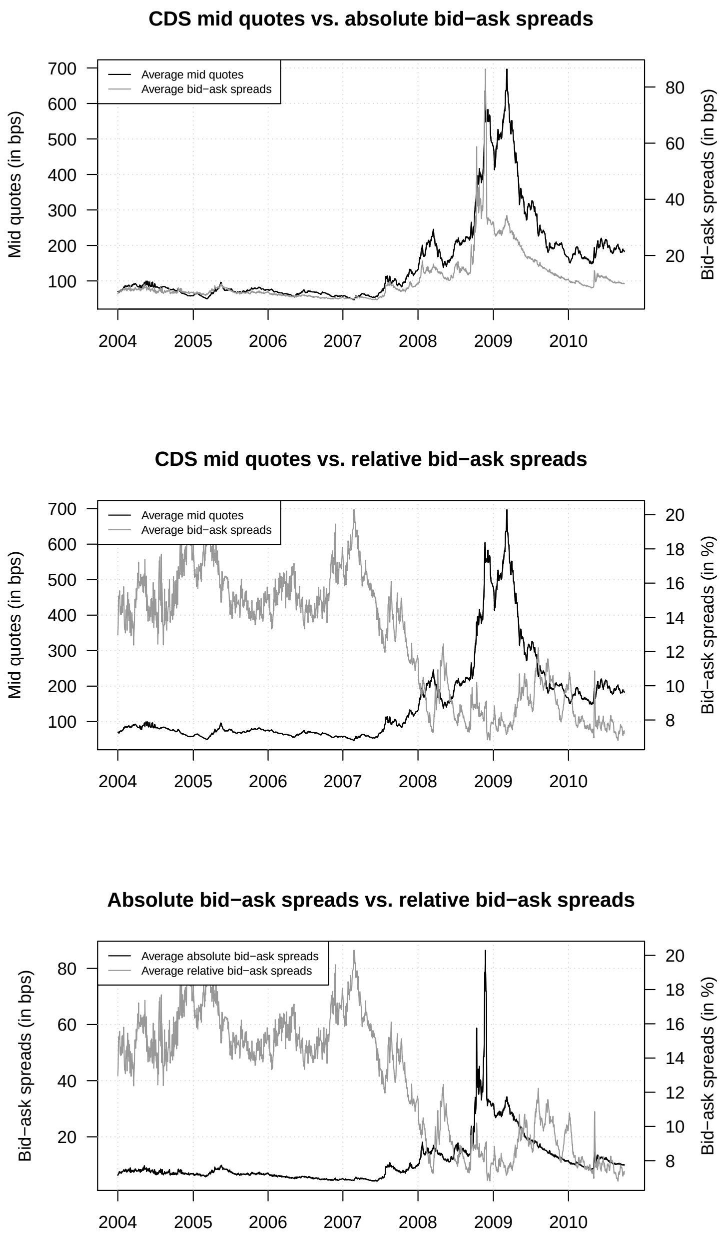
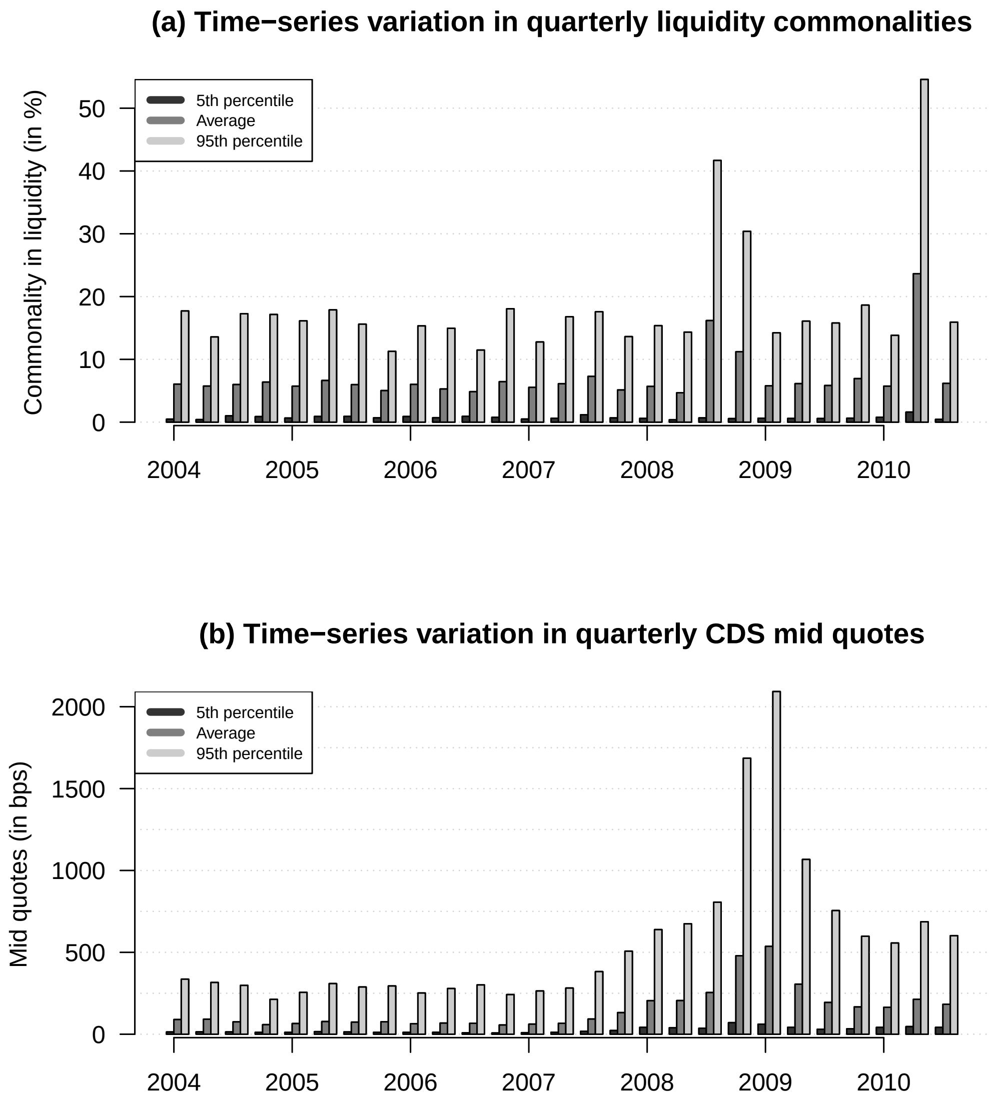


Figure 3.2: CDS mid quotes and liquidity commonalities.

The figure depicts the time-series variation in quarterly CDS liquidity commonalities and CDS mid quotes. For each quarter in our sample period, we calculate equally-weighted cross-sectional averages as well as cross-sectional percentiles at the 5% and 95% level. Commonality in liquidity is calculated as suggested in Karolyi et al. (2012) and defined as the R^2 of the regression of innovations in individual (absolute) bid-ask spreads on innovations in market-wide (absolute) bid-ask spreads. Details on the computation of commonality in CDS liquidity can be found in Section 3.2.3.2. CDS mid quotes are measured in basis points (bps), while commonality in liquidity is denominated in %. Our sample encompasses 228 financial and non-financial companies for the period from January 2004 to September 2010.



Relative bid-ask spreads, on the other hand, are characterized by a reversed time-series pattern, with relative bid-ask spreads being high in the pre-crisis period and decreasing sharply during the crisis. Panel (b) of Figure 3.1 compares the different time-series patterns and shows that CDS mid quotes and absolute bid-ask spreads appear to be positively related, while CDS mid quotes and relative bid-ask spreads as well as absolute and relative bid-ask spreads seem to be negatively related. Figure 3.2 depicts the time evolution of quarterly CDS liquidity commonalities (Panel (a)) and quarterly CDS mid quotes (Panel (b)). The panels support the results from Table 3.1 and show that liquidity commonalities surged after the collapse of Lehman Brothers in 2008, declined sharply during the subsequent market turmoil, and again increased dramatically in 2010. Comparing the two panels provides mixed evidence on the relation between liquidity commonalities and CDS mid quotes.

In our empirical study, we are also interested in how industry-specific liquidity and commonality in liquidity impact CDS prices. Therefore, Tables 3.2 and 3.3 report descriptive statistics separately for each industry. As we can see from the tables, the 228 companies in our sample comprise 19 industries and are unevenly distributed across the industrial sectors, with most firms (a total of 32) being in the Industrial Goods & Services sector and only one firm in the Telecommunications sector. Table 3.2 shows descriptive statistics on industry-specific CDS mid quotes as well as liquidity and documents strong variation across industries. Mid quotes range from 61.8 bps (Telecommunications) to 511.5 bps (Automobiles & Parts), while absolute bid-ask spreads vary from 4.8 bps (Banks) to 23.9 bps (Automobiles & Parts). Interestingly, industries with higher absolute bid-ask spreads (i.e., lower liquidity) appear to have higher CDS mid quotes. The opposite is true for relative bid-ask spreads, that is, higher relative spreads are generally associated with lower CDS mid quotes. Accordingly, the Healthcare sector exhibits the highest relative bid-ask spread (17.8% on average), while the Automobiles & Parts sector has the lowest relative bid-ask spread of 8.2% on average. Finally, the table also documents substantial cross-sectional variation of the UDF, indicating that variations in industry-specific liquidity are not driven by the choice of the liquidity measure.

Table 3.2: Industry-specific CDS mid quotes and liquidity measures.

The table reports summary statistics sorted by industry for CDS mid quotes and the measures of contract-specific liquidity. We use the absolute and relative bid-ask spreads as well as the updating frequency as proxies for liquidity. Absolute bid-ask spreads are calculated as the difference between ask and bid prices, while relative bid-ask spreads result from dividing the absolute bid-ask spreads by the corresponding CDS mid quotes. The updating frequency is computed as the ratio of zero CDS spread changes to the number of reported bid-ask quotes within a quarter. Increasing values of our contract-specific liquidity measures correspond to decreasing levels of liquidity. CDS mid quotes and absolute bid-ask spreads are measured in basis points (bps), while the remaining variables are denominated in %. Corresponding variable definitions can be found in Table B.1 in Appendix B. Our sample encompasses 228 financial and non-financial companies for the period from January 2004 to September 2010. Each of the 228 companies is assigned to one of the 19 different industries based on the Industry Classification Benchmark (ICB) Level 3 Supersector Codes which are retrieved from *Datastream*.

Industrial sector	No. of companies	CDS mid quotes			Absolute bid-ask spreads			Relative bid-ask spreads			Updating frequency		
		Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Ind. Goods & Services	32	98.8	140.8	864	8.6	9.3	864	14.0	9.7	864	15.7	18.1	864
Healthcare	17	85.6	145.5	459	7.1	6.1	459	17.8	13.3	459	16.4	14.0	459
Insurance	13	171.7	344.4	351	12.6	23.8	351	12.2	11.8	351	14.5	17.1	351
Technology	6	308.1	683.4	162	20.1	50.9	162	11.9	10.6	162	12.0	12.2	162
Utilities	18	97.8	107.9	486	8.7	6.8	486	12.0	6.9	486	16.5	18.4	486
Chemicals	11	134.2	240.5	297	9.5	10.6	297	11.9	7.4	297	10.0	9.3	297
Basic Resources	6	165.6	200.6	162	11.4	11.9	162	10.7	6.1	162	10.3	9.5	162
Pers & Household Goods	21	188.6	367.4	567	11.7	20.8	567	12.2	12.5	567	16.5	23.7	567
Automobiles & Parts	6	511.5	850.4	162	23.9	37.7	162	8.2	8.2	162	8.2	12.1	162
Financial Services	5	278.2	488.4	135	18.8	49.8	135	8.3	3.9	135	10.3	12.2	135
Real Estate	17	212.6	298.2	459	17.5	25.6	459	10.1	4.8	459	26.3	29.5	459
Retail	20	144.2	359.3	540	10.2	32.2	540	11.0	10.8	540	11.8	15.5	540
Oil & Gas	20	92.2	114.7	540	7.4	5.6	540	12.8	10.8	540	12.7	14.5	540
Food & Beverage	11	69.8	104.6	297	6.6	4.9	297	17.5	12.4	297	15.9	15.0	297
Telecommunications	1	61.8	69.4	27	5.4	2.0	27	15.8	11.7	27	11.5	8.2	27
Banks	4	77.7	96.2	108	4.8	4.5	108	9.7	5.6	108	14.7	17.0	108
Media	6	207.3	318.3	162	13.5	26.0	162	9.3	6.2	162	9.2	8.6	162
Travel & Leisure	9	226.3	432.3	243	16.2	34.4	243	9.7	5.9	243	15.1	22.2	243
Construct. & Material	5	138.8	167.8	135	10.5	8.3	135	14.9	16.4	135	15.7	20.2	135
Total	228	152.7	319.1	6156	11.1	22.0	6156	12.5	10.3	6156	15.0	18.4	6156

Table 3.3: Market-wide and industry-specific estimates of CDS liquidity commonality.

The table reports summary statistics on market-wide and industry-specific estimates of commonality in CDS liquidity separately for each industry. Commonality in CDS liquidity is calculated as suggested in Karolyi et al. (2012) and defined as the R^2 of the regression of innovations in individual bid-ask spreads on innovations in market-wide and industry-specific bid-ask spreads. Details on the computation of commonality in CDS liquidity can be found in Section 3.2.3.2. Our sample encompasses 228 financial and non-financial companies for the period from January 2004 to September 2010. Each of the 228 companies is assigned to one of the 19 different industries based on the Industry Classification Benchmark (ICB) Level 3 Supersector Codes which are retrieved from *Datastream*.

Industrial sector	No. of companies	CDS liquidity commonality					
		Market-wide estimates			Industry-specific estimates		
		Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.
Ind. Goods & Services	32	7.7	8.9	861	7.8	9.3	861
Healthcare	17	7.6	8.2	457	9.3	9.2	457
Insurance	13	7.0	7.8	348	10.0	10.7	348
Technology	6	6.7	6.0	162	7.7	9.1	162
Utilities	18	6.7	6.6	479	8.0	7.2	479
Chemicals	11	6.6	7.0	295	8.6	8.0	295
Basic Resources	6	6.9	6.3	162	8.2	7.7	162
Pers & Household Goods	21	7.5	7.2	553	8.7	8.6	553
Automobiles & Parts	6	7.6	6.9	162	8.4	7.8	162
Financial Services	5	7.8	8.4	135	10.1	9.4	135
Real Estate	17	6.4	6.1	432	8.9	9.2	432
Retail	20	7.6	8.3	535	7.8	8.3	535
Oil & Gas	20	6.4	6.2	538	8.4	7.3	538
Food & Beverage	11	7.0	7.8	297	8.8	8.3	297
Telecommunications	1	4.5	3.5	27	n.a.	n.a.	n.a.
Banks	4	8.5	9.8	107	21.5	19.9	107
Media	6	6.3	7.4	162	7.2	6.7	162
Travel & Leisure	9	7.4	7.6	239	6.5	6.9	239
Construct. & Material	5	6.5	6.6	133	8.1	7.2	133
Total	228	7.1	7.5	6084	8.6	9.0	6057

Turning to Table 3.3, we additionally find strong evidence for considerable variation in CDS liquidity commonalities across industries. The table reports market-wide liquidity commonalities for each industry as well as industry-specific liquidity commonalities. To obtain the latter, we follow the procedure described in Section 3.2.3.2 and replace market-wide liquidity by industry-specific liquidity, which is calculated by averaging across the (absolute) bid-ask spreads of the companies in the respective industry sector.[10] We can draw two main conclusions from the results in the table. First, both market-wide and industry-specific estimates reveal strong cross-sectional variation. While the means of the former range from 4.5% (Telecommunications) to 8.5% (Banks), the means of the

[10]Note that, in case of the liquidity commonalities of firm i, we exclude this firm from the calculation of the corresponding industry-specific liquidity to avoid mechanical correlations.

latter vary from 6.5% (Travel & Leisure) to 21.5% (Banks). Hence, parts of the cross-sectional variation in liquidity commonalities may be driven by the industry classifications of our sample firms, which needs to be addressed and controlled for in our empirical study in Section 3.3. Interestingly, comparing industry-specific commonality in liquidity to the industry-specific CDS mid quotes in Table 3.3, we find a predominantly negative relation, i.e., industries with strong commonality in liquidity appear to have lower CDS mid quotes than industries with weak commonality in liquidity (see, e.g., Banks, Food & Beverage, and Healthcare). Second, Table 3.3 shows that industry-specific liquidity commonalities are consistently stronger than the corresponding market-wide estimates. Expectedly, shocks to industry-specific liquidity appear to have a greater impact on firm-specific liquidity innovations than shocks to market-wide liquidity. That is, firm-specific liquidity is much more sensitive to industry-specific than to market-wide liquidity.

3.3 Liquidity and CDS spread movements: Empirical evidence

This section provides evidence from multiple regression models. We estimate both time-series and panel data models to analyze the role of liquidity and liquidity commonality in explaining movements in CDS spreads over time and in the cross-section. We carry out all regressions in first-differences rather than in levels. It is important to estimate the time-series regressions in differences to mitigate concerns arising from potentially co-integrated dependent and independent variables (see Ericsson et al., 2009). Consistent with our time-series regressions, we also use first-differences in the panel data models.[11]

3.3.1 Time-series evidence

First, we examine the relationship between changes in CDS spreads and changes in the variables suggested by theory (see Merton, 1974): firm value, interest rate, and equity

[11] This seems appropriate given the evidence for a unit root presented in Corò et al. (2013) for a comparable set of variables.

volatility.[12] We run firm-by-firm time-series regressions on the quarterly-sampled data and report average coefficient estimates, associated t-statistics, the average adjusted R^2, as well as the average number of available quotes in Table 3.4. All statistics are calculated as outlined in Collin-Dufresne et al. (2001).

Table 3.4: Time-series regressions.

The table reports coefficient estimates and corresponding t-statistics from time-series regressions in differences of quarterly CDS mid quotes on credit risk and liquidity variables. In terms of the former, we include the firm value, interest rate, and volatility. Concerning the CDS liquidity variables, we include the individual absolute bid-ask spread (BAS_{abs}), our measure of commonality in CDS liquidity (R^2_{liq}), the updating frequency (UDF), and the market-wide absolute bid-ask spread ($\text{BAS}^{\text{M}}_{\text{abs}}$). For each firm i, we estimate the following regression model for the period from January 2004 to September 2010:

$$\Delta\text{CDS}_i^t = \alpha + \beta\Delta\text{Merton-type}_i^t + \gamma\Delta\text{Liquidity}_i^t + \delta\Delta\text{R}^{2,t}_{\text{liq,i}} + \epsilon_i^t.$$

The credit risk and liquidity variables are discussed in detail in Section 3.2. Variable definitions, data sources, and summary statistics are reported in Tables B.1 and B.2 in Appendix B. The reported coefficients and t-statistics are calculated as outlined in Collin-Dufresne et al. (2001) and Ericsson et al. (2009). ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
ΔFirm value	-0.757***		-0.536***	-0.560***	-0.414***
	(-7.73)		(-6.19)	(-5.86)	(-5.39)
ΔInterest rate	-19.676***		-17.793***	-19.178***	
	(-6.08)		(-6.24)	(-6.13)	
ΔVolatility	19.271***		13.248***	13.349***	
	(11.05)		(8.73)	(9.00)	
$\Delta\text{BAS}_{\text{abs}}$		5.491***	4.899***	4.911***	5.248***
		(15.31)	(13.91)	(13.8)	(14.91)
$\Delta\text{R}^2_{\text{liq}}$			-0.793**	-0.946**	-0.971**
			(-2.15)	(-2.36)	(-2.52)
ΔUDF		-56.219***		-37.894**	-40.673*
		(-2.68)		(-2.00)	(-1.83)
$\Delta\text{BAS}^{\text{M}}_{\text{abs}}$		10.565***			10.964***
		(5.99)			(6.53)
Constant	2.552***	1.721***	1.775***	0.460	1.712***
	(4.16)	(5.63)	(5.93)	(0.44)	(2.75)
Adj. R^2	0.47	0.56	0.60	0.59	0.59
Avg. obs.	25.90	26.00	25.50	25.47	25.47

Column (1) of Table 3.4 shows that changes in fundamental variables are jointly significantly correlated with changes in the CDS mid quote. We find a negative relation between CDS spread changes and changes in firm value. The coefficient on the interest rate is also negative. However, changes in CDS spreads and equity volatility are significantly positively correlated. All estimation results are in line with their theoretical predictions.

[12]In the following, we refer to these variables as theoretical variables or credit risk variables.

With an average adjusted R^2 of 47%, the explanatory power of credit risk fundamentals is substantial; they explain almost half of the variation in CDS spread changes over time. With respect to the explanatory power of the theoretical variables, our results differ from Ericsson et al. (2009) who only report a modest R^2 for the variables suggested by theory. In their study, the theoretical variables explain only about 23% of the variation in CDS spreads. It is natural to ask which factors can account for the differences in the explanatory power. First, Ericsson et al. (2009) conduct their analysis on a comparatively much smaller sample (between 39 and 76 companies on average, depending on the regression specification, and 90 in total) and second, over a different time period (1999 to 2002). Third, we find that the contribution (as measured by the adjusted R^2) of stock volatility is highest among the set of theoretical variables and substantially higher as in Ericsson et al. (2009). When regressing changes in CDS spreads on equity volatility, about 38% of the variation can be explained. In contrast, Ericsson et al. (2009) report a maximum R^2 of approximately 10% for their univariate equity volatility regression. We find our results to be more in line with Tang and Yan (2013), who report similar evidence for a slightly different set of fundamental controls but perform their analyses over a comparable sample period.

Although recent evidence from the literature suggests that liquidity is an important driver of CDS spreads in the cross-section (see Lesplingart et al., 2012; Corò et al., 2013), time-series evidence on the effect of liquidity on CDS spread movements is rather scarce in the literature. For example, Ericsson et al. (2009) account for liquidity but do not directly test to what extent CDS spreads co-move with changes in the level of liquidity. In line with Tang and Yan (2013), we find that a substantial part of the time-series variation in CDS spreads can be attributed to changes in contract-specific liquidity. For example, changes in the absolute bid-ask spread alone explain, on average, 39% of the time-series variation in CDS mid quotes and, hence, are comparable to equity volatility in terms of the explanatory power. However, the portion of variation that can be explained by changes in relative bid-ask spreads is much lower, with an average adjusted R^2 of 4%.[13]

[13]We do not report univariate regression results but make them available upon request.

Nevertheless, changes in both variables are significantly correlated with changes in CDS spreads. We further extend our analyses to the inclusion of two additional liquidity factors: the market-wide absolute bid-ask spread, $\mathrm{BAS}^{\mathrm{M}}_{\mathrm{abs}}$, and the updating frequency, UDF. The estimation results are shown in Column (2) of Table 3.4. The three liquidity variables are significant at the 1% level. We find a negative coefficient on the UDF variable, indicating that an increase in UDF decreases CDS spreads. That is, less frequent quote updates (and, hence, less liquid contracts) are associated with lower CDS spreads. The evidence on market-wide liquidity, however, is different. Just as the coefficient on the contract-specific liquidity proxy ($\mathrm{BAS}_{\mathrm{abs}}$), the coefficient on $\mathrm{BAS}^{\mathrm{M}}_{\mathrm{abs}}$ is positive. This suggests two things. First, CDS spreads move with changes in market-wide liquidity and second, strained market-wide liquidity is reflected in higher CDS spreads. This finding is consistent with Corò et al. (2013) who also document a positive impact of industry-wide liquidity levels on CDS spreads.

Altogether, the three liquidity factors explain 56% of the time-series variation in CDS spreads. In other words, factors related to liquidity explain more of the time-series variation in CDS spreads than variables related to credit risk. We note that the correlation between contract-specific liquidity factors and market-wide liquidity is modest, with values of around 0.15 and, therefore, cannot be a driver of this finding (see Table B.3 in Appendix B).

Turning to the performance of our key variable, CDS liquidity commonality, we show estimation results of the commonality regressions in Columns (3) to (5) of Table 3.4. We obtain two major findings. First, we document a statistically significant and negative relation between liquidity commonality and CDS spread movements while controlling for the impact of contract-specific liquidity and credit risk variables. Hence, an increase in liquidity commonality, i.e., the degree to which innovations in market-wide liquidity explain innovations in firm-level liquidity, decreases CDS spreads. This finding is robust at the 5% significance level and supports the view that liquidity co-movement risk leads to a discount on CDS spreads and, hence, to a liquidity risk premium earned by the protection buyer. Second, when estimating the model with a combined set of credit risk and liquidity factors, we observe a sharp increase in the average adjusted R^2 up to 60%. The fact that the model performance can be improved substantially when controlling for both types of variables (credit risk and liquidity factors) adds to the notion of the so-called ”credit puzzle” and confirms that liquidity may indeed be an omitted factor in the Merton (1974) framework.

To further test the robustness of liquidity commonality as a determinant in the time-series variation of CDS spreads, in Columns (4) and (5) we include two additional liquidity factors. When estimated together with UDF, commonality in liquidity remains significant although the overall explanatory power of the regression marginally decreases by one percentage point. Finally, in Column (5) of Table 3.4, we include the market-wide absolute bid-ask spread. We do not estimate $\mathrm{BAS}^{\mathrm{M}}_{\mathrm{abs}}$ together with the interest rate and equity volatility variable to mitigate imprecision from multicollinearity. Pairwise correlations between the variables are above 0.5, respectively. The estimated coefficient sign on $\mathrm{BAS}^{\mathrm{M}}_{\mathrm{abs}}$ remains unchanged as compared to our liquidity regression in Column (1) and CDS liquidity commonality remains a negative and significant covariate in the time series of CDS spreads.

As can be seen from the regression results, liquidity is an important driver of the time-series variation in CDS spreads. Further, our variable of interest, CDS liquidity commonality, complements existing liquidity factors suggested in the literature. We find that liquidity commonality is significantly negatively correlated with CDS spread movements. Hence, we find evidence for a liquidity risk premium earned by the protection buyer who may demand compensation for impaired hedging opportunities or potentially lower returns from speculative activities. The results hold through various regression specifications.

3.3.2 Panel-data evidence

In this section, we present estimation results from various panel data regressions for our 228 companies. We conduct several tests and sub-sample analyses to examine the relation between CDS spread movements, liquidity factors, liquidity commonality, and credit risk variables in the cross-section of CDS spreads. We run our benchmark regressions with industry-fixed effects and cluster standard errors at the industry level. Hence, we allow standard errors to be correlated among firms within a certain industry. That is, given the relatively strong dispersion of companies across industrial sectors in our sample, we expect that shocks to the U.S. economy affect firms to a varying extent, depending on the relative importance and crisis resilience of their sector-specific business model. Nevertheless, we also test different specifications (firm- and time-fixed effects) in the robustness tests in Section 3.4 and find that our results remain unchanged.

3.3.2.1 Comparing explanatory power: Liquidity vs. credit risk

For our initial analysis, we again focus on differences in the explanatory power of liquidity and credit risk factors, this time in the cross-section of CDS spreads. Regression (1) in Table 3.5 includes the variables suggested by theory. The results are consistent with the time-series regressions reported in the previous section. We find a negative and significant slope coefficient for changes in the firm value and interest rate. Volatility enters the regression with a positive sign and also differs significantly from zero at the 1% level. The adjusted R^2 is 17% and, as expected, considerably lower than in the corresponding time-series regression (47%). Regression (2) in Table 3.5 repeats the liquidity regression. The estimated coefficient signs are also in line with the time-series evidence. For the two liquidity measures, $\mathrm{BAS}_{\mathrm{abs}}$ and $\mathrm{BAS}^{\mathrm{M}}_{\mathrm{abs}}$, we obtain significantly positive coefficients while the correlation between the updating frequency, UDF, and CDS spread movements is significant but negative. With an R^2 of 32%, the explanatory power of the liquidity variables is almost twice as high as that of the credit risk variables.

As with the time-series results, it is interesting to observe that the coefficient on market-wide liquidity is larger in magnitude than the coefficient on contract-specific liquidity. However, when considering the economic impact of the two direct liquidity measures, we find that contract-specific liquidity has a significantly stronger impact on CDS spreads. An increase of the bid-ask spread by 19.5% increases the CDS spread by 99 bps (5.1×19.5), whereas a one standard deviation increase in market-wide illiquidity increases the CDS spread by approximately 47 bps (13.4×3.5), which is only half of the economic impact.[14] Although the information in $\text{BAS}^{\text{M}}_{\text{abs}}$ may not be entirely independent of BAS_{abs} (and vice versa), the impact of market-wide liquidity on CDS spreads is substantial and, to the best of our knowledge, has not been considered together with contract-specific liquidity factors in previous studies.[15]

Table 3.5: Panel benchmark regressions.

The table reports results from panel regressions in first-differences on the quarterly sampled data. We regress changes in the CDS mid quote on a set of credit risk and liquidity variables. Regarding the former, we include the firm value, interest rate, and volatility. Concerning the CDS liquidity variables, we include the individual absolute bid-ask spread (BAS_{abs}), our measure of commonality in CDS liquidity (R^2_{liq}), the updating frequency (UDF), as well as the industry-specific ($\text{BAS}^{\text{I}}_{\text{abs}}$) and market-wide absolute bid-ask spread ($\text{BAS}^{\text{M}}_{\text{abs}}$). For each firm i in sector j, we estimate the following regression model for the period from January 2004 to September 2010:

$$\Delta\text{CDS}_{i,t} = \alpha + \beta\Delta\text{Merton-type}_{i,t} + \gamma\Delta\text{Liquidity}_{i,t} + \delta\Delta\text{R}^2_{\text{liq,i,t}} + \nu_j + \epsilon_{i,t}.$$

All regressions include industry-fixed effects, ν_j, based on the ICB supersector classifications. Standard errors are clustered at the industry level and corresponding t-statistics are reported in parentheses. The credit risk and liquidity variables are discussed in detail in Section 3.2. Variable definitions, data sources, and summary statistics are reported in Tables B.1 and B.2 in Appendix B. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔFirm value	-1.534***		-1.178***	-1.180***	-1.161***	-1.085***
	(5.83)		(3.66)	(3.67)	(3.59)	(3.35)
ΔInterest rate	-12.894**		-9.849*	-9.723*	-7.863	
	(2.35)		(1.86)	(1.83)	(1.51)	
ΔVolatility	25.471***		20.536***	20.626***	19.795***	
	(7.24)		(5.22)	(5.23)	(4.71)	
$\Delta\text{BAS}_{\text{abs}}$		5.069***	4.407***	4.408***	4.364***	4.668***
		(6.31)	(6.89)	(6.89)	(6.99)	(6.07)
$\Delta\text{R}^2_{\text{liq}}$			-1.049***	-1.049***	-1.061***	-0.990***
			(3.00)	(2.99)	(3.04)	(3.03)
ΔUDF		-0.220**		-0.267**	-0.261**	-0.185*
		(2.17)		(2.32)	(2.30)	(1.86)
$\Delta\text{BAS}^{\text{I}}_{\text{abs}}$					1.174*	
					(1.81)	
$\Delta\text{BAS}^{\text{M}}_{\text{abs}}$		13.448***				11.914***
		(5.23)				(4.74)
Constant	2.900***	2.112***	2.747***	2.574***	2.624***	2.856***
	(11.44)	(9.65)	(15.30)	(13.31)	(13.44)	(17.15)
Industry FE	x	x	x	x	x	x
Clustered SE	x	x	x	x	x	x
Adj. R^2	0.17	0.32	0.35	0.35	0.35	0.33
Obs.	5,891	5,928	5,785	5,785	5,759	5,785

[14] The standard deviation is calculated on the first-differenced variable.

[15] Note that we eliminate the influence of mechanical correlation in the market-wide liquidity measure by excluding firm i from the computation of averages.

Corò et al. (2013) examine industry-wide liquidity effects in the context of CDS pricing. However, we find that results differ substantially with respect to the explanatory power. In unreported tests, we use industry-specific instead of market-wide bid-ask spreads in regression (2) of Table 3.5 and find that this specification yields a lower R^2 of 28% and a substantially lower economic impact on CDS spreads. An increase of 8.6% in industry-specific liquidity increases CDS spreads by roughly 10.3 bps (8.6×1.2), which is less than one quarter of the impact of market-wide liquidity on CDS spreads. Related work has also been presented by Arakelyan et al. (2013). Nevertheless, they do not incorporate measures of contract-specific liquidity and, hence, comparability is limited.

3.3.2.2 CDS liquidity commonalities and the cross-section of CDS spreads

We next investigate whether CDS liquidity commonalities are priced in the cross-section of credit spreads. And indeed, we find strong evidence that it is. Column (3) of Table 3.5 shows that commonality in liquidity significantly co-moves with CDS spread changes. Throughout the regression specifications in Table 3.5, the estimated coefficient is negative. Corresponding t-statistics for the coefficient on commonality are around 3.00 through specifications (3) to (6), indicating significance at the 1% level. Moreover, we do not only find a statistically significant relation but also a considerable economic impact of commonality on CDS spreads. An increase in commonality by about 10.7% (one standard deviation) decreases the CDS spread by approximately 11 bps (-1.05×10.7). Compared to the measures of liquidity considered above, the economic effect of commonality on CDS spreads appears to be comparatively small. However, considering that this is a discount on the premium payment, the effect is meaningful. The overall size of the effect may indicate that buyers of credit protection may have relatively small negotiation power in CDS contracts, especially when the overall demand for credit protection increases as a consequence of an increase in aggregated market-wide credit risk.

When extending regression (1) with respect to the inclusion of the bid-ask spread and our measure of commonality in liquidity, the R^2 increases up to 35%. In Columns (4) and (6), we show that the effect is robust to the inclusion of further liquidity controls:

industry-specific liquidity (4), the updating frequency (5), and market-wide liquidity (6). The coefficient on UDF is negative and significant at the 5% level, indicating that lower levels of liquidity are associated with lower CDS spreads. In Column (5), we add the industry-specific liquidity factor. The coefficient on BAS^{I}_{abs} is positive and significant, suggesting that CDS spreads co-move with industry-specific liquidity. The coefficient is, however, relatively small in magnitude and only significantly different from zero at the 10% level. Finally, in Column (6) we include the market-wide liquidity measure. The coefficient is highly significant and large in magnitude. Market-wide liquidity appears to be a more reliable co-variate than industry-specific liquidity in the context of CDS pricing.

The results of specification (6) are informative to only a limited extent. To mitigate concerns arising from multicollinearity, as with the time-series regressions, we omit the interest rate and volatility variable. Nevertheless, when estimated together with market-wide liquidity, commonality is still a priced factor in the cross-section of CDS spreads. Notably, the R^2 decreases only marginally when excluding the two credit risk variables.

One potential concern is that CDS spread movements might be driven by other factors than the ones used in the regression specifications above. Indeed, the literature has focused extensively on so-called state variables such as the VIX or the S&P500 index. We include both of these variables in Table 3.6 together with the variables used in the above settings. Additionally, we control for the impact of firm size and book leverage. One could question the adequacy of our proxy for firm value in that it does not fully reflect the default-related information incorporated in the leverage ratio. We note that some of the variables exhibit high pairwise correlations such as changes in the S&P500 and our measure of volatility. This is why we limit our interpretation of the regressions in Table 3.6 to a sensitivity analysis of our main finding. Throughout the regressions in Table 3.6, our main result holds. Commonality in liquidity is significant at the 5% level and negatively correlated with CDS spread changes.

Table 3.6: Panel benchmark regressions with additional control variables.

The table reports results from panel regressions in first-differences on the quarterly sampled data. We regress changes in the CDS mid quote on a set of credit risk, liquidity, and additional control variables. Regarding the former, we include the firm value, interest rate, and volatility. Concerning the CDS liquidity variables, we include the individual absolute bid-ask spread (BAS_{abs}), our measure of commonality in CDS liquidity (R^2_{liq}), and the updating frequency (UDF). As additional control variables, we include the option-implied volatility index (VIX), book leverage, the logarithm of quarterly total assets (Assets), and values of the S&P500 index (S&P500). For each firm i in sector j, we estimate the following regression model for the period from January 2004 to September 2010:

$$\Delta \text{CDS}_{i,t} = \alpha + \beta \Delta \text{Merton-type}_{i,t} + \gamma \Delta \text{Liquidity}_{i,t} + \delta \Delta \text{R}^2_{\text{liq,i,t}} + \omega \Delta \text{Controls}_{i,t} + \nu_j + \epsilon_{i,t}.$$

All regressions include industry-fixed effects, ν_j, based on the ICB supersector classifications. Standard errors are clustered at the industry level and corresponding t-statistics are reported in parentheses. The credit risk and liquidity variables are discussed in detail in Section 3.2. Variable definitions, data sources, and summary statistics are reported in Tables B.1 and B.2 in Appendix B. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
ΔFirm value	-1.405***	-1.368***
	(4.26)	(4.18)
ΔInterest rate	-4.052	4.545
	(0.82)	(1.09)
ΔVolatility	21.436***	18.508***
	(4.35)	(3.74)
ΔBAS_{abs}	4.548***	4.549***
	(6.86)	(6.90)
ΔR^2_{liq}	-1.283**	-1.244**
	(2.44)	(2.79)
ΔUDF	-0.291*	-0.243
	(1.84)	(1.64)
ΔVIX	1.103	
	(1.45)	
ΔBook leverage	-31.020	-26.342
	(0.80)	(0.63)
ΔAssets	-23.765	-23.998
	(1.56)	(1.67)
ΔS&P500		-0.221**
		(2.63)
Constant	2.918***	3.862***
	(11.55)	(10.49)
Industry FE	x	x
Clustered SE	x	x
Adj. R2	0.30	0.31
Obs.	4,766	4,766

3.3.2.3 Comparing explanatory power: Pre-crisis vs. crisis evidence

In general, the demand and level of liquidity appear to be inversely related. In other words, liquidity is usually scarce in times when it is needed the most. Naturally, it is reasonable to expect that frictions in CDS market liquidity are particularly pronounced during the recent crisis period. Likewise, we assume that the absolute level as well as the impact of liquidity commonality on CDS spreads changes with the overall state of the economy. One reason might be that, when demand for credit protection spikes in times of financial distress, correlated trading behavior in CDS markets also increases. Indeed, we find anecdotal evidence for this hypothesis in Figure 3.2. The degree of commonality peaks in Q3:2008 when Lehman Brothers filed bankruptcy. Whether the notion of time-varying liquidity commonality finds support in the data is tested in Table 3.7. We present evidence from a sub-sample analysis by splitting up the sample into a pre-crisis (Q1:2004 to Q2:2007) and a crisis period (Q3:2007 to Q3:2010) and re-estimate the regression models from Table 3.5.

In a first step, we again compare the impact and explanatory power of credit risk and liquidity factors on CDS spreads in the pre-crisis and crisis regime. In Column (1) of Panel A, we report results for the variables suggested by theory in the pre-crisis period. Results on the corresponding crisis-period regression are shown in Column (1) of Panel B. Prior to the crisis, theoretical variables are significant but have only limited explanatory power, with an R^2 of 7%. After mid-2007, variation in CDS spreads increases dramatically and, consequently, the R^2 increases as well. Now, 18% of the variation can be explained by credit-sensitive variables. As compared to the full sample estimate, credit risk variables explain only a marginally greater portion (precisely, one percentage point) of the variation in CDS during the crisis period.

Table 3.7: Sub-sample analysis: Pre-crisis vs. crisis period.

The table reports results from sub-sample panel regressions in first-differences on the quarterly sampled data. We split the sample into two periods, the pre-crisis and the crisis period. The pre-crisis period covers Q1:2004 to Q2:2007, while the crisis period comprises Q3:2007 to Q3:2010. We regress changes in CDS mid quotes on a set of credit risk and liquidity variables. Regarding the former, we include the firm value, interest rate, and volatility. Concerning the CDS liquidity variables, we include the individual absolute bid-ask spread (BAS_{abs}), our measure of commonality in CDS liquidity (R^2_{liq}), the updating frequency (UDF), as well as the industry-specific ($\text{BAS}^{\text{I}}_{\text{abs}}$) and market-wide absolute bid-ask spread ($\text{BAS}^{\text{M}}_{\text{abs}}$). For each firm i in sector j, we estimate the following regression model for the period from Q1:2004 to Q3:2010:

$$\Delta\text{CDS}_{i,t} = \alpha + \beta\Delta\text{Merton-type}_{i,t} + \gamma\Delta\text{Liquidity}_{i,t} + \delta\Delta\text{R}^2_{\text{liq,i,t}} + \nu_j + \epsilon_{i,t}.$$

All regressions include industry-fixed effects, ν_j, based on the ICB supersector classifications. Standard errors are clustered at the industry level and corresponding t-statistics are reported in parentheses. The credit risk and liquidity variables are discussed in detail in Section 3.2. Variable definitions, data sources, and summary statistics are reported in Tables B.1 and B.2 in Appendix B. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Pre-crisis evidence						Panel B: Crisis evidence					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ΔFirm value	-0.456***		-0.435***	-0.435***	-0.430***	-0.439***	-1.778***		-1.377***	-1.385***	-1.368***	-1.257***
	(4.52)		(4.21)	(4.21)	(4.19)	(4.77)	(5.84)		(3.52)	(3.53)	(3.46)	(3.07)
ΔInterest rate	-5.526**		-4.996**	-5.059**	-5.481**		-6.938		-4.829	-3.447	-0.332	
	(2.24)		(2.17)	(2.20)	(2.34)		(0.85)		(-0.53)	(-0.37)	(-0.04)	
ΔVolatility	3.199**		2.648**	2.648**	2.667**		27.505***		22.574***	23.000***	22.300***	
	(2.68)		(2.33)	(2.33)	(2.42)		(7.03)		(4.84)	(4.85)	(4.45)	
$\Delta\text{BAS}_{\text{abs}}$		6.801**	1.705***	1.707***	1.668***	1.740***		5.001***	4.407***	4.407***	4.368***	4.716***
		(2.10)	(3.75)	(3.75)	(3.76)	(3.67)		(6.21)	(6.75)	(6.76)	(6.84)	(5.89)
$\Delta\text{R}^2_{\text{liq}}$			0.011	0.011	0.001	0.009			-1.488***	-1.495***	-1.505***	-1.339***
			(0.15)	(0.15)	(0.01)	(0.12)			(3.09)	(3.08)	(3.11)	(3.00)
ΔUDF		-0.056		-0.017	-0.021	-0.008		-0.503*		-0.908**	-0.895**	-0.515
		(1.12)		(0.48)	(0.59)	(0.24)		(2.00)		(2.15)	(2.14)	(1.47)
$\Delta\text{BAS}^{\text{I}}_{\text{abs}}$					0.907*						1.082	
					(1.92)						(1.70)	
$\Delta\text{BAS}^{\text{M}}_{\text{abs}}$		-0.584				2.212*		13.724***				11.805***
		(0.16)				(1.96)		(5.19)				(4.48)
Constant	0.160	-0.297	0.385	0.404	0.751	-0.456	5.072*	1.167	4.375	3.458	4.225	2.912**
	(0.25)	(0.70)	(0.61)	(0.64)	(1.15)	(1.51)	(1.85)	(0.98)	(1.53)	(1.21)	(1.47)	(2.54)
Industry FE	x	x	x	x	x	x	x	x	x	x	x	x
Clustered SE	x	x	x	x	x	x	x	x	x	x	x	x
Adj. R^2	0.07	0.36	0.11	0.11	0.12	0.10	0.18	0.31	0.36	0.36	0.36	0.34
Obs.	2,938	2,964	2,913	2,913	2,900	2,913	2,953	2,964	2,872	2,872	2,859	2,872

Next, we turn to the liquidity regression in Column (2) of Panels A and B, respectively. We find that, prior to the crisis, only the bid-ask spread is significantly correlated with CDS spread movements. Nevertheless, the explanatory power is high with an R^2 of 36%. Although all liquidity factors are jointly significant during the crisis, the explanatory power is, with an R^2 of 31%, slightly lower when compared to the pre-crisis period. Most interestingly, however, market-wide liquidity is only significantly related to CDS spread movements during the crisis.

Finally, in Columns (3) to (6) we revisit the commonality regressions. The main finding from Panel A is that commonality in CDS liquidity is not a priced factor in the cross-section of credit spreads prior to the crisis. The coefficients are positive and insignificant. While the theoretical variables and BAS_{abs} are mostly significant at either the 5% or the 1% level, industry-specific and market-wide liquidity are also positive but have coefficients that are significantly different from zero only at the 10% level. During the crisis period in Panel B, however, we find strong evidence for liquidity commonalities as drivers of CDS spread movements. We document a significantly negative impact of commonality in liquidity on CDS spreads. Coefficients range from -1.505 to -1.339 and are higher in absolute levels as compared to the full sample estimates. In contrast, industry-specific and market-wide liquidity are positively correlated with CDS spread changes. However, only changes in market-wide liquidity are significantly related to CDS spread changes. Further, it is important to note that our set of variables explains a significantly greater portion of the variation in CDS spreads during the crisis, with corresponding R^2s ranging between 34% and 36%. In contrast, the R^2s from the pre-crisis period are only at levels of 10% to 12%.

3.4 Robustness tests

This section presents the results of several tests that underline the robustness of our findings to the use of alternative regression model specifications. Up to this point, all our analyses have been based on regressions with industry-fixed effects to capture unobserved effects that are common to firms within an industrial sector but that could differ across firms from different sectors.

One potential concern regarding this approach, however, might be that some of the effects we observe can be explained by time-invariant unobserved differences between firms and not between industries. Consequently, in Columns (1) and (2) of Table 3.8, we replace the previously used industry-fixed effects with firm-fixed effects and again compare the explanatory power of the variables suggested by theory with the liquidity factors. In this specification, all Merton-type and liquidity variables enter the regressions with a statistically significant coefficient (1% level). The adjusted R^2, however, decreases slightly in comparison to our regression specification with industry-fixed effects.

Further, it could be argued that in addition to the entity-fixed effects, unobserved effects that vary over time but not across industries or firms could be present in the data and drive our results.[16] We incorporate year-fixed effects in our benchmark regression together with firm-fixed effects in Columns (4) to (7), and industry-fixed effects in Columns (8) to (11). The main conclusion from these tests is that our findings concerning the significance of the commonality in liquidity is robust to these alternative regression specifications. Throughout all specifications, the coefficient on our liquidity commonality proxy remains negative and statistically significantly different from zero at the 1% level. The remaining controls keep their expected signs with the exception of the interest rate which is no longer statistically significant when including time-fixed effects in addition to the industry dummies.

Including firm- instead of industry-fixed effects lowers the R^2 slightly as compared to the specification with industry-fixed effects. This may be due to the fixed-effects capturing most of the heterogeneity between firms. Further, the results show no evidence for an economically or statistically significant time-fixed effect in the data. We thus conclude that our clustering at the industry level is appropriate in this context.

[16]See Petersen (2009) for a comprehensive discussion on the estimation of standard errors in panel data.

Table 3.8: Robustness checks using industry-, firm-, and year-fixed effects.

The table reports results from panel regressions in first-differences on the quarterly sampled data, testing the robustness of our benchmark specification in Table 3.5. We regress changes in CDS mid quotes on a set of credit risk and liquidity variables. Regarding the former, we include the firm value, interest rate, and volatility. Concerning the CDS liquidity variables, we include the individual absolute bid-ask spread (BAS_{abs}), our measure of commonality in CDS liquidity (R^2_{liq}), the updating frequency (UDF), as well as the industry-specific ($\text{BAS}^{\text{I}}_{\text{abs}}$) and market-wide absolute bid-ask spread ($\text{BAS}^{\text{M}}_{\text{abs}}$). For each firm i in sector j, we estimate the following regression model for the period from Q1:2004 to Q3:2010:

$$\Delta\text{CDS}_{i,t} = \alpha + \beta\Delta\text{Merton-type}_{i,t} + \gamma\Delta\text{Liquidity}_{i,t} + \delta\Delta\text{R}^2_{\text{liq,i,t}} + \epsilon_{i,t}.$$

In Columns (1) to (3), we compare the explanatory power of credit risk and liquidity variables, this time using firm-fixed effects and standard errors clustered at the firm level. Columns (4) to (7) report results from a two-way fixed-effects model including industry- and year-fixed effects, with standard errors being clustered at the industry level. Finally, Columns (8) to (11) report results from a two-way fixed-effects specification including firm- and year-fixed effects, where standard errors are clustered at the firm level. Corresponding t-statistics are reported in parentheses. The credit risk and liquidity variables are discussed in detail in Section 3.2. Variable definitions, data sources, and summary statistics are reported in Tables B.1 and B.2 in Appendix B. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ΔFirm value	-1.536***		-1.120***	-1.178***	-1.179***	-1.164***	-1.025***	-1.179***	-1.181***	-1.165***	-1.026***
	(6.06)		(4.08)	(3.67)	(3.67)	(3.60)	(3.17)	(4.26)	(4.26)	(4.21)	(3.65)
ΔInterest rate	-12.898***		-10.039***	-8.620	-8.730	-7.284		-8.629**	-8.737**	-7.292*	
	(3.09)		(2.67)	(1.35)	(1.36)	(1.13)		(2.00)	(2.03)	(1.69)	
ΔVolatility	25.448***		18.941***	19.571***	19.636***	19.314***		19.552***	19.617***	19.296***	
	(7.31)		(4.93)	(4.65)	(4.67)	(4.40)		(4.51)	(4.52)	(4.54)	
$\Delta\text{BAS}_{\text{abs}}$		5.068***	4.495***	4.399***	4.400***	4.362***	4.702***	4.398***	4.399***	4.361***	4.701***
		(4.84)	(4.88)	(6.83)	(6.83)	(6.94)	(6.16)	(4.84)	(4.84)	(4.80)	(4.75)
$\Delta\text{R}^2_{\text{liq}}$				-1.052***	-1.052***	-1.064***	-1.049***	-1.053***	-1.052***	-1.065***	-1.050***
				(3.03)	(3.01)	(3.06)	(3.09)	(3.43)	(3.43)	(3.47)	(3.38)
ΔUDF		-0.220***			-0.274**	-0.265**	-0.176*		-0.275**	-0.266**	-0.177*
		(2.65)			(2.40)	(2.36)	(1.80)		(2.57)	(2.48)	(1.77)
$\Delta\text{BAS}^{\text{I}}_{\text{abs}}$						1.123*				1.125**	
						(1.74)				(2.06)	
$\Delta\text{BAS}^{\text{M}}_{\text{abs}}$		13.450***					16.085***				16.085***
		(6.56)					(4.20)				(5.90)
Constant	2.901***	2.112***	2.737***	0.739	0.811	0.521	3.052	0.785	0.854	0.568	3.070*
	(19.85)	(14.50)	(22.63)	(0.23)	(0.25)	(0.16)	(1.52)	(0.31)	(0.34)	(0.23)	(1.76)
Industry FE	-	-	-	x	x	x	x	-	-	-	-
Firm FE	x	x	x	-	-	-	-	x	x	x	x
Year FE	-	-	-	x	x	x	x	x	x	x	x
Clustered SE Industry	-	-	-	-	x	x	x	-	-	-	-
Clustered SE Firm	x	x	x	-	-	-	-	x	x	x	x
Adj. R^2	0.14	0.29	0.32	0.35	0.35	0.35	0.33	0.32	0.32	0.33	0.31
Obs.	5,891	5,928	5,891	5,785	5,785	5,759	5,785	5,785	5,785	5,759	5,785

Lesplingart et al. (2012) argue that potential spillover effects from related securities, in this case equity, are also drivers of CDS spreads. They directly test the impact of equity liquidity conditions on CDS spreads and find a positive but insignificant relation between the two variables. In unreported tests, we also empirically investigate the relation between CDS spreads and equity market liquidity. We include the absolute equity bid-ask spread into our commonality benchmark regression model outlined in Table 3.5 and find that the coefficient on equity liquidity is significant and positive.[17] The estimated coefficient on the equity liquidity factor suggests that deteriorating liquidity in equity markets is associated with higher CDS spreads. Our measure of CDS liquidity commonality, however, remains negative and significant at the 1% level when estimated together with the equity liquidity measure.

Nevertheless, this result has to be treated with caution since the direction of causality might not be obvious. Boehmer et al. (2014) establish a theoretical link between CDS trading and equity market quality, and in particular equity liquidity. They argue that investors may wish to hedge their exposure from CDS contracts by shorting the underlying equity position. This, however, decreases equity market liquidity since order flows in the same direction increase together with the pressure to sell the asset. In this case, causality would run from the CDS to the equity market in that CDS trading impacts equity market liquidity, and not vice versa.

Finally, we consider a different specification of the CDS liquidity variables. In the existing literature on this topic, several authors use absolute bid-ask spreads while others, however, also use relative bid-ask spreads. Naturally, one could argue that the absolute bid-ask spread already is a spread and thus does not need to be transformed. In contrast, the relative spread is the absolute CDS bid-ask spread normalized by the CDS mid quote. This, however, implies that in times of financial turmoil and potentially sharply increasing CDS spreads, relative liquidity may decrease although absolute measures of liquidity increase. We also present evidence for this notion in Section 3.2.4. It may well be argued that neither of the two spread measures purely captures liquidity. However, the dispro-

[17] Note that we can only perform this analysis for the sample period after Q2:2006 since we do not obtain equity-related bid and ask quotes from *Datastream* prior to this date.

portional increase in CDS spreads during the crisis is likely to have distorted percentage measures. As a consequence, the two liquidity measures are inversely related to CDS spreads. Tang and Yan (2013), for example, regress CDS spreads on both liquidity measures and obtain positive signs for the absolute and negative signs for the relative bid-ask spread.

Thus far, we have used absolute bid-ask spreads and now test the robustness of our results when replacing absolute with relative spreads. To this end, we repeat our benchmark regression and report the estimation results in Table 3.9.

Table 3.9: Robustness checks using relative bid-ask spreads.

The table reports results from panel regressions in first-differences on the quarterly sampled data, testing the robustness of our benchmark specification in Table 3.5 with respect to using relative instead of absolute bid-ask spreads. We regress changes in CDS mid quotes on a set of credit risk and liquidity variables. Regarding the former, we include the firm value, interest rate, and volatility. Concerning the CDS liquidity variables, we include the individual relative bid-ask spread ($\mathrm{BAS}_{\mathrm{rel}}$), our measure of commonality in CDS liquidity ($\mathrm{R}^2_{\mathrm{liq}}$), the updating frequency (UDF), as well as the industry-specific ($\mathrm{BAS}^{\mathrm{I}}_{\mathrm{rel}}$) and market-wide relative bid-ask spread ($\mathrm{BAS}^{\mathrm{M}}_{\mathrm{rel}}$). For each firm i in sector j, we estimate the following regression model for the period from January 2004 to September 2010:

$$\Delta\mathrm{CDS}_{i,t} = \alpha + \beta\Delta\text{Merton-type}_{i,t} + \gamma\Delta\text{Liquidity(\%)}_{i,t} + \delta\Delta\mathrm{R}^2_{\mathrm{liq,i,t}} + \nu_j + \epsilon_{i,t}.$$

All regressions include industry-fixed effects, ν_j, based on the ICB supersector classifications. Standard errors are clustered at the industry level and corresponding t-statistics are reported in parentheses. The credit risk and liquidity variables are discussed in detail in Section 3.2. Variable definitions, data sources, and summary statistics are reported in Tables B.1 and B.2 in Appendix B. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
ΔFirm value		-1.578***	-1.580***	-1.567***	-1.534***
		(5.87)	(5.88)	(5.86)	(5.78)
ΔInterest rate		-12.148**	-12.049**	-11.578**	-8.590*
		(2.50)	(2.48)	(2.39)	(1.84)
ΔVolatility		27.371***	27.451***	27.475***	27.276***
		(6.61)	(6.61)	(6.57)	(6.57)
$\Delta\mathrm{BAS}_{\mathrm{rel}}$	-0.105	-0.258*	-0.237	-0.130	0.029
	(0.62)	(1.84)	(1.71)	(0.90)	(0.21)
$\Delta\mathrm{R}^2_{\mathrm{liq}}$		-0.825**	-0.826**	-0.821**	-0.751**
		(2.49)	(2.48)	(2.45)	(2.30)
ΔUDF	0.015		-0.234*	-0.238*	-0.236*
	(0.12)		(2.01)	(2.02)	(1.91)
$\Delta\mathrm{BAS}^{\mathrm{I}}_{\mathrm{rel}}$				-1.306**	
				(2.52)	
$\Delta\mathrm{BAS}^{\mathrm{M}}_{\mathrm{rel}}$	-0.150***				-0.068***
	(6.30)				(5.24)
Constant	-1.232***	2.673***	2.527***	2.169***	0.590
	(11.44)	(10.70)	(10.21)	(7.50)	(1.15)
Industry FE	x	x	x	x	x
Clustered SE	x	x	x	x	x
Adj. R^2	0.01	0.18	0.18	0.18	0.19
Obs.	5,928	5,785	5,785	5,759	5,785

The most important observation from Table 3.9 is that our main results hold. CDS liquidity commonality is significantly negatively correlated with CDS spread movements when estimated together with relative instead of absolute bid-ask spreads. In addition, we find that contract-specific (relative) liquidity cannot explain the variation in CDS spreads, whereas industry-specific and, in particular, market-wide liquidity levels appear to be significant drivers of CDS spreads. For both variables, we find a negative relation to CDS spreads. In Column (1), the liquidity regression yields an R^2 of only 1% and thus cannot explain the variation in CDS spreads. The same regression specification with absolute measures of liquidity, however, can explain 32% of the variation. Also note that the overall R^2 strongly decreases when replacing absolute with relative levels of liquidity. In contrast to the previous specifications, in regression (5) we can use the full set of variables since market-wide liquidity measured in percent exhibits substantially lower correlations with the remaining covariates. The effect on the R^2 is only marginal with an increase in the adjusted R^2 of one percentage point.

In summary, we find our main result of a highly significant relation between changes in liquidity commonality and CDS spreads movements to be robust to several different specifications of i) the regression model, ii) spillover effects from equity markets, and iii) the alternative use of relative instead of absolute measures of liquidity.

3.5 Conclusion

In this paper, we analyze the question whether commonality in liquidity affects the pricing of single-name credit default swaps. To measure commonality in liquidity, we follow the rich literature on commonality in stock liquidity (see Chordia et al., 2000; Karolyi et al., 2012) and employ the R^2 of regressions of individual CDS liquidity on market-wide CDS liquidity. Using this proxy for liquidity risk, we first document significant commonality in CDS liquidity in our full sample running from 2004 to 2010. During the financial crisis, illiquidity as measured by absolute bid-ask spreads of CDS contracts and liquidity commonality spiked significantly.

We then show that commonality in CDS liquidity is indeed priced in both the cross-section and time series of CDS spreads. Protection buyers earn a statistically significant and economically important discount for bearing the risk of individual CDS illiquidity co-moving with CDS market illiquidity. The pricing of commonality in CDS liquidity, however, is different for calm and crisis periods as we find liquidity risk to be a priced factor in CDS spreads only during the recent financial crisis when CDS markets were highly illiquid. Furthermore, we confirm earlier results of Corò et al. (2013) and Tang and Yan (2013) that illiquidity in CDS markets plays a far more important role for the pricing of credit derivatives than fundamentals from the structural model of Merton (1974).

In combination, both our main findings have important implications for firms that use credit derivatives for hedging and financial economists that employ CDS spreads as direct measures of default risk (see, e.g., Blanco et al., 2005). As our results show, CDS spreads are not only driven by fundamental determinants of default risk but are also significantly affected by both liquidity and liquidity risk. Even more importantly, the pricing of liquidity risk in CDS spreads becomes more pronounced when liquidity is needed the most: during a financial crisis.

Chapter 4

Dynamic Dependence in Prices, Liquidity, and Credit Risk. A Vine Copula Approach.

4.1 Introduction

Since the first use of copulas in financial econometrics and quantitative risk management (see, e.g., Li, 2000; Embrechts et al., 2002) most applications of copulas have focused on a multivariate modeling of different risk types at the macro-level to estimate and forecast the total risk exposure of a given firm's complete credit and trading portfolios (see McNeil et al., 2005; Embrechts et al., 2003). In this paper, we propose to model different risk types at the level of individual securities by modeling the joint distribution of market price, liquidity, and credit risk of individual stocks in a portfolio. To be precise, we model the stock returns, bid-ask spreads, and default intensities of firms in a multivariate portfolio using dynamic regular vine (R-vine) copulas. We then propose and forecast a liquidity- and credit-adjusted Value-at-Risk (VaR) that is in the spirit of the liquidity-adjusted VaR of Berkowitz (2000), Bangia et al. (2002), and Weiß and Supper (2013) but that additionally incorporates information on the credit risk of the underlying securities. Confirming several predictions from the financial economics literature (see, e.g., Bekaert et al., 2007; Friewald et al., 2014; Boehmer et al., 2014), this paper is the first to document the existence of significant tail dependence between the stock returns, stock liquidity, and default intensities of companies. Furthermore, we show that adjusting the standard Value-at-Risk for liquidity and credit risk enables risk managers to reliably forecast the total risk exposure of a stock investment. Finally, we show that our dynamic vine copula model captures time-varying tail dependence significantly better than static copula or dynamic correlation-based models.

In our econometric framework, we aim to model the joint distribution of stock returns, bid-ask spreads, and default intensities (extracted from credit default swap premia) of a stock portfolio. We use a dynamic vine copula model to capture the time-varying dependences in the portfolio and to reproduce the potentially intricate spillover effects and interactions between stock markets, stock liquidity, and credit markets. More precisely, in our model, we consider the dependence between (1) a stock's return and its liquidity, (2) a stock's return and the default intensity of the underlying firm, (3) stock liquidity and the default intensity of a given firm, and (4) all relevant cross-dependences (e.g., between a stock's return and the liquidity of another stock).[1] Our state-of-the-art copula approach is motivated by a substantial body of literature on how the concept of stock liquidity is related to stock returns and credit default swap premia (CDS spreads hereafter) and how stock and credit markets are interconnected.

Starting with the relation between stock returns and liquidity, the seminal work by Amihud and Mendelson (1986) finds that market-observed average returns are an increasing function of the bid-ask spread. Further, stocks with higher sensitivities to market liquidity exhibit higher expected returns (Pastor and Stambaugh, 2003), liquidity predicts future returns (Bekaert et al., 2007), and expected stock excess returns reflect compensation for expected market illiquidity (Amihud, 2002). Acharya and Pedersen (2005) provide a theoretical asset pricing model with liquidity risk that helps explain these empirical findings and in which required returns depend on expected liquidity. Since liquidity exhibits commonalities and is characterized by strong temporal variation (Watanabe and Watanabe,

[1] Note that, as we use an R-vine copula for dependence modeling, we are also capable of specifying the conditional dependence structure of the joint distribution. See Section 4.2 for details.

2008; Hasbrouck and Seppi, 2001; Chordia et al., 2000), our dynamic modeling approach is especially appropriate for capturing the potentially time-varying nature of the dependences in our multivariate portfolio.

Regarding the dependence between stock returns and default intensities (i.e., credit risk), the theoretical basis is given by the structural model of Merton (1974). In his model, equity can be viewed as a call option on the firm's assets with a strike price equal to the value of the firm's debt, which suggests a precise pricing relationship between equity- and debt-linked securities (Boehmer et al., 2014). Further, as stated in Friewald et al. (2014), risk premia in equity and credit markets must be related because Merton's (1974) model implies that the market price of risk must be the same for all contingent claims written on a firm's assets. The empirical evidence on the relation of stock returns and credit risk, however, is mixed. Some studies document a positive relation (Vassalou and Xing, 2004; Chava and Purnanandam, 2010), whereas various other papers find a negative relation between stock returns and credit risk (Dichev, 1998; Campbell et al., 2008). Moreover, an increasing branch of literature investigates the interconnectedness of equity and CDS markets and provides empirical evidence on the relation between CDS spreads and stock returns (see, e.g., Acharya and Johnson, 2007; Han and Zhou, 2011).

Finally, modeling the dependence of stock liquidity and default intensities is economically relevant due to the relation between CDS and stock markets.[2] The theoretical and empirical motivation is given in Boehmer et al. (2014), who investigate the effect of CDS markets on equity market quality, that is, liquidity and market efficiency. From a theoretical point of view, the authors discuss two potential channels by which CDS markets could affect liquidity in equity markets, risk sharing and trader-driven information spillovers. Risk sharing might be based on dynamic delta hedging strategies by informed traders and is expected to reduce market liquidity. Trader-driven information spillovers, on the other hand, result from informed speculators' trading on private information which causes all securities to be priced more efficiently and increases market liquidity. While the theoretical effect of CDS markets on equity market liquidity is ambiguous, the empirical study

[2] Consider that we extract default intensities from CDS spreads.

in Boehmer et al. (2014) documents this effect to be adverse. That is, empirically, CDS trading is associated with significant declines in equity market liquidity. Although not giving any evidence on the particular relation between stock liquidity and CDS spreads, the study of Boehmer et al. (2014) indicates that bid-ask spreads and default intensities must somehow be related, thereby providing further motivation for our multivariate modeling approach.[3]

Our paper is related to several studies in the literature but complements these studies by making several major contributions. First, this paper is the first to document strong time-varying tail dependence at the individual security-level between stock returns and default intensities, as well as between stock liquidity and default intensities. While previous studies have documented extreme dependence in stock returns (see, e.g., Poon et al., 2004; Bollerslev and Todorov, 2011; Christoffersen et al., 2012), credit risk (see, e.g., Christoffersen et al., 2013), and between stock returns and liquidity (Ruenzi et al., 2013; Weiß and Supper, 2013), our study provides the first empirical evidence of significant tail dependence across equity and CDS markets. The variant of the standard VaR that we propose is closely related to the liquidity-adjusted VaR of Berkowitz (2000) and Bangia et al. (2002). In contrast to their work, however, we propose a VaR that together with market and liquidity risk additionally incorporates credit risk. The idea to use copulas for modeling different risk factors of a single security is closely related to the work of Nolte (2008) and Weiß and Supper (2013). However, we do not consider a multivariate transaction process model like it is done in the former study, but directly model the stock returns and bid-ask spreads of multiple stocks in a portfolio. In comparison to the latter study, we additionally address the question whether equity returns and liquidity also depend non-linearly on default risk. Finally, our paper builds on several previous studies on the use of vine copulas (see, e.g., Aas et al., 2009; Min and Czado, 2010; Dißmann et al., 2013) and dynamic copula models (see, e.g., Patton, 2006; Christoffersen et al., 2012; Oh and Patton, 2013) in financial econometrics. To the best of our knowledge, we present the first empirical study that employs dynamic R-vine copulas and show that a dynamic

[3]Note that we explore this relation in more detail in Section 4.4, where we provide anecdotal evidence on both linear and non-linear dependences between bid-ask spreads and default intensities.

vine is indeed significantly better suited to capture the time-varying dependence in the returns, liquidity, and default intensities of our sample firms than competing linear or static models.[4]

The rest of this paper is organized as follows. In Section 4.2, we present the marginal and multivariate models we employ in our study. The data used in the empirical study are presented and discussed in Section 4.3, while Section 4.4 contains a discussion of our empirical results. Section 4.5 concludes.

4.2 Econometric methodology

We now turn to the econometric models for the marginal distributions and the multivariate dependence structure. Our modeling strategy consists of two steps. In a first step, we model the marginal densities of stock returns, bid-ask spreads, and default intensities. In a second step, we then employ a dynamic R-vine copula model to capture the time-varying dependences between the marginals.

4.2.1 Univariate models for returns, bid-ask spreads, and default intensities

To apply copula theory and consistently estimate the dependence structure between returns, spreads, and intensities, our univariate modeling approach must be capable of generating white-noise residuals. The univariate filtering techniques should therefore be able to pick up most of the first- and second-moment dependence inherent in the time-series data. To this purpose, we first model mean dynamics using autoregressive (AR) processes and then capture variance dynamics by employing GARCH (Generalized Autoregressive Heteroskedastic) processes as introduced by Bollerslev (1986).

[4]Note that Heinen and Valdesogo (2008) also propose a dynamization approach of vine copulas. The authors, however, restrict their study to the specific case of canonical vines (C-vines) and use a dynamic conditional correlation specification to account for time-varying dependence. In contrast, we make use of the more general class of R-vines and follow Patton (2006) to incorporate dynamics into standard copulas.

4.2.1.1 Mean dynamics

In the financial econometrics literature, it has now become a stylized fact that stock returns are characterized by significant autocorrelation (see, e.g., Amihud and Mendelson, 1987; Fama and French, 1988, for early empirical evidence). Furthermore, as found in Groß-Klußmann and Hautsch (2013), bid-ask spreads exhibit strong long-range dependence.[5] Regarding CDS spreads and default intensities, Oh and Patton (2013) find that CDS spreads are characterized by strong autocorrelation and, more precisely, that daily log-differences of CDS spreads exhibit more autocorrelation than is commonly found for stock returns. Christoffersen et al. (2013) provide support for this finding and show that log-differences of CDS spreads and default intensities are strongly autocorrelated.

In modeling mean dynamics, Christoffersen et al. (2012) use an AR model of order two (denoted as AR(2)), whereas Oh and Patton (2013) use an AR(5) model and find the first three lags to be strongly significant. We therefore include three lags in our AR specification to capture first-moment dependence.

Formally, with $R_i = \{R_{i,t}\}_{t=1}^{T}$, $i = 1, 2, 3$, denoting the log-differenced time series of stock prices, bid-ask spreads, and default intensities, respectively, the AR(3) process is estimated as

$$R_{i,t} = \mu + \phi_{1,i} R_{i,t-1} + \phi_{2,i} R_{i,t-2} + \phi_{3,i} R_{i,t-3} + e_{i,t}, \tag{4.1}$$

where estimation is conducted via conditional least squares. The conditional mean, $\mu_{i,t}$, thus evolves according to the following dynamics

$$\mu_{i,t} = \mu + \phi_{1,i} R_{i,t-1} + \phi_{2,i} R_{i,t-2} + \phi_{3,i} R_{i,t-3}, \tag{4.2}$$

leaving the residuals $e_{i,t} = R_{i,t} - \mu_{i,t}$ for GARCH-filtering in the next step.[6]

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[5] Note that much of this long-range dependence is eliminated by log-differencing. The remaining short-run dependence, however, needs to be filtered by appropriate AR processes.

[6] In our empirical study in Section 4.4, we show that our AR(3) model for conditional mean dynamics passes the standard specification tests.

4.2.1.2 Variance dynamics

A critical issue in capturing second-moment dependence is time-varying and asymmetric volatility. Asymmetry in volatility is commonly referred to as the leverage effect and is well investigated in the econometrics literature (see, e.g., Christie, 1982; Nelson, 1991). The leverage effect arises from asymmetric volatility responses to bad and good news on a firm and is based on the finding that the upward revision of conditional volatility due to bad news is more pronounced than the downward revision due to good news. In case of stock returns, bad news comes in the form of a negative AR residual (that is, $e_{i,t} < 0$). In case of bid-ask spreads and default intensities, on the other hand, bad news is associated with a positive AR residual (i.e., $e_{i,t} > 0$).

Another critical issue is the specification of an adequate distributional model for the margins. As stated in existing studies, skewness and fat tails might lead to misspecified marginal distributions and, consequently, to biased estimates for the parameters of the dependence model.[7]

Christoffersen et al. (2013) and Oh and Patton (2013) find that stock returns and log-differences of CDS spreads and default intensities are characterized by asymmetry in volatility as well as by skewness and fat tails. Therefore, we follow Oh and Patton (2013) and employ the GJR-GARCH model as proposed by Glosten et al. (1993) to capture asymmetric volatility, where we use the skewed t distribution of Fernandez and Steel (1998) to additionally account for skewness and fat tails in the marginal distributions. More precisely, we fit a GJR-GARCH(1,1) model to the AR residuals, $e_{i,t}$, so that conditional volatility evolves according to the following dynamics

$$\begin{aligned} e_{i,t} &= \sigma_{i,t}\varepsilon_{i,t}, \qquad \varepsilon_{i,t}|\mathcal{F}_{i,t-1} \sim iid\ skt(\nu_i, \gamma_i) \\ \sigma_{i,t}^2 &= \omega_i + \beta_i\sigma_{i,t-1}^2 + \alpha_i e_{i,t-1}^2 + \delta_i e_{i,t-1}^2 \mathbf{1}_{(-\infty,0)}(e_{i,t-1}) \end{aligned} \tag{4.3}$$

where the parameters in the conditional variance equation are constrained to be positive, $\mathcal{F}_{i,t}$ denotes the set of information available on series R_i up to and including time t, $\mathbf{1}_{[\cdot,\cdot]}(\cdot)$ is the indicator function, and $skt(\nu_i, \gamma_i)$ denotes the skewed t distribution as proposed by

[7] See McNeil et al. (2005) and Kim et al. (2007) for details.

Fernandez and Steel (1998) with degrees of freedom parameter $\nu_i \in (2, \infty)$ and skewness parameter $\gamma_i \in (0, \infty)$. With f_t denoting the probability density function (pdf) of a univariate standard t distribution, the pdf of $skt(\nu_i, \gamma_i)$, f_{skt}, is given by

$$f_{skt}(\varepsilon; \nu_i, \gamma_i) = \frac{2}{\gamma_i + \frac{1}{\gamma_i}} \left[f_t\left(\frac{\varepsilon}{\gamma_i}\right) \mathbf{1}_{[0,\infty)}(\varepsilon) + f_t(\gamma_i \varepsilon) \mathbf{1}_{(-\infty,0)}(\varepsilon) \right] \tag{4.4}$$

As becomes apparent from (4.4), the γ_i parameter controls the allocation of mass to each side of the mode, and $skt(\nu_i, \gamma_i)$ nests the standard t distribution in case of $\gamma_i = 1$. That is, $\gamma_i \neq 1$ indicates skewness in the marginal time series, R_i, $i = 1, 2, 3$.[8]

Note that the distribution of the return shocks, $e_{i,t}$, differs across the individual time series, R_i, but is constant over time, whereas the distribution of R_i does vary through time due to the conditional mean and variance dynamics discussed above. The GJR-GARCH(1,1) model in (4.3) is straightforwardly estimated via maximum likelihood.

4.2.2 Dependence modeling with dynamic R-vine copulas

We now turn to the task of modeling the joint distribution of stock returns, bid-ask spreads, and default intensities of multiple firms. To capture both linear dependences and potential non-linearities in the dependence structure, we rely on copulas in our modeling approach. More precisely, we employ dynamic R-vine copulas which provide us with a powerful tool to model high-dimensional distributions and to capture complex and time-varying dependences in an extremely flexible way. Subsequently, we discuss R-vine copulas and present our dynamization approach. We start with a brief review on copulas and pair-copula constructions.

4.2.2.1 Copulas and pair-copula constructions

Generally speaking, a d-dimensional copula function is a multivariate distribution function on the unit cube $[0, 1]^d$ with standard uniform margins. More precisely, a copula specifies the link between a multivariate distribution and its one-dimensional marginal dis-

[8] We refer to Fernandez and Steel (1998) for a detailed discussion on the statistical properties of $skt(\nu_i, \gamma_i)$.

tributions (see Nelsen, 2006). Formally, with $(X_1, ..., X_d)$ denoting a d-dimensional random vector with joint density $\boldsymbol{f} = (f_1, ..., f_d)$ and distribution function $\boldsymbol{F} = (F_1, ..., F_d)$, the copula $\boldsymbol{C}$ of the distribution $\boldsymbol{F}$ is given by

$$\boldsymbol{C}(u_1, ..., u_d) = \boldsymbol{F}(F_1^{-1}(u_1), ..., F_d^{-1}(u_d)), \tag{4.5}$$

where F_i^{-1} is the generalized inverse of F_i and $u_i \in [0, 1]$, $i = 1, ..., d$. The theoretical framework of copulas goes back to Sklar (1959) who shows that, under certain conditions, every copula is a joint distribution function and vice versa (see Nelsen, 2006, for a detailed discussion). Using (4.5), the joint density, $\boldsymbol{f}$, can be expressed as

$$\boldsymbol{f}(x_1, ..., x_d) = \boldsymbol{c}(F_1(x_1), ..., F_d(x_d)) \prod_{i=1}^{d} f_i(x_i), \tag{4.6}$$

where $\boldsymbol{c}$ denotes the density of $\boldsymbol{C}$. Hence, we can separate the dependence structure from the marginal structure and thus model the joint distribution by first modeling the marginal distributions and then specifying a model for the dependence structure.[9]

In case of bivariate data (i.e., $d = 2$), there is a wide range of Archimedean and elliptical copulas available that allow for flexible dependence modeling.[10] In case of multivariate data sets (that is, $d > 2$), however, this becomes much more difficult so that existing studies in the econometrics and statistics literature emphasize the need for flexible copula models in high dimensions (see Chollete et al., 2009; Aas et al., 2009; Dißmann et al., 2013).[11] While some papers attempt to construct multivariate extensions of (bivariate) Archimedean copulas (Embrechts et al., 2003; Savu and Trede, 2010; Hofert, 2011), another strand in the literature aims to construct flexible multivariate dependence models by splitting up the copula density, $\boldsymbol{c}$, into a cascade of bivariate (unconditional and conditional) copulas.[12] The resulting expression is called a pair-copula construction (PCC

[9]Note that the expression in (4.6) provides the theoretical basis for our modeling strategy since we first model the marginal densities using GARCH processes and then model the dependence structure with R-vine copulas.

[10]See Nelsen (2006) for a detailed overview.

[11]Note that, in high dimensions, the choice of copulas is virtually reduced to elliptical copulas such as the normal and the t copula which are only useful if the assumption of elliptical dependence is valid.

[12]For details, see the seminal works by Joe (1997); Bedford and Cooke (2001, 2002); Whelan (2004).

hereafter) and can be derived as follows.

Let $f_{j|k} = f_{j|k}(x_j|x_k)$, $F_{j|k} = F_{j|k}(x_j|x_k)$, $c_{ij|k} = c_{ij|k}(F_{i|k}, F_{j|k})$, and be η a $(d-1)$-dimensional vector satisfying $\eta_\ell \in \{1, ..., d\} \setminus \{i\}$ and $\eta_{\ell_1} \neq \eta_{\ell_2}$ for $\ell_1 \neq \ell_2$. Then, we can decompose the multivariate density, $\boldsymbol{f}$, in the following way

$$\boldsymbol{f} = f_d \prod_{i=1}^{d-1} f_{d-i|d-i+1,...,d}. \tag{4.7}$$

Further, as stated in Aas et al. (2009), the conditional density, $f_{j|\eta}$, can be factorized as

$$f_{j|\eta} = \boldsymbol{c}_{j\eta_m|\eta_{-m}} f_{j|\eta_{-m}}, \tag{4.8}$$

where η_m is an arbitrarily chosen component of η and η_{-m} results from removing η_m from η, $m \in \{1, ..., d-1\}$. Combining the two factorizations in (4.7) and (4.8) then yields the following expression for a PCC

$$\boldsymbol{f} = \prod_{k=1}^{d} f_k \prod_{h=1}^{d-1} \prod_{i=1}^{d-h} \boldsymbol{c}_{i\eta_m|\eta_{-m}}, \tag{4.9}$$

where $h = \dim(\eta)$ and $m = m(h, i) \in \{1, ..., h\}$ is arbitrarily chosen.[13]

Based on the pioneering works by Joe (1996, 1997) and Bedford and Cooke (2001, 2002), Aas et al. (2009) introduced the concept of pair-copulas to the finance literature and spurred a surge in empirical applications of PCCs (see, e.g., Heinen and Valdesogo, 2008; Aas and Berg, 2009; Chollete et al., 2009; Min and Czado, 2010, 2011). For our modeling framework, the use of PCCs is especially appropriate in many respects. First, splitting up the multivariate density according to (4.9) results in a computationally feasible density for likelihood estimation and, therefore, enables us to handle the high dimensionality of our modeling approach. Moreover, PCCs provide us with an extremely flexible tool to capture the presumably intricate dependences between stock returns, bid-ask spreads, and default intensities. Using PCCs, we are able to choose each pair-copula from a different parametric copula family and, further, PCCs permit the modeling of not

[13]We use the convention $i\eta_m|\varnothing = i\eta_m$. Thus, $h = 1$ yields unconditional pair-copulas $\boldsymbol{c}_{i\eta_m}$, $i = 1, ..., d-1$.

only the pairs of the original variables but also pairs of conditional distributions of re-computed variables (see Weiß and Supper, 2013).[14] Since we follow Patton (2006) and estimate dynamic processes for the parameters of the pair-copulas, the dynamic PCCs are also capable of accounting for potentially time-varying patterns in the dependence structure.

4.2.2.2 Regular vines

As can be seen from the expression in (4.9), there exist many different PCCs for a given multivariate distribution, $\boldsymbol{F}$.[15] To select a particular PCC and to determine the way in which the marginals are to be coupled, Bedford and Cooke (2001, 2002) introduce so-called (regular) vines. Vines are convenient tools with a graphical representation that facilitate the description of the conditional specifications made for the joint distribution, $\boldsymbol{F}$. More precisely, an R-vine is a graphical tree model that is based on a nested set of trees satisfying certain conditions.

To formally describe the concept of R-vines, we label the components of $\boldsymbol{X}$ from 1 to d and recall that a tree, $T = \{N, E\}$, is an acyclical graph, where $N \subset \mathbb{N}$ and $E \subset \binom{N}{2}$ denote the set of nodes and edges, respectively. Bedford and Cooke (2002) define a regular vine on d elements, $\mathcal{V}$, as a nested set of trees, $\mathcal{V} = \{T_1, ..., T_{d-1}\}$, that satisfies the following conditions

(c1) T_1 is a tree with nodes $N_1 = \{1, ..., d\}$ and a set of edges denoted E_1.

(c2) For $i = 2, ..., d$, T_i is a tree with nodes $N_i = E_{i-1}$ and $|N_i| = i + 1$.

(c3) For $i = 2, ..., d-1$ and $\{a, b\} \in E_i$, it must hold that $|a \cap b| = 1$.

To derive the PCC induced by $\mathcal{V}$, each edge in T_i is associated with a bivariate (un-)conditional copula, $i = 1, ..., d-1$. The edges of the R-vine trees are computed according to (c1)-(c3) and on the basis of set operations on so-called conditioning and conditioned sets, which are given as follows.[16] With U_{e_i} denoting the set of all indices contained

[14]That is, we are capable of specifying the conditional dependence structure for the joint distribution.
[15]This results from the fact that η_m is arbitrarily chosen.
[16]We follow the presentation in Dißmann et al. (2013).

in $e_i = \{a, b\} \in E_i$, the conditioning set, D_{e_i}, is given by $D_{e_i} = U_a \cap U_b$, and the conditioned set, C_{e_i}, is defined to be $C_{e_i} = U_a \Delta U_b$, with Δ denoting the symmetric difference operator.[17]

As shown in Bedford and Cooke (2001, 2002), there is a unique PCC associated with $\mathcal{V}$, which can be expressed as

$$\boldsymbol{f} = \prod_{k=1}^{d} f_k \prod_{h=1}^{d-1} \prod_{e \in E_h} \boldsymbol{c}_{C_e|D_e}. \tag{4.10}$$

Hence, R-vine copulas as used in our modeling approach are particular PCCs, i.e. PCCs with a particular decomposition (4.9), which are determined according to the combinatorial rules presented above.[18]

4.2.2.3 Fitting an R-vine copula

Fitting an R-vine copula can be organized into three steps: (1) Selection of R-vine structure, (2) Selection of bivariate copula families, and (3) Estimation of copula parameters. These steps are accomplished following the sequential method as proposed in Dißmann et al. (2013) and Hobæk Haff (2013), which exploits the tree-by-tree structure of vines and under which selection and estimation are performed treewise, conditioning on the precedingly selected trees and estimated copula parameters.[19] More precisely, for a given tree, $T_i \in \mathcal{V}$, we first calculate the empirical Kendall's tau, $\hat{\tau}_{j,k}$, for all possible variable pairs, $\{j, k\}$, $j, k = 1, ..., d$, and determine the edges of T_i by selecting the spanning tree that maximizes the sum of absolute empirical taus.[20] Then, each of the resulting edges is associated with a bivariate (un-)conditional copula, which is selected according to the Akaike information criterion (AIC).[21] We calculate the AIC for each copula fam-

[17]Note that $|C_{e_i}| = 2$ and $C_{e_i} \cap D_{e_i} = \varnothing$.

[18]A detailed description on the construction of R-vines and R-vine copulas as well as examples and illustrations can be found in Bedford and Cooke (2001, 2002); Aas et al. (2009); Dißmann et al. (2013).

[19]Note that this method does not necessarily lead to a global optimum. Most of the dependence is, however, captured in the first tree so that the model fit is considerably influenced by the fit of the copulas in the first tree.

[20]Actually, we use Prim's (1957) algorithm and calculate the minimum spanning tree with weights $-\hat{\tau}_{j,k}$.

[21]As found in Manner (2007), the AIC provides a reliable criterion, especially when compared to alternative criteria such as copula goodness-of-fit tests.

ily considered and choose the copula with the minimum AIC.[22] Using the fitted copulas in tree T_i, we now compute the transformed variables by means of the corresponding h-functions and repeat the above procedure until we reach tree T_{d-1} (see Dißmann et al., 2013, for details), resulting in a total of $d(d-1)/2$ dynamic (un-)conditional pair-copulas.

Since we need standard uniform data to consistently estimate copulas, fitting the R-vine copula in our econometric approach should be based on white-noise time series. Assuming that the GARCH processes discussed above correctly specify the marginal densities, we apply the R-vine copula to the corresponding GARCH residuals, $\varepsilon_{i,t}$. The pseudo-observations used for estimation, u_i, are then computed as the ranks of the residuals, i.e. $u_i = F_i(\varepsilon_i)$.

4.3 Data

This section presents the data used in our empirical study and provides descriptive statistics. Starting with a description of the data sources, we also discuss the procedure applied to extract default intensities from CDS spreads.

4.3.1 Data sources

To implement our econometric modeling strategy discussed in the preceding section, we need to collect data on stock prices, bid-ask spreads, and default intensities. In our empirical study, we focus on S&P 500 constituents, and obtain the corresponding mid, bid, and ask quotes from *Thomson Reuters Datastream*. More precisely, we collect daily quotes of all constituents in the S&P 500 index as reported by *Datastream* from January 2008 to December 2013. Bid-ask spreads are then calculated as the difference between ask and bid quotes to proxy for the liquidity of the underlying stock.

Further, since default intensities are not observable in the market, we follow the study in Christoffersen et al. (2013) and extract default intensities from CDS spreads (see below). Daily CDS spreads are retrieved from *Datastream*, where we start with an initial

[22] We include dynamic extensions of the normal, t, (rotated) Clayton, (rotated) Gumbel, and (rotated) Joe copula. Details can be found in Appendix C.

sample of all constituents of the S&P 500 index between January 2008 and December 2013. Since we need to restrict our sample to companies with traded CDS contracts, we apply the following screening procedures to identify these companies. First, we match *Datastream*'s equity codes with CDS codes.[23] If there is no match according to this criterion, we additionally perform a search using the 'related series' function in *Datastream* to confirm that there is no corresponding CDS spread to the respective company's name as it appears in the S&P 500 constituents list. Moreover, we focus on dollar-denominated CDS contracts with a five-year maturity and a modified restructuring clause, since these are the most frequently traded contracts in the U.S. market and, consequently, unlikely to be distorted from low levels of liquidity. These restrictions reduce the initial sample to a total of 209 companies. For increased transparency, we list the names of all sample firms in Table C.1 in Appendix C.

Finally, as discussed in the next section, extracting default intensities from CDS spreads relies on the valuation of CDS contracts and, therefore, requires the construction of spot rate curves to derive discount rates. We follow existing studies in the literature and use the bootstrapping procedure suggested by Longstaff et al. (2001) to compute spot rate curves with maturities reaching from one day up to five years for each trading day between January 2008 and December 2013 (see, e.g., Jarrow et al., 2007; Longstaff and Rajan, 2008).[24] Using *Datastream*, we collect daily observations for the overnight, one-week, one-month, three-month, six-month, and one-year LIBOR rates as well as for the midmarket two-year, three-year, four-year, and five-year par swap rates. As in Longstaff et al. (2001), we then use a standard cubic spline algorithm to interpolate the par curve at semi-annual intervals, and compute spot rates by bootstrapping the interpolated par curve. The resulting semi-annual spot rates, in turn, are interpolated employing cubic splines and are used to compute the discount factors required in the CDS valuation formula.

[23]The corresponding *Datastream* CDS codes are constructed as follows. First, we decompose each firm's Mnemonics (*Datastream* code) into its general (i.e., 'U' and '@') and firm-specific component. To each three- or four-digit firm-specific component, we add the dollar sign to specify the currency. Finally, we complement the CDS Mnemonic with the two-digit string 'MR' to specify the restructuring clause.

[24]That is, the five-year spot rate curve contains daily spot rates and is updated each day.

4.3.2 Extracting default intensities from CDS spreads

A credit default swap is essentially an insurance contract that provides protection against credit loss due to default. The buyer of a CDS contract makes periodic payments (referred to as premiums) to the seller of the contract and, in exchange, receives a payoff from the seller if the reference entity defaults on a loan or a bond prior to the maturity date of the contract. The periodic amount that the protection buyer pays the protection seller is quoted in terms of a spread, which is commonly measured in basis points and can be converted into a dollar amount by multiplying with the contract size (i.e., the notional principal).[25]

There now exists a substantial body of literature on CDS contracts. As stated in Oh and Patton (2013), the pronounced interest is largely driven by the close relation between CDS spreads and the market perception of default probabilities. For instance, CDS spreads are higher for entities which the market perceives to have higher default probabilities or higher losses given default (see Creal et al., 2012). Since we require default probabilities for our empirical study in Section 4.4, we shall exploit this relation and subsequently show how default probabilities (or rather, default intensities) can be extracted from CDS spreads.[26]

We follow Christoffersen et al. (2013) and Hull and White (2003) in our presentation and denote the periodic payments from the protection buyer to the seller as the premium payment leg of the CDS contract, and the compensating payoff from the protection seller to the buyer in case of default as the payoff leg of the CDS. Further, we assume that the CDS contract has quarterly payment dates $T = \{t_i | i = 1, ..., N\}$ (with t_N denoting the maturity of the contract), spread S_t, and notional 1, where the payment dates fall on the 20th of March, June, September and December, and $N = 20$ (corresponding to a maturity of five years). If default occurs, the reference entity recovers a certain percentage, r, of the notional where the (risk-neutral) probability that the entity defaults before time t is given by $P(t) = \Pr[\tau \leqslant t]$, with τ denoting the time of default.[27] The corresponding default

[25] See, e.g., Duffie and Singleton (2003) for details.
[26] See (4.11) for the formal link between default intensities and probabilities.
[27] Consequently, in case of default the protection buyer receives a payoff equal to the difference between

intensity, h, is defined by $h(t)\mathrm{d}t = \Pr\left[\tau \in \mathrm{d}t|\tau > t\right]$ and can be computed according to

$$P(t) = 1 - \exp\left(-\int_0^t h(s)\mathrm{d}s\right). \tag{4.11}$$

Finally, let $v(t, T_i)$ denote the discount factors calculated from the spot rate curve, and let $\Delta_i = t_i - t_{i-1}$ be the time period between two payment dates. With $q(s,t)$, $s < t$, being the risk-neutral survival probability, the value of the premium payment leg, V_{prem}, can then be calculated according to

$$V_{\text{prem}}(t,T,S_t) = S_t \sum_{i=1}^{N} v(t,t_i) \left[\Delta_i q(t,t_i) + \int_{t_{i-1}}^{t_i} (s - t_{i-1})\, P(\mathrm{d}s)\right], \tag{4.12}$$

where the integral accounts for the accrual payment the protection buyer has to make for the time frame from the last payment date to the time of default.[28] The value of the payoff leg, V_{pay}, is given by

$$V_{\text{pay}}(t,T,S_t) = (1-r)\int_t^{t_N} v(t,s)P(\mathrm{d}s). \tag{4.13}$$

Following Christoffersen et al. (2013), we compute the integrals in (4.12) and (4.13) by numerical approximations and, for this purpose, define a grid of daily maturities, $\{s_i|i = 0, ..., m\}$, where $s_0 = t$ and $s_m = t_N$. Furthermore, we assume default intensities to be constant, i.e. $h(t) \equiv h$. The integrals can then be approximated as follows

$$\begin{aligned}\int_{t_{i-1}}^{t_i} (s - t_{i-1})\, P(\mathrm{d}s) &\approx \sum_{\{j|s_j \in (t_{i-1}, t_i]\}} (s_j - t_{i-1}) \left(\exp\left(ht_{i-1}\right) - \exp\left(ht_i\right)\right), \\ \int_t^{t_N} v(t,s)P(\mathrm{d}s) &\approx \sum_{\{j|s_j \in (t_{i-1}, t_i]\}} v(t_{i-1}, s_j) \left(\exp\left(ht_{i-1}\right) - \exp\left(ht_i\right)\right)\end{aligned} \tag{4.14}$$

In a final step, the equation $V_{\text{pay}}(t,T,S_t) - V_{\text{prem}}(t,T,S_t) = 0$ is solved numerically to obtain the default intensity, h. The default probability, $P(t)$, can now be calculated using (4.11).

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the notional of the contract and the recovered value, i.e. $1 - r$.

[28]Note that $q(s,t) = 1 - [P(t) - P(s)]$.

4.3.3 Descriptive statistics

In our empirical study, we use monthly log-differences of daily mid prices, bid-ask spreads, and default intensities to estimate the marginal and dependence parameters, and employ monthly default probabilities to incorporate credit risk into conventional VaR. More precisely, for each trading day, t, between January 2008 and December 2013, monthly log-differences are calculated using the mid prices, bid-ask spreads, and default intensities at days t and $t - 30$. Daily bid-ask spreads are computed as the difference between daily ask and bid quotes, and daily default intensities are extracted from daily CDS spreads as discussed in the preceding section using a fixed recovery rate of 30% (i.e., $r = 0.3$).[29] Monthly default probabilities are derived employing (4.11) adjusted for a monthly horizon, that is

$$P(t) = 1 - \exp\left(\frac{30}{360}h\right) \tag{4.15}$$

As a simple first step, we start our empirical investigation by analyzing the cross-sectional variation in our data. Table 4.1 presents descriptive statistics on the cross-sectional distribution of daily mid prices, bid-ask spreads, default intensities, and default probabilities for the period from January 2008 to December 2013.

Panel (A) of Table 4.1 reports descriptive statistics for the mid prices of the 209 sample firms. As indicated by the statistics on the time-series means, our sample is characterized by strong cross-sectional variation of mid prices, with the time-series means ranging from 8.23 U.S. dollars (USD hereafter) to 258.54 USD and being 45.13 USD on average. Further, mid prices are positively skewed and weakly leptokurtic on average, with an average skewness and excess kurtosis of 0.4088 and 0.0611, respectively. Not surprisingly, mid prices exhibit significant autocorrelation with the average first-order autocorrelation being about 99.43%.

[29] Note that holding the recovery percentage at a constant level is fairly standard in existing studies involving CDS or (defaultable) bond valuation (see, e.g., Duffie, 1999; Duffie and Singleton, 1999; Longstaff et al., 2005; Christoffersen et al., 2013). As stated by Hull and White (2000), the fixed recovery rate assumption has little impact on CDS valuation when the expected recovery rate is in the 0% to 50% range.

Turning to the bid-ask spreads in Panel (B), we find the average bid-ask spread to be 0.05 USD. Again, our panel data exhibit considerable cross-sectional variation with the time-series means ranging from 0.01 USD to 0.31 USD. This finding is further supported by the statistics on the percentiles of the cross-sectional distribution. As we employ the bid-ask spreads of the companies as a proxy for stock liquidity, these results indicate that the trading costs associated with immediately trading the shares of a particular firm differ remarkably across our sample. Thus, in view of the substantial variation in bid-ask spreads, incorporating liquidity risk into conventional VaR appears to be economically essential to adequately capture losses from potential liquidity shocks. Finally, the time-series distributions of bid-ask spreads are heavily skewed and leptokurtic on average.

In Panels (C) and (D) of Table 4.1, we present descriptive statistics for the default intensities and default probabilities extracted from the CDS spreads of our sample firms. Regarding the latter, the average time-series mean is at a comparatively modest level of 0.18%, whereas the minimum and maximum time-series means are given by 0.04% and 3.25%, respectively, indicating that default risk varies considerably across our sample firms. Of particular note is the substantial amount of default risk of some S&P 500 constituents in our sample during the period from January 2008 to December 2013. To be precise, as follows from the statistics on the time-series maxima, the monthly default probabilities amount to a maximum of about 10%.

Table 4.1: Summary statistics for mid prices, bid-ask spreads, and default intensities/probabilities.

The table reports descriptive statistics on the cross-sectional distribution of daily mid prices, bid-ask spreads, default intensities, and default probabilities for the period from January 2008 to December 2013. The sample consists of the 209 companies listed in Table C.1 in Appendix C. We first calculate the time-series percentiles and moments for each firm in the sample, and then compute the cross-sectional percentiles and mean in a second step. That is, the columns present the percentiles and mean from the cross-sectional distribution of the measures listed in the rows. Mid prices and bid-ask spreads are denominated in U.S. dollar, where the latter are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 4.3 and have a horizon of one year. Default probabilities are derived from the intensities using the formula in (4.15) and thus have a horizon of one month.

		Percentiles						
	Min	5th	25th	Median	75th	95th	Max	Mean
Panel A: Mid prices								
Percentiles								
- Min	0.8400	3.6280	9.9300	17.0900	26.9000	45.8640	89.0900	20.2645
- 1st	1.2760	5.0117	11.8050	19.9050	31.0920	50.2999	105.5355	23.3106
- 5th	2.3325	6.3485	14.8925	23.3652	36.7150	55.4575	115.3875	27.0530
- 25th	6.0900	11.2805	20.2625	32.3463	47.9500	76.1260	150.8350	36.2797
- Median	7.4300	14.0420	24.8525	37.8950	55.8950	84.1910	255.6450	43.6447
- 75th	9.9475	17.5680	31.5783	45.5750	65.0250	103.7060	368.5473	52.3385
- 95th	12.8400	23.6085	42.0950	57.4525	82.7050	138.7835	736.6686	70.1802
- 99th	13.5535	25.9969	44.8700	63.3770	89.6535	153.0323	921.4764	76.6626
- Max	14.1100	26.8480	46.4800	67.4800	92.1000	161.2720	993.9536	80.0887
Moments								
- Mean	8.2180	14.9015	26.7132	40.0617	57.8519	88.2465	258.5393	45.1288
- St. Dev.	1.8085	4.0083	6.8227	10.1979	14.3946	28.3231	208.9269	13.0255
- Skewness	-1.2140	-0.5642	-0.0150	0.3789	0.7668	1.5137	2.8058	0.4088
- Exc. Kurt.	-1.5268	-1.2267	-0.6563	-0.1856	0.3355	1.9105	6.5508	0.0611
- AC(1)	0.9834	0.9891	0.9931	0.9949	0.9963	0.9976	0.9983	0.9943
Panel B: Bid-ask spreads								
Percentiles								
- Min	0.0025	0.0050	0.0100	0.0100	0.0100	0.0100	0.0100	0.0094
- 1st	0.0025	0.0050	0.0100	0.0100	0.0100	0.0100	0.0100	0.0094
- 5th	0.0025	0.0054	0.0100	0.0100	0.0100	0.0100	0.0100	0.0096
- 25th	0.0025	0.0088	0.0100	0.0100	0.0100	0.0100	0.0600	0.0104
- Median	0.0075	0.0100	0.0100	0.0200	0.0200	0.0300	0.1200	0.0180
- 75th	0.0100	0.0200	0.0200	0.0300	0.0400	0.0760	0.1899	0.0369
- 95th	0.0200	0.0300	0.0500	0.0700	0.1090	0.1900	1.0056	0.0908
- 99th	0.0300	0.0600	0.1272	0.1800	0.3044	0.6206	4.5000	0.2715
- Max	0.0900	0.6300	3.0000	6.0500	10.5475	55.4340	194.0000	12.2525
Moments								
- Mean	0.0126	0.0179	0.0280	0.0383	0.0550	0.1087	0.3186	0.0494
- St. Dev.	0.0061	0.0352	0.1090	0.2156	0.3732	1.7631	4.9038	0.4049
- Skewness	3.6236	8.0310	17.6093	21.9631	26.4984	36.6845	39.4965	22.2276
- Exc. Kurt.	24.0800	114.8145	337.4985	529.0167	775.7203	1398.1281	1558.6459	616.4122
- AC(1)	-0.0011	0.0172	0.0941	0.2140	0.3463	0.4755	0.6675	0.2255

Table 4.1: Summary statistics for mid prices, bid-ask spreads, and default intensities/probabilities (continued).

	Min	Percentiles 5th	25th	Median	75th	95th	Max	Mean
Panel C: Default intensities								
Percentiles								
- Min	0.0015	0.0023	0.0039	0.0056	0.0092	0.0229	0.0452	0.0080
- 1st	0.0020	0.0027	0.0045	0.0068	0.0102	0.0256	0.0453	0.0090
- 5th	0.0020	0.0036	0.0053	0.0081	0.0120	0.0292	0.0484	0.0105
- 25th	0.0030	0.0047	0.0071	0.0113	0.0163	0.0359	0.1205	0.0145
- Median	0.0037	0.0056	0.0085	0.0135	0.0209	0.0462	0.1474	0.0179
- 75th	0.0052	0.0067	0.0105	0.0178	0.0285	0.0606	0.5800	0.0256
- 95th	0.0062	0.0101	0.0154	0.0299	0.0530	0.1153	1.2542	0.0486
- 99th	0.0067	0.0114	0.0183	0.0362	0.0658	0.1626	1.2552	0.0619
- Max	0.0082	0.0122	0.0201	0.0409	0.0720	0.1949	1.2618	0.0718
Moments								
- Mean	0.0044	0.0062	0.0094	0.0146	0.0249	0.0530	0.4055	0.0219
- St. Dev.	0.0003	0.0012	0.0030	0.0057	0.0125	0.0327	0.4631	0.0124
- Skewness	-10.1455	-0.8015	0.6270	1.4298	2.1049	3.0180	11.0968	1.3137
- Exc. Kurt.	-1.6157	-0.7029	0.3303	2.4236	4.8407	10.7446	172.9344	4.8357
- AC(1)	0.5482	0.9604	0.9904	0.9938	0.9960	0.9979	0.9986	0.9835
Panel D: Monthly default probabilities								
Percentiles								
- Min	0.0001	0.0002	0.0003	0.0005	0.0008	0.0019	0.0038	0.0007
- 1st	0.0002	0.0002	0.0004	0.0006	0.0009	0.0021	0.0038	0.0007
- 5th	0.0002	0.0003	0.0004	0.0007	0.0010	0.0024	0.0040	0.0009
- 25th	0.0003	0.0004	0.0006	0.0009	0.0014	0.0030	0.0100	0.0012
- Median	0.0003	0.0005	0.0007	0.0011	0.0017	0.0038	0.0122	0.0015
- 75th	0.0004	0.0006	0.0009	0.0015	0.0024	0.0050	0.0472	0.0021
- 95th	0.0005	0.0008	0.0013	0.0025	0.0044	0.0096	0.0992	0.0040
- 99th	0.0006	0.0009	0.0015	0.0030	0.0055	0.0135	0.0993	0.0051
- Max	0.0007	0.0010	0.0017	0.0034	0.0060	0.0161	0.0998	0.0059
Moments								
- Mean	0.0004	0.0005	0.0008	0.0012	0.0021	0.0044	0.0325	0.0018
- St. Dev.	0.0000	0.0001	0.0002	0.0005	0.0010	0.0027	0.0365	0.0010
- Skewness	-10.1516	-0.8023	0.6249	1.4276	2.1030	3.0159	11.0892	1.3107
- Exc. Kurt.	-1.6162	-0.7069	0.3297	2.4192	4.8266	10.5930	172.7859	4.8158
- AC(1)	0.5482	0.9604	0.9904	0.9938	0.9960	0.9979	0.9986	0.9836

Consequently, the significant variation and serious amounts of default risk further motivate our approach of adjusting standard VaR for credit risk. Turning to the higher-order moments, we find that default probabilities are positively skewed, leptokurtic, and significantly autocorrelated on average.

In addition to the summary statistics on stock prices, bid-ask spreads, and default intensities, we also present corresponding statistics for all data in differences. The descriptive statistics for the log-differences of mid prices, bid-ask spreads, and default intensities are presented in Table 4.2.

Table 4.2: Summary statistics for log-differences of mid prices, bid-ask spreads, and default intensities.

The table reports descriptive statistics on the cross-sectional distribution of monthly log-differences of mid prices, bid-ask spreads, and default intensities for the period from January 2008 to December 2013. For each trading day, t, log-differences are calculated using the prices, spreads, and intensities at days t and $t-30$. The sample consists of the 209 companies listed in Table C.1 in Appendix C. We first calculate the time-series percentiles and moments for each firm in the sample, and then compute the cross-sectional percentiles and mean in a second step. That is, the columns present the percentiles and mean from the cross-sectional distribution of the measures listed in the rows. Bid-ask spreads are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 4.3 and have a horizon of one year.

		Percentiles						
	Min	5th	25th	Median	75th	95th	Max	Mean
Panel A: Stock returns								
Percentiles								
- Min	-2.4172	-1.1086	-0.6718	-0.5019	-0.3763	-0.2487	-0.1456	-0.5646
- 1st	-1.7198	-0.6902	-0.4206	-0.3245	-0.2442	-0.1524	-0.1105	-0.3612
- 5th	-0.5608	-0.2909	-0.2092	-0.1570	-0.1182	-0.0799	-0.0660	-0.1698
- 25th	-0.1242	-0.0795	-0.0534	-0.0392	-0.0278	-0.0188	-0.0113	-0.0427
- Median	-0.0129	0.0013	0.0090	0.0130	0.0191	0.0271	0.0411	0.0137
- 75th	0.0274	0.0373	0.0500	0.0622	0.0735	0.0945	0.1195	0.0630
- 95th	0.0656	0.0785	0.1110	0.1412	0.1737	0.2530	0.3481	0.1492
- 99th	0.0882	0.1116	0.1705	0.2237	0.2995	0.4728	0.9937	0.2549
- Max	0.1155	0.1534	0.2532	0.3534	0.4798	0.8391	1.3251	0.4010
Moments								
- Mean	-0.0436	-0.0089	0.0003	0.0051	0.0091	0.0159	0.0217	0.0044
- St. Dev.	0.0438	0.0546	0.0744	0.0978	0.1231	0.1801	0.3478	0.1059
- Skewness	-2.8099	-1.8866	-1.2889	-0.8675	-0.5818	-0.1877	0.7702	-0.9438
- Exc. Kurt.	0.4175	0.9385	2.1253	3.6449	5.4871	9.6011	15.1429	4.2101
- AC(1)	0.8984	0.9172	0.9360	0.9447	0.9537	0.9626	0.9698	0.9437
Panel B: Log-differences of bid-ask spreads								
Percentiles								
- Min	-9.8730	-8.4583	-6.7719	-6.2832	-5.5984	-3.5666	-1.6094	-6.1205
- 1st	-3.7483	-2.8421	-2.3979	-2.1846	-1.9459	-1.6094	-1.0986	-2.1828
- 5th	-2.3988	-1.5593	-1.3863	-1.0986	-1.0986	-0.6931	-0.6931	-1.1752
- 25th	-0.7215	-0.6931	-0.4700	-0.4055	-0.2231	0.0000	0.0000	-0.3449
- Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
- 75th	0.0000	0.0000	0.0000	0.2877	0.4055	0.5596	0.6948	0.2473
- 95th	0.6931	0.6931	1.0986	1.0986	1.2528	1.4642	2.6378	1.1241
- 99th	1.0986	1.4390	1.9459	2.1972	2.4965	2.8916	3.7677	2.1941
- Max	1.7918	3.6687	5.6168	6.2766	6.7719	8.4841	9.8730	6.1533
Moments								
- Mean	-0.0710	-0.0328	-0.0255	-0.0216	-0.0166	-0.0098	0.0014	-0.0213
- St. Dev.	0.3300	0.6064	0.7596	0.8368	0.9172	1.0662	1.4616	0.8384
- Skewness	-0.2592	-0.1267	-0.0086	0.0444	0.1147	0.2441	0.3778	0.0518
- Exc. Kurt.	0.7405	2.9375	8.2886	12.5335	16.6561	23.5607	58.6048	12.8523
- AC(1)	0.0381	0.1510	0.2237	0.2635	0.2989	0.3522	0.4762	0.2586

Table 4.2: Summary statistics for log-differences of mid prices, bid-ask spreads, and default intensities (continued).

	Min	Percentiles 5th	25th	Median	75th	95th	Max	Mean
Panel C: Log-differences of default intensities								
Percentiles								
- Min	-1.9458	-0.6973	-0.3701	-0.2705	-0.2120	-0.1338	-0.0512	-0.3332
- 1st	-0.2704	-0.1347	-0.1030	-0.0883	-0.0784	-0.0542	-0.0423	-0.0918
- 5th	-0.0730	-0.0592	-0.0482	-0.0395	-0.0285	-0.0017	-0.0015	-0.0354
- 25th	-0.0210	-0.0119	-0.0053	-0.0016	-0.0012	-0.0006	-0.0004	-0.0038
- Median	-0.0007	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0001	-0.0005
- 75th	-0.0005	-0.0005	-0.0003	0.0000	0.0006	0.0082	0.0211	0.0013
- 95th	-0.0004	0.0004	0.0285	0.0433	0.0535	0.0660	0.0825	0.0389
- 99th	0.0922	0.0973	0.1023	0.1083	0.1192	0.1553	0.2137	0.1148
- Max	0.0937	0.1603	0.2518	0.3338	0.4543	0.8304	2.1231	0.4007
Moments								
- Mean	-0.0015	-0.0008	-0.0003	0.0001	0.0003	0.0008	0.0023	0.0001
- St. Dev.	0.0131	0.0225	0.0294	0.0334	0.0364	0.0533	0.1565	0.0351
- Skewness	-19.3336	-1.1683	0.4377	1.0662	1.9198	6.2680	23.9300	1.3678
- Exc. Kurt.	5.4259	9.1788	14.2182	27.1295	48.2334	217.8431	622.8101	57.0487
- AC(1)	-0.4265	-0.2422	-0.0711	0.0611	0.1297	0.1805	0.2660	0.0183

Panel (A) of Table 4.2 reports summary statistics on the cross-sectional distribution of stock returns. As can be seen from the panel, the stock returns of our sample firms exhibit the usual stylized facts of a negligible mean of 0.44%, pronounced negative skewness, and significant leptokurtosis on average. The average autocorrelation of stock returns is around 94% and thus slightly smaller than that of mid prices. As expected, given the fact that our sample period partly comprises the financial crisis, the stock returns are characterized by considerable time-series variation, with the average time-series minimum and maximum being given by about -56% and 40%, respectively. Further, as indicated by the statistics on the percentiles and the time-series means, the stock returns also vary considerably in the cross-section.

Turning to the cross-sectional statistics on log-differenced bid-ask spreads in Panel (B), we find that the time-series means of log-differences vary from approximately -7% to 0.14% and are -2% on average. Interestingly, as in the case of stock returns, bid-ask spread changes exhibit strong time-series variation, as indicated by, e.g., the average interquartile range which reaches from about -34% to 25% and, therefore, implies considerable dispersion in the time-series distributions of log-differenced bid-ask spreads. That is, our sample period is characterized by substantial changes in the stock liquidity of the average sample firm. Finally, the log-differences are slightly skewed and considerably autocorrelated on average.

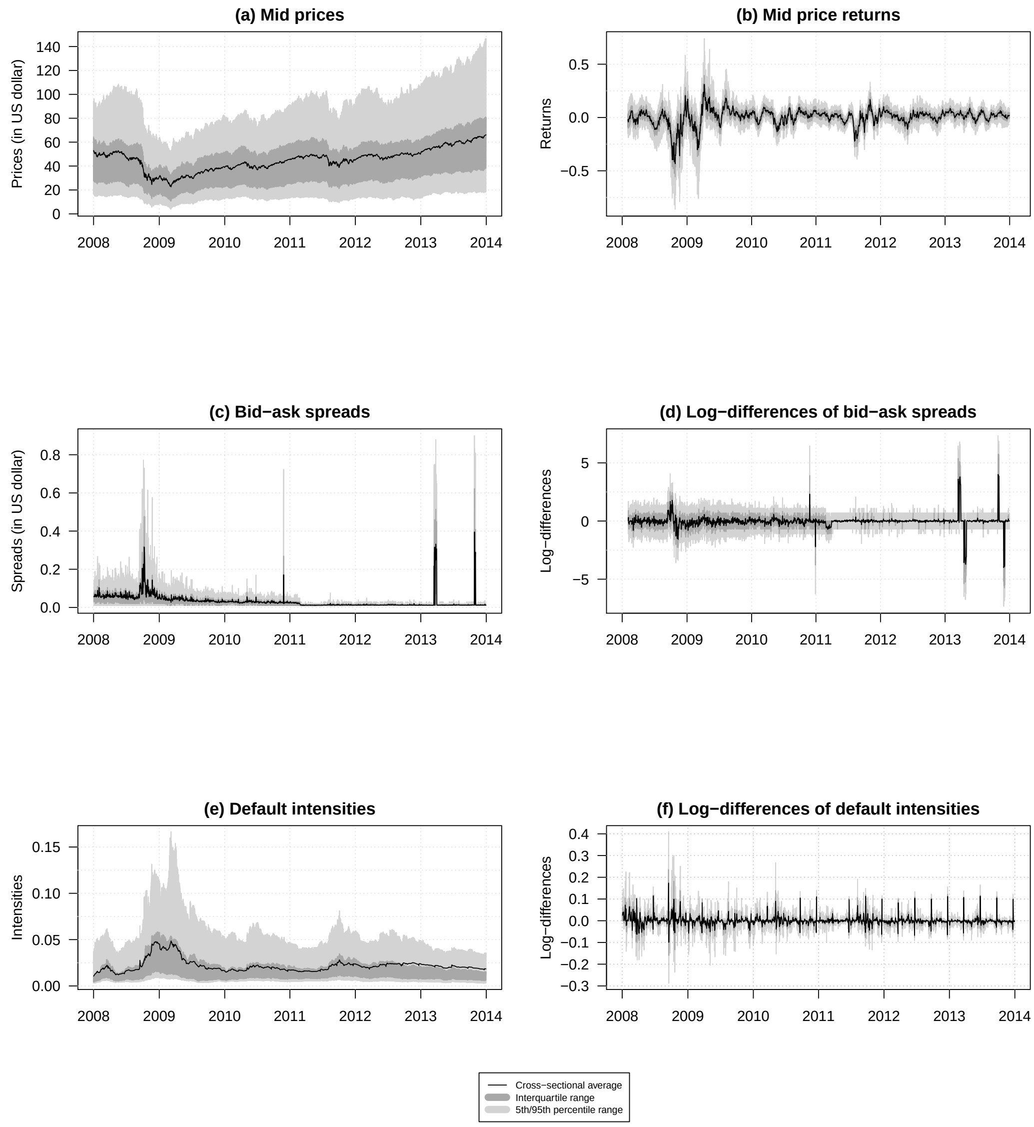
Regarding the log-differences of default intensities in Panel (C) of Table 4.2, we find that the corresponding time-series means vary from -0.15% to 0.23% and are 0.01% on average, implying only slight cross-sectional variation. Turning to the time-series variation, however, we can see from the panel that changes in the default intensities of the sample firms vary considerably from -33% to 40% on average, indicating fundamental changes in the market perception of default risk during the sample period. Furthermore, log-differences of default intensities are heavily skewed and only slightly autocorrelated, so that log-differencing already eliminates most of the serial dependence in default intensities.

Figure 4.1 illustrates the temporal variation in the cross-section of our data. More precisely, the figure plots the time evolution of daily mid prices, bid-ask spreads, and default intensities, as well as of the corresponding log-differences, where we calculate the cross-sectional average across all 209 sample firms for each trading day between January 2008 and December 2013.

Panels (a) and (b) show the time evolution of average mid prices and stock returns, respectively. As can be seen from Panel (a), stock prices experienced sharp declines during the financial crisis and decreased significantly from more than 50 USD in 2008 to approximately 20 USD in 2009. The post-crisis years as of the second quarter in 2009 are characterized by a strong and stable upward trend, with the mid prices rising to pre-crisis levels. Turning to the time evolution of monthly stock returns, we find that the temporal variation of average returns is as expected. The time period comprising the financial crisis is characterized by substantial price changes and pronounced volatility, with stock returns ranging from -50% to 50%. In the post-crisis period, however, volatility of average returns declines remarkably and returns stay relatively flat, varying between -20% and 20%.

Figure 4.1: Time evolution of cross-sectional data.

The figure shows the time evolution of daily mid prices, bid-ask spreads and default intensities, as well as of the corresponding monthly log-differences for the period from January 2008 to December 2013. The sample consists of the 209 companies listed in Table C.1 in Appendix C. For each day of the sample period, we calculate the cross-sectional average (black line) as well as the cross-sectional interquartile (dark-gray shaded area) and 5th/95th percentile range (light-gray shaded area). Mid prices and bid-ask spreads are denominated in US dollar, where the latter are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 4.3 and have a horizon of one year. Monthly log-differences are calculated for each day in the sample period using the prices, spreads, and intensities at days t and $t - 30$.



Panels (c) and (d) of Figure 4.1 present the time evolution of average daily bid-ask spreads and the corresponding monthly log-differences. Not surprisingly, average bid-ask spreads increased steeply during the financial crisis, indicating a severe deterioration of stock liquidity and, consequently, implying increased trading costs for the stocks of the average sample firm. The increased log-differences in Panel (b) in the second half of 2008 result from the temporary surge in (average) bid-ask spreads and reflect the considerable changes in the stock liquidity of the sample firms. In subsequent years, bid-ask spreads and the corresponding log-differences return to low levels and stay relatively flat, indicating that liquidity restores and trading costs decline to pre-crisis levels.[30]

Finally, Panels (e) and (f) show the time evolution of average default intensities and the corresponding log-differences. The temporal variation of default intensities is as expected and shows that default risk significantly increased during the financial crisis. Average default intensities increased from approximately 1% in 2008 to nearly 5% in 2009 and returned to pre-crisis levels in the following years. Interestingly, as indicated by the 5th to 95th percentile range and as discussed above, the sample is characterized by strong cross-sectional variation, with the average 95th percentile default intensity peaking at about 15% in 2009. Turning to the log-differences, we find that the increased intensities during the financial crisis coincide with increased log-differences and increased volatility of log-differences.

4.4 Empirical study

In this section, we implement our econometric modeling approach and investigate the performance of our model in a comprehensive VaR simulation study. We propose a new approach to VaR computation, which considers market price risk and liquidity risk as well as credit risk, and show that our dynamic vine copula model outperforms static and correlation-based dependence models.

[30]Note that the surges in bid-ask spreads and log-differences in the post-crisis period are predominantly driven by outliers lacking any economic relevance. In our empirical study, however, we remove spurious outliers by winsorising to assure the validity of our results.

4.4.1 Anecdotal evidence

As a simple first step, we start our empirical study by reporting anecdotal evidence on the relation between stock returns, bid-ask spreads, and default intensities, providing further motivation for our risk management application in the next section. Taking returns, spreads, and intensities as proxies for market price, liquidity, and credit risk, we are especially interested in the dynamic dependence of these risk types and shall document linear dependences as well as potential non-linearities in the dependence structure. To this purpose, we implement the following simple econometric modeling strategy. First, for each trading day between January 2008 and December 2013 and for each of the 209 firms in the sample, we calculate monthly log-differences of mid prices, bid-ask spreads, and default intensities (extracted from daily CDS spreads, see Section 4.3), resulting in the respective time series $\{R_{i,t}^{j}\}_{t=1}^{T}$, $i = 1, 2, 3$; $j = 1, ..., 209$, where $T = 1542$. To filter the time series and compute white-noise residuals, we then apply standard AR(3)-GARCH(1,1) processes with normally distributed innovations to the log-differenced time series, capturing most of the first- and second-moment dependence.[31] That is,

$$
\begin{aligned}
R_{i,t} &= \mu_{i,t} + e_{i,t} = \mu_{i,t} + \sigma_{i,t}\varepsilon_{i,t}, \qquad \varepsilon_{i,t}|\mathcal{F}_{i,t-1} \sim iid\, \mathcal{N}(0,1), \\
\mu_{i,t} &= \mu_i + \phi_{1,i}R_{i,t-1} + \phi_{2,i}R_{i,t-2} + \phi_{3,i}R_{i,t-3}, \\
\sigma_{i,t}^2 &= \omega_i + \alpha_i e_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2,
\end{aligned}
\tag{4.16}
$$

where the subscript denoting the respective firm, j, is omitted for convenience. Pseudo-observations, u_i, are then obtained by calculating the corresponding ranks, i.e. $u_i = F_i(\varepsilon_i)$.

In a next step, we then calculate dynamic correlations and tail dependences between the stock returns, bid-ask spreads, and default intensities of the *same* firm.[32] The former

[31] Note that we merely aim to provide first evidence on the time-varying linear and non-linear dependences between stock returns, bid-ask spreads, and default intensities. Due to computational feasibility, in this section, we therefore neglect such issues as asymmetry in volatility and fat tails as well as skewness in the marginal distributions. These issues are however addressed in our risk management application in the next section.

[32] This restriction is necessary to ensure computational feasibility. Note, however, that the model approach discussed in Section 4.2 and employed in the next section, accounts for all relevant cross-dependences.

are computed using the Dynamic Conditional Correlation (DCC) model as proposed by Engle (2002).[33] The DCC model uses the residuals from the univariate GARCH processes as building blocks and assumes that the dynamics in the correlation matrix, R_t, are driven by some autoregressive term and the cross-product of return shocks, i.e.

$$\begin{aligned} R_t^j &= \text{diag}(Q_t^j)^{-1} Q_t^j \, \text{diag}(Q_t^j)^{-1}, \\ Q_t^j &= (1 - \psi_1^j - \psi_2^j) Q^j + \psi_2^j Q_{t-1}^j + \psi_1^j \tilde{\varepsilon}_{t-1}^j \tilde{\varepsilon}_{t-1}^{j\top}, \end{aligned} \tag{4.17}$$

where ψ_1^j and ψ_2^j are non-negative parameters, Q^j is the unconditional correlation matrix, and $\tilde{\varepsilon}_t^j = \left(\tilde{\varepsilon}_{1,t}^j, \tilde{\varepsilon}_{2,t}^j, \tilde{\varepsilon}_{3,t}^j\right)^\top$ with $\tilde{\varepsilon}_{i,t}^j$ given by $\varepsilon_{i,t}^j \sqrt{Q_{ii,t}^j}$, $j = 1, ..., 209$ (see Aielli, 2009, for details).

Dynamic tail dependences, on the other hand, are calculated using Patton's (2006) dynamic t copula, which is outlined in Appendix C. Copula estimation is conducted for each of the three possible pairs of returns, spreads, and intensities on the basis of the corresponding pseudo-observations, (u_{i_1}, u_{i_2}), where $i_1, i_2 = 1, 2, 3$; $i_1 \neq i_2$.

Table 4.3 reports the cross-sectional distribution of estimates for the marginal and dependence parameters. The former are captured in Panel (A) and presented separately for stock returns, bid-ask spreads, and default intensities. The estimation results for stock returns are fairly standard. We find the first two AR lags to be strongly significant, capturing the autocorrelation evidenced in Section 4.3. Further, the conditional variance models reveal an only mild effect of lagged return shocks on current volatility, as indicated by the α parameter being around 0.05 on average. The autoregressive β parameter is, however, dominating with the cross-sectional average being around 0.94. As is commonly found in the literature, volatility persistence is quite high (0.99 on average).[34]

[33] In fact, we use the modified DCC model according to Aielli (2009).
[34] See, e.g., Christoffersen et al. (2012) and Engle (2002).

Table 4.3: Cross-sectional distribution of parameter estimates.

The table shows summary statistics of the parameter estimates for the marginal distributions as well as the correlation and copula models used to report first evidence on the dependence of prices, liquidity, and credit risk. The marginals are modeled as AR(3)-GARCH(1,1) processes with standard normally distributed innovations, and correlations are computed from Engle's (2002) Dynamic Conditional Correlation (DCC) model (using the Aielli (2009) modification). The copula models are based on Patton's (2006) dynamic t copula as discussed in Appendix C. For each of the 209 firms in the sample (see Table C.1 in Appendix C), the models are estimated on monthly log-differences of the mid prices, bid-ask spreads, and default intensities of the *same* firm for the period from January 2008 to December 2013, where estimation of the DCC and the t copula models is based on the corresponding AR-GARCH residuals. Descriptive statistics are then calculated cross-sectionally across all sample firms. Persistence for the marginal and DCC models is computed as $\alpha + \beta$ and $\psi_1 + \psi_2$, respectively.

	Cross-sectional distribution												
		Percentiles								Moments			
	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.
Panel A: Parameter estimates for AR-GARCH processes													
Stock returns													
μ	0.7099	0.7521	0.8032	0.9053	0.9425	0.9778	1.0150	1.0698	1.1261	0.9345	0.0664	-0.7963	1.2636
ϕ_1	-0.1705	-0.1231	-0.0948	-0.0385	-0.0050	0.0448	0.1369	0.1982	0.2309	0.0062	0.0721	0.5639	0.1035
ϕ_2	-0.1733	-0.1218	-0.0897	-0.0247	0.0093	0.0396	0.0753	0.1100	0.1170	0.0046	0.0510	-0.5435	0.4564
ϕ_3	-0.0017	-0.0008	-0.0004	0.0001	0.0003	0.0006	0.0011	0.0017	0.0018	0.0003	0.0005	-0.0800	2.0703
ω	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	2.8841	14.0772
α	0.0000	0.0232	0.0291	0.0420	0.0527	0.0611	0.0789	0.0956	0.0994	0.0527	0.0155	0.2690	0.4786
β	0.8946	0.9025	0.9114	0.9289	0.9398	0.9484	0.9638	0.9718	0.9994	0.9391	0.0157	-0.0100	0.7668
Persistence	0.9560	0.9747	0.9825	0.9890	0.9929	0.9953	0.9993	1.0016	1.0024	0.9918	0.0056	-1.9519	8.6149
Bid-ask spreads													
μ	0.0376	0.0857	0.1265	0.1774	0.2127	0.2455	0.3084	0.3869	0.4848	0.2137	0.0592	0.6655	2.5100
ϕ_1	-0.1078	-0.0498	0.0262	0.0723	0.1049	0.1377	0.1879	0.2141	0.2590	0.1037	0.0545	-0.3384	1.1941
ϕ_2	-0.0469	-0.0264	0.0513	0.0979	0.1311	0.1585	0.1980	0.2612	0.2888	0.1276	0.0502	-0.2115	1.3672
ϕ_3	-0.0381	-0.0241	-0.0204	-0.0142	-0.0113	-0.0083	-0.0015	0.0014	0.0045	-0.0113	0.0056	-0.2702	2.2573
ω	0.0000	0.0003	0.0017	0.0093	0.0140	0.0216	0.0403	0.1652	0.3870	0.0201	0.0350	7.6350	68.2337
α	0.0304	0.0325	0.0442	0.0635	0.0784	0.1013	0.1409	0.1917	0.2919	0.0849	0.0341	1.8250	6.6965
β	0.4415	0.5391	0.8387	0.8796	0.8991	0.9139	0.9411	0.9639	0.9644	0.8881	0.0622	-4.4872	24.6484
Persistence	0.6417	0.7072	0.9461	0.9664	0.9785	0.9897	1.0040	1.0181	1.0680	0.9729	0.0440	-5.4572	36.1846
Default intensities													
μ	-0.5321	-0.5137	-0.2581	-0.0644	0.0550	0.1216	0.1766	0.2091	0.2701	0.0119	0.1473	-1.2988	2.0961
ϕ_1	-0.4508	-0.2737	-0.1172	-0.0047	0.0394	0.0712	0.1100	0.1263	0.1474	0.0196	0.0823	-2.3825	8.6786
ϕ_2	-0.1694	-0.1162	-0.0739	-0.0159	0.0132	0.0392	0.0816	0.1273	0.1492	0.0106	0.0480	-0.3077	1.0732
ϕ_3	-0.0017	-0.0010	-0.0007	-0.0003	0.0000	0.0003	0.0009	0.0020	0.0022	0.0000	0.0005	0.7591	3.5747
ω	0.0000	0.0000	0.0000	0.0001	0.0002	0.0004	0.0008	0.0012	0.0014	0.0003	0.0003	1.4110	1.8542
α	0.0000	0.0002	0.0112	0.1114	0.2326	0.3815	0.7161	1.0000	1.0000	0.2901	0.2326	1.2397	1.4225
β	0.0000	0.0000	0.0000	0.2441	0.6017	0.8359	0.9722	0.9915	0.9998	0.5326	0.3304	-0.2887	-1.3085
Persistence	0.0374	0.0930	0.3301	0.6327	0.9123	0.9927	1.1087	1.4202	1.5210	0.8227	0.2647	-0.5796	0.4133

Table 4.3: Cross-sectional distribution of parameter estimates (continued).

	Cross-sectional distribution												
		Percentiles								Moments			
	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.
Panel B: Parameter estimates for DCC models													
ψ_1	0.0000	0.0000	0.0002	0.0007	0.0031	0.0073	0.0164	0.0237	0.0320	0.0051	0.0056	1.7866	3.7179
ψ_2	0.0007	0.0494	0.2750	0.9447	0.9636	0.9776	0.9895	0.9940	0.9955	0.8950	0.2076	-3.0676	8.4476
Persistence	0.0207	0.0515	0.2758	0.9504	0.9681	0.9815	0.9926	0.9962	0.9966	0.9000	0.2065	-3.0832	8.5102
Panel C: Parameter estimates for copula models													
Stock returns - Bid-ask spreads													
c	-0.3755	-0.2286	-0.1579	-0.0086	0.0048	0.0416	0.1881	0.2938	0.3214	0.0148	0.0963	-0.0505	2.5971
b	-2.0121	-2.0086	-1.9593	-1.3570	-0.0164	1.5862	1.9352	1.9700	2.0356	0.0850	1.4664	-0.0645	-1.5590
a	-0.7829	-0.7021	-0.4633	-0.1025	0.0233	0.0994	0.3801	0.5293	0.7382	-0.0162	0.2460	-0.4087	1.1521
ν	6.1908	8.9543	12.1979	20.7282	37.5850	63.6554	93.8263	99.9548	99.9995	44.4172	26.0986	0.4750	-0.9234
Stock returns - Default intensities													
c	-0.1870	-0.1385	-0.0333	0.0086	0.0693	0.2590	0.6596	0.8174	1.1433	0.1653	0.2209	1.5093	2.2150
b	-2.1471	-2.0622	-2.0168	-1.3190	0.3870	1.6951	1.9810	2.0028	2.0363	0.1837	1.4668	-0.2149	-1.4834
a	-0.6104	-0.4915	-0.3039	-0.0615	0.0224	0.1072	0.4002	0.6315	0.9743	0.0318	0.2025	0.6263	3.0254
ν	8.2157	8.6381	10.4262	15.3369	24.2336	44.4626	79.4284	99.6542	99.9992	32.7019	22.9692	1.2417	0.8157
Bid-ask spreads - Default intensities													
c	-0.3462	-0.2171	-0.1323	-0.0437	-0.0066	0.0086	0.0994	0.2263	0.2777	-0.0167	0.0752	-0.1227	3.8508
b	-2.0353	-2.0130	-1.9991	-1.7140	-0.2303	1.1646	1.8970	2.0045	2.0118	-0.2421	1.4562	0.1702	-1.5744
a	-0.8831	-0.6167	-0.3822	-0.1680	-0.0132	0.1279	0.3330	0.4137	0.4695	-0.0202	0.2216	-0.4639	0.6792
ν	8.6169	9.5970	14.3452	31.5501	54.2957	78.5693	99.9412	99.9996	99.9999	56.0324	27.7647	0.0326	-1.2075

Turning to the marginal parameters of bid-ask spreads, we find all three AR lags to be strongly significant. Moreover, as in the case of stock returns, the variance parameters indicate low values for the estimates of the news-arrival parameter, α, (0.08 on average) and high values for the autoregressive β parameter (0.89 on average). As above, volatility persistence is high at 0.97 on average.

Regarding default intensities, we can see from the marginal parameter estimates that the first two AR lags turn out to be significant. Interestingly, the α parameter is around 0.29 on average and, thus, considerably higher for default intensities than for stock returns and bid-ask spreads, indicating that news arrival affects volatility of default intensities to a greater extent than volatility of stock returns and bid-ask spreads. At the same time, the autoregressive β parameter is much smaller and about 0.53 on average. Volatility persistence, on the other hand, remains high at 0.82 on average, but appears to be relatively low when compared to volatility persistence of stock returns and bid-ask spreads.

Turning to the DCC parameter estimates in Panel (B) of Table 4.3, we find the autoregressive ψ_2 parameter to be clearly dominating (0.90 on average). Further, the estimates indicate considerable persistence in the conditional correlation of stock returns, bid-ask spreads, and default intensities of the *same* firm.

Panel (C) reports the parameter estimates for the dynamic t copulas and, on the one hand, shows that there is substantial cross-sectional variation in the dependence between stock returns, bid-ask spreads, and default intensities. On the other hand, the estimates reveal that the dependence between returns and spreads, returns and intensities, and between spreads and intensities differ considerably, indicating that each pair of returns, spreads, and intensities is characterized by specific patterns in dependence.

The temporal variation of correlations and tail dependences is depicted in Figure 4.2. Panel (a) plots the corresponding correlations and shows that correlations exhibit considerable time variation and differ materially across the three pairs of returns, spreads, and intensities.

Figure 4.2: Dynamic correlations and tail dependences.

The figure shows the minimum/maximum range of dynamic correlations and tail dependences of stock returns, bid-ask spreads, and default intensities. For each trading day between January 2008 and December 2013 and for each of the 209 firms in the sample (see Table C.1 in Appendix C), we calculate dynamic correlations and tail dependences between the returns, spreads, and intensities of the *same* firm, resulting in a total of each 627 correlation and tail dependence coefficients per firm and day. We then calculate cross-sectional minimum and maximum values for each day. Dynamic correlations are computed from Engle's (2002) Dynamic Conditional Correlation (DCC) model (using the Aielli (2009) modification), and dynamic tail dependence coefficients from Patton's (2006) dynamic t copula (see Appendix C). The models are estimated on the basis of the residuals from AR(3)-GARCH(1,1) processes applied to monthly log-differences of mid prices, bid-ask spreads, and default intensities.

(a) Dynamic correlations

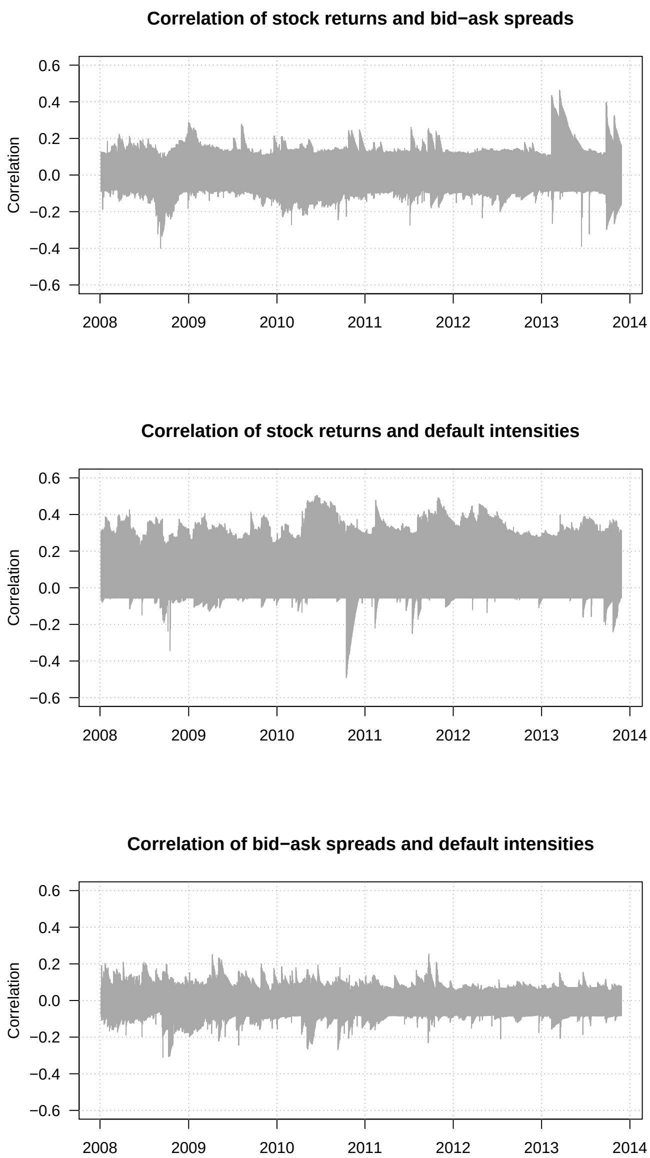
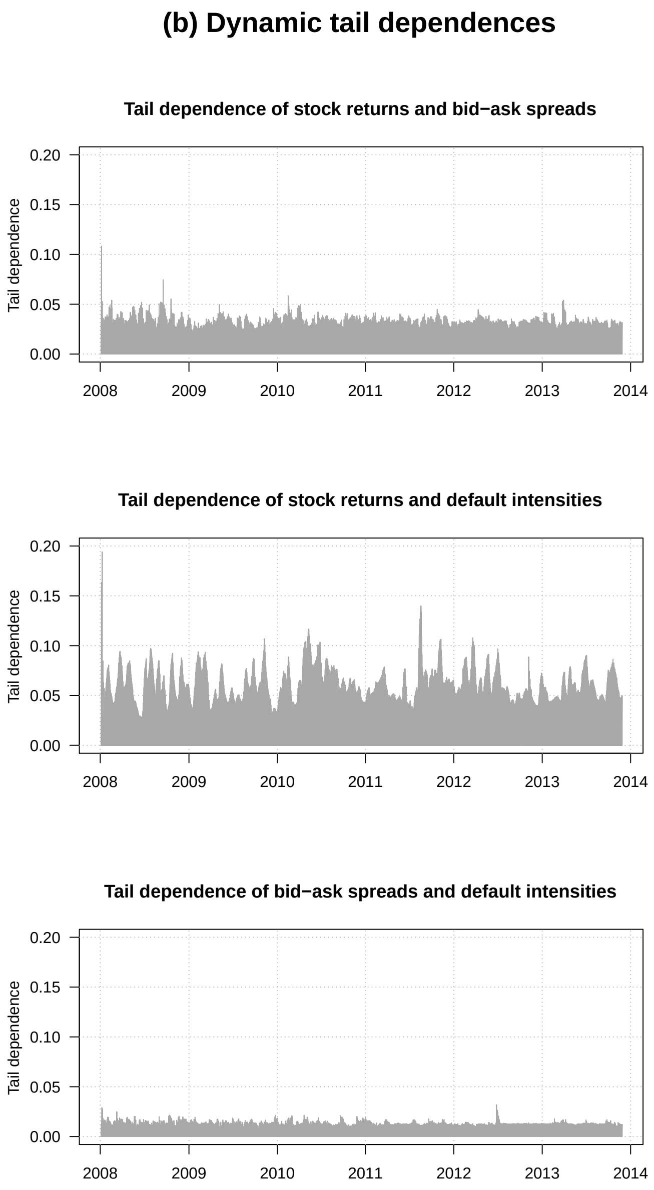


Figure 4.2: Dynamic correlations and tail dependences (continued).



While dynamic correlations between returns and spreads and between returns and intensities range from approximately -40% up to 50%, correlations between spreads and intensities stay at comparatively moderate levels and vary in the range of -30% to 25%. These patterns can also be found for the dynamic tail dependences in Panel (b). To be precise, dynamic tail dependences also exhibit considerable variation across time as well as across the three pairs of returns, spreads, and intensities. With the tail dependences between returns and spreads and between returns and intensities varying between 0% and 15% and between 0% and 20%, respectively, the tail dependence between spreads and intensities is somewhat less pronounced and remains in the 0% to 2.5% range.

4.4.2 Forecasting liquidity- and credit-adjusted Value-at-Risk

We now turn to our VaR simulation study, which applies the dynamic vine copula model discussed in Section 4.2 to forecasting liquidity- and credit-adjusted VaR. We first discuss our approach to incorporate liquidity and credit risk into the standard VaR framework and present the simulation design. We then discuss the simulation and forecasting results and compare the performance of competing dependence models.

4.4.2.1 Simulation design

The onset of the VaR concept as a de-facto industry standard has spurred a surge in theoretical and empirical VaR studies in the risk management literature. Since then, a recurring topic has been the incorporation of liquidity risk into the standard VaR framework which only accounts for market price risk. Being subject of an intense and controversial debate in the literature, much effort has been spent on the incorporation of liquidity risk into standard VaR and many different extensions have been proposed in existing studies (see, e.g., Berkowitz, 2000; Bangia et al., 2002; Qi and Ng, 2009). The incorporation of credit risk, on the other hand, has also been widely discussed in the literature (see Crouhy et al., 2000, for an overview), but has so far been restricted to portfolios of credit-linked securities, i.e., bond portfolios (Andersson et al., 2001) and portfolios of derivatives with defaultable counterparties or borrowers (Duffie and Pan, 2001). Following the notion of stockholders as the residual claimants on a firm's assets (Vassalou and Xing, 2004), we argue that VaR measures of stock portfolios as well need to be modified by considering potential future losses from credit events since stock portfolios are subject to credit risk and might suffer severe losses in case of the underlying firm being in financial distress. Because a firm defaults when it fails to service its debt obligations and equity, in turn, is serviced subordinately to debt, credit losses might be passed to stockholders causing stock values to suffer sharp declines and forcing stockholders to significantly write off their portfolios.

To formally describe our liquidity- and credit-adjusted VaR (subsequently denoted as LC-VaR) as well as the simulation design, we adopt the notation introduced in the preceding sections and, in the first step, estimate the AR(3)-GJR-GARCH(1,1) processes for the marginal time series of log-differences, $\{R_{i,t}^j\}$, with $i = 1, 2, 3$ denoting the type of series (returns, spreads, intensities) and $j = 1, ..., d$ denoting the corresponding firm. The resulting residuals, $\{\hat{\varepsilon}_{i,t}^j\}$, are then used to compute pseudo-observations (i.e., copula data), $\{\hat{u}_{i,t}^j\}$, by calculating the corresponding ranks via the transformation $\hat{u}_i^j = \hat{F}_i^j(\hat{\varepsilon}_i^j)$, with $\hat{F}_i^j$ denoting the empirical distribution function. In the next step, we estimate the dynamic R-vine copula model as discussed in Section 4.2, where estimation is based on the copula data, $\{\hat{u}_{i,t}^j\}$. Note that, for each day t in the estimation period, there are three observations for each of the d firms, resulting in a $3d$-dimensional random vector given as

$$\left(\hat{u}_{1,t}^1, \hat{u}_{2,t}^1, \hat{u}_{3,t}^1, ..., \hat{u}_{1,t}^d, \hat{u}_{2,t}^d, \hat{u}_{3,t}^d\right)^\top . \tag{4.18}$$

Having estimated the R-vine copula, we employ the sampling algorithm as discussed in Dißmann et al. (2013) and simulate $K = 500$ independent observations, $\{{}_k\breve{u}_{i,t+1}^j\}_{k=1}^K$, from the specified copula model.[35] The simulated (or rather, forecasted) copula data can then be converted to simulated log-differences of mid prices, bid-ask spreads, and default intensities in the following way. With $q_{skt}(\,\cdot\,; \nu_i^j, \gamma_i^j)$ denoting the quantile function of the skewed t distribution of Fernandez and Steel (1998), the simulated time series can be

[35]This results in 500 vectors of the form as in (4.18). Note that, as indicated by the time subscript, we identify these vectors as the forecasted pseudo-observations for day $t + 1$.

calculated as

$$
\begin{aligned}
{}_k\breve{R}^j_{i,t+1} &= \breve{\mu}^j_{i,t+1} + \breve{e}^j_{i,t+1} = \breve{\mu}^j_{i,t+1} + \breve{\sigma}^j_{i,t+1}\breve{\varepsilon}^j_{i,t+1}, \\
\breve{\varepsilon}^j_{i,t+1} &= q_{skt}({}_k\breve{u}^j_{i,t+1}; \hat{\nu}^j_i, \hat{\gamma}^j_i),
\end{aligned}
\tag{4.19}
$$

where $\breve{\mu}^j_{i,t+1}$ and $\breve{\sigma}^j_{i,t+1}$ are computed by inserting the estimated AR-GJR-GARCH parameters into equations (4.2) and (4.3), respectively. The forecasted mid prices, $\left\{{}_k\breve{m}^j_{t+1}\right\}$, bid-ask spreads, $\left\{{}_k\breve{s}^j_{t+1}\right\}$, and default intensities, $\left\{{}_k\breve{h}^j_{t+1}\right\}$, are given by

$$
{}_k\breve{m}^j_{t+1} = m^j_t \exp\left({}_k\breve{R}^j_{1,t+1}\right), \quad {}_k\breve{s}^j_{t+1} = s^j_t \exp\left({}_k\breve{R}^j_{2,t+1}\right), \quad {}_k\breve{h}^j_{t+1} = h^j_t \exp\left({}_k\breve{R}^j_{3,t+1}\right),
\tag{4.20}
$$

where the forecasted monthly default probabilities, $\left\{{}_k\breve{p}^j_{t+1}\right\}$, can be calculated according to (4.15) as follows

$$
{}_k\breve{p}^j_{t+1} = 1 - \exp\left(\frac{30}{360}\, {}_k\breve{h}^j_{t+1}\right).
\tag{4.21}
$$

Computing LC-VaR forecasts, $\widetilde{\text{LC-VaR}}^j_{t+1}(\theta)$, now essentially reduces to calculating empirical quantiles of forecasted mid price returns, bid-ask spreads, and default probabilities, where θ denotes the corresponding confidence level. More precisely, with $rs^j_t = s^j_t/m^j_t$ being the relative spread and b^j_t denoting the bid price, LC-VaR forecasts are calculated according to

$$
\widetilde{\text{LC-VaR}}^j_{t+1}(\theta) = \widetilde{\text{VaR}}^j_{t+1}(\theta) + \widetilde{\text{L-VaR}}^j_{t+1}(\theta) + \widetilde{\text{C-VaR}}^j_{t+1}(\theta),
\tag{4.22}
$$

where

$$
\widetilde{\text{VaR}}^j_{t+1}(\theta) = m^j_t \left(1 - \exp\left(\hat{q}\left(\left\{{}_k\breve{R}^j_{1,t+1}\right\}; \theta\right)\right)\right)
\tag{4.23}
$$

is the standard VaR and

$$\widetilde{\text{L-VaR}}^{j}_{t+1}(\theta) = \frac{1}{2} m^j_t \hat{q}\left(\left\{{}_k\check{rs}^{j}_{t+1}\right\}; 1-\theta\right), \qquad \widetilde{\text{C-VaR}}^{j}_{t+1}(\theta) = b^j_t \hat{q}\left(\left\{{}_k\check{p}^{j}_{t+1}\right\}; 1-\theta\right) \tag{4.24}$$

denote the liquidity- and credit-adjustment, respectively, with $\hat{q}(\,\cdot\,;\theta)$ denoting the empirical quantile function evaluated at probability θ.

The liquidity-adjustment in (4.24) is proposed by Bangia et al. (2002) and accounts for the exogenous liquidity risk of the underlying stock. Exogenous liquidity risk is proxied by the bid-ask spread and refers to the cost of immediate trading, which results from the liquidity suppliers' purchasing at the bid and selling at the ask price (see Kyle, 1985; Amihud and Mendelson, 1986). Further, C-VaR^j_t denotes the credit-adjustment we propose to account for default risk of the underlying firm. The idea of incorporating credit risk into VaR calculation is based on the fact that stockholders are serviced subordinately to debt holders in case of financial distress and might bear a large portion of the credit losses when default occurs. Note that we base the calculation of C-VaR^j_t on the simplifying assumption that stockholders loose all of their capital invested in a particular firm in the event of default, i.e. they suffer a loss equal to the bid price of the corresponding stock.[36] Thus, we define C-VaR^j_t to be the maximum (expected) credit loss over the next month that will not be exceeded with probability $1-\theta$.

4.4.2.2 Forecasting LC-VaR: The baseline approach

In our baseline approach, we estimate and forecast portfolio LC-VaR based on a portfolio consisting of six firms from the S&P 500, resulting in an 18-dimensional vector of prices, bid-ask spreads, and default intensities for each trading day in the sample period.[37] The firms included in LC-VaR forecasting are printed in bold type in Table C.1 in Appendix C and comprise *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet*

[36]Note, however, that the potential recovery for stockholders in the event of default is a result from renegotiation between claim holders and depends on the degree of shareholder advantage (see Garlappi et al., 2008). To make C-VaR computation feasible for our purposes, we rely on the assumption of zero stockholder recovery.

[37]That is, we set $d = 6$ and obtain vectors of the form as in (4.18) for each day t.

Healthcare, *Textron*, and *Wal-Mart Stores*. Portfolio LC-VaR is calculated at a monthly time horizon with a confidence level of 95% (i.e., $\theta = 0.95$). Formally, portfolio LC-VaR forecasts are derived by replacing m_t^j, ${}_k\check{R}_{1,t+1}^j$, ${}_k\check{rs}_{t+1}^j$, b_t^j, and ${}_k\check{p}_{t+1}^j$ in (4.23) and (4.24) with the corresponding portfolio prices, returns, spreads, and intensities calculated using cross-sectional equally-weighted averages.

The marginal models and the dependence model are estimated on an in-sample comprising monthly log-differences of prices, bid-ask spreads, and default intensities for the 261 trading days in 2010. The estimated models are then used to forecast LC-VaR numbers for the trading days in January 2011. The in- and out-of-samples are subsequently shifted forward one month and the models are re-estimated based on the period from February 1st, 2010 to February 1st, 2011, where forecasting is now conducted for February 2011. We repeat this procedure ten times, resulting in 230 LC-VaR forecasts for the 230 trading days following January 1st, 2011. The marginal models are re-estimated every day, whereas the dynamic R-vine copula model is re-estimated every month due to computational complexity.

Descriptive statistics on the sample firms' stock prices, bid-ask spreads, and default intensities in levels and log-differences are provided in Tables C.2 and C.3 in Appendix C, respectively. The time evolution of the stock returns, bid-ask spreads, and default intensities of the six companies are plotted in Figure 4.3.

The different panels of Figure 4.3 highlight that all six companies in our sample are characterized by volatile stock returns and increasing liquidity. For several sample companies, default intensities exhibit a U-shaped time evolution with default risk reaching its minimum at the start of 2011 and increasing through most of 2011. Furthermore, almost all time series exhibit extreme data points underlining the need to account for the non-linear dependence structure in our data. For example, the shares of *3M Company* plummeted by more than 40% on one day in August 2011 with *American Express*, *Hewlett-Packard*, and *Textron* experiencing losses of similar magnitude on their equity.

Figure 4.3: Time evolution of stock returns, bid-ask spreads, and default intensities of firms included in the Value-at-Risk study.

The figure plots the time series of stock returns, bid-ask spreads, and default intensities for the six firms included in the Value-at-Risk (VaR) study. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The plots refer to the in- and out-of-sample time periods in the VaR study, which cover the period from January 2010 to November 2011. For each day, t, in the sample period, stock returns are calculated using the mid prices at days t and $t-30$. Bid-ask spreads are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 4.3 and have a horizon of one year.

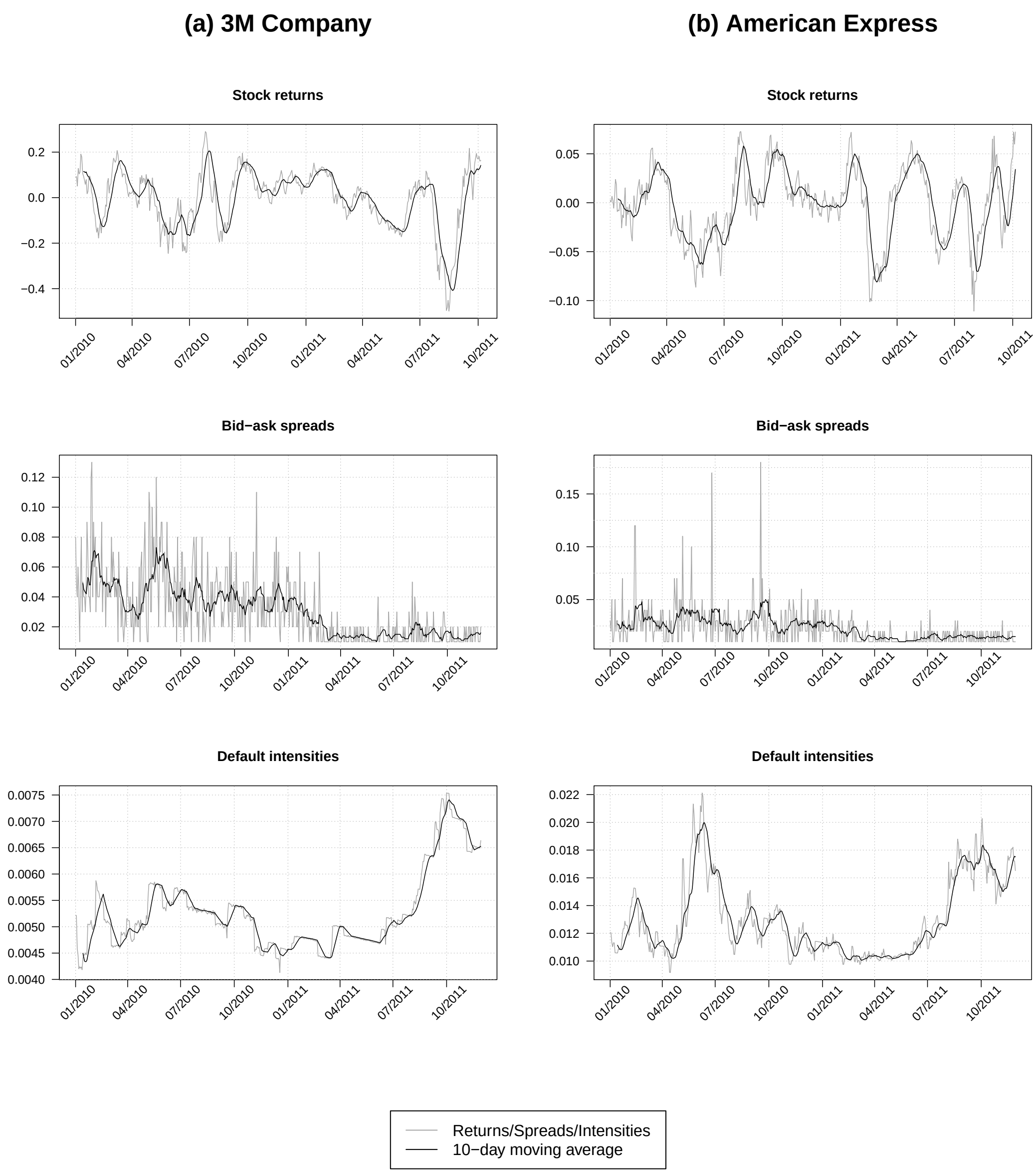


Figure 4.3: Time evolution of stock returns, bid-ask spreads, and default intensities of firms included in the Value-at-Risk study (continued).

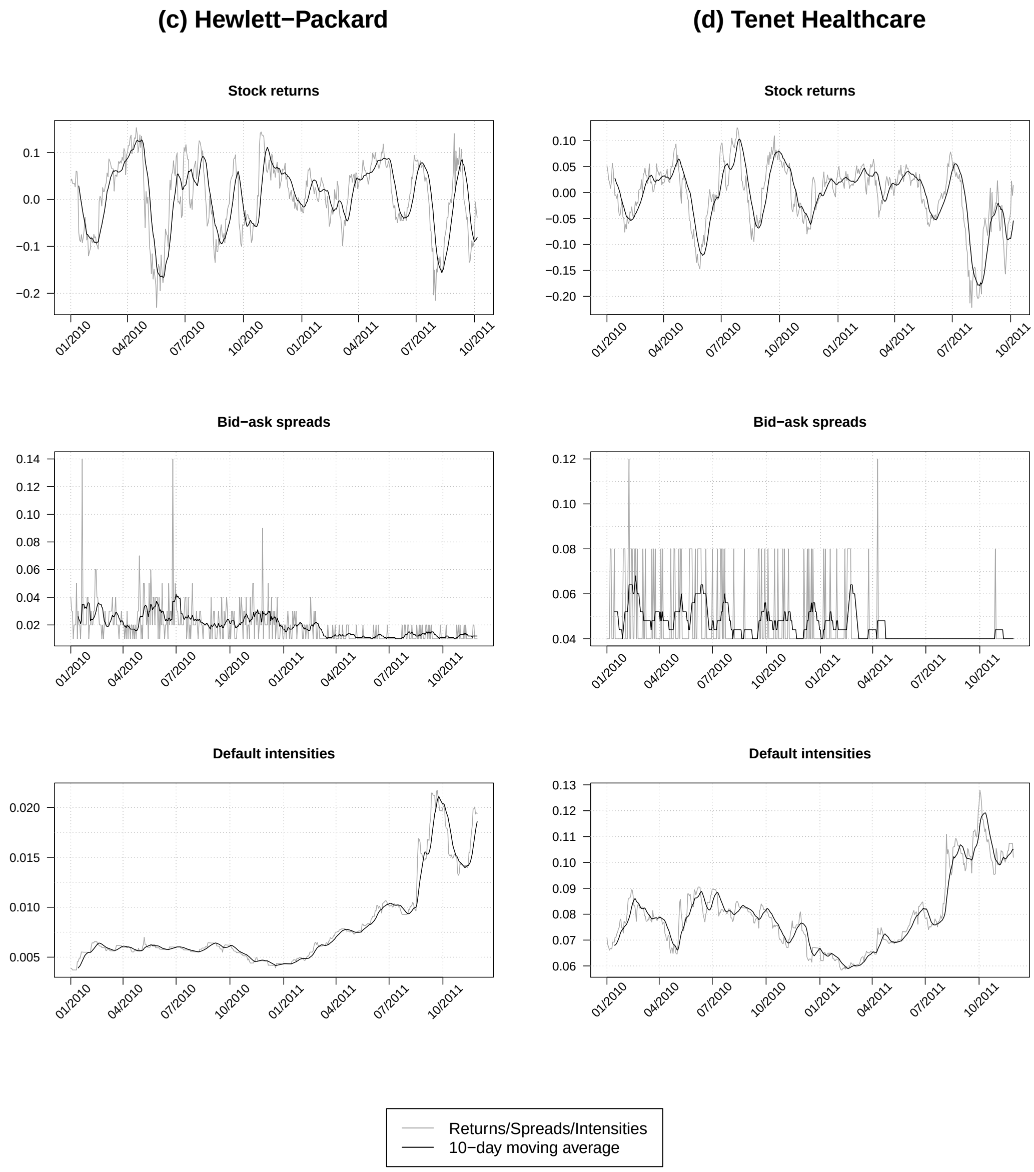
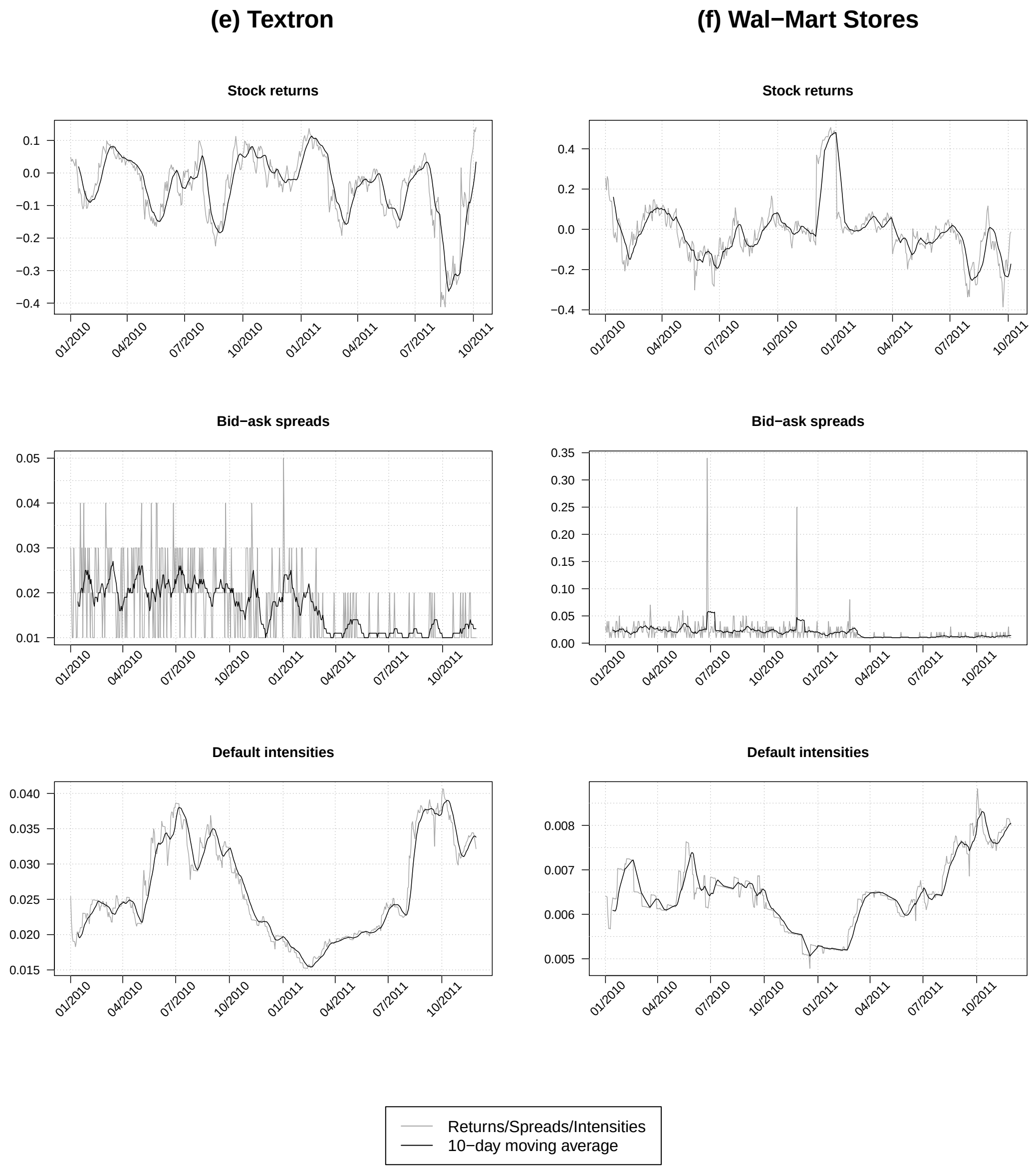


Figure 4.3: Time evolution of stock returns, bid-ask spreads, and default intensities of firms included in the Value-at-Risk study (continued).



Quite similarly, the illiquidity of our sample firms' stocks spiked as well during the sample period (see, e.g., the bid-ask spreads of *3M Company* and *Hewlett-Packard* in 2010). Finally, the time series of default intensities are expectedly less volatile than the companies' stock returns but are also characterized by few extreme observations.

In the next step, we shortly comment on the parameter estimates for the marginal models of the six sample companies in our Value-at-Risk study. Average parameter estimates for the marginal distributions of monthly log-differences on daily mid prices, bid-ask spreads, and default intensities are presented in Table 4.4.

The parameter estimates for the mean dynamics show that at least the first two AR lags are strongly significant for stock returns, bid-ask spreads, and default intensities. The results on the Ljung-Box test up to ten lags (denoted as LB(10) test) further indicate that the AR(3) processes are successful in capturing the serial dependence evidenced in Section 4.3. The estimation results for the variance dynamics, on the other hand, are fairly standard. Of particular note are the estimates for the δ parameter which captures asymmetry in volatility. While the δ estimates for stock returns and bid-ask spreads predominantly reveal only mild statistical evidence of asymmetry in volatility, volatility of default intensities appears to be characterized by strong asymmetry across all six firms.[38] Further, the estimates for the skewed t distribution indicate fat tails and slight skewness for the returns, spreads, and intensities of most firms. Finally, to check the adequacy of the variance models, we apply the LB(10) test to the squared standardized GARCH residuals. Impressively, the GJR-GARCH models are able to pick up most of the second-moment dependence inherent in the time-series data, as indicated by the low number of rejections for the LB(10) test. We conclude from Table 4.4 that the marginal AR-GJR-GARCH models are capable of delivering the white-noise residuals required to obtain unbiased estimates for the dependence parameters of our dynamic R-vine copula model.

[38]Note, however, that the estimated values for the δ parameter of default intensities are positive throughout the sample firms, which is somewhat counterintuitive since negative AR residuals are associated with good news (see Section 4.2). That is, the positive values imply an upward revision of volatility in response to good news.

Table 4.4: Average parameter estimates for marginal distributions.

The table reports average parameter estimates for the marginal distributions of monthly log-differences on daily mid prices, bid-ask spreads, and default intensities for the six firms investigated in our Value-at-Risk (VaR) study. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The marginal distributions are modeled using AR(3)-GJR-GARCH(1,1) processes with skewed-t distributed innovations as discussed in Section 4.2. Starting with an in-sample comprising the 261 trading days in 2010, the estimation period for the marginal models is subsequently shifted forward one day after each VaR forecast, resulting in 230 re-estimations. The parameter estimates shown in the table result from averaging across the re-estimations. Variance persistence (denoted Var. Pers. in the table) is calculated as $\beta + \alpha + \frac{1}{2}\delta$. The last two columns show the number of rejections (at the 0.01 level) across all 230 re-estimations from Ljung-Box tests for serial correlation up to 10 lags as applied to the standardized and squared standardized residuals.

	Mean dynamics				Variance dynamics							#Rej. of LB(10) test	
	μ	ϕ_1	ϕ_2	ϕ_3	ω	β	α	δ	Var. Pers.	ν	γ	Resid.	Sq. Resid.
Panel A: Stock returns													
3M Company	0.9980	0.0238	-0.0762	0.0006	0.0000	0.9190	0.0550	0.0239	0.9859	17.5909	0.8578	0	0
American Express	0.9460	0.0292	-0.0317	0.0001	0.0000	0.9097	0.0305	0.0176	0.9490	11.4982	0.8934	0	7
Hewlett-Packard	0.9328	0.0993	-0.1152	0.0011	0.0000	0.9252	0.0157	0.0599	0.9709	6.6431	0.9982	9	0
Tenet Healthcare	0.9501	0.1252	-0.1455	0.0004	0.0000	0.9620	0.0143	0.0126	0.9826	9.8417	0.8842	2	16
Textron	1.0466	0.0071	-0.1040	-0.0013	0.0000	0.9307	0.0015	0.0801	0.9722	5.2423	1.0024	0	0
Wal-Mart Stores	0.8942	0.0459	0.0090	0.0009	0.0000	0.9931	0.0051	-0.0204	0.9880	3.2150	0.9207	0	0
Panel B: Log-differences of bid-ask spreads													
3M Company	-0.0131	-0.0665	-0.0448	-0.0457	0.0018	0.9807	0.0347	-0.0515	0.9896	3.3627	0.9713	1	0
American Express	0.0189	0.0745	0.1175	-0.0390	0.0029	0.8766	0.0652	0.1195	1.0015	5.5385	0.9406	0	0
Hewlett-Packard	0.1082	-0.0116	-0.0103	-0.0467	0.0092	0.9862	0.0281	-0.0576	0.9855	29.9999	1.0737	0	0
Tenet Healthcare	0.0317	0.0119	0.0467	-0.0763	0.0046	0.9963	0.0055	-0.0196	0.9920	8.9658	1.0573	0	0
Textron	-0.0532	0.0741	0.0498	-0.0490	0.0066	0.9910	0.0249	-0.0637	0.9841	29.8826	1.0429	9	0
Wal-Mart Stores	0.0055	0.0357	-0.1111	-0.0123	0.0568	0.8016	0.2413	-0.1613	0.9623	2.1100	0.8096	0	0
Panel C: Log-differences of default intensities													
3M Company	-0.0545	0.0511	0.0244	0.0005	0.0000	0.8921	0.0035	0.1667	0.9790	3.8639	1.0657	0	0
American Express	-0.2948	-0.1048	0.0061	0.0001	0.0001	0.4055	0.1286	0.3970	0.7326	2.9294	0.9821	0	61
Hewlett-Packard	-0.1336	0.0266	-0.0025	0.0006	0.0001	0.6981	0.0082	0.2532	0.8330	4.0834	1.0327	0	42
Tenet Healthcare	-0.1938	-0.0026	-0.0125	0.0002	0.0001	0.5834	0.0612	0.3558	0.8225	3.0183	0.9840	0	0
Textron	-0.0668	0.0419	0.0231	-0.0011	0.0001	0.7984	0.0000	0.2218	0.9093	3.1483	0.9319	0	0
Wal-Mart Stores	-0.0910	-0.0142	0.0034	0.0008	0.0000	0.9336	0.0025	0.1194	0.9958	2.9655	1.1106	0	0

To get a better understanding of our model's ability to account for non-linear dependences in market price, liquidity, and credit risk, we quickly review the temporal variation in the selected parametric pair-copulas in our dynamic R-vine copula. The percentages of selected parametric bivariate pair-copulas are shown in Table 4.5.

The percentages given in Table 4.5 show that for around 50% of the bivariate pair-copulas, the tail independent normal copula is selected. Between 5.88% to 12.42% of the pair-copulas are modeled using the symmetrically tail dependent Student's t copula. Conversely, 30% up to 45% of the pair-copulas are modeled using either upper- or lower-tail dependent copulas underlining the notion that the dependence structure of our data is indeed significantly non-linear and asymmetric. Furthermore, the percentages for several parametric copulas vary considerably during the course of our sample period thus confirming the need to employ time-varying copulas. For example, the upper-tail dependent Gumbel copula is chosen for 8.50% of the pair-copulas for the first of our estimation periods with this percentage plummeting to 3.27% for the period of June 2010 to June 2011 and increasing again to 13.73% for the period of September 2010 to September 2011.

The results so far emphasize that, while much of the dependence inherent in market price, liquidity, and credit risk can be adequately modeled using tail independent normal copulas, the dependence structure of our data is also characterized by significant asymmetric tail dependence. However, our particular estimation approach for the R-vine copulas specifically tries to capture as much dependence as possible in the upper trees of the vine structure. As a consequence, it could be that most of the unconditional dependence in our data is actually linear while the tail dependent parametric copulas are only selected in lower (less important) trees in which the conditional dependence is modeled. To answer this question, Table 4.6 presents corresponding percentages of selected parametric pair-copulas separately by the respective tree in the R-vine model.

The results of Table 4.6 show an opposite picture. The normal copula is selected for only 35.88% of the pair-copulas in the first tree while the vast majority of bivariate (unconditional) data pairs are modeled using tail dependent parametric copulas.[39]

[39] In Table C.4 in Appendix C, we additionally tabulate the selected parametric pair-copulas in the first R-vine tree for all bivariate data pairs.

Table 4.5: Temporal variation of selected parametric pair-copulas.

The table reports results on the selected bivariate parametric pair-copulas in our dynamic R-vine copula model for each estimation period included in our Value-at-Risk (VaR) study. The R-vine copula model is estimated on pseudo-observations of standardized log-differences of mid prices, bid-ask spreads, and default intensities for six firms from the S&P 500, resulting in 153 ($= 18 \cdot 17/2$) parametric pair-copulas that need to be specified and estimated for each R-vine copula estimation. The results in the table show the number of a particular parametric copula family being selected as a percentage of the number of pair-copulas to be specified in each R-vine copula estimation (that is, 153). The candidate copulas include dynamic versions of the standard normal, t, (rotated) Clayton, (rotated) Gumbel, and (rotated) Joe copula, where we follow the dynamization approach suggested by Patton (2006) (as outlined in Appendix C). The selection of the bivariate pair-copulas is based on the sequential method as proposed by Dißmann et al. (2013) and conducted using Akaike's Information Criterion (AIC) as the selection criterion to be minimized.

Estimation period	Parametric copula families (in %)							
	Normal	t	Clayton	Rotated Clayton	Gumbel	Rotated Gumbel	Joe	Rotated Joe
01/2010 - 01/2011	51.63	12.42	1.31	2.61	8.50	14.38	2.61	6.54
02/2010 - 02/2011	55.56	5.88	1.96	3.92	5.88	9.15	12.42	5.23
03/2010 - 03/2011	51.63	5.88	2.61	0.65	7.84	15.69	3.27	12.42
04/2010 - 04/2011	56.21	11.76	3.27	3.92	5.23	9.80	5.23	4.58
05/2010 - 05/2011	56.21	12.42	1.96	1.96	8.50	11.76	3.92	3.27
06/2010 - 06/2011	57.52	11.11	3.27	5.23	3.27	7.84	5.88	5.88
07/2010 - 07/2011	54.25	7.84	0.00	4.58	9.15	16.99	2.61	4.58
08/2010 - 08/2011	56.21	8.50	3.27	2.61	5.23	13.73	5.23	5.23
09/2010 - 09/2011	48.37	6.54	2.61	3.27	13.73	14.38	7.19	3.92
10/2010 - 10/2011	49.02	8.50	3.27	2.61	11.76	15.03	3.27	6.54

Table 4.6: Treewise selection of parametric pair-copulas.

The table reports average results on the treewise selection of bivariate parametric pair-copulas in our dynamic R-vine copula model across the estimation periods included in our Value-at-Risk (VaR) study. The R-vine copula model is estimated on pseudo-observations of standardized log-differences of mid prices, bid-ask spreads, and default intensities for six firms from the S&P 500, resulting in 153 ($= 18 \cdot 17/2$) parametric pair-copulas that need to be specified and estimated for each R-vine copula estimation. The 18-dimensional R-vine copula is composed of 17 trees, where copula selection is based on the sequential method as proposed by Dißmann et al. (2013) and conducted using Akaike's Information Criterion (AIC) as the selection criterion to be minimized. Each tree, i, requires the selection and estimation of $18 - i$ bivariate parametric pair-copulas. The results in the table show the number of a particular parametric copula family being selected in tree i, $i = 1, \ldots, 17$, as a percentage of the total number of pair-copulas to be specified in tree i (that is, $18 - i$). The resulting percentages are averaged across all ten re-estimations conducted in our VaR study (see Section 4.4). The candidate copulas include dynamic versions of the standard normal, t, (rotated) Clayton, (rotated) Gumbel, and (rotated) Joe copula, where we follow the dynamization approach suggested by Patton (2006) (as outlined in Appendix C).

Tree	Parametric copula families (in %)							
	Normal	t	Clayton	Rotated Clayton	Gumbel	Rotated Gumbel	Joe	Rotated Joe
1	35.88	18.82	0.59	1.18	7.06	22.94	1.76	11.76
2	46.88	5.00	5.00	2.50	11.25	12.50	6.88	10.00
3	57.33	8.00	0.00	9.33	10.00	10.00	2.67	2.67
4	47.14	15.00	3.57	2.86	5.71	17.86	4.29	3.57
5	52.31	11.54	3.85	0.77	9.23	13.85	1.54	6.92
6	55.00	9.17	1.67	1.67	9.17	10.00	8.33	5.00
7	56.36	10.00	4.55	3.64	6.36	8.18	5.45	5.45
8	62.00	9.00	1.00	6.00	3.00	9.00	6.00	4.00
9	64.44	7.78	1.11	3.33	7.78	6.67	5.56	3.33
10	62.50	1.25	5.00	1.25	3.75	11.25	10.00	5.00
11	61.43	7.14	1.43	0.00	11.43	11.43	4.29	2.86
12	61.67	1.67	0.00	1.67	6.67	13.33	8.33	6.67
13	52.00	6.00	4.00	4.00	8.00	12.00	10.00	4.00
14	65.00	5.00	0.00	2.50	10.00	10.00	5.00	2.50
15	56.67	3.33	3.33	3.33	10.00	13.33	3.33	6.67
16	65.00	0.00	0.00	5.00	5.00	15.00	5.00	5.00
17	50.00	0.00	0.00	10.00	10.00	20.00	10.00	0.00

In the lower trees of the R-vines, the percentage for the normal copula increases up to 65% while several of the tail dependent parametric copulas are no longer selected. These results further underline our finding that our data indeed exhibit strong non-linear dependence.

We now turn to the main results of our VaR study in which we intend to calculate LC-VaR forecasts for the portfolio profits and losses (P/L) at time t, $\mathrm{PL}_t^{\mathrm{pf}}$. The portfolio P/L are calculated according to

$$\mathrm{PL}_t^{\mathrm{pf}} = b_t - a_{t-1}, \tag{4.25}$$

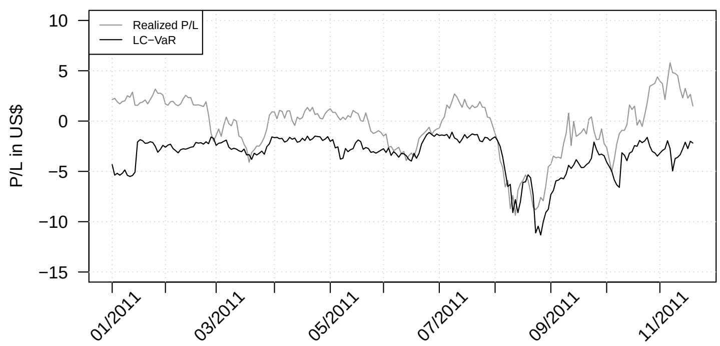
where b_t and a_t denote the portfolio bid and ask price, respectively. The actual portfolio P/L are then compared to the LC-VaR forecasts estimated at a confidence level of $\theta = 0.95$ using monthly log-differences of mid prices, bid-ask spreads, and default intensities. In Figure 4.4, we plot the realized out-of-sample portfolio P/L against the corresponding LC-VaR forecasts calculated from our dynamic R-vine copula model.

In Panel (a) of Figure 4.4, we first plot the realized portfolio P/L against the estimated LC-VaR forecasts for the out-of-sample period that covers the full year 2011. The plot shows that our LC-VaR forecasts stay relatively close to the realized P/L throughout the out-of-sample. Even more importantly, the LC-VaR estimates appear to capture the downward movements of the portfolio P/L quite adequately without underestimating portfolio risk. This last finding is emphasized by the plot in Panel (b) in which we illustrate the distance between the realized portfolio P/L and the LC-VaR forecasts as well as the LC-VaR exceedances. First, we note that the distances between the P/L and the LC-VaR in case the LC-VaR is not exceeded are relatively small throughout the out-of-sample. Consequently, companies employing the LC-VaR based on our dynamic R-vine copula model are able to limit their excess regulatory capital derived from the LC-VaR forecasts. At the same time, the distances are also small to non-existent in case the portfolio losses exceeded the LC-VaR. Our model thus appears to produce small Expected Shortfall estimates as well.

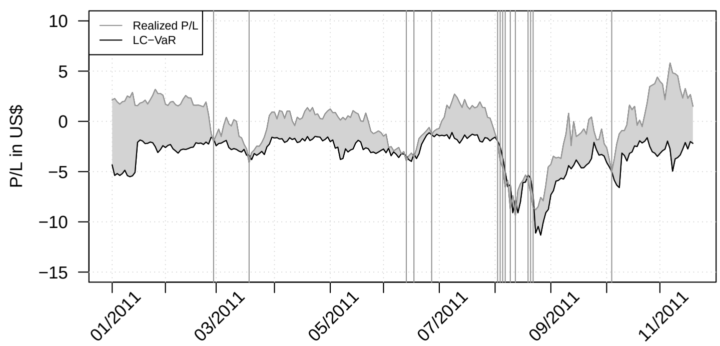
Figure 4.4: Realized portfolio losses and Value-at-Risk forecasts.

The figure shows the realized out-of-sample portfolio profits and losses (P/L) on our sample portfolio as well as the forecasts of liquidity- and credit-adjusted Value-at-Risk (LC-VaR) calculated from our dynamic R-vine copula model. The portfolio P/L at time t, $\mathrm{PL}_t^{\mathrm{pf}}$, is calculated according to $\mathrm{PL}_t^{\mathrm{pf}} = b_t - a_{t-1}$, where b_t and a_t denote the portfolio bid and ask price, respectively. The sample portfolio is composed of six firms from the S&P 500 including *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The forecasting period covers the 230 trading days following January 1st, 2011. Starting with an in-sample comprising the 261 trading days in 2010 and an out-of-sample covering January 2011, the in- and out-of-samples are shifted forward one month with the R-vine copula model being re-estimated. LC-VaR forecasts are calculated at a confidence level of $\theta = 0.95$ based on monthly log-differences of mid prices, bid-ask spreads, and default intensities.

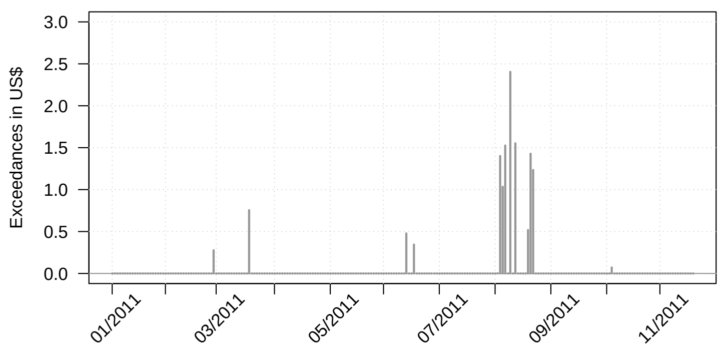
(a) Realized portfolio P/L vs. LC−VaR



(b) Distance between realized portfolio P/L and LC−VaR



(c) LC−VaR exceedances



Second, our R-vine model also seems to forecast portfolio P/L quite adequately based on the number of times the portfolio losses exceed the respective daily LC-VaR forecast. This second finding is highlighted in Panel (c) of Figure 4.4 in which we only plot the losses that exceed the LC-VaR forecasts.

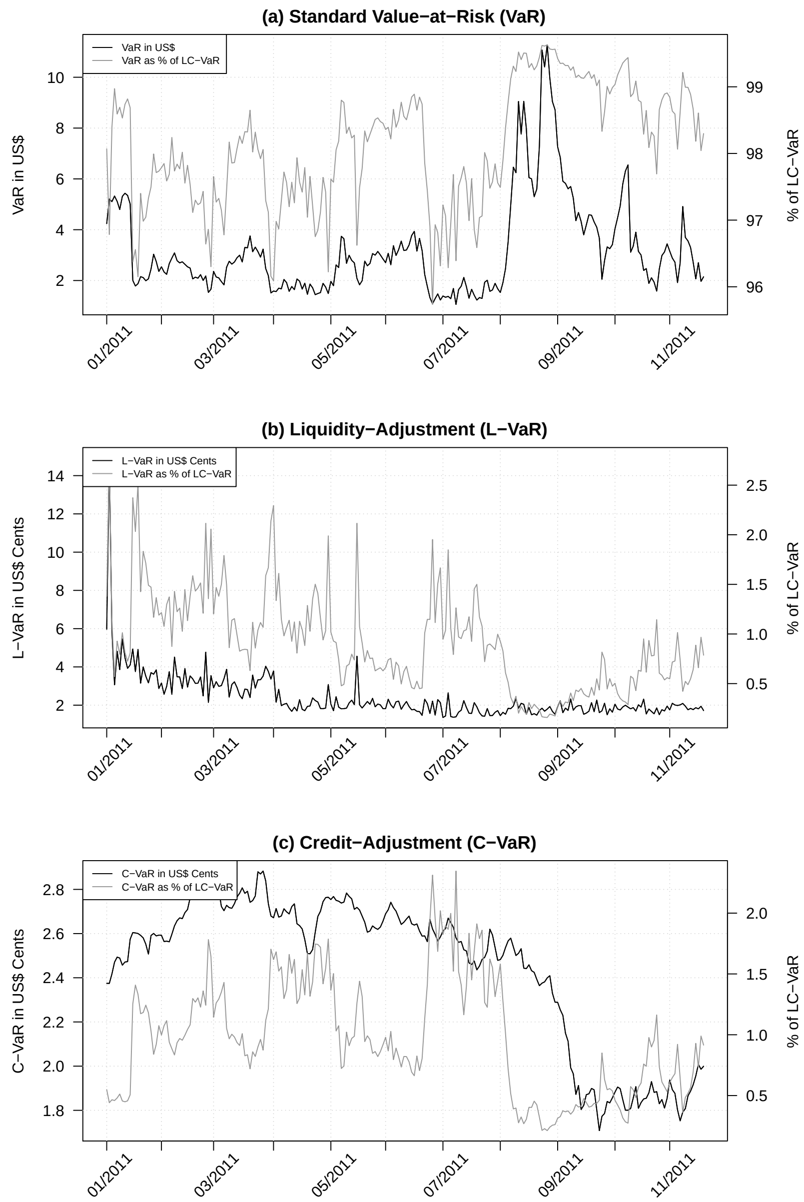
Our analysis so far has shown that the LC-VaR forecasts from our dynamic R-vine copula model adequately predict portfolio losses. Consequently, our results support the notion that integrating information on the dependence between market price, liquidity, and credit risk into a VaR model is vital for accurate risk forecasting. However, we cannot rule out the possibility that the LC-VaR forecasts we estimate solely capture market price risk and that the effect of liquidity and credit risk is negligible. If this were the case, the good fit of our LC-VaR model would simply be due to chance as it simply forecasts market price risk employing a significant amount of redundant information on liquidity and credit risk. Figure 4.5 shows that the opposite is true.

In Figure 4.5, we decompose the LC-VaR forecasts into their market price (VaR), liquidity risk (L-VaR) and credit risk component (C-VaR) and plot the time evolution of the three components. The upper Panel (a) of Figure 4.5 compares the time evolution of the standard market price VaR of our stock portfolio to the LC-VaR forecasts. As expected, the LC-VaR forecasts predominantly consist of the standard VaR with the market price component. However, a significant part of the LC-VaR forecasts (1% to 5%) are due to the liquidity and/or credit components. The plot for the liquidity component given in Panel (b) shows that liquidity risk plays a significant role in the forecasting of LC-VaR as the liquidity component accounts for up to 2.5% of the LC-VaR forecasts. Furthermore, the percentage of the liquidity component of the LC-VaR shows only little time variation and decreases during the course of our out-of-sample.[40] Finally, Panel (c) of Figure 4.5 shows that up to 2% of the absolute LC-VaR forecasts are due to credit risk. More importantly, the relative weight of the credit component in the LC-VaR forecasts varies significantly during our sample period, thus again underlining the need to account for the time dynamics in market price and credit risk.

[40]This finding again reflects the increase in the overall liquidity of stocks during our sample period as shown in Figure 4.3.

Figure 4.5: Decomposing liquidity- and credit-adjusted Value-at-Risk.

The figure presents the time evolution for the market price (VaR), liquidity (L-VaR), and credit component (C-VaR) of liquidity- and credit-adjusted Value-at-Risk (LC-VaR) forecasts. LC-VaR forecasts are computed from the our dynamic R-vine copula model at a confidence level of $\theta = 0.95$ based on monthly log-differences of mid prices, bid-ask spreads, and default intensities for the six firms in our sample portfolio. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The forecasting period covers the 230 trading days following January 1st, 2011. Starting with an in-sample comprising the 261 trading days in 2010 and an out-of-sample covering January 2011, the in- and out-of-samples are shifted forward one month with the R-vine copula model being re-estimated.



4.4.2.3 Neglecting dynamics and non-linearities in dependence

In the last part of our empirical study, we address the question whether the additional flexibility of using (a) a dynamic instead of a static model and (b) a copula instead of a correlation-based model is indeed necessary for accurate risk forecasting. To this end, we compare the forecasting accuracy of our proposed dynamic R-vine copula model to that of a static R-vine model as well as Engle's (2002) DCC model.

As a first step, we compare the realized out-of-sample portfolio profits and losses on our sample portfolio with the forecasts of the LC-VaR calculated from the respective dependence model. Here, we are especially interested in documenting the differences of both dependence models relating to the portfolio profits and losses in our sample. The results of this comparison are presented in Figure 4.6.

The upper parts of Panels (a) and (b) of Figure 4.6 plot the realized profits and losses of our portfolio against the LC-VaR forecasts estimated from our static R-vine copula and DCC model, respectively. The plots show that for both models, the LC-VaR forecasts stay relatively close to the realized portfolio losses. This finding is confirmed by the middle plots in both panels in which we illustrate the distances between the realized portfolio P/L and the LC-VaR forecasts. Compared to the corresponding plots for our dynamic R-vine copula model, however, both models appear to be more conservative as both the distances between the realized P/L and the LC-VaR forecasts are larger and the number of VaR-exceedances are (unnecessarily) smaller.[41] This finding is confirmed in a direct comparison of the different models. The results of this comparison are plotted in Figure 4.7.

The plots presented in Figure 4.7 clearly show that both the static vine copula and the DCC model overestimate portfolio risk to a significant degree. While both models yield LC-VaR forecasts that are exceeded on only few trading days, our dynamic R-vine copula model produces forecasts that not only adequately capture extreme losses but also limit the use of (regulatory) capital.

[41]In untabulated results, we further check the forecasting accuracy of all three models by performing tests of the models' conditional coverage (see Christoffersen and Pelletier, 2004). The results of these tests show that none of the models is rejected.

Figure 4.6: Realized portfolio losses and Value-at-Risk forecasts from alternative dependence models.

The figure shows the realized out-of-sample portfolio profits and losses (P/L) on our sample portfolio as well as the forecasts of liquidity- and credit-adjusted Value-at-Risk (LC-VaR) calculated from alternative dependence models. The alternative dependence models include a static R-vine copula model as well as Engle's (2002) Dynamic Conditional Correlation (DCC) model. The portfolio P/L at time t, $\mathrm{PL}_t^{\mathrm{pf}}$, is calculated according to $\mathrm{PL}_t^{\mathrm{pf}} = b_t - a_{t-1}$, where b_t and a_t denote the portfolio bid and ask price, respectively. The sample portfolio is composed of six firms from the S&P 500 including *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The forecasting period covers the 230 trading days following January 1st, 2011. Starting with an in-sample comprising the 261 trading days in 2010 and an out-of-sample covering January 2011, the in- and out-of-samples are shifted forward one month with the dependence models being re-estimated every day. LC-VaR forecasts are calculated at a confidence level of $\theta = 0.95$ based on monthly log-differences of mid prices, bid-ask spreads, and default intensities.

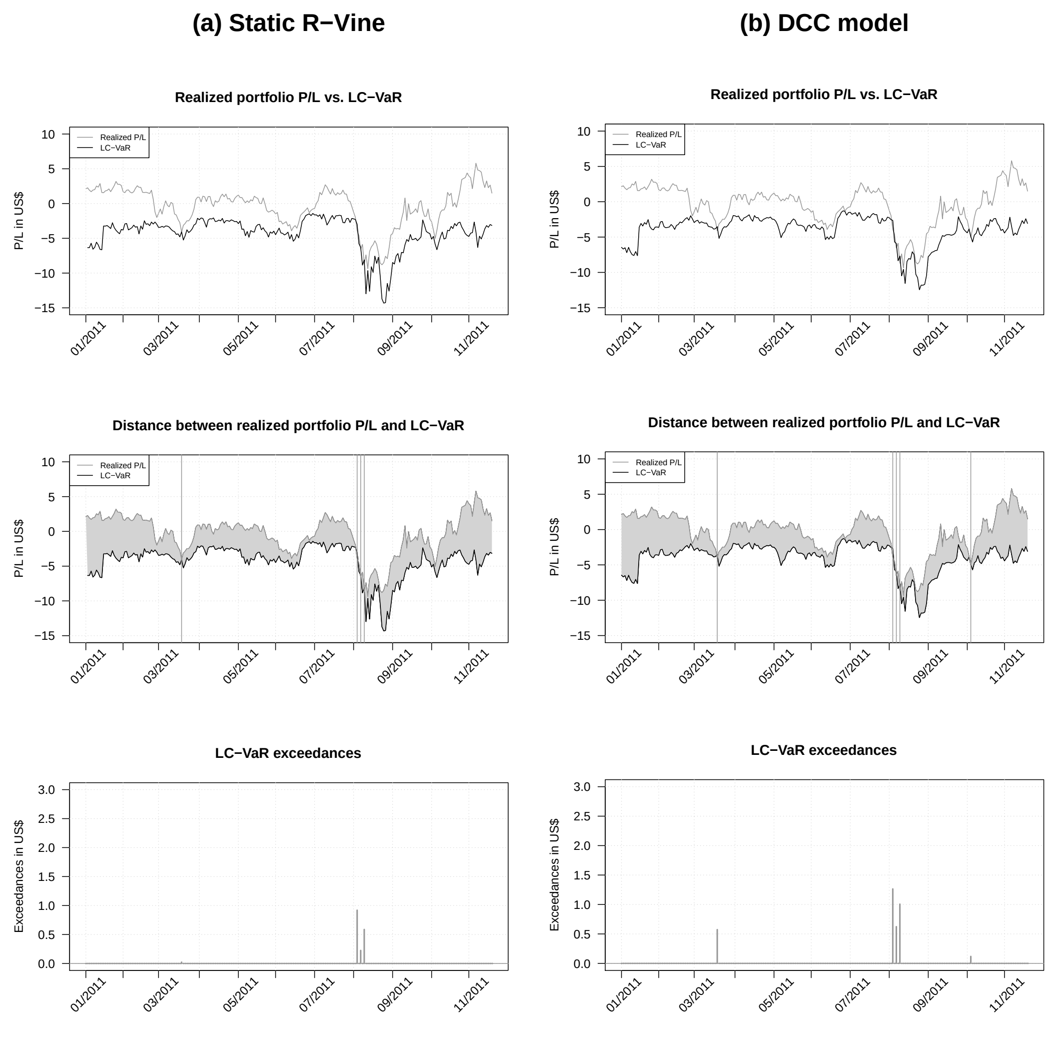


Figure 4.7: Dynamic R-vine copula model versus alternative dependence models.

The figure compares the liquidity- and credit-adjusted Value-at-Risk (LC-VaR) forecasts from the dynamic R-vine copula model to the LC-VaR forecasts from the static R-vine copula model and Engle's (2002) Dynamic Conditional Correlation (DCC) model. LC-VaR forecasts are calculated at a confidence level of $\theta = 0.95$ based on monthly log-differences of mid prices, bid-ask spreads, and default intensities of six firms from the S&P 500 including *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The forecasting period covers the 230 trading days following January 1st, 2011. Starting with an in-sample comprising the 261 trading days in 2010 and an out-of-sample covering January 2011, the in- and out-of-samples are shifted forward one month with the dynamic R-vine model and the alternative dependence models being re-estimated every month and every day, respectively. Portfolio profits and losses (P/L) at time t, $\mathrm{PL}_t^{\mathrm{pf}}$, are calculated according to $\mathrm{PL}_t^{\mathrm{pf}} = b_t - a_{t-1}$, where b_t and a_t denote the portfolio bid and ask price, respectively.

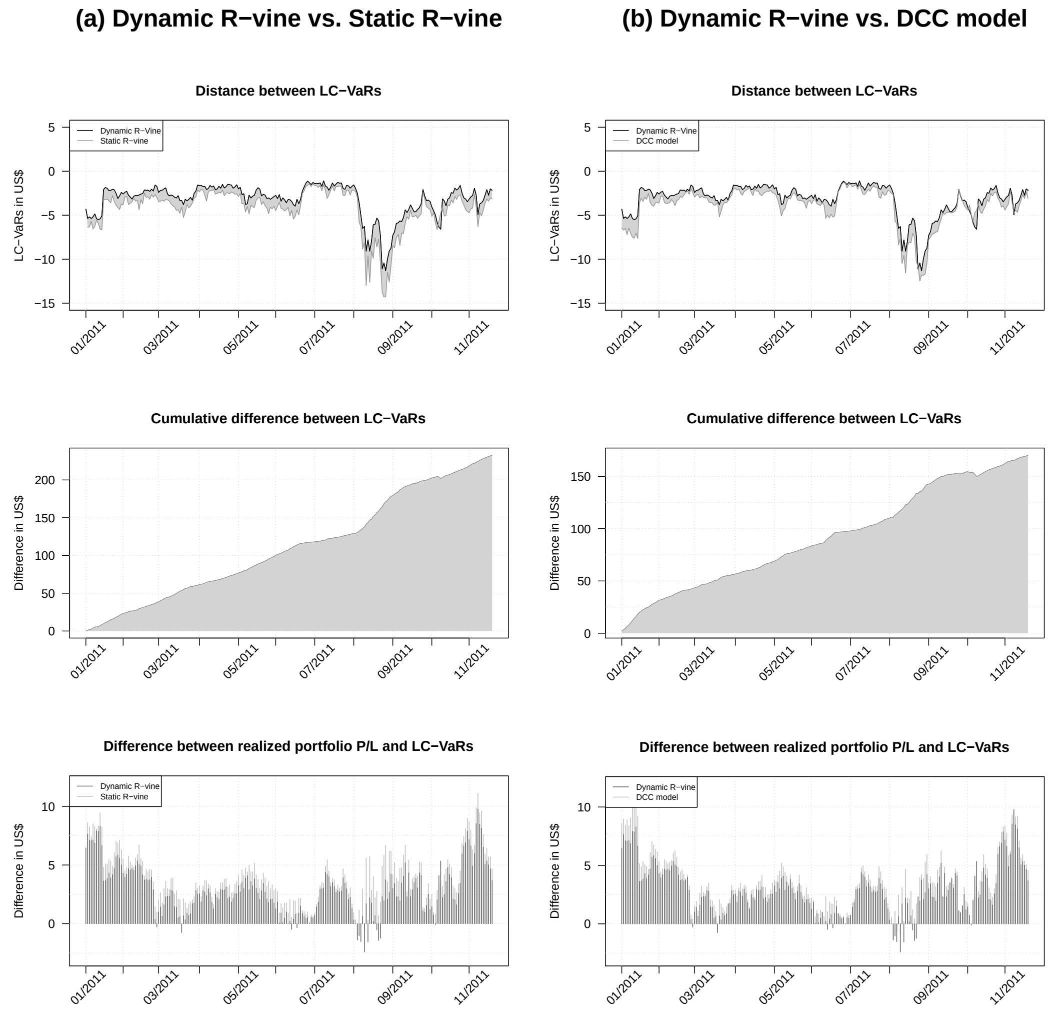
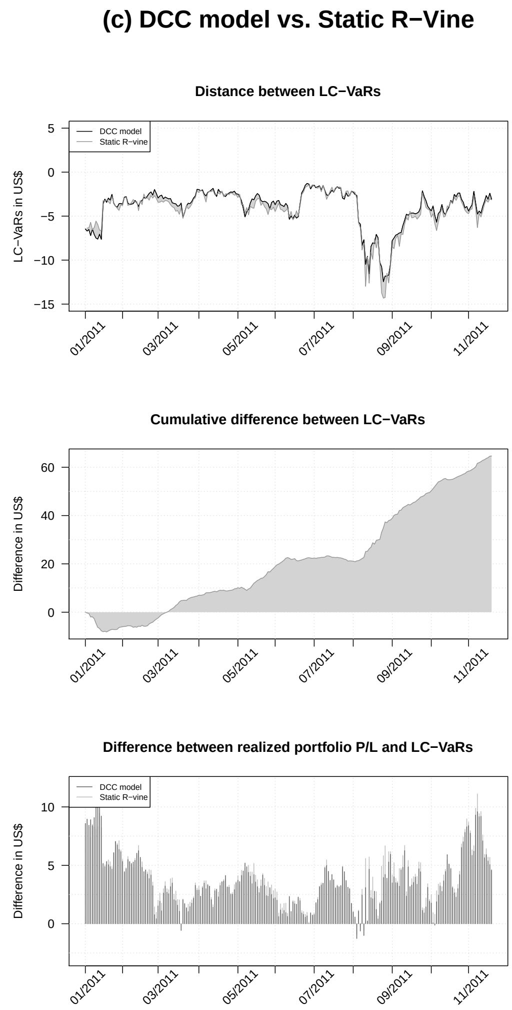


Figure 4.7: Dynamic R-vine copula model versus alternative dependence models (continued).



Neglecting the time dynamics and non-linearities in the dependence structure between market price, liquidity, and credit risk thus leads to an excessive allocation of capital that is not needed and that ultimately leads to unnecessarily high capital costs. In fact, the cumulative difference between our dynamic R-vine copula and the static R-vine alternative increases to more than 200 USD at the end of our out-of-sample period showing the economically highly significant potential to limit capital costs. Furthermore, as evidenced by Panel (c) of Figure 4.7, accounting for time variation in the dependence structure of the three LC-VaR components seems to be more important than accounting for non-linear dependence.

4.5 Conclusion

In this paper, we propose to use dynamic R-vine copulas to model the joint distribution of the market price, liquidity, and credit risk of a multivariate stock portfolio at the security-level. Our model is extremely flexible yet at the same time still tractable even for high-dimensional multivariate distributions and accounts for possible time variation in a distribution's linear and non-linear dependence structure. Using the dynamic R-vine copula model, we document the existence of significant time-varying tail dependence between the returns, the liquidity, and the default intensities of companies listed in the S&P 500. While non-linear dependence has been shown to exist in stock returns and between individual stock and market liquidity, this paper is the first to confirm that the joint distribution of equity returns, liquidity, and default risk is characterized by strong tail dependence as well.

We then propose a liquidity- and credit-adjusted Value-at-Risk (LC-VaR) that not only accounts for market price risk, but also for sudden peaks in illiquidity and default probabilities. Using a portfolio of six companies from the S&P 500, we forecast the portfolio's LC-VaR with the help of our dynamic R-vine copula model. Not only do we find the LC-VaR forecasts to adequately capture downside risk, we also find our dynamic R-vine copula model to significantly outperform static vine copula or dynamic correlation-based models. While both benchmarks overestimate portfolio risk, our dynamic R-vine model significantly saves on risk capital while at the same time yielding an acceptable number of VaR-violations.

Although our empirical study primarily deals with risk forecasting, our main finding is not limited to the field of risk management. In fact, our proposed dynamic R-vine copula model can be used in any context in financial economics in which one wishes to model the dynamic tail dependence in a high-dimensional data set. Consequently, future research should address the question whether dynamic R-vines are (economically) significantly superior to static or correlation-based models in other application like, e.g., asset pricing studies in the spirit of Meine et al. (2013); Ruenzi and Weigert (2013) and Ruenzi et al. (2013).

Chapter 5

Extreme dependence in finance: Does the choice of estimator matter?

5.1 Introduction

Recent research has seen a steep increase in the number of studies that focus on extreme dependence in financial economics. Several of these analyses revisit classical problems in asset pricing (see, e.g., Ruenzi and Weigert, 2013), financial intermediation (Oh and Patton, 2013), credit risk (see Christoffersen et al., 2013; Oh and Patton, 2012), and portfolio management (Christoffersen et al., 2012) and substitute linear correlations by measures of extreme dependence. The consensus underlying these studies is that joint extreme co-movements in equity prices, default intensities, and liquidity are not adequately captured by correlation, but should rather be modeled using estimates of tail dependence. The empirical finance literature, however, is far from agreeing on the question how extreme dependence should be measured.[1] In this paper, we review various commonly used techniques for estimating the tail dependence of a joint distribution and show that several of these techniques produce severely biased estimates of tail dependence in

[1]To better understand how researchers deal with the estimation of extreme dependence, Table D.1 in Appendix D provides a survey of recent studies on extreme dependence published in the *Review of Financial Studies*, the *Journal of Financial and Quantitative Analysis*, the *Journal of Banking and Finance*, and others in the period from 2006 to 2014. As one can easily see from the table, existing studies employ a great variety of different extreme dependence estimators, reaching from nonparametric to fully parametric and from static to dynamic estimators.

simulations. We then apply these estimators in empirical settings in which tail dependence coefficients have been previously used to model extreme dependence. As our key finding, we show that the systematic overestimation of tail dependence found in the simulation study translates into the empirical applications leading to dramatic overestimations of the economic significance of tail dependence in these empirical settings: Not only do we find economically significant differences in the results for the different estimators in these applications, the economic significance of several key results from recent studies in financial economics significantly decreases when switching from a static to a dynamic estimator of tail dependence. Consequently, our results imply that findings from the related literature need to be interpreted with care and critically depend on the choice of estimator.

Several results from both theoretical and empirical finance stress the need to account for extreme disasters in the modeling of financial data. For example, Barro (2006, 2009) finds that the potential for rare economic disasters explains several puzzles from the asset pricing literature (the high equity premium, low risk-free rate, and volatile stock returns).[2] In a related earlier study, Poon et al. (2004) show how the tail behavior of financial assets can be adequately modeled by the use of extreme value theory (EVT). Additionally, extreme events have also been found to be relevant for option pricing as the implicit pricing kernel puzzle (see Jackwerth, 2000) is consistent with the results found by Liu et al. (2005) and Collin-Dufresne and Hugonnier (2014) who incorporate imprecise knowledge about extreme events into asset pricing models. In a different strand of the literature, the possible implications of extreme tail risk on the pricing of the cross-section of aggregate and individual stock returns have been studied. Bollerslev and Todorov (2011) and Kelly and Jiang (2013) analyze the time-variation and the pricing of tail risk in aggregate stock returns. While the former show that the compensation for rare events accounts for a large fraction of the average equity and variance risk premia, the latter isolate a common tail risk factor in the cross-section of individual stocks and find this factor to be a strong predictor for aggregate market returns.[3] However, tail risk appears to be priced not only in

[2] Similarly, Bollerslev and Todorov (2011) explain the aggregate equity risk premium by considering the risk of rare disasters while Gabaix (2012) finds that several puzzles in macro-finance can be explained by the time-varying risk of rare disasters.

[3] In a related study, Bali et al. (2009) document a positive and significant relation between different

aggregate stock prices, but also in the cross-section and time series of returns on individual assets. For example, Jiang and Kelly (2013) show that tail risk is a key driver of hedge fund returns. Kole and Verbeek (2006) and Ruenzi and Weigert (2013) find a similar result for the cross-section of stock returns using lower tail dependence (LTD) coefficients as a proxy for equity tail risk. Moreover, the results of Ruenzi et al. (2013) indicate that stock returns could also be driven by (a) the LTD between individual stock returns and market liquidity and (b) the LTD between individual stock liquidity and market returns. Finally, Meine et al. (2013) test and confirm the hypothesis that CDS spreads of banks include a premium for high upper tail dependence (UTD) between individual CDS spreads and a sector CDS index.[4]

Despite the consensus in the literature on the importance of accounting for extreme dependence in asset returns, numerous models have been employed in the recent empirical literature for estimating the tail dependence inherent in financial data. Most of these studies comprise a parametric copula model from which the estimates of tail dependence are derived. For example, in the early studies of Rodriguez (2007), Okimoto (2008), and Garcia and Tsafack (2011) the estimates of the lower tail dependence in equity returns are extracted from simple static and static regime-switching copula models. More recent studies like, e.g., Patton (2006), Christoffersen et al. (2012), and Oh and Patton (2012, 2013) propose to use dynamic copula models to account for possibly time-varying extreme dependence in financial data. Furthermore, the statistical literature includes additional nonparametric estimators like, e.g., the one proposed by Schmidt and Stadtmueller (2006), that eliminate the model risk of selecting a non-optimal parametric model at the expense of being purely data-driven and static. Finally, the two asset pricing studies of Ruenzi and Weigert (2013) and Ruenzi et al. (2013) use convex combinations of different static parametric copulas to estimate the tail dependence between equity returns and liquidity, respectively. Interestingly, the literature still lacks a comparison of these different

measures of downside risk (Value-at-Risk, Expected Shortfall, and the variance of losses larger than VaR) and the portfolio returns on NYSE, AMEX, and Nasdaq stocks.

[4]The use of tail dependence as a proxy of extreme risk is not limited to asset pricing and the study of credit risk. For example, De Jonghe (2010), Oh and Patton (2012, 2013), and Weiß et al. (2014) employ measures of tail dependence to proxy for systemic fragility in the financial sector.

estimators of a distribution's tail dependence. But even more importantly, the empirical relevance of selecting the right estimator for a data sample's tail dependence for applications in financial economics remains completely unacknowledged.

The findings from both our simulations as well as our asset pricing study have highly relevant consequences for financial economics in general and our understanding of extreme dependence in asset prices in particular. As our first main contribution, we show in this paper that several tail dependence estimators which have been proposed in the literature are severely biased. Especially when applied to data samples with time-varying extreme dependence, static estimators tend to significantly overestimate the actual level of tail dependence in the data. This finding casts reasonable doubt on the frequent finding that extreme dependence in financial markets has increased and is high (especially during a time of crisis). What we find most striking is that this tendency to overestimate extreme dependence is common to almost all estimators that we identified from previous empirical studies in financial economics and econometrics. As this paper's second main contribution, we show in our empirical application that the choice of the correct tail dependence estimator has significant effects on the outcomes of asset pricing studies which rely on tail dependence estimates. More precisely, we show that the crash sensitivity of stocks (proxied by the lower tail dependence in the returns on individual stocks and the market) does no longer qualify as a (highly significant) priced factor in the cross-section of stock returns when using different tail dependence estimators. The implications of these findings are straightforward: The role of extreme dependence in financial assets requires to be reassessed in several areas of interest (stock returns, liquidity, systemic risk of banks, etc.) whenever empirical findings have been based on tail dependence estimates stemming from inaccurate static estimators. Second, results in asset pricing need to be handled with care even if several competing estimators of tail dependence are used to construct new factors that supposedly drive asset returns.

The rest of this paper is organized as follows. Section 5.2 quickly reviews the most popular estimators of the coefficient of lower tail dependence that have been proposed in the literature. In Section 5.3, we present the results of our comprehensive simulation study on the finite sample properties of the various estimators of tail dependence. In Section 5.4, we illustrate the economic importance of our findings by performing an empirical study on the significance of stock crash-sensitivity as a priced factor in the cross-section of stock returns. Section 5.5 concludes.

5.2 Copulas and tail dependence

The lower tail dependence (LTD) estimators included in our simulation study are based on copulas. Thus, in this section we provide a brief overview of copulas and show how they can be used to measure tail dependence. Further details and a complete introduction to copulas can be found in Nelsen (2006) and Joe (1997).

Loosely speaking, a copula is a function that specifies the link between a multivariate distribution function and its one-dimensional marginal distribution functions. Formally, a copula can be defined as a multivariate distribution function with standard uniform margins. With $\boldsymbol{X} = (X_1, X_2)$ denoting a two-dimensional random vector with joint density $\boldsymbol{f} = (f_1, f_2)$ and distribution function $\boldsymbol{F} = (F_1, F_2)$, the copula $\boldsymbol{C}$ of the distribution $\boldsymbol{F}$ is given by

$$\boldsymbol{C}(u_1, u_2) = \boldsymbol{F}(F_1^{-1}(u_1), F_2^{-1}(u_2)) \tag{5.1}$$

where F_i^{-1} is the generalized inverse of F_i and $u_i \in [0, 1]$, $i = 1, 2$.

The theoretical framework of copulas goes back to the work of Sklar (1959) who shows that, under certain conditions, every copula is a joint distribution function and vice versa. More precisely, Sklar's (1959) Theorem states that, if F_1 and F_2 are continuous, $\boldsymbol{C}$ exists and is unique. Conversely, if $\boldsymbol{C}$ is a copula, the theorem states that $\boldsymbol{F}$ is a joint distribution function with margins F_i, $i = 1, 2$.[5]

[5] Note that Sklar's (1959) Theorem is not restricted to dimension two but holds for arbitrarily high dimensions. A general presentation and a formal proof can be found in Schweizer and Sklar (1983).

Using (5.1), the joint density, $\boldsymbol{f}$, can be expressed as

$$\boldsymbol{f}(x_1, x_2) = \boldsymbol{c}(F_1(x_1), F_2(x_2)) \cdot f_1(x_1) f_2(x_2) \tag{5.2}$$

where $\boldsymbol{c}$ denotes the density of $\boldsymbol{C}$. Hence, the dependence structure can be separated from the marginal structure implying the following important applications of Sklar's (1959) Theorem. On the one hand, we can characterize the complete dependence structure in a multivariate data set and, on the other hand, are able to generate highly flexible multivariate models.

In our simulation study, however, we shall use copulas to simulate and estimate coefficients of (lower) tail dependence. Thus, in the following, we discuss the concept of tail dependence and the computation of tail dependence coefficients.

Intuitively, the concept of tail dependence refers to the amount of dependence in the lower-left or upper-right quadrant of the joint distribution, $\boldsymbol{F}$, and thus provides measures for the dependence between extreme realizations of X_1 and X_2. More precisely, the coefficient of lower (upper) tail dependence is defined as the conditional probability that X_1 takes on a realization in the left (right) tail of F_1 given that X_2 has already realized a value in the left (right) tail of F_2. In our simulation study, we are merely interested in the coefficient of lower tail dependence so that we will exclude the coefficient of upper tail dependence from the further discussion.[6]

Formally, the LTD coefficient, τ^L, is given by

$$\tau^L = \lim_{u \downarrow 0} \Pr\left[X_1 \leqslant F_1^{-1}(u) \middle| X_2 \leqslant F_2^{-1}(u) \right]. \tag{5.3}$$

According to McNeil et al. (2005), we can express τ^L in terms of the copula $\boldsymbol{C}$ of the joint distribution $\boldsymbol{F}$ if the marginal distributions F_1 and F_2 are continuous, and obtain the

[6]Note that the properties and formulas for the LTD coefficient given in this section can be easily transferred to the coefficient of upper tail dependence. See, e.g., McNeil et al. (2005).

following simple formula

$$\tau^L = \lim_{u \downarrow 0} \frac{\boldsymbol{C}(u,u)}{u}. \tag{5.4}$$

Hence, tail dependence can be viewed as a copula property where the copula $\boldsymbol{C}$ is said to have lower tail dependence if $\tau^L \in (0,1]$. In case of τ^L being equal to zero, $\boldsymbol{C}$ has no lower tail dependence implying that X_1 and X_2 are asymptotically independent in the lower tail.

5.3 Simulation study

We now turn to a comparison of various copula-based LTD estimators that are frequently used in the financial economics literature. We conduct a comprehensive Monte-Carlo simulation study to investigate the performance of the estimators with respect to different performance metrics as well as varying simulation environments. We start with a brief overview of the models under study. A formal description of the models and details on estimation procedures can be found in Section D.1 in Appendix D.

5.3.1 Models under study

The LTD estimators included in our simulation study comprise three dynamic models allowing for time-varying LTD coefficients and eight static models which assume that LTD coefficients are constant over time. Table D.2 in Appendix D provides an overview of the basic copulas underlying the dynamic and static LTD models.

The dynamic models are based on the t copula which has received much recent attention in financial modeling and has been shown to be superior to other copulas such as, e.g., the Gaussian copula (see Demarta and McNeil, 2004). The method of dynamizing the t copula, however, differs across the three models. As can be seen from Table D.2, the t copula is parameterized by the degree of freedom parameter, ν, and the correlation parameter, ρ, with the implied LTD coefficient being given in closed form. The first dynamic model we consider is Patton's (2006) model that parameterizes time variation in the t copula by assuming an ARMA(1,10)-type process for the correlation parameter, ρ, to capture both persistence in correlation and any variation in dependence. We refer to this model as the *Patton model* hereafter. The second model dynamizes the t copula by applying Engle's (2002) Dynamic Conditional Correlation (DCC) model to copula correlations, which are correlations between the copula shocks implied by the t copula. This model is denoted as the *DCC model* in our study. In the same manner, we also apply the Dynamic Symmetric Copula (DSC) model as proposed by Christoffersen et al. (2012) to the copula correlations of the t copula and call this model the *DSC model* in the following. Hence, the dynamic LTD estimators can be expressed as

$$\tau_t^L = 2t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho_t}}{\sqrt{1+\rho_t}}\right) \tag{5.5}$$

with the correlation dynamics being given by

$$\rho_t = \Lambda\left(\omega + \beta\rho_{t-1} + \alpha\frac{1}{10}\sum_{i=1}^{10} t_\nu^{-1}(u_{1,t-i})t_\nu^{-1}(u_{2,t-i})\right) \quad \textit{(Patton)} \tag{5.6}$$

$$\rho_t = \frac{Q_{12,t}}{\sqrt{Q_{11,t}Q_{22,t}}},\ Q_t = (1-\phi-\psi)\Omega + \psi Q_{t-1} + \phi\bar{z}^c_{t-1}\bar{z}^{c\top}_{t-1} \quad \textit{(DCC)} \tag{5.7}$$

$$\rho_t = \frac{\tilde{Q}_{12,t}}{\sqrt{\tilde{Q}_{11,t}\tilde{Q}_{22,t}}},\ \tilde{Q}_t = (1-\tilde{\phi}-\tilde{\psi})\left[(1-\kappa)\Omega + \kappa D_t\right] + \tilde{\psi}\tilde{Q}_{t-1} + \tilde{\phi}\bar{z}^c_{t-1}\bar{z}^{c\top}_{t-1} \quad \textit{(DSC)} \tag{5.8}$$

where ω, β, α, ϕ, ψ, $\tilde{\phi}$, $\tilde{\psi}$, and κ are scalar parameters, $\Lambda(x) \equiv (1-e^{-x})(1+e^{-x})^{-1}$ is a normalizing function, $u_{1,t}$ and $u_{2,t}$ denote the ranks of the residuals from univariate GARCH processes, Ω and D_t are two-by-two correlation matrices containing constant correlations and time trends, respectively, and $\bar{z}^c_t$ denotes a vector of (modified) copula shocks.[7]

Turning to the static LTD estimators, we first include two mixture copulas in our simulation study which are based on two different convex combinations of the basic copulas

[7]Technical details can be found in Section D.1 in Appendix D. Note that the DSC model incorporates a time trend into copula correlations and that setting $\kappa = 0$ in the DSC model yields the DCC model.

shown in Table D.2.[8] In the spirit of Ruenzi and Weigert (2013), Rodriguez (2007), and Hong et al. (2007), we select the basic copulas such that the resulting mixture copula allows for the maximum possible flexibility and is capable of modeling upper and lower tail dependence as well as independence and asymmetry in the tails. Accordingly, the first mixture is based on the Joe, Rotated-Joe, and the F-G-M copula and is given by

$$\boldsymbol{C}_{\text{mix,1}} = w_1 \boldsymbol{C}_{\text{Joe}} + w_2 \boldsymbol{C}_{\text{rJoe}} + w_3 \boldsymbol{C}_{\text{FGM}} \tag{5.9}$$

where $w_i \in [0, 1]$ for $i = 1, 2, 3$ with $\sum_{i=1}^{3} w_i = 1$. Following the same line of reasoning, the second mixture is composed of the t copula as well as the Clayton and Frank copula, and can be expressed as

$$\boldsymbol{C}_{\text{mix,2}} = w_1 \boldsymbol{C}_t + w_2 \boldsymbol{C}_{\text{Cl}} + w_3 \boldsymbol{C}_{\text{Fr}}. \tag{5.10}$$

The corresponding constant LTD coefficients can then be computed as

$$\tau^L_{\text{mix},1} = w_2 \left(2 - 2^{\frac{1}{\theta}}\right) \quad \text{and} \quad \tau^L_{\text{mix},2} = 2 w_1 t_{\nu+1} \left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho}}{\sqrt{1+\rho}}\right) + 2^{-\frac{1}{\theta}} w_2. \tag{5.11}$$

Following existing empirical studies in the finance literature, both mixture models are estimated in two different ways, respectively. On the one hand, we estimate the mixtures via maximum likelihood (ML) where the likelihood is maximized with respect to both copula parameters and the weights (see, e.g., Ruenzi et al., 2013; Ruenzi and Weigert, 2013). The respective models are denoted as *Mix1*$_{ML}$ and *Mix2*$_{ML}$. On the other hand, we estimate the mixtures via the Expectation-Maximization (EM) algorithm as proposed by Dempster et al. (1977) and call the respective models *Mix1*$_{EM}$ and *Mix2*$_{EM}$ (Okimoto, 2008; Chollete et al., 2009). Note, however, that estimating mixture copulas by maximizing the log likelihood with respect to the copula parameters and the weights is statistically incorrect so that the parameter estimates may be biased. The estimation of mixtures con-

[8] Tawn (1988) shows that any convex combination of a given (finite) set of copulas is again a copula. See Section D.1 in Appendix D for details.

stitutes an incomplete-data problem which needs to be estimated via the EM algorithm. Being aware of this fact, in our simulation study we shall investigate how this potential bias translates into the calculation of LTD coefficients.

Further, we include a static LTD estimator that is based on a regime-switching copula model and referred to as the *RS model*. More precisely, we follow Okimoto (2008) and Garcia and Tsafack (2011) and identify two regimes where we assume the first regime to be Gaussian and the second regime to be specified by the Clayton copula. Formally, the LTD estimator is based on a mixture of the regime copulas and thus given by

$$\boldsymbol{C}_{\mathrm{RS}} = s_t \boldsymbol{C}_{\mathrm{GA}} + (1 - s_t)\boldsymbol{C}_{\mathrm{Cl}} \tag{5.12}$$

where $\boldsymbol{C}_{\mathrm{GA}}$ and $\boldsymbol{C}_{\mathrm{Cl}}$ denote the Gaussian and the Clayton copula, respectively, and can be found in Table D.2 in Appendix D. The variable s_t is a latent state variable taking the values 1 (Gaussian regime) and 2 (Clayton regime) and follows a Markov chain with a constant transitional probability matrix

$$P = \begin{pmatrix} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{pmatrix}, \quad p_{ii} = \Pr[s_t = i | s_{t-1} = i] \text{ for } i = 1, 2. \tag{5.13}$$

Since the Gaussian copula is asymptotically independent in the tails, the LTD coefficients generated by this model are based on the LTD coefficient of the Clayton copula which is given in closed form and is listed in Table D.2.

Moreover, we include two simple static LTD estimators that are based on the Clayton copula. The difference between the two estimators lies in the method used for modeling the margins. While the first estimator is based on a nonparametric approach and uses the empirical distribution function, the second estimator exploits results from Extreme Value Theory (EVT) and models the margins semi-parametrically by assuming the Generalized Pareto Distribution (GPD) for the distribution of excesses and the empirical distribution for the remaining portion. The two estimators are called *CL* and CL_{EVT}, respectively, and are discussed in more detail in Section D.1 in Appendix D.

Finally, we follow Schmidt and Stadtmueller (2006) and include a nonparametric LTD estimator in our simulation study, denoted as *Nonparam*. Schmidt and Stadtmueller (2006) build on the concept of empirical tail copulas and introduce tail dependence estimators that are based on the empirical copula. Formally, with X_1 and X_2 denoting two n-dimensional random vectors and with $\boldsymbol{R}_{m,1} = (R^j_{m,1})_{j=1,\ldots,n}$ and $\boldsymbol{R}_{m,2} = (R^j_{m,2})_{j=1,\ldots,n}$ denoting the rank of X_1 and X_2, respectively, they propose the following empirical LTD estimator

$$\tau^L_m = \frac{1}{k}\sum_{j=1}^{n} \mathbf{1}_{\left\{R^j_{m,1}\leqslant k \text{ and } R^j_{m,2}\leqslant k\right\}} \tag{5.14}$$

where the parameter k needs to be specified adequately.[9]

The LTD estimators included in our simulation study are summarized in Table D.3 in Appendix D along with the expressions for the corresponding LTD coefficients and the correlation dynamics for the time-varying estimators.

5.3.2 Simulation design

We now present the setup of our simulation study. To investigate the performance of the LTD estimators introduced in the previous section, we organize each simulation trial into two steps, a simulation step and an estimation step. In the first step, we simulate copula data and LTD coefficients from a specified data-generating process (DGP) and generate artificial price return data on the basis of the simulated copula data. In the second step, we then apply the LTD estimators to the artificial return data and evaluate the performance by comparing the estimated LTD coefficients to the true LTD coefficients from the simulation step in terms of an appropriate performance metric. We repeat these steps a large number of times and evaluate the performance in each simulation trial, resulting in a vector of values for the corresponding performance metric.[10] In the following, we discuss the two steps in more detail.

[9] Further details can be found in Section D.1 in Appendix D.

[10] Note that in our baseline simulation approach we simulate 500 data points from the DGP, use the mean squared error to evaluate performance, and repeat the simulation and estimation step for a total of 1000 trials. Further details are provided in Section 5.3.3.

The simulation step comprises two tasks, simulating LTD coefficients and generating artificial price return data to embed the simulation into an environment that is comparable to real-data applications. To simulate LTD coefficients which will be assumed to describe the true LTD inherent to the data, we identify the three dynamic LTD estimators as the DGPs throughout the simulation study.[11] To simulate from the dynamic models, we first need to specify the parameters driving the correlation dynamics in equations (5.6) to (5.8). The parameter choices as well as the resulting expressions for the correlation dynamics are given in Table D.4 in Appendix D. For increased comparability with real-data applications, parameter choices are based on the empirical studies in Engle (2002), Patton (2006), and Christoffersen et al. (2012). Having determined the parameters, we are now able to conduct the simulation of true LTD coefficients. Using the notation introduced in the previous section, the simulation involves the following steps.[12] First, as a starting point we randomly draw $\boldsymbol{u}^{(0)} = (u_{1,0}, u_{2,0})^\top$ from a bivariate standard uniform distribution, $\mathcal{U}_{[0,1]}$. Then, we calculate ρ_1 and τ_1^L using $\boldsymbol{u}^{(0)}$ and, finally, simulate $\boldsymbol{u}^{(1)}$ from the t copula, $\boldsymbol{C}_{t^2_{\nu,\rho_1}}$, implied by a bivariate t distribution with correlation parameter ρ_1. We repeat the latter steps for $t = 2, ..., T$ and generate true LTD coefficients, $(\tau_t^L)_{t=1}^T$, as well as copula data, $(\boldsymbol{u}^{(t)})_{t=1}^T$. Estimation of LTD coefficients in the second step is based on the series $(\boldsymbol{u}^{(t)})_{t=1}^T$. Since copula data are not directly observable, we transform the series $(\boldsymbol{u}^{(t)})_{t=1}^T$ into artificial price return data before moving on to the estimation step. As is standard in the econometrics literature, we assume that the returns come from a GARCH(1,1) process with zero mean and t-distributed innovations. With $\boldsymbol{r}^{(t)} = (r_{1,t}, r_{2,t})^\top$ denoting the (artificial) return corresponding to $\boldsymbol{u}^{(t)}$, we thus define

$$r_{i,t} = \sqrt{h_{i,t}} z_{i,t}, \quad z_{i,t} | \mathcal{F}_{i,t-1} \sim t_{\nu_i} \tag{5.15}$$

$$h_{i,t} = c_i + a_i r_{i,t-1}^2 + b_i h_{i,t-1} \tag{5.16}$$

where $\mathcal{F}_{i,t}$ denotes the information available on the ith series up to and including the tth

[11] Note that, due to the time-varying nature of LTD, simulating from the dynamic LTD estimators will provide simulated LTD coefficients that are comparable to the LTD coefficients implied by real data.

[12] Technical details on the simulation from the Patton, DCC, and DSC model can be found in Section D.2 in Appendix D.

observation, $i = 1, 2$ and $t = 1, ..., T$. With $\theta_i = (\nu_i, c_i, a_i, b_i)^\top$ being the parameter vector of the GARCH processes, we follow the empirical applications in Engle (2002), Kang et al. (2010), Christoffersen et al. (2012) and set $\theta_1 = (0.0005, 0.1, 0.85, 5)^\top$ and $\theta_2 = (0.0001, 0.05, 0.9, 10)^\top$ to generate artificial returns in line with the stylized facts on real price return series. To simulate return data from the copula data, we set $r_{1,0} = r_{2,0} = 0$ and $\sigma_{1,0} = \sigma_{2,0} = 0$ as starting points and compute return innovations via $z_{i,t} = t_{\nu_i}^{-1}(u_{i,t})$.

Having simulated return data $(\boldsymbol{r}^{(t)})_{t=1}^T$ with (true) LTD coefficients $(\tau_t^L)_{t=1}^T$, the second step of our simulation study deals with computing estimated LTD coefficients, $(\hat{\tau}_t^L)_{t=1}^T$, according to the models discussed in the previous section. Since our LTD estimators are based on copulas and copula theory requires white-noise residuals for the computation of unbiased LTD coefficient estimates, we first apply the GARCH(1,1) filter to transform the marginal return series, $(r_{i,t})_{t=1}^T$, into white-noise series, $(\hat{u}_{i,t})_{t=1}^T$, where $\hat{\boldsymbol{u}}^{(t)} = (\hat{u}_{1,t}, \hat{u}_{2,t})^\top$. Then, we apply our LTD estimators summarized in Table D.3 to $(\hat{\boldsymbol{u}}^{(t)})_{t=1}^T$ to obtain the series $(\hat{\tau}_t^L)_{t=1}^T$ of estimated LTD coefficients.[13] To evaluate the performance of the LTD estimators, we apply an appropriate performance metric, Π, to the true and the estimated LTD coefficients. Thus, with $\boldsymbol{\tau} = (\tau_t^L)_{t=1}^T$ and $\hat{\boldsymbol{\tau}} = (\hat{\tau}_t^L)_{t=1}^T$, the performance of the corresponding LTD estimator is given by $\Pi = \Pi(\boldsymbol{\tau}, \hat{\boldsymbol{\tau}})$.
Altogether, our simulation study is organized into the following steps:

1. Simulation step

   1.1. Draw $\boldsymbol{u}^{(0)} = (u_{1,0}, u_{2,0})^\top \sim \mathcal{U}_{[0,1]}$.

   1.2. Calculate ρ_1 and τ_1^L using $\boldsymbol{u}^{(0)}$.

   1.3. Simulate $\boldsymbol{u}^{(1)}$ from $\boldsymbol{C}_{t^2_{\nu,\rho_1}}$.

   1.4. Repeat steps 1.2. and 1.3. for $t = 2, ..., T$ and obtain $(\tau_t^L)_{t=1}^T$ and $(\boldsymbol{u}^{(t)})_{t=1}^T$.

   1.5. Calculate $z_{i,t} = t_{\nu_i}^{-1}(u_{i,t})$, $i = 1, 2$.

   1.6. Compute $r_{i,t} = \sqrt{h_{i,t}} z_{i,t}$, where $h_{i,t} = c_i + a_i r_{i,t-1}^2 + b_i h_{i,t-1}$ and $r_{i,0} = h_{i,0} = 0$.

[13]Details on estimation and statistical inference can be found in Section D.1 in Appendix D.

2. Estimation step

   2.1. Apply the GARCH(1,1) filter to $(r_{i,t})_{t=1}^{T}$ and obtain $(\hat{u}_{i,t})_{t=1}^{T}$, $i = 1, 2$.

   2.2. Apply LTD estimators to $(\hat{\boldsymbol{u}}^{(t)})_{t=1}^{T}$ and obtain $(\hat{\tau}_t^L)_{t=1}^{T}$.

   2.3. Apply the performance metric to $(\tau_t^L)_{t=1}^{T}$ and $(\hat{\tau}_t^L)_{t=1}^{T}$ and obtain $\Pi = \Pi\left(\boldsymbol{\tau}, \hat{\boldsymbol{\tau}}\right)$.

These two steps are repeated for a total of N simulation trials resulting in the performance vector $\boldsymbol{\Pi} = (\Pi_n)_{n=1}^{N}$, where $\Pi_n = \Pi(\boldsymbol{\tau}_n, \hat{\boldsymbol{\tau}}_n)$ with $\boldsymbol{\tau}_n$ and $\hat{\boldsymbol{\tau}}_n$ denoting the true and estimated LTD coefficients drawn from the nth simulation trial.

5.3.3 Simulation results

We now turn to the results of our simulation study. We first introduce our baseline approach and discuss the corresponding results. In the following, we then extend our baseline approach with respect to the sample size and performance metric and check the robustness of the conclusions drawn from the baseline approach. Finally, we conduct a ranking approach to identify the best performing LTD estimator across all simulation settings (i.e., across all sample sizes and performance metrics).

5.3.3.1 Does the choice of estimator matter? The baseline approach.

The baseline approach is based on the following simulation setting. Given the notation introduced in the previous section, we set

$$T = 500, \quad N = 1000, \quad \text{and} \quad \Pi = \Pi(\boldsymbol{\tau}, \hat{\boldsymbol{\tau}}) = T^{-1} \sum_{t=1}^{T} (\tau_t - \hat{\tau}_t)^2. \tag{5.17}$$

That is, performance is measured in terms of the mean squared error (MSE). Thus, we simulate 500 LTD coefficients from the Patton, the DCC, and the DSC model, respectively, and then apply the LTD models presented in Section 5.3.1 to the resulting series of artificial returns to generate estimated LTD coefficients. For each of the three DGPs, these steps are repeated for a total of 1000 trials.

Table 5.1: Descriptive statistics of true and estimated lower tail dependence.

The table presents descriptive statistics of true and estimated lower tail dependence (LTD) coefficients. True LTD coefficients are simulated from the Patton, DCC, and DSC model and the corresponding results are shown separately for each of these data-generating processes (DGP) throughout the panels of the table. To compute estimated LTD coefficients, we first generate artificial return data on the basis of the true LTD coefficients and then apply the different LTD estimators to the artificial returns. The descriptive statistics listed in the table arise from the baseline simulation approach, which is based on a sample size of $T = 500$ and a number of simulation trials equal to $N = 1000$, i.e., we estimate LTD coefficients on the basis of 500 simulated returns and repeat the simulation and estimation step for a total of 1000 trials. Except for the number of observations, skewness, and (excess) kurtosis, all entries are denominated in %. In case of the DGP and the LTD estimator being identical, corresponding statistics are printed in bold type. The names of the LTD estimators are abbreviated according to the notation introduced in Section 5.3.1.

Panel A: DGP Patton				Percentiles								Moments			
		Number	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.
Patton	**True LTD**	**499,000**	**0.00**	**2.55**	**5.27**	**9.46**	**13.73**	**20.02**	**33.98**	**47.59**	**93.65**	**15.90**	**9.30**	**1.57**	**6.87**
	Est. LTD	**499,000**	**0.00**	**0.01**	**0.46**	**7.41**	**15.36**	**24.21**	**38.80**	**51.65**	**85.18**	**16.84**	**12.03**	**0.80**	**3.68**
DCC	True LTD	499,000	0.00	2.55	5.31	9.47	13.66	19.86	33.83	47.51	93.19	15.83	9.23	1.58	6.93
	Est. LTD	499,000	0.00	0.01	0.43	8.24	16.13	24.14	36.50	46.70	76.52	16.88	11.15	0.54	3.05
DSC	True LTD	499,000	0.00	2.55	5.32	9.48	13.77	20.06	33.95	48.03	97.47	15.94	9.33	1.60	7.12
	Est. LTD	499,000	0.00	0.32	4.73	15.71	23.27	30.41	41.32	51.16	78.82	23.22	10.99	0.20	3.11
Mix1_{ML}	True LTD	499,000	0.00	2.55	5.28	9.44	13.66	19.80	33.45	47.38	96.67	15.76	9.15	1.60	7.17
	Est. LTD	1,000	15.00	21.66	27.74	31.49	33.11	34.29	38.25	42.09	52.07	32.92	3.49	-0.32	8.33
Mix1_{EM}	True LTD	499,000	0.00	2.55	5.31	9.49	13.79	20.06	33.92	47.86	94.26	15.93	9.29	1.59	7.02
	Est. LTD	1,000	13.46	17.82	20.96	24.34	27.06	29.62	33.48	37.77	41.05	27.07	3.95	0.12	3.37
Mix2_{ML}	True LTD	499,000	0.00	2.55	5.30	9.49	13.71	20.01	33.77	47.19	96.60	15.88	9.22	1.56	6.90
	Est. LTD	1,000	0.01	0.08	5.90	14.12	20.61	29.39	40.14	42.31	54.20	21.89	10.45	0.24	2.32
Mix2_{EM}	True LTD	499,000	0.00	2.55	5.27	9.46	13.74	19.99	33.90	48.09	88.42	15.89	9.30	1.58	6.89
	Est. LTD	1,000	0.04	0.68	3.56	12.39	19.86	26.37	34.63	39.34	43.67	19.47	9.46	0.00	2.29
RS	True LTD	499,000	0.00	2.55	5.27	9.45	13.63	19.85	33.84	47.74	96.86	15.81	9.27	1.61	7.14
	Est. LTD	1,000	0.00	0.00	0.00	3.45	20.10	44.46	71.63	87.26	95.78	25.30	23.64	0.76	2.67
CL	True LTD	500,000	0.00	2.55	5.27	9.43	13.68	19.86	33.59	47.23	96.16	15.79	9.18	1.58	7.07
	Est. LTD	1,000	25.23	34.15	39.77	47.41	51.37	55.05	59.98	62.06	65.82	50.98	5.94	-0.49	3.57
CL_{EVT}	True LTD	500,000	0.00	2.55	5.30	9.51	13.77	20.01	33.83	47.49	98.60	15.90	9.25	1.59	7.12
	Est. LTD	1,000	14.82	23.70	29.53	36.06	40.23	44.15	49.51	52.15	55.42	39.96	6.21	-0.39	3.23
Nonparam	True LTD	500,000	0.00	2.55	5.27	9.47	13.74	20.06	33.94	47.44	96.64	15.89	9.25	1.55	6.79
	Est. LTD	1,000	0.00	12.50	20.00	46.02	57.00	64.36	72.80	76.92	84.45	53.07	15.73	-0.95	3.35

Table 5.1: Descriptive statistics of true and estimated lower tail dependence (continued).

Panel B: DGP DCC				Percentiles								Moments			
		Number	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.
Patton	True LTD	499,000	0.00	11.64	22.78	37.48	45.27	51.82	60.21	66.60	84.60	43.97	11.37	-0.59	3.57
	Est. LTD	499,000	0.00	11.82	23.87	36.98	43.92	50.30	59.55	67.95	89.80	43.18	10.96	-0.44	3.94
DCC	**True LTD**	**499,000**	**0.01**	**11.85**	**22.94**	**37.48**	**45.17**	**51.75**	**60.19**	**66.24**	**87.92**	**43.95**	**11.29**	**-0.60**	**3.57**
	Est. LTD	**499,000**	**0.00**	**6.26**	**17.95**	**32.95**	**41.87**	**49.79**	**60.17**	**67.51**	**88.54**	**40.88**	**12.80**	**-0.39**	**3.15**
DSC	True LTD	499,000	0.10	11.51	23.18	37.66	45.34	51.87	60.43	66.89	85.51	44.12	11.34	-0.59	3.62
	Est. LTD	499,000	0.02	6.31	17.96	34.40	43.82	51.68	61.41	68.33	92.49	42.34	13.16	-0.50	3.16
Mix1_{ML}	True LTD	499,000	0.00	11.81	23.34	37.61	45.23	51.66	60.27	66.94	89.90	44.03	11.25	-0.57	3.65
	Est. LTD	1,000	6.31	22.09	30.14	33.08	34.37	36.39	46.04	54.77	69.72	35.54	5.61	1.34	10.93
Mix1_{EM}	True LTD	499,000	0.00	12.70	23.39	37.48	45.21	51.69	60.22	66.46	87.11	44.01	11.18	-0.55	3.49
	Est. LTD	1,000	21.81	23.96	27.85	32.34	35.60	38.92	44.18	47.58	51.70	35.76	4.95	0.10	2.89
Mix2_{ML}	True LTD	499,000	0.01	12.22	23.27	37.61	45.25	51.73	60.23	66.57	94.62	44.04	11.25	-0.57	3.63
	Est. LTD	1,000	0.06	11.75	20.80	32.24	39.47	47.18	58.07	62.43	66.10	39.36	11.08	-0.21	3.07
Mix2_{EM}	True LTD	499,000	0.01	12.25	23.45	37.59	45.27	51.68	60.12	66.32	93.68	44.03	11.19	-0.58	3.62
	Est. LTD	1,000	1.54	5.84	15.36	25.84	33.16	41.62	48.26	50.96	53.93	33.02	10.23	-0.33	2.58
RS	True LTD	499,000	0.00	12.13	23.10	37.37	45.08	51.54	59.96	66.19	87.00	43.85	11.21	-0.58	3.56
	Est. LTD	1,000	0.00	0.00	0.00	15.22	32.81	46.35	61.00	78.69	94.01	31.28	19.80	0.10	2.40
CL	True LTD	500,000	0.06	12.18	23.02	37.43	45.25	51.77	60.23	66.47	87.23	43.98	11.29	-0.57	3.52
	Est. LTD	1,000	36.29	49.19	58.28	64.67	68.68	72.05	76.05	78.00	80.35	68.00	5.84	-1.05	5.64
CL_{EVT}	True LTD	500,000	0.03	11.89	23.06	37.45	45.24	51.80	60.35	66.56	88.81	43.99	11.33	-0.57	3.51
	Est. LTD	1,000	25.54	41.32	47.59	54.29	59.00	62.77	67.71	69.92	73.26	58.32	6.31	-0.62	3.86
Nonparam	True LTD	500,000	0.00	12.44	23.57	37.60	45.15	51.64	60.17	66.44	88.97	44.01	11.15	-0.56	3.58
	Est. LTD	1,000	12.50	28.57	45.45	60.52	66.00	71.16	77.13	82.71	91.07	64.60	10.08	-1.36	6.25

Table 5.1: Descriptive statistics of true and estimated lower tail dependence (continued).

Panel C: DGP DSC				Percentiles								Moments			
		Number	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.
Patton	True LTD	499,000	0.00	5.51	13.54	30.67	43.90	53.48	62.88	68.66	85.45	41.55	15.28	-0.43	2.45
	Est. LTD	499,000	0.00	6.35	18.18	33.79	42.04	49.52	60.27	69.16	90.57	41.15	12.62	-0.37	3.45
DCC	True LTD	499,000	0.00	5.48	13.42	30.68	43.63	53.18	62.92	68.86	85.55	41.40	15.25	-0.42	2.47
	Est. LTD	499,000	0.00	4.93	13.09	29.35	40.25	50.17	62.93	70.57	89.87	39.46	14.92	-0.18	2.61
DSC	**True LTD**	**499,000**	**0.10**	**5.91**	**13.87**	**30.89**	**43.93**	**53.45**	**63.04**	**68.85**	**88.62**	**41.65**	**15.21**	**-0.42**	**2.45**
	Est. LTD	**499,000**	**0.00**	**3.03**	**9.32**	**28.06**	**41.50**	**51.89**	**63.62**	**70.86**	**89.34**	**39.52**	**16.42**	**-0.32**	**2.42**
$Mix1_{ML}$	True LTD	499,000	0.00	5.64	13.74	30.69	43.81	53.35	63.09	69.20	93.03	41.55	15.27	-0.41	2.47
	Est. LTD	1,000	7.62	21.16	28.07	32.46	34.14	37.02	44.53	50.86	62.67	34.84	5.16	0.29	7.22
$Mix1_{EM}$	True LTD	499,000	0.00	5.36	13.59	30.83	44.03	53.54	63.22	68.93	90.19	41.68	15.33	-0.43	2.47
	Est. LTD	1,000	21.01	23.95	26.51	31.03	33.87	37.33	42.44	45.98	49.35	34.18	4.81	0.22	2.89
$Mix2_{ML}$	True LTD	499,000	0.01	5.57	13.39	30.75	43.79	53.34	62.92	68.78	91.19	41.48	15.30	-0.42	2.46
	Est. LTD	1,000	0.30	8.31	19.58	30.78	38.46	47.05	56.54	61.58	72.24	38.50	11.47	-0.23	3.00
$Mix2_{EM}$	True LTD	499,000	0.01	5.34	13.35	30.81	43.89	53.31	62.91	68.99	95.31	41.52	15.31	-0.43	2.49
	Est. LTD	1,000	1.38	5.29	14.11	24.33	31.25	39.48	47.08	50.96	53.70	31.27	10.25	-0.24	2.63
RS	True LTD	499,000	0.02	5.15	13.27	30.64	43.99	53.60	63.22	69.13	92.44	41.59	15.45	-0.43	2.46
	Est. LTD	1,000	0.00	0.00	0.00	11.91	29.15	42.34	57.83	70.51	90.49	28.06	18.76	0.14	2.29
CL	True LTD	500,000	0.02	5.31	13.44	30.79	43.81	53.31	62.92	68.89	87.04	41.49	15.28	-0.43	2.48
	Est. LTD	1,000	32.86	46.17	54.50	61.17	65.62	69.24	73.52	76.25	81.17	64.89	6.16	-0.79	4.37
CL_{EVT}	True LTD	500,000	0.03	5.98	14.01	31.00	44.12	53.71	63.30	69.08	88.26	41.83	15.27	-0.42	2.44
	Est. LTD	1,000	17.59	36.47	42.15	50.72	55.77	60.08	66.15	69.42	74.87	55.19	7.21	-0.55	3.86
Nonparam	True LTD	500,000	0.05	5.67	13.52	30.60	43.84	53.44	62.98	68.86	87.94	41.52	15.31	-0.42	2.44
	Est. LTD	1,000	0.00	23.05	36.35	57.14	64.00	69.00	75.34	81.82	89.75	61.46	11.86	-1.47	6.14

The panels of Table 5.1 report descriptive statistics of true and estimated LTD coefficients separately for each DGP.[14] As can be seen from Panel A of the table, specifying the Patton model as the DGP according to the parameterization in Table D.4 leads to true LTD coefficients ranging from 0% to 98.60%, where the means are close to 16%.[15] Comparing the means of the true and estimated LTD coefficients provides first evidence on the performance of the different estimators. Regarding the dynamic estimators, the Patton and DCC model show an exceptionally good performance, with the means of the estimated LTDs deviating by approximately 1% from the means of the true LTDs in absolute terms.[16] Not surprisingly, the Patton model, when determined to be the DGP, is the best performing LTD estimator. The DSC model, however, shows a somewhat worse performance, with the mean true and estimated LTD differing by more than 7% (in absolute terms). Turning to the static estimators, the performance deteriorates considerably for most estimators, with the differences in the means increasing dramatically to levels ranging between 3.58% to more than 37% in absolute terms. Interestingly, the Mix2_{ML} and Mix2_{EM} model outperform the DSC model as well as all other static estimators (including the Mix1_{ML} and Mix1_{EM} model) in terms of the differences between the means. Further, with respect to the CL and the CL_{EVT} model, the table shows that modeling the excess distributions of the marginals by the GPD substantially improves the estimates and decreases the differences in the means from 35% to 24%. The worst performing estimator is the Nonparam model, with the difference being more than 37% in absolute terms. These results are supported by the percentiles and the higher moments captured in Panel A of Table 5.1, which show the superior ability of the dynamic estimators to reproduce the distributional properties of the true LTD coefficients. Panels B and C show corresponding results for the cases in which the DCC and the DSC model are specified as the DGP. As can be seen from the panels, in these cases the true LTDs are 44% and 42% on average, respectively, indicating

[14]Note that the estimation of most LTD models included in our study requires removing pseudo observations equal to 1. To preserve comparability of true and estimated LTD coefficients, we remove the corresponding value from the series of true LTD coefficients as well, resulting in $499 \times 1000 = 499,000$ true and estimated LTD coefficients for the majority of LTD models.

[15]True LTD coefficients are simulated independently and separately for each LTD estimator in each simulation trial.

[16]In the following, we will use the terms LTD coefficient and LTD interchangeably.

that the parameterization of these models leads to remarkably higher LTDs than that of the Patton model. The main conclusions, however, remain the same.

To further study the performance of the different estimators, we compute and compare the MSEs across all estimators for each of the three DGPs and report the corresponding results in Table 5.2. This table presents descriptive statistics of the MSEs and splits up the MSEs into mean squared positive deviations (denoted as MSE^+) and mean squared negative deviations (denoted as MSE^-) to assess whether MSEs result from underestimation or overestimation of true LTD coefficients. As can be seen from the table, the MSE results confirm the first evidence and support the above conclusions. Irrespective of the choice of DGP, the dynamic LTD estimators consistently outperform the static estimators in terms of MSE. Interestingly, when determined to be the DGP, the Patton model has the lowest average MSE (0.0099) and is the best performing LTD estimator, whereas the DSC model has a considerably worse (average) MSE of 0.0152 and is the most inaccurate dynamic LTD estimator. In case of the DCC and the DSC model being the DGP, the DSC model clearly outperforms the Patton and the DCC model, with the average MSE being around 0.0080 in both cases. Turning to the static LTD estimators, the mixture copula models dominate the remaining LTD models irrespective of the DGP. When we specify the Patton model as the DGP, the results are as expected; due to their greater flexibility, the Mix2_{ML} and Mix2_{EM} model outperform the Mix1_{ML} and Mix1_{EM} model as indicated by the consistently lower average MSEs. Moreover, estimating the mixtures via the EM algorithm yields considerably better results than ML estimation for both mixture models. Somewhat surprisingly, these results do not hold anymore for the Mix2_{ML} and Mix2_{EM} model when specifying either the DCC or the DSC model as the DGP. As can be seen from the table, in these cases the corresponding average MSEs of the Mix2_{ML} and Mix2_{EM} model are greater than those of the Mix1_{ML} and Mix1_{EM} model and increase from 0.0236 to 0.0319 and from 0.0336 to 0.0411 when changing from ML to the EM algorithm, respectively.

Table 5.2: Performance of lower tail dependence estimators.

The table shows descriptive statistics on mean squared errors (MSE) for the lower tail dependence (LTD) estimators included in our simulation study. MSE is computed according to $\text{MSE} = \Pi(\boldsymbol{\tau}, \hat{\boldsymbol{\tau}}) = T^{-1} \sum_{t=1}^{T} (\tau_t - \hat{\tau}_t)^2$, where $\boldsymbol{\tau} = (\tau_t)_{t=1}^{T}$ and $\hat{\boldsymbol{\tau}} = (\hat{\tau}_t)_{t=1}^{T}$ denote the series of true and estimated LTD coefficients, respectively. The statistics in the table result from the baseline approach, which is determined by setting the sample size, T, to 500 and the number of simulation trials, N, to 1000. MSE is computed in each simulation trial, resulting in a total of 1000 MSEs for each combination of data-generating process (DGP) and LTD estimator. In addition to the mean, median, minimum, and maximum MSE, the table reports statistics on mean squared positive and negative deviations (denoted as MSE^+ and MSE^-, respectively), where $\text{MSE}^+ = T^{-1} \sum_{t=1}^{T} [\max\{0; \tau_t - \hat{\tau}_t\}]^2$ and $\text{MSE}^- = T^{-1} \sum_{t=1}^{T} [\min\{0; \tau_t - \hat{\tau}_t\}]^2$. The first column of the statistics on MSE^+ and MSE^- reports the corresponding average across the simulation trials, the second column shows the average of the ratios MSE^+/MSE and MSE^-/MSE, and the third column reports the average of the numbers $T^{-1} \sum_{t=1}^{T} \mathbf{1}_{\{\tau_t > \hat{\tau}_t\}}$ and $T^{-1} \sum_{t=1}^{T} \mathbf{1}_{\{\tau_t < \hat{\tau}_t\}}$ (with $\mathbf{1}$ denoting the indicator function), respectively. In case of the DGP and the LTD estimator being identical, corresponding statistics are printed in bold type. The names of the LTD estimators are abbreviated according to the notation introduced in Section 5.3.1.

	MSE				MSE^+			MSE^-		
Panel A: DGP Patton	Mean	Median	Min	Max	Mean	% of MSE	# Underest. (in %)	Mean	% of MSE	# Overest. (in %)
Patton	**0.0099**	**0.0069**	**0.0004**	**0.0560**	**0.0048**	**51.69**	**55.69**	**0.0051**	**48.15**	**44.31**
DCC	0.0115	0.0077	0.0012	0.0548	0.0054	49.57	55.51	0.0061	50.28	44.49
DSC	0.0152	0.0121	0.0016	0.0634	0.0020	22.77	78.86	0.0132	77.07	21.14
Mix1_{ML}	0.0388	0.0384	0.0059	0.1379	0.0008	2.66	94.14	0.0379	97.18	5.86
Mix1_{EM}	0.0220	0.0208	0.0050	0.0633	0.0016	9.04	88.16	0.0203	90.80	11.84
Mix2_{ML}	0.0220	0.0139	0.0034	0.1336	0.0049	41.20	68.37	0.0171	58.63	31.63
Mix2_{EM}	0.0179	0.0138	0.0034	0.0772	0.0061	45.86	62.60	0.0118	53.98	37.40
RS	0.0739	0.0299	0.0040	0.6382	0.0114	48.11	56.02	0.0624	51.73	43.98
CL	0.1343	0.1344	0.0219	0.2328	0.0001	0.06	99.36	0.1342	99.94	0.64
CL_{EVT}	0.0687	0.0677	0.0077	0.1416	0.0004	0.77	97.34	0.0684	99.23	2.66
Nonparam	0.1705	0.1746	0.0046	0.4606	0.0005	4.18	96.15	0.1700	95.82	3.85
Panel B: DGP DCC										
Patton	0.0117	0.0095	0.0033	0.1564	0.0066	49.48	46.49	0.0052	50.40	53.51
DCC	**0.0095**	**0.0049**	**0.0007**	**0.2038**	**0.0075**	**59.22**	**38.50**	**0.0020**	**40.65**	**61.50**
DSC	0.0081	0.0056	0.0007	0.1433	0.0060	60.02	45.85	0.0021	39.86	54.15
Mix1_{ML}	0.0223	0.0214	0.0052	0.1515	0.0191	82.89	21.97	0.0032	16.99	78.03
Mix1_{EM}	0.0199	0.0184	0.0032	0.0647	0.0174	84.57	21.77	0.0025	15.30	78.23
Mix2_{ML}	0.0236	0.0186	0.0052	0.2036	0.0169	62.59	35.97	0.0067	37.29	64.03
Mix2_{EM}	0.0319	0.0240	0.0043	0.1578	0.0291	80.99	21.02	0.0028	18.88	78.98
RS	0.0609	0.0309	0.0044	0.2471	0.0533	70.47	29.03	0.0075	29.41	70.97
CL	0.0698	0.0705	0.0141	0.1097	0.0000	0.07	98.96	0.0698	99.93	1.04
CL_{EVT}	0.0334	0.0330	0.0090	0.0673	0.0004	1.66	90.88	0.0330	98.34	9.12
Nonparam	0.0629	0.0605	0.0064	0.2654	0.0011	4.48	92.86	0.0618	95.52	7.14

Table 5.2: Performance of lower tail dependence estimators (continued).

Panel C: DGP DSC	MSE				MSE^{+}			MSE^{-}		
	Mean	Median	Min	Max	Mean	% of MSE	# Underest. (in %)	Mean	% of MSE	# Overest. (in %)
Patton	0.0157	0.0140	0.0069	0.0633	0.0078	48.61	46.69	0.0079	51.25	53.31
DCC	0.0106	0.0073	0.0018	0.1587	0.0067	48.22	41.62	0.0040	51.65	58.38
DSC	**0.0080**	**0.0049**	**0.0008**	**0.1586**	**0.0059**	**60.42**	**42.05**	**0.0021**	**39.45**	**57.95**
Mix1_{ML}	0.0300	0.0287	0.0079	0.1235	0.0226	73.25	32.18	0.0074	26.62	67.82
Mix1_{EM}	0.0296	0.0289	0.0098	0.0789	0.0233	76.95	30.38	0.0062	22.92	69.62
Mix2_{ML}	0.0336	0.0296	0.0075	0.1707	0.0200	54.79	41.46	0.0135	45.08	58.54
Mix2_{EM}	0.0411	0.0354	0.0065	0.1765	0.0349	76.68	27.76	0.0062	23.19	72.24
RS	0.0719	0.0431	0.0074	0.3680	0.0618	72.56	28.20	0.0099	27.31	71.80
CL	0.0780	0.0791	0.0178	0.1119	0.0002	0.31	95.99	0.0778	99.69	4.01
CL_{EVT}	0.0417	0.0413	0.0109	0.0734	0.0015	4.51	79.53	0.0402	95.49	20.47
Nonparam	0.0744	0.0718	0.0105	0.2619	0.0026	7.18	87.32	0.0718	92.82	12.68

Furthermore, the most inaccurate LTD estimates are generated by the CL and the Nonparam model, with the average MSEs ranging from 0.0698 to 0.1343 and from 0.0629 to 0.1705 across the DGPs, respectively. Remarkably, with the Patton model being the DGP, the average MSEs for the two estimators are substantially greater than those resulting from choosing the DCC or the DSC model as the DGP (e.g., the average MSEs for the CL and Nonparam model decrease from 0.1343 to 0.0698 and from 0.1705 to 0.0629 when switching from the Patton model to the DCC model, respectively). Further, confirming the evidence from Table 5.1, the CL_{EVT} model has a much lower average MSE than the CL model across all DGPs, indicating that the EVT approach of applying the GPD to the marginal distributions prior to estimating the copula model results in a material improvement in the accuracy of LTD estimates. More precisely, as shown in Table 5.2, MSEs of the CL_{EVT} model are roughly half the MSEs of the CL model on average, irrespective of the DGP. With respect to under- and overestimation, Table 5.2 shows that there is no specific pattern in the statistics of MSE^{+} and MSE^{-} for most of the LTD estimators. In case of the Patton model, however, approximately 50% of MSE results, on average, from under- or overestimation of true LTD coefficients across all DGPs. Interestingly, in case of the CL, CL_{EVT}, and the Nonparam model, the percentages of MSE that on average result from underestimation are consistently low across all DGPs, ranging from 0.06% (CL, DGP Patton) to 7.18% (Nonparam, DGP DSC) and indicating that these models systematically overestimate LTD.

The results discussed above are illustrated and supported by Figure D.1 in Appendix D. The figure plots MSEs separately for each of the three DGPs as well as for each of the LTD estimators studied in our simulation approach. As can be seen from the plots, MSEs remain relatively flat for the dynamic models with sporadic peaks across the simulation replications for some of the DGP specifications. The MSEs for the static LTD estimators, on the other hand, are for the most part characterized by considerable fluctuations and a generally higher level than that of the dynamic estimators' MSEs. Supporting the evidence from Table 5.2, the mixture copula models show the best performance among the static estimators, whereas the MSEs of the remaining static models exhibit an increased variability and magnitude.

5.3.3.2 How important is sample size? Extending the baseline approach.

When estimating copula models, sample size is a critical issue. In this section, we extend our baseline approach and examine the performance of the LTD estimators with respect to varying sample sizes. More precisely, we include two additional simulation specifications that arise from the baseline approach by altering the number of simulated (true) LTD coefficients, T, from 500 to 250 and to 1,000, respectively.

The results of the extended simulation approach are reported in Table 5.3 and illustrated in Figure 5.1. As can be seen from the figure, the general conclusions drawn in the previous section remain valid when varying the sample size, i.e., the dynamic models are the best performing LTD estimators and the mixture copula models clearly dominate the remaining static models across all three sample sizes. Further, the figure shows that the performance of the dynamic LTD estimators substantially improves with increasing sample size, irrespective of the specified DGP. This effect is particularly pronounced when the DCC model is specified as the DGP. In this case, when increasing the sample size, T, from 250 to 1,000, the average MSE for the Patton, the DCC, and the DSC model decreases considerably from 0.0224 to 0.0083, from 0.0224 to 0.0041, and from 0.0146 to 0.0047, respectively. Put differently, reducing sample size from 1,000 to 250 (that is, by a factor of 4.00) increases the average MSE by a factor of 2.94 for the Patton model, a factor of 5.46 for the DCC model, and a factor of 3.11 for the DSC model, leading to a remarkable deterioration in performance. Hence, we find clear evidence of consistency for the dynamic LTD estimators studied in our simulation approach so that the dynamic models provide statistically consistent estimates of LTD coefficients.

However, the pattern is not as pronounced for the static estimators. In fact, for most of the static models, increasing the sample size does not necessarily result in a better performance, i.e., decreasing MSEs.

Table 5.3: Mean squared errors of lower tail dependence estimators for different sample sizes.

The table reports descriptive statistics on mean squared errors (MSE) of the lower tail dependence (LTD) estimators for different sample sizes. MSE is computed according to $\text{MSE} = \Pi(\boldsymbol{\tau}, \hat{\boldsymbol{\tau}}) = T^{-1} \sum_{t=1}^{T} (\tau_t - \hat{\tau}_t)^2$, where $\boldsymbol{\tau} = (\tau_t)_{t=1}^{T}$ and $\hat{\boldsymbol{\tau}} = (\hat{\tau}_t)_{t=1}^{T}$ denote the series of true and estimated LTD coefficients, respectively. The statistics listed in the table comprise the mean, median, minimum, and maximum MSE and are based on three different simulation specifications. In addition to the baseline specification, which is determined by setting the sample size, T, to 500 and the number of simulation trials, N, to 1000, the table reports results on MSE for alternative specifications based on sample sizes of $T = 250$ and $T = 1000$. The results for the different specifications are reported separately for each of the three data-generating processes (Patton, DCC, and DSC model) throughout the panels of the table. In case of the data-generating process (DGP) and the LTD estimator being identical, corresponding statistics are printed in bold type. The names of the LTD estimators are abbreviated according to the notation introduced in Section 5.3.1.

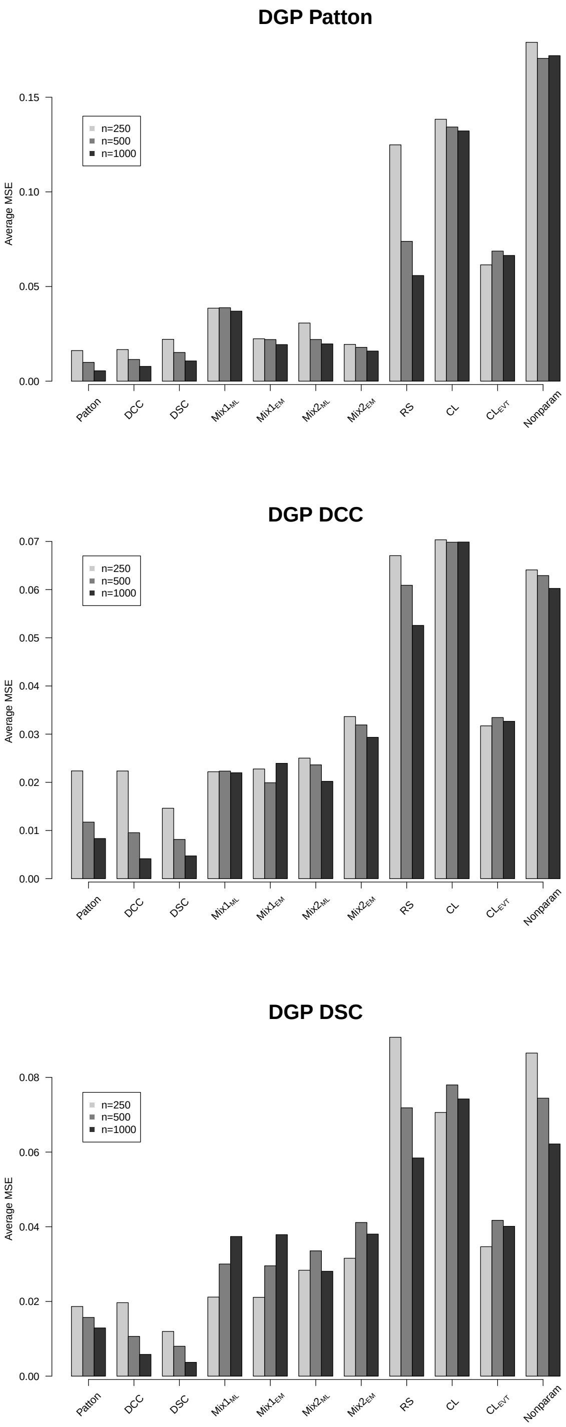
Panel A: DGP Patton	$T = 250$				$T = 500$				$T = 1000$			
	Mean	Median	Min	Max	Mean	Median	Min	Max	Mean	Median	Min	Max
Patton	**0.0162**	**0.0115**	**0.0004**	**0.1169**	**0.0099**	**0.0069**	**0.0004**	**0.0560**	**0.0055**	**0.0034**	**0.0003**	**0.0402**
DCC	0.0167	0.0121	0.0012	0.0916	0.0115	0.0077	0.0012	0.0548	0.0078	0.0058	0.0015	0.0435
DSC	0.0221	0.0198	0.0012	0.0948	0.0152	0.0121	0.0016	0.0634	0.0107	0.0078	0.0015	0.0536
Mix 1 (ML)	0.0386	0.0360	0.0035	0.1598	0.0388	0.0384	0.0059	0.1379	0.0370	0.0363	0.0068	0.1597
Mix 1 (EM)	0.0224	0.0201	0.0033	0.0823	0.0220	0.0208	0.0050	0.0633	0.0193	0.0187	0.0069	0.0437
Mix 2 (ML)	0.0307	0.0195	0.0025	0.1568	0.0220	0.0139	0.0034	0.1336	0.0197	0.0138	0.0041	0.1177
Mix 2 (EM)	0.0194	0.0148	0.0027	0.0920	0.0179	0.0138	0.0034	0.0772	0.0159	0.0134	0.0043	0.0572
RS	0.1248	0.0494	0.0042	0.6834	0.0739	0.0299	0.0040	0.6382	0.0558	0.0227	0.0044	0.6063
CL	0.1384	0.1396	0.0129	0.2634	0.1343	0.1344	0.0219	0.2328	0.1322	0.1319	0.0618	0.2029
CL (EVT)	0.0615	0.0587	0.0024	0.1796	0.0687	0.0677	0.0077	0.1416	0.0664	0.0660	0.0219	0.1202
Nonparam	0.1790	0.1750	0.0031	0.7617	0.1705	0.1746	0.0046	0.4606	0.1720	0.1712	0.0044	0.7064
Panel B: DGP DCC												
Patton	0.0224	0.0133	0.0028	0.2529	0.0117	0.0095	0.0033	0.1564	0.0083	0.0077	0.0040	0.0471
DCC	**0.0224**	**0.0110**	**0.0006**	**0.2353**	**0.0095**	**0.0049**	**0.0007**	**0.2038**	**0.0041**	**0.0027**	**0.0005**	**0.0514**
DSC	0.0146	0.0086	0.0006	0.1796	0.0081	0.0056	0.0007	0.1433	0.0047	0.0034	0.0006	0.0632
Mix 1 (ML)	0.0222	0.0204	0.0036	0.1426	0.0223	0.0214	0.0052	0.1515	0.0220	0.0211	0.0054	0.1924
Mix 1 (EM)	0.0228	0.0199	0.0037	0.0871	0.0199	0.0184	0.0032	0.0647	0.0239	0.0224	0.0089	0.0772
Mix 2 (ML)	0.0250	0.0192	0.0021	0.1648	0.0236	0.0186	0.0052	0.2036	0.0202	0.0168	0.0056	0.2121
Mix 2 (EM)	0.0336	0.0244	0.0029	0.1593	0.0319	0.0240	0.0043	0.1578	0.0293	0.0189	0.0063	0.1430
RS	0.0671	0.0350	0.0031	0.3605	0.0609	0.0309	0.0044	0.2471	0.0526	0.0270	0.0056	0.2308
CL	0.0703	0.0716	0.0149	0.1240	0.0698	0.0705	0.0141	0.1097	0.0699	0.0702	0.0418	0.0914
CL (EVT)	0.0317	0.0314	0.0032	0.0798	0.0334	0.0330	0.0090	0.0673	0.0327	0.0326	0.0114	0.0549
Nonparam	0.0641	0.0599	0.0035	0.3545	0.0629	0.0605	0.0064	0.2654	0.0602	0.0566	0.0062	0.2501

Table 5.3: Mean squared errors of lower tail dependence estimators for different sample sizes (continued).

Panel C: DGP DSC	$T = 250$				$T = 500$				$T = 1000$			
	Mean	Median	Min	Max	Mean	Median	Min	Max	Mean	Median	Min	Max
Patton	0.0186	0.0137	0.0027	0.1582	0.0157	0.0140	0.0069	0.0633	0.0129	0.0123	0.0066	0.0283
DCC	0.0197	0.0118	0.0014	0.1457	0.0106	0.0073	0.0018	0.1587	0.0058	0.0047	0.0015	0.0760
DSC	**0.0120**	**0.0070**	**0.0007**	**0.1295**	**0.0080**	**0.0049**	**0.0008**	**0.1586**	**0.0037**	**0.0028**	**0.0005**	**0.0514**
Mix 1 (ML)	0.0212	0.0189	0.0051	0.1113	0.0300	0.0287	0.0079	0.1235	0.0374	0.0372	0.0130	0.1358
Mix 1 (EM)	0.0211	0.0197	0.0040	0.0667	0.0296	0.0289	0.0098	0.0789	0.0379	0.0368	0.0133	0.0890
Mix 2 (ML)	0.0284	0.0245	0.0055	0.1249	0.0336	0.0296	0.0075	0.1707	0.0281	0.0260	0.0099	0.1469
Mix 2 (EM)	0.0316	0.0258	0.0040	0.1219	0.0411	0.0354	0.0065	0.1765	0.0380	0.0293	0.0106	0.1413
RS	0.0907	0.0706	0.0055	0.5374	0.0719	0.0431	0.0074	0.3680	0.0584	0.0334	0.0106	0.2785
CL	0.0706	0.0729	0.0052	0.1396	0.0780	0.0791	0.0178	0.1119	0.0742	0.0745	0.0450	0.0930
CL (EVT)	0.0347	0.0330	0.0047	0.0937	0.0417	0.0413	0.0109	0.0734	0.0401	0.0402	0.0225	0.0604
Nonparam	0.0865	0.0809	0.0085	0.3984	0.0744	0.0718	0.0105	0.2619	0.0622	0.0599	0.0125	0.2408

Figure 5.1: Average mean squared errors for different sample sizes.

The figure shows average mean squared errors (MSE) for the lower tail dependence (LTD) estimators with respect to different sample sizes and separately for each of the three data-generating processes (Patton, DCC, and DSC model). MSE is computed according to $\text{MSE} = \Pi(\boldsymbol{\tau}, \hat{\boldsymbol{\tau}}) = T^{-1}\sum_{t=1}^{T}(\tau_t - \hat{\tau}_t)^2$, where $\boldsymbol{\tau} = (\tau_t)_{t=1}^{T}$ and $\hat{\boldsymbol{\tau}} = (\hat{\tau}_t)_{t=1}^{T}$ denote the series of true and estimated LTD coefficients, respectively. For each LTD estimator, the figure plots three bars showing the average MSE for each of the three sample sizes considered ($T = 250; 500; 1000$), where the average is calculated across a total of $N = 1000$ simulation replications. The names of the LTD estimators are abbreviated according to the notation introduced in Section 5.3.1.



As can be seen from Figure 5.1, except for the RS and the Nonparam models, which exhibit decreasing (average) MSEs for increasing sample sizes across all DGP specifications, the relation between performance and sample size is not as clear for the remaining static estimators. In case of the Mix1_{ML} model, for example, we can see from Table 5.3 that, when the Patton model is determined to be the DGP, the average MSE slightly decreases from 0.0386 to 0.0370 when increasing sample size from 250 to 1,000. When specifying the DSC model as the DGP, the average MSE increases substantially from 0.0212 to 0.0374, implying a worse performance for a greater sample size. Consequently, we do not find evidence of consistency for most of the static LTD estimators in our simulation approach so that most static models in our study seem to deliver inconsistent estimates of LTD coefficients.

Overall, the extended baseline approach shows the robustness of our results with respect to sample size on the one hand, and demonstrates the importance of considering sample size when estimating LTD models on the other hand. Based on our results, the issue of sample size is particularly relevant for the dynamic estimators. Increasing the sample size results in a material improvement in the performance of the estimators, or put the other way round, decreasing sample size deteriorates LTD estimates substantially.

5.3.3.3 Is performance measurement crucial? Reevaluating simulation results.

One concern about our simulation study might be the choice of performance metric we used to evaluate the accuracy of the LTD estimates. Up to this point, performance evaluation exclusively relied on the mean squared error criterion and neglected any other performance measures. Hence, in this section we introduce additional performance metrics and check the robustness of the results presented in the preceding sections with respect to performance measurement. More precisely, we include three additional performance metrics in the evaluation of our simulation results, namely a slight variation of MSE (denoted as MSE_2) and two metrics based on the absolute deviation between true and estimated LTD coefficients (denoted as MAD_1 and MAD_2). The additional performance metrics are computed according to the following formulas

$$\mathrm{MSE}_2 = T^{-1}\sum_{t=1}^{T}\left(\tau_t^2 - \hat{\tau}_t^2\right)^2 \tag{5.18}$$

$$\mathrm{MAD}_1 = T^{-1}\sum_{t=1}^{T}\left|\tau_t - \hat{\tau}_t\right| \tag{5.19}$$

$$\mathrm{MAD}_2 = T^{-1}\sum_{t=1}^{T}\left|\tau_t^2 - \hat{\tau}_t^2\right|. \tag{5.20}$$

Results on average values of the performance metrics are reported in Table 5.4 and illustrated in Figure 5.2 separately for each DGP, performance metric, and each sample size ($T = 250; 500; 1,000$). As can be seen from Table 5.4, average MSE_2 values range from 0.0013 (DGP Patton, $T = 1,000$, Patton) to 0.1072 (DGP Patton, $T = 250$, Nonparam), whereas average values for MAD_1 and MAD_2 vary between 0.0450 (DGP DSC, $T = 1,000$, DSC) and 0.3892 (DGP Patton, $T = 250$, Nonparam) and between 0.0211 (DGP Patton, $T = 1,000$, Patton) and 0.2864 (DGP Patton, $T = 250$, Nonparam), respectively. Figure 5.2 demonstrates that the main results and conclusions drawn in the previous sections remain valid when altering the performance metric, indicating that our findings from above are robust towards performance measurement and do not depend on the specific properties of MSE. More precisely, we can see from the figure that the dynamic LTD estimators clearly outperform the static models across all DGPs and across all performance metrics, with the superiority becoming increasingly evident as sample size grows. Further, as in the case of MSE being the performance metric, both MSE_2 and the MAD measures decrease with increasing sample size, indicating better performance for larger sample sizes.[17] Moreover, the mixture copula models are the dominating static LTD estimators across all DGPs, performance metrics, and sample sizes.

[17] An exception to this pattern is constituted by the Patton model when the DSC model is specified as the DGP. As shown in Table 5.4, in this setting average MSE_2 and MAD_2 increase from 0.0083 to 0.0105 and from 0.0679 to 0.0824, respectively.

Table 5.4: Alternative performance metrics.

The table reports average values for the alternative performance measures, which comprise a modified version of the mean squared error (denoted as MSE_2) and two measures based on mean absolute deviations (MAD_1 and MAD_2). The alternative performance measures are calculated according to $\text{MSE}_2 = T^{-1}\sum_{t=1}^{T}\left(\tau_t^2 - \hat{\tau}_t^2\right)^2$, $\text{MAD}_1 = T^{-1}\sum_{t=1}^{T}\left|\tau_t - \hat{\tau}_t\right|$, and $\text{MAD}_2 = T^{-1}\sum_{t=1}^{T}\left|\tau_t^2 - \hat{\tau}_t^2\right|$, where $\boldsymbol{\tau} = (\tau_t)_{t=1}^{T}$ and $\hat{\boldsymbol{\tau}} = (\hat{\tau}_t)_{t=1}^{T}$ denote the series of true and estimated lower tail dependence (LTD) coefficients, respectively. The averages listed in the table are calculated across a total of 1000 simulation trials for each of the three data-generating processes (Patton, DCC, and DSC model), each LTD estimator, and for three different sample sizes ($T = 250; 500; 1000$). In case of the data-generating process (DGP) and the LTD estimator being identical, corresponding statistics are printed in bold type. The names of the LTD estimators are abbreviated according to the notation introduced in Section 5.3.1.

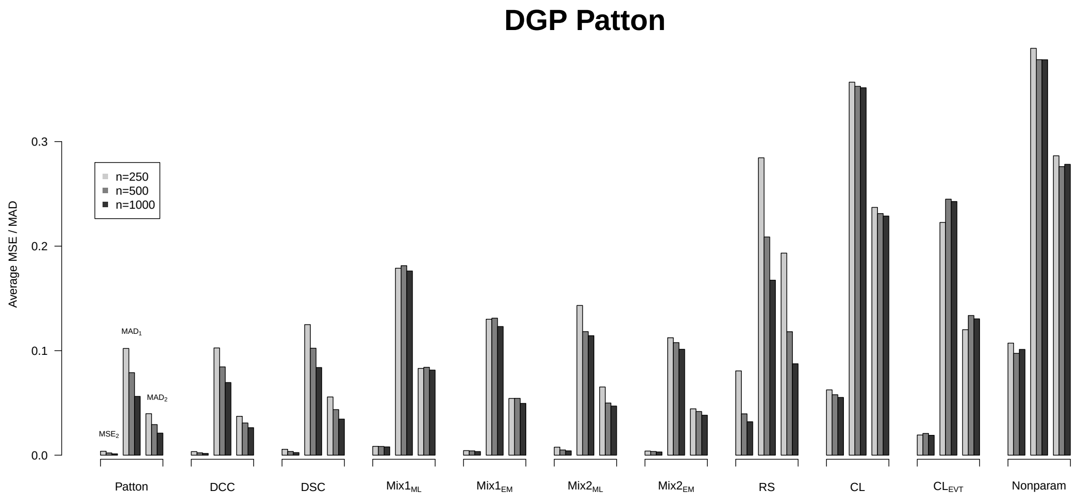
Panel A: DGP Patton	$T = 250$			$T = 500$			$T = 1000$		
	MSE_2	MAD_1	MAD_2	MSE_2	MAD_1	MAD_2	MSE_2	MAD_1	MAD_2
Patton	**0.0038**	**0.1021**	**0.0397**	**0.0021**	**0.0789**	**0.0293**	**0.0013**	**0.0562**	**0.0211**
DCC	0.0034	0.1026	0.0372	0.0023	0.0844	0.0308	0.0017	0.0695	0.0263
DSC	0.0056	0.1249	0.0557	0.0035	0.1023	0.0436	0.0025	0.0839	0.0345
Mix1_{ML}	0.0084	0.1788	0.0830	0.0083	0.1813	0.0841	0.0079	0.1762	0.0814
Mix1_{EM}	0.0044	0.1301	0.0543	0.0041	0.1311	0.0544	0.0035	0.1231	0.0495
Mix2_{ML}	0.0077	0.1432	0.0652	0.0050	0.1182	0.0499	0.0041	0.1143	0.0470
Mix2_{EM}	0.0039	0.1123	0.0443	0.0035	0.1077	0.0417	0.0031	0.1013	0.0382
RS	0.0806	0.2845	0.1933	0.0395	0.2087	0.1181	0.0320	0.1674	0.0874
CL	0.0625	0.3568	0.2370	0.0578	0.3529	0.2312	0.0552	0.3515	0.2288
CL_{EVT}	0.0193	0.2227	0.1201	0.0208	0.2449	0.1336	0.0190	0.2427	0.1304
Nonparam	0.1072	0.3892	0.2864	0.0974	0.3783	0.2761	0.1012	0.3783	0.2782
Panel B: DGP DCC									
Patton	0.0126	0.1128	0.0871	0.0081	0.0834	0.0700	0.0061	0.0714	0.0613
DCC	**0.0112**	**0.1131**	**0.0824**	**0.0057**	**0.0708**	**0.0564**	**0.0029**	**0.0478**	**0.0401**
DSC	0.0081	0.0862	0.0674	0.0052	0.0653	0.0534	0.0031	0.0473	0.0398
Mix1_{ML}	0.0161	0.1246	0.1018	0.0163	0.1247	0.1029	0.0162	0.1241	0.1027
Mix1_{EM}	0.0155	0.1253	0.1000	0.0147	0.1174	0.0970	0.0174	0.1311	0.1072
Mix2_{ML}	0.0159	0.1265	0.1010	0.0154	0.1225	0.0995	0.0139	0.1133	0.0943
Mix2_{EM}	0.0187	0.1504	0.1111	0.0188	0.1464	0.1111	0.0180	0.1393	0.1078
RS	0.0379	0.2085	0.1540	0.0282	0.1977	0.1350	0.0238	0.1830	0.1258
CL	0.0791	0.2414	0.2604	0.0778	0.2410	0.2607	0.0780	0.2418	0.2627
CL_{EVT}	0.0288	0.1476	0.1430	0.0294	0.1523	0.1478	0.0286	0.1509	0.1470
Nonparam	0.0716	0.2194	0.2322	0.0695	0.2190	0.2333	0.0671	0.2119	0.2262

Table 5.4: Alternative performance metrics (continued).

Panel C: DGP DSC	$T = 250$			$T = 500$			$T = 1000$		
	MSE_2	MAD_1	MAD_2	MSE_2	MAD_1	MAD_2	MSE_2	MAD_1	MAD_2
Patton	0.0083	0.1068	0.0679	0.0108	0.1004	0.0815	0.0105	0.0900	0.0824
DCC	0.0071	0.1088	0.0630	0.0060	0.0773	0.0584	0.0041	0.0548	0.0481
DSC	**0.0048**	**0.0812**	**0.0497**	**0.0048**	**0.0659**	**0.0505**	**0.0029**	**0.0450**	**0.0400**
$\mathrm{Mix1}_{\mathrm{ML}}$	0.0099	0.1189	0.0782	0.0208	0.1461	0.1157	0.0309	0.1681	0.1467
$\mathrm{Mix1}_{\mathrm{EM}}$	0.0102	0.1187	0.0769	0.0208	0.1457	0.1155	0.0313	0.1701	0.1484
$\mathrm{Mix2}_{\mathrm{ML}}$	0.0123	0.1365	0.0864	0.0207	0.1488	0.1160	0.0220	0.1339	0.1208
$\mathrm{Mix2}_{\mathrm{EM}}$	0.0123	0.1442	0.0848	0.0244	0.1685	0.1251	0.0289	0.1642	0.1406
RS	0.0519	0.2499	0.1668	0.0332	0.2173	0.1453	0.0349	0.1960	0.1533
CL	0.0500	0.2303	0.1938	0.0691	0.2379	0.2340	0.0816	0.2329	0.2577
$\mathrm{CL}_{\mathrm{EVT}}$	0.0186	0.1515	0.1103	0.0291	0.1609	0.1413	0.0343	0.1530	0.1517
Nonparam	0.0651	0.2538	0.2187	0.0668	0.2265	0.2205	0.0664	0.2024	0.2175

Figure 5.2: Average alternative performance metrics for different sample sizes.

The figure shows average values of the alternative performance metrics for the lower tail dependence (LTD) estimators with respect to different sample sizes and separately for each of the three data-generating processes (Patton, DCC, and DSC model). The alternative performance measures include a modified version of the mean squared error (denoted as MSE_2) and two mean absolute deviation measures (MAD_1 and MAD_2), which are computed according to $\text{MSE}_2 = T^{-1}\sum_{t=1}^{T}\left(\tau_t^2 - \hat{\tau}_t^2\right)^2$, $\text{MAD}_1 = T^{-1}\sum_{t=1}^{T}|\tau_t - \hat{\tau}_t|$, and $\text{MAD}_2 = T^{-1}\sum_{t=1}^{T}\left|\tau_t^2 - \hat{\tau}_t^2\right|$, where $\boldsymbol{\tau} = (\tau_t)_{t=1}^{T}$ and $\hat{\boldsymbol{\tau}} = (\hat{\tau}_t)_{t=1}^{T}$ denote the series of true and estimated LTD coefficients, respectively. For each LTD estimator, the figure plots three bars for each performance metric showing the average MSE_2, MAD_1, and MAD_2 for each of the three sample sizes considered ($T = 250; 500; 1000$), where the average is calculated across a total of $N = 1000$ simulation replications. The names of the LTD estimators are abbreviated according to the notation introduced in Section 5.3.1.



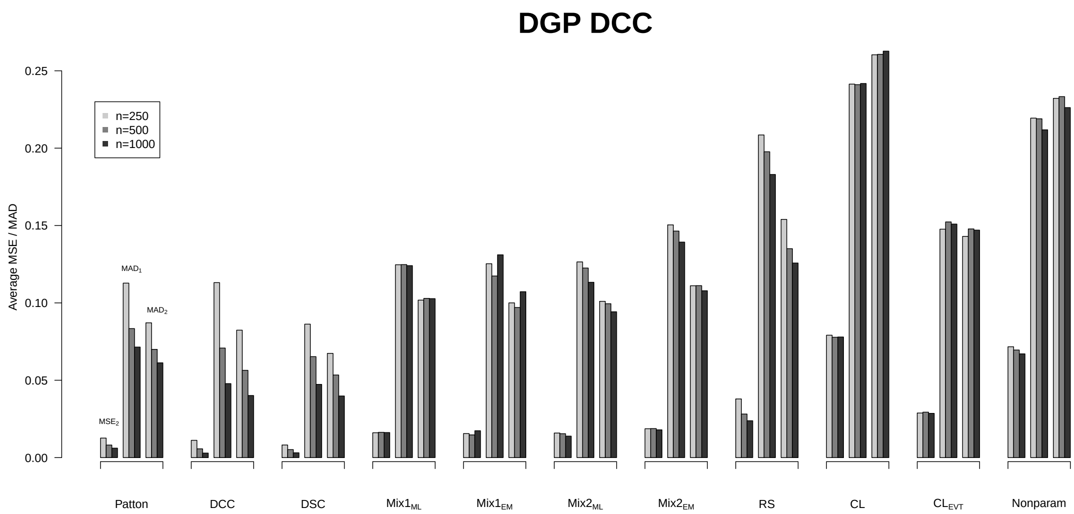
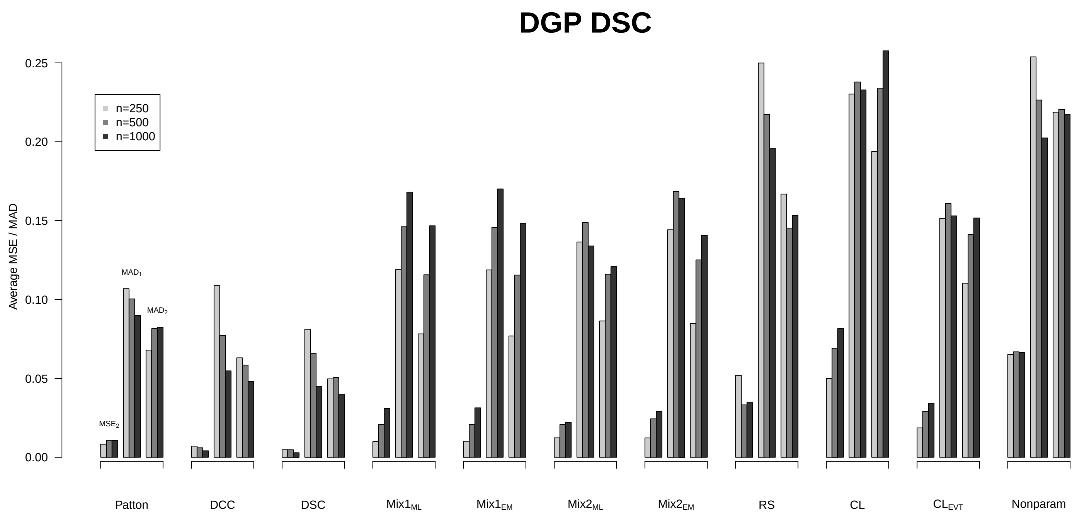


Figure 5.2: Average alternative performance metrics for different sample sizes (continued).



For example, assuming the Patton model as the DGP and a sample size of $T = 1,000$, Table 5.4 shows that average MAD_2 for the Mix2_{EM} model is equal to 0.0382, whereas the corresponding average MAD_2 for the RS, CL, CL_{EVT}, and Nonparam model is at a considerably higher level of 0.0874, 0.2288, 0.1304, and 0.2782, respectively.[18] Regarding the mixture copula models, the results do not provide evidence of one of the two mixture models being superior to the other or of the EM algorithm leading to more accurate LTD estimates. Further, similar to the results in the previous sections, the CL and the Nonparam model are the worst performing LTD estimators across all simulation settings, with the performance metrics being substantially higher than those of the other estimators.[19] Assuming the Patton model as the DGP and a sample size equal to 1,000, for example, average MSE_2 for the CL and the Nonparam model is approximately 42 ($0.0552/0.0013$) and 77 ($0.1012/0.0013$) times the average MAD_2 of the Patton model. As expected, the effect of the EVT approach remains significant across all DGPs and sample sizes as can be seen from the considerable reduction in the average values of the MSE and MAD

[18] Also note that the Mix2_{EM} model is clearly outperformed by, e.g., the Patton model with the (average) MAD_2 of the latter being around half the MAD_2 of the former.

[19] In some settings, the RS model performs even worse than the CL or the Nonparam model. These settings are, however, restricted to the small sample size specifications. When sample size is increased, the performance metrics consistently decrease to values below those of the CL and Nonparam model.

measures for the $\mathrm{CL}_{\mathrm{EVT}}$ model when compared to the CL model in Table 5.4 and Figure 5.2.

5.3.3.4 Which estimator performs best? Summary and conclusions.

This section summarizes the results from our simulation study and shortly reviews the most important conclusions. Table 5.5 provides a ranking of the LTD estimators included in our study for each of the simulation specifications investigated in the previous sections (i.e., for each performance metric, DGP, and sample size), where each estimator is assigned a number between 1 (best performer) and 11 (worst performer). For each performance metric and LTD estimator, the rankings are summed up and the values of the corresponding performance metric are averaged across all DGPs and sample sizes (see the last two columns in Table 5.5), with low sums and average values implying global superior performance (that is, across all simulation settings). The rankings, sums, and averages reported in the table summarize our general findings, which can be stated as follows.

First, the dynamic LTD estimators clearly dominate the static estimators, with the superiority of the former becoming increasingly evident with growing sample sizes. Among the dynamic estimators, the Patton model is the best performing model only when at the same time assumed to be the DGP. Otherwise, the DSC model outperforms the Patton and the DCC model.[20] Second, the mixture copula models are the best performing static LTD estimators, irrespective of the specification of the mixture and the estimation method. Occasionally, when sample size is low ($T = 250$), the mixture copula models outperform some of the dynamic LTD estimators, but as sample size increases, the mixtures considerably underperform the dynamic models.

[20]Note the corresponding pattern in Table 5.5. When specified as the DGP, the Patton model ranks on first place for the most part, while the rankings of the DSC model range between the third and fifth place. Changing the DGP from the Patton to the DCC or DSC model, however, results in the Patton model ranking between the second and fourth place and the DSC model ranking on first place for most specifications.

Table 5.5: Ranking and overall performance of lower tail dependence estimators.

The table provides a ranking of the lower tail dependence (LTD) estimators for each of the simulation specifications investigated in our simulation study, i.e., for each performance metric, data-generating process (Patton, DCC, DSC), and sample size ($T = 250; 500; 1000$). Each LTD estimator is assigned a number between 1 (best performer) and 11 (worst performer) and for each performance metric and estimator the rankings are summed up and the values of the corresponding performance metric are averaged across all data-generating processes (DGP) and sample sizes (see the last two columns in the table). The performance metrics included are two versions of the mean squared error (denoted as MSE and MSE$_2$) and mean absolute deviation (MAD$_1$ and MAD$_2$), which are computed according to MSE $= T^{-1}\sum_{t=1}^{T}(\tau_t - \hat{\tau}_t)^2$, MSE$_2 = T^{-1}\sum_{t=1}^{T}\left(\tau_t^2 - \hat{\tau}_t^2\right)^2$, MAD$_1 = T^{-1}\sum_{t=1}^{T}\left|\tau_t - \hat{\tau}_t\right|$, and MAD$_2 = T^{-1}\sum_{t=1}^{T}\left|\tau_t^2 - \hat{\tau}_t^2\right|$, where $\boldsymbol{\tau} = (\tau_t)_{t=1}^{T}$ and $\hat{\boldsymbol{\tau}} = (\hat{\tau}_t)_{t=1}^{T}$ denote the series of true and estimated LTD coefficients, respectively. In case of the DGP and the LTD estimator being identical, corresponding statistics are printed in bold type. The names of the LTD estimators are abbreviated according to the notation introduced in Section 5.3.1.

Panel A: MSE	DGP Patton			DGP DCC			DGP DSC			Sum	Average MSE
	$n = 250$	$n = 500$	$n = 1000$	$n = 250$	$n = 500$	$n = 1000$	$n = 250$	$n = 500$	$n = 1000$		
Patton	**1**	**1**	**1**	4	3	3	2	3	3	21	**0.0162**
DCC	2	2	2	3	2	**1**	3	2	2	19	0.0167
DSC	4	3	3	**1**	**1**	2	**1**	**1**	**1**	**17**	0.0221
Mix1$_{\text{ML}}$	7	7	7	2	5	5	5	5	5	48	0.0386
Mix1$_{\text{EM}}$	5	5	5	5	4	6	4	4	6	44	0.0224
Mix2$_{\text{ML}}$	6	6	6	6	6	4	6	6	4	50	0.0307
Mix2$_{\text{EM}}$	3	4	4	8	7	7	7	7	7	54	0.0194
RS	9	9	8	10	9	9	**11**	9	9	83	0.1248
CL	10	10	10	**11**	**11**	**11**	9	**11**	**11**	**94**	0.1384
CL$_{\text{EVT}}$	8	8	9	7	8	8	8	8	8	72	0.0615
Nonparam	**11**	**11**	**11**	9	10	10	10	10	10	92	**0.1790**
Panel B: MSE$_2$											
Patton	2	**1**	**1**	3	3	3	3	3	3	22	0.0038
DCC	**1**	2	2	2	2	**1**	2	2	2	**16**	**0.0034**
DSC	5	4	3	**1**	**1**	2	**1**	**1**	**1**	19	0.0056
Mix1$_{\text{ML}}$	7	7	7	6	6	5	4	6	6	54	0.0084
Mix1$_{\text{EM}}$	4	5	5	4	4	6	5	5	7	45	0.0044
Mix2$_{\text{ML}}$	6	6	6	5	5	4	7	4	4	47	0.0077
Mix2$_{\text{EM}}$	3	3	4	7	7	7	6	7	5	49	0.0039
RS	10	9	9	9	8	8	10	9	9	81	0.0806
CL	9	10	10	**11**	**11**	**11**	9	**11**	**11**	93	0.0625
CL$_{\text{EVT}}$	8	8	8	8	9	9	8	8	8	74	0.0193
Nonparam	**11**	**11**	**11**	10	10	10	**11**	10	10	**94**	**0.1072**

Table 5.5: Ranking and overall performance of lower tail dependence estimators (continued).

Panel C: MAD_1	DGP Patton			DGP DCC			DGP DSC			Sum	Average MAD
	$n = 250$	$n = 500$	$n = 1000$	$n = 250$	$n = 500$	$n = 1000$	$n = 250$	$n = 500$	$n = 1000$		
Patton	**1**	**1**	**1**	2	3	3	2	3	3	19	**0.1021**
DCC	2	2	2	3	2	2	3	2	2	20	0.1026
DSC	4	3	3	**1**	**1**	**1**	**1**	**1**	**1**	**16**	0.1249
$Mix1_{ML}$	7	7	8	4	6	5	5	5	7	54	0.1788
$Mix1_{EM}$	5	6	6	5	4	6	4	4	8	48	0.1301
$Mix2_{ML}$	6	5	5	6	5	4	6	6	4	47	0.1432
$Mix2_{EM}$	3	4	4	8	7	7	7	8	6	54	0.1123
RS	9	8	7	9	9	9	10	9	9	79	0.2845
CL	10	10	10	**11**	**11**	**11**	9	**11**	**11**	**94**	0.3568
CL_{EVT}	8	9	9	7	8	8	8	7	5	69	0.2227
Nonparam	**11**	**11**	**11**	10	10	10	**11**	10	10	**94**	**0.3892**
Panel D: MAD_2											
Patton	2	**1**	**1**	3	3	3	3	3	3	22	0.0397
DCC	**1**	2	2	2	2	2	2	2	2	**17**	**0.0372**
DSC	5	4	3	**1**	**1**	**1**	**1**	**1**	**1**	18	0.0557
$Mix1_{ML}$	7	7	7	6	6	5	5	5	6	54	0.0830
$Mix1_{EM}$	4	6	6	4	4	6	4	4	7	45	0.0543
$Mix2_{ML}$	6	5	5	5	5	4	7	6	4	47	0.0652
$Mix2_{EM}$	3	3	4	7	7	7	6	7	5	49	0.0443
RS	9	8	8	9	8	8	9	9	9	77	0.1933
CL	10	10	10	**11**	**11**	**11**	10	**11**	**11**	**95**	0.2370
CL_{EVT}	8	9	9	8	9	9	8	8	8	76	0.1201
Nonparam	**11**	**11**	**11**	10	10	10	**11**	10	10	94	**0.2864**

Third, neither the specification of the mixture nor the estimation method has a distinct impact on the accuracy of LTD estimates. The two mixture models provide similarly accurate LTD estimates and, somewhat surprisingly, the bias arising from using ML instead of the EM algorithm for estimation of the mixtures does not translate into a consistent deterioration in performance. Fourth, the worst performing LTD estimators are the CL and the Nonparam model, where the performance of the former improves significantly when modified by the EVT approach of applying the GPD to the marginal distributions prior to estimating the copula. The resulting $\mathrm{CL}_{\mathrm{EVT}}$ model as well as the RS model fall somewhere in between the mixture models and the CL and Nonparam model regarding their performance, with the lowest values of their corresponding performance metrics reaching those of the mixtures and the highest reaching those of the CL and Nonparam model.

5.4 Replication study

We now turn to our empirical study and investigate the implications of our simulation study for real-data applications. Here, we are especially interested in how the results from our simulations translate into existing empirical studies in the finance literature and whether the validity as well as the economic significance of existing empirical findings depend on the choice of tail dependence estimator. To this purpose, we shall focus on extreme dependence in asset pricing and revisit the empirical study in Ruenzi and Weigert (2013), since rare-disaster risk has attracted worldwide attention during the recent financial crisis and spurred a surge in empirical studies regarding the pricing of tail risk in the cross-section of stock returns (see, e.g., Bollerslev and Todorov, 2011; Gabaix, 2012).

5.4.1 Replication in a wide sense: Differences in data and methodology

The central research question underlying our empirical study is whether the choice of tail dependence estimator impacts the validity and economic significance of crash sensitivity being priced in the cross-section of stock returns. Thus, we do not aim to strictly replicate Ruenzi and Weigert (2013) and rather provide a replication in a wide sense, i.e., we replicate their empirical study employing a different body of data and methodologies to compute the crash-sensitivity (lower tail dependence) of stocks. For increased transparency, we therefore discuss differences in data and methodology prior to moving on to our estimation results.

5.4.1.1 Differences in data

The sample used in the empirical study of Ruenzi and Weigert (2013) consists of all common stocks from *CRSP* trading on the NYSE and AMEX between January 1, 1963 through December 31, 2009. Having employed several filters, they end up with a total of 96,676 firm-year observations, where the number of firms in each year ranges from 1,489 to 2,440.

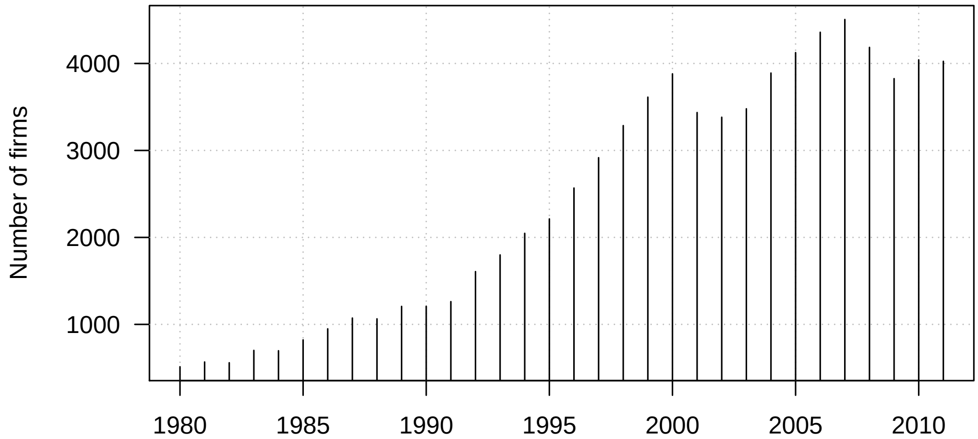
In contrast, we collect daily stock price data from *Thomson Reuters Datastream*. We start our sample construction with all stocks trading on the NYSE, AMEX, and NASDAQ, which are included in the active- and dead-firm lists provided by *Datastream* from January 1, 1980 to December 31, 2011, amounting to a total of more than 14,000 stocks.[21] To eliminate non-common equity from our sample, we exclude depositary receipts (DRs), real estate investment trusts (REITs), closed-end funds, exchange-traded funds, warrants, preferred stocks, and other stocks with special features.[22] We exclude all secondary listings and non-primary issues.

[21] Note that we include dead stocks to limit the effect of survivorship bias (see, e.g., Karolyi et al., 2012).

[22] Since neither *Datastream* nor *Worldscope* provide codes for discerning non-common shares from common shares, we follow Karolyi et al. (2012) and exclude these stocks manually by examining the names of the individual stocks. More precisely, we drop stocks with names including specific strings that are indicative of non-common equity, such as ’REIT’, ’GDR’, and ’PREF’. A complete list of those strings can be found in Karolyi et al. (2012).

Figure 5.3: Number of firms across sample period.

The figure depicts the temporal variation in the number of firms across the sample period. Our sample encompasses all U.S. common stocks trading on the NYSE, AMEX, and NASDAQ from January 1, 1980 to December 31, 2011. Data are retrieved from *Thomson Reuters Datastream* and filtered employing the usual screening procedures as discussed in Ince and Porter (2006) and Hou et al. (2011).



To enter the sample, firms must have available return data for at least 100 days in the observation year. To further minimize potential biases resulting from low-price and illiquid stocks, we discard firm-year observations if the average stock price in the observation year is less than $1. Moreover, to eliminate potential data errors and ensure data integrity, we apply several screening procedures as suggested by Ince and Porter (2006). Among others, we employ the following commonly used data screens.[23] First, we set daily returns to missing if the value of the total return index for either the previous or the current day is below 0.01. Second, we eliminate any return greater than or equal to 300% that is reversed within one month. Also, we exclude firms with missing country or firm identifiers. Having imposed the above sampling criteria, our final sample encompasses 77,810 firm-year observations, with the number of firms in each year ranging from 513 to 4,506. The temporal variation of the number of firms across our sample period is depicted

[23]For detailed overviews and descriptions of the screening procedures see Ince and Porter (2006), Hou et al. (2011), and Karolyi et al. (2012).

in Figure 5.3.[24]

5.4.1.2 Differences in methodology

To measure the crash sensitivity of stocks, Ruenzi and Weigert (2013) calculate the lower tail dependence of the respective stock with the market based on convex combinations of simple parametric bivariate Archimedean and elliptical copulas. For each stock and year, the authors estimate tail dependence coefficients based on daily return data. Choosing from a total of 64 different convex combinations, they select the best fitting mixture copula based on Integrated Anderson-Darling distances. Estimation of the mixture parameters (i.e., the copula parameter and the weights) is then conducted semi-parametrically employing the canonical maximum likelihood procedure of Genest et al. (1995).[25]

In contrast, to investigate the economic implications of the choice of tail dependence estimator, we replicate the asset pricing study in Ruenzi and Weigert (2013) using three of the estimators included in our simulation study in the preceding section. First, in the spirit of the authors' econometric approach, we estimate the Mix1_{EM} model and compute corresponding tail dependence coefficients for each stock and year.[26] To study how the different performances of the tail dependence estimators in our simulation study translate into the pricing of crash sensitivity in the cross-section of stock returns, we additionally include two estimators in our empirical study, one that underperformed and one that outperformed the Mix1_{EM} model in our simulations. Regarding the former, we estimate the CL_{EVT} model. In terms of the outperforming estimator, however, we choose Patton's

[24] Descriptive statistics on stock returns can be found in Table 5.6 and are discussed in Section 5.4.2.1.

[25] Note that this approach suffers from some theoretical concerns. First, as pointed out in our simulation study, the lack of a sufficient number of data points used for estimation has serious consequences for the accuracy of tail dependence estimators. With the number of trading days per year varying around 250, estimated tail dependence is presumably characterized by significant deviations from the true tail dependence inherent to the data. Second, using static models neglects intra-year variation and deteriorates accuracy. Finally, as pointed out in Section 5.3.1, estimating mixture copulas via maximum likelihood is statistically incorrect and might introduce severe biases into the parameter estimates.

[26] As found in Ruenzi and Weigert (2013), the Mix1 model consisting of the Joe, F-G-M, and the Rotated-Joe copula is the most frequently selected convex combination. Further, the authors state that their main findings do not depend on the choice of tail dependence estimator and that the estimation procedure can be dramatically simplified by just picking a reasonable convex copula combination. Note, however, that we use the EM algorithm as proposed by Dempster et al. (1977) (instead of ML) to obtain unbiased estimates of the copula parameters and weights.

(2006) dynamic t copula. As in Ruenzi and Weigert (2013), we estimate the tail dependence estimators for each stock and year based on daily returns, ending up with a panel of tail dependence coefficients at the year-firm level.[27]

5.4.2 Results

In their asset pricing study, Ruenzi and Weigert (2013) claim validity of their results irrespective of the estimation procedure applied to compute tail dependence coefficients. More precisely, they state:

> ”These results document that our main findings are not driven by the tail dependence coefficient estimation procedure. [...] This might be a helpful result for researchers working on the impact of tail dependence in similar settings.”

Since this finding has potentially far-reaching consequences for practical applications and future research, the aim of this section is to check the validity of this result and to investigate whether the pricing of tail risk is indeed independent of the choice of tail dependence estimation procedure.

Following Ruenzi and Weigert (2013), we first discuss summary statistics and then move on to univariate and bivariate portfolio sorts to get a first impression of whether the relation between crash sensitivity and excess returns is affected by the choice of tail dependence estimator. Finally, we replicate the authors’ main analysis and run (multivariate) Fama-MacBeth (1973) regressions on the individual firm level including the tail dependence coefficients computed from the three estimators as well as the same combinations of control variables as in Ruenzi and Weigert (2013).

5.4.2.1 Summary statistics

Descriptive statistics on excess returns over the risk-free rate, tail dependence coefficients, and other key variables are reported in Table 5.6.

[27] Details on the $\mathrm{Mix1}_{\mathrm{EM}}$, $\mathrm{CL}_{\mathrm{EVT}}$, and the Patton model can be found in Sections 5.3.1 and D.1 (Appendix D). Summary statistics on estimated tail dependence coefficients are discussed in Section 5.4.2.1.

Table 5.6: Summary statistics.

The table reports descriptive statistics for the main variables used in our empirical study. Following Ruenzi and Weigert (2013), we compute the mean, the 25th, 50th (median), and 75th percentile as well as the standard deviation of yearly excess returns over the one-month T-bill rate (return), lower tail dependence (LTD) coefficients computed from the Mix1_{EM}, CL_{EVT}, and the Patton model, regular (β) as well as upside (β^{+}) and downside (β^{-}) beta, market capitalization (size), book-to-market ratio (bookmarket), illiquidity (*illiq*), idiosyncratic volatility (*idiovola*), coskewness (*coskew*), cokurtosis (*cokurt*), and the maximum daily return over the last year (*max*). Corresponding variable definitions can be found in Table D.5 in Appendix D. The second part of the table (columns 6 to 14) shows mean values for the variables conditional on LTD being above (below) its median as well as the differences with corresponding significance levels, where results are reported separately for each of the three tail dependence estimators included in our study. ***, **, and * indicate significance at the 1%, 5%, and the 10% level, respectively. Our sample encompasses all U.S. common stocks trading on the NYSE, AMEX, and NASDAQ from January 1, 1980 to December 31, 2011.

						Above LTD Median			Below LTD Median			Above - Below		
	Mean	25th	Median	75th	Std. Dev.	Mix1_{EM}	CL_{EVT}	Patton	Mix1_{EM}	CL_{EVT}	Patton	Mix1_{EM}	CL_{EVT}	Patton
return	-9.31%	-30.78%	-2.11%	21.54%	0.622	-1.61%	0.41%	-3.94%	-17.03%	-16.86%	-13.49%	15.42%***	17.26%***	9.55%***
LTD														
- Mix1_{EM}	0.130	0.060	0.130	0.192	0.085	0.201	0.187	0.174	0.060	0.080	0.090	0.141***	0.107***	0.083***
- CL_{EVT}	0.103	0.017	0.066	0.159	0.112	0.169	0.190	0.151	0.038	0.025	0.060	0.131***	0.166***	0.091***
- Patton	0.046	0.001	0.015	0.067	0.066	0.077	0.080	0.088	0.013	0.018	0.003	0.064***	0.062***	0.085***
β	0.613	0.234	0.573	0.959	0.570	0.873	0.935	0.788	0.353	0.325	0.457	0.520***	0.610***	0.331***
β^{-}	0.733	0.273	0.688	1.154	0.842	1.068	1.037	0.916	0.398	0.432	0.566	0.670***	0.604***	0.350***
β^{+}	0.508	0.067	0.501	0.975	0.902	0.708	0.818	0.696	0.309	0.242	0.342	0.399***	0.577***	0.355***
size	12.576	11.160	12.529	13.977	2.024	13.360	13.516	13.172	11.609	11.506	11.974	1.750***	2.010*	1.198**
bookmarket	2.445	0.523	1.444	2.954	8.039	2.317	2.309	2.300	2.591	2.665	2.592	-0.274***	-0.356***	-0.292***
illiq	1.323	0.016	0.159	1.222	3.925	1.128	1.042	1.182	1.500	1.516	1.395	-0.373***	-0.475***	-0.213*
idiovola	0.037	0.018	0.027	0.045	0.031	0.029	0.027	0.031	0.045	0.046	0.041	-0.016***	-0.018***	-0.010***
coskew	-0.141	-0.268	-0.133	-0.007	0.193	-0.205	-0.183	-0.177	-0.076	-0.087	-0.107	-0.129***	-0.096***	-0.070***
cokurt	1.996	0.831	1.850	3.025	1.528	2.875	2.942	2.638	1.119	1.083	1.411	1.756***	1.859***	1.227***
max	17.09%	7.56%	11.78%	19.80%	0.183	12.81%	12.04%	13.51%	18.89%	19.14%	17.50%	-6.08%*	-7.10%**	-3.99%**

As in Ruenzi and Weigert (2013), the first five columns show the corresponding means, standard deviations, interquartile ranges, and medians, while the following nine columns present average values of the variables conditional on LTD being above and below its median to provide a first impression on the relation between crash sensitivity and excess returns as well as other variables included in the asset pricing study. As can be seen from the table, excess returns are characterized by strong variation as indicated by a wide interquartile range of about 50% and a standard deviation of 0.62.[28] Mean excess returns are negative at -9.31% on average, reflecting the fact that our sample encompasses the main part of the recent financial crisis. Turning to the LTD coefficients, we observe that LTD as well exhibits significant variation, irrespective of the specific tail dependence estimator.[29] Interestingly and most importantly for our analysis, LTD varies substantially across the different estimators providing support for the results from our simulations. To be precise, the corresponding mean values range from 0.05 for the Patton model to 0.10 and 0.13 for the CL_{EVT} and $Mix1_{EM}$ model, respectively. Inspection of the interquartile ranges and standard deviations further supports the finding that the less sophisticated the tail dependence model is, the greater is the amount and variation of estimated LTD. While the Patton model is characterized by a relatively tight interquartile range (0.06) and low standard deviation (0.07), the corresponding values for the CL_{EVT} and $Mix1_{EM}$ model are given by 0.14 and 0.11 as well as 0.13 and 0.09, respectively, and thus considerably higher than for the Patton model.

Regarding the second part of the table (columns 6 to 14), we find strong support for the results in Ruenzi and Weigert (2013) and see that, across all three tail dependence estimators, contemporaneous excess returns for high LTD stocks are significantly higher than for low LTD stocks. Averaging across the three estimators, high LTD stocks earn excess returns that are about 14% higher than those of low LTD stocks. Comparing the results for the estimators, we find first evidence against the result in Ruenzi and Weigert

[28]Note that we follow Ruenzi and Weigert (2013) and compute excess returns with respect to the one-month T-bill rate.

[29]Note that, in contrast to Ruenzi and Weigert (2013), we only consider lower tail dependence and exclude upper tail dependence (UTD) from our empirical study since the tail dependence estimators included in the study either imply symmetry in the tails (LTD equals UTD, $Mix1_{EM}$ and Patton model) or are independent in the upper tail (UTD is equal to zero, CL_{EVT} model).

(2013) that the pricing of tail risk is independent of the choice of tail dependence estimation procedure. More precisely, as reported in the last three columns of the table, the difference between the excess returns on high and low LTD stocks varies considerably across the tail dependence estimators, with the more sophisticated estimators implying a smaller (yet still statistically significant) difference. For instance, using the Patton model leads to a difference of about 9%, whereas the CL_{EVT} model implies a difference that is nearly twice as high and amounts to more than 17%.

The remainder of the table refers to summary statistics on other firm characteristics and return patterns that are also employed in Ruenzi and Weigert (2013) and are later used in the portfolio sorts in Section 5.4.2.2 as well as the multivariate analysis in Section 5.4.2.3. Variable definitions conform to those in Ruenzi and Weigert (2013) and can be found in Table D.5 in Appendix D.

To get some idea of the temporal variation in lower tail dependence, Figures 5.4 and 5.5 depict and compare the time series of aggregate LTD for the three tail dependence estimators. Conforming to Ruenzi and Weigert (2013), we define aggregate LTD as the yearly cross-sectional and equal-weighted average LTD over all stocks in our sample. As can be seen from the panels in Figure 5.4, the general patterns in the temporal variation of aggregate LTD are similar across all estimators. Peaking in 1987 (the year of Black Monday), aggregate LTD stayed relatively flat during the 1990s and has been on a strong and stable upward trend since the turn of the millennium.[30] Confirming the above results, the panels show considerable differences in the amount and variation of aggregate LTD across the estimators, with the less sophisticated estimators implying a greater and more volatile amount of tail dependence.

[30]Note that Ruenzi and Weigert (2013) find no specific pattern in aggregate LTD. Their estimates of aggregate LTD are somewhat more erratic and characterized by occasional spikes. This may be due to the differences in data as stated in Section 5.4.1.1. More likely, however, this is a consequence of the shortcomings of their estimation procedure as pointed out in Section 5.4.1.2.

Figure 5.4: Aggregate lower tail dependence over time.

The figure depicts the time evolution of aggregate lower tail dependence (LTD) estimated from the three tail dependence models employed in our empirical study, including the Mix1$_{EM}$, CL$_{EVT}$, and the Patton model. Aggregate LTD is defined as the cross-sectional, equal-weighted average of the individual LTD coefficients computed between stock returns and market returns over all stocks and years in the sample. Our sample encompasses all U.S. common stocks trading on the NYSE, AMEX, and NASDAQ from January 1, 1980 to December 31, 2011.

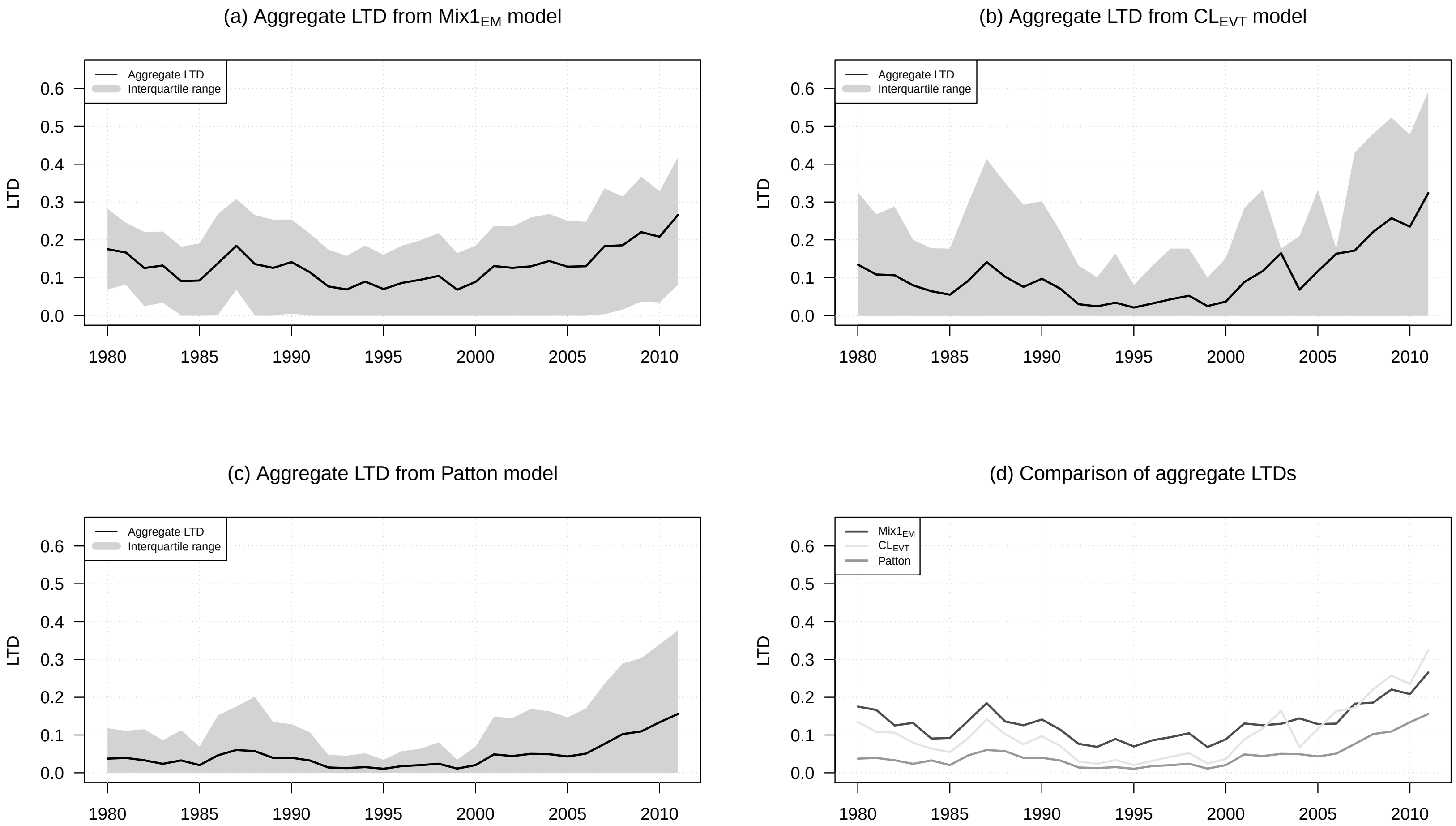
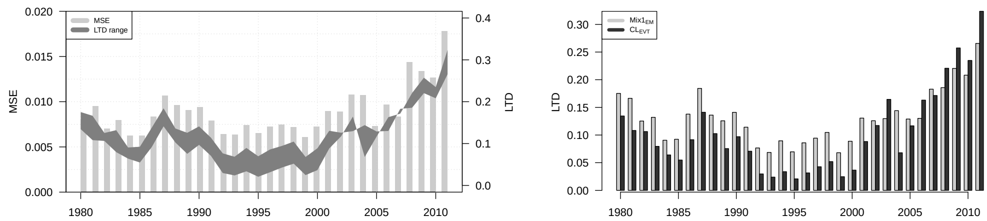


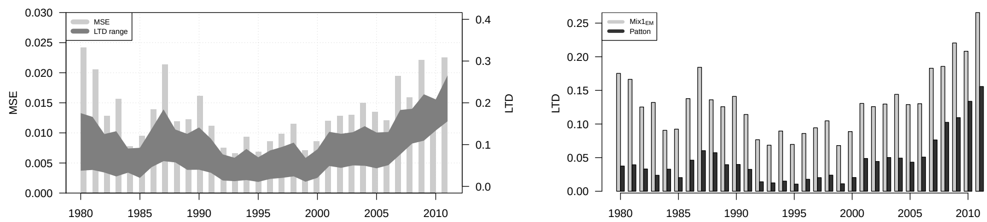
Figure 5.5: Comparing aggregate lower tail dependence across estimators.

The panels of the figure compare the time evolution of aggregate lower tail dependence (LTD) across the LTD estimators included in our empirical study. Aggregate LTD is defined as the cross-sectional, equal-weighted average of the individual LTD coefficients computed between stock returns and market returns over all stocks and years in the sample. The estimators included in our study comprise the Mix1$_{EM}$, CL$_{EVT}$, and the Patton model. The left-hand panels show the range between the aggregate LTD coefficients computed from the different estimators (shaded area) as well as corresponding mean squared errors (MSE, light-gray bars) calculated according to the formula in (5.17) for each stock and year in the sample. The right-hand panels directly compare the amounts of tail dependence over time by means of bar plots. Our sample encompasses all U.S. common stocks trading on the NYSE, AMEX, and NASDAQ from January 1, 1980 to December 31, 2011.

(a) Aggregate LTD: Mix1$_{EM}$ vs. CL$_{EVT}$



(b) Aggregate LTD: Mix1$_{EM}$ vs. Patton



(c) Aggregate LTD: CL$_{EVT}$ vs. Patton

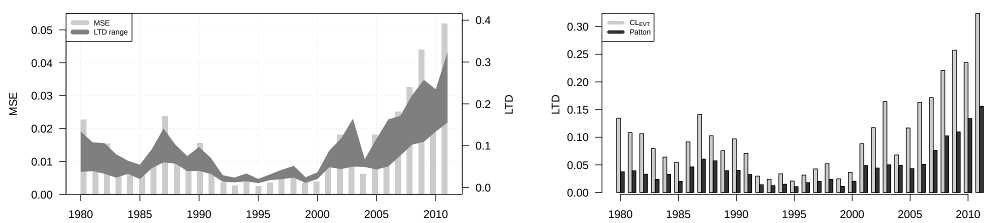


Figure 5.5 investigates the differences in aggregate LTD across the three tail dependence estimators in more detail. As can be seen from the panels, there are considerable differences between the estimates from the Patton model and the two static models, whereas the differences between the estimates from the Mix1_{EM} and CL_{EVT} model are somewhat less pronounced but still significant. In line with the results from our simulations, neglecting intra-year time dynamics appears to have severe consequences for the tail dependence estimates.

5.4.2.2 Portfolio sorts

In this section, we follow Ruenzi and Weigert (2013) and conduct univariate and bivariate portfolio sorts to further examine the initial evidence that the pricing of crash sensitivity depends on the choice of tail dependence estimator and whether this finding is robust with respect to the inclusion of alternative risk measures. The results on univariate portfolio sorts are reported in Table 5.7. As in Ruenzi and Weigert (2013), for each year we sort stocks into five quintile portfolios based on their realized LTD in the same year. The results provide support for the evidence from Table 5.6 and show that the return spread between high and low LTD stocks is statistically significant for all three tail dependence estimators but, at the same time, varies substantially across the different estimators. The first column of the table shows the average LTD in each quintile and reports the difference between the first and fifth quintile LTD in the bottom line. Expectedly, the difference is highest for the CL_{EVT} model (0.28) and lowest for the Patton model (0.16). In the second column, we present annual equal-weighted average excess returns over the risk-free rate for each of the five quintile portfolios, with the difference between high and low LTD portfolios being reported at the bottom. As can be seen from the results, the return spread between portfolio 1 and 5 is highly significant for all estimators, further supporting the results in Ruenzi and Weigert (2013).

Table 5.7: Univariate sorts.

The table presents results from univariate portfolio sorts based on realized lower tail dependence (LTD). In each year, we rank stocks into quintiles (1-5) with respect to realized LTD and form equal-weighted portfolios. As in Ruenzi and Weigert (2013), for each of the five quintile portfolios we calculate average yearly excess stock returns over the one-month T-bill rate (column 1) as well as average yearly alphas with regard to Sharpe's (1964) capital asset pricing model (CAPM-Alpha, column 2), the three-factor model of Fama and French (1993) (FF-Alpha, column 3), and Carhart's (1997) four-factor model (CAR-Alpha, column 4). The last row reports the difference between the returns of the strong and weak LTD quintile portfolios (portfolios 5 and 1) along with corresponding statistical significance levels, where ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Results are presented separately for each of the three tail dependence estimators used in our empirical study, including the $Mix1_{EM}$, CL_{EVT}, and the Patton model. Our sample encompasses all U.S. common stocks trading on the NYSE, AMEX, and NASDAQ from January 1, 1980 to December 31, 2011.

Portfolio	LTD	Return	CAPM-Alpha	FF-Alpha	CAR-Alpha
Panel A: Univariate sorts for $Mix1_{EM}$ model					
1 Weak LTD	0.02	-22.21%	-24.71%	-25.58%	-25.27%
2	0.08	-15.45%	-18.49%	-19.72%	-19.62%
3	0.13	-8.36%	-12.07%	-13.36%	-13.21%
4	0.18	-2.37%	-6.74%	-7.66%	-7.72%
5 Strong LTD	0.25	2.32%	-3.91%	-4.28%	-4.94%
Strong - Weak	0.23***	24.52%***	20.80%***	21.30%***	20.33%***
		(7.29)	(4.22)	(4.31)	(4.06)
Panel B: Univariate sorts for CL_{EVT} model					
1 Weak LTD	0.01	-23.04%	-25.18%	-26.49%	-26.51%
2	0.02	-17.20%	-20.06%	-21.03%	-20.94%
3	0.06	-9.50%	-12.98%	-13.87%	-13.97%
4	0.14	-3.12%	-7.66%	-8.40%	-8.23%
5 Strong LTD	0.29	4.39%	-1.84%	-1.79%	-2.39%
Strong - Weak	0.28***	27.42%***	23.34%***	24.70%***	24.12%***
		(7.57)	(4.33)	(4.83)	(4.60)
Panel C: Univariate sorts for Patton model					
1 Weak LTD	0.00	-17.84%	-20.48%	-21.72%	-21.50%
2	0.00	-10.88%	-14.68%	-15.88%	-15.78%
3	0.02	-9.83%	-13.97%	-14.89%	-14.87%
4	0.05	-4.73%	-8.77%	-9.60%	-9.71%
5 Strong LTD	0.16	0.23%	-5.20%	-5.50%	-5.87%
Strong - Weak	0.16***	18.07%***	15.28%***	16.22%***	15.63%***
		(6.80)	(3.84)	(4.10)	(3.88)

Comparing the return spreads across the different estimators provides additional evidence against the authors' finding that the relation between stock returns and crash sensitivity does not depend on the tail dependence coefficient estimation procedure. To be precise, for the Mix1_{EM} model in Panel A of Table 5.7 the return spread amounts to approximately 24%, while employing the CL_{EVT} (Panel B) and Patton model (Panel C) results in a return spread of about 27% and 18%, respectively, thus indicating that the return spread varies across the estimators and is negatively related to the refinement of the tail dependence model. In light of our simulation study in Section 5.3, we conclude that the overestimation of LTD translates into overestimating the premium investors receive for investing in crash-sensitive (that is, high LTD) stocks. Conforming to the results from our simulations, the overestimation of the premium appears to be greater for less sophisticated tail dependence estimators. Following Ruenzi and Weigert (2013), we additionally conduct univariate portfolio sorts with respect to alphas from the one-factor CAPM (Sharpe, 1964), the three-factor Fama and French (1993), and the four-factor Carhart (1997) model. The remaining columns in Table 5.7 confirm the above findings and show that the alphas are monotonically increasing from the weakest to the strongest LTD quintile portfolios. High LTD alphas are significantly higher than low LTD alphas (irrespective of the estimator) and the spread between the alphas of portfolio 5 and 1 is substantially higher for the Mix1_{EM} (20.80% on average) and CL_{EVT} (24.03%) than for the Patton model (15.70%).

To further investigate the robustness of these results with respect to alternative risk measures, we follow Ruenzi and Weigert (2013) and conduct bivariate portfolio sorts controlling for the impact of one alternative risk measure at a time. More precisely, we double-sort average annual excess returns on realized LTD and realized beta, downside beta, and coskewness.[31] Table 5.8 reports results for the double-sorts on realized LTD and realized regular beta. As in Ruenzi and Weigert (2013), we first form quintile portfolios sorted on beta and, in a second step, then sort stocks into quintiles based on LTD within each of the five beta quintile portfolios.

[31] Descriptive statistics on the alternative risk measures can be found in Table 5.6.

Table 5.8: Dependent portfolio sorts: Lower tail dependence and regular beta.

The table reports average yearly excess stock returns over the one-month T-bill rate double-sorted on realized lower tail dependence (LTD) and realized regular beta (β). First, we form quintile portfolios sorted on beta. Then, within each of the five quintile portfolios, we sort stocks into quintiles based on LTD. Finally, for each of the 25 resulting portfolios, we calculate average yearly excess returns. In the last row, we report the difference between the returns of the strong and weak LTD quintile portfolios (portfolios 5 and 1) for each of the five beta quintiles, where ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Results are presented separately for each of the three tail dependence estimators used in our empirical study, including the Mix1_{EM}, CL_{EVT}, and the Patton model. Our sample encompasses all U.S. common stocks trading on the NYSE, AMEX, and NASDAQ from January 1, 1980 to December 31, 2011.

Portfolio	1 Low β	2	3	4	5 High β	Average
Panel A: Double-sorts for Mix1_{EM} model						
1 Weak LTD	-23.18%	-14.39%	-20.24%	-22.42%	-35.04%	-23.05%
2	-23.19%	-8.64%	-6.27%	-6.52%	-12.27%	-11.38%
3	-20.25%	-4.81%	-5.24%	-0.94%	-5.42%	-7.33%
4	-17.61%	-3.09%	-0.69%	2.02%	-0.68%	-4.01%
5 Strong LTD	-14.40%	0.19%	3.54%	4.35%	5.10%	-0.24%
Strong - Weak	8.78%***	14.57%***	23.78%***	26.77%***	40.14%***	22.81%***
	(3.69)	(3.95)	(5.55)	(7.00)	(6.68)	(7.46)
Panel B: Double-sorts for CL_{EVT} model						
1 Weak LTD	-27.50%	-15.64%	-24.69%	-26.19%	-37.65%	-26.33%
2	-24.52%	-11.09%	-9.89%	-7.70%	-15.21%	-13.68%
3	-22.64%	-6.78%	-3.83%	-1.64%	-6.15%	-8.21%
4	-15.46%	-1.94%	1.58%	4.10%	-0.57%	-2.46%
5 Strong LTD	-12.15%	0.34%	2.88%	5.59%	7.82%	0.90%
Strong - Weak	16.64%***	17.90%***	29.61%***	31.78%***	45.47%***	28.28%***
	(4.20)	(3.95)	(6.04)	(6.53)	(7.18)	(7.57)
Panel C: Double-sorts for Patton model						
1 Weak LTD	-19.93%	-11.00%	-14.30%	-14.83%	-23.67%	-16.75%
2	-19.27%	-5.55%	-6.11%	-5.50%	-11.81%	-9.65%
3	-18.66%	-7.19%	-6.55%	-3.59%	-6.73%	-8.55%
4	-20.47%	-4.32%	-2.37%	0.35%	-4.17%	-6.20%
5 Strong LTD	-16.95%	-1.07%	1.92%	2.08%	2.66%	-2.27%
Strong - Weak	2.98%	9.93%***	16.22%***	16.91%***	26.33%***	14.47%***
	(0.89)	(3.58)	(4.85)	(5.77)	(6.01)	(6.32)

We can draw two main conclusions from the results. First, for all beta quintiles and irrespective of the specific tail dependence estimator, we document a nearly monotonic increase in annual excess returns from the weak to the strong LTD quintile portfolio. The differences between the excess returns on high and low LTD stocks are statistically significant and increase from low to high beta quintile portfolios, thus indicating that the strong relation between LTD and stock returns found in the univariate sorts remains significant after controlling for the impact of realized regular beta and, consequently, is not driven by beta.[32] Second, comparing the results for the different tail dependence estimators, we additionally find that the variation in the excess returns of the LTD quintile portfolios across the three estimators remains significant after controlling for the impact of beta. For each beta quintile portfolio, the return spread between strong and weak LTD stocks is considerably larger for the $\mathrm{Mix1}_{\mathrm{EM}}$ (Panel A) and $\mathrm{CL}_{\mathrm{EVT}}$ (Panel B) than for the Patton model (Panel C). Averaging the return spreads across the beta quintiles for all three estimators, we find that the average return spread is 22.81% for the $\mathrm{Mix1}_{\mathrm{EM}}$ model, 28.28% for the $\mathrm{CL}_{\mathrm{EVT}}$ model, and 14.47% for the Patton model, implying the robustness of our above finding that return spreads are negatively related to the refinement of the tail dependence model and that overestimation of LTD translates into greater crash risk premia.

Furthermore, as pointed out in Harvey and Siddique (2000) and Ang et al. (2006a), downside beta (β^-) and coskewness (*coskew*) are associated with higher expected returns.[33] Hence, to explicitly control for the impact of downside beta and coskewness, we follow Ruenzi and Weigert (2013) and conduct double-sorts on realized LTD and realized downside beta as well as realized coskewness. The results are reported in Tables 5.9 and 5.10 and provide further support for the two conclusions drawn above. As for regular beta, we find that excess returns are monotonically increasing from weak to strong LTD portfolios for all downside beta and coskewness quintiles, irrespective of the tail dependence estimator. At the same time, there is considerable variation in the quintile excess returns across the different estimators. Regarding the differences between the excess returns of strong and weak LTD quintile portfolios, we find that, after controlling for the impact of downside beta (coskewness), average return spreads of the $\mathrm{Mix1}_{\mathrm{EM}}$, $\mathrm{CL}_{\mathrm{EVT}}$, and the Patton model amount to 27.10% (20.89%), 29.14% (23.55%), and 16.83% (13.88%), respectively.

[32]Note that this finding is not valid for the first beta quintile when estimating LTD from the Patton model. In this case, the return spread is positive but statistically insignificant.

[33]We refer to Table D.5 (Appendix D) for corresponding variable definitions.

Table 5.9: Dependent portfolio sorts: Lower tail dependence and downside beta.

The table reports average yearly excess stock returns over the one-month T-bill rate double-sorted on realized lower tail dependence (LTD) and realized downside beta (β^-). First, we form quintile portfolios sorted on downside beta. Then, within each of the five quintile portfolios, we sort stocks into quintiles based on LTD. Finally, for each of the 25 resulting portfolios, we calculate average yearly excess returns. In the last row, we report the difference between the returns of the strong and weak LTD quintile portfolios (portfolios 5 and 1) for each of the five downside beta quintiles, where ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Results are presented separately for each of the three tail dependence estimators used in our empirical study, including the Mix1_{EM}, CL_{EVT}, and the Patton model. Our sample encompasses all U.S. common stocks trading on the NYSE, AMEX, and NASDAQ from January 1, 1980 to December 31, 2011.

Portfolio	1 Low β^-	2	3	4	5 High β^-	Average
Panel A: Double-sorts for Mix1_{EM} model						
1 Weak LTD	-21.84%	-15.04%	-19.45%	-21.84%	-49.82%	-25.60%
2	-18.99%	-7.38%	-6.19%	-8.40%	-22.71%	-12.73%
3	-17.79%	-3.29%	-1.49%	-0.89%	-8.32%	-6.36%
4	-14.53%	-0.10%	2.61%	1.03%	-3.19%	-2.84%
5 Strong LTD	-8.41%	2.26%	4.29%	4.79%	4.59%	1.50%
Strong - Weak	13.43%***	17.30%***	23.74%***	26.63%***	54.41%***	27.10%***
	(5.31)	(5.05)	(6.83)	(6.66)	(8.93)	(8.92)
Panel B: Double-sorts for CL_{EVT} model						
1 Weak LTD	-24.80%	-14.61%	-19.45%	-23.15%	-51.95%	-26.79%
2	-26.41%	-9.69%	-8.33%	-9.89%	-20.85%	-15.03%
3	-15.35%	-2.81%	-2.34%	-3.39%	-12.27%	-7.23%
4	-12.98%	-1.27%	1.75%	2.51%	-2.37%	-2.47%
5 Strong LTD	-11.00%	2.01%	3.44%	3.83%	6.52%	0.96%
Strong - Weak	15.54%***	16.62%***	25.35%***	29.72%***	58.47%***	29.14%***
	(4.15)	(4.69)	(6.89)	(7.12)	(9.78)	(8.80)
Panel C: Double-sorts for Patton model						
1 Weak LTD	-19.07%	-10.11%	-12.66%	-15.01%	-34.49%	-18.27%
2	-14.99%	-4.21%	-3.79%	-7.41%	-20.25%	-10.13%
3	-16.23%	-4.07%	-3.50%	-3.90%	-14.08%	-8.36%
4	-14.84%	-3.69%	-0.73%	0.27%	-6.19%	-5.04%
5 Strong LTD	-12.33%	0.41%	2.22%	2.75%	-0.24%	-1.44%
Strong - Weak	6.74%**	10.52%***	14.88%***	17.77%***	34.25%***	16.83%***
	(2.05)	(3.69)	(4.75)	(5.57)	(7.76)	(7.22)

Table 5.10: Dependent portfolio sorts: Lower tail dependence and coskewness.

The table reports average yearly excess stock returns over the one-month T-bill rate double-sorted on realized lower tail dependence (LTD) and realized coskewness (*coskew*). First, we form quintile portfolios sorted on coskewness. Then, within each of the five quintile portfolios, we sort stocks into quintiles based on LTD. Finally, for each of the 25 resulting portfolios, we calculate average yearly excess returns. In the last row, we report the difference between the returns of the strong and weak LTD quintile portfolios (portfolios 5 and 1) for each of the five coskewness quintiles, where ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Results are presented separately for each of the three tail dependence estimators used in our empirical study, including the Mix1_{EM}, CL_{EVT}, and the Patton model. Our sample encompasses all U.S. common stocks trading on the NYSE, AMEX, and NASDAQ from January 1, 1980 to December 31, 2011.

Portfolio	1 Low *coskew*	2	3	4	5 High *coskew*	Average
Panel A: Double-sorts for Mix1_{EM} model						
1 Weak LTD	-19.32%	-17.49%	-20.94%	-25.06%	-19.43%	-20.45%
2	-8.58%	-10.16%	-14.49%	-17.19%	-14.65%	-13.01%
3	-6.32%	-5.68%	-10.11%	-10.15%	-12.46%	-8.95%
4	-1.43%	-1.93%	-4.12%	-4.78%	-8.20%	-4.09%
5 Strong LTD	4.76%	1.26%	1.40%	-2.88%	-2.32%	0.44%
Strong - Weak	24.08%***	18.74%***	22.33%***	22.18%***	17.11%***	20.89%***
	(7.41)	(6.41)	(7.88)	(5.01)	(4.41)	(7.21)
Panel B: Double-sorts for CL_{EVT} model						
1 Weak LTD	-20.27%	-18.83%	-22.30%	-25.20%	-21.34%	-21.59%
2	-9.43%	-11.46%	-17.84%	-17.42%	-15.71%	-14.37%
3	-6.07%	-7.67%	-9.66%	-12.67%	-14.60%	-10.13%
4	-1.76%	-1.44%	-3.18%	-7.31%	-9.79%	-4.70%
5 Strong LTD	2.63%	0.64%	-0.06%	0.93%	-1.05%	0.62%
Strong - Weak	24.69%***	21.64%***	24.49%***	26.62%***	20.29%***	23.54%***
	(6.98)	(6.53)	(7.56)	(5.22)	(4.79)	(7.15)
Panel C: Double-sorts for Patton model						
1 Weak LTD	-11.09%	-11.63%	-15.19%	-21.06%	-18.06%	-15.41%
2	-9.38%	-9.03%	-11.23%	-14.18%	-14.36%	-11.64%
3	-5.36%	-8.92%	-9.35%	-10.80%	-7.88%	-8.46%
4	-3.70%	-4.33%	-8.12%	-6.63%	-8.72%	-6.30%
5 Strong LTD	0.07%	1.36%	-0.22%	-3.89%	-4.95%	-1.53%
Strong - Weak	11.16%***	12.98%***	14.96%***	17.18%***	13.11%***	13.88%***
	(4.34)	(6.06)	(4.75)	(4.74)	(3.30)	(5.70)

Overall, we find mixed evidence on the results in Ruenzi and Weigert (2013). Supportive of their findings, our univariate and bivariate sortings document that strong LTD stocks earn significantly higher excess returns than weak LTD stocks and that this result holds irrespective of the selected tail dependence estimator and after controlling for the impact of alternative risk measures. In contrast to Ruenzi and Weigert (2013), we find that the amount of crash risk premium is heavily affected by the choice of tail dependence estimator. In view of the results from our simulations in Section 5.3, we conclude that the overestimation of LTD translates into overestimating the premium investors receive for investing in crash-sensitive stocks and that this overestimation is negatively related to the refinement of the tail dependence model. To further investigate the robustness and generality of this result, in the next section we conduct a multivariate analysis to account for the joint impact of additional control variables.

5.4.2.3 Multivariate analysis

Following Ruenzi and Weigert (2013), we run multivariate Fama-MacBeth (1973) regressions on the individual firm-level based on non-overlapping data for the period from 1980 to 2011. We employ the same control variables and regression specifications as in Ruenzi and Weigert (2013) and report the corresponding results separately for each of the three tail dependence estimators in Table 5.11. As can be seen from the panels of the table, our results on the control variables conform to the results in Ruenzi and Weigert (2013) for the most part and are consistent with broadly recognized findings from the existing literature. For instance, irrespective of the selected tail dependence estimator, we find the book-to-market ratio and coskewness to have a positive impact (see, e.g., Fama and French, 1993; Harvey and Siddique, 2000), while idiosyncratic volatility and the past 12-month excess returns have negative coefficients (Ang et al., 2006b, 2009). More importantly, however, we find only slight supportive evidence for the results in Ruenzi and Weigert (2013) with respect to LTD and, in addition, document that the pricing of a stock's crash sensitivity remains heavily affected by the choice of tail dependence estimator in the presence of various return and firm characteristics.

Table 5.11: Multivariate Fama-MacBeth (1973) regressions.

The table reports results from multivariate Fama-MacBeth (1973) regressions of yearly stock-level excess returns over the one-month T-bill rate on various combinations of lower tail dependence (LTD) and further control variables separately for each of the three tail dependence estimators included in our empirical study (Mix1_{EM}, CL_{EVT}, and Patton model). We employ the same regression specifications as in Ruenzi and Weigert (2013) and include the following independent variables: LTD coefficients computed from the Mix1_{EM} (Panel A), CL_{EVT} (Panel B), and the Patton model (Panel C), regular (β) as well as upside (β^+) and downside beta (β^-), market capitalization (size), book-to-market ratio (bookmarket), coskewness (*coskew*), illiquidity (*illiq*), the past 12-month excess returns (past return), idiosyncratic volatility (*idiovola*), cokurtosis (*cokurt*), and the maximum daily return over the last year (*max*). LTD, β^-, β^+, β, *coskew*, *idiovola*, and *cokurt* are calculated contemporaneously to the yearly excess return. Size, bookmarket, and *illiq* for year t are calculated using data from (the end of) year $t-1$. In regressions (6) to (8) we employ the alphas from Sharpe's (1964) capital asset pricing model (capm-alpha), the three-factor model of Fama and French (1993) (ff-alpha), and Carhart's (1997) four-factor model (car-alpha) as the dependent variable. Corresponding definitions for all (in-)dependent variables can be found in Table D.5 in Appendix D. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and the 10% level, respectively. The bottom lines of the table report the economic significance of LTD and the adjusted R^2 of the respective regression. Our sample encompasses all U.S. common stocks trading on the NYSE, AMEX, and NASDAQ from January 1, 1980 to December 31, 2011.

Panel A: Computing LTD from the Mix1_{EM} model								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	return	return	return	return	return	capm-alpha	ff-alpha	car-alpha
LTD	1.0235***		0.5220**	0.2084	0.3389*	0.2466	0.2610	0.2687
	(7.97)		(2.53)	(1.43)	(1.71)	(1.15)	(1.34)	(1.26)
β^-		-0.0395**			0.0513	0.0284	0.0563	0.0525
		(-2.06)			(0.63)	(0.34)	(0.56)	(0.52)
β^+		0.0851***			-0.0152	-0.0082	-0.0139	0.0176
		(5.11)			(-0.26)	(-0.13)	(-0.20)	(0.30)
β			-0.0497	0.0431				
			(-1.12)	(0.55)				
size			-0.0004	-0.0021	-0.0166	-0.0155	-0.0174	-0.0158
			(-0.13)	(-0.50)	(-1.45)	(-1.31)	(-1.43)	(-1.20)
bookmarket			0.0335***	0.0264***	0.0264***	0.0278***	0.0247***	0.0217***
			(4.08)	(3.59)	(3.62)	(3.73)	(3.35)	(2.88)
coskew			0.1170	0.1222	0.3827	0.3348	0.4238	0.3295
			(1.25)	(1.41)	(1.26)	(1.11)	(1.14)	(0.92)
illiq			-0.0300*	-0.0248	0.0093	0.0136	0.0142	0.0155
			(-1.89)	(-1.67)	(0.74)	(1.11)	(1.10)	(1.14)
past return				-0.0469	-0.0718***	-0.0690**	-0.0653**	-0.0849***
				(-1.35)	(-2.77)	(-2.56)	(-2.48)	(-3.39)
idiovola				-6.9824**	-12.0499***	-12.5346***	-12.8052**	-13.5515**
				(-2.24)	(-2.83)	(-2.92)	(-2.65)	(-2.64)
cokurt				-0.0038	-0.0541	-0.0781	-0.0887	-0.1158
				(-0.07)	(-1.03)	(-1.47)	(-1.31)	(-1.69)
max				0.5303	0.6797*	0.6425	0.7238*	0.7288*
				(1.15)	(1.75)	(1.68)	(1.85)	(1.90)
constant	-0.2333***	-0.1078**	-0.0976*	0.1149**	0.1887**	0.1990**	0.1806	0.2121*
	(-4.28)	(-2.70)	(-1.80)	(2.06)	(2.20)	(2.23)	(1.69)	(1.86)
Econ. sign. LTD	0.0870	-	0.0444	0.0177	0.0288	0.0210	0.0222	0.0228
Adj. R^2	0.0264	0.0329	0.1016	0.1487	0.1963	0.2130	0.1620	0.1624

Table 5.11: Multivariate Fama-MacBeth (1973) regressions (continued).

Panel B: Computing LTD from the CL_{EVT} model								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	return	return	return	return	return	capm-alpha	ff-alpha	car-alpha
LTD	0.7546***		0.7242***	0.4556*	0.2955	0.2019	0.3792	0.2851
	(6.29)		(4.33)	(1.81)	(1.42)	(1.10)	(1.69)	(1.61)
β^{-}		-0.0395**			0.0311	0.0046	0.0227	0.0210
		(-2.06)			(0.52)	(0.08)	(0.31)	(0.29)
β^{+}		0.0851***			0.0139	0.0194	0.0226	0.0471
		(5.11)			(0.22)	(0.30)	(0.33)	(0.81)
β			-0.0951**	0.0110				
			(-2.07)	(0.16)				
size			-0.0105	-0.0081	-0.0148**	-0.0130*	-0.0164*	-0.0131
			(-1.67)	(-1.08)	(-2.09)	(-1.84)	(-1.81)	(-1.50)
bookmarket			0.0325***	0.0276***	0.0258***	0.0256***	0.0226***	0.0196**
			(3.65)	(3.79)	(3.41)	(3.15)	(3.05)	(2.39)
coskew			0.0477	0.1356	0.2230	0.1675	0.2037	0.1243
			(0.54)	(1.63)	(0.94)	(0.71)	(0.74)	(0.47)
illiq			-0.0273**	-0.0242	0.0031	0.0064	0.0006	0.0023
			(-2.10)	(-1.57)	(0.23)	(0.50)	(0.05)	(0.18)
past return				-0.0525	-0.0617*	-0.0590*	-0.0697*	-0.0905**
				(-1.51)	(-1.92)	(-1.71)	(-1.89)	(-2.50)
idiovola				-7.4774***	-13.1295***	-13.3992***	-12.6675***	-12.8374***
				(-3.32)	(-5.11)	(-5.53)	(-5.10)	(-4.73)
cokurt				-0.0041	-0.0347	-0.0587	-0.0805	-0.1026*
				(-0.11)	(-0.82)	(-1.33)	(-1.43)	(-1.83)
max				0.5368	0.7174*	0.6666	0.6657	0.6674*
				(1.28)	(1.79)	(1.66)	(1.66)	(1.73)
constant	-0.1653***	-0.1078**	-0.055	0.1325**	0.2145***	0.2270***	0.2331***	0.2331***
	(-3.13)	(-2.70)	(-1.07)	(2.58)	(4.28)	(4.29)	(3.33)	(3.33)
Econ. sign. LTD	0.0845	-	0.0811	0.0510	0.0331	0.0226	0.0425	0.0319
Adj. R^2	0.0225	0.0329	0.1116	0.1868	0.2059	0.2161	0.1798	0.1732

Table 5.11: Multivariate Fama-MacBeth (1973) regressions (continued).

Panel C: Computing LTD from the Patton model								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	return	return	return	return	return	capm-alpha	ff-alpha	car-alpha
LTD	0.8735***		0.2772	-0.1459	0.2657	0.2679	0.5874	0.5517
	(7.01)		(0.83)	(-0.43)	(0.66)	(0.67)	(1.25)	(1.31)
β^-		-0.0395**			0.0934	0.0661	0.0772	0.0710
		(-2.06)			(1.15)	(0.81)	(0.74)	(0.68)
β^+		0.0851***			-0.0544	-0.0463	-0.0749	-0.0551
		(5.11)			(-0.67)	(-0.55)	(-0.72)	(-0.56)
β			-0.0029	0.0737				
			(-0.08)	(1.14)				
size			-0.0004	0.0008	-0.0098	-0.0077	-0.0114	-0.0089
			(-0.10)	(0.13)	(-1.17)	(-0.90)	(-1.06)	(-0.84)
bookmarket			0.0309***	0.0251***	0.0215**	0.0210**	0.0182*	0.0171*
			(3.09)	(3.10)	(2.29)	(2.05)	(1.87)	(1.71)
coskew			0.0387	0.1271	0.3797	0.3010	0.3576	0.2771
			(0.42)	(1.57)	(1.15)	(0.91)	(0.89)	(0.69)
illiq			-0.0362*	-0.0388*	-0.0181	-0.0156	-0.0172	-0.0145
			(-1.99)	(-1.89)	(-1.09)	(-1.05)	(-1.03)	(-0.88)
past return				-0.0681*	-0.0769***	-0.0737**	-0.0618**	-0.0763***
				(-1.90)	(-2.77)	(-2.51)	(-2.16)	(-3.10)
idiovola				-6.4751*	-11.8111***	-12.1595***	-12.7624***	-13.0676***
				(-1.84)	(-3.28)	(-3.37)	(-2.90)	(-2.91)
cokurt				0.0042	-0.0322	-0.0660*	-0.0634	-0.0827*
				(0.08)	(-0.94)	(-2.03)	(-1.54)	(-1.92)
max				0.4445	0.6028	0.5504	0.7293*	0.7134*
				(1.00)	(1.56)	(1.46)	(1.96)	(2.01)
constant	-0.1234**	-0.1078**	-0.0599	0.1186**	0.2261***	0.2410***	0.2262**	0.2508**
	(-2.71)	(-2.70)	(-1.33)	(2.09)	(3.59)	(3.68)	(2.46)	(2.62)
Econ. sign. LTD	0.0577	-	0.0183	-0.0096	0.0175	0.0177	0.0388	0.0364
Adj. R^2	0.0111	0.0329	0.0882	0.1691	0.1872	0.1977	0.1275	0.1157

To be precise, in regression (1) we only include LTD as explanatory variable and confirm our above finding that LTD has a strongly positive and highly significant impact on excess returns for each of the three LTD estimators, with the corresponding coefficients varying from 0.7546 (CL_{EVT} model, Panel B) to 0.8735 (Patton model, Panel C) and 1.0235 ($Mix1_{EM}$ model, Panel A). Including the control variables in regressions (3) to (8), however, drives out most of the significance and results in a positive but statistically insignificant impact of LTD on excess returns and alphas. Regarding the results for the $Mix1_{EM}$ model in Panel A, we can see from the estimated coefficients in regression (3) that including regular beta, firm size, the book-to-market ratio, coskewness, and the Amihud (2002) measure of illiquidity as control variables substantially lowers the coefficient of LTD (and, consequently, its economic significance) as well as its statistical significance. While being around 1.0235 and statistically significant at the 1% level in regression (1), the coefficient is only half as high in regression (3) and significant at the 5% level. Further including the remaining controls in regressions (4) to (8) additionally lowers both economic and statistical significance of the coefficient on LTD and, hence, provides somewhat contradictory evidence that is not in line with the results in Ruenzi and Weigert (2013). As can be seen from Panels B and C, this finding remains valid when computing LTD coefficients from the CL_{EVT} and the Patton model. Regarding the former, we find LTD to have a positive and significant impact on excess returns in regressions (3) and (4), with the corresponding coefficients amounting to 0.7242 and 0.4556, respectively. Replacing regular beta by downside and upside beta (regression (5)) and employing firm-individual yearly alphas estimated from the CAPM (Sharpe, 1964), the Fama and French (1993), and the Carhart (1997) model, respectively, as the dependent variable (regressions (6) to (8)), however, results in positive but insignificant coefficients ranging from 0.2019 to 0.3792. Using the Patton model yet amplifies the contradictory evidence and results in a statistically insignificant impact of LTD in any but the univariate regression specification in (1).[34]

To investigate how the economic impact of LTD on excess returns varies across the

[34] Note that regression (4) in Panel C even yields a negative (but insignificant) coefficient on LTD.

three LTD estimators, the bottom line of the panels in Table 5.11 reports the economic significances for regressions (1) and (3) to (8) for each estimator. As can be seen from the results, the economic significance of LTD varies considerably across the estimators with the less sophisticated estimators implying a greater economic significance of LTD. To be precise, regarding regression (1) the Mix1_{EM} and CL_{EVT} model imply an economic significance of about 8%, while the economic significance resulting from the Patton model is around 5%. That is, a one-standard-deviation increase in LTD results in an increase in excess returns of about 8% for the Mix1_{EM} and CL_{EVT} model and an increase of 5% for the Patton model. Further examining the results, we find that the economic significance of LTD is negatively related to the refinement of the LTD estimator. Thus, the overestimation of the variation and magnitude of LTD by the less sophisticated LTD estimators found in our simulations in Section 5.3 finally translates into overly optimistic estimates of the economic significance of LTD.[35]

Overall, we can draw two conclusions from the results of the Fama-MacBeth (1973) regressions. On the one hand, we find only slight supportive evidence on LTD being a priced factor in the cross-section of stock returns. While being highly significant in the univariate regressions, the impact of LTD becomes less significant when including further control variables and finally vanishes in the full regression specifications. On the other hand, the economic significance of LTD varies considerably across the different LTD estimators indicating that the choice of tail dependence estimator is critical. Thus, we cannot confirm the finding in Ruenzi and Weigert (2013) that the pricing of crash sensitivity is independent of the tail dependence coefficient estimation procedure.

5.5 Conclusion

In this paper, we have demonstrated that several estimators of tail dependence used in the finance literature produce severely biased estimates, especially when static models

[35]Note that Ruenzi and Weigert (2013) find that a one-standard-deviation increase in LTD leads to an increase in the Carhart (1997) four factor alpha of 5.01%. In contrast, our results in Table 5.11 indicate a considerably lower economic significance of 2.28% for the Mix1_{EM}, 3.19% for the CL_{EVT}, and 3.64% for the Patton model.

are used to describe time-varying extreme dependence in data samples. Estimators that do not account for time-varying tail dependence or that are incorrectly used (e.g., using Maximum Likelihood in finite mixture models), and nonparametric estimators regularly overestimate the actual level of tail dependence in simulated samples. Our findings suggest that several key results from the financial economics literature like, e.g., the studies of Okimoto (2008), Kang et al. (2010), Garcia and Tsafack (2011), Ruenzi and Weigert (2013), and Ruenzi et al. (2013) need to be treated with care as the actual extreme dependence in asset prices could be lower than stated in the literature.

We confirm this conjecture from our Monte Carlo experiments in a comprehensive empirical analysis of the factors that drive the cross-sectional variation of U.S. stocks between 1980 and 2011. Several estimators of tail dependence that have been extensively used in the previous literature significantly overestimate the level of lower tail dependence inherent in stock returns. Furthermore, we show that this systematic overestimation of the extreme dependence between the returns on individual stocks and the market index directly translates into asset pricing. Contrary to previous findings in the literature, we find that an individual stock's crash-sensitivity with the market is not a priced factor in the cross-section of stock returns. Even more surprisingly, the statistical and economic significance of a stock's crash-sensitivity in portfolio sorts and multivariate regressions of stock returns critically depends on the choice of tail dependence estimators. Less sophisticated estimators lead to significantly stronger evidence in support of the hypothesis that stocks with strong contemporaneous crash sensitivity outperform stocks with a low crash sensitivity with the market.

The implications of our article for future investigations into the role of extreme dependence in financial economics are simple, yet important. Choosing a static, nonparametric, or statistically incorrectly estimated model for measuring extreme dependence in financial assets invalidates any conclusions drawn from potential applications, e.g., in asset pricing. Economic intuition and previous findings in the literature (even from those studies that later on employ static models) state that extreme dependence in most financial data (stock, bond, option, CDS prices) is time-varying. Consequently, future studies in this field need to account for the time-variation in extreme dependence by using sophisticated dynamic models, of which some have been proposed almost a decade ago.

Appendix A

Supplementary Material for Chapter 2

A.1 Are CDS spreads sensitive to crashes in equity markets?

Although the findings in our main analysis are consistent with the notion of risk-averse CDS investors, we now consider an alternative source of joint crash risk. It could be argued that sellers of credit protection do not price an individual bank's exposure with respect to the CDS market, but rather consider the exposure of the bank to stock market crashes as a determinant of default risk.[1] Hence, in the following we repeat our benchmark regression this time using the lower tail dependence (LTD) coefficient estimated between the respective equity return series and the return on the stock price index.

We define our variable *Equity tail beta* as the equity LTD coefficient and simply calculate the stock price index as the daily equally-weighted average stock return over all 35 banks.[2] Equity tail beta is estimated using the DAC model of Christoffersen et al. (2012). To generate white-noise residuals, we first apply the NGARCH model of Engle and Ng (1993) to the univariate return series assuming that the return innovations follow a skewed t distribution (see Hansen, 1994).[3] In a second step, we then estimate bivariate DAC

[1] This argument is in spirit of the theoretical model of Acharya et al. (2010). They associate systemic risk with an undercapitalization of a bank when the market as a whole is undercapitalized.

[2] Ruenzi and Weigert (2013) refer to stocks with high values of LTD as crash-sensitive stocks.

[3] More precisely, to account for serial correlation in the return series, we apply the NGARCH model to the residuals from autoregressive models of order two, see Christoffersen et al. (2012) for details.

models on the basis of the NGARCH filtered equity return series with each estimation employing the filtered returns on the corresponding bank's equity prices and the price index. Finally, equity tail betas are estimated from the DAC models using numerical integration.

The results given in Columns (1) and (2) of Table A.6 show that our main finding is robust to the additional inclusion of the banks' *Equity tail beta*. In fact, the *Equity tail beta* enters both regressions with an insignificant coefficient.

A.2 Conceptual differences of tail beta and alternative risk measures: A Monte-Carlo simulation study.

This section performs an in-depth analysis of the relation between tail beta as introduced in Section 2.2 and alternative risk measures. For this purpose, we conduct a comprehensive Monte-Carlo simulation study and provide numerical evidence on the conceptual differences between tail beta and regular beta, upside and downside beta, as well as coskewness. Complementing our empirical study in Section 2.3, we show that the differences between tail beta and the alternative risk measures are neither driven by chance nor a purely empirical phenomenon. Moreover, our simulations show that the dependence in the extreme tails of a bivariate distribution, i.e., the propensity of both variables to jointly experience an extreme surge (or crash) is only captured by the tail beta. In contrast, all alternative measures of co-movement that we consider in our robustness do not pick up differences in extreme dependence in these simulations.

The simulation design of our Monte-Carlo study is as follows. First, we specify a bivariate dynamic copula model and simulate $T = 1,000$ independent observations and tail dependence coefficients from the specified copula. In a second step, we then specify the marginal distributions and transform the copula data into a bivariate time series of returns. Finally, we apply the alternative risk measures to the simulated returns. We repeat these steps for a total of $K = 500$ times and compare the averages of the alternative risk measures to average simulated tail dependence coefficients.

More precisely, to illustrate the differences between tail dependence (i.e., tail beta) and regular beta, upside and downside beta, as well as coskewness, we choose to simulate copula data from the tail-dependent t copula and the tail-independent normal copula using the Patton (2006) dynamics to account for time variation in the dependence structure. Formally, tail dependence coefficients for the t copula, $\{\tau_t\}_{t=1}^T$, are simulated according to

$$\tau_t = 2t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho_t}}{\sqrt{1+\rho_t}}\right) \tag{A1}$$

with the correlation dynamics being given by

$$\rho_t = \Lambda\left(\omega + \beta\rho_{t-1} + \alpha\frac{1}{10}\sum_{i=1}^{10} t_\nu^{-1}(u_{1,t-i})t_\nu^{-1}(u_{2,t-i})\right) \tag{A2}$$

where $\Lambda(x) \equiv (1-e^{-x})(1+e^{-x})^{-1}$ is a normalizing function and t_ν^{-1} denotes the quantile function of a standard univariate t distribution.[4]

With $\{u_{1,t}, u_{2,t}\}_{t=1}^T$ denoting the simulated copula data, we then use GARCH(1,1) processes with standard t distributed innovations to specify the marginal densities and to transform the copula data into time series of returns, $\{r_{1,t}, r_{2,t}\}_{t=1}^T$. That is,

$$\begin{aligned} r_{i,t} &= \sqrt{h_{i,t}}z_{i,t}, \quad z_{i,t}|\mathcal{F}_{i,t-1} \sim t_{\nu_i}, \\ h_{i,t} &= c_i + a_i r_{i,t-1}^2 + b_i h_{i,t-1} \end{aligned} \tag{A3}$$

where $\mathcal{F}_{i,t}$ denotes the information available on the ith series up to and including time t, $i = 1, 2$ and $t = 1, ..., T$.

Regular beta (β), upside ($\beta_{q\%}^+$) and downside beta ($\beta_{q\%}^-$), as well as coskewness (*coskew*)

[4]Note that, for the normal copula, we have $\tau_t = 0$ and replace t_ν^{-1} by the quantile function of the standard normal distribution, Φ^{-1}.

are then calculated according to

$$\beta = \frac{\text{cov}(r_{1,t}, r_{2,t})}{\text{var}(r_{2,t})}, \quad \beta^{+}_{q\%} = \frac{\text{cov}(r_{1,t}, r_{2,t} | r_{2,t} > r^{q}_{2,t})}{\text{var}(r_{2,t} | r_{2,t} > r^{q}_{2,t})}, \quad \beta^{-}_{q\%} = \frac{\text{cov}(r_{1,t}, r_{2,t} | r_{2,t} < r^{q}_{2,t})}{\text{var}(r_{2,t} | r_{2,t} < r^{q}_{2,t})} \tag{A4}$$

and

$$\textit{coskew} = \frac{\mathbb{E}[(r_{1,t} - \mu_{1,t})(r_{2,t} - \mu_{2,t})^3]}{\sqrt{\text{var}(r_{1,t})}\text{var}(r_{2,t})^{3/2}} \tag{A5}$$

where $r^{q}_{2,t}$ and $\mu_{i,t}$ denote the qth quantile and average return, respectively.

With $\theta^{c}_{t} = (\omega, \beta, \alpha, \nu)^{\top}$ and $\theta^{c}_{n} = (\omega, \beta, \alpha)^{\top}$ denoting the parameter vectors of the dynamic t and normal copula, respectively, and with $\theta^{m}_{i} = (\nu_i, c_i, a_i, b_i)^{\top}$ being the parameter vectors of the marginal GARCH processes, we specify the dependence structure and the marginals in our simulation study by setting

$$\theta^{c}_{t} = (0.5, 0.9, 0.6, 10)^{\top}, \qquad \theta^{c}_{n} = (0.5, 0.9, 0.6)^{\top} \tag{A6}$$

and

$$\theta^{m}_{1} = (0.0005, 0.1, 0.85, 5)^{\top}, \qquad \theta^{m}_{2} = (0.0001, 0.05, 0.9, 10)^{\top} \tag{A7}$$

The results from our simulation approach are reported in Tables A.7 and A.8 as well as in Figures A.1 and A.2.

The plots given in Figures A.1 and A.2 show several key findings. First, the time evolution, variation, and level of all alternative risk measures do not appear to differ significantly between the tail dependent and tail independent data samples. While their is some variation in these measures across the two samples, it appears that the presence of significant tail dependence is not captured by any of these measures. Second, the time evolution of neither alternative measure exhibits a plot that could be regarded as similar to the plot of the tail dependence for the sample from the t copula. Again, it appears that none of the alternatives is able to capture the level or the time evolution of the tail dependence inherent in the data. Turning to the results reported in Table A.8, we can see that the correlations between all risk measures underline this finding as the correlations between the tail dependence coefficient and any alternative range between just -10.8% and 10.5%. In contrast, the correlations between the alternative risk measures underline the notion that the alternative measures of co-movement are all closely related to each other. Conversely, the plots given in Figure A.2 highlight that all alternative measures exhibit considerable time variation while the tail dependence of the data is constantly zero. Consequently, the differences we find between our tail beta and the competing alternative measures should be due to the conceptual differences in their definitions rather than being a purely empirical phenomenon.

In summary, we find two major conceptual differences between our measure of tail risk and the alternatives used in our robustness checks. First, in contrast to the linear alternative betas that measure the co-movement especially in the middle of the bivariate distribution, our tail beta measures an asymptotic probability of an observation being in the extreme tail of the joint distribution. Second, simulations reveal that all alternatives strongly depend on the distribution of the marginal models as well, whereas the tail beta is a function of the copula only. As a result of this, the alternative betas and coskewness cannot sufficiently describe an increase in the extreme dependence in either credit or equity.

Figure A.1: Simulating from a Student's t copula: Tail dependence and alternative risk measures.

The figure depicts the evolution of average simulated tail dependence coefficients and average values of simulated regular beta, upside, and downside beta, as well as coskewness. First, we specify a bivariate dynamic Student's t copula model and simulate $T = 1,000$ independent observations and tail dependence coefficients from the specified t copula. In a second step, we then specify the marginal distributions via GARCH(1,1) processes with standard t distributed innovations, and transform the copula data into a bivariate time series of returns. Finally, we estimate the alternative risk measures on the basis of the simulated returns by applying the formulas in A4 and A5 to rolling windows of 100 observations. We repeat these steps for a total of $K = 500$ times and plot average simulated tail dependence coefficients as well as the averages of the alternative risk measures. The dynamics of the t copula are captured in A2 and specified by $(0.5, 0.9, 0.6, 10)^\top$. The GARCH(1,1) processes in A3 are specified by $\theta_1^m = (0.0005, 0.1, 0.85, 5)^\top$ and $\theta_2^m = (0.0001, 0.05, 0.9, 10)^\top$.

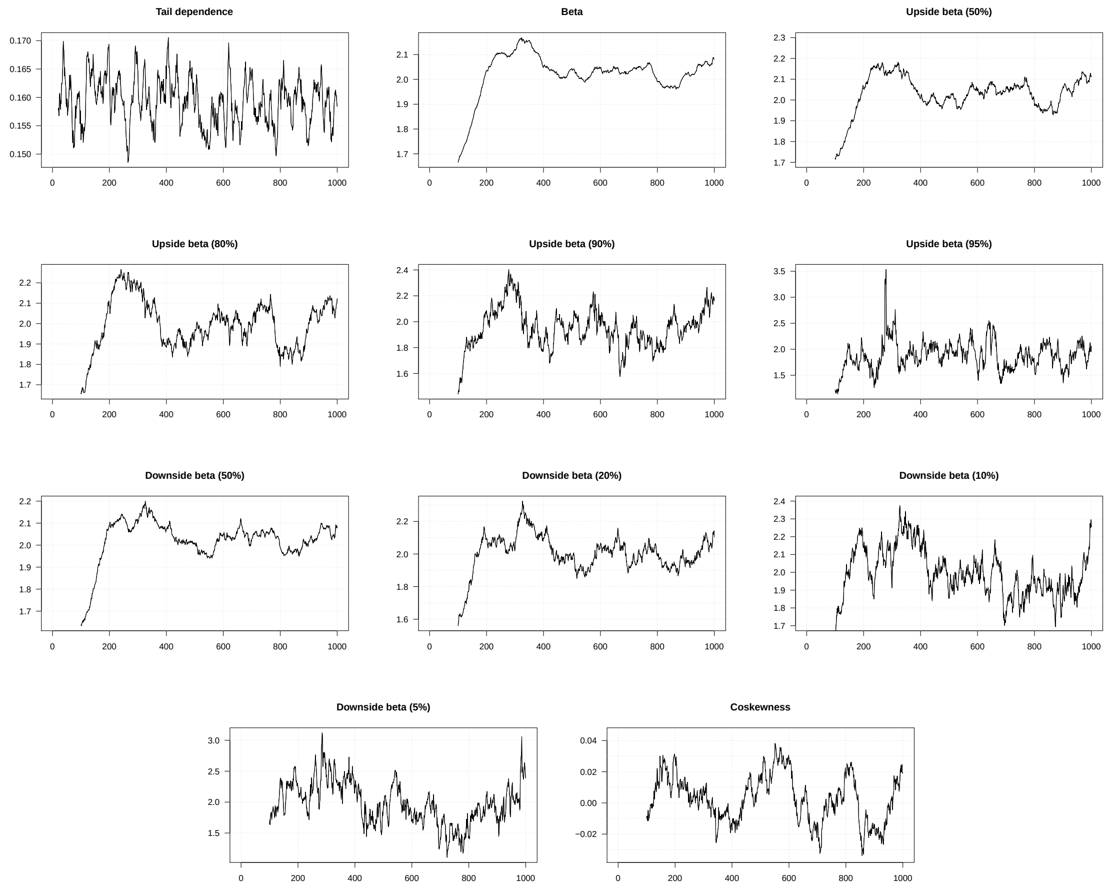


Figure A.2: Simulating from a normal copula: Alternative risk measures.

The figure depicts the evolution of average values of simulated regular beta, upside, and downside beta, as well as coskewness. First, we specify a bivariate dynamic normal copula model and simulate $T = 1,000$ independent observations from the specified normal copula. In a second step, we then specify the marginal distributions via GARCH(1,1) processes with standard t distributed innovations, and transform the copula data into a bivariate time series of returns. Finally, we estimate the alternative risk measures on the basis of the simulated returns by applying the formulas in A4 and A5 to rolling windows of 100 observations. We repeat these steps for a total of $K = 500$ times and plot the averages of the alternative risk measures. The dynamics of the normal copula are specified by $(0.5, 0.9, 0.6)^\top$. The GARCH(1,1) processes in A3 are specified by $\theta_1^m = (0.0005, 0.1, 0.85, 5)^\top$ and $\theta_2^m = (0.0001, 0.05, 0.9, 10)^\top$.

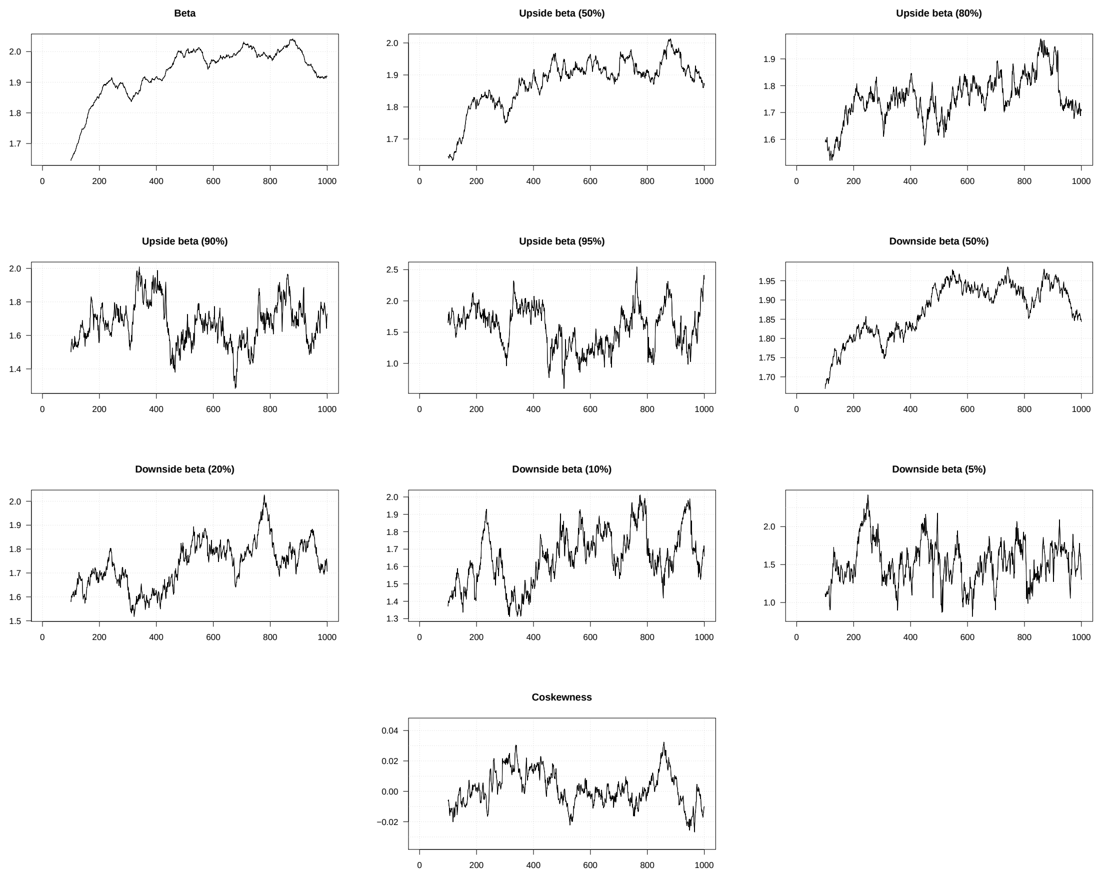


Table A.1: Sample banks.

The table lists all sample banks. Shown are the company name and the ticker symbol as they appear in the *Worldscope* data items WC06001 and WC05601.

Bank	*Ticker symbol*
Allied Irish Banks	AIBSF
Alpha Bank	ALPHA
Banca Italease	BILMI
Banca Monte dei Paschi di Siena	BMDPF
Banca Popolare di Milano	BPMLF
Banca Popolare Italiana	BPI
Banco Bilbao Vizcaya Argentaria	BBVA
Banco Comercial Português	BPCGF
Banco Espírito Santo	BKESF
Banco Pastor	BCPSF
Banco Popular Espanol	BPESF
Banco Português de Investimento	BBPI
Banco Sabadell	SAB
Banco Santander Central Hispano	SAN
Bank of Ireland	IRLBF
Bankinter	BKT
BNP Paribas	BNP
Commerzbank	CBK
Crédit Agricole	ACA
Deutsche Bank	DBK
Dexia Group	DEXB
EFG Eurobank Ergasias	EFG
Erste Group Bank	EBKOF
Fortis	FSVVF
IKB Deutsche Industriebank	IKB
ING Bank	ING
Intesa Sanpaolo	IITSF
Irish Life and Permanent	ILB
KBC Group	KBC
Mediobanca	MDIBF
Natixis	KN
Société Générale	GLE
UBI Banca	UBI
Unibail Holding	UNBLF
Unicredito Italiano	CRIH

Table A.2: Descriptive statistics of equity log returns.

The table presents descriptive statistics on daily equity log returns of the 35 sample banks for the period from January 2004 to October 2010. We report the number of observations, minimum and maximum values, percentiles and moments as well as first order autocorrelations (denoted as AC(1)), where the minimum and maximum of each column is printed in bold type. Except for the number of observations, skewness and (excess) kurtosis, all entries are denominated in %. Company names are abbreviated by their corresponding Bloomberg ticker symbols listed in Table A.1 in Appendix A.

			Percentiles							Moments				
	Obs	Min	1st	5th	20th	80th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.	AC(1)
ACA	1760	-14.35	-7.91	-4.10	-1.48	1.45	3.91	7.90	23.36	-0.02	2.70	0.42	8.20	2.49
AIBSF	1760	-88.24	-15.53	**-6.81**	-1.82	1.37	6.31	16.37	32.87	-0.18	5.09	-2.91	57.22	**23.34**
ALPHA	1760	-12.91	-7.79	-4.50	-1.80	**1.71**	4.16	7.75	13.92	-0.05	2.73	0.01	**2.97**	4.00
BBPI	1760	-11.65	-5.21	-2.96	-1.01	0.95	2.81	5.41	23.02	-0.03	1.95	1.08	16.35	-0.63
BBVA	1760	-13.67	-6.54	-2.97	-1.15	1.08	2.85	5.90	19.91	0.00	2.04	0.43	11.02	8.39
BCPSF	1760	-10.19	-4.72	-2.82	-1.07	0.97	2.71	5.37	12.33	-0.02	1.73	0.36	4.98	2.96
BILMI	1257	-29.02	-12.12	-5.38	**-2.08**	1.68	5.25	10.73	**65.01**	-0.12	4.33	**3.13**	51.74	-2.53
BKESF	1760	-9.59	-5.11	-2.67	**-0.70**	**0.65**	2.26	5.05	12.88	-0.04	1.66	0.45	9.93	10.49
BKT	1760	-8.41	-5.60	-3.42	-1.21	1.10	3.36	5.91	13.54	-0.01	2.09	0.67	5.50	-2.93
BMDPF	1760	-11.79	-4.93	-2.93	-1.14	1.08	2.90	4.85	12.34	-0.04	1.82	-0.05	5.12	6.33
BNP	1760	-18.93	-7.75	-3.47	-1.36	1.30	3.34	7.09	18.98	0.00	2.51	0.47	11.74	-2.44
BPCGF	1760	-13.05	-5.48	-3.24	-1.17	1.03	3.11	5.51	15.43	-0.05	1.98	0.25	5.91	9.20
BPESF	1760	-10.06	-6.19	-3.16	-1.06	0.94	2.71	6.68	18.80	-0.04	2.02	0.76	10.08	7.33
BPI	1760	-17.87	-7.12	-3.68	-1.22	1.19	3.51	7.19	15.52	-0.06	2.45	-0.30	9.15	10.42
BPMLF	1760	-14.55	-5.78	-3.18	-1.36	1.33	3.22	5.73	20.15	-0.02	2.16	0.43	8.80	0.35
CBK	1760	-28.25	-9.16	-4.34	-1.51	1.47	4.25	8.73	19.46	-0.05	3.02	-0.36	12.18	5.00
CRIH	1760	-14.05	-7.86	-3.78	-1.31	1.19	3.44	7.36	19.01	-0.04	2.58	0.21	9.98	0.99
DBK	1760	-18.07	-8.32	-3.76	-1.36	1.30	3.34	7.71	22.31	-0.02	2.59	0.38	12.42	6.38
DEXB	1760	-35.17	-9.57	-4.32	-1.35	1.21	4.00	9.04	28.93	-0.08	3.19	-0.43	22.54	10.06
EBKOF	1760	-20.01	-10.09	-4.46	-1.67	1.66	4.50	10.35	17.03	0.01	3.10	-0.18	7.13	6.87
EFG	1760	-11.12	-7.36	-4.59	-1.79	1.52	4.33	8.22	14.31	-0.05	2.74	0.31	3.24	8.19
FSVVF	1760	**-149.49**	-10.31	-4.58	-1.38	1.32	4.11	11.22	25.89	-0.11	4.84	**-16.80**	**516.56**	4.90
GLE	1760	-16.91	-8.33	-4.06	-1.43	1.44	3.88	8.26	21.43	-0.02	2.69	0.05	8.43	7.71
IITSF	1760	-18.46	-7.56	-3.29	-1.21	1.29	3.05	6.13	17.96	-0.01	2.31	-0.11	12.15	4.68
IKB	1760	-27.27	-10.66	-4.88	-1.55	1.15	3.81	9.42	49.27	**-0.19**	3.60	2.09	37.19	**-7.70**
ILB	1760	-69.31	-14.79	-6.20	-1.81	1.65	6.63	12.99	36.77	-0.13	5.01	-2.14	35.34	11.55
ING	1760	-32.14	-11.54	-4.54	-1.43	1.38	4.15	9.75	25.65	-0.04	3.38	0.04	16.86	3.49
IRLBF	1760	-79.31	**-15.69**	-6.55	-1.99	1.46	**7.04**	**17.74**	39.27	-0.14	**5.36**	-1.35	36.99	5.39
KBC	1760	-28.66	-13.10	-4.90	-1.36	1.48	4.38	12.25	40.48	-0.01	3.70	-0.12	20.95	11.23
KN	1760	-19.22	-10.79	-4.92	-1.49	1.48	4.62	10.45	32.79	-0.02	3.32	0.70	13.58	6.13
MDIBF	1760	-10.04	-4.67	-2.51	-1.03	1.00	2.61	4.52	15.33	-0.01	1.67	0.38	7.12	2.95
SAB	1760	**-7.95**	**-4.33**	**-2.31**	-0.92	0.84	**2.14**	**3.99**	16.78	0.00	**1.50**	0.81	12.54	4.13
SAN	1760	-12.72	-7.00	-3.09	-1.09	1.15	2.97	5.93	20.88	0.00	2.14	0.46	11.70	1.35
UBI	1760	-13.14	-5.80	-2.81	-1.01	0.99	2.43	5.55	11.51	-0.04	1.79	-0.05	7.22	-2.44
UNBLF	1760	-18.36	-5.10	-3.08	-1.12	1.27	2.91	5.38	**8.81**	**0.04**	1.89	-0.56	7.00	-3.33
Average	1746	-26.11	-8.28	-3.95	-1.36	1.26	3.74	8.07	22.91	-0.05	2.79	-0.33	29.42	4.69

Table A.3: Variable definitions and data sources

The table presents definitions as well as data sources for all dependent and independent variables that are used in the empirical study. The bank CDS and equity data are taken from *Credit Market Analysis* (CMA) and the *Thomson Reuters Datastream* (DS) database. The country control variables are taken from *Datastream* and from the *OECD statistics Database* (OECD). EST indicates that the variable is estimated or computed based on data from the respective data source(s).

Variable name	*Definition*	*Data source*
CDS spreads	Daily end-of-quarter CDS spreads, denoted in basis points and obtained from *Credit Market Analysis (CMA).*	CMA, DS
Volatility	End-of-quarter VSTOXX implied volatility index values.	DS
Risk-free interest rate	1-year Euro interest rate swap ISDA mid-market rate, denoted in per cent.	ISDA, DS
CDS tail beta	End-of-Quarter upper tail dependence (UTD) coefficients estimated between the log differences of the banks' CDS spreads and the log differences of the spread index. UTD coefficients are computed from the Dynamic Asymmetric Copula (DAC) model as proposed in Christoffersen et al. (2012). UTD time series are filtered using a simple moving average including a lag of the past 20 trading days.	DS, EST
Firm value	Quarterly arithmetic bank stock returns denoted in per cent.	DS, EST
Business climate	End-of-quarter values of the S&P 500 index.	DS, EST
GDP growth	Country-level GDP growth rates in comparison to previous quarter, denoted in per cent.	OECD
Slope	A country's respective 10-year minus 2-year government bond benchmark yields.	DS
Beta	Realized regular beta calculated on the basis of daily log differences of CDS spreads from rolling windows of 100 data points according to the definition $\beta := \frac{\text{cov}(R_{i,t}, R_{m,t})}{\text{var}(R_{m,t})}$.	DS, EST
Upside beta (median, 80%, 90%, 95%)	Realized upside beta defined as regular beta conditional on the log differences of the CDS index being above its median (50% quantile) and its 80%, 90%, and 95% quantiles, where the computation is based on daily log differences of CDS spreads and implemented via rolling windows of 100 data points. With $r^q_{m,t}$ denoting the respective quantile of the log-differenced spreads, the formal definition is given by $\beta_{q\%} := \frac{\text{cov}(R_{i,t}, R_{m,t} \mid R_{m,t} > R^q_{m,t})}{\text{var}(R_{m,t} \mid R_{m,t} > R^q_{m,t})}$.	DS, EST
Coskewness	Realized coskewness based on daily log differences of CDS spreads and computed from rolling windows of 100 data points according to Coskewness$=\frac{\mathbb{E}[(R_{i,t}-\mu_{i,t})(R_{m,t}-\mu_{m,t})^3]}{\sqrt{\text{var}(R_{i,t})}\text{var}(R_{m,t})^{3/2}}$.	DS, EST
MES	Marginal Expected Shortfall calculated from alternative models including the static MES according to Acharya et al. (2010) as well as various dynamic model specifications proposed in Brownlees and Engle (2012). Static MES is computed non-parametrically from rolling windows of 100 data points, and the dynamic MES models include the VCT model, the Dynamic Conditional Beta model as well as the Dynamic Conditional Copula model that is based on Patton's (2006) dynamic t-copula (see Brownlees and Engle, 2012, for details).	DS, EST
Equity tail beta	End-of-Quarter lower tail dependence (LTD) coefficients estimated between the banks' equity return series and the returns on the stock price index. LTD coefficients are computed from the Dynamic Asymmetric Copula (DAC) model as proposed in Christoffersen et al. (2012). LTD time series are filtered using a simple moving average including a lag of the past 20 trading days.	DS, EST

Table A.4: Panel benchmark regressions (bid-quotes)

The table reports results from bank-fixed effects regressions in first differences of quarterly CDS bid-spreads on *CDS tail beta* and further control variables. We estimate the following regression model:

$$\Delta\text{CDS}_{i,t} = \alpha + \beta_1 \cdot \Delta\text{Firm value}_{i,t} + \beta_2 \cdot \Delta\text{Interest rate}_{i,t} + \beta_3 \cdot \Delta\text{Volatility}_{i,t} + \gamma \cdot \Delta\text{CDS tail beta}_{i,t} + \delta \cdot \Delta X_{i,t} + \epsilon_{i,t}$$

where $X_{i,t}$ denotes the set of further control variables: *Business climate*, *GDP growth*, and the *slope of the yield curve*. Column (1) reports results for the regression using the variables suggested by theory. In Column (2), we assess the isolated explanatory power of the coefficient on *CDS tail beta*. Column (3) denotes our baseline regression. Columns (4) to (6) report estimation results when including further relevant controls. Bank-fixed effects are included in all regressions. Corresponding t-statistics are reported in parentheses. Standard errors are clustered at the bank level and adjusted for heteroskedasticity. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. All variables and data sources are defined in Table A.3 in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔFirm value	-0.124		-0.135	-0.118	-0.118	-0.101
	(1.56)		(1.68)	(1.49)	(1.49)	(1.23)
ΔInterest rate	0.924		-0.748	9.421	9.785	7.508
	(0.17)		(0.13)	(1.92)*	(1.96)*	(0.89)
ΔVolatility	6.921		6.831	5.633	5.631	5.63
	(8.86)***		(9.00)***	(6.98)***	(7.03)***	(7.05)***
ΔCDS tail beta		1.725	1.501	1.329	1.263	1.282
		(2.96)***	(3.85)***	(3.40)***	(3.24)***	(3.20)***
ΔBusiness climate				-0.133	-0.14	-0.14
				(3.30)***	(3.26)***	(3.20)***
ΔGDP growth					2.121	1.948
					(1.19)	(1.07)
ΔSlope						-6.251
						(0.36)
Constant	9.537	9.299	8.224	8.927	9.013	8.906
	(30.47)***	(22.21)***	(17.75)***	(19.43)***	(18.64)***	(15.00)***
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.24	0.01	0.25	0.26	0.26	0.26
Obs	868	865	865	865	865	865

Table A.5: Panel benchmark regressions (ask-quotes)

The table reports results from bank-fixed effects regressions in first differences of quarterly CDS ask-spreads on *CDS tail beta* and further control variables. We estimate the following regression model:

$$\Delta\text{CDS}_{i,t} = \alpha + \beta_1 \cdot \Delta\text{Firm value}_{i,t} + \beta_2 \cdot \Delta\text{Interest rate}_{i,t} + \beta_3 \cdot \Delta\text{Volatility}_{i,t} + \gamma \cdot \Delta\text{CDS tail beta}_{i,t} + \delta \cdot \Delta X_{i,t} + \epsilon_{i,t}$$

where $X_{i,t}$ denotes the set of further control variables: *Business climate*, *GDP growth*, and the *slope of the yield curve*. Column (1) reports results for the regression using the variables suggested by theory. In Column (2), we assess the isolated explanatory power of the coefficient on *CDS tail beta*. Column (3) denotes our baseline regression. Columns (4) to (6) report estimation results when including further relevant controls. Bank-fixed effects are included in all regressions. Corresponding t-statistics are reported in parentheses. Standard errors are clustered at the bank level and adjusted for heteroskedasticity. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. All variables and data sources are defined in Table A.3 in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔFirm value	-0.135		-0.145	-0.127	-0.126	-0.106
	(2.01)*		(2.10)**	(1.86)*	(1.86)*	(1.43)
ΔInterest rate	0.578		-0.832	10.205	10.42	7.627
	(0.12)		(0.17)	(2.48)**	(2.46)**	(0.99)
ΔVolatility	6.24		6.162	4.862	4.861	4.86
	(9.10)***		(9.22)***	(7.17)***	(7.20)***	(7.25)***
ΔCDS tail beta		1.432	1.237	1.05	1.011	1.035
		(2.75)***	(3.62)***	(3.10)***	(2.98)***	(2.95)***
ΔBusiness climate				-0.144	-0.148	-0.148
				(3.73)***	(3.61)***	(3.54)***
ΔGDP growth					1.256	1.044
					(0.69)	(0.56)
ΔSlope						-7.668
						(0.47)
Constant	9.173	9.041	8.063	8.826	8.877	8.746
	(33.06)***	(24.21)***	(20.73)***	(23.78)***	(22.09)***	(16.58)***
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.24	0.01	0.25	0.26	0.26	0.26
Obs	868	865	865	865	865	865

Table A.6: Are CDS spreads sensitive to crashes in equity markets?

The table reports results from bank-fixed effects regressions in first differences of quarterly CDS mid-spreads on *CDS tail beta*, *Equity tail beta*, and further control variables.

$$\Delta \text{CDS}_{i,t} = \alpha + \beta_1 \cdot \Delta \text{Merton-type}_{i,t} + \gamma \cdot \Delta \text{CDS tail beta}_{i,t} + \gamma \cdot \Delta \text{Equity tail beta}_{i,t} + \delta \cdot \Delta X_{i,t} + \epsilon_{i,t}$$

Firm value, interest rate and volatility are the Merton-type control variables. Column (1) reports results form our benchmark regression, this time including an equity-based measure of tail risk: *Equity tail beta*. In Column (2), we include both *CDS* and *Equity tail beta* as well as further controls denoted by $X_{i,t}$. Bank-fixed effects are included in all regressions. Corresponding t-statistics are reported in parentheses. Standard errors are clustered at the bank level and adjusted for heteroskedasticity. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. All variables and data sources are defined in Table A.3 in Appendix A.

	(1)	(2)
Δ Firm value	-0.095	-0.105
	(1.22	(1.33)
ΔInterest rate	10.499	8.36
	(1.29)	(1.02)
ΔVolatility	5.574	5.588
	(7.29)***	(7.45)***
ΔCDS tail beta		1.221
		(3.25)***
ΔEquity tail beta	-0.541	-0.588
	(1.48)	(1.64)
ΔBusiness climate	-0.144	-0.135
	(3.85)***	(3.36)***
ΔGDP growth	2.483	1.995
	(1.40)	(1.05)
ΔSlope	-4.815	-5.203
	(0.28)	(0.30)
Constant	10.09	8.95
	(24.37)***	(15.53)***
Adj. R^2	0.25	0.26
Avg. obs	868	865

Table A.7: Summary statistics of risk measures estimated from simulated data.

The table reports summary statistics on simulated tail dependence, regular beta, upside and downside beta, as well as coskewness. The simulation approach is conducted as follows. First, we specify a bivariate dynamic t and normal copula model and simulate $T = 1,000$ independent observations and tail dependence coefficients from the specified copulas. In a second step, we then specify the marginal distributions via GARCH(1,1) processes with standard t distributed innovations, and transform the copula data into a bivariate time series of returns. Finally, we estimate the alternative risk measures on the basis of the simulated returns by applying the formulas in A4 and A5 to rolling windows of 100 observations. We repeat these steps for a total of $K = 500$ times and present summary statistics on simulated tail dependence coefficients and alternative risk measures across the simulation replications. The dynamics of the t and normal copula are specified by $(0.5, 0.9, 0.6, 10)^\top$ and $(0.5, 0.9, 0.6)^\top$, respectively. The GARCH(1,1) processes in A3 are specified by $\theta_1^m = (0.0005, 0.1, 0.85, 5)^\top$ and $\theta_2^m = (0.0001, 0.05, 0.9, 10)^\top$.

	Percentiles						
	5th	25th	Median	75th	95th	Mean	St. Dev.
Panel A: Simulation from t copula							
τ	0.054	0.095	0.137	0.199	0.336	0.159	0.092
β	0.798	1.258	1.687	2.357	4.261	2.023	1.451
$\beta^+_{50\%}$	0.501	1.133	1.678	2.453	4.632	2.030	1.724
$\beta^+_{80\%}$	-0.334	0.803	1.617	2.720	5.546	1.997	2.142
$\beta^+_{90\%}$	-1.763	0.398	1.579	3.104	6.921	1.951	3.298
$\beta^+_{95\%}$	-5.587	-0.411	1.530	3.841	10.585	1.883	7.220
$\beta^-_{50\%}$	0.500	1.122	1.680	2.469	4.629	2.023	1.670
$\beta^-_{20\%}$	-0.382	0.773	1.610	2.774	5.580	2.005	2.242
$\beta^-_{10\%}$	-1.781	0.343	1.557	3.191	7.195	1.999	3.251
$\beta^-_{5\%}$	-5.545	-0.386	1.505	3.999	10.766	1.984	6.387
coskew	-0.565	-0.193	0.003	0.198	0.577	0.003	0.378
Panel B: Simulation from normal copula							
τ	0.000	0.000	0.000	0.000	0.000	0.000	0.000
β	0.756	1.152	1.570	2.221	4.206	1.935	1.493
$\beta^+_{50\%}$	0.438	0.975	1.486	2.257	4.474	1.878	1.694
$\beta^+_{80\%}$	-0.421	0.584	1.322	2.369	5.293	1.755	2.260
$\beta^+_{90\%}$	-1.904	0.151	1.177	2.646	6.763	1.673	3.530
$\beta^+_{95\%}$	-5.910	-0.587	1.076	3.377	10.143	1.569	7.210
$\beta^-_{50\%}$	0.456	0.977	1.481	2.252	4.472	1.876	1.666
$\beta^-_{20\%}$	-0.398	0.580	1.291	2.358	5.196	1.736	2.187
$\beta^-_{10\%}$	-1.882	0.115	1.157	2.643	6.734	1.653	3.396
$\beta^-_{5\%}$	-5.607	-0.647	1.006	3.249	10.186	1.528	6.870
coskew	-0.495	-0.171	0.000	0.174	0.506	0.002	0.331

Table A.8: Correlations of risk measures estimated from simulated data.

The table reports correlations between simulated tail dependence, regular beta, upside and downside beta, as well as coskewness. The simulation approach is conducted as follows. First, we specify a bivariate dynamic t and normal copula model and simulate $T = 1,000$ independent observations and tail dependence coefficients from the specified copulas. In a second step, we then specify the marginal distributions via GARCH(1,1) processes with standard t distributed innovations, and transform the copula data into a bivariate time series of returns. Finally, we estimate the alternative risk measures on the basis of the simulated returns by applying the formulas in A4 and A5 to rolling windows of 100 observations. We repeat these steps for a total of $K = 500$ times and present the correlations of simulated tail dependence coefficients and alternative risk measures across the simulation replications. The dynamics of the t and normal copula are specified by $(0.5, 0.9, 0.6, 10)^\top$ and $(0.5, 0.9, 0.6)^\top$, respectively. The GARCH(1,1) processes in A3 are specified by $\theta_1^m = (0.0005, 0.1, 0.85, 5)^\top$ and $\theta_2^m = (0.0001, 0.05, 0.9, 10)^\top$.

	τ	β	$\beta^+_{50\%}$	$\beta^+_{80\%}$	$\beta^+_{90\%}$	$\beta^+_{95\%}$	$\beta^-_{50\%}$	$\beta^-_{20\%}$	$\beta^-_{10\%}$	$\beta^-_{5\%}$	*coskew*
Panel A: Simulation from t copula											
τ	**1.000**										
β	-0.077	**1.000**									
$\beta^+_{50\%}$	-0.108	0.940	**1.000**								
$\beta^+_{80\%}$	-0.092	0.752	0.900	**1.000**							
$\beta^+_{90\%}$	-0.008	0.544	0.641	0.732	**1.000**						
$\beta^+_{95\%}$	-0.084	0.308	0.266	0.234	0.454	**1.000**					
$\beta^-_{50\%}$	-0.006	0.966	0.922	0.736	0.490	0.273	**1.000**				
$\beta^-_{20\%}$	0.074	0.853	0.794	0.606	0.375	0.237	0.903	**1.000**			
$\beta^-_{10\%}$	0.105	0.457	0.385	0.306	0.286	0.199	0.482	0.709	**1.000**		
$\beta^-_{5\%}$	0.103	0.223	0.213	0.268	0.383	0.219	0.210	0.364	0.677	**1.000**	
coskew	-0.076	-0.106	-0.051	0.078	0.233	0.168	-0.158	-0.071	0.143	0.103	**1.000**
Panel B: Simulation from normal copula											
τ	-										
β	-	**1.000**									
$\beta^+_{50\%}$	-	0.946	**1.000**								
$\beta^+_{80\%}$	-	0.680	0.705	**1.000**							
$\beta^+_{90\%}$	-	-0.049	0.029	0.396	**1.000**						
$\beta^+_{95\%}$	-	-0.243	-0.165	0.134	0.505	**1.000**					
$\beta^-_{50\%}$	-	0.929	0.910	0.571	-0.156	-0.304	**1.000**				
$\beta^-_{20\%}$	-	0.609	0.554	0.357	-0.216	-0.264	0.757	**1.000**			
$\beta^-_{10\%}$	-	0.551	0.506	0.214	-0.304	-0.296	0.673	0.824	**1.000**		
$\beta^-_{5\%}$	-	0.130	0.091	0.026	-0.106	0.058	0.094	0.174	0.397	**1.000**	
coskew	-	0.065	0.085	0.355	0.496	0.200	-0.153	-0.439	-0.446	-0.029	**1.000**

Appendix B

Supplementary Material for Chapter 3

Table B.1: Variable definitions and data sources.

The table presents definitions and data sources for all dependent and independent variables that are used in our empirical study. The data sources are *Credit Market Analysis* (CMA) and *Thomson Reuters Datastream* (DS). EST indicates that the variable is estimated or computed based on data from the respective data source(s). Our sample encompasses 228 financial and non-financial companies for the period from January 2004 to September 2010.

Variable	Definition	Source
CDS	End-of-quarter CDS mid quote, denoted in basis points (bps).	CMA
Firm value	Quarterly arithmetic stock return, denoted in %.	DS, EST
Interest rate	End-of-quarter two-year U.S. Treasury Benchmark yield, measured in %.	DS
Volatility	Annualized quarterly stock return volatility, denoted in %.	DS, EST
BAS_{abs}	End-of-quarter absolute bid-ask spread, calculated as daily ask minus bid price and denoted in bps.	CMA
R^2_{liq}	Measure of commonality in CDS liquidity, calculated as the R^2 from quarterly regressions of firm-level liquidity innovations on innovations in market-wide liquidity. Details on the computation can be found in Section 3.2.3.2 and Karolyi et al. (2012). The R^2 is reported in %.	CMA, EST
UDF	Updating frequency, defined as the sum of zero spread changes over the number of quoted spreads per quarter. A value of one (zero) indicates a perfectly illiquid (liquid) market. Corresponding values are reported in %.	CMA, EST
BAS^I_{abs}	Cross-sectional average of absolute bid-ask spreads of all firms within an industry. ICB supersector industry classifications are obtained from DS. Averages are calculated excluding the current firm and are reported in bps.	CMA, EST
BAS^M_{abs}	Cross-sectional average of relative bid-ask spreads of all sample firms. Averages are calculated excluding the current firm and are reported in bps.	CMA, EST
VIX	Quarterly values of the option-implied volatility index.	DS
Assets	Natural logarithm of quarterly total assets.	DS
S&P500	Quarterly values of the S&P500 index.	DS
Book leverage	Quarterly book leverage, calculated as total debt over the sum of total debt and market capitalization.	DS, EST

Table B.2: Descriptive statistics.

The table presents summary statistics for all dependent and independent variables that are used in our empirical study. We report the mean, standard deviation, minimum, maximum, and the number of observations. We define the CDS mid quote (CDS) as our dependent variable. As independent variables, we include credit risk and liquidity variables as well as additional controls. Concerning the former, we include the firm value, interest rate, and volatility. Regarding the liquidity variables, we consider the individual absolute bid-ask spread (BAS_{abs}), our measure of commonality in CDS liquidity (R^2_{liq}), the updating frequency (UDF), as well as the industry-specific ($\text{BAS}^{\text{I}}_{\text{abs}}$) and market-wide absolute bid-ask spread ($\text{BAS}^{\text{M}}_{\text{abs}}$). As additional control variables, we include the option-implied volatility index (VIX), the logarithm of quarterly total assets (Assets), values of the S&P500 index (S&P500), and book leverage. The credit risk and liquidity variables are discussed in detail in Section 3.2. Variable definitions and data sources are reported in Table B.1 in Appendix B. Our sample encompasses 228 financial and non-financial companies for the period from January 2004 to September 2010.

Variable	Mean	St. Dev.	Min.	Max.	Obs.
CDS	152.7	319.1	1.1	6158.6	6156
Firm value	2.2	21.4	-87.4	319.4	6119
Interest rate	2.8	1.6	0.4	5.2	6156
Volatility	4.3	3.4	0.8	38.6	6121
BAS_{abs}	11.1	22.0	0.0	608.0	6156
R^2_{liq}	7.1	7.5	0.0	74.3	6084
UDF	15.0	18.4	0.0	100.0	6156
$\text{BAS}^{\text{I}}_{\text{abs}}$	11.1	11.4	1.0	159.0	6129
$\text{BAS}^{\text{M}}_{\text{abs}}$	11.1	7.0	4.9	31.7	6156
VIX	20.4	9.4	11.4	44.1	6156
Assets	15.3	1.0	12.3	18.8	5084
S&P500	1206.8	175.4	797.9	1526.8	6156
Book leverage	0.3	0.2	0.0	1.0	6136

Table B.3: Pairwise correlations.

The table reports pairwise linear correlations between the variables used in our regression analyses. We define the CDS mid quote (CDS) as our dependent variable. As independent variables, we include credit risk and liquidity variables as well as additional controls. Concerning the former, we include the firm value, interest rate, and volatility. Regarding the liquidity variables, we consider the individual absolute bid-ask spread ($\mathrm{BAS}_{\mathrm{abs}}$), our measure of commonality in CDS liquidity ($\mathrm{R}^2_{\mathrm{liq}}$), the updating frequency (UDF), as well as the industry-specific ($\mathrm{BAS}^{\mathrm{I}}_{\mathrm{abs}}$) and market-wide absolute bid-ask spread ($\mathrm{BAS}^{\mathrm{M}}_{\mathrm{abs}}$). As additional control variables, we include the option-implied volatility index (VIX), the logarithm of quarterly total assets (Assets), values of the S&P500 index (S&P500), and book leverage. The credit risk and liquidity variables are discussed in detail in Section 3.2. Variable definitions, data sources, and summary statistics are reported in Tables B.1 and B.2 in Appendix B. Our sample encompasses 228 financial and non-financial companies for the period from January 2004 to September 2010.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	ΔCDS	**1.00**	-	-	-	-	-	-	-	-	-	-	-	-
(2)	ΔFirm value	-0.29	**1.00**	-	-	-	-	-	-	-	-	-	-	-
(3)	ΔInterest rate	-0.16	0.10	**1.00**	-	-	-	-	-	-	-	-	-	-
(4)	ΔVolatility	0.35	-0.21	-0.37	**1.00**	-	-	-	-	-	-	-	-	-
(5)	$\Delta\mathrm{BAS}_{\mathrm{abs}}$	0.52	-0.18	-0.10	0.21	**1.00**	-	-	-	-	-	-	-	-
(6)	$\Delta\mathrm{R}^2_{\mathrm{liq}}$	0.02	-0.12	-0.04	0.12	0.06	**1.00**	-	-	-	-	-	-	-
(7)	ΔUDF	-0.00	-0.03	-0.01	0.07	0.01	0.01	**1.00**	-	-	-	-	-	-
(8)	$\Delta\mathrm{BAS}^{\mathrm{I}}_{\mathrm{abs}}$	0.19	-0.13	-0.22	0.29	0.14	0.05	0.01	**1.00**	-	-	-	-	-
(9)	$\Delta\mathrm{BAS}^{\mathrm{M}}_{\mathrm{abs}}$	0.30	-0.30	-0.53	0.63	0.15	0.12	0.05	0.40	**1.00**	-	-	-	-
(10)	ΔVIX	0.21	-0.28	-0.33	0.32	0.12	0.36	0.00	0.27	0.66	1.00	-	-	-
(11)	ΔAssets	-0.03	0.02	0.08	-0.03	-0.01	0.00	-0.01	-0.03	-0.05	-0.03	**1.00**	-	-
(12)	ΔS&P500	-0.28	0.25	0.48	-0.47	-0.14	-0.14	0.02	-0.32	-0.78	-0.60	0.03	**1.00**	-
(13)	ΔBook leverage	0.04	-0.03	-0.24	0.13	0.04	0.04	0.00	0.08	0.21	0.03	-0.06	-0.11	**1.00**

Appendix C

Supplementary Material for Chapter 4

Dynamic pair-copulas

This appendix presents the dynamic pair-copulas used in the construction of our dynamic R-vine copula model. The dynamization of the standard elliptical and Archimedean copulas is based on Patton (2006), who incorporates time variation by estimating appropriate dynamic processes for the evolution of the copula parameters. We discuss the most important properties and show the (log) likelihoods for statistical inference.

C.1 Normal copula

The bivariate normal copula, $\boldsymbol{C}_N$, is given by

$$\boldsymbol{C}_N(u_{1,t}, u_{2,t}; \rho_t) = \boldsymbol{\Phi}_{\rho_t}\left(\Phi^{-1}(u_{1,t}), \Phi^{-1}(u_{2,t})\right), \tag{C1}$$

where $\boldsymbol{\Phi}_{\rho_t}$ and Φ^{-1} denote the bivariate Gaussian distribution function with correlation parameter ρ_t and the univariate Gaussian quantile function, respectively, and $u_{1,t}, u_{2,t} \in [0,1]$, $t = 1, ..., T$. The correlation parameter, ρ_t, follows the dynamic

$$\rho_t = \tilde{\Lambda}\left(c + b\rho_{t-1} + a\frac{1}{10}\sum_{i=1}^{10}\Phi^{-1}(u_{1,t-i})\Phi^{-1}(u_{2,t-i})\right), \tag{C2}$$

where $\tilde{\Lambda}(x) \equiv (1-e^{-x})(1+e^{-x})^{-1}$ ensures that $\rho_t \in [-1,1]$ at all times. The normal copula allows for equal degrees of positive and negative dependence and is independent in the tails, i.e., the asymptotic probabilities

$$\begin{aligned}\lambda_L &= \lim_{\xi\to 0} \Pr\left[U_1 \leqslant \xi | U_2 \leqslant \xi\right] = \lim_{\xi\to 0} \frac{C_N(\xi,\xi)}{\xi},\\ \lambda_U &= \lim_{\xi\to 1} \Pr\left[U_1 \geqslant \xi | U_2 \geqslant \xi\right] = \lim_{\xi\to 1} \frac{1-2\xi+C_N(\xi,\xi)}{1-\xi}\end{aligned} \tag{C3}$$

are equal to zero. With $x_{i,t} = \Phi^{-1}(u_{i,t})$ for $i = 1,2$ and T denoting the sample size, the log likelihood, $\mathcal{L}$, is given by

$$\mathcal{L} = \sum_{t=1}^{T} \frac{1}{2}\left[x_{1,t}^2 + x_{2,t}^2 - \log(1-\rho_t^2) - \frac{x_{1,t}^2 - 2\rho_t x_{1,t}x_{2,t} + x_{2,t}^2}{1-\rho_t^2}\right]. \tag{C4}$$

C.2 *t* copula

The bivariate t copula, $\boldsymbol{C}_t$, is given by

$$\boldsymbol{C}_t(u_{1,t}, u_{2,t}; \nu, \rho_t) = \boldsymbol{t}_{\nu,\rho_t}(t_\nu^{-1}(u_{1,t}), t_\nu^{-1}(u_{2,t})), \tag{C5}$$

where $\boldsymbol{t}_{\nu,\rho_t}$ and t_ν^{-1} denote the bivariate distribution and univariate quantile function of a (standard) Student's t distribution with degrees of freedom parameter ν and correlation ρ_t, and $u_{1,t}, u_{2,t} \in [0,1]$, $t = 1, ..., T$. The correlation parameter, ρ_t, follows the dynamic

$$\rho_t = \tilde{\Lambda}\left(c + b\rho_{t-1} + a\frac{1}{10}\sum_{i=1}^{10} t_\nu^{-1}(u_{1,t-i})t_\nu^{-1}(u_{2,t-i})\right), \tag{C6}$$

where $\tilde{\Lambda}(x) \equiv (1-e^{-x})(1+e^{-x})^{-1}$ ensures that $\rho_t \in [-1,1]$ at all times. The t copula allows for equal degrees of positive and negative dependence and is asymptotically dependent in the tails, with the coefficients of lower and upper tail dependence, $\lambda_{L,t}$ and $\lambda_{U,t}$, being equal and given by

$$\lambda_{L,t} = \lambda_{U,t} = 2t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho_t}}{\sqrt{1+\rho_t}}\right). \tag{C7}$$

With $x_{i,t} = t_\nu^{-1}(u_{i,t})$ for $i = 1, 2$, $\nu_j = \frac{1}{2}(\nu + j)$ for $j = 0, 1, 2$, and T denoting the sample size, the log likelihood, $\mathcal{L}$, is given by

$$\mathcal{L} = \sum_{t=1}^{T} \log\left[\frac{\Gamma(\nu_2)\Gamma(\nu_0)}{\sqrt{1-\rho_t^2}\,\Gamma(\nu_1)^2}\right] + \log\left[\left(1 + \frac{x_{1,t}^2 - 2\rho_t x_{1,t}x_{2,t} + x_{2,t}^2}{\nu(1-\rho_t^2)}\right)^{-\nu_2}\right] + \log\left[\left(\left[1 + \frac{x_{1,t}^2}{\nu}\right]\left[1 + \frac{x_{2,t}^2}{\nu}\right]\right)^{\nu_1}\right]. \tag{C8}$$

C.3 Clayton and rotated Clayton copula

The bivariate Clayton copula, $\boldsymbol{C}_C$, is given by

$$\boldsymbol{C}_C(u_{1,t}, u_{2,t}; \theta_t) = \left(u_{1,t}^{-\theta_t} + u_{2,t}^{-\theta_t} - 1\right)^{-\frac{1}{\theta_t}}, \tag{C9}$$

where $\theta_t \in [-1, \infty)\backslash\{0\}$ and $u_{1,t}, u_{2,t} \in [0, 1]$, $t = 1, ..., T$. The Clayton copula is an asymmetric copula and implies greater dependence for joint negative events than for joint positive events. While being asymptotically independent in the upper tail, its lower tail dependence coefficient, $\lambda_{L,t}$, can be calculated according to

$$\lambda_{L,t} = 2^{-\frac{1}{\theta_t}} \tag{C10}$$

Since the parameter of the Clayton copula, θ_t, has little economic interpretation, Patton (2006) suggests using the tail dependence coefficients as the forcing variable for the time dynamics equation. Using (C10), we assume that θ_t evolves according to

$$\begin{aligned} \lambda_{L,t} &= \Lambda\left(c + b\lambda_{L,t-1} + a\frac{1}{10}\sum_{i=1}^{10}|u_{1,t-i} - u_{2,t-i}|\right), \\ \theta_t &= -\frac{\log(2)}{\log(\lambda_{L,t})} \end{aligned} \tag{C11}$$

where $\Lambda(x) \equiv (1+e^{-x})^{-1}$ ensures that $\lambda_{L,t} \in [0,1]$ at all times. With T denoting the sample size, the log likelihood of the dynamic Clayton copula, $\mathcal{L}$, is given by

$$\mathcal{L} = \sum_{t=1}^{T} \log(1+\theta_t) - (1+\theta_t)\log(u_{1,t}u_{2,t}) - \left(2+\theta_t^{-1}\right)\log\left(u_{1,t}^{-\theta_t} + u_{2,t}^{-\theta_t} - 1\right). \quad \text{(C12)}$$

The rotated Clayton copula, C_{rC}, is defined via $C_{rC}(u_{1,t}, u_{2,t}; \theta_t) = C_C(1-u_{1,t}, 1-u_{2,t}; \theta_t)$, where $\lambda_{L,t} = 0$ and $\lambda_{U,t} = 2^{-\frac{1}{\theta_t}}$. The time evolution equation and the log likelihood for the rotated version of the dynamic Clayton copula can be derived using (C11) and (C12).

C.4 Gumbel and rotated Gumbel copula

The bivariate Gumbel copula, $\boldsymbol{C}_G$, is given by

$$\boldsymbol{C}_G(u_{1,t}, u_{2,t}; \theta_t) = \exp\left(-\left[(-\log(u_{1,t}))^{\theta_t} + (-\log(u_{2,t}))^{\theta_t}\right]^{\frac{1}{\theta_t}}\right), \quad \text{(C13)}$$

where $\theta_t \in [1, \infty)$ and $u_1, u_2 \in [0,1]$, $t = 1, ..., T$. The Gumbel copula is an asymmetric copula and implies greater dependence for joint positive events than for joint negative events. While being asymptotically independent in the lower tail, its upper tail dependence coefficient, $\lambda_{U,t}$, can be calculated according to

$$\lambda_{U,t} = 2 - 2^{\frac{1}{\theta_t}}. \quad \text{(C14)}$$

Since the parameter of the Gumbel copula, θ_t, has little economic interpretation, Patton (2006) suggests using the tail dependence coefficients as the forcing variable for the time dynamics equation. Using (C14), we assume that θ_t evolves according to

$$\begin{aligned} \lambda_{U,t} &= \Lambda\left(c + b\lambda_{U,t-1} + a\frac{1}{10}\sum_{i=1}^{10}|u_{1,t-i} - u_{2,t-i}|\right), \\ \theta_t &= \frac{\log(2)}{\log(2-\lambda_{U,t})} \end{aligned} \quad \text{(C15)}$$

where $\Lambda(x) \equiv (1+e^{-x})^{-1}$ ensures that $\lambda_{U,t} \in [0,1]$ at all times.

With $x^j_{i,t} = (-\log(u_{i,t}))^{\theta_t - j}$ for $i = 1,2$; $j = 0,1$, and T denoting the sample size, the log likelihood of the dynamic Gumbel copula, $\mathcal{L}$, is given by

$$\mathcal{L} = \sum_{t=1}^{T} \log\left(\frac{x^1_{1,t}x^1_{2,t}}{u_{1,t}u_{2,t}}\right) - \left(x^0_{1,t} + x^0_{2,t}\right)^{\frac{1}{\theta_t}} + \log\left(\left(x^0_{1,t} + x^0_{2,t}\right)^{\frac{2}{\theta_t}-2} + (\theta_t - 1)\left(x^0_{1,t} + x^0_{2,t}\right)^{\frac{1}{\theta_t}-2}\right). \quad \text{(C16)}$$

The rotated Gumbel copula, C_{rG}, is defined via $C_{rG}(u_{1,t}, u_{2,t}; \theta_t) = C_G(1 - u_{1,t}, 1 - u_{2,t}; \theta_t)$, where $\lambda_{U,t} = 0$ and $\lambda_{L,t} = 2 - 2^{\frac{1}{\theta_t}}$. The time evolution equation and the log likelihood for the rotated version of the dynamic Gumbel copula can be derived using (C15) and (C16).

C.5 Joe and rotated Joe copula

The bivariate Joe copula, $\boldsymbol{C}_J$, is given by

$$\boldsymbol{C}_J(u_{1,t}, u_{2,t}; \theta_t) = 1 - \left((1-u_{1,t})^{\theta_t} + (1-u_{2,t})^{\theta_t} - (1-u_{1,t})^{\theta_t}(1-u_{2,t})^{\theta_t}\right)^{\frac{1}{\theta_t}}, \quad \text{(C17)}$$

where $\theta_t \in [1, \infty)$ and $u_{1,t}, u_{2,t} \in [0,1]$, $t = 1, ..., T$. The Joe copula is an asymmetric copula and implies greater dependence for joint positive events than for joint negative events. While being asymptotically independent in the lower tail, its upper tail dependence coefficient, $\lambda_{U,t}$, can be calculated according to

$$\lambda_{U,t} = 2 - 2^{\frac{1}{\theta_t}}. \quad \text{(C18)}$$

Since the parameter of the Joe copula, θ_t, has little economic interpretation, Patton (2006) suggests using the tail dependence coefficients as the forcing variable for the time dynamics equation. Using (C18), we assume that θ_t evolves according to

$$\begin{aligned}\lambda_{U,t} &= \Lambda\left(c + b\lambda_{U,t-1} + a\frac{1}{10}\sum_{i=1}^{10}|u_{1,t-i} - u_{2,t-i}|\right)\\ \theta_t &= \frac{\log(2)}{\log(2-\lambda_{U,t})},\end{aligned} \tag{C19}$$

where $\Lambda(x) \equiv (1+e^{-x})^{-1}$ ensures that $\lambda_{U,t} \in [0,1]$ at all times. With $x_{i,t}^{j} = (1-u_{i,t})^{\theta_t - j}$ for $i = 1,2$; $j = 0,1$, and T denoting the sample size, the log likelihood of the dynamic Joe copula, $\mathcal{L}$, is given by

$$\mathcal{L} = \sum_{t=1}^{T}\log\left[\left(x_{1,t}^{0} + x_{2,t}^{0} - x_{1,t}^{0}x_{2,t}^{0}\right)^{\frac{1}{\theta_t}-2} x_{1,t}^{1}x_{2,t}^{1}\left(\theta_t - 1 + x_{1,t}^{0} + x_{2,t}^{0} - x_{1,t}^{0}x_{2,t}^{0}\right)\right]. \tag{C20}$$

The rotated Joe copula, C_{rJ}, is defined via $C_{rJ}(u_{1,t}, u_{2,t}; \theta_t) = C_J(1-u_{1,t}, 1-u_{2,t}; \theta_t)$, where $\lambda_{U,t} = 0$ and $\lambda_{L,t} = 2 - 2^{\frac{1}{\theta_t}}$. The time evolution equation and the log likelihood for the rotated version of the dynamic Joe copula can be derived using (C19) and (C20).

Table C.1: Sample S&P 500 Companies.

The table lists a total of 209 companies included in the S&P 500 stock market index as reported by *Thomson Reuters Datastream* between January 2008 and December 2013. Starting with an initial sample of all constituents of the S&P 500 index, we exclude firms with missing/incomplete stock price data and further restrict the sample to firms with traded credit default swaps (CDS). The stock price and CDS spread data of the remaining 209 companies are retrieved from *Datastream* and used to document linear and non-linear dependences between stock returns, bid-ask spreads, and default intensities. The six companies printed in bold type are included in our Value-at-Risk (VaR) study and are used to forecast liquidity- and credit-adjusted VaR.

3M Company	Abbott Laboratories	ACE Limited	Aetna Inc	Air Products & Chemicals Inc
Allegheny Technologies Inc	Allergan Inc	Allstate Corp	Ameren Corp	American Electric Power
American Express Co	American International Group, Inc.	Amerisource Bergen Corp	Anadarko Petroleum Corp	Apache Corporation
Archer-Daniels-Midland Co	Assurant Inc	Automatic Data Processing	AutoZone Inc	AvalonBay Communities, Inc.
Avery Dennison Corp	Avon Products	Baker Hughes Inc	Ball Corp	Bank of America Corp
Baxter International Inc.	BB&T Corporation	Becton Dickinson	Bemis Company	Best Buy Co. Inc.
BorgWarner	Boston Properties	Boston Scientific	Bristol-Myers Squibb	Cameron International Corp.
Campbell Soup	Capital One Financial	Cardinal Health Inc.	Caterpillar Inc.	CBS Corp.
CenterPoint Energy	CenturyLink Inc	Chesapeake Energy	Chevron Corp.	The Clorox Company
CMS Energy	Coca-Cola Enterprises	Computer Sciences Corp.	ConAgra Foods Inc.	ConocoPhillips
Constellation Brands	Corning Inc.	CVS Caremark Corp.	D. R. Horton	Danaher Corp.
Darden Restaurants	DaVita Inc.	Devon Energy Corp.	DirecTV	Dover Corp.
Dow Chemical	Dr Pepper Snapple Group	DTE Energy Co.	Eastman Chemical	Eaton Corp.
Edison Int’l	EMC Corp.	Emerson Electric	Ensco plc	Entergy Corp.
EOG Resources	Equifax Inc.	Exelon Corp.	Exxon Mobil Corp.	FedEx Corporation
Fluor Corp.	FMC Technologies Inc.	Freeport-McMoran Cp & Gld	Gannett Co.	Gap (The)
General Mills	Genworth Financial Inc.	Halliburton Co.	Harris Corporation	Hartford Financial Svc.Gp.
Hasbro Inc.	HCP Inc.	Health Care REIT, Inc.	Hess Corporation	**Hewlett-Packard**
Honeywell Int’l Inc.	Hospira Inc.	Host Hotels & Resorts	Humana Inc.	Illinois Tool Works
International Bus. Machines	International Game Technology	Interpublic Group	Iron Mountain Incorporated	Jabil Circuit
Johnson & Johnson	Johnson Controls	Joy Global Inc.	JPMorgan Chase & Co.	KeyCorp
Kimberly-Clark	Kimco Realty	Kohl’s Corp.	Leggett & Platt	Lennar Corp.
Lilly (Eli) & Co.	Lincoln National	Lockheed Martin Corp.	Lowe’s Cos.	Marathon Oil Corp.
Marriott Int’l.	Marsh & McLennan	Masco Corp.	Mattel Inc.	McDonald’s Corp.
McKesson Corp.	MeadWestvaco Corporation	Medtronic Inc.	Merck & Co.	MetLife Inc.
Molson Coors Brewing Company	The Mosaic Company	Murphy Oil	Mylan Inc.	Newell Rubbermaid Co.
Newmont Mining Corp.	NIKE Inc.	Noble Energy Inc	Norfolk Southern Corp.	Northrop Grumman Corp.
NRG Energy	Nucor Corp.	Occidental Petroleum	Omnicom Group	ONEOK
P G & E Corp.	Pentair Ltd.	Pepco Holdings Inc.	PepsiCo Inc.	PerkinElmer
Pfizer Inc.	Pioneer Natural Resources	Pitney-Bowes	PNC Financial Services	PPG Industries
Principal Financial Group	Progressive Corp.	Prologis	Prudential Financial	Pulte Homes Inc.
PVH Corp.	Quest Diagnostics	Raytheon Co.	Republic Services Inc	Reynolds American Inc.
Rockwell Automation Inc.	Safeway Inc.	SCANA Corp	Schlumberger Ltd.	Seagate Technology
Sealed Air Corp.	Sempra Energy	Sherwin-Williams	Simon Property Group Inc	SLM Corporation
Snap-On Inc.	Southwest Airlines	Stanley Black & Decker	Starwood Hotels & Resorts	Sysco Corp.
Target Corp.	**Tenet Healthcare Corp.**	Tesoro Petroleum Co.	Texas Instruments	**Textron Inc.**
The Hershey Company	The Travelers Companies Inc.	Time Warner Inc.	TJX Companies Inc.	Torchmark Corp.
Transocean	Tyson Foods	Tyco International	U.S. Bancorp	Union Pacific
United Health Group Inc.	United Parcel Service	United Technologies	Unum Group	V.F. Corp.
Valero Energy	Vornado Realty Trust	**Wal-Mart Stores**	The Walt Disney Company	WellPoint Inc.
Wells Fargo	Western Digital	Whirlpool Corp.	Williams Cos.	Windstream Communication
Wisconsin Energy Corporation	Xerox Corp.	Yum! Brands Inc	Zimmer Holdings	

Table C.2: Summary statistics for level data of firms included in the Value-at-Risk study.

The table reports descriptive statistics on the time-series distribution of daily mid prices, bid-ask spreads, default intensities, and default probablities (at a monthly horizon) for the six firms investigated in our Value-at-Risk (VaR) study. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The summary statistics refer to the in- and out-of-sample time periods in the VaR study, which cover the period from January 2010 to November 2011 resulting in 499 daily observations. Mid prices and bid-ask spreads are denominated in US dollar, where the latter are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 4.3 and have a horizon of one year. Default probabilities are derived from the intensities using the formula in (4.15) and thus have a horizon of one month.

		Percentiles								Moments				
	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.	AC(1)
Panel A: Mid prices														
3M Company	70.93	73.586	76.855	81	84.72	89.615	95.388	96.9258	97.97	85.3225	5.739	0.1499	-0.7167	0.9749
American Express	36.79	37.709	38.384	41.465	44.17	46.94	51.258	52.3412	53.59	44.4242	3.8702	0.2353	-0.7618	0.9729
Hewlett-Packard	22.2	22.6486	24.439	36.4125	42.1	47.075	53.069	53.8702	54.52	41.0519	8.4451	-0.6218	-0.3825	0.992
Tenet Healthcare	14.36	16	16.72	18.12	21.52	25.46	28.168	30.0424	30.52	21.978	4.006	0.2134	-1.2524	0.9814
Textron	14.88	15.259	16.719	18.91	21.42	23.49	27.171	27.9612	28.5	21.4874	3.1636	0.2213	-0.6451	0.9827
Wal-Mart Stores	48	48.5668	50.274	52.105	53.6	54.625	56.73	58.1308	59.32	53.4569	1.9611	-0.0272	0.2277	0.9583
Panel B: Bid-ask spreads														
3M Company	0.01	0.01	0.01	0.01	0.02	0.04	0.08	0.11	1.12	0.0329	0.0537	16.7505	334.9984	0.0784
American Express	0.01	0.01	0.01	0.01	0.02	0.03	0.05	0.1002	0.18	0.0228	0.018	3.8209	24.1701	0.2213
Hewlett-Packard	0.01	0.01	0.01	0.01	0.02	0.02	0.04	0.06	0.14	0.0195	0.0135	3.7733	25.9914	0.2291
Tenet Healthcare	0.04	0.04	0.04	0.04	0.04	0.04	0.08	0.08	7.76	0.0615	0.3456	22.2102	492.1938	-0.0033
Textron	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.04	7.6	0.0319	0.3396	22.2527	493.4575	-0.0036
Wal-Mart Stores	0.01	0.01	0.01	0.01	0.02	0.02	0.04	0.0502	0.34	0.0195	0.0207	10.466	145.0211	0.1117
Panel C: Default intensities														
3M Company	0.0041	0.0042	0.0044	0.0048	0.0051	0.0055	0.007	0.0074	0.0075	0.0053	0.0007	1.2603	0.9934	0.9845
American Express	0.0092	0.0098	0.0101	0.0108	0.0121	0.0148	0.0181	0.0206	0.0221	0.013	0.0027	0.976	0.0338	0.9709
Hewlett-Packard	0.0037	0.0037	0.0043	0.0055	0.0061	0.0093	0.0183	0.0212	0.0217	0.0079	0.0042	1.7035	1.9721	0.9876
Tenet Healthcare	0.0584	0.059	0.0613	0.0695	0.078	0.0845	0.1074	0.1167	0.1279	0.0798	0.014	0.8984	0.4018	0.9837
Textron	0.0152	0.0153	0.0167	0.0204	0.0242	0.0325	0.0378	0.0391	0.0406	0.0262	0.0069	0.3656	-1.1715	0.9908
Wal-Mart Stores	0.0048	0.0051	0.0052	0.0061	0.0064	0.0069	0.0079	0.0083	0.0088	0.0065	0.0008	0.3221	-0.1403	0.9788
Panel D: Monthly default probabilities														
3M Company	0.0003	0.0004	0.0004	0.0004	0.0004	0.0005	0.0006	0.0006	0.0006	0.0004	0.0001	1.2602	0.993	0.9845
American Express	0.0008	0.0008	0.0008	0.0009	0.001	0.0012	0.0015	0.0017	0.0018	0.0011	0.0002	0.9757	0.0328	0.9709
Hewlett-Packard	0.0003	0.0003	0.0004	0.0005	0.0005	0.0008	0.0015	0.0018	0.0018	0.0007	0.0004	1.703	1.97	0.9876
Tenet Healthcare	0.0049	0.0049	0.0051	0.0058	0.0065	0.007	0.0089	0.0097	0.0106	0.0066	0.0012	0.8956	0.3957	0.9837
Textron	0.0013	0.0013	0.0014	0.0017	0.002	0.0027	0.0031	0.0033	0.0034	0.0022	0.0006	0.365	-1.1719	0.9908
Wal-Mart Stores	0.0004	0.0004	0.0004	0.0005	0.0005	0.0006	0.0007	0.0007	0.0007	0.0005	0.0001	0.3219	-0.1405	0.9788

Table C.3: Summary statistics for log-differenced data of firms included in the Value-at-Risk study.

The table reports descriptive statistics on the time-series distribution of monthly log-differences of mid prices, bid-ask spreads, and default intensities for the six firms investigated in our Value-at-Risk (VaR) study. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The summary statistics refer to the in- and out-of-sample time periods in the VaR study, which cover the period from January 2010 to November 2011 resulting in 460 daily observations. For each day, t, in the sample period, log-differences are calculated using the prices, spreads, and intensities at days t and $t-30$. Bid-ask spreads are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 4.3 and have a horizon of one year.

		Percentiles								Moments				
	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.	AC(1)
Panel A: Stock returns														
3M Company	-0.4987	-0.4059	-0.2380	-0.0831	0.0198	0.0884	0.1669	0.2208	0.2902	-0.0042	0.1282	-0.9150	1.2774	0.9525
American Express	-0.1108	-0.0898	-0.0667	-0.0250	0.0024	0.0232	0.0545	0.0704	0.0727	-0.0009	0.0367	-0.3641	-0.2060	0.9271
Hewlett-Packard	-0.2302	-0.1791	-0.1339	-0.0438	0.0168	0.0639	0.1125	0.1383	0.1528	0.0062	0.0759	-0.4930	-0.3404	0.9298
Tenet Healthcare	-0.2214	-0.1975	-0.1191	-0.0386	0.0085	0.0351	0.0778	0.1046	0.1249	-0.0041	0.0599	-0.9563	1.2339	0.9434
Textron	-0.4119	-0.3703	-0.2261	-0.0982	-0.0207	0.0339	0.0902	0.1199	0.1400	-0.0389	0.1034	-1.1114	1.5305	0.9521
Wal-Mart Stores	-0.3858	-0.3013	-0.2063	-0.0808	-0.0162	0.0392	0.2651	0.4786	0.5059	-0.0109	0.1410	1.3039	3.6138	0.9374
Panel B: Log-differences of bid-ask spreads														
3M Company	-5.9402	-1.0986	-1.0986	-0.4055	0.0000	0.0000	1.0986	1.2194	6.6333	-0.0316	0.6936	0.6742	28.4284	-0.0005
American Express	-2.5257	-1.6094	-1.0986	-0.4055	0.0000	0.4055	0.9163	1.3863	3.2189	-0.0318	0.6301	0.1000	2.7220	0.0278
Hewlett-Packard	-2.4849	-1.7918	-1.3863	-0.6931	0.0000	0.4055	1.2661	1.7918	2.8904	-0.0347	0.7884	0.1789	0.5025	0.1207
Tenet Healthcare	-3.6199	-1.6860	-1.1066	-0.6931	0.0000	0.4055	1.0986	1.6495	3.1091	-0.0690	0.7414	0.0842	1.4815	0.0662
Textron	-1.9459	-1.5694	-1.0986	-0.6931	0.0000	0.4055	1.0986	1.6094	2.6391	-0.0470	0.6397	0.1725	0.6715	-0.0033
Wal-Mart Stores	-5.2679	-0.6931	-0.6931	0.0000	0.0000	0.0000	0.6931	0.6931	5.2679	-0.0115	0.4942	-0.0074	54.6338	0.0038
Panel C: Log-differences of default intensities														
3M Company	-0.1282	-0.0833	-0.0422	-0.0150	-0.0016	0.0112	0.0456	0.0986	0.1351	-0.0005	0.0290	0.3665	3.8761	-0.0621
American Express	-0.0688	-0.0366	-0.0164	-0.0056	-0.0002	0.0046	0.0144	0.0522	0.1072	-0.0001	0.0142	2.3588	20.5839	-0.2622
Hewlett-Packard	-0.0941	-0.0607	-0.0321	-0.0093	-0.0002	0.0101	0.0327	0.0622	0.1199	0.0004	0.0221	0.3707	5.8719	-0.1556
Tenet Healthcare	-0.0610	-0.0502	-0.0272	-0.0073	-0.0005	0.0074	0.0239	0.0566	0.1106	-0.0001	0.0177	0.9112	7.3419	-0.2213
Textron	-0.2241	-0.0679	-0.0348	-0.0099	-0.0010	0.0090	0.0258	0.0557	0.1690	-0.0015	0.0249	-0.7232	20.8471	-0.0782
Wal-Mart Stores	-0.1922	-0.0948	-0.0489	-0.0159	-0.0017	0.0127	0.0508	0.0854	0.4379	-0.0007	0.0375	3.0806	42.2552	-0.0904

Table C.4: Variable pairs and parametric pair-copulas selected in first R-vine trees.

The table reports the (unconditional) variable pairs and bivariate parametric pair-copulas selected in the first tree of the R-vine copula model for each estimation period included in our Value-at-Risk (VaR) study. The R-vine copula model is estimated on pseudo-observations of standardized log-differences of mid prices (m), bid-ask spreads (s), and default intensities (h) for six firms from the S&P 500, resulting in 17 variable pairs and parametric pair-copulas that need to be specified in the first tree. The six firms include *3M Company* (MMM), *American Express* (AXP), *Hewlett-Packard* (HPQ), *Tenet Healthcare* (THC), *Textron* (TXT), and *Wal-Mart Stores* (WMT). The candidate copulas include dynamic versions of the standard normal (C_N), t (C_t), (rotated) Clayton (C_C and C_{rC}), (rotated) Gumbel (C_G and C_{rG}), and (rotated) Joe copula (C_J and C_{rJ}), where we follow the dynamization approach suggested by Patton (2006) (as outlined in Appendix C). The selection of the variable pairs and the bivariate pair-copulas is based on the sequential method as proposed by Dißmann et al. (2013), where the former results from some maximum spanning tree algorithm based on Kendall's tau and the latter is conducted using Akaikes Information Criterion (AIC) as the selection criterion to be minimized.

01/2010 - 01/2011			02/2010 - 02/2011			03/2010 - 03/2011			04/2010 - 04/2011			05/2010 - 05/2011		
Pair		Copula	Pair		Copula	Pair		Copula	Pair		Copula	Pair		Copula
MMM(m)	AXP(m)	C_N	MMM(m)	MMM(h)	C_N	MMM(m)	MMM(h)	C_{rG}	MMM(m)	MMM(s)	C_N	MMM(m)	MMM(s)	C_N
MMM(m)	AXP(h)	C_N	MMM(m)	AXP(m)	C_N	MMM(m)	AXP(m)	C_N	MMM(m)	MMM(h)	C_{rG}	MMM(m)	AXP(m)	C_{rG}
MMM(s)	AXP(s)	C_N	MMM(m)	AXP(h)	C_N	MMM(m)	AXP(s)	C_N	MMM(m)	AXP(m)	C_N	MMM(m)	AXP(s)	C_N
MMM(h)	AXP(s)	C_N	MMM(s)	AXP(s)	C_N	MMM(m)	AXP(h)	C_N	MMM(m)	AXP(s)	C_N	MMM(m)	AXP(h)	C_N
AXP(s)	AXP(h)	C_N	AXP(s)	AXP(h)	C_N	MMM(s)	AXP(s)	C_N	MMM(m)	AXP(h)	C_N	MMM(s)	MMM(h)	C_N
AXP(s)	WMT(s)	C_{rJ}	AXP(s)	WMT(s)	C_C	AXP(s)	WMT(s)	C_{rJ}	MMM(m)	HPQ(m)	C_G	MMM(s)	THC(m)	C_t
HPQ(m)	THC(m)	C_{rJ}	HPQ(m)	THC(m)	C_N	HPQ(m)	THC(m)	C_N	AXP(s)	WMT(s)	C_{rJ}	AXP(s)	WMT(s)	C_N
HPQ(s)	HPQ(h)	C_{rG}	HPQ(s)	HPQ(h)	C_{rG}	HPQ(s)	HPQ(h)	C_{rG}	HPQ(m)	THC(m)	C_N	HPQ(m)	THC(m)	C_G
HPQ(s)	THC(s)	C_{rJ}	HPQ(s)	THC(s)	C_N	HPQ(s)	THC(s)	C_N	HPQ(s)	HPQ(h)	C_{rJ}	HPQ(s)	HPQ(h)	C_{rJ}
HPQ(s)	THC(h)	C_G	HPQ(s)	THC(h)	C_{rJ}	HPQ(h)	THC(m)	C_J	HPQ(s)	THC(s)	C_{rG}	HPQ(s)	THC(s)	C_{rG}
HPQ(h)	THC(m)	C_N	HPQ(h)	THC(m)	C_J	THC(s)	TXT(s)	C_N	HPQ(h)	THC(m)	C_{rC}	HPQ(h)	THC(m)	C_G
THC(s)	TXT(s)	C_{rG}	THC(s)	TXT(s)	C_{rG}	THC(s)	WMT(h)	C_{rG}	THC(s)	THC(h)	C_{rG}	THC(s)	THC(h)	C_{rG}
THC(s)	WMT(h)	C_{rJ}	THC(s)	WMT(h)	C_{rG}	THC(h)	TXT(m)	C_G	THC(s)	TXT(s)	C_{rC}	THC(s)	TXT(s)	C_{rG}
TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t	TXT(m)	TXT(s)	C_{rG}	TXT(m)	TXT(s)	C_N	TXT(m)	TXT(s)	C_N
TXT(s)	TXT(h)	C_t	TXT(s)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t
WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t
WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t

06/2010 - 06/2011			07/2010 - 07/2011			08/2010 - 08/2011			09/2010 - 09/2011			10/2010 - 10/2011		
Pair		Copula	Pair		Copula	Pair		Copula	Pair		Copula	Pair		Copula
MMM(m)	AXP(m)	C_{rG}	MMM(m)	AXP(m)	C_{rJ}	MMM(m)	AXP(m)	C_{rJ}	MMM(m)	AXP(m)	C_{rG}	MMM(m)	AXP(s)	C_N
MMM(m)	AXP(s)	C_N	MMM(m)	AXP(s)	C_N	MMM(m)	AXP(s)	C_N	MMM(m)	AXP(s)	C_N	MMM(s)	MMM(h)	C_{rG}
MMM(m)	AXP(h)	C_N	MMM(m)	AXP(h)	C_N	MMM(m)	AXP(h)	C_N	MMM(m)	AXP(h)	C_N	MMM(s)	AXP(s)	C_N
MMM(s)	MMM(h)	C_G	MMM(s)	MMM(h)	C_N	MMM(m)	HPQ(m)	C_G	MMM(s)	MMM(h)	C_{rG}	MMM(h)	AXP(m)	C_N
MMM(s)	AXP(s)	C_N	MMM(s)	AXP(m)	C_{rG}	MMM(s)	MMM(h)	C_{rG}	MMM(s)	AXP(s)	C_N	AXP(m)	AXP(h)	C_N
MMM(s)	THC(m)	C_N	AXP(s)	WMT(s)	C_N	MMM(s)	AXP(s)	C_N	AXP(s)	WMT(s)	C_{rG}	AXP(s)	WMT(s)	C_N
AXP(s)	WMT(s)	C_N	HPQ(m)	THC(m)	C_{rJ}	AXP(s)	WMT(s)	C_N	HPQ(m)	THC(s)	C_{rG}	HPQ(m)	TXT(m)	C_{rJ}
HPQ(m)	THC(m)	C_{rJ}	HPQ(s)	HPQ(h)	C_{rG}	HPQ(s)	HPQ(h)	C_{rG}	HPQ(s)	TXT(s)	C_J	HPQ(s)	HPQ(h)	C_N
HPQ(s)	HPQ(h)	C_{rG}	HPQ(h)	THC(m)	C_N	HPQ(s)	TXT(s)	C_t	HPQ(h)	THC(m)	C_{rG}	HPQ(s)	TXT(s)	C_G
HPQ(s)	THC(s)	C_{rJ}	THC(m)	THC(s)	C_{rJ}	HPQ(h)	THC(m)	C_{rG}	HPQ(h)	THC(h)	C_{rG}	HPQ(h)	THC(m)	C_G
HPQ(h)	THC(m)	C_N	THC(s)	THC(h)	C_N	THC(m)	THC(s)	C_{rJ}	THC(m)	THC(s)	C_{rJ}	THC(m)	THC(s)	C_{rG}
THC(s)	THC(h)	C_{rJ}	THC(s)	TXT(s)	C_N	THC(s)	THC(h)	C_{rJ}	THC(s)	WMT(h)	C_G	THC(s)	THC(h)	C_{rG}
THC(s)	TXT(s)	C_{rG}	THC(s)	WMT(h)	C_N	THC(s)	WMT(h)	C_N	TXT(m)	TXT(s)	C_t	TXT(m)	TXT(s)	C_{rG}
TXT(m)	TXT(s)	C_{rG}	TXT(m)	TXT(s)	C_t	TXT(m)	TXT(s)	C_G	TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t
TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_G	TXT(m)	TXT(h)	C_t	TXT(s)	WMT(s)	C_N	TXT(s)	WMT(s)	C_{rG}
WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_{rG}
WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_{rG}	WMT(s)	WMT(h)	C_{rG}	WMT(m)	WMT(h)	C_t

Appendix D

Supplementary Material for Chapter 5

D.1 LTD estimators

In this section, we discuss the LTD estimators included in our simulation study in more detail and present their most important statistical properties.

D.1.1 Patton's (2006) dynamic t copula

The first dynamic LTD estimator is based on the dynamic t copula as proposed by Patton (2006), who dynamizes the t copula by assuming that the correlation parameter of the t copula follows an ARMA(1,10)-type process to capture both correlation persistence and any variation in dependence. With $\boldsymbol{t}^2_{\nu,\rho}$ denoting a (standard) bivariate Student's t distribution with degree of freedom parameter ν and correlation parameter ρ, the implied t copula is given by

$$\boldsymbol{C}^t_{\nu,\rho}(u_1, u_2) = \boldsymbol{t}^2_{\nu,\rho}(t^{-1}_\nu(u_1), t^{-1}_\nu(u_2)) \tag{D1}$$

where t^{-1}_ν is the quantile function of a standard univariate t distribution and $u_1, u_2 \in [0, 1]$.

The t copula implies symmetric threshold correlations; therefore, the coefficients of lower and upper tail dependence, τ^L and τ^U, coincide and can be calculated according the following simple formula (see Demarta and McNeil, 2004), where we set $\tau := \tau^L = \tau^U$:

$$\tau = 2t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho}}{\sqrt{1+\rho}}\right) \tag{D2}$$

with $t_{\nu+1}$ denoting the cumulative distribution function (cdf) of a standard univariate t distribution with degrees of freedom equal to $\nu + 1$.

Patton's (2006) dynamization approach is based on assuming the correlation parameter ρ to follow the dynamic process

$$\rho_t = \Lambda\left(\omega + \beta\rho_{t-1} + \alpha\frac{1}{10}\sum_{i=1}^{10} t_\nu^{-1}(u_{1,t-i})t_\nu^{-1}(u_{2,t-i})\right) \tag{D3}$$

where $\Lambda(x) \equiv (1-e^{-x})(1+e^{-x})^{-1}$ ensures that $\rho_t \in [-1, 1]$ at all times. Hence, the correlation dynamics are driven by the lagged correlation paramter ρ_{t-1} and the mean of the product of the last 10 observations of the transformed variables $t_\nu^{-1}(u_{1,t-i})$ and $t_\nu^{-1}(u_{2,t-i})$. In this way, we can use the LTD estimator in (D2) to generate time-varying LTD coefficients in our simulation study.

The estimation of Patton's (2006) dynamic t copula is conducted straightforwardly via Maximum Likelihood (ML), where the corresponding log likelihood function is given by

$$\mathcal{L}(\boldsymbol{u_1}, \boldsymbol{u_2}; \nu, \boldsymbol{\rho}) = \sum_{t=1}^{T} \log\left(\boldsymbol{f}_{\nu,\rho_t}(t_\nu^{-1}(u_{1,t}), t_\nu^{-1}(u_{2,t}))\right) - \log\left(f_\nu(t_\nu^{-1}(u_{1,t}))f_\nu(t_\nu^{-1}(u_{2,t}))\right) \tag{D4}$$

with $\boldsymbol{f}_{\nu,\rho}$ and f_ν denoting the density of a $\boldsymbol{t}^2_{\nu,\rho}$ and a t_ν distribution, respectively, and $\boldsymbol{u_1} = (u_{1,1}, ..., u_{1,T})^\top$, $\boldsymbol{u_2} = (u_{2,1}, ..., u_{2,T})^\top$, $\boldsymbol{\rho} = (\rho_1, ..., \rho_T)^\top$.

D.1.2 DCC *t* copula

The second dynamic LTD estimator is also based on the t copula and achieves dynamization of equations (D1) and (D2) by assuming correlation dynamics according to Engle's (2002) Dynamic Conditional Correlation (DCC) model. Hence, we follow

Heinen and Valdesogo (2008) as well as Christoffersen et al. (2012) and apply the DCC model to the copula shocks $z^c_{1,t} = t^{-1}_\nu(u_{1,t})$ and $z^c_{2,t} = t^{-1}_\nu(u_{2,t})$, where we assume that $u_{1,t} = F_{1,t}(z_{1,t})$ and $u_{2,t} = F_{2,t}(z_{2,t})$ denote the ranks of the residuals from univariate GARCH processes applied to the margins.[1] The dynamic process for the correlation parameter is then given by

$$\rho_t = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \tag{D5}$$

with the matrix $Q_t = (q_{ij,t})_{i,j=1,2}$ following

$$Q_t = (1-\phi-\psi)\Omega + \psi Q_{t-1} + \phi \bar{z}^c_{t-1}\bar{z}^{c\top}_{t-1} \tag{D6}$$

where Ω is a constant correlation matrix, ϕ and ψ are non-negative parameters, and $\bar{z}^c_t = (\bar{z}^c_{1,t}, \bar{z}^c_{2,t})^\top$ with $\bar{z}^c_{i,t}$ given by $z^c_{i,t}\sqrt{Q_{ii,t}}$ (see Aielli, 2009, for details). Consequently, time-varying LTD coefficients can be generated by substituting the dynamic correlations into formula (D2).

Estimation is done by first estimating the parameters of the univariate GARCH processes and then estimating the parameters driving the correlation dynamics in (D6). The estimation of the latter ones is straightforward via ML, where the log likelihood results from inserting the dynamics in (D5) into equation (D4).

D.1.3 DSC *t* copula

The third dynamic LTD estimator builds on a similar technique as the DCC t Copula and dynamizes the t copula by applying the Dynamic Symmetric Copula (DSC) model as proposed by Christoffersen et al. (2012) to copula correlations. The DSC model constitutes a generalization of Engle's (2002) DCC model and additionally allows for the incorporation of a time trend into the correlation dynamics. As in the DCC t Copula model, dynamic correlations are based on a multivariate GARCH process, where the uni-

[1] Note that a crucial assumption in the DCC framework is that correlation dynamics are driven by a multivariate GARCH process, i.e., the correlations are driven by the cross-product of lagged standardized residuals from univariate GARCH processes. See Engle (2002) for details.

variate GARCH residuals $z_{1,t}$ and $z_{2,t}$ are replaced by the copula shocks $z^c_{1,t}$ and $z^c_{2,t}$, with $z_{i,t}$ and $z^c_{i,t}$ as defined above ($i = 1, 2$). The dynamics, however, are now driven by the cross-product of the (Aielli (2009) modified) copula shocks and a time trend parameter, resulting in the following dynamic process for the correlation parameter

$$\rho_t = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \tag{D7}$$

with the matrix $Q_t = (q_{ij,t})_{i,j=1,2}$ following

$$Q_t = (1 - \phi - \psi)\left[(1 - \kappa)\Omega + \kappa D_t\right] + \psi Q_{t-1} + \phi \bar{z}^c_{t-1}\bar{z}^{c\top}_{t-1} \tag{D8}$$

where Ω, ϕ, ψ, and $\bar{z}^c_t$ are as above, κ is a non-negative parameter, and D_t is a time trend correlation matrix with trend parameter δ, where the off-diagonal elements are equal to

$$\frac{\delta^2 t^2}{1 + \delta^2 t^2}, \quad t = 1, ..., T. \tag{D9}$$

We refer to Christoffersen et al. (2012) for further details on the DSC model. Note, however, that the DSC t Copula model nests the DCC t Copula model and that setting $\kappa = 0$ yields equation (D6). Thus, inserting the dynamic correlations resulting from (D7) and (D8) into equation (D2) allows us to generate dynamic LTD coefficients with a specific time trend.

Estimation is conducted straightforwardly by ML. As for the DCC t Copula, we first need to estimate the GARCH parameters for the margins, and then estimate the parameters of the dynamic correlations in (D8). The log likelihood results from substituting ρ in equation (D2) with ρ_t in (D7).

D.1.4 Mixture copula 1 (ML)

The LTD estimator implied by the Mixture Copula 1 (ML) model is a static estimator and, therefore, merely capable of generating constant LTD coefficients. The estimator is based on a specific mixture copula, i.e., a specific convex combination of several basic copulas. Tawn (1988) shows that any convex combination of existing copulas is again a copula. Formally, for any copulas $\boldsymbol{C}_1, ..., \boldsymbol{C}_n$, the linear combination

$$\sum_{i=1}^{n} w_i \boldsymbol{C}_i \tag{D10}$$

is a copula for $w_i \in [0,1]$ and $\sum_{i=1}^{n} w_i = 1$. The LTD coefficient implied by a mixture of copulas is given by the weighted sum of the LTD coefficients of the individual copulas, where the weights are taken from (D10). Hence, we can calculate the LTD coefficient, τ^L, according to the formula

$$\tau^L = \sum_{i=1}^{n} w_i \tau_i^L \tag{D11}$$

where τ_i^L denotes the LTD coefficient of the ith copula in the mixture ($i = 1, ..., n$).

For the Mixture Copula 1 (ML) model included in our simulation study, we set $n = 3$ and choose the Joe, Rotated-Joe, and the F-G-M copula as building blocks for the mixture.[2] Hence, the Mixture Copula 1, $\boldsymbol{C}_{\text{mix,1}}$, is given by

$$\boldsymbol{C}_{\text{mix,1}} = w_1 \boldsymbol{C}_{\text{Joe}} + w_2 \boldsymbol{C}_{\text{rJoe}} + w_3 \boldsymbol{C}_{\text{FGM}} \tag{D12}$$

where $w_i \in [0,1]$ for $i = 1,2,3$ with $\sum_{i=1}^{3} w_i = 1$, and

$$\boldsymbol{C}_{\text{Joe}}(u_1, u_2; \theta) = 1 - \left((1-u_1)^\theta + (1-u_2)^\theta - (1-u_1)^\theta (1-u_2)^\theta\right)^{\frac{1}{\theta}}, \ \theta \in [1, \infty), \tag{D13}$$

$$\boldsymbol{C}_{\text{rJoe}}(u_1, u_2; \theta) = u_1 + u_2 - \left(u_1^\theta + u_2^\theta - u_1^\theta u_2^\theta\right)^{\frac{1}{\theta}}, \ \theta \in [1, \infty), \tag{D14}$$

$$\boldsymbol{C}_{\text{FGM}}(u_1, u_2; \theta) = u_1 u_2 \left(1 + \theta(1-u_1)(1-u_2)\right), \ \theta \in [-1, 1]. \tag{D15}$$

[2]Note that Ruenzi and Weigert (2013) use this mixture copula in their asset pricing framework and find it to be most often selected in their copula selection approach based on the Integrated Anderson-Darling distance.

The LTD coefficients of the individual copulas are given by

$$\tau_{\text{Joe}}^{L} = 0, \quad \tau_{\text{rJoe}}^{L} = 2 - 2^{\frac{1}{\theta}}, \quad \tau_{\text{FGM}}^{L} = 0. \tag{D16}$$

To calculate the LTD coefficient implied by the Mixture Copula 1 (ML) model, $\tau_{\text{mix,1}}^{L}$, we apply (1) and get

$$\tau_{\text{mix,1}}^{L} = w_2 \left(2 - 2^{\frac{1}{\theta}}\right). \tag{D17}$$

Estimation of the Mixture Copula 1 (ML) model is straightforwardly done via ML, where the log likelihood function is given by

$$\mathcal{L}(\boldsymbol{u_1}, \boldsymbol{u_2}; \boldsymbol{\theta}, \boldsymbol{w}) = \sum_{t=1}^{T} \log \left(\boldsymbol{w}^{\top} \boldsymbol{c}(u_{1,t}, u_{2,t}; \boldsymbol{\theta})\right) \tag{D18}$$

where $\boldsymbol{u_i}$ is defined as above ($i = 1, 2$), $\boldsymbol{\theta} = (\theta_1, \theta_2, \theta_3)^{\top}$ contains the copula parameters, $\boldsymbol{w} = (w_1, w_2, w_3)^{\top}$ denotes the vector of weights, and $\boldsymbol{c} = (c_{\text{Joe}}, c_{\text{rJoe}}, c_{\text{FGM}})^{\top}$ is a vector containing the copula densities of the Joe, the Rotated-Joe, and the F-G-M copula, respectively.

Note, however, that estimating mixture copulas by maximizing the log likelihood with respect to the copula parameters and the weights is statistically incorrect so that the parameter estimates may be biased. The estimation of mixtures constitutes an incomplete data problem which needs to be estimated via the Expectation-Maximization (EM) algorithm proposed by Dempster et al. (1977). Being aware of this fact, in our simulation study we shall investigate how this potential bias translates into the calculation of LTD coefficients.

D.1.5 Mixture copula 1 (EM)

The LTD estimator resulting from the Mixture Copula 1 (EM) is a static estimator and based on the same mixture of copulas as the Mixture Copula 1 (ML) model. Hence, the estimator builds on a mixture of the Joe, Rotated-Joe, and the F-G-M copula and calculates LTD coefficients as a weighted sum of the LTD coefficients of these individual copulas. Corresponding formulas can be found in equations (D12) to (D17).

The difference between the two mixture models, however, lies in the method used for estimation. Whereas the estimation procedure applied to the Mixture Copula 1 (ML) model yields potentially biased estimates by maximizing the log likelihood in (D18) with respect to both copula parameters and the weights of the mixture, estimation of the Mixture Copula 1 (EM) model considers the incomplete-data structure we encounter when estimating mixture copulas and, therefore, is based on the EM algorithm as proposed by Dempster et al. (1977).

The EM algorithm is a generic method to compute ML estimates for incomplete-data problems, which is based on two steps that are iteratively repeated, the Expectation Step (E-Step) and the Maximization Step (M-Step). In case of estimating mixtures, the incomplete-data structure arises from the fact that the mixing proportions w_i constitute unobservable data and, therefore, need to be handled prior to maximizing the likelihood. This is done in the E-Step, which calculates the conditional expectation yielding the posterior probability that a specified member of the sample belongs to a certain component of the mixture. Substituting the mixing proportions in the likelihood with the conditional expectations from the E-Step, the M-Step then maximizes the likelihood with respect to the copula parameters. These two steps are alternated repeatedly until convergence, where the estimates of the mixing proportions are updated independently of the parameter estimates. In our simulation study, we follow McLachlan and Peel (2000) and determine convergence by the difference of subsequent likelihood values in case of convergence of the sequence of likelihood values. For a formal description and further details on the EM algorithm we refer to Dempster et al. (1977) and McLachlan and Peel (2000).

D.1.6 Mixture copula 2 (ML)

The LTD estimator implied by the Mixture Copula 2 (ML) model is a static estimator and based on a mixture copula that is composed of a convex combination of three basic copulas, the t copula as well as the Clayton and Frank copula. The formal definition of mixture copulas and the formula for calculating corresponding LTD coefficients can be found in equations (D10) and (D11), respectively. Hence, the Mixture Copula 2, $\boldsymbol{C}_{\text{mix,2}}$, is given by

$$\boldsymbol{C}_{\text{mix,2}} = w_1 \boldsymbol{C}_t + w_2 \boldsymbol{C}_{\text{Cl}} + w_3 \boldsymbol{C}_{\text{Fr}} \tag{D19}$$

where $w_i \in [0,1]$ for $i = 1,2,3$ with $\sum_{i=1}^{3} w_i = 1$, and

$$\boldsymbol{C}_t(u_1, u_2; \theta) = t^2_{\nu,\rho}(t_\nu^{-1}(u_1), t_\nu^{-1}(u_2)),\ \nu \in (0,\infty),\ \rho \in [-1,1], \tag{D20}$$

$$\boldsymbol{C}_{\text{Cl}}(u_1, u_2; \theta) = \left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{-\frac{1}{\theta}},\ \theta \in [-1,\infty)\backslash\{0\}, \tag{D21}$$

$$\boldsymbol{C}_{\text{Fr}}(u_1, u_2; \theta) = -\frac{1}{\theta} \log \left(\frac{1 - e^{-\theta} - (1 - e^{-\theta u_1})(1 - e^{-\theta u_2})}{1 - e^{-\theta}} \right),\ \theta \in (-\infty,\infty)\backslash\{0\}. \tag{D22}$$

The LTD coefficients of the individual copulas are given by

$$\tau_t^L = 2t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho}}{\sqrt{1+\rho}}\right), \qquad \tau_{\text{Cl}}^L = 2^{-\frac{1}{\theta}}, \qquad \tau_{\text{Fr}}^L = 0. \tag{D23}$$

To calculate the LTD coefficients implied by the Mixture Copula 2 (ML) model, we apply (D11) and get

$$\tau_{\text{mix,2}}^L = 2w_1 t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho}}{\sqrt{1+\rho}}\right) + 2^{-\frac{1}{\theta}} w_2. \tag{D24}$$

Estimation of the Mixture Copula 2 (ML) model is straightforwardly done via ML, where the log likelihood function is given by

$$\mathcal{L}(\boldsymbol{u_1}, \boldsymbol{u_2}; \boldsymbol{\theta}, \boldsymbol{w}) = \sum_{t=1}^{T} \log\left(\boldsymbol{w}^\top \boldsymbol{c}(u_{1,t}, u_{2,t}; \boldsymbol{\theta})\right) \tag{D25}$$

where $\boldsymbol{u_i}$ is defined as above ($i = 1,2$), $\boldsymbol{\theta} = (\nu, \rho, \theta_1, \theta_2)^\top$ contains the copula parameters, $\boldsymbol{w} = (w_1, w_2, w_3)^\top$ denotes the vector of weights, and $\boldsymbol{c} = (c_t, c_{\text{Cl}}, c_{\text{Fr}})^\top$ is a vector containing the copula densities of the t copula as well as the Clayton and Frank copula, respectively.

As in case of the Mixture Copula 1 (ML) model, we are aware of the fact that estimating mixtures in this way yields potentially biased parameter estimates due to ignoring the incomplete-data problem and maximizing the likelihood with respect to both copula parameters and the weights. Again, we are interested in how this potential bias shows up in the computation of LTD coefficients.

D.1.7 Mixture copula 2 (EM)

The LTD estimator based on the Mixture Copula 2 (EM) is a static estimator and based on the same mixture of copulas as the LTD estimator based on the Mixture Copula 2 (ML) model. Hence, the estimator builds on a mixture of the t copula as well as the Clayton and Frank copula, and calculates LTD coefficients as a weighted sum of the LTD coefficients of these individual copulas. Corresponding formulas can be found in equations (D19) to (D24).

The difference between the two mixture models, however, lies in the method used for estimation. Whereas the estimation procedure applied to the Mixture Copula 2 (ML) model yields potentially biased estimates by maximizing the log likelihood in (D25) with respect to both copula parameters and the weights of the mixture, estimation of the Mixture Copula 2 (EM) model considers the incomplete-data structure we encounter when estimating mixture copulas and, therefore, is based on the EM algorithm as proposed by Dempster et al. (1977). A description of the EM algorithm can be found in the discussion of the Mixture Copula 1 (EM) model above.

D.1.8 Regime-switching copula

The LTD estimator implied by the Regime-Switching Copula model is a static estimator and based on identifying two regimes for characterizing the dependence structure and computing LTD coefficients. We follow Okimoto (2008) as well as Garcia and Tsafack (2011) and assume the first regime to be Gaussian with symmetric dependence and zero tail dependence, and the second regime to be specified by the Clayton copula that is capable of capturing asymmetry in extreme dependence. As is standard in the literature on regime-switching models, we assume the two regimes and the transitions between them to be reflected by a latent state variable that follows a Markov chain with a constant transitional probability matrix.

Formally, the Regime-Switching Copula is the mixture of the regime copulas and thus given by

$$\boldsymbol{C}_{\text{RS}} = s_t \boldsymbol{C}_{\text{GA}} + (1 - s_t)\boldsymbol{C}_{\text{Cl}} \tag{D26}$$

where $\boldsymbol{C}_{\text{GA}}$ and $\boldsymbol{C}_{\text{Cl}}$ denote the Gaussian and the Clayton copula, respectively, and $s_t \in \{1, 2\}$ is the latent state variable with transition probability matrix

$$P = \begin{pmatrix} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{pmatrix}, \quad p_{ii} = \text{Pr}[s_t = i | s_{t-1} = i] \text{ for } i = 1, 2. \tag{D27}$$

Note that the labeling of each regime is determined ex-ante, where the Gaussian regime is reflected by $s_t = 1$ and the asymmetric regime is indicated by $s_t = 2$. The Gaussian copula, $\boldsymbol{C}_{\text{Ga}}$, and the Clayton copula, $\boldsymbol{C}_{\text{Cl}}$, are given by

$$\boldsymbol{C}_{\text{Ga}}(u_1, u_2; \theta) = \boldsymbol{\Phi}_\theta \left(\Phi^{-1}(u_1), \Phi^{-1}(u_2) \right), \ \theta \in (-1, 1), \tag{D28}$$

$$\boldsymbol{C}_{\text{Cl}}(u_1, u_2; \theta) = \left(u_1^{-\theta} + u_2^{-\theta} - 1 \right)^{-\frac{1}{\theta}}, \ \theta \in [-1, \infty) \backslash \{0\}, \tag{D29}$$

where $\boldsymbol{\Phi}_\theta$ and Φ^{-1} denote the bivariate Gaussian distribution function with correlation parameter θ and the univariate Gaussian quantile function, respectively. The implied LTD coefficients can be computed according to

$$\tau^L_{\text{Ga}} = 0 \quad \text{and} \quad \tau^L_{\text{Cl}} = 2^{-\frac{1}{\theta}}. \tag{D30}$$

The Gaussian copula is asymptotically independent in the tails; hence, the LTD coefficients generated by the Regime-Switching Copula model are based on the LTD coefficients of the Clayton copula in the asymmetric regime.

Since the latent state variable s_t is unobservable, estimation of the Regime-Switching Copula model constitutes an incomplete-data problem and needs to be conducted via the EM algorithm as proposed by Dempster et al. (1977), which is outlined above and discussed in detail by McLachlan and Peel (2000). Further, to deal with the transitional probabilities when calculating ML estimates, we use the Hamilton filter, a general presentation of which can be found in Hamilton (1994).

D.1.9 Clayton copula

The LTD estimator based on the Clayton Copula is a static estimator and equal to the LTD coefficient implied by the Clayton Copula, which is given by

$$\boldsymbol{C}_{\text{Cl}}(u_1, u_2; \theta) = \left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{-\frac{1}{\theta}} \tag{D31}$$

where $\theta \in [-1, \infty)\backslash\{0\}$. The copula density can be expressed as

$$\boldsymbol{c}_{\text{Cl}}(u_1, u_2; \theta) = (1+\theta)(u_1 u_2)^{-\theta-1}(u_1^{-\theta} + u_2^{-\theta} - 1)^{-2-\frac{1}{\theta}} \tag{D32}$$

and the LTD coefficient can be calculated according to

$$\tau_{\text{Cl}}^{L} = 2^{-\frac{1}{\theta}}. \tag{D33}$$

The Clayton Copula is estimated straightforwardly via ML, where the log likelihood is given by

$$\begin{aligned}\mathcal{L}(\boldsymbol{u_1}, \boldsymbol{u_2}; \theta) &= \sum_{t=1}^{T} \log\left(\boldsymbol{c}_{\text{Cl}}(u_{1,t}, u_{2,t}; \theta)\right) \\ &= \sum_{t=1}^{T} \log\left(1+\theta\right) - (1+\theta)\log\left(u_{1,t}u_{2,t}\right) - (2+\theta^{-1})\log\left(u_{1,t}^{-\theta} + u_{2,t}^{-\theta} - 1\right)\end{aligned} \tag{D34}$$

with $\boldsymbol{u_i} = (u_{i,1}, ..., u_{i,T})^{\top}$ for $i = 1, 2$.

D.1.10 Clayton copula (EVT)

The LTD estimator based on the Clayton Copula (EVT) model is a static estimator and equal to the LTD coefficient implied by the Clayton Copula. The corresponding expression for the copula function and density as well as the formula for the calculation of LTD coefficients can be found in equations (D31) to (D33), respectively. Hence, the Clayton Copula (EVT) builds on the same technique as the Clayton Copula model.

In contrast to the latter, however, the Clayton Copula (EVT) model is based on a semi-parametric model for the marginal distributions. More precisely, with $(X_1, X_2) \sim (F_{X_1}, F_{X_2})$ denoting a two-dimensional random vector with marginal distributions F_{X_1} and F_{X_2}, we follow Hilal et al. (2011) and use the results from Extreme Value Theory (EVT) to model the excess distributions of $-X_1$ and $-X_2$ by the Generalized Pareto Distribution (GPD). Thus, assuming the GPD for the lower tail and a nonparametric model for the remaining portion, the marginal distribution of X_i, F_{X_i} $(i = 1, 2)$, is estimated as

$$\hat{F}_{X_i}(x) = \begin{cases} \tilde{F}_{X_i}(\ell_{X_i}) \left[1 - F_{\text{GPD}}(\ell_{X_i} - x; \hat{\xi}_i, \hat{\sigma}_i)\right], & x < \ell_{X_i} \\ \tilde{F}_{X_i}(x), & x \geqslant \ell_{X_i} \end{cases} \tag{D35}$$

where $\tilde{F}_{X_i}$ is the empirical distribution function, ℓ_{X_i} denotes a suitably chosen low threshold, F_{GPD} is the distribution function of the GPD, and the parameters $\hat{\sigma}_i > 0$ and $\hat{\xi}_i \in (-\infty, \infty)$ denote the ML estimates of the scale and shape parameters of F_{GPD}, respectively.

Regarding the marginal threshold ℓ_{X_i}, we follow Hilal et al. (2011) and choose ℓ_{X_i} as high as possible on the basis of a goodness-of-fit test for the GPD. More precisely, in preliminary (unreported) tests we estimate the ML estimates of the GPD for various levels of the threshold and conduct the goodness-of-fit test on the basis of the Anderson-Darling statistic. The corresponding asymptotic critical values (under the null hypothesis that the exceedances fit the GPD) are tabulated in Choulakian and Stephens (2001). The results from our tests indicate that, on average, the 5% empirical quantile is a suitable choice for the threshold of the GPD.[3]

D.1.11 Nonparametric estimator

This LTD estimator delivers constant LTD coefficients and is based on the nonparametric estimator as proposed by Schmidt and Stadtmueller (2006). More precisely, the authors build on the concept of empirical tail copulas and introduce tail dependence estimators that are based on the empirical copula.

Formally, with X_1 and X_2 being two n-dimensional random vectors with $(X_1, X_2) \sim \boldsymbol{F} = (G, H)$ and copula $\boldsymbol{C}$, the empirical copula, $\boldsymbol{C}_m$, can be expressed as

$$\boldsymbol{C}_m(u_1, u_2) = \boldsymbol{F}_m(G_m^{-1}(u_1), H_m^{-1}(u_2)) \tag{D36}$$

where $\boldsymbol{F}_m$, G_m, and H_m denote the empirical distribution functions of $\boldsymbol{F}$, G, and H, respectively. Further, let $\boldsymbol{R}_{m,i} = (R_{m,i}^j)_{j=1,\ldots,n}$ be the rank of X_i, $i = 1, 2$.
Schmidt and Stadtmueller (2006) then propose the following empirical LTD estimator:

$$\tau_m^L = \frac{m}{k}\boldsymbol{C}_m\left(\frac{k}{m}, \frac{k}{m}\right) \approx \frac{1}{k}\sum_{j=1}^{n} \mathbf{1}_{\left\{R_{m,1}^j \leqslant k \text{ and } R_{m,2}^j \leqslant k\right\}} \tag{D37}$$

where the parameter k needs to be specified adequately. In our simulation study, we follow Schmidt and Stadtmueller (2006) and utilize the homogeneity property of tail copulas which transfers to the nonparametric estimator in (D37) yielding a characteristic plateau while plotting the estimates for successive k. Accordingly, we estimate the optimal threshold k via a simple plateau-finding algorithm subsequent to smoothing the estimates by a Gaussian kernel with bandwidth equal to 0.05.

[3]Further details on the goodness-of-fit testing procedure can be found in Hilal et al. (2011).

D.2 Simulating from DGPs

This section presents technical details on the simulation from the three dynamic LTD estimators used as data-generating processes (DGPs) in our simulation study.

D.2.1 Simulating from Patton's (2006) dynamic t copula.

Simulating lower tail dependence (LTD) coefficients and copula data from Patton's (2006) Dynamic t Copula is based on the simulation of the process describing the correlation dynamics, ρ_t, which is given by

$$\begin{aligned}\rho_t &= \Lambda\left(\omega + \beta\rho_{t-1} + \alpha\frac{1}{10}\sum_{i=1}^{10} t_\nu^{-1}(u_{1,t-i})t_\nu^{-1}(u_{2,t-i})\right)\\ &= \Lambda\left(0.5 + 0.9\rho_{t-1} + 0.6\frac{1}{10}\sum_{i=1}^{10} t_{10}^{-1}(u_{1,t-i})t_{10}^{-1}(u_{2,t-i})\right)\end{aligned} \tag{D38}$$

where $\Lambda(x) \equiv (1-e^{-x})(1+e^{-x})^{-1}$ is a normalizing function.

To this purpose, as a starting point we first draw an observation $\boldsymbol{u}^{(0)} = (u_{1,0}, u_{2,0})^\top$ from a standard Uniform distribution, $\mathcal{U}_{[0,1]}$. Further, we set $\rho_0 = \Lambda(0.5)$ and calculate $\rho_1 = \Lambda(0.5 + 0.9\rho_0 + 0.6t_{10}^{-1}(u_{1,0})t_{10}^{-1}(u_{2,0}))$. To compute ρ_2, we need ρ_1 as well as $\boldsymbol{u}^{(0)}$ and $\boldsymbol{u}^{(1)}$. The latter is computed by simulating from a bivariate t copula, $\boldsymbol{C}_{t^2_{10,\rho_1}}$, with degrees of freedom equal to 10 and correlation parameter ρ_1. Having determined starting points, we then calculate $\boldsymbol{u}^{(t-1)}$ and ρ_t alternately for $t = 3, ..., T$, where the former is computed via simulation from $\boldsymbol{C}_{t^2_{10,\rho_{t-1}}}$ and the latter by applying the iteration in (D38). Note, however, that since we calculate the average of the transformed variables $t_{10}^{-1}(u_{1,t-i})$ and $t_{10}^{-1}(u_{2,t-i})$ over the previous 10 lags, we compute ρ_t according to

$$\rho_t = \begin{cases} \Lambda\left(0.5 + 0.9\rho_{t-1} + 0.6\frac{1}{t}\sum\limits_{i=1}^{t} t_{10}^{-1}(u_{1,t-i})t_{10}^{-1}(u_{2,t-i})\right), & t = 1, ..., 9\\ \Lambda\left(0.5 + 0.9\rho_{t-1} + 0.6\frac{1}{10}\sum\limits_{i=1}^{10} t_{10}^{-1}(u_{1,t-i})t_{10}^{-1}(u_{2,t-i})\right), & t = 10, ..., T\end{cases} \tag{D39}$$

Having simulated the correlations, $(\rho_t)_{t=1}^T$, we compute simulated (true) LTD coefficients,

τ_t^L, according to

$$\tau_t^L = 2t_{11}\left(-\frac{\sqrt{11}\sqrt{1-\rho_t}}{\sqrt{1+\rho_t}}\right). \tag{D40}$$

D.2.2 Simulating from the DCC t copula

Simulating lower tail dependence (LTD) coefficients and copula data from the DCC t Copula is based on the simulation of the process describing the correlation dynamics, ρ_t, which is given by

$$\rho_t = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \tag{D41}$$

with the matrix $Q_t = (q_{ij,t})_{i,j=1,2}$ following

$$\begin{aligned} Q_t &= (1-\phi-\psi)\Omega + \psi Q_{t-1} + \phi \bar{z}^c_{t-1}\bar{z}^{c\top}_{t-1} \\ &= 0.05\Omega + 0.9Q_{t-1} + 0.05\bar{z}^c_{t-1}\bar{z}^{c\top}_{t-1} \end{aligned} \tag{D42}$$

where $\Omega = (\omega_{ij})_{i,j=1,2}$ is a correlation matrix with off-diagonal entries, ω_{12} and ω_{21}, equal to 0.8, and $\bar{z}^c_t = (\bar{z}^c_{1,t}, \bar{z}^c_{2,t})^\top$ with $\bar{z}^c_{i,t}$ given by $z^c_{i,t}\sqrt{Q_{ii,t}}$ and $z^c_{i,t} = t_5^{-1}(u_{i,t})$, $i = 1, 2$.[4]

To this purpose, as a starting point we first draw an observation $\boldsymbol{u}^{(0)} = (u_{1,0}, u_{2,0})^\top$ from a standard Uniform distribution, $\mathcal{U}_{[0,1]}$. Setting $q_{11,0} = q_{22,0} = 1-\phi-\psi = 0.05$ and $q_{12,0} = q_{21,0} = (1-\phi-\psi)\Omega_{12} = 0.04$, we use (D41) and calculate $\rho_0 = 0.8$. Further, the initial modified copula shocks, $\bar{z}^c_{i,0}$, are calculated as $\bar{z}^c_{i,0} = \sqrt{0.05}t_5^{-1}(u_{i,0})$, $i = 1, 2$. To compute ρ_1, we need Q_0 as well as the cross-product of lagged (modified) copula shocks, $\bar{z}^c_0$. Hence, ρ_1 results from substituting the above starting values into equations (D41) and (D42). Updated copula data, $\boldsymbol{u}^{(1)}$, are then received by simulating from a bivariate t copula, $\boldsymbol{C}_{t^2_{5,\rho_1}}$, with degrees of freedom equal to 5 and correlation parameter ρ_1. Having determined starting values, we now calculate ρ_t and $\boldsymbol{u}^{(t)}$ alternately for $t = 2, ..., T$, where the former is computed according to equations (D41) and (D42), and the latter via

[4]Note that we follow Christoffersen et al. (2012) and use the modified copula shocks $\bar{z}^c_t$ instead of z^c_t for the correlation dynamics. See Aielli (2009) for details on this modification.

simulation from $\boldsymbol{C}_{t^2_{5,\rho_t}}$.

Based on the simulated correlations, $(\rho_t)_{t=1}^{T}$, we compute simulated (true) LTD coefficients, τ_t^L, as

$$\tau_t^L = 2t_6\left(-\frac{\sqrt{6}\sqrt{1-\rho_t}}{\sqrt{1+\rho_t}}\right). \tag{D43}$$

D.2.3 Simulating from the DSC t copula

Simulating lower tail dependence (LTD) coefficients and copula data from the DSC t Copula is based on the simulation of the process describing the correlation dynamics, ρ_t, which is given by

$$\rho_t = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \tag{D44}$$

with the matrix $Q_t = (q_{ij,t})_{i,j=1,2}$ following

$$\begin{aligned} Q_t &= (1-\phi-\psi)\left[(1-\kappa)\Omega + \kappa D_t\right] + \psi Q_{t-1} + \phi \bar{z}^c_{t-1}\bar{z}^{c\top}_{t-1} \\ &= 0.05\left[0.6\Omega + 0.4D_t\right] + 0.95Q_{t-1} + 0.05\bar{z}^c_{t-1}\bar{z}^{c\top}_{t-1} \end{aligned} \tag{D45}$$

where $\Omega = (\omega_{ij})_{i,j=1,2}$ is a correlation matrix with off-diagonal entries, ω_{12} and ω_{21}, equal to 0.8, D_t is a time trend correlation matrix with time trend parameter, δ, equal to 0.01 and off-diagonal entries, $D_{12,t}$ and $D_{21,t}$, given by $0.01^2t^2(1+0.01^2t^2)^{-1}$, and $\bar{z}^c_t = (\bar{z}^c_{1,t}, \bar{z}^c_{2,t})^\top$ with $\bar{z}^c_{i,t}$ given by $z^c_{i,t}\sqrt{Q_{ii,t}}$ and $z^c_{i,t} = t_5^{-1}(u_{i,t})$, $i = 1, 2$.

To this purpose, as a starting point we first draw an observation $\boldsymbol{u}^{(0)} = (u_{1,0}, u_{2,0})^\top$ from a standard Uniform distribution, $\mathcal{U}_{[0,1]}$. Setting $q_{11,0} = q_{22,0} = 1-\phi-\psi = 0.05$ and $q_{12,0} = q_{21,0} = (1-\phi-\psi)\left[(1-\kappa)\Omega_{12} + \kappa D_{12,1}\right] = 0.024$, we use (D44) and calculate $\rho_0 = 0.48$. Further, the initial modified copula shocks, $\bar{z}^c_{i,0}$, are calculated as $\bar{z}^c_{i,0} = \sqrt{0.05}t_5^{-1}(u_{i,0})$, $i = 1, 2$. To compute ρ_1, we need Q_0 as well as the cross-product of lagged (modified) copula shocks, $\bar{z}^c_0$. Hence, ρ_1 results from substituting the above starting values into equations (D44) and (D45).[5] Updated copula data, $\boldsymbol{u}^{(1)}$, are then

[5]Note that Ω is a constant correlation matrix and D_t only depends on the time trend parameter, δ, as well

received by simulating from a bivariate t copula, $\boldsymbol{C}_{t^2_{5,\rho_1}}$, with degrees of freedom equal to 5 and correlation parameter ρ_1. Having determined starting values, we now calculate ρ_t and $\boldsymbol{u}^{(t)}$ alternately for $t = 2, ..., T$, where the former is computed according to equations (D44) and (D45), and the latter via simulation from $\boldsymbol{C}_{t^2_{5,\rho_t}}$.

Based on the simulated correlations, $(\rho_t)_{t=1}^T$, we compute simulated (true) LTD coefficients, τ_t^L, according to

$$\tau_t^L = 2t_6\left(-\frac{\sqrt{6}\sqrt{1-\rho_t}}{\sqrt{1+\rho_t}}\right). \tag{D46}$$

as the point in time, t, at which the matrix is evaluated. Hence, Ω and D_t can be calculated independently of ρ_t and $\bar{z}_t^c$ for all $t = 1, ..., T$ once the parameters have been determined.

Figure D.1: Mean squared errors of lower tail dependence estimators.

The figure shows the mean squared errors (MSE) separately for each of the three data-generating processes (Patton, DCC, and DSC model) and each of the lower tail dependence (LTD) estimators included in the simulation study. The plots in the figure result from the baseline approach, which is determined by setting the sample size, T, to 500 and the number of simulation replications, N, to 1000. MSE is computed in each simulation trial, resulting in a total of 1000 MSEs for each combination of data-generating process (DGP) and LTD estimator. The MSE formula is given by MSE $= \Pi(\boldsymbol{\tau}, \hat{\boldsymbol{\tau}}) = T^{-1} \sum_{t=1}^{T} (\tau_t - \hat{\tau}_t)^2$, where $\boldsymbol{\tau} = (\tau_t)_{t=1}^{T}$ and $\hat{\boldsymbol{\tau}} = (\hat{\tau}_t)_{t=1}^{T}$ denote the series of true and estimated LTD coefficients, respectively. The names of the LTD estimators are abbreviated according to the notation introduced in Section 5.3.1.

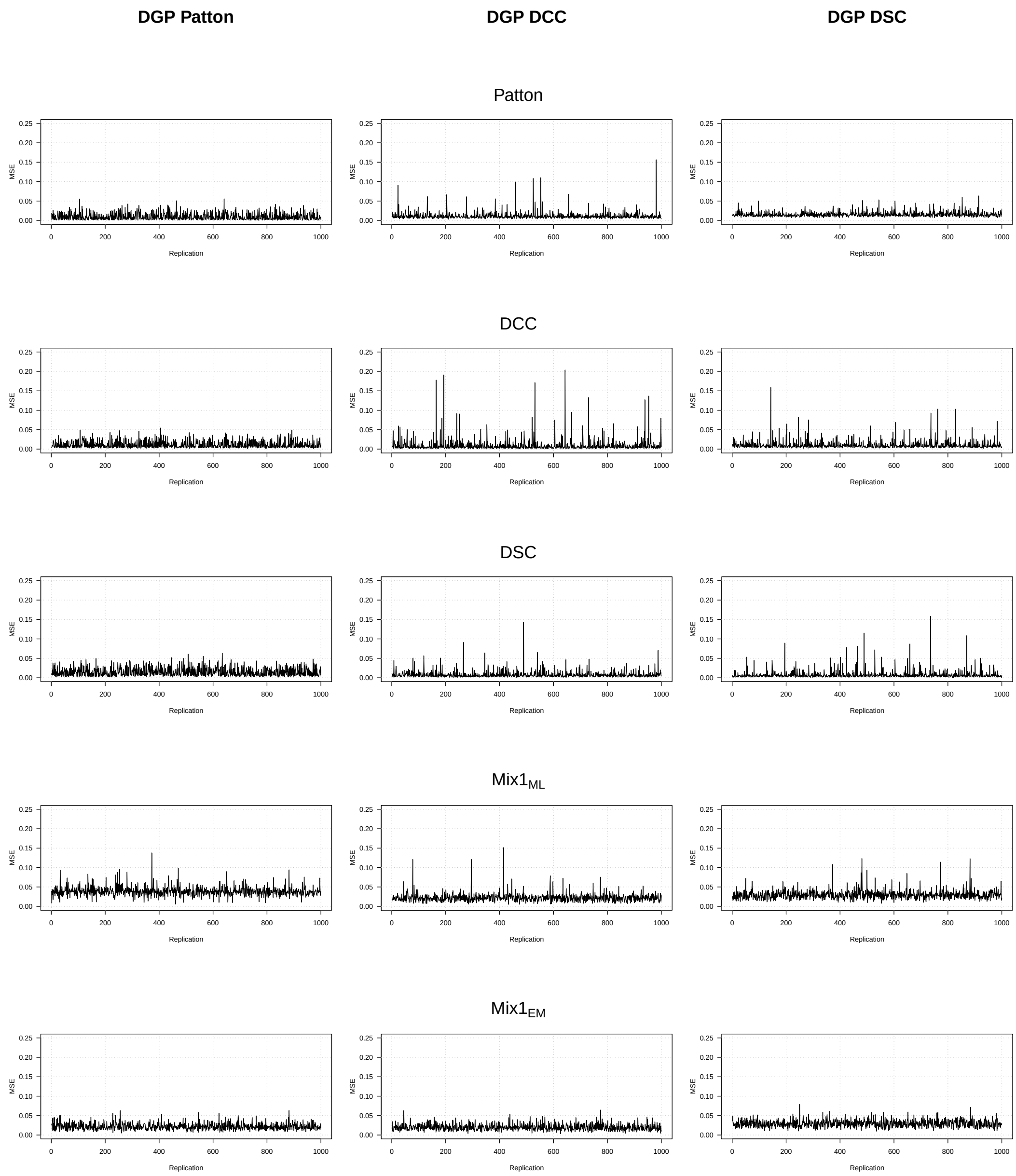


Figure D.1: Mean squared errors of lower tail dependence estimators (continued).

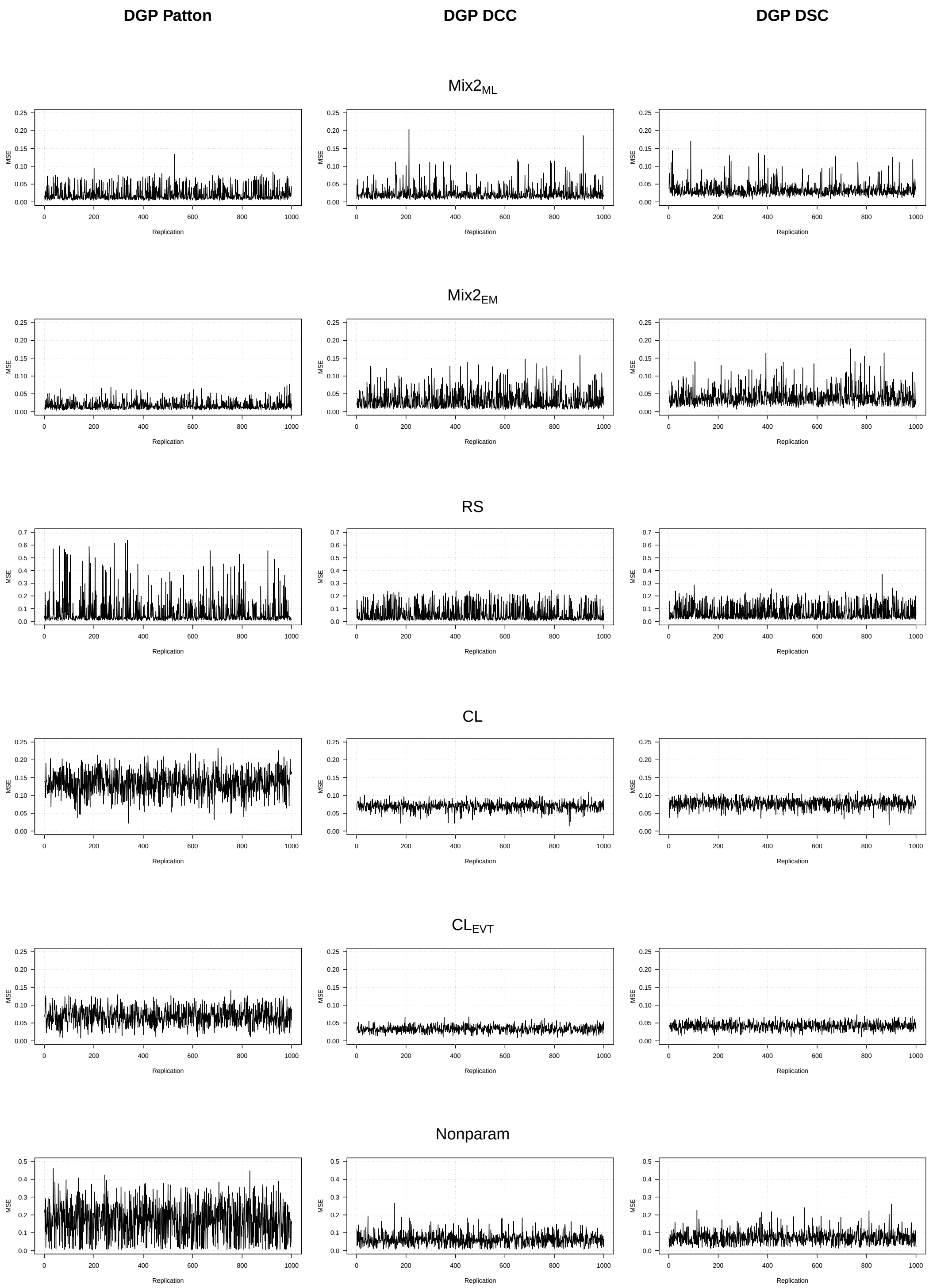


Table D.1: Survey of recent studies on extreme dependence in financial economics.

The table provides a survey on recent studies in the financial economics literature that focus on extreme dependence in the context of asset pricing, credit risk, financial intermediation, risk management, and portfolio management. For each study listed in the first column of the table, we first specify the main issue of the study (column two) and then briefly summarize the corresponding key findings (column four). Next, we provide an overview of the extreme dependence estimation procedure employed in the respective study and, finally, list the journal in which the study has been published. Regarding the journals, we employ the following commonly used abbreviations: (i) Applied Financial Economics (AFE), (ii) International Economic Review (IER), (iii) Journal of Banking & Finance (JBF), (iv) Journal of Empirical Finance (JEF), (v) Journal of Financial and Quantitative Analysis (JFQA), (vi) Journal of Financial Econometrics (JFEC), (vii) Journal of International Money and Finance (JIMF), (viii) Review of Financial Studies (RFS).

Study	*Main issue*	*Key finding*	*Extreme dependence estimator*	*Journal*
Aloui et al. (2011)	Extreme financial interdependences of selected emerging markets with the US	Time-varying dependence between each of the BRIC markets and the US markets	Static Gumbel/Galambos copula	JBF
Beine et al. (2010)	Implications of trade and financial integration for portfolio diversification	Open financial markets increase the likeliness of a joint crash in all markets	Quantile regression	JBF
Chollete et al. (2009)	Modeling asymmetric dependence with multivariate regime-switching copulas	Canonical vines dominate alternative dependence structures and the choice of copula has important implications for risk management	Regime-switching copula	JFEC
Chollete et al. (2012)	International diversification with correlations and extreme dependence	Correlations and extreme dependence deliver ambiguous risk management signals	Extreme value theory	JBF
Christoffersen et al. (2012)	International diversification across emerging and developed markets	Correlations and tail dependence have increased and are lower for emerging markets	Dynamic asymmetric t copula	RFS
Christoffersen and Langlois (2013)	Joint distributional dynamics of equity market factors	Asymmetric tail dependence across equity market factors and overestimation of diversification benefits across the factors by linear correlations	Dynamic asymmetric t copula	JFQA
Christoffersen et al. (2013)	Time-varying diversification benefits from selling credit protection	Increases in cross-sectional dependence following the financial crisis have reduced diversification benefits from selling credit protection	Dynamic asymmetric t copula	Working paper
DiTraglia and Gerlach (2013)	Implications of lower tail dependence for portfolio selection	Lower tail dependence generates a risk premium and is different from other risk measures	Extreme value theory	JBF
Dudley and Nimalendran (2011)	Role of funding risk in explaining hedge fund contagion	Identification of the mechanism by which changes in funding liquidity affect hedge fund contagion	Dynamic Clayton copula	JFQA
Garcia and Tsafack (2011)	Extreme comovements in international equity and bond markets	Dependence is strong for assets of the same type and weak between equities and bonds	Regime-switching copula	JBF

Table D.1: Survey of recent studies on extreme dependence in financial economics (continued).

Study	*Main issue*	*Key finding*	*Extreme dependence estimator*	*Journal*
Heinen and Valdesogo (2008)	Dynamic dependence modeling in high dimensions	Canonical vine autoregressive model captures asymmetric and dynamic dependence and yields accurate Value-at-Risk forecasts	Dynamic elliptical/Archimedean copulas	Working paper
Herrera and Eichler (2011)	Asymmetric extreme dependence between EMU, UK, and US stock markets	Extreme dependence is asymmetrical in the pre-EMU and symmetrical in the EMU period	Extreme value theory	JBF
Hilal et al. (2011)	Estimation of hedge ratios based on the S&P500 index and VIX futures contracts	Hedge ratios based on extreme value theory outperform minimum variance OLS hedge ratios	Extreme value theory	JBF
Hong et al. (2007)	Model-free testing for asymmetries in stock returns	Substantial economic importance of incorporating asymmetries into investment decisions with a disappointment aversion preference	Static mixture copulas	RFS
Hu (2011)	Estimating the dependence structure of stock market indices	Cross-market dependence is asymmetric and characterized by lower tail dependence	Static mixture copulas	AFE
Junker et al. (2006)	Extreme dependence in the term structure of US Treasury yields	US Treasury yields are upper-tail dependent and using the normal copula prevents accurate risk measurement	Static elliptical/Archimedean copulas	JBF
Kang et al. (2010)	Asymmetric dependence between hedge fund returns and market returns	Nonlinearity in hedge fund exposure to market risk is more short term in nature	Static mixture copulas/Nonparametric estimator	JFQA
Meine et al. (2013)	Tail risk in credit default swap pricing	Protection sellers receive a premium for bearing the risk of extreme upward comovements in default risk	Dynamic asymmetric t copula	Working paper
Min and Czado (2010)	Modeling multivariate dependence structures with pair copula constructions	Development of a Markov chain Monte Carlo algorithm used to reveal (un-)conditional independences in Norwegian financial returns and Euro swap rates	Static t copula	JFEC
Ning (2010)	Dependence structure between the equity and foreign exchange market	Significant upper and lower tail dependence between equity and foreign exchange markets that becomes weaker after the launch of the euro	Static elliptical/Archimedean copulas	JIMF

Table D.1: Survey of recent studies on extreme dependence in financial economics (continued).

Study	*Main issue*	*Key finding*	*Extreme dependence estimator*	*Journal*
Oh and Patton (2012)	High-dimensional dependence modeling	Tail dependence, heterogeneous dependence, and asymmetric dependence between the stock returns of the S&P100 constituents	Factor copula	Working paper
Oh and Patton (2013)	Measuring systemic risk with a new class of copula-based dynamic models	Systemic risk is substantially higher now than in the pre-crisis period	Dynamic copula models	Working paper
Okimoto (2008)	Asymmetric dependence structures in international equity markets	Two distinct regimes in the dependence of G7 stock market indices: normal and asymmetric extreme dependence	Regime-switching copula	JFQA
Patton (2006)	Asymmetry in the dependence of exchange rates	The mark-dollar and yen-dollar exchange rates are more correlated when they are depreciating against the dollar than when they are appreciating	Dynamic elliptical/Archimedean copulas	IER
Rodriguez (2007)	Measuring financial contagion with switching-parameter copulas	Dependence changes during periods of turmoil and structural breaks in tail dependence are a dimension of the contagion phenomenon	Static mixture copulas	JEF
Ruenzi et al. (2013)	Asset pricing with extreme downside liquidity risk	Investors receive a compensation for holding stocks with strong systematic liquidity risk in the form of extreme downside liquidity risk	Static mixture copulas	Working paper
Ruenzi and Weigert (2013)	Crash risk in asset pricing	Investors receive a compensation for holding crash-sensitive stocks	Static mixture copulas	Working paper
Weiß and Supper (2013)	Incorporation of nonlinear liquidity risk into Value-at-Risk forecasting	Strong tail dependence between bid-ask spreads and equity returns and accurate forecasting of portfolio profits and losses	Static vine copulas	JBF

Table D.2: Bivariate copulas used in the simulation study.

The table presents the cumulative distribution functions (cdf), parameter domains, and closed-form expressions for the lower tail dependence (LTD) coefficients of the bivariate copulas included in our simulation study. The Clayton, Rotated-Joe, and Student's t copula exhibit lower tail dependence, while the F-G-M, Frank, Gaussian, and Joe copula are asymptotically independent in the lower tail. $\boldsymbol{\Phi}_\theta$ and Φ^{-1} denote the cdf of a bivariate normal distribution with correlation parameter θ and the univariate Gaussian quantile function, respectively. $\boldsymbol{t}_\theta^2$, t_ν, and t_ν^{-1} denote the bivariate and univariate cdf as well as the univariate quantile function of the Student's t distribution, respectively, with θ denoting the corresponding parameter vector containing the degrees of freedom parameter, ν, and the correlation parameter, ρ.

Copula	CDF	θ-Domain	LTD
Clayton	$\boldsymbol{C}_{\text{Cl}}(u_1, u_2; \theta) = \left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{-\frac{1}{\theta}}$	$\theta \in [-1, \infty)\backslash\{0\}$	$\tau^L = 2^{-\frac{1}{\theta}}$
F-G-M	$\boldsymbol{C}_{\text{FGM}}(u_1, u_2; \theta) = u_1 u_2 \left(1 + \theta(1-u_1)(1-u_2)\right)$	$\theta \in [-1, 1]$	$\tau^L = 0$
Frank	$\boldsymbol{C}_{\text{Fr}}(u_1, u_2; \theta) = -\frac{1}{\theta}\log\left([1 - e^{-\theta} - (1 - e^{-\theta u_1})(1 - e^{-\theta u_2})][1 - e^{-\theta}]^{-1}\right)$	$\theta \in (-\infty, \infty)\backslash\{0\}$	$\tau^L = 0$
Gauss	$\boldsymbol{C}_{\text{Ga}}(u_1, u_2; \theta) = \boldsymbol{\Phi}_\theta\left(\Phi^{-1}(u_1), \Phi^{-1}(u_2)\right)$	$\theta \in (-1, 1)$	$\tau^L = 0$
Joe	$\boldsymbol{C}_{\text{Joe}}(u_1, u_2; \theta) = 1 - \left((1-u_1)^\theta + (1-u_2)^\theta - (1-u_1)^\theta(1-u_2)^\theta\right)^{\frac{1}{\theta}}$	$\theta \in [1, \infty)$	$\tau^L = 0$
Rotated-Joe	$\boldsymbol{C}_{\text{rJoe}}(u_1, u_2; \theta) = u_1 + u_2 - \left(u_1^\theta + u_2^\theta - u_1^\theta u_2^\theta\right)^{\frac{1}{\theta}}$	$\theta \in [1, \infty)$	$\tau^L = 2 - 2^{\frac{1}{\theta}}$
Student's t	$\boldsymbol{C}_t(u_1, u_2; \theta) = \boldsymbol{t}_\theta^2(t_\nu^{-1}(u_1), t_\nu^{-1}(u_2))$	$\theta \in (0, \infty) \times (-1, 1)$	$\tau^L = 2t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho}}{\sqrt{1+\rho}}\right)$

Table D.3: Lower tail dependence estimators under study.

The table presents the lower tail dependence (LTD) estimators included in our simulation study along with the expressions for the corresponding LTD coefficients and the correlation dynamics for the time-varying estimators. We consider eight static LTD estimators (Mix1$_{\text{ML}}$, Mix1$_{\text{EM}}$, Mix2$_{\text{ML}}$, Mix2$_{\text{EM}}$, RS, CL, CL$_{\text{EVT}}$, Nonparam) and three dynamic estimators based on different dynamizations of the Student's t copula (Patton, DCC, DSC). The notation is as follows: t_ν and t_ν^{-1} denote the univariate distribution and quantile function of the Student's t distribution with degrees of freedom parameter ν, respectively; w_1 and w_2 denote the weights of the mixture copulas. Regarding the correlation dynamics, ω, β, α, ϕ, ψ, $\tilde{\phi}$, $\tilde{\psi}$, and κ are scalar parameters, $\Lambda(x) \equiv (1-e^{-x})(1+e^{-x})^{-1}$ is a normalizing function, $u_{1,t}$ and $u_{2,t}$ denote the ranks of the residuals from univariate GARCH processes, Ω and D_t are two-by-two correlation matrices containing constant correlations and time trends, respectively, and $\bar{z}_t^c$ denotes a vector of (modified) copula shocks. The DSC model incorporates a time trend into copula correlations and nests the DCC model in case of $\kappa = 0$. Technical details can be found in Section D.1 in Appendix D.

Model	LTD estimator	Correlation dynamics
Patton	$\tau_t^L = 2t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho_t}}{\sqrt{1+\rho_t}}\right)$	$\rho_t = \Lambda\left(\omega + \beta\rho_{t-1} + \alpha\frac{1}{10}\sum_{i=1}^{10} t_\nu^{-1}(u_{1,t-i})t_\nu^{-1}(u_{2,t-i})\right)$
DCC		$\rho_t = \frac{Q_{12,t}}{\sqrt{Q_{11,t}Q_{22,t}}},\ Q_t = (1-\phi-\psi)\Omega + \psi Q_{t-1} + \phi\bar{z}_{t-1}^c\bar{z}_{t-1}^{c\top}$
DSC		$\rho_t = \frac{Q_{12,t}}{\sqrt{\tilde{Q}_{11,t}\tilde{Q}_{22,t}}},\ \tilde{Q}_t = (1-\tilde{\phi}-\tilde{\psi})\left[(1-\kappa)\Omega + \kappa D_t\right] + \tilde{\psi}\tilde{Q}_{t-1} + \tilde{\phi}\bar{z}_{t-1}^c\bar{z}_{t-1}^{c\top}$
Mix1$_{\text{ML}}$	$\tau^L = w_2\left(2 - 2^{\frac{1}{\theta}}\right)$	–
Mix1$_{\text{EM}}$		–
Mix2$_{\text{ML}}$	$\tau^L = 2w_1 t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho}}{\sqrt{1+\rho}}\right) + 2^{-\frac{1}{\theta}}w_2$	–
Mix2$_{\text{EM}}$		–
RS	$\tau^L = 2^{-\frac{1}{\theta}}$	–
CL		–
CL$_{\text{EVT}}$		–
Nonparam	$\tau^L = \frac{1}{k}\sum_{j=1}^{n}\mathbf{1}_{\left\{R_{m,1}^j \leqslant k \text{ and } R_{m,2}^j \leqslant k\right\}}$	–

Table D.4: Parameterization of data-generating processes.

The table shows the parameter choices for the dynamic lower tail dependence (LTD) estimators and presents the resulting expressions for the corresponding correlation dynamics. The dynamic estimators are employed as data-generating processes (DGP) in our simulation study and include the Patton, DCC, and DSC model. The notation is as follows: ω, β, α, ϕ, ψ, $\tilde{\phi}$, $\tilde{\psi}$, and κ are scalar parameters, $\Lambda(x) \equiv (1 - e^{-x})(1 + e^{-x})^{-1}$ is a normalizing function, $u_{1,t}$ and $u_{2,t}$ denote the ranks of the residuals from univariate GARCH processes, Ω and D_t are two-by-two correlation matrices containing constant correlations and time trends, respectively, and $\bar{z}_t^c$ denotes a vector of (modified) copula shocks. The DSC model incorporates a time trend into copula correlations and nests the DCC model in case of $\kappa = 0$. Technical details can be found in Section D.1 in Appendix D.

DGP	Parameter	Correlation dynamics
Patton	$\omega = 0.5$ $\beta = 0.9$ $\alpha = 0.6$ $\nu = 10$	$\rho_t = \Lambda\left(0.5 + 0.9\rho_{t-1} + 0.6\frac{1}{10}\sum_{i=1}^{10} t_{10}^{-1}(u_{1,t-i})t_{10}^{-1}(u_{2,t-i})\right)$
DCC	$\phi = 0.05$ $\psi = 0.9$ $\omega_{12} = 0.80$ $\nu = 5$	$\rho_t = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}},\ Q_t = 0.05\Omega + 0.9Q_{t-1} + 0.05\bar{z}_{t-1}^c\bar{z}_{t-1}^{c\top}$
DSC	$\tilde{\phi} = 0.05$ $\tilde{\psi} = 0.90$ $\kappa = 0.4$ $\omega_{12} = 0.8$ $\delta = 0.01$ $\nu = 10$	$\rho_t = \frac{\tilde{Q}_{12,t}}{\sqrt{\tilde{Q}_{11,t}\tilde{Q}_{22,t}}},\ \tilde{Q}_t = 0.05\left[0.6\Omega + 0.4D_t\right] + 0.9\tilde{Q}_{t-1} + 0.05\bar{z}_{t-1}^c\bar{z}_{t-1}^{c\top}$

Table D.5: Variable definitions and data sources.

The table presents definitions as well as data sources for all dependent and independent variables that are used in our empirical study. The data sources are: (i) *Thomson Reuters Datastream* (DS), (ii) *Worldscope* (WS), and (iii) *Kenneth French Data Library* (KF). EST indicates that the variable is estimated or computed based on data from the respective data source(s).

Variable name	*Definition*	*Data source*
Return (return)	Excess return of a portfolio (stock) over the riskfree rate. We use the one-month T-bill rate as the riskfree rate.	DS, KF, EST
CAPM-Alpha, FF-Alpha, CAR-Alpha	Portfolio performance alphas from Sharpe's (1964) capital asset pricing model, the three-factor model of Fama and French (1993), and Carhart's (1997) four-factor model. Estimation of the alphas is conducted on the basis of monthly portfolio returns.	DS, KF, EST
capm-alpha, ff-alpha, car-alpha	Individual stock performance alphas from Sharpe's (1964) capital asset pricing model, the three-factor model of Fama and French (1993), and Carhart's (1997) four-factor model. Estimation of the alphas is conducted for each stock and year on the basis of daily return data.	DS, KF, EST
LTD	Lower tail dependence coefficient of a stock estimated between the stock's returns and market returns. Estimation is conducted on the basis of daily return data from one year using the Mix1_{EM}, CL_{EVT}, and the Patton model. Details on the tail dependence models and the estimation procedure can be found in Sections 5.3.1 and 5.4.1.2, respectively.	DS, EST
β	Factor loading on the market factor from a CAPM one-factor regression estimated based on daily return data from one year. Formally, we compute β according to $\beta = \frac{\text{cov}(r_i, r_m)}{\text{var}(r_m)}$.	DS, KF, EST
β^-	Downside beta estimated based on daily return data from one year. Following Ang et al. (2006a), we compute β^- according to $\beta^- = \frac{\text{cov}(r_i, r_m \mid r_m < \mu_m)}{\text{var}(r_m \mid r_m < \mu_m)}$, where μ_m denotes the mean of the daily market return.	DS, KF, EST
β^+	Upside beta estimated based on daily return data from one year. Following Ang et al. (2006a), we compute β^+ according to $\beta^+ = \frac{\text{cov}(r_i, r_m \mid r_m > \mu_m)}{\text{var}(r_m \mid r_m > \mu_m)}$, where μ_m denotes the mean of the daily market return.	DS, KF, EST
size	A firm's equity market capitalization in million U.S. dollars.	WS
bookmarket	A firm's book-to-market ratio computed as the ratio of book and market value of equity per share.	WS
illiq	The Amihud (2002) measure of illiquidity calculated for each stock and year according to $illiq_{i,t} = \frac{1}{Days_t^i} \sum_{d=1}^{Days_t^i} \frac{\lvert r_{i,d} \rvert}{Vol_{i,d}}$, where $Vol_{i,d}$ is the trading volume of stock i on day d (in U.S. dollars) and $Days_t^i$ is the number of trading days in year t.	DS, EST
idiovola	A stock's idiosyncratic volatility, defined as the standard deviation of the CAPM-residuals of the stock's daily returns.	DS, KF, EST
coskew	The coskewness of a stock's daily returns with the market. Following Ang et al. (2006a), we compute *coskew* according to *coskew*$= \frac{\mathbb{E}[(r_i - \mu_i)(r_m - \mu_m)^2]}{\sqrt{\text{var}(r_i)}\text{var}(r_m)}$, where μ_i and μ_m denote the mean of the daily stock and market return, respectively.	DS, EST
cokurt	The cokurtosis of a stock's daily returns with the market. Following Ang et al. (2006a), we compute *cokurt* according to *cokurt*$= \frac{\mathbb{E}[(r_i - \mu_i)(r_m - \mu_m)^3]}{\sqrt{\text{var}(r_i)}\text{var}(r_m)^{3/2}}$, where μ_i and μ_m denote the mean of the daily stock and market return, respectively.	DS, EST
max	The maximum daily return over the last year.	DS, EST

Appendix E

Publication Details

The cumulative dissertation is composed of four self-contained chapters. Each chapter is based on a distinct research paper that makes an independent contribution to the existing literature. This appendix shortly reviews the research papers and provides publication details.

Paper I (Chapter 2):

Is Tail Risk Priced in Credit Default Swap Premia?

Authors:

Christian Meine, Hendrik Supper, Gregor Weiß

Abstract:

We show that the propensity of a bank to experience extreme co-movements in its credit default swap premia together with the market is priced in the bank's default swap spread during the financial crisis. We measure a bank's CDS tail beta by estimating the upper tail dependence between its default swap spreads and a credit default swap market index. Our study shows that protection sellers receive a premium for bearing the risk of extreme upward co-movements in default risk. The economic significance of this effect is large yet limited to the recent financial crisis. Banks in the upper quintile of CDS tail beta have spreads that are on average 140 basis points higher than those of banks in the lower CDS tail beta quintile.

Publication details:

Revise and resubmit at the *Review of Finance*.

Paper II (Chapter 3):

Do CDS spreads move with commonality in liquidity?

Authors:

Christian Meine, Hendrik Supper, Gregor Weiß

Abstract:

We show that commonality in liquidity is priced in both the cross-section and time-series of credit default swap (CDS) premia. Protection buyers earn a statistically significant and economically important discount for bearing the risk of individual CDS illiquidity co-moving with CDS market illiquidity. The pricing of commonality in CDS liquidity is different for calm and crisis periods as we find liquidity risk to be a priced factor in CDS spreads only during the recent financial crisis. Additionally, we find evidence that liquidity seems to be more important for the pricing of CDS than fundamentals from structural models of default risk.

Publication details:

Under review at the *Journal of Financial and Quantitative Analysis*.

Paper III (Chapter 4):

Dynamic Dependence in Prices, Liquidity, and Credit Risk. A Vine Copula Approach.

Authors:

Hendrik Supper, Christopher Bierth, Gregor Weiß

Abstract:

We model the joint distribution of the market price, liquidity, and credit risk of a multivariate stock portfolio at the security-level using dynamic vine copulas. We first document the existence of significant time-varying tail dependence between the stock returns, stock liquidity, and the respective firms' default intensities. We then propose a liquidity- and credit-adjusted Value-at-Risk and show that our adjusted Value-at-Risk enables risk managers to reliably forecast the total risk exposure of a stock investment. Finally, we find that our dynamic vine copula model captures time-varying tail dependence significantly better than static copula or dynamic correlation-based models.

Publication details:

Working paper.

Paper IV (Chapter 5):

Extreme dependence in finance: Does the choice of estimator matter?

Authors:

Hendrik Supper

Abstract:

We review several commonly used methods for estimating the tail dependence in a given data sample. In simulations, we show that especially static estimators produce severely biased estimates of tail dependence when applied to samples with time-varying extreme dependence. We then show in an empirical study that the choice of estimator significantly affects the importance of tail dependence in asset pricing. Contrary to earlier findings in the literature, the economic significance of the crash-sensitivity of stocks as a priced factor in the cross-section of stock returns is small and critically depends on the choice of extreme dependence estimator.

Publication details:

Working paper.

Appendix F

Bibliography

AAS, K. AND D. BERG (2009): "Models for construction of multivariate dependence: a comparison study," *European Journal of Finance*, 15, 639–659.

AAS, K., C. CZADO, A. FRIGESSI, AND H. BAKKEN (2009): "Pair-copula constructions of multiple dependence," *Insurance, Mathematics and Economics*, 44, 182–198.

ACHARYA, V. V., S. T. BHARATH, AND A. SRINIVASAN (2007): "Does Industry wide Distress Affect Defaulted Firms? Evidence from Creditor Recoveries," *Journal of Financial Economics*, 85, 787–821.

ACHARYA, V. V. AND T. C. JOHNSON (2007): "Insider trading in credit derivatives," *Journal of Financial Economics*, 84, 110–141.

ACHARYA, V. V. AND L. H. PEDERSEN (2005): "Asset pricing with liquidity risk," *Journal of Financial Economics*, 77, 375–410.

ACHARYA, V. V., L. H. PEDERSEN, T. PHILIPPON, AND M. RICHARDSON (2010): "Measuring Systemic Risk," Working paper.

ACHARYA, V. V. AND M. RICHARDSON (2009): "Causes of the Financial Crisis," *Critical Review*, 21, 195–210.

ADRIAN, T. AND M. K. BRUNNERMEIER (2011): "CoVaR," Working paper.

AIELLI, G. P. (2009): "Dynamic Conditional Correlations: On Properties and Estimation," Working paper.

AÏT-SAHALIA, Y. AND A. LO (2000): "Nonparametric risk management and implied risk aversion," *Journal of Econometrics*, 94, 9–51.

ALEXANDER, C. AND A. KAECK (2008): "Regime dependent determinants of credit default swap spreads," *Journal of Banking and Finance*, 32, 1008–1021.

ALOUI, R., M. S. B. AÏSSA, AND D. K. NGUYEN (2011): "Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure?" *Journal of Banking and Finance*, 35, 130–141.

AMIHUD, Y. (2002): "Illiquidity and stock returns: cross-section and time-series effects," *Journal of Financial Markets*, 5, 31–56.

AMIHUD, Y. AND H. MENDELSON (1986): "Asset pricing and the bid-ask spread," *Journal of Financial Economics*, 17, 223–249.

——— (1987): "Trading Mechanisms and Stock Returns: An Empirical Investigation," *Journal of Finance*, 42, 533–553.

ANDERSSON, F., H. MAUSSER, D. ROSEN, AND S. URYASEV (2001): "Credit risk optimization with Conditional Value-at-Risk criterion," *Mathematical Programming*, 89, 273–291.

ANG, A. AND G. BEKAERT (2002): "International Asset Allocation with Regime Shifts," *Review of Financial Studies*, 15, 1137–1187.

ANG, A., J. CHEN, AND Y. XING (2006a): "Downside risk," *Review of Financial Studies*, 19, 1191–1239.

ANG, A., R. J. HODRICK, Y. XING, AND X. ZHANG (2006b): "The Cross-Section of Volatility and Expected Returns," *Journal of Finance*, 61, 259–299.

——— (2009): "High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence," *Journal of Financial Economics*, 91, 1–23.

ANNAERT, J., M. DE CEUSTER, P. VAN ROY, AND C. VESPRO (2013): "What determines Euro area bank CDS spreads," *Journal of International Money and Finance*, 32, 444–461.

ARAKELYAN, A., G. RUBIO, AND P. SERRANO (2013): "Market-Wide Liquidity in Credit Default Swap Spreads," Working paper.

ARORA, N., P. GANDHI, AND F. A. LONGSTAFF (2012): "Counterparty Credit Risk and the Credit Default Swap Market," *Journal of Financial Economics*, 103, 280–293.

BALI, T. G., K. O. DEMITRAS, AND H. LEVY (2009): "Is there an intertemporal relation between downside risk and expected returns?" *Journal of Financial and Quantitative Analysis*, 44, 883–909.

BANGIA, A., F. X. DIEBOLD, T. SCHUERMANN, AND J. D. STROUGHAIR (2002): *Modeling Liquidity Risk, With Implications for Traditional Market Risk Measurement and Management*, Kluwer Academic Publishers, vol. 8, chap. 1, 3–13.

BARRO, R. J. (2006): "Rare disasters and asset markets in the twentieth century," *Quarterly Journal of Economics*, 121, 823–866.

——— (2009): "Rare disasters, asset prices, and welfare costs," *American Economic Review*, 99, 243–264.

BEDFORD, T. AND R. M. COOKE (2001): "Probability density decomposition for conditionally dependent random variables modeled by vines," *Annals of Mathematics and Artificial Intelligence*, 32, 245–268.

——— (2002): "Vines - a new graphical model for dependent random variables," *Annals of Statistics*, 30, 1031–1068.

BEINE, M., A. COSMA, AND R. VERMEULEN (2010): "The dark side of global integration: Increasing tail dependence," *Journal of Banking and Finance*, 34, 184–192.

BEKAERT, G., C. R. HARVEY, AND C. T. LUNDBLAD (2007): "Liquidity and Expected Returns: Lessons from Emerging Markets," *Review of Financial Studies*, 20, 1783–1831.

BENKERT, C. (2004): "Explaining credit default swap premia," *Journal of Futures Markets*, 24, 71–92.

BENOIT, S., G. COLLETAZ, C. HURLIN, AND C. PÉRIGNON (2013): "A Theoretical and Empirical Comparison of Systemic Risk Measures," Working paper.

BERA, A. K. AND M. L. HIGGINS (1993): "ARCH Models: Properties, Estimation and Testing," *Journal of Economic Surveys*, 7, 305–362.

BERKOWITZ, J. (2000): "Incorporating Liquidity Risk into Value-at-Risk Models," Working paper.

BISIAS, D., M. FLOOD, A. W. LO, AND S. VALAVANIS (2012): "A Survey of Systemic Risk Analytics," *Annual Review of Financial Economics*, 4, 255–296.

BLANCO, R., S. BRENNAN, AND I. MARSH (2005): "An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps," *Journal of Finance*, 60, 2255–2281.

BOEHMER, E., S. CHAVA, AND H. E. TOOKES (2014): "Related Securities and Equity Market Quality: The Case of CDS," *Journal of Financial and Quantitative Analysis*, forthcoming.

BOLLERSLEV, T. (1986): "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, 31, 307–327.

BOLLERSLEV, T., R. F. ENGLE, AND D. B. NELSON (1994): "ARCH Models," in *Handbook of Econometrics*, ed. by R. F. Engle and D. L. McFadden, Amsterdam: Elsevier, North-Holland, 2959–3038.

BOLLERSLEV, T., R. F. ENGLE, AND J. M. WOOLDRIDGE (1988): "A Capital Asset Pricing Model with Time-varying Covariances," *Journal of Political Economy*, 96, 116–131.

BOLLERSLEV, T. AND V. TODOROV (2011): “Tails, fears, and risk premia,” *Journal of Finance*, 66, 2165–2211.

BONGAERTS, D., F. DE JONG, AND J. DRIESSEN (2011): “Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market,” *Journal of Finance*, 66, 203–240.

BONGAERTS, D., F. DE JONG, AND J. DRIESSEN (2012): “An Asset Pricing Approach to Liquidity Effects in Corporate Bond Markets,” Working paper.

BROWNLEES, C. T. AND R. F. ENGLE (2012): “Volatility, Correlation and Tails for Systemic Risk Measurement,” Working paper.

CAMPBELL, J. AND G. TAKSLER (2003): “Equity Volatility and Corporate Bond Yields,” *Journal of Finance*, 58, 2321–2349.

CAMPBELL, J. Y., J. HILSCHER, AND J. SZILAGYI (2008): “In search of distress risk,” *Journal of Finance*, 63, 2899–2939.

CARHART, M. (1997): “On persistence in mutual fund performance,” *Journal of Finance*, 52, 57–82.

CHAVA, S. AND A. PURNANANDAM (2010): “Is default risk negatively related to stock returns?” *Review of Financial Studies*, 23, 2523–2559.

CHOLLETE, L., V. DE LA PEÑA, AND C.-C. LU (2012): “International diversification: An extreme value approach,” *Journal of Banking and Finance*, 36, 871–885.

CHOLLETE, L., A. HEINEN, AND A. VALDESOGO (2009): “Modeling International Financial Returns with a Multivariate Regime-switching Copula,” *Journal of Financial Econometrics*, 7, 437–480.

CHORDIA, T., A. SUBRAHMANYAM, AND R. ROLL (2000): “Commonality in liquidity,” *Journal of Financial Economics*, 56, 3–28.

CHOULAKIAN, V. AND M. A. STEPHENS (2001): "Goodness-of-fit tests for the generalized Pareto distribution," *Technometrics*, 43, 478–484.

CHRISTIE, A. A. (1982): "The stochastic behavior of common stock variances: Value, leverage and interest rate effects," *Journal of Financial Economics*, 10, 407–432.

CHRISTOFFERSEN, P., V. ERRUNZA, K. JACOBS, AND H. LANGLOIS (2012): "Is the Potential for International Diversification Disappearing? A Dynamic Copula Approach," *Review of Financial Studies*, 25, 3711–3751.

CHRISTOFFERSEN, P., K. JACOBS, X. JIN, AND H. LANGLOIS (2013): "Dynamic Dependence in Corporate Credit," Working paper.

CHRISTOFFERSEN, P. AND H. LANGLOIS (2013): "The Joint Dynamics of Equity Market Factors," *Journal of Financial and Quantitative Analysis*, 48, 1371–1404.

CHRISTOFFERSEN, P. AND D. PELLETIER (2004): "Backtesting Value-at-Risk: A Duration-Based Approach," *Journal of Financial Econometrics*, 2, 84–108.

COLLIN-DUFRESNE, P., R. S. GOLDSTEIN, AND J. S. MARTIN (2001): "The Determinants of Credit Spread Changes," *Journal of Finance*, 56, 2177–2207.

COLLIN-DUFRESNE, P. AND J. HUGONNIER (2014): "Event risk, contingent claims and the temporal resolution of uncertainty," *Mathematics and Financial Economics*, 8, 29–69.

COMMITTEE ON THE GLOBAL FINANCIAL SYSTEM (2011): "The Impact of Sovereign Credit Risk on Bank Funding Conditions," CGFS Papers.

CONT, R. AND Y. H. KAN (2011): "Statistical modeling of credit default swap portfolios," Working paper.

CORÒ, F., A. DUFOUR, AND S. VAROTTO (2013): "Credit and liquidity components of corporate CDS spreads," *Journal of Banking and Finance*, 37, 5511–5525.

CREAL, D. D., R. B. GRAMACY, AND R. S. TSAY (2012): "Market-Based Credit Ratings," Working paper.

CREMERS, M., J. DRIESSEN, P. MAENHOUT, AND D. WEINBAUM (2008): "Individual Stock-Option Prices and Credit Spreads," *Journal of Banking and Finance*, 32, 2706–2715.

CROUHY, M., D. GALAI, AND R. MARK (2000): "A comparative analysis of current credit risk models," *Journal of Banking and Finance*, 24, 59–117.

DE JONGHE, O. (2010): "Back to the Basics in Banking? A Micro-Analysis of Banking System Stability," *Journal of Financial Intermediation*, 19, 387–417.

DEMARTA, S. AND A. J. MCNEIL (2004): "The t Copula and Related Copulas," *International Statistical Review*, 73, 111–129.

DEMPSTER, A. P., N. M. LAIRD, AND D. B. RUBIN (1977): "Maximum Likelihood from Incomplete Data via the EM Algorithm," *Journal of the Royal Statistical Society (Series B)*, 39, 1–38.

DIAMOND, D. W. AND P. H. DYBVIG (1983): "Bank Runs, Deposit Insurance, and Liquidity," *Journal of Political Economy*, 91, 401–419.

DICHEV, I. D. (1998): "Is the risk of bankruptcy a systematic risk?" *Journal of Finance*, 53, 1131–1147.

DISSMANN, J., E. C. BRECHMANN, C. CZADO, AND D. KUROWICKA (2013): "Pair-copula constructions of multiple dependence," *Computational Statistics and Data Analysis*, 59, 52–69.

DITRAGLIA, F. J. AND J. R. GERLACH (2013): "Portfolio selection: An extreme value approach," *Journal of Banking and Finance*, 37, 305–323.

DOSHI, H., J. ERICSSON, K. JACOBS, AND S. M. TURNBULL (2013): "Pricing Credit Default Swaps with Observable Covariates," *Review of Financial Studies*, 26, 2049–2094.

DUDLEY, E. AND M. NIMALENDRAN (2011): "Margins and Hedge Fund Contagion," *Journal of Financial and Quantitative Analysis*, 46, 1227–1257.

DUFFIE, D. (1999): "Credit Swap Valuation," *Financial Analysts Journal*, 55, 73–87.

——— (2010): "The failure mechanics of dealer banks," *Journal of Economic Perspectives*, 24, 51–72.

DUFFIE, D. AND J. LIU (2001): "Floating-Fixed Credit Spreads," *Financial Analysts Journal*, 57, 76–87.

DUFFIE, D. AND J. PAN (2001): "Analytical value-at-risk with jumps and credit risk," *Finance and Stochastics*, 5, 155–180.

DUFFIE, D. AND K. J. SINGLETON (1997): "An Econometric Model of the Term Structure of Interest Rate Swap Yields," *Journal of Finance*, 52, 1287–1323.

——— (1999): "Modeling Term Structures of Defaultable Bonds," *Review of Financial Studies*, 12, 687–720.

——— (2003): *Credit Risk: Pricing, Measurement, and Management*, Princeton University Press.

EMBRECHTS, P., F. LINDSKOG, AND A. J. MCNEIL (2003): *Modelling Dependence with Copulas and Applications to Risk Management*, Elsevier, chap. 8, 329–384.

EMBRECHTS, P., A. J. MCNEIL, AND D. STRAUMANN (2002): "Correlation and dependence in risk management: properties and pitfalls," in *Risk Management: Value at Risk and Beyond*, ed. by M. Dempster, Cambridge University Press, 176–223.

ENGLE, R. F. (1982): "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica*, 50, 987–1007.

——— (2002): "Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models," *Journal of Business and Economic Statistics*, 20, 339–350.

ENGLE, R. F. AND K. KRONER (1995): "Multivariate Simultaneous GARCH," *Econometric Theory*, 11, 122–150.

ENGLE, R. F. AND V. K. NG (1993): "Measuring and Testing the Impact of News on Volatility," *Journal of Finance*, 48, 1749–1778.

ERB, C. B., C. R. HARVEY, AND T. E. VISKANTA (1994): "Forecasting International Equity Correlations," *Financial Analysts Journal*, 50, 32–45.

ERICSSON, J., K. JACOBS, AND R. OVIEDO (2009): "The Determinants of Credit Default Swap Premia," *Journal of Financial and Quantitative Analysis*, 44, 109–132.

ERICSSON, J. AND O. RENAULT (2006): "Liquidity and credit risk," *Journal of Finance*, 61, 2219–2250.

FAMA, E. F. (1965): "The behavior of stock market prices," *Journal of Business*, 38, 34–105.

FAMA, E. F. AND K. R. FRENCH (1988): "Permanent and Temporary Components of Stock Prices," *Journal of Political Economy*, 96, 246–273.

——— (1993): "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 33, 3–56.

FAMA, E. F. AND J. D. MACBETH (1973): "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81, 607–636.

FERNANDEZ, C. AND M. F. J. STEEL (1998): "On Bayesian Modeling of Fat Tails and Skewness," *Journal of the American Statistical Association*, 93, 359–371.

FRIEWALD, N., C. WAGNER, AND J. ZECHNER (2014): "The Cross-Section of Credit Risk Premia and Equity Returns," *Journal of Finance*, forthcoming.

GABAIX, X. (2012): "Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance," *Quarterly Journal of Economics*, 127, 645–700.

GARCIA, R. AND G. TSAFACK (2011): "Dependence structure and extreme comovements in international equity and bond markets," *Journal of Banking and Finance*, 35, 1954–1970.

GARLAPPI, L., T. SHU, AND H. YAN (2008): "Default Risk, Shareholder Advantage, and Stock Returns," *Review of Financial Studies*, 21, 2743–2778.

GARLEANU, N., L. PEDERSEN, AND A. POTESHMAN (2009): "Demand-based option pricing," *Review of Financial Studies*, 22, 4259–4299.

GENEST, C., K. GHOUDI, AND L.-P. RIVEST (1995): "A Semiparametric Estimation Procedure of Dependence Parameters in Multivariate Families of Distributions," *Biometrika*, 82, 543–552.

GLOSTEN, L. R., R. JAGANNATHAN, AND D. E. RUNKLE (1993): "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *Journal of Finance*, 48, 1779–1801.

GORTON, G. AND A. METRICK (2012): "Securitized banking and the run on repo," *Journal of Financial Economics*, 104, 425–451.

GROSS-KLUSSMANN, A. AND N. HAUTSCH (2013): "Predicting Bid-Ask Spreads Using Long-Memory Autoregressive Conditional Poisson Models," *Journal of Forecasting*, 32, 724–742.

GUILLOU, A. AND P. HALL (2001): "A diagnostic for selecting the threshold in extreme value analysis," *Journal of the Royal Statistical Society (Series B)*, 63, 293–305.

HAMILTON, J. D. (1994): *Time Series Analysis*, Princeton University Press.

HAN, B. AND Y. ZHOU (2011): "Term Structure of Credit Default Swap Spreads and Cross-Section of Stock Returns," Working paper.

HANSEN, B. E. (1994): "Autoregressive Conditional Density Estimation," *International Economic Review*, 35, 705–730.

HARVEY, C. AND A. SIDDIQUE (2000): "Conditional skewness in asset pricing tests," *Journal of Finance*, 55, 1263–1295.

HASBROUCK, J. AND D. J. SEPPI (2001): "Common factors in prices, order flows and liquidity," *Journal of Financial Economics*, 59, 383–411.

HAUTSCH, N., J. SCHAUMBURG, AND M. SCHIENLE (2014): "Financial Network Systemic Risk Contributions," *Review of Finance*, forthcoming.

HEINEN, A. AND A. VALDESOGO (2008): "Asymmetric CAPM Dependence for Large Dimensions: The Canonical Vine Autoregressive Copula Model," Working paper.

HERRERA, R. AND S. EICHLER (2011): "Extreme dependence with asymmetric thresholds: Evidence for the European Monetary Union," *Journal of Banking and Finance*, 35, 2916–2930.

HILAL, S., S.-H. POON, AND J. TAWN (2011): "Hedging the black swan: Conditional heteroskedasticity and tail dependence in S&P500 and VIX," *Journal of Banking and Finance*, 35, 2374–2387.

HILL, B. M. (1975): "A simple general approach to inference about the tail of a distribution," *Annals of Statistics*, 3, 1163–1174.

HOBÆK HAFF, I. (2013): "Parameter estimation for pair-copula constructions," *Bernoulli*, 19, 462–491.

HOFERT, M. (2011): "Efficiently sampling nested archimedean copulas," *Computational Statistics and Data Analysis*, 55, 57–70.

HONG, Y., J. TU, AND G. ZHOU (2007): "Asymmetries in Stock Returns: Statistical Tests and Economic Evaluation," *Review of Financial Studies*, 20, 1547–1581.

HOU, K., A. KAROLYI, AND B.-C. KHO (2011): "What Factors Drive Global Stock Returns?" *Review of Financial Studies*, 24, 2527–2574.

HOVAKIMIAN, A., E. KANE, AND L. LAEVEN (2012): “Variation in Systemic Risk at US Banks During 1974-2010,” Working paper.

HU, L. (2011): “Dependence patterns across financial markets: a mixed copula approach,” *Applied Financial Economics*, 16, 717–729.

HUANG, X., H. ZHOU, AND H. ZHU (2011): “Systemic Risk Contribution,” Working paper.

HULL, J. AND A. WHITE (2000): “Valuing credit default swaps I: no counterparty default risk,” *Journal of Derivatives*, 8, 29–40.

——— (2003): “The valuation of credit default swap options,” *Journal of Derivatives*, 10, 40–50.

IMF (2009): “Responding to the Financial Crisis and Measuring Systemic Risk.” Global Financial Stability Report.

——— (2010): “Meeting New Challenges to Stability and Building a Safer System,” Global Financial Stability Report.

INCE, O. AND R. PORTER (2006): “Individual Equity Return Data From Thomson Datastream: Handle With Care!” *Journal of Financial Research*, 29, 463–479.

JACKWERTH, J. C. (2000): “Recovering Risk Aversion from Option Prices and Realized Returns,” *Review of Financial Studies*, 13, 433–451.

JACKWERTH, J. C. AND M. RUBINSTEIN (1996): “Recovering probability distributions from option prices,” *Journal of Finance*, 51, 1611–1631.

JARROW, R., H. LI, AND F. ZHAO (2007): “Interest Rate Caps ”Smile” Too! But Can the LIBOR Market Models Capture the Smile?” *Journal of Finance*, 62, 345–382.

JIANG, H. AND B. KELLY (2013): “Tail Risk and Hedge Fund Returns,” Working paper.

JOE, H. (1996): *Families of m-Variate Distributions with Given Margins and m(m-1)/2 Bivariate Dependence Parameters*, Institute of Mathematical Statistics, 120–141.

——— (1997): *Multivariate Models and Dependence Concepts*, Chapman and Hall.

JUNGE, B. AND A. TROLLE (2014): "Liquidity Risk in Credit Default Swap Markets," Working paper.

JUNKER, M., A. SZIMAYER, AND N. WAGNER (2006): "Nonlinear term structure dependence: Copula functions, empirics, and risk implications," *Journal of Banking and Finance*, 4, 1171–1199.

KAHNEMAN, D. AND A. TVERSKY (1979): "Prospect theory: an analysis of decision under risk," *Econometrica*, 47, 263–291.

KANG, B. U., F. IN, G. KIM, AND T. S. KIM (2010): "A Longer Look at the Asymmetric Dependence between Hedge Funds and the Equity Market," *Journal of Financial and Quantitative Analysis*, 45, 763–789.

KAROLYI, A., K.-H. LEE, AND M. A. VAN DIJK (2012): "Understanding commonality in liquidity around the world," *Journal of Financial Economics*, 105, 82–112.

KELLY, B. AND H. JIANG (2013): "Tail risk and asset prices," Working paper.

KIM, G., M. J. SILVAPULLE, AND P. SILVAPULLE (2007): "Comparison of semiparametric and parametric methods for estimating copulas," *Computational Statistics and Data Analysis*, 51, 2836–2850.

KOLE, E. AND M. VERBEEK (2006): "Crash risk in the cross section of stock returns," Working paper.

KRAUS, A. AND R. LITZENBERGER (1976): "Skewness preference and the valuation of risk assets," *Journal of Finance*, 31, 1085–1100.

KYLE, A. S. (1985): "Continuous Auctions and Insider Trading," *Econometrica*, 53, 1315–1335.

LESMOND, D. A., J. P. OGDEN, AND C. A. TRZCINKA (1999): "A New Estimate of Transaction Costs," *Review of Financial Studies*, 12, 1113–1141.

LESPLINGART, C., C. MAJOIS, AND M. PETITJEAN (2012): "Liquidity and CDS premiums on European companies around the Subprime crisis," *Review of Derivatives Research*, 15, 257–281.

LI, D. X. (2000): "On Default Correlation: A Copula Function Approach," *Journal of Fixed Income*, 9, 43–54.

LIN, H., J. WANG, AND C. WU (2011): "Liquidity risk and expected corporate bond returns," *Journal of Financial Economics*, 99, 628 – 650.

LINTNER, J. (1965): "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets," *Review of Economics and Statistics*, 47, 13–37.

LIU, J., J. PAN, AND T. WANG (2005): "An Equilibrium Model of Rare-Event Premia and Its Implication for Option Smirks," *Review of Financial Studies*, 18, 131–164.

LONGIN, F. AND B. SOLNIK (2001): "Extreme correlation of international equity markets," *Journal of Finance*, 56, 649–676.

LONGSTAFF, F. A., S. MITHAL, AND E. NEIS (2005): "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market," *Journal of Finance*, 60, 2213–2253.

LONGSTAFF, F. A. AND A. RAJAN (2008): "An Empirical Analysis of the Pricing of Collateralized Debt Obligations," *Journal of Finance*, 63, 529–563.

LONGSTAFF, F. A., P. SANTA-CLARA, AND E. SCHWARTZ (2001): "The relative valuation of caps and swaptions: Theory and evidence," *Journal of Finance*, 56, 2067–2109.

MANDELBROT, B. (1963): "The variation of certain speculative prices," *Journal of Business*, 36, 394–419.

MANNER, H. (2007): "Estimation and model selection of copulas with an application to exchange rates," Working paper.

MARKOWITZ, H. (1959): *Portfolio selection*, Yale University Press.

MAYORDOMO, S. AND J. I. PEÑA (2014): "An empirical analysis of the dynamic dependencies in the European corporate credit markets: Bonds vs. credit derivatives," *Applied Financial Economics*, forthcoming.

MAYORDOMO, S., J. I. PEÑA, AND E. S. SCHWARTZ (2014a): "Are All Credit Default Swap Databases Equal?" *European Financial Management*, forthcoming.

MAYORDOMO, S., M. RODRIGUEZ-MORENO, AND J. I. PEÑA (2014b): "Liquidity commonalities in the corporate CDS market around the 2007-2012 financial crisis," *International Review of Economics and Finance*, 31, 171–192.

MCLACHLAN, G. AND D. PEEL (2000): *Finite mixture models*, Wiley.

MCNEIL, A. J., R. FREY, AND P. EMBRECHTS (2005): *Quantitative Risk Management: Concepts, Techniques, Tools*, Princeton University Press.

MEINE, C., H. SUPPER, AND G. WEISS (2013): "Is Tail Risk Priced in Credit Default Swap Premia?" Working paper.

MERTON, R. C. (1974): "On the pricing of corporate debt: The risk structure of interest rates," *Journal of Finance*, 29, 449–479.

MIN, A. AND C. CZADO (2010): "Bayesian Inference for Multivariate Copulas using Pair-copula Constructions," *Journal of Financial Econometrics*, 8, 511–546.

——— (2011): "Bayesian model selection for D-vine pair-copula constructions," *Canadian Journal of Statistics*, 39, 239–258.

NELSEN, R. B. (2006): *An Introduction to Copulas*, Springer.

NELSON, D. B. (1991): "Conditional Heteroskedasticity in Asset Returns: A New Approach," *Econometrica*, 59, 347–370.

NING, C. (2010): "Dependence structure between the equity market and the foreign exchange market - A copula approach," *Journal of International Money and Finance*, 29, 743–759.

NOLTE, I. (2008): “Modeling a Multivariate Transaction Process,” *Journal of Financial Econometrics*, 6, 143–170.

OH, D. H. AND A. J. PATTON (2012): “Modelling Dependence in High Dimensions with Factor Copulas,” Working paper.

——— (2013): “Time-Varying Systemic Risk: Evidence from a Dynamic Copula Model of CDS Spreads,” Working paper.

OKIMOTO, T. (2008): “New Evidence of Asymmetric Dependence Structures in International Equity Markets,” *Journal of Financial and Quantitative Analysis*, 43, 787–816.

PASTOR, L. AND R. F. STAMBAUGH (2003): “Liquidity Risk and Expected Stock Returns,” *Journal of Political Economy*, 111, 642–685.

PATTON, A. J. (2006): “Modelling Asymmetric Exchange Rate Dependence,” *International Economic Review*, 47, 527–556.

PETERSEN, M. A. (2009): “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches,” *Review of Financial Studies*, 22, 435–480.

POON, S.-H., M. ROCKINGER, AND J. TAWN (2004): “Extreme value dependence in financial markets: diagnostics, models, and financial implications,” *Review of Financial Studies*, 17, 581–610.

PRIM, R. C. (1957): “Shortest Connection Networks And Some Generalizations,” *Bell System Technical Journal*, 36, 1389–1401.

PU, X. (2009): “Liquidity Commonality Across the Bond and CDS Markets,” *Journal of Fixed Income*, 19, 26–39.

QI, J. AND W. L. NG (2009): “Liquidity Adjusted Intraday Value at Risk,” Working paper.

RODRIGUEZ, J. (2007): “Measuring Financial Contagion: A Copula Approach,” *Journal of Empirical Finance*, 14, 401–423.

ROY, A. (1952): "Safety first and the holdings of assets," *Econometrica*, 20, 431–449.

RUENZI, S., M. UNGEHEUER, AND F. WEIGERT (2013): "Extreme Downside Liquidity Risk," Working paper.

RUENZI, S. AND F. WEIGERT (2013): "Crash Sensitivity and the Cross-Section of Expected Stock Returns," Working paper.

SAID, S. E. AND D. A. DICKEY (1984): "Testing for unit roots in autoregressive-moving average models of unknown order," *Biometrika*, 71, 599–607.

SAVU, C. AND M. TREDE (2010): "Hierarchical Archimedean copulas," *Quantitative Finance*, 10, 295–304.

SCHMIDT, R. AND U. STADTMUELLER (2006): "Non-parametric Estimation of Tail Dependence," *Scandinavian Journal of Statistics*, 33, 307–335.

SCHWAAB, B., S.-J. KOOPMAN, AND A. LUCAS (2011): "Systemic risk diagnostics, coincident indicators and early warning signals," Technical report.

SCHWEIZER, B. AND A. SKLAR (1983): *Probabilistic Metric Spaces*, Elsevier.

SHARPE, W. (1964): "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk," *Journal of Finance*, 19, 425–442.

SHLEIFER, A. AND R. W. VISHNY (1992): "Liquidation Values and Debt Capacity: A Market Equilibrium Approach," *Journal of Finance*, 47, 1343–1366.

SHUMWAY, T. (1997): "Explaining returns with loss aversion," Working paper.

SKLAR, A. (1959): "Fonctions de Répartition á n Dimensions et Leurs Marges," *Publications de l' Institut Statistique de l' Université de Paris*, 8, 229–231.

TANG, D. Y. AND H. YAN (2008): "Liquidity and Credit Default Swap Spreads," Working paper.

——— (2013): "What moves CDS spreads?" Working paper.

TAWN, J. (1988): "Bivariate extreme value theory: Models and estimation," *Biometrika*, 75, 397–415.

TSE, Y. K. AND A. K. C. TSUI (2002): "A Multivariate Generalized Autoregressive Conditional Heteroskedasticity Model With Time-Varying Correlations," *Journal of Business and Economic Statistics*, 20, 351–362.

VASSALOU, M. AND Y. XING (2004): "Default risk in equity returns," *Journal of Finance*, 59, 831–868.

WATANABE, A. AND M. WATANABE (2008): "Time-Varying Liquidity Risk and the Cross Section of Stock Returns," *Review of Financial Studies*, 21, 2449–2486.

WEISS, G., S. NEUMANN, AND D. BOSTANDZIC (2014): "Systemic Risk and Bank Consolidation: International Evidence," *Journal of Banking and Finance*, 40, 165–181.

WEISS, G. AND H. SUPPER (2013): "Forecasting Liquidity-Adjusted Intraday Value-at-Risk with Vine Copulas," *Journal of Banking and Finance*, 37, 3334–3350.

WHELAN, N. (2004): "Sampling from Archimedean copulas," *Quantitative Finance*, 4, 339–352.

WHITE, H., T.-H. KIM, AND S. MANGANELLI (2012): "VAR for VaR: Measuring Tail Dependence Using Multivariate Regression Quantiles," Working paper.

ZHANG, B., H. ZHOU, AND H. ZHU (2009): "Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms," *Review of Financial Studies*, 22, 5099–5131.

Eidesstattliche Versicherung

Hiermit versichere ich, dass ich die vorliegende Dissertation selbstständig verfasst habe und mich ausschließlich der angegebenen Hilfsmittel bedient habe. Die Dissertation ist nicht bereits Gegenstand eines erfolgreich abgeschlossenen Promotions- oder sonstigen Prüfungsverfahrens gewesen.

Kamen, 01. Juli 2014