
THE IMPACT OF CRISES ON FIRMS' STAKEHOLDERS AND THE MODERATING EFFECT OF INNOVATION

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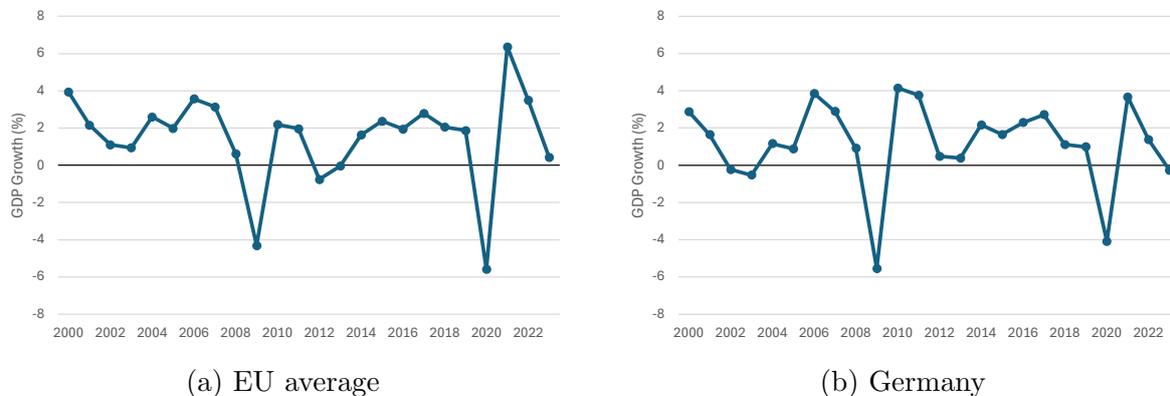
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Part I

Introduction

The global economy has faced numerous disruptions since the beginning of the 21st century. Among these were the Dot-com Bubble burst in the early 2000s, the Global Financial Crisis (GFC, 2007–2009), the European Sovereign Debt Crisis (2010–2012), and the recent COVID-19 pandemic. Figure 1 illustrates annual GDP growth rates for the European Union (average, panel a) and Germany (panel b). The crises are clearly reflected in the figures as decreases in GDP growth rates, with the GFC and the COVID-19 pandemic causing the most significant downturns. In Germany, the GDP decreased by almost 6% in 2009 and by more than 4% in 2020.

Figure 1: GDP growth rates for (a) the European Union and (b) Germany

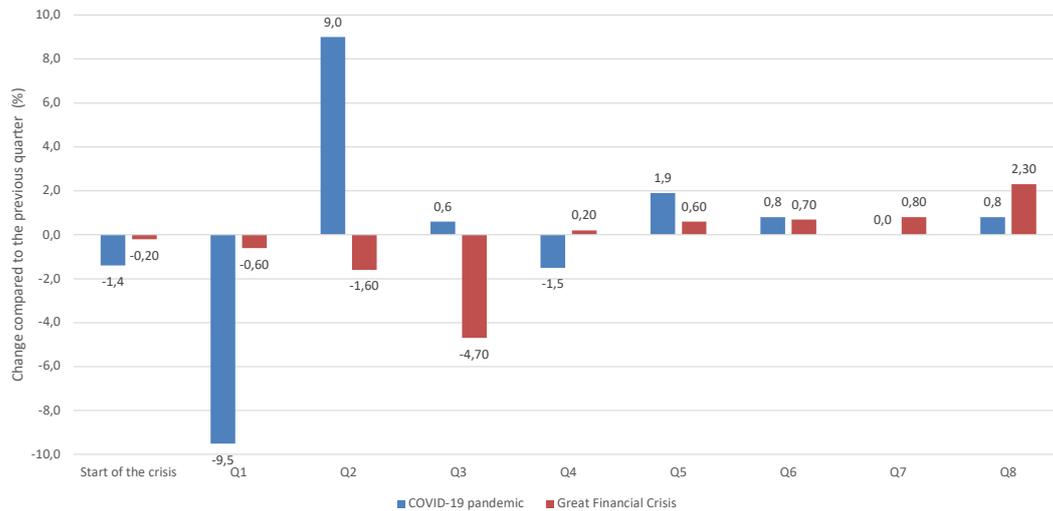


Notes: Plot of GDP growth rates for the European Union (panel a) and Germany (panel b) based on World Bank national accounts data, and OECD National Accounts data files (World Bank, 2025).

Despite the fact that both crises had major economic consequences, they were quite different in their origin and in the way they evolved. While the GFC had mainly an economic impact, the COVID-19 pandemic introduced additional extensive effects on health and social coexistence. Figure 2 shows quarterly GDP trends in Germany following the two crises. The pandemic had a major economic impact in the first quarter after the beginning of the crisis, followed by a strong recovery. The negative effects of the GFC, in contrast, built up until the third quarter after the start of the crisis. Therefore, the way the crises unfolded was fundamentally different. The GFC first impacted the financial sector which led to higher overall uncertainty and a reluctance by banks to grant new loans (Ivashina and Scharfstein, 2010; Puri et al., 2011). This manifested itself into the real sector as a decrease in both supply and demand (Dwenger et al., 2020). During the COVID-19 pandemic, supply disruptions arose primarily from nationwide lockdowns that restricted production capacity and caused delays in supply chains, especially in non-

essential industries. On the demand side, the impact was heterogeneous, with industries such as transportation and tourism suffering significant losses due to reduced consumer demand for services like air travel and public transport (Pichler and Farmer, 2022).

Figure 2: Quarterly GDP trends in Germany during the COVID-19 pandemic and the Global Financial Crisis



Notes: Figure is based on data from the German Federal Statistical Office (2023). For the Pandemic the first quarter of 2020 and for the Great Financial Crisis the second quarter of 2008 are defined to be the start of the crisis.

This dissertation empirically examines the effects of the GFC and the COVID-19 pandemic on German firms and their stakeholders, with a particular focus on how (i) vocational training provision and (ii) payments to stakeholders were affected. Both vocational training and wages are highly relevant economic factors. The former is a key component of human capital growth, increasing workers' skills and productivity, and thus driving economic growth and improving firms' competitiveness. Wages play an important role in labor supply, reflecting workers' value in the economy, while also affecting consumers demand.

This thesis contributes to the existing literature by analyzing potential differences in the crises' effects on stakeholders of innovative and non-innovative firms (Chapter 1 and 3) and by distinguishing between various groups of stakeholders (Chapter 2 and 3).

It is important to distinguish between innovative and non-innovative firms since previous research has found significant differences in times of crises regarding their survival probability and their overall performance (Bogetoft et al., 2024; Cefis and Marsili, 2005, 2006, 2012; Cefis et al., 2020; Makkonen et al., 2014). Thus, it is reasonable to assume that innovation acts as a moderating factor influencing the effects of crises on stakeholder

outcomes.

Furthermore, empirical evidence suggests systematic differences between innovative and non-innovative firms regarding training provision and wages when no crisis is present. For instance, Gerlach and Jirjahn (2001) and Roshchin and Travkin (2017) show that being innovative has a positive effect on training provision. Similarly, Cirera and Martins-Neto (2023) and Van Reenen (1996) find that innovative firms tend to pay higher wages.

(i) Training, Innovation and the Financial Crisis

The first chapter, entitled “Training in innovative and non-innovative firms during the financial crisis”, investigates the impact of the GFC on training expenditures in German firms, with a particular focus on the differences between innovative and non-innovative companies. As argued by Acemoglu (1997) and Aghion and Saint-Paul (1998a), training is especially important for innovative firms due to their need for highly skilled employees who are needed in innovation activities. The financial crisis led to a trade-off regarding training investments. On the one hand, the opportunity costs of training decreased during the downturn because reduced demand allowed firms to redirect underutilized employees to training without meaningful productivity losses. Conversely, financial constraints became more binding during the crisis, forcing firms to cut costs, including training (Brunello, 2009). This trade-off is likely to differ between innovative and non-innovative firms due to variations in external financing, labor demand, and the opportunity costs of training.

The majority of empirical studies investigating the effects of crises on training provision identifies a negative impact (see, e.g., Popov, 2014; Mason and Bishop, 2015). In the German context, Bellmann et al. (2014) and Dietz and Zwick (2020) show that the GFC had significant negative effects on training. As an exception, Felstead et al. (2012) do not find significant crisis-related effects on training in the UK. In contrast, research regarding the cyclicity of training measures mainly identifies a countercyclical development (Bertoni and Brunello, 2022; DeJong and Ingram, 2001; López-García et al., 2013; Saint-Paul, 1997; Sepúlveda, 2004). Turning to the determinants of training, there is broad agreement in the literature that innovation is positively correlated with expenditures on training (Baldwin and Johnson, 1996; Gerlach and Jirjahn, 2001; Roshchin and Travkin, 2017; Wotschack, 2020). However, innovation as a possible mediator of the effects of crises on training expenditures has not been considered so far.

Therefore, data from the Mannheim Innovation Panel (MIP) is used to examine the differences between innovative and non-innovative companies with regard to their training activities during the financial crisis. The final sample consists of 1,337 firms covering the years 2003 to 2009. The analysis focuses on two main variables: training incidence and training intensity. The former is a binary measure indicating whether a company offers training, while the latter captures training expenditure per employee. In addition, various control variables such as company size, workforce composition, and dummies for industry and region are included.

The results show that both innovative and non-innovative companies increased their training intensity during the crisis, although the extent of these increases differs significantly. Non-innovative firms in comparison to innovative firms increased it to a greater extent, which can be explained by their stronger decline in sales during the crisis. This finding is consistent with the opportunity cost theory (Aghion and Saint-Paul, 1998a). Interestingly, there were no significant differences between innovative and non-innovative firms regarding the training incidence.

The findings underscore the relevance of financial constraints and opportunity costs in shaping firms' training strategies during economic downturns. Innovative firms generally invest more in training due to their reliance on skilled labor for innovation activities (Baldwin and Johnson, 1996; Bauernschuster et al., 2009). However, non-innovative firms used the crisis as an opportunity to enhance workforce skills, demonstrating countercyclical behavior, which is in line with broader evidence from the literature on the cyclicity of skill acquisition (Méndez and Sepúlveda, 2012).

(ii) The COVID-19 Pandemic and Pay Adjustments

The second chapter, entitled "Who Pays for the COVID-19 Pandemic?: A Comparison of Stakeholders' Income Reductions in German Firms During the Crisis", investigates pay adjustment strategies in German firms during the COVID-19 pandemic, focusing on pay cuts incurred by different internal stakeholders. Using data from the German Business Panel (GBP), the study analyzes how firms affected by revenue declines during the pandemic plan to pass on costs to shareholders, executives, middle managers, and other employees.

Reducing payments to each individual group is associated with separate disadvan-

tages. For shareholders, dividend cuts can be a sign of financial instability (e.g., Miller and Rock, 1985; Nguyen and Tran, 2016). Regarding executives, a compensation reduction may increase the risk of talent loss and strategic inefficiency (Fabbri and Marin, 2016; Beiner et al., 2011). Reducing payments to middle managers poses significant risks as they play a critical role in ensuring organizational operations and contribute specialized expertise that is essential to the operational success of the company (Bonsiepe, 2002). Because they are positioned between upper management and employees, they are under particular pressure that can lead to dissatisfaction, lower commitment or attrition if their contributions are undervalued, which ultimately disrupts the stability of the organization (Dopson and Stewart, 1990). Reducing payments to employees is a challenge due to institutional wage rigidity in Germany, as collective agreements and minimum wage laws limit short-term adjustments while protecting less-skilled workers from significant income cuts (Franz and Pfeiffer, 2006). In addition, experienced employees form the operational backbone of companies, which makes wage cuts risky as they cause valuable employees to resign. Considering relative wage adjustments between stakeholders may also be important because perceived inequalities, especially between neighboring hierarchical groups, can lead to reduced effort and dissatisfaction, as suggested by the fair wage-effort hypothesis (Akerlof and Yellen, 1990). Therefore, ensuring fairness in wage cuts minimizes the risk of productivity losses.

Using survey data from the German Business Panel (GBP) multiple probit regressions are performed with a sample of 6,550 firms. By doing this, the effect of the COVID-19 pandemic on the probability of pay cuts to the different stakeholders is estimated. The degree to which firms are affected is measured by their revenue declines. Moreover, various control variables, such as firm size, legal structure, and decision-makers' risk aversion, are included.

Key findings reveal that all stakeholder groups within affected firms experienced pay reductions during this period. Dependent on stakeholder group, affected firms were found to be between 20.6–24.4 percentage points more likely than unaffected ones to impose payment reductions. In the baseline specification, executives faced the highest probability of pay cuts, followed by employees, middle managers, and shareholders. The findings suggest that the Fair Wage-Effort hypothesis is supported: firms tended to impose similar levels of pay reductions within proximate hierarchical groups, reflecting an effort to

maintain perceived fairness. The application of an IV approach to address endogeneity issues as well as multiple robustness checks confirm the main results.

(iii) Innovation and Pay Adjustments during the COVID-19 Pandemic

The third chapter, entitled “A Comparison of Pay Adjustments to Stakeholders During COVID-19 Between Innovative and Non-Innovative Firms”, explores how innovative and non-innovative firms in Germany differed in their pay adjustments to various stakeholder groups during the COVID-19 pandemic. The chapter focuses on four key stakeholder groups: shareholders, executives, middle managers, and other employees. It provides insights into how innovation influences firms’ ability to adapt cost structures and address cost reduction needs during times of crisis.

Innovative firms may differ from non-innovative firms in their adjustment strategies due to various reasons such as the stock of (specific) human capital, wage structure, and financial constraints. Skilled workers with a high level of specific human capital are particularly important for the success of innovative firms (see, e.g., Fonseca et al., 2019; Lenihan et al., 2019; Protogerou et al., 2017). Therefore, the potential loss of human capital due to employees resigning as a result of pay reductions might be higher for innovative firms. However, higher human capital is associated with higher wages, which often exceed collectively bargained wages (Aghion et al., 2017; Ammermueller et al., 2009; Pianta and Tancioni, 2008). Therefore, wage reductions may be easier to implement in innovative firms than in non-innovative ones. Furthermore, they often face stricter financial constraints due to the risky nature of R&D investments (Hottenrott and Peters, 2012; Lahr and Mina, 2020; Lee et al., 2015). This could increase the overall need for cost reductions to ensure their liquidity.

Data from the German Business Panel (GBP) and financial records from 2012–2020 are used to investigate the differences in both planned and realized pay adjustments. Firms are categorized as innovative or non-innovative based on measures of innovation input (R&D intensity) and innovation output (patent activities). A difference-in-differences (DiD) methodology and a triple differences (DDD) approach are applied to examine whether innovation acted as a mediator for the effect of the COVID-19 pandemic on pay adjustments. Standard control variables, such as firm size, legal structure, and industry dummies, are

included.

The findings show that innovative firms were significantly more likely to cut pay for shareholders and executives compared to non-innovative firms. This may be explained by the greater reliance on performance-based variable compensation among executives in innovative firms. As it is easier to reduce variable payments compared to a fixed salary, innovative companies face fewer obstacles to reducing total compensation. The higher likelihood of pay cuts to shareholders might reflect innovative firms' reliance on internal financing and the necessity to preserve cash for R&D investments. There are no significant differences in the baseline model regarding middle managers and other employees. Additional analysis using firm-level balance sheet data indicated that innovative firms reduced personnel expenses to a higher degree during the pandemic, emphasizing again that they were both more easily able to reduce costs and more dependent on pay reductions.

Part II

Main Chapters

Chapter 1

Training in innovative and non-innovative firms during the financial crisis

Co-authored with Kornelius Kraft

Kraft, K. and Seidinger, T. (2025). Training in innovative and non-innovative firms during the financial crisis. Unpublished.

The Great Recession had major effects on various fields of the German economy, in spite of this there were rather small effects on the labor market, specifically regarding employment. There is evidence that this is not true for further training. We contribute to this strand of research by studying the heterogeneity of the effect between innovative and non-innovative companies. To tackle this issue, we utilize detailed data on innovations from the Mannheim Innovation Panel in a difference-in-differences setting. We find that both kinds of firms raise their expenditures for training per employee. However, the increases by non-innovative firms are significantly higher. There is some evidence that this is due to different levels of opportunity costs. Our results remain robust across a variety of specifications and estimation models.

1.1 Introduction

Innovation and human capital are the key factors for wealth and growth of countries. The two factors are not independent of each other but mutually reinforcing. Better-educated employees produce more innovations and advanced products and processes require highly qualified personnel who also need to be constantly trained (Acemoglu, 1997; Aghion and Saint-Paul, 1998b). This is the reason why innovative firms on average spend more on training than non-innovative companies.

The financial crisis after the collapse of Lehman Brothers in 2008 led to major disruptions in the financial markets and unfavorable credit conditions for corporate customers (Dwenger et al., 2020; Giebel and Kraft, 2020; Huber, 2018). Since innovative companies generally have problems accessing debt capital, they were especially affected by the deterioration in conditions of the financial markets during this crisis (Giebel and Kraft, 2024; Hardy and Sever, 2021; Lee et al., 2015). This study examines how the financial crisis has affected training expenditures in general and whether any differences can be found between innovative and non-innovative companies.

Due to the general context, it is unclear whether innovative firms have changed their training expenditures more or less than non-innovative companies. On the one hand, innovative firms were forced to cut non-essential expenditures during the crisis. On the other hand, the opportunity costs of training measures generally fall in a crisis, as employees are underutilized (Aghion and Saint-Paul, 1998a,b). Based on the controversial discussion, an empirical test to verify the hypotheses seems warranted.

We use data from the Mannheim Innovation Panel (MIP) and the financial crisis as an exogenous shock in order to compare the change in training expenditures of innovative and non-innovative companies. We have data available for 1,337 firms over the years 2003-2009. This allows us to estimate a difference-in-differences model and additionally use reweighting approaches to adjust for possible selection effects.

Our analysis shows that innovative firms generally spend more on training than non-innovative ones and train more often. We find very interesting distinctions between the two types of companies during the recession, because while the two types do not have differing decisions in favor or against training (training incidence), there is a substantial difference in the training intensity (expenditures per employee). In both types of firms, training expenditures per employee are increasing, albeit to a lesser extent in the innova-

tive companies. Since the innovative firms were not as severely affected by the crisis, the opportunity costs of training fell less than in the non-innovative companies. In fact, the financial restrictions of innovative firms may have enhanced this effect, but nevertheless these results show that companies can use the crises for productivity-enhancing measures.

In Section 1.2, the theoretical framework is presented. We then discuss previous empirical results related to our research question in Section 1.3. Section 1.4 presents the research methodology and data, followed by the results in Section 1.5. In the final Section 1.6, the conclusions are drawn.

1.2 Theoretical framework

The development of further training activities in a crisis is based on various competing influences, where both theory and empirical results do not suggest a simple solution (cf. e.g., Bellmann et al., 2014; Dietz and Zwick, 2020; Mason and Bishop, 2015). At the center of the discussion is a trade-off between two factors: the opportunity costs of training and the financial resources available for training, where both factors tend to fall during a crisis (Brunello, 2009).

On the one hand, crises obviously reduce the financial resources available, which means that companies have to review all expenditures, including those on training. This consideration is particularly appropriate when prolonged crises are expected. The financial constraints are then significant and companies can only finance the most important expenses. In such situations, training budgets may well be reduced or even cut altogether. On the other hand, a crisis will also reduce the opportunity costs of training. A low demand for the goods and services produced means that employees are not working at full capacity. This, in turn, implies that firms could use the time available for training measures, as the costs of lost production are lower than in other phases of the economy (Aghion and Saint-Paul, 1998a). A crisis thus offers the opportunity for counter-cyclical training activities by reallocating the working time no longer required for production.¹ This strategy would lead to future increases in productivity, and consequently it provides firms a chance to combat the long-term effects of a recession. Training that imparts firm-

¹This has already been extensively discussed in the context of business cycles (see e.g., Bertoni and Brunello, 2022; DeJong and Ingram, 2001; López-García et al., 2013; Méndez and Sepúlveda, 2012; Saint-Paul, 1997; Sepúlveda, 2004)

specific skills, among other things, would reduce the tendency of employees to quit, as they acquired specific knowledge that would not be valued in other firms. The incentive for higher investment in training is particularly relevant if management assumes that the crisis is only temporary.

The complexity of this discussion becomes even more intense when a distinction is made between innovative and non-innovative firms. Innovative companies often employ a highly qualified workforce and constantly update their knowledge through further training activities (Acemoglu, 1997). This is necessary in order to keep innovation activities high (Bauernschuster et al., 2009).

In a crisis, innovative firms are then exposed to competing interests. Although, the need to cut costs creates an incentive to reduce training expenditures, investing in training during a crisis has a positive effect on future productivity. This can improve the competitiveness of these firms in a later recovery phase.

Another factor is the extent to which a company is affected by a crisis. During past recessions, including the Great Recession, innovative firms have been more resilient to fluctuations in the business cycle, and often suffered smaller declines in sales relative to non-innovative firms (Santos et al., 2021; Spescha and Woerter, 2019). Due to this resilience, innovative firms will realize lower decreases in the opportunity costs of training during a recession. For instance, their workforce will continue to be actively needed in production, which means less time is available for further training. It follows from this reasoning that if innovative companies were more resilient to crises, they would have a lower level of countercyclical investment in training than non-innovative firms.

It is well known that innovative companies generally have major problems accessing external capital (Giebel and Kraft, 2020; Hall, 2002). This can be aggravated in a crisis, which can generally jeopardize the financial feasibility of training (Giebel and Kraft, 2019). Aghion et al. (2012) point out that although the opportunity costs for R&D may be lower during a crisis, this does not lead to higher countercyclical spending if a firm is financially constrained. López-García et al. (2013) apply this argument to training within the context of business cycles. Overall, this suggests that innovative firms might not expand their training activities during a crisis due to liquidity problems in a downturn and the associated intensified pressure to cut costs.

In essence, it is not a trivial task to predict the relationship between crises and train-

ing expenditures, as this depends upon each firm's individual situation. Non-innovative companies are more likely to intensify employee training during a crisis, whereas the circumstances are far more complex for innovative firms. Although they need well-qualified employees who require continuous training, they are also confronted with severe financial restrictions and will realize higher opportunity costs of training due to their resilience to crises. Ultimately, the effects of crises on training expenditure in innovative and non-innovative firms can only be clarified empirically. This is due to specific factors such as the duration of the crisis, the extent to which the company is affected, and access to external financing.

1.3 Previous empirical literature

There are a number of empirical studies on the relationship between crises and investment in training. On this basis and together with the theoretical analysis, we can attempt to draw conclusions for our study.

Crises and investment in training

Empirically, a negative correlation is usually estimated between crises and expenditures on further training. Differences may occur depending, for example, on the access to external financing and the form of training. Using British data, Popov (2014) finds that crises have a negative impact on training, with financial restrictions playing a reinforcing role. The result with regard to financial restrictions corresponds to the theoretical arguments presented in the previous section. Similarly, Mason and Bishop (2015) use British data and report a decline in training activities during crises. In their case, external training is particularly affected. In contrast to these two studies, Felstead et al. (2012) find no significant effect of the crisis on training expenditures in the UK.

Turning to empirical evidence regarding German firms, Bellmann et al. (2014) show that establishments affected by the crisis reduced training activities to a greater extent than comparable units not affected by the crisis. Dietz and Zwick (2020) use linked employee-employer data and a difference-in-differences approach and point out that the crisis has negative but delayed effects on training. The effects are stronger for unskilled than for skilled workers, which indicates the greater importance of skilled workers for

firms.

The economic literature analyzing the cyclicity of skill acquisition and productivity-enhancing measures in general and particularly training measures, mainly identifies a countercyclical development (Bertoni and Brunello, 2022; DeJong and Ingram, 2001; López-García et al., 2013; Saint-Paul, 1997; Sepúlveda, 2004). In line with Aghion et al. (2012), López-García et al. (2013) show that the cyclicity of R&D investments depends on financial constraints. However, when analyzing the share of training expenditure in relation to total investment, they find no evidence of dependence on credit constraints.²

In contrast, Méndez and Sepúlveda (2012) find that training financed by companies is procyclical. This result remains consistent even when firm size is considered as a measure of credit constraints. As López-García et al. (2013) suggest, this result is in line with the broader literature when training spending declines less than other investments during downturns. Overall, the empirical literature speaks in favor of the opportunity cost theory rather than against it.

Innovative vs. non-innovative companies and training intensity

There are also studies on possible differences in training activities between innovative and non-innovative companies, although the relationship during the crisis is not considered. Wotschack (2020) and Gerlach and Jirjahn (2001) use firm data to examine the determinants of training activities. In both studies, innovative companies have higher training expenditures. These results are consistent with the theoretical hypothesis that innovation and training are positively correlated and mutually reinforcing.

Baldwin and Johnson (1996), using Canadian data, find that there are clear differences between innovative and non-innovative firms. Innovation-intensive companies offer more formal and informal training, train more employees, and have higher expenditure per employee. Based on Russian data, Roshchin and Travkin (2017) show that innovation activity proves to be a factor for higher training activities. Other important drivers are the production technology and the competitive situation. Based on data from an international survey, Hansson (2007) finds that innovative companies are more likely to finance training measures, although significant results cannot always be estimated. However, not

²In a more general context, not investigating crises, this result is confirmed by the findings of Montresor and Vezzani (2022).

all studies report positive correlations between innovation and training. Guisado-González et al. (2016), for example, find no significant correlation between training and radical or incremental innovation.

While most studies point to a positive relationship between innovation and educational activities, other factors probably affect the results as well. This conclusion also follows from the literature review by Neycheva (2024). She points out that innovation, market dynamics and company size interact in determining training decisions.

In summary, there is empirical evidence for both, a negative and positive impact of crises on investment in training. Furthermore, it can be said that innovative firms generally have better educated employees and realize more training activities than non-innovative companies. This is presumably the result of their efforts to be successful in a dynamic environment. However, other factors affect the result, such as the presence of financial restrictions, the competitive environment, or the type of training, all of which can complicate the analysis. This underlines the relevance of an empirical study on the connection between training efforts during the Great Recession with a distinction between innovative and non-innovative companies.

1.4 Data and methodology

1.4.1 Data

In this section, we describe the variables used in this study. We distinguish between dependent, key independent, and control variables. The data is based on the Mannheim Innovation Panel (MIP) and covers the period from 2003 to 2009. The MIP is the German part of the Community Innovation Survey (CIS) and provides firm-level data on innovation activity and other important company indicators.³ With the information collected, our research question on the effects of the crisis on training activities as a function of innovation behavior can be examined in detail.

Data source

The MIP is a firm survey that has been conducted annually since 1993 and contains information on innovation activities such as R&D and innovations introduced or planned.

³See Aschhoff et al. (2013) for a detailed description.

It also provides information on key firm indicators such as turnover and expenditures on further training. Our analysis uses data from firms in the manufacturing industry and knowledge-intensive services. This covers almost all sectors included in the MIP, with the exception of economic activities belonging to the NACE industries Rev. 1.0 codes A and L to Q (agriculture, public administration, health, and other public or community service activities). These observations are not included in the study because the firms in these sectors are either financed by the public sector or regulated differently than the private sector. As they are subject to specific financing conditions, their behavior during the crisis will presumably deviate from that of privately managed firms without regulatory constraints.

Dependent variables

We use two dependent variables based on expenditures for further vocational training. These expenditures include both internal and external training expenditures:

1. Training incidence: This variable is a dummy variable that takes on unit value if a company realized expenditures on further training above zero. This reflects the basic decision for or against further training, and it is examined whether this decision has changed during the crisis.
2. Training intensity: This continuous variable records the amount of training expenditures per employee. This indicator is frequently used in the literature (e.g. Gerlach and Jirjahn, 2001) to quantify a firm's engagement in further training.

Key independent variables

1. Crisis period: In line with studies such as Bellmann et al. (2014) and Dietz and Zwick (2020), we use 2008 and 2009 as the crisis period. This time period covers the years with the strongest negative effect after the collapse of the Lehman Brothers in September 2008. However, tensions on the financial markets were already noticeable from the end of 2007 onward (Hochfellner et al., 2015). In the robustness section, we therefore use the years 2007-2009 as an alternative crisis period (similarly to, e.g., Dietrich and Vollmer, 2012; Puri et al., 2011).
2. Innovation indicator: We identify innovative companies using a dummy variable

that takes unit value if a firm introduced a product or process innovation at least once in the periods before 2007. The restriction to the period before 2007 reduces the risk of endogeneity and avoids the influence of possible anticipation effects of the crisis on innovation behavior. We include planned innovations as well to capture all innovative firms, ensuring that control firms are likely non-innovative. In the robustness section, we use alternative measures of innovation.

Control variables

To account for additional factors that possibly influence training expenditures, we include various control variables:

In(sales): This variable captures firm size and is standard in studies related to innovation and the impact of innovation. The availability of financial resources increases with the size of the company, for example, because access to external financing is easier for larger firms. This, in turn, is associated with more resources for investment in training.

Share of part-time employees: This variable controls for the composition of the workforce. Part-time employees should have a lower return on investment in training, as by definition they work fewer hours.

Regional dummy for eastern Germany: Economic conditions were still different between Western and Eastern Germany in the 2000s. This regional dummy is intended to control for structural regional effects.

Proportion of highly qualified employees: It is a common hypothesis that a higher level of education is associated with more further training (Brunello, 2004). This variable controls for this possible correlation.

Industry dummies (3-digit WZ93 classification): These variables are standard in studies with innovation variables. They capture sectoral differences in innovation and training behavior.

1.4.2 Methodology

We use the difference-in-differences (DiD) model to investigate whether there are significant differences between the two types of firms in terms of their training activities during the crisis. The model also examines the direction of the differences, such as whether innovative firms are generally more engaged in training and whether training expenditures

rose or fell during the crisis. The model is displayed in equation 1:

$$y_{it} = \beta_0 + \beta_1 \text{innov}_i + \beta_2 \text{crisis}_t + \theta \text{innov}_i \cdot \text{crisis}_t + \beta_c X_c + \pi_t + \eta_i + \epsilon_{it}. \quad (1.1)$$

y_{it} is either training incidence or training intensity in the respective estimation equations. innov_i and crisis_t are the treatment and crisis dummies as described in the previous section. The vector X_c includes all control variables. π_t represents time fixed effects, while η_i represents firm fixed effects (unless OLS is used).

We estimate equation 1.1 with ordinary least squares and with fixed effects. In the latter case, all time-invariant variables are excluded (e.g. innovation dummy and industry dummies).

Assumptions

As is well known, the DiD model is based on various assumptions, the relevance of which we will discuss next. First, the common trend assumption must be valid. This is examined graphically in the first step with the help of Figure 1.1. While the development of both company types is very similar for the years 2003 to 2008, Figure 1.1 indicates differences in the change from 2008 to 2009. For a more detailed analysis, we use the formal test of Mora and Reggio (2015).⁴

To do so, we change equation 1.1 by interacting the innovation dummy with all years instead of the crisis dummy, as can be seen in the following equation:

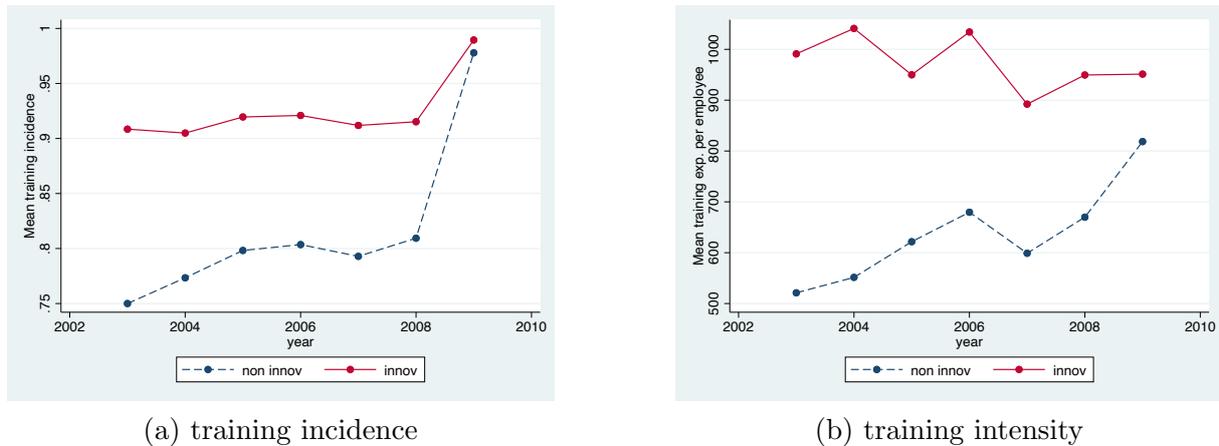
$$y_{it} = \beta_0 + \beta_1 \text{innov}_i + \beta_2 \text{crisis}_t + \sum_{t=2004}^{2009} \tau_t \text{innov}_i \cdot \text{year}_t + \beta_c X_c + \pi_t + \eta_i + \epsilon_{it} \quad (1.2)$$

To test whether the common trend assumption holds, we test the following null hypothesis $H_0 : \tau_t = 0 \forall t < 2008$. If we do not reject the H_0 hypothesis at the 10% level, then the common trend assumption is likely to be met. We report the p-values of this test at the bottom of the regression tables.

Another assumption is that the control variables are not influenced by the treatment, i.e., they are exogenous. This problem could arise, for example, in the case of part-time employees. It is possible that firms in the crisis now employ part-time workers who were

⁴See e.g., Giebel and Kraft (2019), Hangoma et al. (2018), and Yamamura (2016) for recent papers applying a similar approach.

Figure 1.1: Training incidence (a) and intensity (b) between 2003 and 2009



previously working full-time. To test for robustness against potential endogeneity, all specifications are also estimated without control variables.

1.5 Empirical analysis

Several firms participate in the MIP surveys only irregularly. We limit the data to firms that are observed at least once before and during the financial crisis and have a minimum of five total observations. In doing so, we exclude for instance firms that have gone bankrupt, thereby making the sample more consistent over time. The maximum number of observations per firm is seven due to the number of years in the sample (2003 to 2009). An overview of the distribution of observations per firm is given in Table 1.1.

Table 1.1: Number of observations per firm

Number of observations	Number of firms with that many observations	share
5	591	38 %
6	413	32 %
7	333	30 %
Σ	1337	100%

Data based on the Mannheim Innovation Panel 2003 - 2009.

Table 1.2 shows descriptive statistics for the baseline data set used in this study. About 73 % of all firms are innovative and a majority of 89 % spend at least 1 € for training. The mean spending for training is 83,548 € per year. When scaled by the number of employees around 879 € are spend for each employee per year. Regarding the control variables, the average firm has sales amounting to 49 million euros, about 15 % part-time employment, and 21 % of all employees have a university degree. About one-third of all

firms are located in East Germany.

Table 1.2: Descriptive analysis

	mean	sd	min	max
training incidence	0.89	0.31	0	1
training expenditure	83548.19	139385.35	0	528074
training exp. per employee	879.16	1438.74	0	31594
innovative	0.73	0.45	0	1
sales (thous.)	49391.92	87790.06	29.34	359873
number of employees	130.42	195.66	1	800
share part time employees	0.15	0.18	0	1
east germany	0.38	0.48	0	1
share college degree	0.21	0.24	0	1
Observations	7764			

Data based on Mannheim Innovation Panel 2005 - 2009.

Table 1.3 shows the variable values for the innovative and non-innovative firms separately and the results of a test on significant differences between the mean values. All values refer to the pre-crisis year 2006. The results confirm the hypothesis that innovative firms are more likely to provide further training (92 % versus 80 %) and spend more on training (in absolute terms and per employee).

Table 1.3: Test for mean differences

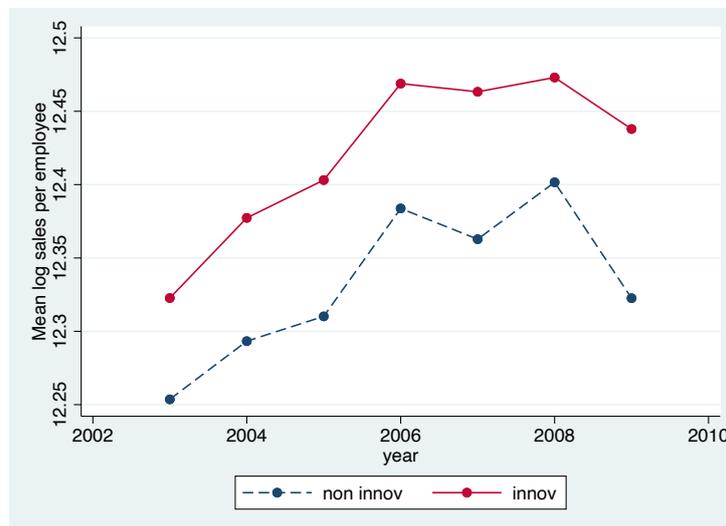
	non-innov		innov		diff
	mean	sd	mean	sd	b
training incidence	0.80	0.40	0.92	0.27	-0.12***
training expenditure	49483.67	103762.02	98495.01	147941.10	-49011.34***
training exp. per employee	679.61	1081.80	1034.12	1436.57	-354.52***
sales (thous.)	31250.25	59578.36	55593.17	93612.17	-24342.92***
number of employees	83.04	122.78	141.59	206.79	-58.54***
share part time employees	0.16	0.20	0.14	0.18	0.02
east germany	0.40	0.49	0.36	0.48	0.05
share college degree	0.16	0.22	0.24	0.25	-0.07***
Observations	336		860		1196

Data and tests based on the Mannheim Innovation Panel from 2006. Innov and non-innov is based on planned and completed product and process innovations. Entries in the column diff represent a two sided t-test with H_0 : The means of innov and non-innov are equal for the year 2006. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

Before moving on to the regression results, a brief explanation regarding a possible transmission channel. As discussed in Section 1.2, one possible explanation why firms could increase their spending for training is the decrease of opportunity costs. So, if it is the case that innovative firms have more (less) unused capacities their opportunity costs for training are lower (higher) in comparison to non-innovative firms; therefore, they would train more (less).

Figure 1.2 shows the log ratio of sales to employees, which is often used as a proxy for labor productivity. From 2006 to 2007, the productivity of both types of firms decreased. In the following year the productivity of both groups rose. From 2008 to 2009 the productivity decreased again; however, the decline is larger for non-innovative firms. When calculating growth rates we observe a 3.5% decrease for innovative firms and a 7.9% decrease for non-innovative firms. This could imply overemployment, especially in the non-innovative firms, which, in turn, is associated with lower opportunity costs for training. Based on these graphs, it is to be expected that non-innovative firms raise their training expenditures more than innovative firms.

Figure 1.2: Labor productivity of innovative and non-innovative firms



1.5.1 OLS, FE and Probit

Training incidence

First, we analyze the effect of the Great Recession on the training incidence, which is a binary variable and, therefore, is estimated via a probit model. In addition, OLS and fixed effects models are used, with the results shown in Table 1.4. In line with the descriptive statistics, innovative firms are more likely to train in general. Furthermore, the crisis coefficient is positive and significant regardless of the model, which indicates that firms in general started to spend money on training due to the crisis. The coefficients for the interaction term $\text{crisis} \cdot \text{innov}$ are always negative and insignificant except for the OLS models. Accordingly, we do not find robust differences between innovative and non-innovative firms regarding training incidence. Relying on the p-value, the common trend

assumption cannot be rejected.

Table 1.4: DiD estimation - dependent variable: training incidence

	OLS		FE		Probit
	(1)	(2)	(3)	(4)	(5)
innov	0.128*** (0.02)	0.085*** (0.02)			0.474*** (0.10)
crisis	0.164*** (0.02)	0.140*** (0.02)	0.060*** (0.01)	0.057*** (0.01)	1.440*** (0.16)
crisis*innov	-0.061*** (0.01)	-0.059*** (0.01)	-0.015 (0.01)	-0.020 (0.01)	-0.153 (0.10)
lnsales		0.057*** (0.00)		0.059*** (0.01)	0.461*** (0.04)
share parttime		-0.087* (0.05)		-0.070 (0.05)	-0.075 (0.24)
east		0.045*** (0.01)		0.023*** (0.01)	0.351*** (0.10)
share high educ		-0.044 (0.03)		-0.051 (0.05)	-0.228 (0.25)
const	0.772*** (0.02)	-0.174* (0.09)	0.883*** (0.01)	-0.068 (0.22)	-6.379*** (0.62)
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
industry dummies	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>No</i>	<i>Yes</i>
Number of obs	7764	7764	7758	7758	6780
Adj./ Pseudo R-Square	0.04	0.23	0.01	0.64	0.33
p-value for model test	0.00	0.00	0.00	0.00	0.00
p-value for ct test	0.18	0.16	0.26	0.17	0.24

Dependent variable: training incidence. Innov is based on planned and completed product and process innovations. Standard errors are robust and clustered on firm level. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

Training intensity

Next, we analyze the determinants of training intensity. In the case of this continuous dependent variable, we apply OLS and fixed effects models with the results shown in Table 1.5. Here, too, we find that training activities are intensified during the crisis, but now the interaction variable crisis*innov has significantly negative coefficients for all models. This implies that, compared to the non-innovative firms, innovative companies realize smaller increases during the crisis. Again, the common trend assumption is likely to be fulfilled. Our results regarding the crisis dummy are in contrast to those of Bellmann et al. (2014) and Dietz and Zwick (2020), which could be due to the definition of the dependent variable. Unlike our approach of using the expenditures for training per employee, they use the number of trained employees as their dependent variable. The different results may, for example, be explained by a reduction of trained employees, while at the same time the expenditures per worker receiving training increased.

Table 1.5: DiD estimation - dependent variable: training intensity

	OLS		FE	
	(1)	(2)	(3)	(4)
innov	380.496*** (59.83)	301.263*** (61.74)		
crisis	166.795*** (64.43)	144.446** (62.43)	38.269 (64.19)	59.949 (64.62)
crisis*innov	-160.913*** (56.46)	-142.541*** (54.11)	-102.702** (49.64)	-106.717** (50.12)
lnsales		-47.110*** (16.37)		-7.382 (62.69)
share parttime		-371.587* (217.60)		-447.046** (222.07)
east		-229.508*** (59.83)		-0.169 (222.05)
share high educ		686.480*** (168.55)		164.193 (207.25)
const	586.858*** (58.19)	679.307** (319.51)	888.339*** (38.11)	1030.468 (1031.02)
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
industry dummies	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>No</i>
Number of obs	7764	7764	7758	7758
Adj. R-Square	0.011	0.156	0.001	0.486
p-value for model test	0.000	0.000	0.000	0.000
p-value for ct test	0.169	0.197	0.449	0.467

Dependent variable: training intensity measured by training expenditures per employee in €. Innov is based on planned and completed product and process innovations. Standard errors are robust and clustered on firm level. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

1.5.2 Reweighting

It is plausible that innovative and non-innovative firms differ in many respects and that these differences may affect the estimation results. As shown in Table 1.3, the control variables, indeed, differ between the two types of firms. This suggests the presence of selection effects, which need to be considered.

There is a well-developed literature on accounting for selection effects, and one common method is reweighting, which we will also use here. The method is based on removing observable heterogeneity by adjusting for differences between covariates.

In our baseline specification, we apply an entropy balancing method based on the work of Hainmueller (2012).⁵ This method has been utilized by several studies, and an example in the innovation context is Trunschke et al. (2024). We reweight the observations such that the first, second, and third moments of the control variables for innovative and non-

⁵For details see Hainmueller and Xu (2013).

innovative firms are equal in the pre-crisis period. See Table 1.8 for descriptive statistics of the control variables before and after reweighting.

For the training incidence, Table 1.6 shows no significant effects for the fixed effects model. Table 1.7 reports the results regarding the determinants of training expenditures per employee after reweighting. Our results presented before are essentially confirmed. The interaction coefficients again have negative coefficients and even indicate somewhat stronger effects.

Table 1.6: Entropy weighting - dependent variable: training incidence

	OLS		FE	
	(1)	(2)	(3)	(4)
innov	0.076*** (0.02)	0.068*** (0.02)		
crisis	0.145*** (0.02)	0.119*** (0.02)	0.044*** (0.01)	0.043*** (0.01)
crisis*innov	-0.039*** (0.01)	-0.037*** (0.01)	-0.003 (0.01)	-0.008 (0.01)
const	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
industry dummies	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>No</i>
Number of obs	7764	7764	7758	7758
Adj. R-Square	0.023	0.252	0.004	0.679
p-value for model test	0.000	0.000	0.000	0.000
p-value for ct test	0.225	0.168	0.367	0.250

Dependent variable: training incidence. Innov is based on product innovations. Standard errors are robust and clustered on firm level. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

Table 1.7: Entropy weighting - dependent variable: training intensity

	OLS		FE	
	(1)	(2)	(3)	(4)
innov	252.323*** (71.40)	266.421*** (76.54)		
crisis	283.900*** (85.73)	223.909*** (77.41)	96.001 (79.65)	120.827 (80.01)
crisis*innov	-221.665*** (77.02)	-194.788*** (70.34)	-144.706** (62.89)	-145.929** (64.61)
const	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
industry dummies	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>No</i>
Number of obs	7764	7764	7758	7758
Adj. R-Square	0.006	0.157	0.001	0.500
p-value for model test	0.000	0.000	0.000	0.000
p-value for ct test	0.157	0.146	0.266	0.239

Dependent variable: training intensity measured by expenditures per employee in €. Innov is based on planned and completed product and process innovations. Standard errors are robust and clustered on firm level. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

1.5.3 Robustness

In this section, we provide several kinds of robustness checks. They include variation of the crisis period, the definition of the dependent and innovation variables, the method used to calculate weights, and the model choice. For a lucid presentation, we mainly report results for fixed effects models, as the consideration of unobserved heterogeneity is certainly important in our context.

Definition of the crisis period, training intensity and the sample

As argued in Section 1.4, we use 2008 - 2009 as the crisis period regarding the Great Recession. However, other studies define as crisis period the years 2007 to 2009 (Dietrich and Vollmer, 2012; Puri et al., 2011). We therefore specify an alternative crisis dummy that takes unit value in 2007-2009 and zero before. The fixed effects results regarding the training incidence (column (1)) and intensity (column (2)) are displayed in Table 1.9 in the appendix. For both dependent variables, the results remain unchanged. There is still a significant negative difference between innovative and non-innovative firms for the training intensity and no significant difference for the training incidence.

Furthermore, we apply the logarithm to the dependent variable training intensity. To avoid the loss of observations with a training intensity of zero we transform the data using $\ln(\text{training intensity} + 1)$. The results for the fixed effects model are shown in Table 1.9, column (3). Those results indicate that innovative firms increase their training intensity by 25% less than non-innovative firms.

So far, we have restricted our sample to firms with at least five observations over the time period. There is a trade-off between requiring more or fewer observations per firm to include it in our sample. A lower minimum will lead to a greater overall number of observations and, therefore, more precise estimates. However, the comparability of the two groups over time decreases, which might lead to a violation of the common trend assumption.

We re-estimate equation 1 and set the minimum number of observations per firm to o with $o = 2, \dots, 7$. We always restrict the sample to firms that are observed at least once before and once during the crisis. With a lower o , the coefficients become significant at the 1% level. However, the p-value of the common trend test decreases for some specifications below 0.1. In contrast, with a higher o , this p-value increases, while the

significance of the coefficients decreases. Nevertheless, independent of o , all interaction coefficients remain negative, with no relevant changes in their magnitude. The results are available on request.

Definition of size and innovative firms

In our baseline specification, we control for the size of firms by including the logarithm of firms' sales. To account for a possible non-linearity, we include sales and sales squared (both measured in 100 million euros) and use size categories instead of $\ln\text{sales}$.⁶ Results are presented in Table 1.10. Measuring the size of firms differently does not change our main results.

So far, we have defined innovative companies as those that have either planned or realized product and/or process innovations. However, it is possible that planned innovations do not lead to success and that these companies are therefore not innovative in a narrow sense. We therefore define innovative companies in the following as those that have actually realized an innovation. Essentially, there are no differences in the results, which is not surprising, since only 5% of all firms change groups. The detailed results are available on request.

According to the definition used so far, we look at innovation output. In the following, we distinguish among different types of firms according to innovation input by using total innovation expenditures. These expenditures are composed of the following: In-house research and experimental development (internal R&D), awarding of R&D contracts to third parties (external R&D), acquisition of machinery, facilities and software to realize innovation projects, acquisition of other external knowledge (e.g. patents, unpatented inventions, licenses, and trademarks associated with innovation projects), internal or external employee training and continued education directly related to innovation projects, internal or external marketing activities, including market research, directly related to innovation projects, preparations for the introduction of product or process innovations (e.g. design), prototype manufacture, design work as well as all the amount of capital expenditure for innovation.

We assign all firms with non-zero expenditures the status of innovative and all firms

⁶The categories are defined as follows: 1 if sales $\leq 100k$; 2 if sales are between $100k - 350k$; 3 if sales are between $350k - 700k$; 4 if sales are between $700k - 2mil$; 5 if sales are between $2mil - 10mil$; 6 if sales $> 10mil$

without any expenditures for innovation the status of non-innovative. In a second step, we apply a stricter distinction by defining as innovative only those firms that have a higher innovation expenditure to sales ratio than the average firm. To generate the dummy variables, we only use data prior to 2007 in order to avoid possible effects of the crisis itself.

Table 1.11 in the appendix shows the results from the fixed effects model with controls. The results presented in columns (1) to (4) underline that, independent of the definition of being innovative, the results remain insignificant for training incidence and significantly negative for training intensity confirming our previous results.

Finally, we calculate the mean of logarithmized R&D intensity before 2007 and utilize this as a continuous innovation measure.⁷ For an intuitive interpretation, we also logarithmize the training intensity, which allows us to interpret the coefficients as elasticities. Results are shown in Table 1.12 in the appendix. Depending on the model, a ten percent increase in the R&D intensity decreases the training intensity by 1.2-2.6 percent.

Reweighting method

In our baseline specification, we utilize entropy balancing to reweight our observations. We additionally calculate weights based on several propensity score matching specifications (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002). We employ kernel matching with the Epanechnikov, the Gaussian, and the uniform kernel function. Moreover, regarding the matching approach, we apply k-nearest neighbor (with $k = 1, 5, 10,$ and 50) and radius matching with different calipers (0.001, 0.005, 0.01, and 0.1). Furthermore, we apply inverse probability weighting. Table 1.13 shows results for weights based on Epanechnikov kernel matching (column 1), inverse probability weighting (column 2), radius matching with a caliper of 0.1 (column 3), and 1-nearest neighbor matching (column 4). These different approaches again confirm our main results. Furthermore, the results remain mostly unchanged when varying the type of kernel function, the number of neighbors, or the caliper distance.

⁷See Wooldridge (2010, p. 132) for an extension of classical DiD with a continuous treatment.

Tobit

As noted above, about 11% of all firms do not provide training, and therefore their training expenditures per employee are zero. This might be a problem for the linear models. Therefore, we additionally estimate a standard tobit, a random effects tobit, as well as a heteroskedastic tobit model. The results from this approach are presented in the appendix in Table 1.14 and support our previous findings. There is still a significant negative effect of being innovative on the training intensity. The same is true when using innovation input as the basis of the innovation dummy.

1.6 Conclusion

The financial crisis of 2008-2009 was a major crisis with a strong impact on various areas of the economy. Since then, a number of studies have been carried out on the effects in different areas. This study examines the impact of the crisis on training activities, with a particular focus on the comparison between innovative and non-innovative companies.

In line with previous research, we find that innovative firms spend more on further training, on average, than non-innovative companies. Interestingly, we estimate that training activities have increased overall during the crisis, although innovative firms have raised their expenditures per employee less than their non-innovative counterparts. We find no differences between the two types of firms when it comes to the basic question of whether or not to offer further training.

There has been a discussion, at least since Schumpeter's argument, about the positive aspects of crises, such as "cleansing effects", for example, the increase in productivity through the elimination of inefficient firms. During a crisis, one way to increase productivity in future periods is by training employees. We can confirm with our data that expenditures for training were increased. The argument of opportunity costs seems to play a role here, as innovative companies were less affected by the crisis and expanded their training measures to a smaller extent than other firms.

Overall, the results show that crises do not only have negative effects but also positive ones. Many firms want to retain their employees even in a crisis and use the time freed up for further training. Future research could investigate whether our findings also apply to other countries. For instance, Germany has a highly developed employee protection

system, such as short-time working regulations, which serve to keep employees in companies for longer. This also influences incentives for internal training, whereas in other countries, such as the United States, employee protections are weaker. As a result, there may also be different patterns of behavior in crises with regard to further training. Another complicating factor we would like to emphasize is the role of financial constraints in training decisions, as there is still a need for research to examine the practical relevance of such restrictions with corresponding data. Finally, we assume that training measures should increase productivity after the crisis; this effect could also be empirically evaluated in future studies.

1.7 Appendix

Table 1.8: Descriptive statistics before and after reweighting based on entropy balancing

	Innovative			Non-innovative		
	mean	var	skew	mean	var	skew
<i>Before reweighting</i>						
lnsales	16.36	3.40	0.07	15.81	2.97	0.12
share parttime	0.13	0.03	2.50	0.16	0.04	2.03
east	0.36	0.23	0.57	0.41	0.24	0.35
share high educ	0.23	0.06	1.48	0.16	0.05	1.94
<i>After reweighting</i>						
lnsales	16.36	3.40	0.07	16.36	3.40	0.07
share parttime	0.13	0.03	2.50	0.13	0.03	2.50
east	0.36	0.23	0.57	0.36	0.23	0.58
share high educ	0.23	0.06	1.48	0.23	0.06	1.48

Upper (lower) panel displays descriptive statistics before (after) reweighting

Table 1.9: Robustness regarding the crisis period and the dependent variable

Fixed effects regressions			
crisis period	07 - 09		08 - 09
dependent variable	(1)	(2)	(3)
	incidence	intensity	log(intensity+1)
crisis	0.051*** (0.02)	65.578 (70.85)	0.449*** (0.09)
crisis*innov	-0.012 (0.02)	-114.287* (62.31)	-0.257*** (0.08)
controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Number of obs	7758	7758	7758
Adj. R-Square	0.64	0.49	0.67
p-value for model test	0.00	0.00	0.00
p-value for ct test	0.10	0.65	0.31

Dependent variable: training incidence (model 1), training intensity measured by expenditures per employee in € (model 2), and log(training intensity+1) (model 3). Innov is based on planned and completed product and process innovations. Standard errors are robust and clustered on firm level. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

Table 1.10: Robustness regarding the size variable

Fixed effects regressions				
Dep. variable	training incidence		training intensity	
	sales and sales ²	sales categories	sales and sales ²	sales categories
Size measure	(1)	(2)	(3)	(4)
crisis	0.059*** (0.01)	0.061*** (0.01)	65.610 (64.06)	60.294 (64.40)
crisis*innov	-0.019 (0.01)	-0.018 (0.01)	-105.004** (50.16)	-107.823** (50.01)
sales	0.087*** (0.03)		-77.395 (229.39)	
sales ²	-0.019*** (0.01)		-0.861 (46.99)	
sales _{100k-350k}		0.203 (0.13)		222.992 (184.73)
sales _{350k-700k}		0.462*** (0.14)		546.245** (223.76)
sales _{700k-2mil}		0.477*** (0.15)		535.781* (288.08)
sales _{2mil-10mil}		0.532*** (0.15)		530.422* (295.83)
sales _{>10mil}		0.577*** (0.15)		471.226 (308.55)
Other controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Number of obs	7758	7758	7758	7758
Adj. R-Square	0.64	0.65	0.49	0.49
p-value for model test	0.000	0.00	0.00	0.00
p-value for ct test	0.19	0.25	0.49	0.47

Dependent variable: For model (1) and (2): training incidence; for model (3) and (4): training intensity measured by expenditures per employee in €. Innov is based on planned and completed product and process innovations. Standard errors are robust and clustered on firm level. ***p≤0.01, **p≤0.05, *p≤0.10.

Table 1.11: Robustness regarding the innovation variable

Fixed effects regressions				
Dep. variable	training incidence		training intensity	
	exp. for innov	mean exp. for innov	exp. for innov	mean exp. for innov
Innov. variable	(1)	(2)	(3)	(4)
crisis	0.051*** (0.01)	0.053*** (0.01)	49.417 (64.30)	-19.322 (68.47)
crisis*innov	-0.014 (0.01)	-0.018 (0.01)	-106.030** (48.46)	-229.899*** (87.46)
controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Number of obs	7664	6143	7664	6143
Adj. R-Square	0.64	0.66	0.49	0.49
p-value for model test	0.00	0.00	0.00	0.00
p-value for ct test	0.74	0.95	0.77	0.66

Dependent variable: For model (1) and (2): training incidence; for model (3) and (4): training intensity measured by expenditures per employee in €. Innov is based on: the total expenditures for innovations (model (1) and (3)); the mean of expenditures for innovations (model (2) and (4)). Standard errors are robust and clustered on firm level. ***p≤0.01, **p≤0.05, *p≤0.10.

Table 1.12: Training intensity and a continuous innovation measure

	OLS		FE	
	(1)	(2)	(3)	(4)
innov	0.654*** (0.07)	0.143** (0.06)		
crisis	0.804*** (0.08)	0.625*** (0.08)	0.319*** (0.07)	0.291*** (0.07)
crisis*innov	-0.256***	-0.206***	-0.116***	-0.119***
controls	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
industry dummies	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>No</i>
Number of obs	7486	7486	7480	7480
Adj. R-Square	0.033	0.257	0.006	0.674
p-value for model test	0.000	0.000	0.000	0.000

Dependent variable: $\ln(1 + \text{training intensity})$. Innov is based on pre crisis R&D intensity. Standard errors are robust and clustered on firm level. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

Table 1.13: Robustness regarding the calculation of weights - dep. variable: training intensity

Approach to calculate weights	Epanechnikov kernel matching	Inverse probability weighting	Radius matching	Nearest-Neighbor matching
	(1)	(2)	(3)	(4)
crisis	166.082* (90.30)	52.719 (65.34)	198.729* (102.04)	216.259** (101.82)
crisis*innov	-191.862** (76.17)	-120.837** (51.35)	-226.299*** (87.35)	-252.458*** (88.07)
controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Number of obs	7022	7715	6971	6520
Adj. R-Square	0.50	0.01	0.49	0.49
p-value for model test	0.00	0.00	0.00	0.00
p-value for ct test	0.20	0.21	0.15	0.31

Dependent variable: training intensity measured by expenditures per employee in €. Innov is based on planned and completed product and process innovations. For model 3 a caliper of 0.1 is used. Standard errors are robust and clustered on firm level. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

Table 1.14: Robustness regarding the model - dep. variable: training intensity

	Tobit regressions				
	tobit		RE tobit		het. tobit
	(1)	(2)	(3)	(4)	(5)
innov	536.460*** (78.18)	430.840*** (75.62)	541.591*** (78.03)	524.757*** (78.32)	308.542*** (68.22)
crisis	351.301*** (69.90)	310.802*** (67.40)	147.611** (73.03)	156.905** (73.11)	259.643*** (67.20)
crisis*innov	-241.520*** (63.80)	-224.852*** (60.88)	-151.690** (66.85)	-151.646** (66.83)	-219.435*** (63.32)
sales		8.004 (18.42)		-2.647 (18.66)	-17.420 (18.26)
share parttime		-542.135** (250.28)		-519.249*** (141.85)	-635.694*** (158.95)
east		-142.776** (65.04)		-132.020* (71.02)	-138.026*** (49.33)
const	333.025*** (71.42)	-336.953 (364.97)	346.622*** (74.61)	520.404 (318.90)	222.136 (357.25)
time dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
industry dummies	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>No</i>	<i>Yes</i>
Number of obs	7764	7764	7764	7764	7764
p-value for model test	0.000	0.000	0.000	0.000	0.000

Dependent variable: training intensity measured by expenditures per employee in €. Innov is based on planned and completed product and process innovations. Standard errors are robust and clustered on firm level. ***p≤0.01,**p≤0.05,*p≤0.10.

Chapter 2

Who Pays for the COVID-19 Pandemic?

A Comparison of Stakeholders' Income Reductions in German Firms During the Crisis

Co-authored with Tobias Hemker and Kornelius Kraft

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This study examines the extent to which German firms that are affected by the COVID-19 pandemic pass on the costs of the crisis to stakeholders. In particular, we study survey responses on planned pay cuts to four different groups: shareholders, executives, middle management, and other employees. We use a unique firm-level dataset that provides in-depth information during the crisis in which companies are asked if and to what extent they are affected by the pandemic. We find that all these stakeholders of affected firms must pay with either lower dividends or lower future compensation increases. Affected firms are approximately 20.6 – 24.4 percentage points more likely to reduce stakeholders' payoffs. These effects become stronger for firms that are more affected. We also find evidence for effect heterogeneity in firm size as the probability for reductions is larger in firms with higher revenues. An IV approach addressing the potential endogeneity in managerial skills as well as several robustness checks confirm our results. Furthermore, in line with the Fair Wage-Effort hypothesis, correlations suggest that firms choose to pass through costs to groups with a related hierarchical standing.

2.1 Introduction

The COVID-19 pandemic caught the German society and economy completely unprepared. In less than a month after its first appearance in Wuhan, the Sars-Cov2 virus had already reached Germany. Barely two months later, a conference between German Chancellor Angela Merkel and the minister presidents of the 16 German states resulted in the first lockdown to limit the spread of the virus. This came into force on March 22, 2020, and ended on May 4, 2020. During this period, among other things, social contact had to be avoided. On the one hand, this affected the private environment as well as educational institutions, which were forced to switch to digital formats in a very short time. On the other hand, many companies had to shut down their production and/or activities. For instance, entire industries, such as tourism, gastronomy, and personal care services, were closed, and employees in many other industries had to work from home.¹

The drastic interventions at the beginning of the pandemic had the effect that the spread of the coronavirus as well as the number of deaths in Germany remained at a comparatively low level. However, the German economy suffered from the policy measures enacted to address the emergency. In fact, for the first time in 10 years, the price-adjusted GDP did not increase but decreased by 5% in 2020 compared to the previous year.² Although government programs such as coronavirus aid, the deferral of insolvency proceedings, and short-time working allowances are intended to reduce the burden on companies, many firms have been seriously affected by the crisis.

For instance, a survey by KANTAR on behalf of the German Federal Ministry for Economic Affairs and Energy (BMW_i, 2020) shows that three out of four companies are experiencing strong negative economic effects because of the pandemic. These are liquidity constraints that are primarily due to wage payments. Thus, a rational decision for firms might be to reduce payments to stakeholders to ensure the survival of the firm in the crisis. Therefore, we address the question of whether and to what extent the effects of the pandemic are indeed transferred to the firms' stakeholders. To this end, we examine whether firms that are negatively affected by COVID-19 reduce payments to four groups of stakeholders: shareholders, executives, middle managers, and other employees. This adds

¹<https://www.bundesregierung.de/breg-de/themen/coronavirus/besprechung-der-bundeskanzlerin-mit-den-regierungschefinnen-und-regierungschefs-der-laender-vom-22-03-2020-1733248> (last access: March 23, 2024).

²https://www.destatis.de/DE/Presse/Pressemitteilungen/2021/01/PD21_020_811.html (last access: March 23, 2024).

to the existing literature since our data enables us to compare these different stakeholder groups. Furthermore, to the best of our knowledge, we are the first to investigate this issue econometrically with respect to the COVID-19 crisis.

To do so, we use data on the onset of the pandemic in Germany, as provided by the German Business Panel (GBP). We use the decrease in monthly revenue compared to the beginning of 2020 to determine the affectedness of firms. We argue that affected firms reduce payments to stakeholders. Since each group represents another important function for the firms, there is a trade-off regarding which group should be penalized. We explore this trade-off and examine which group of stakeholders is particularly affected.

We place shareholders, executives, middle managers, and other employees at the center of our study as the key stakeholders of companies. The members of these groups are central to the long-term success of the companies. While on the one hand companies need to cut costs in the face of lower revenues, each firm must, on the other hand, weigh the negative effects of reduced payments to stakeholders. These include reduced effort and higher quit rates. Hence, compensating for the losses due to the crisis through pay cuts must be decided very carefully.

Our study is structured as follows. In the second section, we describe possible downsides of reducing stakeholders' payments as well as the state of empirical literature regarding each stakeholder group. The third section defines the database and methodology. Section 4 shows the findings of being affected by the crisis on payments to stakeholders. We perform regressions in Section 6 to account for firm heterogeneity and test for robustness in the seventh section. Finally, this study ends with a summary and a conclusion.

2.2 State of the Literature

Shareholder

The shareholders are the owners of the company. They contribute capital to the company and receive dividends depending on the company's performance. Even if shareholders expect dividends from their investments, it can be appropriate to reduce or cut dividends in times of crisis to ensure additional liquidity and flexibility for the companies (e.g., Hauser, 2013; Kouser et al., 2015; Krieger et al., 2021; Reddemann et al., 2010). However, there is a consensus in the literature that managers should avoid reducing dividends

(Krieger et al., 2021). One possible reason is that a decline in dividends could be seen as a signal of poor financial health for the firm (e.g., Miller and Rock, 1985; Nguyen and Tran, 2016). A reduction in dividends in times of crisis can therefore be interpreted as a signal that the company is in a bad state. Hence, potential shareholders may be discouraged from investing in the company. Additionally, existing shareholders, who usually spread their holdings over several companies, may be given an incentive to sell their shares.

Hauser (2013) finds that the probability of dividend payments by U.S. industrial firms decreases during the financial crisis. He also finds changes in dividend policy that imply a greater importance of cash after the crisis and concludes that companies prioritize financial viability during the crisis. For Pakistan, Kouser et al. (2015) also find that the propensity to pay dividends has declined during the financial crisis and conclude that companies are pursuing a conservative strategy to retain cash. Similarly, Kilincarslan (2021) finds a negative impact of the global financial crisis of 2008 on dividend payments in firms traded on the London Stock Exchange. In contrast, Nguyen and Tran (2016) find that firms in the United States, Thailand and Singapore increased dividends in the post-crisis period from 2008-2012. Regarding the signaling theory, they conclude that firms avoid reducing dividends to send a signal of financial health to investors. However, Reddemann et al. (2010) find for European insurance companies that dividend cuts during the financial crisis are not seen as a signal for future problems.

More recently, for the United States, Krieger et al. (2021) examine the frequency of dividend cuts and cancellations associated with the COVID-19 pandemic and compare these results to quarterly dividend changes since 2015. They find that companies were three to five times more likely to cut dividends in the second quarter of 2020 than in any other quarter. In this context, industrial companies cut dividends more frequently than financial services or utilities. Moreover, they find similar results in relation to dividend omissions, although these are only present for industrial firms and only affect 7% of the firms. The authors conclude that companies cut or omit dividends in times of crisis to preserve more cash and flexibility to respond to uncertainty. For China, in contrast, Jebran and Chen (2022) find that managers with higher abilities tend to pay dividends during the COVID-19 crisis. They argue that the pandemic forces managers to use new strategies to ensure the survival of their operations. Ali (2022a) also finds that in the G-12 countries, most companies were able to maintain or even increase their dividends

during the COVID-19 pandemic, consistent with the signaling theory. However, he finds that the share of dividend cuts and defaults was significantly higher in 2020 than in the pre-crisis period of 2015–2019.

Executives

German firms are characterized by a two-pillar system. This consists of the executive board, which makes the operational decisions, and a supervisory board, which controls the executive board and regulates its composition and compensation. The compensation is usually determined using a complex system based on fixed salaries and incentive-based variable components, which are intended to ensure the long-term success of the firm. Executives make strategic decisions that determine success or failure during the crisis period. Accordingly, lowering compensation could lead to disincentives or encourage talented managers to leave the firm, as tough competition for talented managers (Fabbri and Marin, 2016) may allow them to receive higher pay in other firms. In a different context, Beiner et al. (2011), Raith (2003), and Schmidt (1997) consider the incentive orientation of executive contracts in times of increased competition as a threat to the firm's survival. The results differ, but incentive orientation may well increase in times of a crisis. On the other hand, increasing bonus payments in firms that were rescued with taxpayers' money during the financial crisis led to a high level of public outrage (see again, e.g., Fabbri and Marin, 2016). Thus, increasing executive compensation in the COVID-19 crisis may also lead to public outrage, particularly if the wages of employees are reduced.

Vemala et al. (2014) find that the financial crisis has a positive impact on CEO total compensation in the United States, as cash compensation decreases while equity remuneration increases. Gabaix et al. (2014) find that CEO compensation in the United States declined by 28% during the 2007-2009 financial crisis but increased by 22% after the crisis. Sonenshine et al. (2016) test how determinants of CEO compensation in North America change due to the financial crisis and conclude that the composition of pay turns away from cash toward equity because of the crisis. Fabbri and Marin (2016) examine the trend in executive compensation in Germany and find that the financial crisis causes a stronger link between firm performance and compensation compared to previous recessions.

In a descriptive study, Batish et al. (2020) examine the impact of the COVID-19 crisis in the United States on pay for CEOs and other stakeholders. They find that 17% of the companies adjusted their CEO compensation. Moreover, they find that companies that

change CEO compensation are much more likely to reduce personnel costs or cut or eliminate dividends. With respect to the COVID-19 crisis, Mahaboob (2022) uses secondary data reports (e.g. OECD publications and World Bank reports) dealing with Gulf Cooperation Council countries (Saudi Arabia, Kuwait, United Arab Emirates, Qatar, etc.) to investigate the effect of the crisis on workers compensation. Her data enables her to divide workers in five groups: CEO, senior management, middle management, professionals and support. For each country she reports the median of already implemented percentage reductions on base salaries. The CEO and senior management fit our definition of top management best. For these two groups, she reports a 20% decrease in the base salary in United Arab Emirates, Saudi Arabia, Oman, and Qatar. In Bahrain (Kuwait) CEOs salary decline is stronger with 15% (25%) in comparison to top management with a decline of 10% (24%). However, in all these countries salaries decrease by at least 10%.

Middle Managers

The term “middle manager” is not uniformly defined. Mintzberg (2010), for example, describes a person who simultaneously must report to superior managers and demands reports from subordinate managers. According to Bonsiep (2002), middle management has the responsibility, among other things, to ensure the implementation and achievement of goals and work processes and to contribute its own expertise and experience. Therefore, middle management usually has a high amount of specific human capital that is crucial for the proper running of the processes in the firm. However, the position between the top and bottom levels of the hierarchy can also imply problems for middle management. This position can lead to a high level of dissatisfaction, as middle managers are responsible for the proper functioning of the workforce and simultaneously can be made responsible or bypassed by the upper management (see, e.g., Dopson and Stewart, 1990). Therefore, a decrease in middle managers’ income may lead to a reduction in effort or may even cause them to quit.

Kampkötter and Sliwka (2011) observe the relationship between firm performance and the bonus-to-base ratio (share of bonus payments to base salaries) of all hierarchical levels below top management in German banks and financial institutions. They find a positive relationship between 2003 and 2008, which is particularly strong in the higher hierarchy levels. Moreover, the financial crisis led to a considerable decline in bonus payments,

which were again substantially stronger in higher hierarchy levels, and to an even stronger decline in firm performance. In a similar approach, Kampkötter (2015) analyzes how pay systems in the German and Swiss financial services industry changed in response to the financial crisis. He focuses on non-executive employees which excludes CEOs and top management positions and finds that the financial crisis had a large impact on the variable part of compensation. For the German chemical sector, Grund and Walter (2015) find a decline in bonus payments during the financial crisis while fixed salaries remain relatively stable. However, after the crisis, variable compensation and total compensation actually rise above the pre-crisis level. As mentioned above Mahaboob (2022) also reports salary decreases for middle management. Depending on the country she shows a percentage reduction in base salaries between 14% and 25%.

Other Employees

The employees form the basis of the company and carry out the work processes. Traditionally, the level of their wages is explained by human capital factors, implying that education, work experience, and on-the-job training yield higher wages (see, e.g., Becker, 1964; Mincer, 1974). However, in Germany, collective agreements have a major impact on wage levels. These result from collective bargaining between employers' associations and trade unions and are concluded largely independently of any intervention by the government. A negotiated collectively agreed wage is not to be regarded as a fixed amount, but rather as a wage minimum that may be exceeded. Such a collectively agreed wage cannot be simply undercut, as otherwise unions threaten to take labor actions such as strikes. Franz and Pfeiffer (2006) show that such labor union contracts are particularly important for the wage rigidity of less skilled workers. For the stickiness of high-skilled wages they emphasize that specific human capital and negative signals for new hires are the most important. Furthermore, Germany had a national wide minimum wage of 9.35 € per hour in 2020 that increased in the following years.³ These institutional settings prevent or at least complicate short-term wage adjustments. Moreover, employees with accumulated experience are indispensable as the operational basis of the firm. Therefore, quits due to wage cuts would also cause lasting damage to the company.

Adams-Prassl et al. (2020) use survey data for the US, UK and Germany to study

³For details, see: https://www.destatis.de/EN/Themes/Labour/Earnings/Minimum-Wages/_node.html (last access: March 23, 2024).

heterogeneity in the impact of the COVID-19 crisis. They find that workers in the US and UK face a higher risk of losing their jobs during the crisis and therewith realize wage losses. To a much smaller degree, this is the case for Germany, as many workers who are no longer needed for production purposes receive public support through the short-time working program.⁴ Grabka (2021) uses the German Socio-Economic Panel (SOEP) to investigate the changes in income inequality in Germany. He reports that income inequality decreased slightly since the beginning of the COVID-19 crisis pandemic.⁵ However, he argues that this is might be mainly due to income reductions among the self-employed.

In addition to managers, Mahaboob (2022) also reports salary decreases for professionals and support workers who may be seen as the ordinary employees. For almost all countries both groups are treated equally with two exceptions. In the United Arab Emirates wages of support workers decrease 4 percentage points stronger than those for professionals. In Oman, it is the opposite. Professionals' wages decrease 8 percentage points more than the wages of support workers. In total, the descriptive study of Mahaboob (2022) finds a predominantly similar reduction of wages with a slight tendency to higher reduction at lower hierarchical stages. The paper by Akerman et al. (2022) is closest to ours. They study how the decline in output in Sweden during the pandemic affected workers' incomes. They distinguish workers by age, gender, education, and migration background, among other factors. Our study, in contrast, differentiates the workforce according to the hierarchical positions of the employees and we additionally include shareholders.

Fair Wage-Effort hypothesis

Until now, we considered the consequences of pay cuts for each single stakeholder group separately. However, we expect that there are interactions between workers and that fairness considerations affect the productivity effects of wage cuts. A stakeholder group

⁴The German short-time work program allows companies to retain the employment contracts, while the Federal Employment Agency covers up to 66% of wage costs for a period of up to 12 months. In 2020, on average, almost 3 million workers were affected by short-time work (see, e.g., https://statistik.arbeitsagentur.de/Statistikdaten/Detail/Aktuell/iiiia7/kurzarbeit-zr2/kurzarbeit-zr2-dwolkraa-0-xlsm.xml?_blob=publicationFile&v=1, last access: March 23, 2024). For further information, see, e.g., <https://www.arbeitsagentur.de/en/press/en-2022-42-shorttime-working-benefit-for-temporary-work> (last access: March 23, 2024).

⁵There exist other studies, which consider the effects of COVID-19 on wages and wage distribution, e.g. Adermon et al. (2024) and Braband et al. (2022). Braakmann et al. (2022) consider in addition to wages movements of workers leaving high-risk occupations in the UK.

might feel to be unfairly treated if only the members of their own group are affected by wage reductions, but not others. This fairness consideration is particularly relevant if a stakeholder group “close” in the hierarchy to one’s own is differently treated (executives versus middle managers, middle managers versus other employees). If members of a specific stakeholder group feel (subjectively) unfairly treated, they might react with effort reduction. This is essentially the content of the Akerlof and Yellen (1990) Fair Wage-Effort hypothesis and could be of relevance in our research context.

To avoid the potential problem of a reduction in effort due to pay decreases, it may be appropriate for firms to reduce payments to all stakeholders simultaneously. However, we assume that groups compare their wages, particularly with the neighboring group in the hierarchy. Accordingly, we expect high inequalities between non-managerial employees and middle managers to have a greater impact than between non-managerial employees and executives. In contrast, middle managers are in a position where they compare themselves more closely with both groups. Nonetheless, very large differences in terms of pay reductions are also likely to affect the satisfaction of the other groups. However, we expect that shareholders who are not directly integrated into the operational hierarchy of the company will be less involved in the comparison.

2.3 Data and Methodology

To address our research question, we use the German Business Panel (GBP, Bischof et al., 2024). The GBP is maintained as part of the Collaborative Research Centre TRR 266 Accounting for Transparency, which is funded by the German Research Foundation (DFG). It provides representative longitudinal data on companies in Germany, collected based on surveys of managers about the economic situation, entrepreneurial decisions, and subjective assessments. As the survey was conducted during the COVID-19 pandemic, and since the questions were targeted at the entrepreneurial and political measures taken to face the consequences of the pandemic, this database is particularly suitable for answering our research question. We restrict our sample to the first wave of the GBP surveys which was conducted between July 6 and October 3, 2020, for two reasons. First, with respect to our dependent variables, only dividends are surveyed more than once. Second, we observe the onset of the crisis where the firms faced the greatest uncertainty. Moreover,

we exclude firms that report zero employees, as we expect that this category does not provide valid information about the four groups of stakeholders. In total, we obtain a data set consisting of 6,550 firms. In the following subsections, our main variables and the underlying questions are explained in more detail.

2.3.1 Variables: Definition and Questions

Dependent variables. Our dependent variables take into account the adjustments to the four groups of internal stakeholders. The variables are based on the question: “What measures are you taking in the short term (0-12 months) to cope with the burden of the corona crisis?” Multiple answers were possible, and the questions were closed. The important answers for us are affirmative answers regarding “decrease disbursement shareholders” and “decrease wage or bonus”. For firms that answered the first question in the affirmative, we generate a dummy variable that takes the value one if dividends of the *shareholders* are decreased and zero otherwise. Firms that answered affirmatively regarding reduced wages/bonuses specify in a follow-up question which groups these decreases apply. The possible answers are (i) “salary/bonus reduction management board”, (ii) “salary/bonus reduction middle management”, and (iii) “salary/bonus reduction other employees”. These again elicit yes or no answers. The questionnaire queries reductions in future increases within the next twelve months. This is reasonable, as it is often not possible to reduce current wages in the short term due to long-term contracts (e.g., Bauer et al., 2007). Therefore, we use this question to construct dummy variables taking unit value in the case of salary/bonus reductions for *executives*, *middle managers*, and *other employees*, and zero otherwise.

Independent variables. We use changes in revenues (revenue impact) to determine the extent to which firms are affected by the crisis (see Bloom et al., 2021 for a related measure), as the pandemic has severely impacted firms’ revenues (e.g., Archanskaia et al., 2023; Bruhn et al., 2023; Makni, 2023; Shen et al., 2020). The corresponding question is: “To which extent have the following operating figures been impacted by the corona crisis? Please indicate, by how much percent the operating figures have changed with respect to 31.01.20.” The answers are given as values (percentages) between -100 and +100. However, for better interpretation, we recode the variable to range from +100 to -100,

indicating a more negative affectedness with higher values. Additionally, note that the question explicitly asked about changes due to the crisis. The first variable with respect to being affected is a dummy variable. It takes unit value if monthly revenues decrease compared to the beginning of 2020 and the value zero if revenues remain constant or increase. For the second group of variables, we subdivide the revenue impact into different categories. The first category ($Affected_{[-100,0]}$) contains all firms that report increasing or unchanged revenues. This serves as a reference category in our estimation. The remaining firms are distributed in categories of respectively 25 percentage point steps of the revenue impact. Therefore, the remaining categories are defined as follows: Category 2: 1–25% ($Affected_{[1,25]}$) decrease in revenues, Category 3: 26–50% ($Affected_{[26,50]}$) decrease in revenues, Category 4: 51–75% ($Affected_{[51,75]}$) decrease in revenues and Category 5: 76–100% ($Affected_{[76,100]}$) decrease in revenues. With these variables, we are able to analyze effect heterogeneity in dependence on the degree of affectedness. As a last measure of being affected, we use the continuous revenue impact.

Control variables. We control for firm size using six categories based on 2019 revenues measured in euros ($\leq 100k$, $100k-350k$, $350k-700k$, $700k-2mil$, $2mil-10mil$, $>10mil$), where revenues of less than or equal to 100 thousand euros represent the reference category. Moreover, we include the dummy variable $Limited_i$, which takes the value one if the company has a legal form of limited liability (e.g., limited liability company GmbH or joint-stock company AG) and zero otherwise. Moreover, to reflect the perceived economic uncertainty, we consider four dummy variables indicating the expectation of the respondent regarding the end of the pandemic (2020, 2021, 2022, 2023 or later) with 2020 as reference category. Presumably, if the pandemic is expected to end later and the problems are predicted to last longer, there will be a greater tendency to adjust costs. Note that these restrictions are not specific legal restrictions like a curfew or mandatory nose and mouth coverage with a mask, but rather a more general question. We also control for the general risk aversion of decision-makers in the firm. In order to reduce the likelihood of encountering liquidity constraints, risk-averse decision-makers may be more inclined to reduce payments to stakeholders. However, in contrast to this hypothesis, risk-averse decision-makers may prefer to avoid conflicts with influential stakeholders and therefore may make fewer adjustments. Furthermore, payment reductions entail the risk of losing

investors, top managers and other key employees. As it is uncertain whether these stakeholders can be recruited again after the end of the crisis, risk aversion could lead to lower cost of new hires. For this purpose, we use the queried Likert scale, which ranges from 0 (very risk-averse) to 11 (very risk-seeking). On this basis, we create the dummy variable *RiskAversion*, which takes unit value if the decision makers are very risk-averse (0–2), and zero otherwise (3–10). Finally, regional and sectoral effects are considered by state and industry dummies.

2.3.2 Descriptive Statistics

Table 2.1 reports the means and standard deviations of the variables defined above.⁶ In the first section, the dependent variables are displayed. Since these are zero/one dummies, the means indicate the share of firms that are reporting to execute those activities. According to the descriptive statistics, firms intend to save first on executives followed by shareholders. Payments to middle managers and other employees are similarly likely to be cut. All things considered, those shares are quite similar with a difference of only 5 percentage points from the highest to the lowest value.

Table 2.1: Descriptive statistics

	mean	sd
Shareholders (dummy)	0.34	0.47
Executives (dummy)	0.37	0.48
Middle Managers (dummy)	0.32	0.47
Other Employees (dummy)	0.32	0.47
Affected (continuous)	16.87	41.98
Affected (dummy)	0.60	0.49
Affected (categorical)	2.27	1.33
FirmSize (categorical)	3.58	1.45
Limited (dummy)	0.88	0.32
RiskAversion (dummy)	0.14	0.35
EndRestriction (categorical)	2021.17	0.61
Observations	6,550	

The second section contains the three affectedness measures. On average, revenues have decreased by about 17 percent due to the crisis. Considering our dummy variable, about 60% of firms are defined as being affected. The mean of all firms is Category 2

⁶Due to data confidentiality issues, we are not permitted to report minimum and maximum values.

which represents a decrease in revenues between 1% and 25%. The shares of the revenue categories are as follows: Category 1 (-100% to 0%) 40%, Category 2 (1% to 25%) 22%, Category 3 (26% to 50%) 18%, Category 4 (51% to 75%) 10%, and Category 5 (76% to 100%) 10%.

In the last section, descriptive statistics on the control variables are displayed. According to German firm structures, most of the firms in the representative GBP sample are also quite small. Indeed, 82% of German companies are micro firms (so-called “Kleinstunternehmen”) with up to 9 employees and up to 2 million euros in revenues.⁷ Our data reflects this, since revenues in 2019 are on average between category 3 and 4, and therefore range between €350 thousand and €2 million. The shares of the categories are as follows: \leq €100k: 8%, €100k–350k: 20%, €350k–700k: 17%, €700k–2mil: 26%, €2mil–10mil: 20%, and $>$ €10mil: 9%. About 88% of companies have a legal form that limits their owner’s liability. Finally, 14% of the decision-makers are risk-averse and an average firm expects the restrictions to end in 2021.

For more information on the relatedness of firm decisions on payment reductions, Table 2.2 displays correlations between our four dependent variables. The table shows a decreasing correlation along the hierarchy level. While the correlation coefficient of reductions in dividends and executive compensation is around 0.4, the correlation coefficient of dividend reductions with middle management pay cuts is still around 0.32 and only around 0.23 for the workers. In contrast, higher correlation coefficients are shown within the top management, middle management, and other employees. For instance, the correlation coefficients of the decision to make payment cuts to executives are 0.75 to middle management and 0.55 to other employees. The intermediate hierarchical position of middle management is reflected in the correlations (Executives: 0.75 and Other Employees: 0.64). It appears that firms treat the groups that are “neighboring” similarly in terms of payment reductions. For example, firms that reduce dividends tend to reduce the payments to executives more often than the payments to other employees. It is thus clear that stakeholders compare themselves more closely with neighboring hierarchy groups. This confirms our expectations described by the Fair Wage-Effort hypothesis at a first glance.

⁷<https://www.destatis.de/EN/Themes/Economic-Sectors-Enterprises/Enterprises/Small-Sized-Enterprises-Medium-Sized-Enterprises/Tables/total-cik.html> (last access: March 23, 2024).

Table 2.2: Correlations of dependent variables

	Shareholders	Executives	Mid. Managers	Oth. Emp.
Shareholders	1			
Executives	0.40	1		
Middle Managers	0.32	0.75	1	
Other Employees	0.23	0.55	0.64	1

2.3.3 Econometric Approach

We examine the impact of being affected by the COVID-19 crisis on the pay of four groups of stakeholders in the company. Therefore, we estimate a probit model of the form

$$y_i = \alpha + \beta \text{Affected}_i + \gamma X_i + \varepsilon_i \quad (2.1)$$

where y_i stands for the four dependent variables: a decrease in the disbursement to shareholders, a reduction of future salary increases or bonus payments of the executives, middle managers, or the other employees. The variable Affected_i is either a dummy, a categorical, or the continuous variable, which measures the effects of the crisis on firms' revenues. Furthermore, X_i is a vector including the control variables.

2.4 Empirical Results

Table 2.3 presents average marginal effects of probit estimates of equation 2.1 using the binary affectedness measure. The results for the different groups of stakeholders are presented in columns (1) to (4).

The marginal effects of the affectedness variable are positive in all cases and significant at the 1% level.

Our results show that the probability of dividend reductions is about 20.6 percentage points higher in affected firms than in non-affected ones. Regarding reductions of future increases in salaries or bonus payments, the coefficient of being affected is highest for executives at 0.24. This suggests a 24.4 percentage points higher probability of adjustments to executive compensation for affected firms. Analogously, the probability for pay adjustments to middle managers and other employees is about 21.8 and 22.2 percentage points higher if companies are affected by the crisis. Comparing the results of the four stakeholders, the effects are relatively close to each other. Further tests on the differences

Table 2.3: The impact of being affected (dummy) on stakeholder payments

	Dividends or salary/bonus reduction			
	Shareholders (1)	Executives (2)	Mid. Managers (3)	Oth. Emp. (4)
Affected (dummy)	0.2057*** (0.0113)	0.2439*** (0.0110)	0.2175*** (0.0110)	0.2216*** (0.0111)
FirmSize _{100k–350k}	-0.0110 (0.0232)	0.0013 (0.0230)	-0.0195 (0.0215)	0.0251 (0.0213)
FirmSize _{350k–700k}	0.0109 (0.0240)	0.0437* (0.0238)	0.0402* (0.0225)	0.0775*** (0.0223)
FirmSize _{700k–2mil}	0.0139 (0.0227)	0.0463** (0.0223)	0.0706*** (0.0212)	0.1097*** (0.0209)
FirmSize _{2mil–10mil}	0.0410* (0.0238)	0.1002*** (0.0236)	0.1492*** (0.0227)	0.1664*** (0.0224)
FirmSize _{>10mil}	0.0037 (0.0275)	0.1033*** (0.0277)	0.2041*** (0.0272)	0.1938*** (0.0269)
Limited	0.2180*** (0.0203)	0.1225*** (0.0191)	0.0940*** (0.0187)	0.0240 (0.0181)
RiskAversion	-0.0656*** (0.0164)	-0.0665*** (0.0163)	-0.0328** (0.0157)	0.0333** (0.0155)
EndRestriction ₂₀₂₁	0.0052 (0.0215)	0.0394* (0.0217)	0.0339 (0.0209)	0.0080 (0.0212)
EndRestriction ₂₀₂₂	0.0150 (0.0247)	0.0580** (0.0248)	0.0561** (0.0240)	0.0201 (0.0243)
EndRestriction _{≥2023}	0.0568 (0.0353)	0.0784** (0.0352)	0.0293 (0.0340)	0.0050 (0.0342)
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	6,550	6,550	6,550	6,550

Notes: Results of average marginal effects of the probit regression; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; the variable *Affected* is a dummy variable for being negatively affected by the pandemic; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

between the coefficients of the groups (see Table 2.11 in the Appendix) show that adjustments to executive compensation differ significantly from that to the other stakeholders. As a result, the probability of pay adjustments is highest for the executives. Nevertheless, the results imply that firms reduce payments to all stakeholders and these results are consistent with the descriptive findings of Batish et al. (2020).

In contrast, the control variables reveal greater heterogeneity across stakeholders. In terms of firm size, the effect on reducing dividends is only significantly different from the base category (<100k) in the category of firms with 2019 revenues between €2 million and €10 million. In contrast, pay cuts to executives, middle managers, and other employees become more probable with increasing firm size. The probability of pay reductions to all stakeholders except for other employees is significantly higher in firms with limited liability. For risk-aversion, we find different signs for the group of other employees and the remaining stakeholders. It seems that risk-averse decision-makers tend to avoid pay reductions to shareholders, executives, and middle managers. In contrast, decision-makers appear to be more willing to reduce payments to other employees. This could be due to a higher substitutability of non-managerial employees. Finally, we observe positive significant coefficients on the expected end of the restrictions for executives and middle managers, indicating that a longer expected duration of the crisis increases the propensity of pay cuts.

2.5 Identifying Heterogeneity

The results described above indicate that the payments (or their growth) to each of the four stakeholders are likely to decrease if the related firm is affected by the COVID-19 crisis. However, the results above do not differentiate by the extent of being affected. Therefore, we re-estimate the regression using five categorical variables that measure different levels of affectedness by the pandemic: (1) -100 to 0 (reference category), (2) 1 to 25, (3) 26 to 50, (4) 51 to 75, and (5) 76 to 100.

Table 2.4 provides the results of the categorical revenue impact, where all coefficients must be interpreted in comparison to the group of non-affected firms. In all categories of *Affected_i*, the effect is greatest for executives. Even in the lowest category, measuring a revenue decline of 1 to 25 percent, the probability of pay cuts increases for all stakeholders. In this category, the coefficients are relatively small, ranging between 0.15 and 0.16. From the first to the second category, the coefficients increase by a factor of more than 1.5 times. There is no longer any substantial change between the categories in the interval from 26% to 100%. While no significant differences between pay reductions to different stakeholder groups can be observed in the smallest category of affectedness, adjustments

Table 2.4: The impact of being affected (categorical) on stakeholder payments

	Dividends or salary/bonus reduction			
	Shareholders (1)	Executives (2)	Mid. Managers (3)	Oth. Emp. (4)
Affected _[1; 25]	0.1495*** (0.0149)	0.1636*** (0.0149)	0.1590*** (0.0143)	0.1631*** (0.0145)
Affected _[26; 50]	0.2342*** (0.0166)	0.3090*** (0.0168)	0.2591*** (0.0164)	0.2572*** (0.0165)
Affected _[51; 75]	0.2460*** (0.0210)	0.2998*** (0.0212)	0.2652*** (0.0209)	0.2767*** (0.0212)
Affected _[76; 100]	0.2626*** (0.0227)	0.3021*** (0.0226)	0.2439*** (0.0221)	0.2543*** (0.0225)
Controls	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	6,550	6,550	6,550	6,550

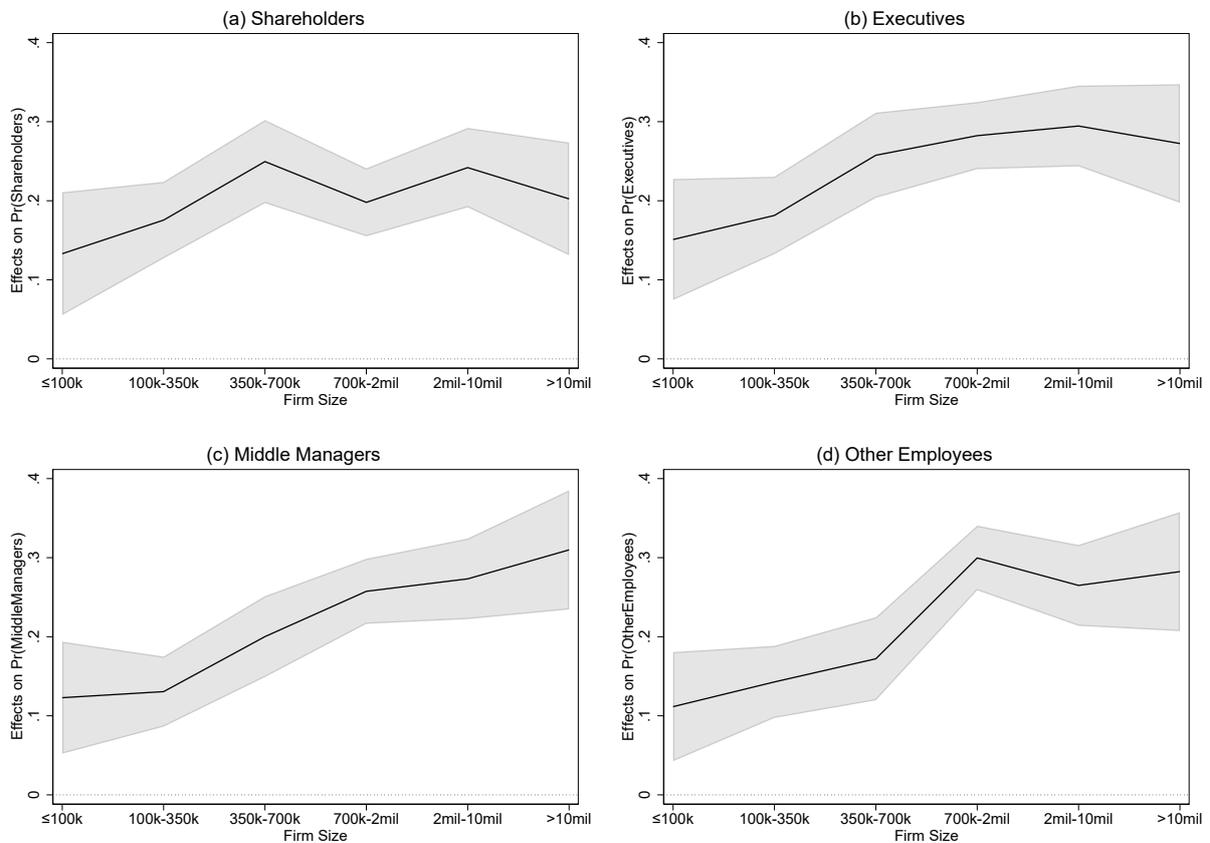
Notes: Results of average marginal effects of the probit regression; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; $Affected_{[x,y]}$: revenue impact is between x and y ; robust standard errors in parentheses; results of control variables are displayed in Table 2.12 in the Appendix; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

differ significantly between executives and the other groups in the three highest categories (see again, Table 2.11 in the Appendix). However, regarding adjustments, in the category of revenue declines between 51% and 75%, no significant difference to the other employees can be found, while in the category of 76%–100% no difference to the shareholders can be found. Nevertheless, the overall result shows that the probability of pay cuts appears to be highest for executives.

Our results as well as previous research indicate a significant impact of firm size on income. Indeed, there can be huge differences between small and large firms. Since the GBP sample is heterogeneous, we further investigate whether firm size has an impact on the probability of a decline in income in the affected firms. To do so, we include interactions between the affectedness variable and the six firm-size dummies and plot the margins and 95% confidence intervals in Figure 2.1.⁸ For all stakeholders we find increasing marginal effects of the interaction between affectedness and firm size up to the third category (350k–750k). The effects of the remaining size categories differ with respect

⁸As an alternative, we re-estimate Table 2.3 but split the sample by firm size categories. The results are shown in Table 2.10 in the Appendix.

Figure 2.1: Margins of interaction between firm size and being affected (dummy) on stakeholder payments



Notes: Plot of average marginal effects and 95% confidence intervals of the interaction terms of being affected and firm size dummies (Probit model); dependent variables on the y-axis—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; the variable *Affected* is a dummy variable for being negatively affected by the pandemic.

to the stakeholder group. Starting with the third category, the impact on shareholders (a) fluctuates between 0.2 and 0.24, which indicates relatively low dispersion for larger companies. In the case of executives (b), the increase in the effect declines with higher firm size and finally drops. For middle managers (c), we observe a steady increase between each category. Finally, with regard to other employees (d), there is a strong increase in the marginal effect between the third and fourth category, which remains almost constant for larger firms.

2.6 Continuous Affectedness Variable and IV Estimation

In Table 2.5, we estimate the impact of being affected on the stakeholders' income using the continuous variable for the revenue impact instead of the dummy variable. This

variable ranges from +100 to -100 and thus measures the extent of being affected by the crisis. In fact, the continuous variable provides more information, but it is also more vulnerable to outliers. As before, an increase in the revenue impact (firms that are more affected) is associated with a higher probability of decreasing payments. When the revenue impact increases by ten percentage point, the probability of pay cuts of the respective stakeholder group increases by about 2–2.5 percentage points. This confirms our previous results. Again, we find that pay adjustments to executives differ significantly from that to the other stakeholder groups (see Table 2.11 in the Appendix).

Table 2.5: The impact of being affected (continuous) on stakeholder payments

	Dividends or salary/bonus reduction			
	Shareholders (1)	Executives (2)	Mid. Managers (3)	Oth. Emp. (4)
Affected (continuous)	0.0020*** (0.0001)	0.0025*** (0.0002)	0.0021*** (0.0001)	0.0021*** (0.0001)
Controls	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	6,550	6,550	6,550	6,550

Notes: Results of average marginal effects of the probit regression; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; the variable *Affected* is the continuous revenue impact; robust standard errors in parentheses; results of control variables are displayed in Table 2.13 in the Appendix; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

It cannot be excluded that our coefficients are biased and therefore an instrumental variable (IV) estimate might be appropriate. It is possible that in the case of high-quality management, the effect of the crisis is less pronounced and cost reductions are realized more frequently. The first part of the hypothesis that competent managers can handle such a crisis better than less skilled ones is probably obvious. Bloom et al. (2013) and Bloom and Van Reenen (2007) provide empirical evidence for a positive link between management quality and firm performance in general and Kumar and Zbib (2022) in context of the COVID-19 crisis. There is also empirical evidence for the second part of this hypothesis that good managers reduce wage costs. Bertrand and Schoar (2003) find that skilled CEOs (measured by MBA degrees) are more aggressive and pay lower dividends. Similarly, Bastos and Monteiro (2011) observe a tendency for more experienced managers to cut wages. While reducing wages is generally difficult, times of crisis offer

opportunities to reduce wages due to higher uncertainty and lower demand for goods. This in turn leads to lower demand for labor which dampens the bargaining power of employees. Gunnigle et al. (2013) show that this is true for the Asian financial crisis of 1997. Since we cannot estimate managerial skills due to a lack of relevant data, we suspect that our results may be subject to omitted variable bias.⁹ We expect a downward bias, indicating that the true coefficients are larger than the OLS coefficients.

However, when using industry-level data, the decisions of single managers have at most a minor impact on the whole industry. Therefore, to ensure that we are indeed measuring the impact of the pandemic and not just managerial decisions, we use a two-stage least squares (2SLS) estimation. For this purpose, we use the average revenue impact in the respective industry and construct an instrument analogous to our revenue impact variable. Higher values of the instruments are therefore associated with a higher level of affectedness measured by greater revenue declines. To preserve the exogeneity assumption between the compensation decisions and the instrument variable, we use industry averages at the 2-digit level of NACE Rev. 2 from Sweden provided by the Structural Business Statistics (SBS) of Eurostat.¹⁰ We thereby follow Böhm and Qendrai (2023), who argue that Sweden is a suitable proxy for industry-level demand changes since Sweden has an economic structure and society relatively similar to those of Germany.

The results are displayed in Table 2.6. The coefficient of the instrument in the first stage is highly significant at the 1% level (column 5). Furthermore, the F-value, corresponding to the null hypothesis that the coefficient of the instrument in the first stage is zero, is about 240. Hence, the relevance assumption is likely to be fulfilled (Staiger and Stock, 1997). Since the industry-based revenue impacts in Sweden are expected to be independent of the management quality in German firms the exogeneity assumption should hold. Therefore, we assume that our instrument is valid.

The results of the second stage regressions are displayed in columns (1) to (4). Compared to Table 2.5, the magnitudes of the continuous variable $Affected_i$ increase by a factor in a range between 1.2 and 2 with the lowest value associated with shareholders and the highest value with other employees. These results confirm our theoretical consid-

⁹Feedback from the dependent variables to our main variables (endogeneity), the affectedness measures, is unlikely, as the dependent variables represent short-term adjustments that have not yet been necessarily implemented at the time of the survey.

¹⁰Further unpublished tests using data from Germany, France, the Netherlands, and Austria as instrumental variable confirm the results.

Table 2.6: The impact of being affected (continuous) on stakeholder payments—2SLS estimation

	2 nd Stage				1 st Stage
	Dividends or salary/bonus reduction				Affected (5)
	Shareholders (1)	Executives (2)	Mid. Managers (3)	Oth. Emp. (4)	
Affected (continuous)	0.0023*** (0.0007)	0.0035*** (0.0007)	0.0035*** (0.0007)	0.0043*** (0.0007)	
FirmSize _{100k–350k}	0.0040 (0.0240)	0.0229 (0.0242)	0.0013 (0.0227)	0.0534** (0.0233)	-5.4992** (2.4542)
FirmSize _{350k–700k}	0.0157 (0.0249)	0.0630** (0.0252)	0.0632*** (0.0239)	0.1130*** (0.0245)	-8.0872*** (2.4756)
FirmSize _{700k–2mil}	0.0200 (0.0239)	0.0742*** (0.0241)	0.1029*** (0.0230)	0.1600*** (0.0234)	-10.7365*** (2.3361)
FirmSize _{2mil–10mil}	0.0523** (0.0250)	0.1392*** (0.0251)	0.1940*** (0.0242)	0.2236*** (0.0246)	-10.3092*** (2.3507)
FirmSize _{>10mil}	0.0268 (0.0295)	0.1640*** (0.0297)	0.2715*** (0.0291)	0.2793*** (0.0294)	-15.4304*** (2.5237)
Limited	0.2125*** (0.0150)	0.1394*** (0.0171)	0.1062*** (0.0164)	0.0305* (0.0181)	-1.7202 (1.6604)
EndRestriction ₂₀₂₁	0.0125 (0.0214)	0.0442** (0.0222)	0.0384* (0.0212)	0.0048 (0.0225)	3.7046* (2.1438)
EndRestriction ₂₀₂₂	0.0188 (0.0247)	0.0584** (0.0253)	0.0585** (0.0245)	0.0110 (0.0255)	3.1967 (2.4227)
EndRestriction _{≥2023}	0.0651* (0.0357)	0.0854** (0.0355)	0.0366 (0.0340)	0.0041 (0.0348)	3.9139 (3.3739)
RiskAversion	-0.0734*** (0.0154)	-0.0701*** (0.0157)	-0.0347** (0.0154)	0.0314* (0.0165)	-2.2567 (1.4419)
Instrument					0.7642*** (0.0493)
Constant	0.0863* (0.0456)	0.0189 (0.0464)	-0.0154 (0.0449)	0.0456 (0.0467)	19.3437*** (4.2186)
State dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No
Observations	6,538	6,538	6,538	6,538	6,538
F-value					240.34

Notes: Results of 2SLS estimation; the F-value corresponds to the null hypothesis that the coefficient of the instrument (revenue impact at the industry level in Sweden) in the first stage is zero; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; the variable *Affected* is the continuous revenue impact and the dependent variable in the first stage; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

erations regarding the bias and its direction. This might indicate that skilled managers lowered the negative impact of the ongoing crisis. However, after eliminating possible

biases, the coefficients do not change their signs. Overall, our main result that all stakeholders have to pay for the COVID-19 crisis is confirmed.

2.7 Robustness Tests

We perform several robustness checks to validate our results. To do so, we (i) change the affectedness measure, (ii) use linear probability model (LPM) and logit instead of probit regressions, and (iii) apply inverse probability weights.¹¹

(i) Affectedness measures

So far, all measures were based on the revenue impact of the COVID-19 crisis. Now we consider three other variables to construct dummy variables: (a) impact on net income, (b) impact on liquidity, and (c) the claim of short-time work. For (a) and (b), we proceed similarly to the revenue dummy. Therefore, the new dummies take a unit value if the impact on net income/liquidity is negative, and zero otherwise. The third variable is already a dummy that indicates if firms have claimed short-time work (dummy equals 1) or not (dummy equals 0). The results are shown in Table 2.7. Overall, there are only minor changes in the coefficients, which are most notable for the short-time work dummy. However, this might be due to the compensatory effects of the wage cost savings from the use of short-time work; therefore, this dummy should only be used as an affectedness measure to a limited extent.

(ii) Estimation model

Since our dependent variables are dummies, we use a probit model. However, to ensure that our results are not driven by the model choice, we present results from linear probability model (LPM) estimates and logit regressions in Table 2.8. Again, the main results are confirmed.

(iii) Inverse probability weighting

The affectedness of firms might not be completely random since the firms that are affected might differ in important aspects from the firms that are not affected. This would

¹¹We also test the use of an alternative measure of firm size in an unpublished estimation. Instead of revenue categories, we use the current number of employees. Again, this change has no effect on our results.

Table 2.7: Robustness – Variation of the affectedness variables

	Dividends or salary/bonus reduction			
	Shareholders (1)	Executives (2)	Mid. Managers (3)	Oth. Emp. (4)
Profit (dummy)	0.2140*** (0.0113)	0.2514*** (0.0109)	0.2172*** (0.0109)	0.2148*** (0.0111)
Liquidity (dummy)	0.1959*** (0.0112)	0.2299*** (0.0109)	0.2103*** (0.0107)	0.2016*** (0.0108)
STW (dummy)	0.1466*** (0.0127)	0.2172*** (0.0120)	0.1968*** (0.0116)	0.2188*** (0.0113)
Controls	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	6,084	6,084	6,084	6,084

Notes: Results of average marginal effects of the probit regression; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; the dummy variables *Profit* and *Liquidity* take a unit value if firms' profits or liquidity decrease and are zero otherwise; *STW* takes unit value if the firm participates in the short-time working program and is zero otherwise; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.8: Robustness – LPM and Logit estimation

	Dividends or salary/bonus reduction			
	Shareholders (1)	Executives (2)	Mid. Managers (3)	Oth. Emp. (4)
<i>LPM</i>				
Affected (dummy)	0.2062*** (0.0116)	0.2485*** (0.0117)	0.2186*** (0.0112)	0.2219*** (0.0113)
<i>Logit</i>				
Affected (dummy)	0.2067*** (0.0114)	0.2451*** (0.0111)	0.2201*** (0.0112)	0.2244*** (0.0113)
Controls	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	6,550	6,550	6,550	6,550

Notes: Results of linear probability model and average marginal effects of logit regressions; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; the variable *Affected* is a dummy variable for being negatively affected by the pandemic; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

bias our results. To tackle this issue, we apply re-weighting as a way to take selectivity on observables into account. In particular, we follow the approach proposed by Abadie and Cattaneo (2018) and Imbens and Wooldridge (2009). Hence, we calculate propensity scores for being affected and re-weight our sample by the inverse of these scores. The corresponding probit model contains the categorical variables firm size and end of restrictions and dummies for restricted legal forms, risk aversion, state, and industry (see Giebel and Kraft, 2023 and Liu, 2023 for a similar approach). For affected firms, the weight is one divided by the propensity score. For non-affected firms, the weight is one divided by one minus the propensity score. Table 2.9 shows that the signs, levels of significance, and magnitudes of the coefficients remain almost unchanged.

Table 2.9: Robustness – IPW estimation

	Dividends or salary/bonus reduction			
	Shareholders (1)	Executives (2)	Mid. Managers (3)	Oth. Emp. (4)
Affected (dummy)	0.1990*** (0.0108)	0.2362*** (0.0106)	0.2094*** (0.0104)	0.2128*** (0.0106)
Controls	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	6,650	6,650	6,650	6,650

Notes: Results of average marginal effects of the probit regression with inverse probability weights (IPW); dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; the variable *Affected* is a dummy variable for being negatively affected by the pandemic; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.8 Conclusion

The COVID-19 pandemic was arguably the worst economic crisis in Germany and probably the world since the financial crisis of 2008/2009. Firms had to deal with, e.g., supply chain problems due to restrictions in China, new work and health regulations as well as general higher uncertainty. These new circumstances probably raise costs but leave open the question of who will pay these costs. Data from the German Business Panel enables us to investigate the pass-through effects of costs on four internal stakeholders: shareholders, executives, middle management, and other employees. The possibility to separate these groups is quite rare.

There are drawbacks to cutting pay to either group, e.g., cutting dividends could be seen as a negative sign to investors while cutting wages or compensation could lower productivity or increase quits. Therefore, it is unclear on which group cuts should be made. The Fair Wage-Effort hypothesis suggests treating all groups equally in order to avoid dissatisfaction due to comparisons between groups. Our findings support this, as correlations suggest that firms choose to pass on costs to groups with a related hierarchical position. Furthermore, our probit results indicate that all stakeholders of affected firms must pay either with lower dividends or lower future pay increases, similarly. Overall, affected firms are about 20.6 – 24.4 percentage points more likely to reduce stakeholders' payoffs. These effects become stronger for firms that are more affected.

We also find evidence for effect heterogeneity regarding firm size. Even when controlling for the extent of affectedness larger firms tend to pass through costs to a higher extent. This is especially true for future pay cuts for executives, middle management, and other employees. Additionally, an IV approach as well as several robustness checks confirm our results.

The answer to the question of who pays for the COVID-19 crisis is particularly important for policymakers to be able to target particularly affected groups and understand what drives economic changes, e.g., lower wage growth, in the aftermath of the crisis. This might also be of particular interest to unions and the relevance of collective bargaining. In analyzing payment reductions for stakeholders, the distribution effects of the COVID-19 crisis can also be examined in dependence on hierarchical position.¹²

Our data is based on surveyed short-term (within the next 0-12 months) measures. Unfortunately, we are not able to investigate to which extent these measures were actually realized. Further research should take this into account. Moreover, additional research is needed regarding the size of the cutbacks since we only have information on the binary decision of whether firms plan to lower payments to stakeholders. To understand crisis-induced cost pass-throughs, the size of reductions is important.

¹²Bellani et al. (2023) examine preferences for redistribution during the crisis and Braband et al. (2022) consider redistribution effects.

2.9 Appendix

Table 2.10: The impact of being affected (differentiated by firm size) on stakeholder payments

	Dividends or salary/bonus reduction			
	Shareholders (1)	Executives (2)	Mid. Managers (3)	Oth. Emp. (4)
<i>FirmSize ≤ €100k</i>				
Affected (dummy)	0.1277*** (0.0428)	0.1184*** (0.0405)	0.1067*** (0.0368)	0.1373*** (0.0372)
Observations	490	497	503	496
<i>FirmSize €100k–350k</i>				
Affected (dummy)	0.1932*** (0.0251)	0.2030*** (0.0255)	0.1493*** (0.0242)	0.1545*** (0.0249)
Observations	1,272	1,272	1,261	1,263
<i>FirmSize €350k–700k</i>				
Affected (dummy)	0.2328*** (0.0277)	0.2505*** (0.0272)	0.2045*** (0.0275)	0.1855*** (0.0279)
Observations	1,049	1,066	1,044	1,072
<i>FirmSize €700k–2mil</i>				
Affected (dummy)	0.2035*** (0.0221)	0.2748*** (0.0205)	0.2513*** (0.0209)	0.2938*** (0.0202)
Observations	1,723	1,719	1,717	1,720
<i>FirmSize €2mil–10mil</i>				
Affected (dummy)	0.2125*** (0.0260)	0.2781*** (0.0241)	0.2679*** (0.0248)	0.2601*** (0.0247)
Observations	1,269	1,277	1,264	1,268
<i>FirmSize > €10mil</i>				
Affected (dummy)	0.2376*** (0.0410)	0.2495*** (0.0372)	0.2798*** (0.0356)	0.2722*** (0.0376)
Observations	578	606	606	606

Notes: Results of average marginal effects of the probit regression; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; the variable *Affected* is a dummy variable for being negatively affected by the pandemic; all regressions include the control variables of Table 2.3 except for firm size dummies; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.11: Difference tests of Tables 2.3, 2.4, and 2.5

	Shareholders			Executives			Mid. Managers		
	Executives	Mid. Managers	Oth. Emp.	Mid. Managers	Oth. Emp.	Mid. Managers	Oth. Emp.	Oth. Emp.	
<i>Differences of Table 2.3</i>									
Affected (dummy)	-0.0382*** (0.0128)	-0.0118 (0.0135)	-0.0159 (0.0142)	0.0264*** (0.0079)	0.0223** (0.0105)	-0.0041 (0.0095)			
<i>Differences of Table 2.4</i>									
Affected _[1; 25]	-0.0141 (0.0170)	-0.0096 (0.0176)	-0.0137 (0.0189)	0.0045 (0.0105)	0.0004 (0.0140)	-0.0041 (0.0123)			
Affected _[26; 50]	-0.0748*** (0.0199)	-0.025 (0.0207)	-0.023 (0.0216)	0.0498*** (0.0130)	0.0518*** (0.0171)	0.0019 (0.0152)			
Affected _[51; 75]	-0.0538** (0.0253)	-0.0193 (0.0261)	-0.0307 (0.0278)	0.0346*** (0.0169)	0.0231 (0.0226)	-0.0115 (0.0202)			
Affected _[76; 100]	-0.0395 (0.0255)	0.0187 (0.0271)	0.0083 (0.0290)	0.0582*** (0.0179)	0.0478** (0.0239)	-0.0104 (0.0210)			
<i>Differences of Table 2.5</i>									
Affected (continuous)	-0.0005*** (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)	0.0004*** (0.0001)	0.0003** (0.0001)	-0.0000 (0.0001)			

Notes: Results of differences and t-tests between stakeholder groups; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; *Affected* is the binary, categorical or continuous affectedness variable as described in the respective tables; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.12: Full estimation results of Table 2.4

	Dividends or salary/bonus reduction			
	Shareholders (1)	Executives (2)	Mid. Managers (3)	Oth. Emp. (4)
Affected _[1; 25]	0.1495*** (0.0149)	0.1636*** (0.0149)	0.1590*** (0.0143)	0.1631*** (0.0145)
Affected _[26; 50]	0.2342*** (0.0166)	0.3090*** (0.0168)	0.2591*** (0.0164)	0.2572*** (0.0165)
Affected _[51; 75]	0.2460*** (0.0210)	0.2998*** (0.0212)	0.2652*** (0.0209)	0.2767*** (0.0212)
Affected _[76; 100]	0.2626*** (0.0227)	0.3021*** (0.0226)	0.2439*** (0.0221)	0.2543*** (0.0225)
FirmSize _{100k–350k}	-0.0066 (0.0231)	0.0050 (0.0228)	-0.0180 (0.0213)	0.0263 (0.0211)
FirmSize _{350k–700k}	0.0178 (0.0239)	0.0507** (0.0237)	0.0436* (0.0225)	0.0808*** (0.0222)
FirmSize _{700k–2mil}	0.0233 (0.0227)	0.0563** (0.0223)	0.0760*** (0.0212)	0.1155*** (0.0209)
FirmSize _{2mil–10mil}	0.0531** (0.0239)	0.1127*** (0.0236)	0.1566*** (0.0227)	0.1745*** (0.0225)
FirmSize _{>10mil}	0.0249 (0.0278)	0.1305*** (0.0279)	0.2219*** (0.0273)	0.2123*** (0.0271)
Limited	0.2187*** (0.0204)	0.1227*** (0.0191)	0.0944*** (0.0186)	0.0247 (0.0181)
RiskAversion	0.0075 (0.0214)	0.0415* (0.0215)	0.0354* (0.0208)	0.0097 (0.0211)
EndRestriction ₂₀₂₁	0.0151 (0.0246)	0.0576** (0.0246)	0.0559** (0.0239)	0.0200 (0.0242)
EndRestriction ₂₀₂₂	0.0583* (0.0352)	0.0801** (0.0350)	0.0305 (0.0339)	0.0059 (0.0341)
EndRestriction _{≥2023}	-0.0645*** (0.0163)	-0.0646*** (0.0162)	-0.0315** (0.0157)	0.0344** (0.0155)
Controls	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	6,550	6,550	6,550	6,550

Notes: Results of average marginal effects of the probit regression; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; $Affected_{[x,y]}$: revenue impact is between x and y ; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.13: Full estimation results of Table 2.5

	Dividends or salary/bonus reduction			
	Shareholders	Executives	Mid. Managers	Oth. Emp.
	(1)	(2)	(3)	(4)
Affected (continuous)	0.0020*** (0.0001)	0.0025*** (0.0002)	0.0021*** (0.0001)	0.0021*** (0.0001)
FirmSize _{100k–350k}	0.0012 (0.0233)	0.0164 (0.0231)	-0.0070 (0.0213)	0.0361* (0.0211)
FirmSize _{350k–700k}	0.0233 (0.0241)	0.0596** (0.0239)	0.0532*** (0.0224)	0.0883*** (0.0222)
FirmSize _{700k–2mil}	0.0280 (0.0228)	0.0654*** (0.0225)	0.0866*** (0.0212)	0.1244*** (0.0209)
FirmSize _{2mil–10mil}	0.0580** (0.0239)	0.1213*** (0.0237)	0.1670*** (0.0227)	0.1828*** (0.0224)
FirmSize _{>10mil}	0.0317 (0.0278)	0.1401*** (0.0279)	0.2365*** (0.0273)	0.2253*** (0.0271)
Limited	0.2189*** (0.0206)	0.1220*** (0.0195)	0.0937*** (0.0190)	0.0234 (0.0184)
RiskAversion	0.0054 (0.0217)	0.0397* (0.0220)	0.0350* (0.0211)	0.0082 (0.0215)
EndRestriction ₂₀₂₁	0.0101 (0.0249)	0.0526** (0.0251)	0.0524** (0.0243)	0.0157 (0.0247)
EndRestriction ₂₀₂₂	0.0576 (0.0359)	0.0788** (0.0356)	0.0294 (0.0340)	0.0046 (0.0344)
EndRestriction _{≥2023}	-0.0655 (0.0166)	-0.0663*** (0.0165)	-0.0322** (0.0159)	0.0338** (0.0157)
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	6,550	6,550	6,550	6,550

Notes: Results of average marginal effects of the probit regression; dependent variables—reductions: shareholders' dividends, growth of salaries/bonus to executives, middle managers, and other employees; the variable *Affected* is a dummy variable for being negatively affected by the pandemic; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 3

A Comparison of Pay Adjustments to Stakeholders During COVID-19 Between Innovative and Non-Innovative Firms

Co-authored with Tobias Hemker and Kornelius Kraft

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This study investigates different pay adjustment strategies of innovative and non-innovative industries and firms during the COVID-19 pandemic. We use crisis-related revenue declines as a measure of affectedness and both industry- and firm-level data on innovation to identify differences in pay reductions towards (a) the workforce in general and (b) to four groups of stakeholders (shareholders, executives, middle managers, and ordinary workers). Our results show that the effect of the pandemic on the probability of pay cuts is significantly higher if firms or their industries are innovative. We argue that innovation-specific characteristics (e.g., pay structure, financial constraints) (i) enable firms to reduce compensation more easily, and (ii) require pay reductions.

3.1 Introduction

The COVID-19 pandemic severely affected both society and the economy. This impact has already been examined in general by many studies (see, e.g., Brodeur et al., 2021; Rathnayaka et al., 2023).¹ There are also multiple strains of literature regarding innovation in the crisis. Besides others, there are studies on the impact of the pandemic on research and development (R&D) (e.g., Belitz, 2022; Diekhof et al., 2021) and on how innovation affects firm survival during the crisis. Despite the high risks of innovation activities, innovative firms are more likely to survive the COVID-19 crisis and perform better in general (Ali, 2022b; de Uña-Álvarez et al., 2023; Khan et al., 2022; Kyrdoda et al., 2023; Özşuca, 2023). This is attributed to the adaptability and efficiency of innovative firms. However, adjustment strategies have not been investigated so far.

Our contribution is to examine the differences between innovative and non-innovative firms' adjustment strategies with regard to the consequences of the COVID-19 crisis. We concentrate on cost reduction strategies via cuts towards stakeholders of German firms, since personnel expenses are reported to be the major issue of liquidity constraints (BMWi, 2020). Adjustment strategies are of interest in themselves, but can also contribute to explaining the higher probability of survival of innovative companies.

The difference in adjustment strategies by innovation status can be attributed to firm-specific characteristics. It is well known that innovative and non-innovative firms differ in many respects such as human capital of employees, government subsidies, export intensity, productivity, survival probability, and growth rates of revenues and profits (Sam-Aggrey, 2009). We focus on two main arguments as to why innovative firms might behave differently. First, financial constraints have been shown to be particularly problematic for investments in innovation during crises (Amore, 2015; Archibugi et al., 2013a,b; Filippetti and Archibugi, 2011; Hottenrott and Peters, 2012; Paunov, 2012). This, in turn, could lead to a greater need for cost reductions when sales decrease and external funding is too expensive or not an option at all. Second, it might be easier for innovative firms to reduce wage costs. Employees of innovative firms have on average a higher amount of human capital, are also more productive and therefore earn salaries above collectively bargained wages, which can be adjusted more easily.

¹Studies on the impact of innovation on firms' survival probability in general can be found in, e.g., Audretsch (1995), Buddelmeyer et al. (2010), Cefis and Marsili (2005, 2006, 2012, 2019), and Fontana and Nesta (2009).

For our empirical analysis, we identify affected firms using revenue declines in response to the crisis in two different datasets.

The first data set combines a firm survey and industry-level R&D information. One cross-section of the survey offers the unique opportunity to distinguish between different stakeholder groups and not merely to consider stakeholders in general or a single group of stakeholders. In particular, we obtain information about cutbacks in shareholders' dividends and reductions of future pay increases to executives, middle managers, and other employees. We apply linear probability models and find that firms in innovative compared to non-innovative industries adjust differently in response to the crisis. The results indicate that the former have a significantly higher probability of reductions in future pay (increases), particularly for shareholders and executives. Furthermore, we deal with potential omitted variable bias by applying an instrumental variable (IV) approach. For this purpose, we instrument the affectedness of firms with revenue changes in corresponding foreign industries. This confirms our main findings and provides evidence that innovative industries also reduce future pay increases to middle managers and other employees.

The second dataset focuses on realized pay cuts in the form of reduced personnel expenses per employee. We combine published company financial data and add firm-level R&D and patent information to identify innovation at the firm level. This panel dataset allows us to carry out difference-in-differences as well as triple differences estimations at the firm-level. The results show that reported adjustments were indeed realized and that the probability of pay adjustments is higher in innovative firms.

Additionally, we can show that financial constraints are more binding and the variable compensation component is higher for firms in innovative industries. Overall, we show that innovation does matter for firms' adjustment strategies in response to the COVID-19 crisis.

Our study is structured as follows. Section 3.2 deals with theoretical considerations on how the crisis affects companies and which adjustment measures are possible. In this context, we consider potential differences between innovative and non-innovative industries. Section 3.3 describes the data, sample selection, methodology, descriptive statistics, and empirical results using industry-level innovation data. Section 3.4 has the same structure, with the difference here being the use of panel data and measuring innovation at the firm level. Subsequently, in Section 3.5, we discuss and provide evidence

for possible underlying mechanisms. Finally, the study closes with a discussion of the results and an outlook.

3.2 Pay Adjustments in Innovative and Non-Innovative Firms

Today, it is widely known that innovations can lead to several advantages for firms, such as higher competitiveness, increasing productivity, higher profits, and a greater ability to quickly adapt to new market conditions (e.g., Aghion et al., 2005; Aw et al., 2007; Cefis and Marsili, 2006). The pandemic led to the introduction of regulations that posed significant challenges for most firms. Studies on previous crises find that innovative firms are more resilient (e.g., Cefis and Marsili, 2019; Cefis et al., 2020; Czarnitzki and Kraft, 2004, 2010; Gupta et al., 2018; Roper and Turner, 2020; Sidorkin and Srholec, 2014; see Ugur and Vivarelli (2021) for a survey). Consistent with those studies, Adam and Alarifi (2021), Khan et al. (2022), and Özşuca (2023) find that innovative firms also performed better during the COVID-19 pandemic than non-innovative firms. However, the role of firms' innovation orientation on their strategies to cope with the challenges of the crisis are ambiguous. In the following, we therefore discuss the most important arguments from a theoretical point of view.

A crucial factor of companies' success is human capital. The literature dealing with human capital has been established and known for a long time. For our research question, the most important part is the distinction between general and specific human capital (Becker, 1962). While general human capital is substitutable, specific human capital is only effective within the firm in which it is accumulated. For this reason, the costs and returns of specific human capital accumulation are assumed to be shared between firms and employees. As skilled workers are crucial for innovation success (Fonseca et al., 2019; Lenihan et al., 2019; Protogerou et al., 2017; Subramaniam and Youndt, 2005; Sun et al., 2020), innovative firms generally have a higher amount of (specific) human capital (D'Amore et al., 2017). Therefore, both sides face negative consequences in case of termination of employment. On the one hand, this would argue in favor of not adjusting payments in order to avoid such termination. On the other hand, the quasi-rent from specific qualifications is relatively high. This would make it possible to reduce payments relatively strongly without causing terminations. We therefore expect different decisions

by innovative and non-innovative firms regarding pay cuts according to the extent of specific human capital. This argument is particularly reasonable for the stakeholder groups of executives, middle managers, and other employees.

Another argument, from an institutional point of view, is on the possibility of wage adjustments. In Germany, wages are determined by industry-wide negotiations between unions and employer associations. These so-called “Tariflöhne” represent lower limits for payment aside from the minimum wage (e.g., Bauer et al., 2007). However, companies are of course free to pay higher wages. Since employees in innovative firms are often better qualified than those in non-innovative companies, the wages in the former are highly likely to be above the collectively agreed wages (Aghion et al., 2017; Ammermueller et al., 2009; Pianta and Tancioni, 2008). This gives innovative firms greater scope to reduce wages than it is the case for their non-innovative counterparts, which are often unable to do so because of the collectively agreed wages. This argument mainly concerns the group of other employees, while middle managers and executives are less likely to be subject to collective agreements.

Finally, investments in innovation are particularly risky as they require high R&D expenditures and have highly uncertain ex ante prospects of success (Hottenrott and Peters, 2012). Moreover, innovation activities themselves can lead to financial constraints (Lahr and Mina, 2020; Lee et al., 2015). Therefore, it is frequently argued (e.g., Hall and Lerner, 2010; Kerr and Nanda, 2015) that R&D investments must be financed from the company’s own resources.² For this purpose, it is necessary to acquire equity and not to induce shareholders to withdraw capital because of the low dividends. On the one hand, dividend cuts can be interpreted by shareholders as signaling of a poor financial situation of the firm, resulting in fewer investments (Miller and Rock, 1985; Nguyen and Tran, 2016). According to this argument, innovative companies would reduce dividends less than other companies because they are more dependent on capital investors. On the other hand, innovative firms would presumably have to save more in a crisis, if they were equally affected, because they would have more difficulties in accessing external financing. The literature often emphasizes that wages are rigid in the short run. If this is true, innovative firms would have to reduce costs where cuts are possible, and that is in dividends. The argument of flexibility also applies to another cost variable, namely

²Giebel and Kraft (2019) show that a credit supply shock during the financial crisis lowered current innovation activities as well as the initiation of future innovations.

executive compensation. A high proportion of this consists of flexible components. In crisis situations, these can be reduced more easily than fixed salaries.

It becomes apparent that the theoretical discussion leads to potentially opposing predictions for innovative and non-innovative firms regarding all stakeholder groups. Empirical studies are therefore all the more important.

3.3 Different Stakeholders and Industry-Level Innovation

3.3.1 Data and Variables

We use different data sources to address our research question of whether firms in innovative industries pass on costs to stakeholders in a different way than firms in non-innovative industries. Our main source is the German Business Panel (GBP, see Bischof et al., 2024) that provides representative data on companies in Germany, based on surveys of managers. This data source provides a unique opportunity to observe the adjustments to payments to different stakeholders during the crisis. The GBP only queries pay cuts to the stakeholder groups in the first survey wave (July 6 to October 3, 2020). We therefore restrict the sample to this period. However, this comes with the advantage that we observe the greatest uncertainty among firms during the outbreak of the COVID-19 pandemic. Due to lack of data, we are not able to identify innovation in the GBP at the firm level. Instead, we use data on R&D intensity provided by the Stifterverband Wissenschaftsstatistik.³ These contain industry-specific information on R&D expenditures and sales data. Smaller industries are aggregated and larger industries (especially the manufacturing sector) are presented in a more detailed manner on the basis of the WZ2008 classification. This allows us to identify the R&D intensity of 24 different industries. However, using innovation data at industry level has the advantage of capturing the total innovation effect, which is a combination of a direct and an indirect effect (Pianta and Tancioni, 2008). While the former represents the effect of innovation within innovative firms, the latter describes spillover effects across the entire industry. In total, we obtain a final dataset consisting of 7,967 observations. We use the following variables to perform our estimations:

³Data is available at <https://www.stifterverband.org/download/file/fid/10273>, see Tables 3.2.1 and 3.2.3 (last access: March 23, 2024).

Dependent variables. We refer to the question in the questionnaire “What measures are you taking in the short term (0–12 months) to cope with the burden of the corona crisis?”.⁴ The relevant answers in our context are reduced disbursements to shareholders and decreases in wages or bonuses. Utilizing a follow-up question, we can distinguish pay cuts to executives, middle managers, and other employees. These dependent variables are dummy variables that take unit value if the respective firm reports such an adjustment, and zero otherwise. With regard to the compensation of executives, middle managers, and other employees, a reduction in growth is queried.

Independent variables. Previous literature finds a strong negative impact of the COVID-19 crisis on firms’ revenues (e.g., Bruhn et al., 2023; Fairlie and Fossen, 2022; Makni, 2023; Shen et al., 2020). Therefore, we proxy affectedness by revenue changes due to the pandemic at the time of the survey compared to January 31, 2020 (see Bloom et al., 2021; Fackler et al., 2024 for a similar approach). We use both a dummy variable with unit value if revenues decrease and a continuous variable ranging from +100 (negatively affected) to -100 (positive affected).⁵

Innovation measure. In our baseline specification, we divide industries based on the R&D intensity. As a measure for R&D intensities, we take the share of R&D expenditures to total revenues within each industry. We define industries with an intensity above the median as innovative. Based on this assumption, we construct a dummy variable that takes unit value when the industry is innovative, and zero otherwise.

Control variables. We use several variables to control for firm or industry effects that may drive our results. First, we use six categories based on 2019 revenues measured in Euros ($\leq 100k$, 100k–350k, 350k–700k, 700k–2mil, 2mil–10mil, >10mil) to control for firm size. Revenues of less than or equal to 100 thousand Euros build the reference category. Second, we use a variable for the legal form with unit value for firms with legal forms

⁴The GBP questionnaire can be found at https://backend.gbpanel.org/app/uploads/2022/01/Codebook_Welle1.pdf (last access: March 23, 2024).

⁵The original variable in the GBP questionnaire ranges from -100 to +100. For reasons of comparability between the dummy and continuous variable, we recode this variable indicating a stronger level of affectedness when the variable increases.

of limited liability (e.g., limited liability company GmbH or joint-stock company AG), and zero otherwise. Third, four dummy variables indicating the time period when the respondents expected the pandemic to be over (2021, 2022, 2023 or later, with 2020 as reference category) reflect the perceived economic uncertainty. Fourth, we take into account the general risk aversion of firms' decision-makers. Since the success prospects of innovation investments are subject to a high level of risk, decision-makers in innovative firms could, on the one hand, have a higher risk tolerance. On the other hand, these risks might cause them to be more risk-averse in other aspects. For this reason, they could seek to avoid reductions in payments to stakeholders. Therefore, we control for decision-makers' risk aversion by generating a dummy variable that takes unit value if the answer to the corresponding question in the 11-point Likert scale takes the three strongest values in the direction of risk aversion, and zero otherwise. Finally, regional and sectoral effects are considered using state and industry dummies.

3.3.2 Methodology

We aim to identify different adjustments for being affected by the COVID-19 pandemic between firms in innovative and non-innovative industries. To do so, we estimate a model of the form

$$y_i = \alpha + \beta_1 \text{Innovative}_i + \beta_2 \text{Affected}_i + \theta \text{Innovative}_i \times \text{Affected}_i + \gamma X_i + \varepsilon_i \quad (3.1)$$

where y_i measures short-term adjustments to stakeholders. The explanatory variable Affected_i is used both as a dummy and as a continuous variable, and measures the effects of the pandemic on firms' revenues based on percentage changes from before, to during the crisis. Innovative_i indicates whether a firm operates in an innovative industry or not. X_i contains the control variables that include dummies for industry, states, firm size, and the legal status.

To test for possible differences in the response of firms to the crisis, we interact the affectedness variable with the innovation dummy. Since the affectedness measure is already a difference (i.e., the change of revenues before and during the crisis) our specification corresponds to a difference-in-differences (DiD) approach, although we only have cross-sectional data available. We estimate equation (3.1) by using a linear probability model (LPM).

3.3.3 Descriptive Statistics

Table 3.1 shows the descriptive statistics for the total sample and separated by innovative and non-innovative industries. It also provides a t-test of group differences regarding means.

Table 3.1: Descriptive statistics

	Total		Innovative		Non-Innovative		Diff
	mean	sd	mean	sd	mean	sd	b
Shareholders (dummy)	0.33	0.47	0.36	0.48	0.30	0.46	0.06***
Executives (dummy)	0.36	0.48	0.39	0.49	0.33	0.47	0.06***
Middle Managers (dummy)	0.31	0.46	0.34	0.47	0.29	0.45	0.05***
Other Employees (dummy)	0.32	0.47	0.32	0.47	0.32	0.47	0.00
Affected (continuous)	17.79	43.01	14.18	38.72	20.80	46.07	-6.62***
Affected (dummy)	0.61	0.49	0.57	0.50	0.64	0.48	-0.07***
Innovative (dummy)	0.46	0.50					
FirmSize (categorical)	3.51	1.45	3.57	1.43	3.46	1.46	0.12***
Limited (dummy)	0.86	0.35	0.92	0.28	0.80	0.40	0.11***
EndRestriction (categorical)	2021.17	0.61	2021.17	0.60	2021.17	0.63	-0.00
RiskAversion (dummy)	0.15	0.36	0.15	0.35	0.15	0.36	-0.01
Observations	7,967		3,626		4,341		

Approximatively one third of all firms plan to adjust payments to stakeholders. Moreover, 61% of all companies report a decline in revenues, with an average decrease of almost 18%. 46% of the companies in our sample operate in innovative industries. When looking at these companies, it is noticeable that they are to a greater extent planning to cut pay to shareholders, executives, and middle managers than their non-innovative counterparts. However, there is no significant difference regarding other employees. In terms of being affected, the descriptive analysis indicates that firms in non-innovative industries are more frequently (measured by the dummy variable) and more strongly (measured by the continuous variable) affected by the pandemic than their counterparts. Furthermore, firms in innovative industries have on average more employees and more often a legal form of limited liability. Regarding the perceived economic uncertainty there is no difference since, on average, firms in innovative as well as non-innovative industries expect the crisis to end in 2021.

3.3.4 Empirical Results

Table 3.2 shows difference-in-differences estimators for each stakeholder group. This table is divided into two panels. Panel A (B) reports the LPM results of the interaction of innovative industries and the binary (continuous) affectedness measure. All specifications include the described control variables as well as state and industry dummies.

Table 3.2: Estimation results

	Shareholders (1)	Executives (2)	Mid. Managers (3)	Other Empl. (4)
<i>Panel A: LPM—Affected (dummy)</i>				
Innovative×Affected	0.0740*** (0.0210)	0.0474** (0.0212)	0.0231 (0.0202)	0.0165 (0.0206)
<i>Panel B: LPM—Affected (continuous)</i>				
Innovative×Affected	0.0011*** (0.0003)	0.0007*** (0.0003)	0.0002 (0.0003)	0.0002 (0.0003)
Controls	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	7,967	7,967	7,967	7,967

Notes: Results of LPM difference-in-differences estimations, robust standard errors in parentheses, control variables include 2019 firm size, end of restrictions, risk aversion, and limited liability dummies, results of control variables are displayed in Table 3.6 in the Appendix, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We find significant coefficients of the interaction term *Innovative×Affected* for shareholders and executives. The probability of pay cuts for shareholders (executives) is about 7.4 (4.7) percentage points higher for affected firms in innovative industries. If we consider the extent of the affectedness through use of the continuous variable, the probability of observing a pay cut to shareholders (executives) in the case of firms operating in innovative industries (in comparison to the other industries) is about 1.1 (0.7) percentage points higher if the affectedness increases by ten percentage points. One reason why we only find significant differences for shareholders and executives might be that these groups generally (i.e., independent of innovation status) have the greatest financial scope for adjustments.

3.3.5 Robustness

So far, we have separated innovative and non-innovative industries using the median of R&D intensity. This is a rather broad definition of being innovative. To check whether

our results are robust if we use a narrower classification, we now use the 4th quartile of R&D intensity as a cutoff. The results, reported in Table 3.7 in the Appendix, confirm our previous findings. Further robustness tests (not presented, but available on request) regarding control variables and the estimation methodology confirm our results. Those include (i) replacing revenues as a firm size measure with employment categories; (ii) including a short-time work dummy; and (iii) removing all control variables except industry and state dummies.

In general, unobservable variables can be a problem in such econometric approaches. For example, firms with more highly qualified management might cope better with the crisis and be able to reduce costs to a greater degree, which could lead to a downward bias of the estimates (see, e.g., Bastos and Monteiro, 2011; Bertrand and Schoar, 2003; Gunnigle et al., 2013; Kumar and Zbib, 2022). Due to lack of management quality data, we apply a 2SLS estimation approach using industry-level revenue changes for Austria in the first stage to deal with this issue.

Regardless of the innovation measure used (based on the median or 4th quartile), for shareholders and executives the results (Table 3.8 in the Appendix) go in the same direction. However, the magnitude of the coefficients increases. Additionally, using innovation based on the median of R&D intensity, we find significant coefficients for the groups of middle management and other employees. We also test the relevance assumption using the first stage F-values of our instrumental variables used (Table 3.9 in the Appendix). It takes the values of 17.3 (10.8) when innovative industries are specified by the median (4th quartile) of R&D intensity. Therefore, the relevance assumption is likely to be fulfilled (Staiger and Stock, 1997).

All in all, our results prove to be robust. They could, however, be influenced by two possible inaccuracies: We measure innovation intensity only at the industry level and we use survey data for the main variable of interest. Therefore, we complement the previous analysis with an empirical study based on a panel of German companies, balance sheet data, and firm-level information on innovative activity.

3.4 Firm-Level Panel Data on Innovation

3.4.1 Data and Variables

In order to test for realized pay cuts at the firm level, we use balance sheet data provided by Bureau van Dijk's Dafne and add two sources of innovation information. First, we use firm-level information on R&D activities as an innovation input measure provided by Stifterverband. As a second source for innovation activities, we utilize patent data from the Orbis Intellectual Property (Orbis IP) database as an output measure. Information on financial figures and firm-level innovation activities come, however, at a cost. With this data we cannot distinguish between different groups of stakeholders. Nevertheless, we can generate an unbalanced panel that comprises a total of 113,781 observations over the years 2012 to 2020.

Dependent variables. Instead of considering different groups of stakeholders, we use employment adjusted personnel expenses (personnel expenses per employee), which are composed of compensation of executives, middle managers, and other employees. Thus, we interpret this variable as the average payments to these firm internal stakeholders. We generate the dummy *PayCut* that takes unit value in case of decreasing average personnel expenses compared to the previous year, and zero otherwise. In contrast to the surveyed planned reductions of future salaries/bonuses of executives, middle managers, and other employees of Section 3.3, this dummy is based on realized pay reductions. Unfortunately, due to lack of data, we are not able to test for reductions in dividends.

Independent variables. We use revenue changes between 2019 and 2020 to identify affected firms. For this purpose, the variable *Affected* measures both, the continuous range from +100 to -100, and the binary classification whether a firm is negatively affected by the crisis. We only look at the change from 2019 to 2020 to identify the effects of the COVID-19 pandemic. Changes between other years are discussed in more detail in Section 3.4.3.

Innovation measure. We use two different measures to identify innovative firms. For both, we observe the period from 2015 to 2019 and generate the dummy variable *Innovative*. It takes unit value if the respective firm (a) reports that it carries out R&D

activities internally or commission them externally (innovation input) or (b) has at least one granted patent (innovation output). In the case of non-innovative firms, the dummy is zero.

Control variables. We run several different specifications that include the following control variables. Again, we control for firm size using five employment categories (1–9, 10–49, 50–249, ≥ 250 employees), with 1–9 employees as a reference category. Moreover, dependent on the estimation model, we include dummy variables controlling for legal forms, industry, time, and states.

3.4.2 Methodology

Using balance sheet panel data enables us to estimate a “classical” difference-in-differences approach. This allows us to rule out the possibility that the measured effects are merely spurious influences between the two years 2019 and 2020. To do so, we use a panel for the period 2012 to 2020 and estimate a difference-in-differences model of the form:

$$PayCut_{it} = \alpha + \beta_1 Innovative_i + \beta_2 Crisis_t + \theta Innovative_i \times Crisis_t + \gamma X_{it} + \varepsilon_{it}. \quad (3.2)$$

Since the COVID-19 affectedness is not taken into account in this specification, an implicit assumption is that this burden would be the same for innovative and non-innovative companies. The dependent variable $PayCut_{it}$ is a dummy variable that takes unit value if the respective firm cuts pay between period t and $t - 1$, and zero otherwise. Moreover, the binary variable $Innovative_i$ indicates whether a firm is innovative ($Innovative_i = 1$) or not ($Innovative_i = 0$). The dummy variable $Crisis_t$ takes unit value if the year is 2020, and zero otherwise. The interaction term between the crisis- and innovative-dummy is the difference-in-differences coefficient of interest and indicates the causal effect of innovative firms during the pandemic. Again, X_{it} is a vector of control variables and ε_{it} stands for the error term.

This approach identifies the crisis effect on pay cuts by differences within time and within firms’ innovation status. One crucial assumption of unbiased DiD results is that the treatment and control group have similar pre-treatment trends (common trend assumption). However, within the innovative and non-innovative firms there might be differences regarding the affectedness by the pandemic. We assume that affected and non-affected

firms differ in characteristics that we cannot observe (e.g., the degree of digitalization and automation). When the distribution of affected and non-affected firms varies within the innovative and non-innovative groups our common trend assumption might not hold. We test this empirically following Mora and Reggio (2015).

We use two approaches to address this issue. First, we add affectedness as a third dimension to estimate a more general model and to increase the probability that the common trend assumption is valid (e.g., Frölich and Sperlich, 2019; Wing et al., 2018; Wooldridge, 2020; Yu et al., 2023; see also Olden and Møen, 2022 for an overview of applications). It is reasonable to assume that innovative firms that are more severely affected by the COVID-19 crisis are more likely to cut pay than non-affected innovative firms. Taking this into account by using all possible interactions of (1) being innovative, (2) being in the crisis period, and (3) being affected by the crisis, we obtain a triple difference (difference-in-difference-in-differences; DDD) approach

$$\begin{aligned} PayCut_{it} = & \alpha + \beta_1 Innovative_i + \beta_2 Crisis_t + \beta_3 Affected_i + \beta_4 Innovative_i \times Crisis_t \\ & + \beta_5 Innovative_i \times Affected_i + \beta_6 Crisis_t \times Affected_i \\ & + \theta Innovative_i \times Crisis_t \times Affected_i + \gamma X_{it} + \varepsilon_{it}. \end{aligned} \quad (3.3)$$

θ is the coefficient of interest and shows the effect of an innovative firm that is affected during the COVID-19 pandemic. This approach mitigates potential problems of a violated common trends assumption in the difference-in-differences approach.

Secondly, we use inverse probability weighting and reweight the DiD regression to compare innovative and non-innovative firms that have a similar propensity score and are thus close to each other as regards their observable characteristics (e.g., Abadie and Cattaneo, 2018; Imbens and Wooldridge, 2009; Stuart et al., 2014).⁶ We estimate the DDD and reweighted DiD models with LPM and a firm fixed-effects approach.

3.4.3 Descriptive Statistics

Table 3.3 shows the summary statistics for our firm-level data. It displays the mean and standard deviation for the total sample and separated into innovative and non-innovative firms (measured by R&D activities), and also provides a t-test of group differences regard-

⁶Our probit model is based on pre-crisis years and includes the employment categories, legal form dummies and the industry, state, and time fixed-effects. For similar applications of this method, see, e.g., Giebel and Kraft (2023) and Liu (2023).

ing the means. In total, we observe 20,162 firms in 2020, resulting in 113,781 observations for the full unbalanced panel of the period 2012–2020. Since our main variables (*PayCut*, *Innovative* and *Affected*) are time-invariant, we only report cross-sectional descriptive statistics of 2020. However, the time-varying variables do not change considerably when using panel data or measuring innovation using patent data.

Table 3.3: Descriptive statistics for R&D intensity in 2020

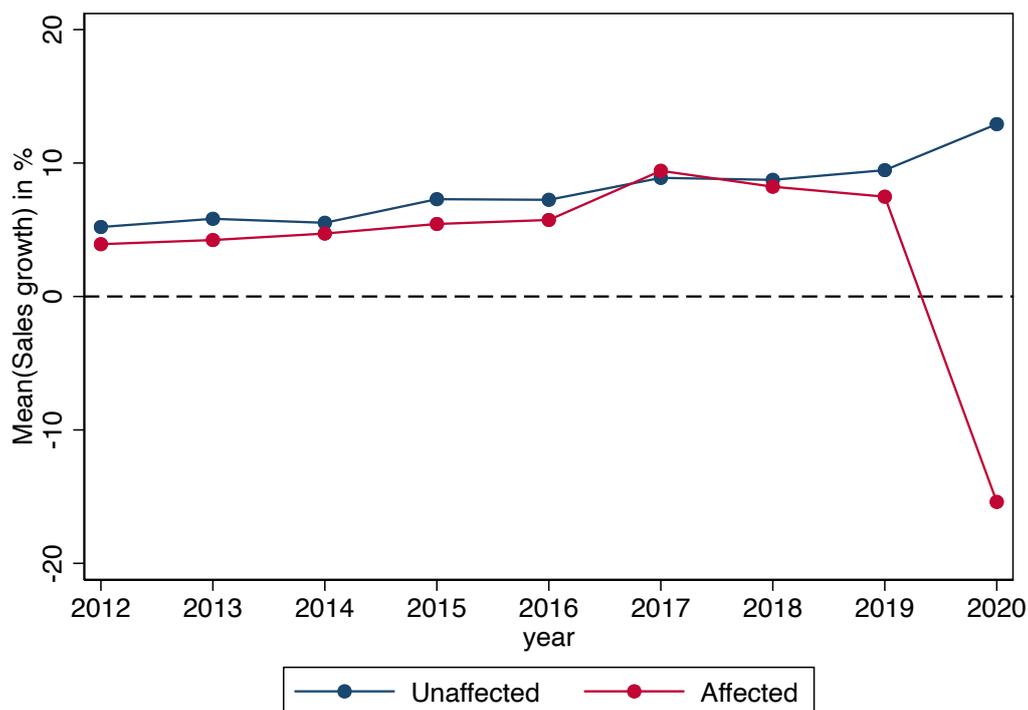
	Total		Innovative		Non-Innovative		Diff
	mean	sd	mean	sd	mean	sd	b
PayCut (dummy)	0.42	0.49	0.51	0.50	0.41	0.49	0.11***
Affected (continuous)	1.53	20.90	4.12	19.90	1.15	21.01	2.97***
Affected (dummy)	0.51	0.50	0.63	0.48	0.49	0.50	0.14***
Innovative (dummy)	0.13	0.33					
Employment (categorical)	3.13	0.89	3.53	0.60	3.07	0.91	0.46***
LegalForm (categorical)	2.27	0.89	2.11	0.69	2.29	0.92	-0.18***
Observations	20,162		2,540		17,622		

Using firm-level data, about 13% of companies are innovative. Moreover, approximately 42% of the firms actually cut payments to the workforce in 2020. We find a positive difference of 11 percentage points between the two types of firms, suggesting that innovative firms reduce pay more frequently than non-innovative firms.

In our sample, 51% of all firms are affected by the crisis and experience on average a decrease of revenues by about 1.5%. Furthermore, innovative firms are affected more often and to a higher degree. We observe considerable differences regarding innovation and affectedness compared to the GBP results. In terms of the innovation dummy, this is not surprising as our definition of innovative industries in Section 3.3 is based on the median R&D intensity. However, we expect the use of firm-level information to provide a more precise measure of firms' innovativeness. Regarding the affectedness, we attribute these differences to different reporting periods. In the balance sheet data, affectedness is based on the annual change of revenues between 2019 and 2020. In contrast, the revenue impact of the GBP sample only covers the difference between January 2020 and the questionnaire period, which mainly relates to the third quarter of 2020. Thus, adjustment effects of the progressed crisis (such as gradual openings after the lockdowns) are likely to explain lower levels of affectedness. These differences might also be the result of the larger companies observed in Dafne.

It might be the case that being affected by the COVID-19 crisis is not completely random, but that, for example, firms that generally perform worse are more likely to be affected. To investigate this, we illustrate the sales growth of both affected and unaffected firms in Figure 3.1. In the pre-crisis period, firms report on average positive sales growth of between 3.9% and 9.4%, regardless of whether they were affected by the pandemic or not. During this time period, the levels of sales growth are relatively similar among both groups with a maximum difference of 2 percentage points. In contrast, in 2020, affected firms experience a revenue decrease of about 15.4% while revenues of unaffected firms increase by approximately 12.9%. We therefore argue that the crisis impacts firms randomly, largely independent of their pre-crisis sales growth.

Figure 3.1: Sales growth by affectedness status



Regarding firm size, in the GBP firms have an average of 6–9 employees, while Dafne’s average is 50–249 employees. Since the disclosure requirement for annual reports generally applies above a certain firm size, Dafne particularly provides valid information from larger firms. For this reason, differences in descriptive statistics are hardly surprising. However, when controlling for firm size, we expect similar results to the GBP.

3.4.4 Empirical Results

Table 3.4 contains the estimation results using firm-level panel data between 2012 and 2020. This table is divided into four panels. Panel A (B) shows the results of the (re-weighted) difference-in-differences approach model of innovative firms during the crisis. Additionally, the binary (Panel C) and continuous (Panel D) affectedness of the company is included as a further dimension, resulting in a triple differences approach. The causal effects are estimated using both linear probability models (Columns 1 and 3) and firm fixed-effects regressions (Columns 2 and 4). Furthermore, the innovation status of the firm

Table 3.4: Estimation results

	PayCut			
	LPM	FE	LPM	FE
	(1)	(2)	(3)	(4)
<i>Panel A: Difference-in-Differences</i>				
Innovative×Crisis	0.1106*** (0.0115)	0.1157*** (0.0121)	0.1357*** (0.0089)	0.1413*** (0.0095)
<i>Panel B: Re-weighted Difference-in-Differences</i>				
Innovative×Crisis	0.0409*** (0.0139)	0.0486*** (0.0148)	0.0310** (0.0122)	0.0345*** (0.0132)
<i>Panel C: Triple Differences—Affected (dummy)</i>				
Innovative×Crisis×Affected	0.0846*** (0.0224)	0.0854*** (0.0236)	0.0756*** (0.0175)	0.0785*** (0.0187)
<i>Panel D: Triple Differences—Affected (continuous)</i>				
Innovative×Crisis×Affected	0.0018*** (0.0006)	0.0012** (0.0006)	0.0016*** (0.0004)	0.0013*** (0.0005)
Innovation measure	R&D	R&D	Patents	Patents
Controls	Yes	Yes	Yes	Yes
State dummies	Yes	No	Yes	No
Industry dummies	Yes	No	Yes	No
Time dummies	Yes	Yes	Yes	Yes
Common trend test (p-values)				
Panel A	0.032	0.006	0.000	0.000
Panel B	0.647	0.608	0.000	0.002
Panel C	0.508	0.413	0.155	0.184
Panel D	0.830	0.850	0.164	0.324
Observations	113,781	113,781	113,781	113,781

Notes: Results of DiD (Panel A), re-weighted DiD (Panel B), and DDD (Panels C and D) estimations, robust and firm-clustered standard errors in parentheses, control variables include employment and legal form dummies, results of control variables are displayed in Table 3.10 in the Appendix, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

is defined by R&D activities (Columns 1 and 2) and additionally by patents (Columns 3 and 4). We report the results of the common trend test of Mora and Reggio (2015) below the other test results.⁷

The results of the four columns are similar regarding the size of the coefficients and their significance. We therefore find that measuring innovation via R&D activities or patents yield similar results. This is not surprising since R&D activities are a crucial input factor for firms' innovation output such as patents. Moreover, using fixed-effects regressions instead of a linear probability model confirms the results. Therefore, as we find robust specifications, we only interpret the coefficients of the fixed-effects model using innovation measured by R&D activities (Column 2).

Starting with the difference-in-differences approach in Panel A, we find that during the COVID-19 pandemic, innovative firms have an approximately 11.6 percentage points higher probability of pay cuts than their non-innovative counterparts. Thus, during the pandemic, innovative firms reduce personnel expenses per employee to a greater extent than non-innovative companies. However, the hypothesis of common trends has to be rejected. In contrast, in the case of the re-weighted regressions (Panel B) based on the R&D innovation measure, the common trend hypothesis is not rejected. The estimated coefficients are somewhat smaller than those reported in Panel A, but still highly significant.

The results of the DDD in Panels C and D again confirm our findings. By including affectedness as a third dimension, we adjust the formal common trend test of Mora and Reggio (2015). For this purpose, we estimate the triple differences models, but substitute the crisis dummy with annual time dummies. In the DDD setting, the null hypothesis requires that all the triple interactions before 2020 are jointly insignificant.⁸ The null hypothesis cannot be rejected as indicated by the p-values in Table 3.4.⁹ Therefore, the common trend assumption is likely to be met.¹⁰

⁷DiD approaches also require that the conditioning covariates are not affected by the treatment. To test this exogeneity assumption, we also estimate our regressions without controls and obtain similar results.

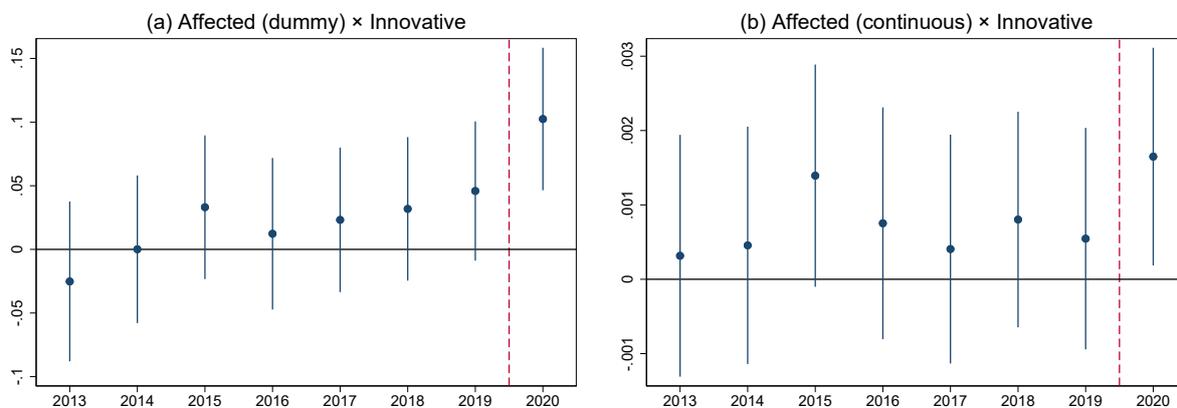
⁸For similar applications of a common trend test, see, e.g., Akosa Antwi et al. (2023), Wilson et al. (2023), and Yu et al. (2023).

⁹Using inverse probability weighting based on affectedness yields similar results of coefficients, their significance, and the F-value of the common trend test. This is unsurprising since both methods aim to reduce problems with a violation of common trends.

¹⁰As mentioned above, in the industry-level cross-section setting of Section 3.3, we are unable to test for common trends. However, our panel data approach shows that the affectedness is a decisive factor for the common trend assumption to hold. Since we include the affectedness in Section 3.3, we assume the common trend to apply.

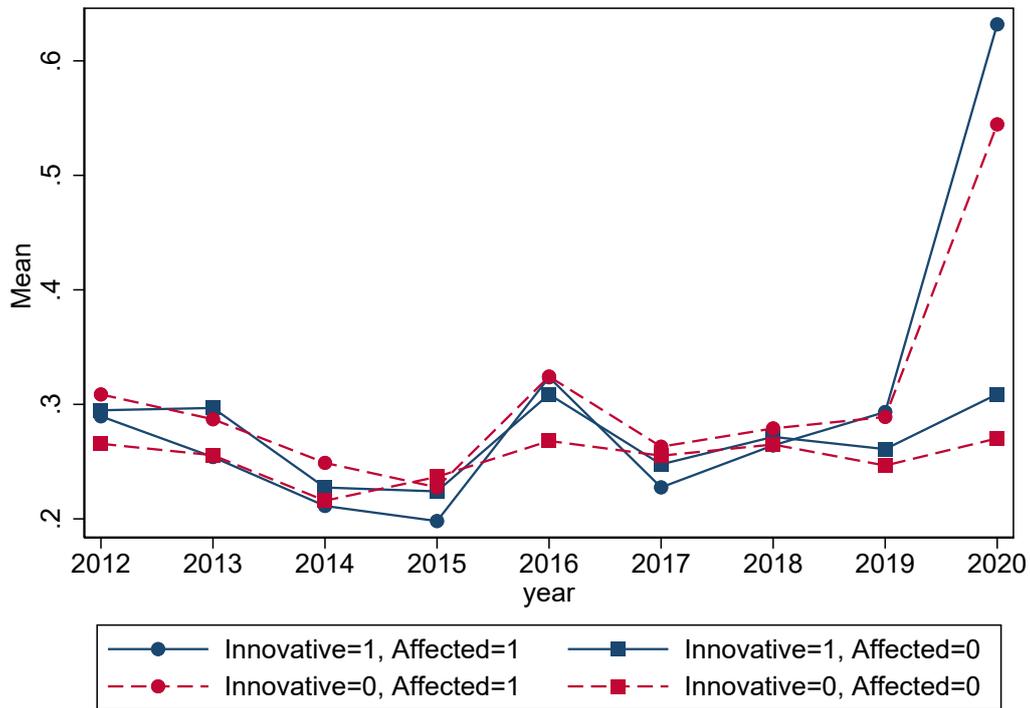
The test can also be displayed graphically. For this purpose, Figure 3.2 shows the point estimates and the 90% confidence intervals of the triple interaction of the (a) binary and (b) continuous affectedness measure with the innovation and time dummies. We find that the coefficients are insignificant for each year before 2020 for both the binary and continuous measurements of affectedness. These coefficients capture group differences within the years. In contrast to the pre-crisis interaction terms, the interaction in 2020 is significantly positive.

Figure 3.2: Common trend—dependent variable: *PayCut*



In the DDD case, we observe four relevant groups: innovative and affected, innovative and non-affected, non-innovative and affected, and non-innovative and non-affected firms. Figure 3.3 illustrates the share of firms within these groups that cut payments. (Non-)innovative firms are presented in (dashed red) solid blue lines while being (un)affected is indicated by (circles) squares. The pre-crisis trends seem to be fairly similar, with relatively little variation over time. The levels from 2012 and 2019 are almost unchanged. However, there are prominent changes in 2020. First, we observe an increase for all groups. Secondly, we see that the shares of affected firms that cut payments (circles) increase substantially in comparison to the non-affected (squares) for both innovative and non-innovative firms.

Figure 3.3: Impact of innovation (R&D) and affectedness on *PayCut*



The “simple” two period DDD estimator without covariates can be calculated with mean differences as shown in equation 3.4.

$$\hat{\delta} = [(\bar{Y}_{a=1,i=1,t=20} - \bar{Y}_{a=1,i=1,t=19}) - (\bar{Y}_{a=0,i=1,t=20} - \bar{Y}_{a=0,i=1,t=19})] - [(\bar{Y}_{a=1,i=0,t=20} - \bar{Y}_{a=1,i=0,t=19}) - (\bar{Y}_{a=0,i=0,t=20} - \bar{Y}_{a=0,i=0,t=19})] \quad (3.4)$$

In this setting, the average pay cuts \bar{Y} depend on affectedness ($a = 1$: affected, $a = 0$: unaffected), innovativeness ($i = 1$: innovative, $i = 0$: non-innovative), and the period ($t = 19, 20$). All these averages are observable in Figure 3.3. The term in the first (second) round bracket of the first row of equation (3.4) equals the distance between the blue circles (squares) from 2019 to 2020. Thereby, the first row captures the effect of being affected by the crisis within innovative firms ($\hat{\delta}_{DiD|i=1}$). Furthermore, the term in the first (second) round bracket of the second row equals the distance between the red circles (squares) from 2019 to 2020. Analogously, the second row captures the effect of being affected by the crisis within non-innovative firms ($\hat{\delta}_{DiD|i=0}$). Consequently, the difference of those DiD models equals the DDD estimator $\hat{\delta}_{DDD} = \hat{\delta}_{DiD|i=1} - \hat{\delta}_{DiD|i=0}$.

3.4.5 Robustness

Table 3.4 shows robust coefficients when using different innovation measures. To validate our results, we additionally perform several robustness tests (not presented) regarding the dependent variable and control variables. Moreover, we re-estimate equation (1) of the GBP sample in Section 3.3 with balance-sheet data and innovation at the firm-level.

The use of fixed-effects regressions offers the advantage that we are able to control for time-constant unobservable heterogeneity. Factors such as management ability should therefore be taken into account. However, regarding the dependent variables, there are differences between the survey data (GBP) and the published company financial data used in this section. While the GBP explicitly queries pay reductions, in the financial data set, we only have information on annual changes in personnel expenses per employee. Adjustments to this variable are either due to changes in (i) personnel expenses or (ii) the number of employees. We expect that we are measuring pay adjustments. However, we cannot exclude the possibility that a change in the employment structure influences our dependent variable. For example, the dismissal of employees with above-average compensation can lead to a reduction in personnel expenses per employee, with the result that the dummy variable would take unit value. Therefore, in robustness tests we restrict the sample to firms whose employment remained constant from 2019 to 2020. This strict assumption is accompanied by a sample reduction to 8% of the original data (9,238 observations). Nevertheless, the results of the DiD regressions are confirmed, and the common trend test can no longer be rejected. With regard to the DDD estimations, the coefficients have identical signs and similar levels, but lose significance due to the substantially smaller sample. Furthermore, we restrict the sample to firms which change employment only up to 5%. This yields a sample size of more than 50% of the original data (61,497 observations). The results also confirm our previous findings with respect to the coefficients and their significance. Alternatively, we include the employment growth rate, which again leads to similar results. These robustness tests largely rule out the possibility that the change in personnel expenses is driven by employment adjustments.

Moreover, our dependent variable may also be influenced by the German short-time work program. In this case, the state covers up to two thirds of wage costs for a limited period in order to avoid dismissals. As long as there are no systematic differences in the usage of short-time work between innovative and non-innovative firms, our methodology

captures this effect. For Germany, Diekhof et al. (2021) report the share of short-time workers by R&D intensity of sectors. Based on this, there is little evidence of systematic differences. If at all, innovative sectors (with the exception of the automotive sector) appear to use short-time working less frequently. However, we include the ratio of employees subject to short-time work to the total number of employees within industries (NACE Rev. 2, level 2 codes) to control for potential short-time work effects. The data on employees on short-time work are taken from the statistics of the Federal Employment Agency, the data on the number of employees per sector from EU Klems. Considering short-time work does not change the results, even if the automotive sector is excluded.

As argued above, the crisis potentially affects employment. Therefore, using firm size categories based on employment of the corresponding year might yield a bad control problem. However, when excluding control variables or using lagged employment to generate firm size categories, we obtain similar results.

Based on Figure 3.2, we have already shown that the impact of the COVID-19 pandemic does not depend on the trend in pre-crisis revenue growth. Nevertheless, we include the annual growth in revenues in a further robustness test, which confirms our results.

Finally, the GBP surveys pay cuts at an early stage of the pandemic, meaning that reported adjustments may not actually be realized. To take this into account, we replicate the cross-sectional GBP approach by restricting the panel data to the year 2020. Subsequently, we re-estimate equation (1) using firm-level innovation and realized cuts to personnel expenses per employee instead of surveyed pay cuts to different stakeholders. The results confirm our findings of Section 3.3.

Overall, we find evidence that innovative firms are more likely to reduce payments due to the crisis. Several robustness tests validate this result. The findings on the impact of affected firms on payment adjustments depending on industry-level innovations can thus be confirmed using firm-level data on innovativeness and realized pay cuts.

3.5 Mechanisms

To strengthen our theoretical argument of financial constraints as a mechanism, we use a Tax Incidence Survey Experiment from the GBP. Firms are assigned randomly to six distinct treatment groups. Each group experiences either a permanent decrease in profit tax burden of 1%, 10%, or 25%, or a permanent increase of 1%, 10%, or 25%. We are

interested in what firms would do with the additional funds. Therefore, we focus on the treatment groups to which a reduction in the profit tax burden is allocated. The experiment offers different options for how firms can distribute the additional funds. In our context, an increase in investments is the relevant response, which leads to a follow-up question regarding the reason for this increase. The reasons are (i) “After the tax cut, more funds are available” and (ii) “After the tax cut, the investment is more worthwhile”. Firms report a value between 0 (reason (i) is decisive) and 100 (reason (ii) is decisive) while a value of 50 would indicate that both reasons are equally important. We suppose that firms reporting a value closer to 0 are more financially constrained. Table 3.5 shows mean values and differences of the reported answers of innovative and non-innovative firms.

Table 3.5: Testing financial constraints

	Innovative		Non-Innovative		Diff
	mean	sd	mean	sd	b
1%	35.46	28.94	34.79	29.63	0.67
Observations	336		319		655
10%	35.29	27.06	38.99	29.13	-3.69*
Observations	372		396		768
25%	29.94	27.27	36.88	28.80	-6.95***
Observations	306		256		562

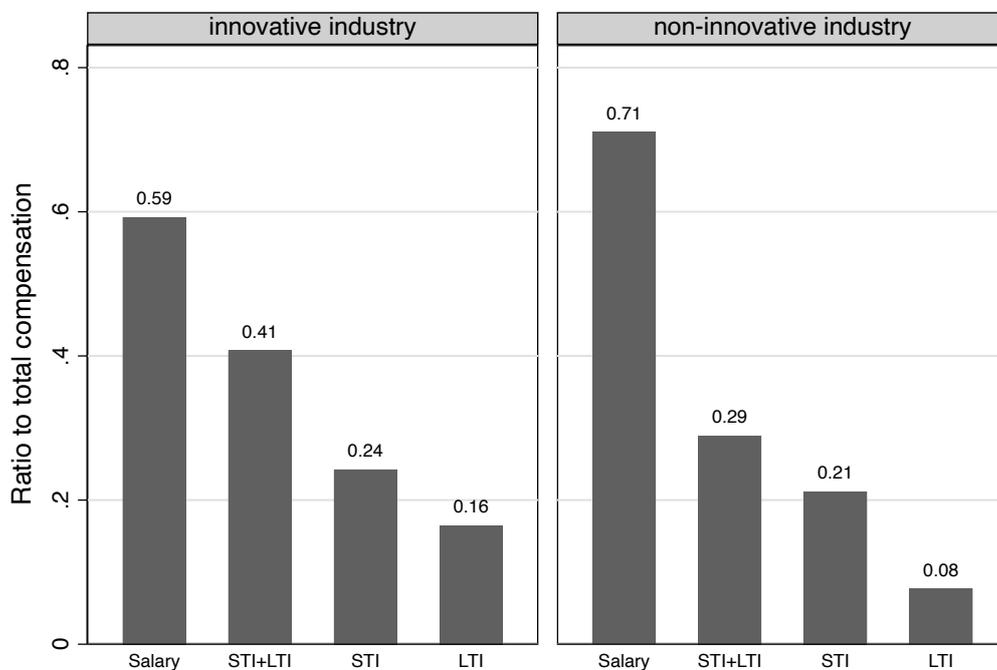
We find that innovative firms tend to report a significantly lower value and are therefore more likely to be financially constrained. The results remain robust when assigning innovative industries by the 4th quartile. Therefore, we conclude that innovative firms are forced, both to a greater degree and more frequently, to defer financial resources during the pandemic to maintain innovativeness and thus ensure the survival of the firm.

Additionally, we argue that innovative firms are also more capable of cutting payments, since they generally pay wages above the collectively agreed rate, especially as the workforce tends to have a higher level of (specific) human capital. Furthermore, in this context, pay cuts to shareholders and executives in particular appear to be easily realized. Dividends to shareholders are determined on an annual basis by the Annual General Meeting and can therefore easily be adjusted downwards in times of financial difficulty, as in the COVID-19 crisis. Generally, firms avoid reducing dividends, as this

can be perceived by shareholders as a signal of a poor economic situation (e.g., Miller and Rock, 1985; Nguyen and Tran, 2016). In the case of the pandemic, however, shareholders are likely to anticipate the existing risk and accept interim reductions.

In the same way, parts of executive compensation can be reduced relatively easily. Figure 3.4 shows the composition of executive remuneration between 2012 and 2019, divided into firms in innovative and non-innovative industries (compare Section 3.3). The data is provided by Kienbaum Consultants International GmbH, which specializes in executive compensation. This data has the advantage of including small companies, which is rare for Germany.

Figure 3.4: Composition of executive compensation



Own calculations based on Kienbaum executive compensation data

Figure 3.4 shows that German executives continue to be primarily compensated using fixed salaries. 59% of executive compensation in innovative industries consists of fixed salaries and 41% of variable components (STI+LTI). In contrast, firms in non-innovative industries compensate their executives to 71% with fixed and to 29% with variable remuneration. Compared with executives from non-innovative industries, top managers from innovative industries are paid on the basis of a more incentive-orientated compensation structure. Moreover, for both types of industries we find that the ratio of annual short-term incentives (STI) is larger than the ratio of long-term incentives (LTI). In innovative industries the STI ratio is 3% higher than is the case for their non-innovative counter-

parts, and for the LTI ratio the difference is about 8%. All differences are significant at the 1%-level. As firms in innovative industries remunerate executives to a greater extent with variable components, we consequently suggest that they can adjust compensation more easily and quickly during the pandemic than their non-innovative counterparts.

3.6 Conclusion

This study investigates the impact of innovation during the COVID-19 pandemic on adjustments to stakeholders. Previous research finds evidence that innovative firms have a higher adaptability and are thus more likely to survive in times of crisis. We contribute to the literature by showing how innovative and non-innovative firms adapt payments during the COVID-19 pandemic. Possible differences in turn might help explain the survival advantages of innovative firms. We argue that several firm-specific aspects, such as specific human capital, financial constraints, and collective bargaining agreements, lead to different cost adjustment strategies between both types of firms.

First, we provide insights on the decisions regarding compensation of four different stakeholder groups: shareholders, executives, middle management, and employees. The possibility that these groups can be separated in this way is quite rare. We combine firm-level survey data with information on innovative industries on the basis of R&D intensities and apply a difference-in-differences approach. Our results indicate that innovative firms are more likely to reduce costs via pay adjustments particularly to shareholders and executives. We validate these findings with an instrumental variable approach to deal with, for example, omitted variable bias from management quality. This set-up confirms the findings for shareholders and executives, and additionally suggests higher pay adjustments to middle managers and workers in innovative industries.

Next, we show that surveyed pay cuts can be confirmed using panel data assigning the innovation status at the firm-level. We use both R&D activities and patent information to identify innovative firms. Besides innovation information at the firm-level, this data set offers the advantage of multiple time periods enabling panel data econometrics. In this part of the study, we cannot distinguish between stakeholder groups, but instead use personnel expenses per employee as a measure of pay cuts. Difference-in-differences, as well as triple differences estimations, show that innovative firms adjust payments to a higher extent during the pandemic, especially when they are negatively affected by it.

We conclude that both the affectedness of a firm and the extent of being affected have an impact on how innovative and non-innovative firms adjust payments during the pandemic. Several robustness tests confirm our results.

To give further insight into the underlying mechanisms, we discuss the role of financial constraints and present some descriptive evidence on compensation compositions in the different kinds of firms. The data emphasizes that innovative firms are (i) more financially constrained, forcing them to reduce costs to a greater degree, and (ii) pay executives a higher share of variable compensation, which enables them to reduce their compensation more easily. This is in line with our results at the firm- and industry-level. Additionally, we argue that collectively bargained wages and higher amounts of specific human capital explain how innovative firms can reduce compensation to an extent greater than their non-innovative counterparts.

All in all, we conclude that innovative firms are indeed able to adapt more flexibly in times of crisis by making adjustments to stakeholder compensation. We interpret these results as possible explanations for the findings of the higher survival probability of innovative firms during crises. These insights into different adjustment strategies of innovative and non-innovative firms to reduce costs in times of crisis provide valuable information for companies and trade unions in particular. We argue that short-term compensation adjustments can be a legitimate strategy to increase firms' survival prospects. Moreover, innovative companies in particular should accumulate reserves to avoid the risk of excessive financial constraints in times of crisis. In this respect, an additional subsidy for innovative companies during crises would also be conceivable from a policy perspective (Giebel and Kraft, 2023; Hud and Hussinger, 2015).

This study has certain limitations that could be subject for further research. First, due to lack of data, we cannot distinguish between different stakeholders when using panel data. Second, more information on the extent of the pay adjustments could provide better insight into whether the compensation of stakeholder groups is adjusted equally. Third, a more detailed examination of the specific reasons for greater wage adjustments in innovative firms would be of interest. To this end, the additional inclusion of information on the (specific) human capital stock and financial restrictions as well as other firm-specific determinants would be useful. Finally, a direct causal attribution of the results to the actual survival probability of innovative firms remains open to be examined more closely.

3.7 Appendix

Table 3.6: Full estimation results of Table 3.2

	Shareholders (1)	Executives (2)	Mid. Managers (3)	Other Emp. (4)
<i>Panel A: LPM—Affected (dummy)</i>				
Innovative	-0.1603 (0.1658)	0.0586 (0.1381)	0.0267 (0.1419)	0.0914 (0.1515)
Affected	0.1591*** (0.0138)	0.2141*** (0.0140)	0.1979*** (0.0133)	0.2045*** (0.0139)
Innovative × Affected	0.0740*** (0.0210)	0.0474** (0.0212)	0.0231 (0.0202)	0.0165 (0.0206)
FirmSize _{100k–350k}	-0.0001 (0.0199)	0.0128 (0.0200)	-0.0020 (0.0184)	0.0365* (0.0189)
FirmSize _{350k–700k}	0.0271 (0.0206)	0.0608*** (0.0207)	0.0643*** (0.0194)	0.1049*** (0.0199)
FirmSize _{700k–2mil}	0.0267 (0.0195)	0.0653*** (0.0194)	0.0896*** (0.0184)	0.1298*** (0.0186)
FirmSize _{2mil–10mil}	0.0517** (0.0207)	0.1151*** (0.0208)	0.1687*** (0.0200)	0.1817*** (0.0201)
FirmSize _{>10mil}	0.0088 (0.0249)	0.1143*** (0.0249)	0.2152*** (0.0243)	0.1988*** (0.0244)
Limited	0.2000*** (0.0127)	0.1224*** (0.0141)	0.0989*** (0.0134)	0.0336** (0.0149)
RiskAversion	-0.0508*** (0.0135)	-0.0435*** (0.0140)	-0.0161 (0.0136)	0.0376*** (0.0145)
EndRestriction ₂₀₂₁	0.0022 (0.0188)	0.0210 (0.0192)	0.0177 (0.0184)	-0.0020 (0.0190)
EndRestriction ₂₀₂₂	0.0095 (0.0216)	0.0475** (0.0221)	0.0483** (0.0213)	0.0195 (0.0219)
EndRestriction _{≥2023}	0.0456 (0.0311)	0.0614** (0.0312)	0.0205 (0.0298)	0.0070 (0.0308)
Constant	0.0654 (0.1637)	-0.1976 (0.1343)	-0.1787 (0.1380)	-0.1554 (0.1470)

(continued on next page)

Table 3.6: Full estimation results of Table 3.2 (continued)

	Shareholders (1)	Executives (2)	Mid. Managers (3)	Other Emp. (4)
<i>Panel B: LPM—Affected (continuous)</i>				
Innovative	-0.1439 (0.1621)	0.0612 (0.1385)	0.0244 (0.1430)	0.0853 (0.1511)
Affected	0.0015*** (0.0002)	0.0020*** (0.0002)	0.0019*** (0.0002)	0.0019*** (0.0002)
Innovative × Affected	0.0011*** (0.0003)	0.0007*** (0.0003)	0.0002 (0.0003)	0.0002 (0.0003)
FirmSize _{100k–350k}	0.0122 (0.0199)	0.0275 (0.0201)	0.0104 (0.0185)	0.0493*** (0.0189)
FirmSize _{350k–700k}	0.0372* (0.0207)	0.0724*** (0.0208)	0.0740*** (0.0196)	0.1148*** (0.0201)
FirmSize _{700k–2mil}	0.0401** (0.0196)	0.0808*** (0.0196)	0.1024*** (0.0186)	0.1429*** (0.0188)
FirmSize _{2mil–10mil}	0.0668*** (0.0209)	0.1327*** (0.0210)	0.1833*** (0.0202)	0.1966*** (0.0204)
FirmSize _{>10mil}	0.0328 (0.0250)	0.1424*** (0.0252)	0.2389*** (0.0247)	0.2230*** (0.0248)
Limited	0.1962*** (0.0127)	0.1178*** (0.0143)	0.0947*** (0.0134)	0.0293** (0.0149)
RiskAversion	-0.0506*** (0.0136)	-0.0436*** (0.0141)	-0.0165 (0.0137)	0.0371** (0.0146)
EndRestriction ₂₀₂₁	0.0009 (0.0189)	0.0205 (0.0194)	0.0181 (0.0185)	-0.0015 (0.0191)
EndRestriction ₂₀₂₂	0.0048 (0.0217)	0.0432* (0.0223)	0.0456** (0.0214)	0.0168 (0.0220)
EndRestriction _{≥2023}	0.0456 (0.0314)	0.0631** (0.0314)	0.0233 (0.0296)	0.0100 (0.0307)
Constant	0.1377 (0.1602)	-0.0994 (0.1348)	-0.0883 (0.1391)	-0.0617 (0.1470)
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	7,967	7,967	7,967	7,967

Notes: Results of LPM difference-in-differences estimations, robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.7: Estimation results (innovation attributed at 4th quartile)

	Shareholders (1)	Executives (2)	Mid. Managers (3)	Other Emp. (4)
<i>Panel A: LPM—Affected (dummy)</i>				
Innovative	-0.1532*** (0.0501)	-0.1074** (0.0536)	-0.0451 (0.0622)	-0.0646 (0.0635)
Affected	0.1733*** (0.0122)	0.2173*** (0.0125)	0.1987*** (0.0119)	0.2069*** (0.0124)
Innovative × Affected	0.0656*** (0.0234)	0.0612*** (0.0232)	0.0324 (0.0222)	0.0170 (0.0222)
FirmSize _{100k–350k}	-0.0009 (0.0199)	0.0125 (0.0200)	-0.0022 (0.0184)	0.0364* (0.0189)
FirmSize _{350k–700k}	0.0265 (0.0206)	0.0602*** (0.0207)	0.0640*** (0.0194)	0.1048*** (0.0199)
FirmSize _{700k–2mil}	0.0264 (0.0195)	0.0651*** (0.0195)	0.0895*** (0.0184)	0.1297*** (0.0186)
FirmSize _{2mil–10mil}	0.0515** (0.0208)	0.1149*** (0.0208)	0.1686*** (0.0200)	0.1816*** (0.0201)
FirmSize _{>10mil}	0.0081 (0.0249)	0.1137*** (0.0249)	0.2148*** (0.0243)	0.1986*** (0.0244)
Limited	0.1999*** (0.0127)	0.1223*** (0.0141)	0.0988*** (0.0134)	0.0335** (0.0149)
RiskAversion	-0.0506*** (0.0135)	-0.0432*** (0.0140)	-0.0160 (0.0136)	0.0376*** (0.0145)
EndRestriction ₂₀₂₁	0.0026 (0.0188)	0.0215 (0.0192)	0.0179 (0.0184)	-0.0019 (0.0190)
EndRestriction ₂₀₂₂	0.0100 (0.0216)	0.0481** (0.0221)	0.0486** (0.0213)	0.0196 (0.0219)
EndRestriction _{≥2023}	0.0456 (0.0311)	0.0617** (0.0312)	0.0207 (0.0297)	0.0070 (0.0308)
Constant	-0.0598 (0.0613)	-0.1131* (0.0628)	-0.1388** (0.0614)	-0.0557 (0.0651)

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Table 3.7: Estimation results (innovation attributed at 4th quartile) (continued)

	Shareholders (1)	Executives (2)	Mid. Managers (3)	Other Emp. (4)
<i>Panel B: LPM—Affected (continuous)</i>				
Innovative	-0.2102*** (0.0496)	-0.1817*** (0.0526)	-0.1163** (0.0575)	-0.1399** (0.0585)
Affected	0.0017*** (0.0001)	0.0021*** (0.0001)	0.0019*** (0.0001)	0.0020*** (0.0001)
Innovative × Affected	0.0008** (0.0003)	0.0006** (0.0003)	0.0002 (0.0003)	0.0001 (0.0003)
FirmSize _{100k–350k}	0.0115 (0.0199)	0.0272 (0.0201)	0.0103 (0.0185)	0.0491*** (0.0189)
FirmSize _{350k–700k}	0.0368* (0.0207)	0.0722*** (0.0209)	0.0739*** (0.0196)	0.1147*** (0.0201)
FirmSize _{700k–2mil}	0.0395** (0.0196)	0.0805*** (0.0196)	0.1023*** (0.0186)	0.1428*** (0.0188)
FirmSize _{2mil–10mil}	0.0664*** (0.0209)	0.1326*** (0.0210)	0.1833*** (0.0202)	0.1965*** (0.0204)
FirmSize _{>10mil}	0.0314 (0.0250)	0.1415*** (0.0252)	0.2386*** (0.0247)	0.2227*** (0.0248)
Limited	0.1963*** (0.0127)	0.1179*** (0.0143)	0.0948*** (0.0134)	0.0294** (0.0149)
RiskAversion	-0.0508*** (0.0137)	-0.0436*** (0.0141)	-0.0166 (0.0137)	0.0371** (0.0146)
EndRestriction ₂₀₂₁	0.0017 (0.0189)	0.0210 (0.0194)	0.0183 (0.0185)	-0.0013 (0.0191)
EndRestriction ₂₀₂₂	0.0059 (0.0217)	0.0438** (0.0222)	0.0458** (0.0214)	0.0170 (0.0220)
EndRestriction _{≥2023}	0.0465 (0.0314)	0.0636** (0.0314)	0.0235 (0.0296)	0.0101 (0.0307)
Constant	0.0059 (0.0613)	-0.0296 (0.0634)	-0.0614 (0.0616)	0.0257 (0.0645)
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	7,967	7,967	7,967	7,967

Notes: Results of LPM difference-in-differences estimations, robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.8: Results of 2SLS regressions (2nd stage)

	Shareholders (1)	Executives (2)	Mid. Managers (3)	Other Emp. (4)
<i>Panel A: LPM—Innovative (median)</i>				
Affected	0.0035*** (0.0007)	0.0040*** (0.0007)	0.0039*** (0.0007)	0.0041*** (0.0007)
Innovative × Affected	0.0094*** (0.0026)	0.0097*** (0.0027)	0.0066*** (0.0024)	0.0073*** (0.0025)
Innovative	-0.0854** (0.0396)	-0.0744* (0.0406)	-0.0393 (0.0363)	-0.0796** (0.0381)
FirmSize _{100k–350k}	0.0570* (0.0331)	0.0706** (0.0341)	0.0349 (0.0296)	0.0917*** (0.0307)
FirmSize _{350k–700k}	0.0823** (0.0340)	0.1251*** (0.0350)	0.1067*** (0.0309)	0.1602*** (0.0322)
FirmSize _{700k–2mil}	0.1031*** (0.0351)	0.1496*** (0.0358)	0.1565*** (0.0313)	0.2167*** (0.0324)
FirmSize _{2mil–10mil}	0.1286*** (0.0346)	0.2065*** (0.0355)	0.2417*** (0.0313)	0.2738*** (0.0324)
FirmSize _{>10mil}	0.1216*** (0.0396)	0.2509*** (0.0405)	0.3334*** (0.0365)	0.3394*** (0.0379)
Limited	0.2095*** (0.0192)	0.1304*** (0.0214)	0.0976*** (0.0193)	0.0255 (0.0211)
RiskAversion	-0.0506*** (0.0193)	-0.0485** (0.0197)	-0.0197 (0.0180)	0.0475** (0.0194)
EndRestriction ₂₀₂₁	-0.0347 (0.0285)	-0.0032 (0.0304)	0.0040 (0.0264)	-0.0267 (0.0281)
EndRestriction ₂₀₂₂	-0.0325 (0.0324)	0.0071 (0.0342)	0.0216 (0.0300)	-0.0255 (0.0317)
EndRestriction _{≥2023}	0.0057 (0.0447)	0.0259 (0.0450)	-0.0056 (0.0406)	-0.0365 (0.0423)
Constant	0.0395 (0.0546)	-0.0138 (0.0558)	-0.0416 (0.0516)	0.0352 (0.0534)

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Table 3.8: Results of 2SLS regressions (2nd stage) (continued)

	Shareholders (1)	Executives (2)	Mid. Managers (3)	Other Emp. (4)
<i>Panel B: LPM—Innovative (4th quartile)</i>				
Affected	0.0041*** (0.0007)	0.0046*** (0.0007)	0.0044*** (0.0007)	0.0051*** (0.0007)
Innovative × Affected	0.0088** (0.0035)	0.0066** (0.0032)	0.0011 (0.0027)	0.0009 (0.0026)
Innovative	-0.0562 (0.0539)	-0.0381 (0.0495)	0.0338 (0.0415)	0.0082 (0.0414)
FirmSize _{100k–350k}	0.0493 (0.0327)	0.0539* (0.0305)	0.0129 (0.0252)	0.0676*** (0.0254)
FirmSize _{350k–700k}	0.0751** (0.0333)	0.1057*** (0.0315)	0.0818*** (0.0266)	0.1319*** (0.0270)
FirmSize _{700k–2mil}	0.0960*** (0.0345)	0.1269*** (0.0319)	0.1263*** (0.0268)	0.1815*** (0.0269)
FirmSize _{2mil–10mil}	0.1325*** (0.0350)	0.1942*** (0.0326)	0.2190*** (0.0277)	0.2461*** (0.0279)
FirmSize _{>10mil}	0.1223*** (0.0381)	0.2324*** (0.0363)	0.3072*** (0.0321)	0.3067*** (0.0323)
Limited	0.2075*** (0.0183)	0.1326*** (0.0195)	0.0988*** (0.0173)	0.0263 (0.0189)
RiskAversion	-0.0484** (0.0190)	-0.0519*** (0.0183)	-0.0278* (0.0165)	0.0366** (0.0176)
EndRestriction ₂₀₂₁	-0.0246 (0.0271)	0.0160 (0.0265)	0.0256 (0.0227)	-0.0035 (0.0238)
EndRestriction ₂₀₂₂	-0.0182 (0.0305)	0.0305 (0.0295)	0.0460* (0.0258)	0.0013 (0.0269)
EndRestriction _{≥2023}	0.0231 (0.0429)	0.0541 (0.0401)	0.0259 (0.0358)	-0.0033 (0.0365)
Constant	0.0039 (0.0525)	-0.0341 (0.0512)	-0.0483 (0.0467)	0.0191 (0.0484)
State dummies	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No
Observations	6,508	6,508	6,508	6,508

Notes: Results of 2SLS difference-in-differences estimations, robust standard errors in parentheses, the instrumental variable of 2SLS estimation is industry-level revenue impact in Austria provided by Eurostat, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.9: Results of 2SLS regressions (1st stage)

	Panel A (median)		Panel B (4 th quartile)	
	Affected (1)	Innovative×Affected (2)	Affected (3)	Innovative×Affected (4)
Innovative	0.1928 (1.2569)	11.5260*** (0.7763)	-0.4521 (1.3426)	11.5128*** (1.0896)
IV	0.9073*** (0.0650)	-0.0064 (0.0055)	0.8524*** (0.0577)	-0.0063* (0.0036)
Innovative×IV	-0.3658*** (0.1148)	0.5559*** (0.0954)	-0.2476 (0.1528)	0.6217*** (0.1424)
FirmSize _{100k–350k}	-5.3273** (2.4611)	-4.5107** (1.7726)	-5.3571** (2.4608)	-3.4752** (1.5908)
FirmSize _{350k–700k}	-7.7090*** (2.4829)	-5.2248*** (1.7959)	-7.7244*** (2.4836)	-3.7322** (1.5731)
FirmSize _{700k–2mil}	-10.1446*** (2.3350)	-6.8529*** (1.6998)	-10.2771*** (2.3354)	-4.9235*** (1.4876)
FirmSize _{2mil–10mil}	-9.0806*** (2.3517)	-5.9194*** (1.6970)	-9.3461*** (2.3583)	-4.8561*** (1.4910)
FirmSize _{>10mil}	-13.6849*** (2.5226)	-7.7042*** (1.8049)	-14.1832*** (2.5346)	-5.2406*** (1.4697)
Limited	-2.5678 (1.6978)	-0.5002 (1.0623)	-2.5770 (1.6961)	-0.5396 (0.8461)
RiskAversion	-1.9760 (1.4537)	-1.9018* (1.0071)	-1.9695 (1.4544)	-1.7934** (0.7988)
EndRestriction ₂₀₂₁	3.2917 (2.1408)	3.8838** (1.5308)	3.3013 (2.1429)	2.5664** (1.2363)
EndRestriction ₂₀₂₂	3.1414 (2.4231)	4.3524** (1.7119)	3.1106 (2.4261)	2.6884* (1.3743)
EndRestriction _{≥2023}	3.6629 (3.3466)	5.3129** (2.4290)	3.6008 (3.3530)	3.5806* (1.9549)
Constant	15.4100*** (4.2330)	0.5120 (2.7995)	15.7466*** (4.2275)	2.6927 (2.2642)
State dummies	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No
F-values	113.5	17.3	118.1	10.8
Observations	6,508	6,508	6,508	6,508

Notes: First stage results of 2SLS difference-in-differences estimations, robust standard errors in parentheses, the instrumental variable (*IV*) of 2SLS estimation is industry-level revenue impact in Austria provided by Eurostat, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.10: Full estimation results of Table 3.4

	PayCut			
	LPM	FE	LPM	FE
	(1)	(2)	(3)	(4)
<i>Panel A: Difference-in-Differences</i>				
Innovative	-0.0070 (0.0044)		-0.0141*** (0.0037)	
Crisis	0.1117*** (0.0060)	0.0985*** (0.0063)	0.0924*** (0.0061)	0.0773*** (0.0066)
Innovative×Crisis	0.1106*** (0.0115)	0.1157*** (0.0121)	0.1357*** (0.0089)	0.1413*** (0.0095)
FirmSize ₁₀₋₄₉	0.0222*** (0.0082)	0.1681*** (0.0269)	0.0205** (0.0082)	0.1710*** (0.0269)
FirmSize ₅₀₋₂₄₉	-0.0329*** (0.0079)	0.2416*** (0.0298)	-0.0356*** (0.0078)	0.2453*** (0.0298)
FirmSize _{≥250}	-0.0754*** (0.0080)	0.3233*** (0.0313)	-0.0788*** (0.0080)	0.3278*** (0.0313)
Constant	0.3039*** (0.0140)	0.0357 (0.0288)	0.3113*** (0.0140)	0.0322 (0.0288)
<i>Panel B: Re-weighted Difference-in-Differences</i>				
Innovative	0.0069 (0.0047)		0.0012 (0.0044)	
Crisis	0.1834*** (0.0115)	0.1690*** (0.0122)	0.2070*** (0.0114)	0.1955*** (0.0123)
Innovative×Crisis	0.0409*** (0.0139)	0.0486*** (0.0148)	0.0310** (0.0122)	0.0345*** (0.0132)
FirmSize ₁₀₋₄₉	0.0053 (0.0387)	0.1684* (0.0940)	0.0262 (0.0264)	0.1691*** (0.0653)
FirmSize ₅₀₋₂₄₉	-0.0306 (0.0366)	0.2364** (0.0950)	-0.0174 (0.0250)	0.2490*** (0.0679)
FirmSize _{≥250}	-0.0619* (0.0366)	0.3077*** (0.0961)	-0.0489* (0.0249)	0.3229*** (0.0692)
Constant	0.2775*** (0.0399)	0.0122 (0.0954)	0.2698*** (0.0299)	-0.0157 (0.0684)

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Table 3.10: Full estimation results of Table 3.4 (continued)

	PayCut			
	LPM	FE	LPM	FE
	(1)	(2)	(3)	(4)
<i>Panel C: Triple Differences—Affected (dummy)</i>				
Innovative	0.0127* (0.0068)		-0.0060 (0.0054)	
Crisis	-0.0098 (0.0068)	-0.0329*** (0.0073)	-0.0169** (0.0070)	-0.0398*** (0.0075)
Affected	0.0129*** (0.0032)		0.0120*** (0.0035)	
Innovative × Crisis	0.0240 (0.0171)	0.0279 (0.0182)	0.0490*** (0.0131)	0.0500*** (0.0141)
Innovative × Affected	-0.0251*** (0.0082)		-0.0061 (0.0066)	
Crisis × Affected	0.2459*** (0.0078)	0.2569*** (0.0086)	0.2321*** (0.0084)	0.2410*** (0.0093)
Innovative × Crisis × Affected	0.0846*** (0.0224)	0.0854*** (0.0236)	0.0756*** (0.0175)	0.0785*** (0.0187)
FirmSize _{10–49}	0.0220*** (0.0082)	0.1741*** (0.0272)	0.0207** (0.0081)	0.1751*** (0.0273)
FirmSize _{50–249}	-0.0345*** (0.0078)	0.2588*** (0.0301)	-0.0363*** (0.0078)	0.2597*** (0.0301)
FirmSize _{≥250}	-0.0758*** (0.0079)	0.3535*** (0.0316)	-0.0781*** (0.0079)	0.3547*** (0.0316)
Constant	0.3008*** (0.0140)	0.0156 (0.0291)	0.3072*** (0.0140)	0.0148 (0.0291)

(continued on next page)

Table 3.10: Full estimation results of Table 3.4 (continued)

	PayCut			
	LPM	FE	LPM	FE
	(1)	(2)	(3)	(4)
<i>Panel D: Triple Differences—Affected (continuous)</i>				
Innovative	-0.0023 (0.0044)		-0.0112*** (0.0037)	
Crisis	0.1053*** (0.0059)	0.0830*** (0.0063)	0.0891*** (0.0061)	0.0660*** (0.0065)
Affected	0.0001 (0.0001)		0.0001 (0.0001)	
Innovative×Crisis	0.0869*** (0.0112)	0.0948*** (0.0119)	0.1091*** (0.0088)	0.1135*** (0.0094)
Innovative×Affected	-0.0005** (0.0002)		-0.0000 (0.0002)	
Crisis×Affected	0.0055*** (0.0002)	0.0065*** (0.0002)	0.0052*** (0.0002)	0.0062*** (0.0003)
Innovative×Crisis×Affected	0.0018*** (0.0006)	0.0012** (0.0006)	0.0016*** (0.0004)	0.0013*** (0.0005)
FirmSize ₁₀₋₄₉	0.0263*** (0.0082)	0.1873*** (0.0278)	0.0244*** (0.0082)	0.1886*** (0.0278)
FirmSize ₅₀₋₂₄₉	-0.0297*** (0.0078)	0.2789*** (0.0307)	-0.0321*** (0.0078)	0.2803*** (0.0306)
FirmSize _{≥250}	-0.0713*** (0.0080)	0.3785*** (0.0321)	-0.0745*** (0.0080)	0.3801*** (0.0321)
Constant	0.3024*** (0.0140)	-0.0043 (0.0296)	0.3096*** (0.0140)	-0.0055 (0.0296)
Innovation measure	R&D	R&D	Patents	Patents
Controls	Yes	Yes	Yes	Yes
State dummies	Yes	No	Yes	No
Industry dummies	Yes	No	Yes	No
Time dummies	Yes	Yes	Yes	Yes
Common trend test (p-values)				
Panel A	0.032	0.006	0.000	0.000
Panel B	0.647	0.608	0.000	0.002
Panel C	0.508	0.413	0.155	0.184
Panel D	0.830	0.850	0.164	0.324
Observations	113,781	113,781	113,781	113,781

Notes: Results of DiD (Panel A), re-weighted DiD (Panel B), and DDD (Panels C and D) estimations, robust and firm-clustered standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Part III

Summary and Conclusion

This dissertation explores the impact of economic crises on firms and their stakeholders, particularly in relation to vocational training and pay adjustment strategies, as well as how innovation influences corporate behavior. By examining the Great Financial Crisis and the COVID-19 pandemic, it aims to contribute to the understanding of firms' responses to economic distress while balancing immediate survival with long-term strategic objectives. The three chapters are connected through their focus on labor market dynamics, innovation, and cost adjustment strategies. This leads to a comprehensive framework for understanding how firms behave during times of economic uncertainty.

The first chapter investigates how the Great Financial Crisis influenced vocational training expenses of firms, distinguishing between innovative and non-innovative companies. From a theoretical view, it is ambiguous to predict the effect because of a trade-off: on the one hand, declining sales may raise the need for cost reductions. On the other hand, the opportunity costs of training decrease if, due to a decline in demand, workers are not needed full-time for production (Aghion and Saint-Paul, 1998a,b). Thus, firms can increase their long-term productivity. This trade-off may vary between innovative and non-innovative firms due to different characteristics such as financial constraints and human capital requirements (Acemoglu, 1997; Lahr and Mina, 2020). The analysis shows that training expenditures increased overall during the crisis. However, non-innovative companies raised their training expenditures per employee significantly more than innovative companies. This can be explained by a greater decline in opportunity costs, as the turnover of non-innovative companies fell more sharply.

In the second chapter, the effects of the COVID-19 pandemic on planned pay adjustments across various stakeholder groups are analyzed: shareholders, executives, middle management, and other employees. Decreasing payments coincides with an increased risk of employee resignations and a distortion of long-term incentives. Furthermore, the Fair Wage-Effort Hypothesis emphasizes that unbalanced pay adjustments may be perceived as unfair and thus lead to declines in effort (Akerlof and Yellen, 1990). The findings show that affected firms planned to decrease payments to all stakeholder groups. However, the likelihood of pay adjustments towards executives was significantly higher than for shareholders.

The third chapter extends findings of the previous chapter in two crucial aspects. Firstly, realized pay adjustments in addition to planned adjustments are considered. Sec-

ondly, the role of innovation in shaping pay adjustment strategies during the COVID-19 pandemic is investigated. Innovative firms are categorized based on R&D intensities and patents. The analysis reveals that innovative firms were more likely to plan a reduction of payments to shareholders and executives compared to their non-innovative counterparts. This may be explained by a more flexible compensation structure and a greater need for reductions due to more binding financial constraints. Furthermore, findings from accounting data confirm that personnel expenses were indeed reduced significantly by innovative firms due to the pandemic.

Together, these chapters deepen the understanding of the effects of crises on firms and their stakeholders and highlight the importance of considering innovation as a mediator in this strand of literature.

While this dissertation provides valuable insights into firm behavior during crises, it is not without limitations. All data used is from Germany, a country with pronounced labor protections and strong institutional frameworks. Thus, the findings may be different for countries with differing labor market regulations. The importance of institutions and regulations might be an interesting focus of future research.

Second, the data that enables the differentiation of various stakeholder groups includes only information about planned pay adjustments. It would be valuable to verify whether, and to what extent, those plans were realized for the specific stakeholder groups. Additionally, instead of firm-level data, employee-level data could be beneficial to provide detailed information about compensation and to be able to control for individual characteristics such as age, education, and tenure.

Third, this dissertation examines short- to medium-term responses to crises. Future research could extend this by investigating the long-term impact on pay adjustments and training. Additionally, it would be of great interest to explore how the increase in training intensity and the planned pay reductions affect key factors, such as firm performance, employment, and innovation outcomes over the long term.

Overall, this dissertation offers valuable insights into how firms respond to crises, particularly in terms of stakeholder payments and vocational training. It highlights how these responses differ depending on a firm's level of innovation and establishes a foundation for future research.

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Hinweis auf die Nutzung von Künstlicher Intelligenz

Während der Vorbereitung dieser Dissertation habe ich ChatGPT 3.5 zur Verbesserung der Grammatik und Lesbarkeit von Einleitung und Zusammenfassung verwendet. Nach der Nutzung dieses Tools habe ich den Inhalt sorgfältig überprüft und überarbeitet und übernehme die volle Verantwortung für den Inhalt der Dissertation.

Eidesstattliche Versicherung

Hiermit erkläre ich an Eides statt, dass ich die Dissertation selbstständig verfasst und alle in Anspruch genommenen Quellen und Hilfen in der Dissertation vermerkt habe. Die den herangezogenen Werken wörtlich oder sinngemäß entnommenen Stellen sind als solche gekennzeichnet. Diese Dissertation ist weder in der gegenwärtigen oder in einer anderen Fassung oder in Teilen an der TU Dortmund noch an einer anderen Hochschule in Zusammenhang mit einer staatlichen oder akademischen Prüfung bereits vorgelegt worden.

Dortmund, 23.01.2025

Tim Seidinger