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For efficiency, tax energy

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Abstract. Using household travel diary data collected in Germany between 1997 and 2012, we employ an instrumental variable (IV) approach to estimate fuel price and efficiency elasticities. The aim is to gauge the relative impacts of fuel economy standards and fuel taxes on distance traveled. We find that the magnitude of the elasticity estimates are statistically indistinguishable: higher fuel prices reduce driving by the same degree as higher fuel efficiency increases driving. This finding indicates an offsetting effect of fuel efficiency standards on the effectiveness of fuel taxation, calling into question the efficacy of the European Commission's current efforts to legislate CO2 emissions limits for new cars given prevailing high fuel taxes.

JEL classification: D13, Q41.

Key words: Automobile travel, instrumental variable approach, rebound effect.

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1 Introduction

Until a few years ago, the United States and the European Union pursued markedly different policies to contain emissions from automobile transport, with the US relying on the corporate average fuel economy (CAFE) standards and the EU relying on fuel taxation. These policies began to converge in April 2009 when the European Commission passed legislation requiring automakers to reduce the average per-kilometer carbon dioxide (CO_2) emissions of newly registered automobiles to 130g/km by 2015 (EC, 2009). The new law marked the end of a 10-year period in which the fuel economy of the new car fleet in Europe increased substantially, rising nearly 20% from 33.5 miles per gallon (mpg) in 2000 to 41.1 mpg in 2009 (ODYSSEE, 2012). In the US, the same time interval saw an increase in fuel efficiency that was considerably more modest, rising 10% from 22.4 to 24.8 mpg (EPA, 2012). Of course, such a comparison does not unequivocally point to the superiority of one policy instrument over the other, but it does raise the question of whether the EU's coupling of an efficiency standard with a system of high fuel taxes – one within which the efficiency of the car fleet has risen relatively rapidly – makes economic sense.

According to a press release published by the Commission in 2007, the CO_2 limits in the new legislation would "reduce the average emissions of CO_2 from new passenger cars in the EU from around 160 grams per kilometer to 130 grams per kilometer", which would "translate into a 19% reduction of CO_2 emissions" (EC, 2007). But whether a CO_2 reduction of this magnitude in fact materializes depends fundamentally on the behavioral response of motorists to increased efficiency. Presuming that mobility is a conventional good, a decrease in the cost of driving due to an improvement in fuel efficiency would result in an increased demand for car travel. This demand increase is referred to as the rebound effect (KHAZZOOM, 1980), as it offsets – at least partially – the reduction in energy demand that would otherwise result from an increase in efficiency. Though the existence of the rebound effect is widely accepted, its magnitude remains a contentious issue (e. g. BROOKES, 2000; BINSWANGER, 2001; SORRELL and DIMITROUPOULOS, 2008).

Proponents of increased efficincy standards generally play down the magnitude of the rebound effect, arguing that the standards not only decrease dependence on imported oil and CO_2 emissions, but also reduce motorists' fuel expenses. Opponents argue that standards are a costly way to reduce gasoline consumption because, unlike a fuel tax, they fail to harness price signals (AUSTIN and DINAN, 2005; CRANDALL, 1992; KARPLUS et al. , 2013; KLEIT, 2004; MANKIW, 2013). This paper scrutinizes both viewpoints by using detailed household travel diary data collected in Germany between 1997 and 2012 to econometrically estimate both fuel price and efficiency elasticities and thereby gauge the relative impacts of fuel economy standards and fuel taxes on distance traveled.

Germany provides an interesting case study of this question because, despite having one of the highest car ownership rates in Europe, the country has reduced emissions from transport by 6% between 1990 and 2009, thereby bucking the 27% increase in transport emissions in the EU as a whole (EEA, 2011a). One contributing factor to this reduction has been high fuel taxes, whose rates of 65.45 cents per liter for petrol and 47.07 cents per liter for diesel are among the highest in the EU. These high taxes result in high prices at the pump: An average German driver pays roughly double the price per gallon of fuel as a US driver.

An immediate challenge in econometrically estimating the rebound effect is endogeneity bias. Contrasting with fuel prices, which can generally be regarded as exogenous to households, fuel efficiency is potentially endogenous owing to unobserved household characteristics that affect both the decision on the distance driven and the fuel economy of the vehicle when it is purchased. Unobserved environmental preferences, for example, may trigger the purchase of a car with a high fuel efficiency, but may also lead to low driving distances. These characteristics may therefore be correlated with regressors capturing fuel efficiency. Moreover, simultaneity biases may result from the fact that drivers who are prepared to drive longer distances, because of a job change, for instance, may tend to purchase more fuel-efficient cars.

Two features of our approach ameliorate these potential problems. First, the panel dimension of our data allows the inclusion of fixed effects to control for the influence of unobserved heterogeneity that stays fixed over time. We additionally address the endogeneity of fuel efficiency by employing motor vehicle tax rates per 100 cm^3 cubic capacity as an instrumental variable (IV). Other IVs are also explored, specifically the fuel prices at the time of the purchase of the vehicle and the average CO_2 emission per kilometer of the fleet of the car manufacturer, but the evidence suggests these to be very weakly correlated with the variable to be instrumented, rendering them weak instruments.

Two main results emerge from our analysis. First, the rebound estimates obtained here for single-vehicle households are in the range of 44 to 71%, which is relatively large compared with evidence from the U.S. , but perfectly in line with earlier German studies (e.g. FRONDEL, RITTER, and VANCE, 2012; and FRONDEL and VANCE, 2013). As these studies do not instrument for efficiency, but rather rely on fuel price elasticities to infer the size of the rebound effect, they cannot formally test whether the response to increased efficieincy is equal in magnitude to the response to increased fuel prices. In this regard, our second key finding is that the magnitudes of the price and efficiency elasticities are statistically indistinguishable: Higher fuel prices reduce driving by the same degree as higher fuel efficiency increases driving, suggesting an offsetting effect of fuel efficiency standards on the effectiveness of fuel taxation.

The following section provides for a concise description of the panel data set. Section 3 offers a concise overview of the common definitions of the direct rebound effect and motivates our choice of definitions for estimation purposes, followed by a description of the estimation method. The presentation and interpretation of the results is given in Section 4. The last section summarizes and concludes.

2 Data

The data used in this research is drawn from the German Mobility Panel (MOP 2013) and covers sixteen years, spanning 1997 through 2012 (see FRONDEL, PETERS, and

VANCE (2008) for more details on this survey). By focusing on single-car households, we abstract from complexities associated with the substitution between cars in multi-vehicle households, thereby obtaining results that are comparable to our former studies. The resulting estimation sample comprises a total of 2,596 observations covering 1,124 households.

Travel survey information, which is recorded at the level of the automobile, is used to derive the dependent and explanatory variables. The dependent variable is given by the total monthly distance driven in kilometers (Table 1). Corresponding to alternate definitions of the rebound effect, elaborated below, the key explanatory variables for identifying the direct rebound effect are efficiency μ and the real price p paid for fuel per liter.[1]

Given an average efficiency of $\mu_d = 15.4$ kilometers per liter for diesel cars versus $\mu_p = 12.5$ kilometers per liter for petrol cars, the well-known fact that the efficiency of diesel cars is substantially higher than that of comparable petrol cars is confirmed by the data. Furthermore, in Germany, diesel fuel is significantly cheaper per liter than petrol due to a lower tax rate of diesel that is about 18 cent less per liter than that of petrol fuel. These are the two major reasons for the fact that the average distance driven is larger for diesel than for petrol cars. To control for potentially further differences between diesel and petrol cars beyond those in fuel prices and fuel efficiencies, which are already captured by the price and efficiency variables μ and p, respectively, we include a diesel dummy as additional regressor.

The suite of additional control variables that are hypothesized to influence the extent of motorized travel encompass, among others, the demographic composition of the household, its income, the surrounding landscape pattern, and dummy variables indicating whether any employed member of the household changed jobs in the preceding year and whether the household undertook a vacation with the car in the year of the survey. The descriptive statistics of the variables and their definitions are presented

[1] The price series was deflated using a consumer price index for Germany obtained from DESTATIS (2012).

in Table 1.

Table 1: Variable Definitions and Descriptive Statistics

Variable Name	Variable Definition	Mean	Std. Dev.
s	Monthly kilometers driven	1,119	686
s_d	Monthly kilometers driven with a diesel car	1,579	839
s_p	Monthly kilometers driven with a petrol car	1,011	595
μ	Fuel efficiency in kilometers per liter	13.1	2.9
μ_d	Efficiency of diesel cars in kilometers per liter	15.4	3.0
μ_p	Efficiency of petrol cars in kilometers per liter	12.5	2.6
p	Real fuel price in € per liter	1.18	0.15
p_d	Real diesel price in € per liter	1.01	0.15
p_p	Real petrol price in € per liter	1.14	0.14
diesel car	Dummy: 1 if the car is a diesel	0.19	–
tax rate	motor vehicle tax rate per 100 cm^3 in € per year	6.66	3.22
# children	Number of children younger than 18 in the household	0.26	0.62
# employed	Number of employed household members	0.75	0.78
income	Real Household income in 1,000 €	2.27	0.79
# high school diploma	Number of household members with a high school diploma	0.62	0.74
job change	Dummy: 1 if an employed household member changed jobs within the preceding year	0.09	–
vacation with car	Dummy: 1 if household undertook vacation with car during the survey period	0.22	–
urban area	percentage of area classified as urban	0.19	0.18
$(mesh_{eff})^{-1}$	landscape fragmentation, see formula (1)	0.95	1.07

The two landscape measures, which are derived from satellite imagery for the years 2000 and 2006 and linked with the MOP data using a Geographic Information System, deserve brief elaboration. Urban area is measured as the percent of area classified in the imagery as urban in the zipcode within which the household resides. We hypothesize that households located in areas characterized by a larger share of urban area are less dependent on the automobile because of the shorter travel distances separating origin from destination for standard activities like shopping, recreation and work. The second landscape metric is a measure of landscape pattern commonly used in ecology:

$$\text{mesh}_{eff} = \frac{1}{A_{total}} \sum_{1}^{n} A_i^2, \tag{1}$$

where the subscript i indexes the patch and A_i measures its area. As described further in JAEGER (2000), the effective mesh size defined by (1) provides a quantitative expression of landscape connectivity, one that has been widely implemented by various European countries as an indicator for environmental monitoring (EEA, 2011b). In our estimations we use the inverse of the effective mesh size, interpreted by ecologists as a measure of landscape fragmentation. The sign of this variable is ambiguous. To the extent that fragmented landscapes reflect a mix of uses, they may reduce car travel by decreasing the distance between destinations serving different purposes. Conversely, this variable may be positively associated with car travel given that highly fragmented landscapes typically necessitate longer travel distances over circuitous routes.

3 Methodological Issues

Following SORRELL and DIMITROUPOULOS (2008), there are three conventional definitions of the rebound effect:

> **Definition 1**: $\eta_\mu(s) := \frac{\partial \ln s}{\partial \ln \mu}$, the elasticity of the demand for a particular energy service in the amount of s with respect to energy efficiency μ,[2]

[2] In line with the economic literature (e. g. BINSWANGER, 2001:121), energy efficiency is defined here by

$$\mu = \frac{s}{e} > 0,$$

where the efficiency parameter μ characterizes the technology with which a service demand s is satisfied and e denotes the energy input employed for a service such as mobility. For the specific example of individual conveyance, parameter μ designates fuel efficiency, which can be measured in terms of

Definition 2: $-\eta_{p_s}(s)$, the negative of the elasticity of service demand s with respect to service price $p_s := p_e/\mu$, which is proportional to the energy price p_e for given efficiency μ, and

Definition 3: $-\eta_{p_e}(e)$, the negative of the energy price elasticity of energy demand e.

Definition 1 is the most natural definition of the direct rebound effect (BERKHOUT *et al.*, 2000), as, formally, the service demand response to energy efficiency changes is described by the elasticity of service demand with respect to efficiency. However, due to the likely endogeneity of energy efficiency (SORRELL, DIMITROUPOULOS, SOMMERVILLE, 2009:1361), FRONDEL, RITTER, and VANCE (2012) argue that none of these definitions should be applied[3] and instead suggest a fourth rebound definition that is based on the negative of the energy price elasticity of service demand, $\eta_{p_e}(s)$:

Definition 4:
$$-\eta_{p_e}(s) = -\frac{\partial \ln s}{\partial \ln p_e} . \qquad (2)$$

Although not plagued by potential endogeneity problems, Definition 4 nonetheless rests on a series of strong assumptions that have to be invoked to ensure that it is equivalent to Definition 1. As elaborated by FRONDEL, RITTER, and VANCE (2012), these assumptions are threefold: distance traveled s solely depends on p_s, fuel prices p_e are exogenous, and energy efficiency μ is constant. As a consequence, while simultaneously identifying the rebound effect via Definition 4, here we focus on the most natural Definition 1 of rebound effect and estimate the rebound employing IV methods to cope with the endogeneity of μ.

vehicle kilometers per liter of fuel input. The efficiency definition reflects the fact that the higher the efficiency μ of a given technology, the less energy $e = s/\mu$ is required for the provision of a service. The above efficiency definition assumes proportionality between service level and energy input regardless of the level – a simplifying assumption that may not be true in general, but provides for a convenient first-order approximation of the relationship of s with respect to e.

[3] An extensive discussion on why Definitions 1-3 appear to be inappropriate for both theoretical and empirical reasons can be found in FRONDEL, RITTER, and VANCE (2012).

In line with this focus, we estimate the following model specification, where the logged monthly vehicle-kilometers traveled, $\ln(s)$, is regressed on logged fuel prices, $\ln(p_e)$, logged fuel efficiency, $\ln(\mu)$, and a vector of control variables $\mathbf{x}$ described in the previous section:

$$\ln(s_{it}) = \alpha_0 + \alpha_\mu \cdot \ln(\mu_{it}) + \alpha_{p_e} \cdot \ln(p_{e_{it}}) + \boldsymbol{\alpha}_{\mathbf{x}}^T \cdot \mathbf{x}_{it} + \xi_i + \nu_{it} . \tag{3}$$

Subscripts i and t are used to denote the observation and time period, respectively. ξ_i denotes an unknown individual-specific term, and ν_{it} is a random component that varies over individuals and time. On the basis of this specification and Definition 1, the rebound effect can be identified by an estimate of the coefficient α_μ on the logged fuel efficiency, whereas Definition 4 implies that, if equivalent to Definition 1, the rebound effect can be obtained by the negative estimate of the coefficient α_{p_e} on the logged fuel price.

To estimate the rebound effect via both definitions simultaneously requires an IV approach in which at least one instrumental variable is employed for the likely endogenous variable μ. For an IV approach to be a reasonable identification strategy, any instrumental variable z is required to be correlated with fuel efficiency μ, i. e. $Cov(\mu, z) \neq 0$ (Assumption 1), while it should not be correlated with the error term ε: $Cov(\mu, \varepsilon) = 0$ (Assumption 2), where the components of ε are given by $\varepsilon_{it} := \xi_i + \nu_{it}$. If either of these two identification assumptions is violated, employing z as an instrument for μ is not a viable approach.

Our use of the tax rates per 100 cm^3 cubic capacity would seem to fulfill these requirements, although the second assumption is principally untestable. In Germany and elsewhere in Europe, the declared aim of this lump-sum tax is to privilege cars with low emissions. Hence, the tax rate, whose level depends on carbon dioxide emissions, but is independent of annual driving distances, is negatively correlated with the endogenous variable fuel efficiency, but uncorrelated with mileage. In theory, therefore, the motor vehicle tax rate per 100 cm^3 should be an appropriate instrument, as it should not affect the dependent variable distance driven, nor the error term.

Apart from motor vehicle tax rates per 100 cm^3, we explored additional instruments, such as fuel prices at the time of the purchase of the vehicle and other lagged fuel prices, all of which turned out to be very weakly correlated with fuel efficiency in terms of partial correlation coefficients. This leaves us with a single instrument for a single endogenous variable, thereby obviating the need for over-identification tests. In this just-identified case, alternative estimators, such as two-stage least squares (2SLS) and the more general methods of moments estimator (GMM), reduce to the IV estimator (CAMERON, TRIVEDI, 2009:174,175).

Although the IV estimates should be estimated from a one-stage regression to obtain correct standard errors (WOOLDRIDGE, 2006:526), it is illuminating to conceive the IV estimation as a two-stage estimation procedure. In the first stage of such a two-stage (generalized) least squares (2SLS) panel estimation approach, the following reduced form is estimated using ordinary fixed- or random-effects estimation methods:

$$\ln(\mu_{it}) = \beta_0 + \beta_{p_e} \cdot \ln(p_{e_{it}}) + \beta_z \cdot \ln(z_{it}) + \boldsymbol{\beta}_{\mathbf{x}}^T \cdot \mathbf{x}_{it} + \eta_{it} \, , \tag{4}$$

where vector $\mathbf{x}$ includes the same control variables as in structural equation (3) and z is called the excluded instrument, because z represents our single instrumental variable tax rate that does not appear in (3). On the basis of the predictions $\widehat{\ln(\mu)}$ resulting from the first-stage estimation, the IV estimates are obtained in a second stage by estimating structural equation (3) using the predicted instead of the observed values of $\ln(\mu)$. It bears noting that performing a t- or an F test on the coefficient β_z of the instrument z in the first stage would allow for testing the validity of Assumption 1.

An important drawback of IV estimates is that the related standard errors are likely to be larger than those of the OLS, fixed- or random effects estimates (BAUER, FERTIG, SCHMIDT, 2009:327). That is, if a variable that is deemed to be endogenous were actually to be exogenous, IV estimators would still be consistent, but less efficient than the OLS, fixed- or random effects estimators. Moreover, if an instrument is only weakly correlated with an endogenous regressor, the standard errors of IV estimators are even much larger, so that the loss of precision will be severe. Even worse is that with weak instruments, IV estimates are inconsistent and biased in the same direction as OLS estimates (Chao and Swanson, 2005). Most disconcertingly, as is pointed out by Bound, Jaeger, and Baker (1993; 1995), when the excluded instruments are only weakly correlated with the endogenous variables, the cure in form of the IV approach can be worse than the disease resulting from biased and inconsistent OLS estimates. Given these potential problems, it is reasonable to perform an endogeneity test that examines whether a potentially endogenous variable is in fact exogenous, a question we take up in the following section.

4 Empirical Results

To provide for a reference point for the results obtained from our IV approach, we estimate structural model (3) using ordinary panel estimation methods, thereby ignoring the endogeneity of the fuel efficiency variable. Starting with the fixed-effects estimator, several features bear highlighting. First, noting from the discussion in Section 2 that, according to Definition 4, the rebound effect can be identified by the negative of the coefficient of $\ln(p_e)$, the relevant estimate suggests that some 44% of the potential energy savings due to an efficiency improvement is lost to increased driving (see Table 2). In contrast, on the basis of Definition 1, which recurs on coefficient α_{μ}, the rebound effect is estimated to amount to about 71%. From a statistical point of view, however, both rebound effects, irrespective of whether identified according to Definition 1 or Definition 4, are identical. In fact, at any conventional level, the null hypothesis $H_0 : \alpha_{p_e} = -\alpha_{\mu}$ cannot be rejected, as the test statistic of $F(1; 1, 123) = 3.75$ is less than the corresponding critical value of $F(1; \infty) = 3.84$ at the 5% significance level.

This finding confirms former results obtained by Frondel, Peters, and Vance (2008). The equality of the size of the coefficients α_{μ} and α_{p_e} reflected by H_0 is highly intuitive: for constant fuel prices p_e, *raising* the energy efficiency μ should have the same effect on the service price p_s, and hence on the distance traveled, as *falling* fuel prices p_e given a constant energy efficiency μ. As proponents of efficiency standards argue, a monetary benefit of higher efficiency to motorists is decreased per kilometer costs of driving (EC, 2007). The results from the ordinary fixed-effects estimates indicate that an immediate consequence of this benefit is that motorists drive more.

Table 2: Fixed-Effects Estimation Results for Travel Demand of Single-Vehicle Households.[4]

	Ordinary		IV Approach			
	Fixed Effects		1. Stage OLS		IV Fixed Effects	
	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors
$\ln(p_e)$	** -0.438	(0.109)	-0.033	(0.039)	** -0.439	(0.109)
$\ln(\mu)$	** 0.707	(0.092)	–	–	0.953	(0.543)
dieselfuel	-0.180	(0.105)	** -0.442	(0.069)	-0.231	(0.152)
# children	-0.058	(0.031)	-0.024	(0.016)	0.067	(0.037)
income	0.002	(0.026)	-0.007	(0.009)	0.001	(0.026)
# employed	0.021	(0.030)	-0.012	(0.010)	0.024	(0.031)
# high school diploma	0.024	(0.033)	-0.005	(0.012)	0.022	(0.034)
job change	0.061	(0.035)	** 0.024	(0.013)	0.055	(0.038)
vacation with car	** 0.266	(0.028)	** 0.035	(0.009)	** 0.257	(0.033)
urban area	**-0.931	(0.355)	** 0.133	(0.195)	** -0.961	(0.342)
$(mesh_{eff})^{-1}$	**-1.512	(0.369)	-0.248	(0.171)	** -1.458	(0.340)
tax rate	–	–	**-0.020	(0.004)	–	–
$H_0 : \alpha_{p_e} = -\alpha_\mu$	F(1; 1,123) = 3.75		–		$\chi^2(1) = 0.89$	

Note: * denotes significance at the 5 %-level and ** at the 1 %-level, respectively.
Observations used for estimation: 2,596. Number of Households: 1,124.

With respect to the remaining fixed-effects estimates, it is perhaps not surprising that many are statistically insignificant. This is clearly the result of very low variability of time-persistent variables, such as the number of children or the number of employed household members. Three exceptions are the car vacation dummy and the landscape metrics measuring urban area and landscape fragmentation, the former two of which

[4]To correct for the non-independence of repeated observations from the same households over the years of the survey, observations are clustered at the level of the household, and the presented standard errors are robust to this survey design feature.

have the expected positive and negative signs, respectively. The negative sign on the measure for landscape fragmentation is consistent with the notion of mixed land uses in reducing the need for travel.

Of course, interpretation of all the estimates from the ordinary fixed-effects regression is subject to the caveat that they may be biased from the potential endogeneity of μ. To explore this possibility, we follow WOOLDRIDGE (2006:532) in testing whether the error term η of the first-stage equation explaining efficiency is correlated with the error term ν of the structural equation. Although both η and ν cannot be observed, one can employ the residuals of the first- and second-stage regressions and test whether they are correlated. Alternatively, one can plug the residual $\hat{\eta}$ as an additional regressor into structural equation (3) and test its statistical significance. In fact, this is the essential idea of the DURBIN-WU-HAUSMAN test for endogeneity (CAMERON, TRIVEDI, 2009:183). With a t statistic of 9.47 for the fixed-effects estimation using a cluster-robust covariance estimator, this test clearly rejects the hypothesis that $\ln(\mu)$ is exogenous.

While this outcome suggests the application of the IV-approach, the validity of the approach depends on the strength of our instrument. An initial indication is given by the highly significant coefficient estimate of the motor vehicle tax rate originating from the first-stage regression in the middle column of Table 2. We obtain the expected result that the tax rate is negatively correlated with the fuel efficiency of cars, reflecting the intention of the legislator to privilege cars with low emissions and, hence, high fuel efficiencies. A more formal gauge of the strength of the instrument is given by the rule of thumb of STAIGER and STOCK (1997), according to which the F statistic for the coefficient β_z of the first-stage regression should exceed the threshold of 10 (BAUM, SCHAFFER, STILLMANN, 2007:490, MURRAY, 2006).[5] With an F statistic of $F(1;992) = 17.82$ resulting from the first-stage estimation using a heteroskedasticity-robust covariance estimator, we reject the hypothesis that the second-stage equation is

[5]This rule accounts for the fact that, as BOUND, JAEGER, and BAKER (1995), STAIGER and STOCK (1997) and others have shown, the weak-instruments problem can arise even if the endogenous variables and the excluded instruments are correlated at conventional significance levels of 5 and 1 % and the researcher is using a large sample (BAUM, SCHAFFER, STILLMANN, 2007:489).

weakly identified.[6]

Moreover, the IV approach is based on the assumption that the excluded instruments affect the dependent variable only indirectly, through their correlations with the included endogenous variables. Yet, if an excluded instrument exerts both direct and indirect influences on the dependent variable, the exclusion restriction must be rejected. This can be readily tested by including an excluded instrument as a regressor in the structural equation. Upon adding our instrumental variable z, the tax rate per 100 cm^3, as an additional regressor to the structural model (3), for the fixed-effects estimation, the resulting t statistics amounts to $t = -0.46$ when calculating heteroscedasticity-robust standard errors (not presented). This results does not allow for rejecting the hypothesis that z exerts no effect on the dependent variable, the logged monthly vehicle-kilometers traveled. With random-effects estimations, we come up with the same conclusion.

Turning to the IV regression in the final column, apart from the coefficient estimate of the fuel efficiency variable, the estimates do not differ substantially from those of the ordinary fixed-effects estimation. Specifically, the estimate of -0.439 on the fuel price coefficient shows that the rebound effect identified via Definition 4 is virtually identical to the rebound estimate of 0.438 resulting from the ordinary fixed-effects estimator.

Taking the drastic increase of the standard error of the instrumented variable μ into account – a phenomenon that is rather typical for IV regressions –, the estimate for α_μ of 0.953 is not statistically different from the fixed-effects estimate of 0.707, nor does the low chi-square statistic of $\chi^2(1) = 0.89$ indicate that the equal-size condition given by H_0 is violated. That said, although our instrument passes the test on weak identification, the statistical insignificance of the α_μ suggests that the IV approach is not a successful strategy to identify the direct rebound effect on the basis of the most

[6] In our case of a single endogenous variable, the F statistic on β_z resulting from the first-stage regression (4) using a heteroskedasticity-robust covariance estimator is identical to the more general *rk* statistic of KLEIBERGEN and PAAP (2006), which has to be employed if the assumption of independent and identically distributed (i. i. d.) errors is invalid.

natural Definition 1. This is particularly unfortunate, as this estimation strategy does not hinge on the additional identification assumptions that are required by Definitions 2 to 4 (see Section 2).

A similar pattern of results emerges from the random-effects estimates in Table 3. While the IV estimate for α_μ is not statistically different from zero, the IV estimate of the rebound effect according to Definition 4 is fairly close to that of the ordinary random-effects estimation, which in turn is almost identical to the rebound estimate of 59.8% resulting from Definition 1. Again, for the ordinary random-effects estimation, the null hypothesis $H_0 : \alpha_{p_e} = -\alpha_\mu$ cannot be rejected, suggesting that from an empirical point of view, it is irrelevant whether the rebound effect is identified via Definition 1 or Definition 4.[7]

In sum, although the IV estimates related to efficiency μ are imprecisely estimated, the other estimates of the rebound effect, which lie between 44 and 71%, are quite close to the rebound range of 57 to 67% estimated by FRONDEL, PETERS, and VANCE (2008) for the sub-sample of single-vehicle German households observed between 1997 and 2005 using ordinary panel estimation methods. The range of rebound effects obtained here even fits better to that identified by FRONDEL and VANCE (2013), who estimate rebound effects in the range of 46 to 70% for the sub-sample of single-vehicle households observed between 1997 and 2009. With our ordinary panel estimations thus confirming our former outcomes, we conclude that for IV estimations to be a sensible identification strategy, it seems most likely that the number of observations has to be drastically larger than in our case in order to improve the precision of the IV estimates of the fuel efficiency coefficient.

[7]A key reason for the high elasticities obtained across the models in Tables 2 and 3 might be that the elasticities from household-level data are generally larger than those from aggregate time series data (WADUD, GRAHAM, NOLAND, 2010:65). It also bears noting that much of the research on this topic, particularly that using household level data, is drawn from the US, where elasticity estimates may be lower because of longer driving distances and fewer alternative modes.

Table 3: Random-Effects Estimation Results for Travel Demand of Single-Vehicle Households.

	Random Effects		1. Stage GLS		IV Random Effects	
	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors
$\ln(p_e)$	** -0.573	(0.081)	**-0.091	(0.029)	** -0.541	(0.086)
$\ln(\mu)$	** 0.598	(0.069)	–	–	0.188	(0.158)
dieselfuel	** 0.148	(0.048)	** 0.638	(0.025)	** 0.240	(0.052)
# children	0.018	(0.018)	*-0.018	(0.008)	0.005	(0.023)
income	** 0.061	(0.018)	** -0.022	(0.006)	** 0.048	(0.018)
# employed	** 0.117	(0.018)	-0.003	(0.006)	** 0.118	(0.019)
# high school diploma	0.030	(0.019)	*0.014	(0.006)	0.036	(0.020)
job change	* 0.067	(0.033)	*0.025	(0.011)	* 0.079	(0.032)
vacation with car	** 0.305	(0.024)	** 0.035	(0.007)	** 0.320	(0.023)
urban area	*-0.231	(0.093)	-0.046	(0.030)	** -0.241	(0.090)
$(mesh_{eff})^{-1}$	-0.136	(0.119)	-0.067	(0.044)	-0.146	(0.134)
tax rate	–	–	**-0.030	(0.001)	–	–
$H_0 : \alpha_{p_e} = -\alpha_\mu$	$\chi^2(1) = 0.06$		–		$\chi^2(1) = 4.44$	

Note: * denotes significance at the 5 %-level and ** at the 1 %-level, respectively.
Observations used for estimation: 2,596. Number of Households: 1,124.

5 Summary and Conclusion

Using detailed household travel diary data collected in Germany between 1997 and 2012 and an instrumental variable approach to deal with the endogeneity of fuel efficiency, this article estimates fuel price and efficiency elasticities. The aim is to provide a basis for assessing the policy impacts of both fuel taxes and fuel economy standards on distance traveled, and in the process to generate an estimate of the direct rebound effect, the behaviorally induced offset in the reduction of energy consumption following efficiency improvements. While the IV approach does not provide for any further insights on the size of the rebound effect in individual mobility, most likely due to the very ambitious data requirements of this approach, the estimates resulting from our panel estimations range between 44 to 71% for single-car households, meaning that between 44 to 71% of the potential energy saving from efficiency improvements in Germany is lost to increased driving. We additionally find that the magnitude of the rebound effect is statistically indistinguishable from that of the fuel price elasticity, which suggests that efficiency standards offset the effects of reduced vehicle travel from fuel taxes.

Taken together, these results call into question the effectiveness of both the European Commission's current emphasis on efficiency standards as a pollution control instrument (FRONDEL, SCHMIDT, VANCE, 2011), as well as the U. S. corporate fuel economy (CAFE) standards. While an assessment of welfare effects from fuel taxation and efficiency standards extends beyond the scope of the present study, our findings complement a long of line of simulation studies finding negative welfare impacts from fuel efficiency standards. KARPLUS and colleagues' (2013) recent estimates from a computable general equilibrium model, for example, suggest that fuel efficiency standards are at least six times more expensive than a tax on fuel, verifying other studies that have found massive costs savings from fuel taxes relative to efficiency standards (e.g. AUSTIN, DINAN, 2005; CRANDALL, 1992; KLEIT, 2004). That these studies all originate from the US, where the responsiveness to fuel costs are likely to be low relative to other parts of the globe BRONS et al. (2008), highlights the potential for even costlier welfare consequences in the German context, a point warranting further investigation.

Notwithstanding the political advantages of efficiency standards, whose costs to consumers and the economy are largely obscured, we would argue that the economic logic in favor of standards is wanting given the large rebound effects identified in this study. It is therefore regrettable that European policy-makers have proceeded down this path. Our results suggest that the efficiency standards introduced with the 2009 legislation will blunt what had been a highly effective climate protection policy based on fuel taxation.

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