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CONTENTS
Energy Economics
The determinants of household energy demand in rural Beijing: Can environmentally friendly technologies be effective?
Z. Jingchao and K. Kotani 381
Factors affecting wood energy consumption by U.S. households
N. Song, F.X. Aguilar, S.R. Shifley and M.E. Goerndt 389
Estimation of elasticities for domestic energy demand in Mozambique
M.d.F.S.R. Arthur, C.A. Bond and B. Willson 398
Urban energy transition and technology adoption: The case of Tigrai, northern Ethiopia
Z. Gebreegziabher, A. Mekonnen, M. Kassie and G. Köhlin 410
Measuring the welfare effects of reducing a subsidy on a commodity using micro-models: An application to Kuwait's residential demand for electricity
M.A.M. BuShehri and M.K. Wohlgenant 419
Exploring the potential for energy conservation in French households through hybrid modeling
L.-G. Giraudet, C. Guivarch and P. Quirion 426
Consumer preferences for automobile energy-efficiency grades
Y. Koo, C.S. Kim, J. Hong, I.-J. Choi and J. Lee 446
Contents continued on the outside back cover
Includes the Journal of
Energy Finance and Development
Available online at www.sciencedirect.com
SciVerse ScienceDirect

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Heterogeneity in the rebound effect: Further evidence for Germany

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ABSTRACT

Rebound effects measure the behaviorally induced offset in the reduction of energy consumption following efficiency improvements. Using both panel estimation and quantile regression methods on household travel diary data collected in Germany between 1997 and 2009, this study investigates the heterogeneity of the rebound effect in private transport. With the average rebound effect being in the range of 57% to 62%, our results are in line with a recent German study by Frondel, Peters, and Vance (2008), but are substantially larger than those obtained from other studies. Furthermore, our quantile regression results indicate that the magnitude of estimated fuel price elasticities – from which rebound effects can be derived – depends inversely on the household's driving intensity: households with low vehicle mileage exhibit fuel price elasticities, and hence rebound effects, that are significantly larger than those for households with high vehicle mileage.

1. Introduction

To maintain climate protection policy on track, the European Commission enacted new legislation in 2009 under the auspices of Regulation No. 443/2009, which sets limits on the allowable per-kilometer CO2 emissions of newly registered automobiles. This regulation includes legally codified targets for the maximum CO2 discharges per kilometer that increase with the mass of vehicles. While non-compliance with the allowable emissions will result in heavy fines starting in 2012, the Commission expects that this measure will induce considerable incentives for the development of fuel-saving technologies (Frondel et al., 2011).

Irrespective of the directive's effectiveness in increasing the fuel efficiency of automobiles, a critical issue in gauging its merits concerns how consumers adjust to altered cost of car travel. While higher fuel prices, as implied by soaring oil prices or increased taxes, raise these costs, improved efficiency effectively reduces them, thereby stimulating the demand for car travel. Such demand increases are referred to as the rebound effect, as it offsets – at least partly – the reduction in energy demand that results from an increase in efficiency.

Though the basic mechanism underlying the rebound effect is widely accepted, its magnitude remains a contentious question (e. g., Binswanger, 2001; Brookes, 2000; Greening et al., 2000; Sorrell and Dimitroupoulos, 2008). A survey by Graham and Glaister (2004), for example, cites mean fuel demand elasticities – from which rebound effects can be derived – varying between −0.25 in the short-run and −0.77 in the long-run. More recent work by West (2004) and Frondel et al. (2008), who use household-level pooled and panel data from the U.S. and Germany, puts the estimated rebound effect at the high end of this range, averaging between 87% and 57%, respectively. In a subsequent article, Frondel and Vance (2010a) employ person-, rather than household-level data to investigate individual mobility behavior, finding fuel price elasticity estimates ranging between −0.50 and −0.45.

Aside from differences in the level of data aggregation, with the vast majority of gasoline demand studies being based on aggregate data at the country or sub-national level (Graham and Glaister, 2002:10), and in the estimation methods employed, one major reason for the diverging results of the empirical studies is that there is no unanimous definition of the direct rebound effect. Instead, several definitions have been employed in the economic literature as determined by the availability of price and efficiency data (Sorrell and Dimitroupoulos, 2008). For this reason, Frondel et al. (2008) estimate the rebound effect using three common definitions, and find robust results across both definitions and panel estimation methods.

The major contribution of the present study is to advance this line of inquiry by drawing on travel-diary data collected in Germany between 1997 and 2009 and investigate the heterogeneity of the rebound effect. Inspired by Wadud et al., 2010), who use interaction terms to examine heterogeneity in the fuel price elasticity of gasoline

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consumption with respect to (1) household income, (2) the existence of both multiple vehicles and (3) multiple earners within a household, we employ both panel estimation and quantile regression methods to capture the heterogeneity in the rebound effect, depending on the households' traveling intensity and other household characteristics.

This research is in line with recent studies suggesting significant heterogeneity in the fuel price sensitivity of different socio-economic groups or geographic areas (e. g. Kayser, 2000; West, 2004; Frondel and Vance, 2010a). It seems plausible, for instance, that low-income households that are located in urban areas may be more sensitive to fuel price changes, since they can more easily switch to other transport modes than households living rural areas. On the other hand, due to income constraints, low-income households may already be driving as little as possible, so that they are unable to further reduce their driving level, resulting in a low fuel price elasticity (Kayser, 2000).

Using data from the German Mobility Panel, this study builds on this empirical literature and the recent analysis of direct rebound effects by Frondel et al. (2008) in several respects. First, the robustness and sensitivity of the results of the former study is checked by employing four additional waves of data for the years 2006 to 2009. Second, expanding on the single-car focus of Frondel et al. (2008), the data set analyzed here includes multiple-vehicle households, thereby allowing us to explore the sensitivity of the estimates to their inclusion. Third, we add a fourth definition of the rebound effect relying on the fuel price elasticity of travel demand and argue that for empirical reasons, the rebound should be preferably estimated on this basis. Finally, in addition to providing for average effects across all types of households, which serve as a reference point, the estimates using quantile regression methods indicate that the magnitude of the estimated rebound effect depends inversely on the household's driving intensity: households with low vehicle mileage exhibit rebound effects that are significantly larger than those for households with high vehicle mileage.

The following section provides for a discussion on the choice of either of the common definitions of the direct rebound effect for estimation purposes. Section 3 presents a concise description of quantile regression approaches, building the basis for the empirical estimation. Section 4 describes the panel data base used in the estimation, followed by the presentation and interpretation of the results in Section 5. The last section summarizes and concludes.

2. A variety of rebound definitions

Along the lines of Sorrell and Dimitroupoulos (2008), we now catalogue three widely known definitions of the *direct* rebound effect that are based on elasticities with respect to changes of either efficiencies, service- or fuel prices. First, the most natural definition of the direct rebound effect is based on the elasticity of the demand for a particular energy service, such as conveyance, with respect to efficiency (see e. g. Berkhout et al., 2000). This definition reflects the relative change in service demand s due to a percentage increase in efficiency μ[1]:

$$\text{Definition } 1: \eta_\mu(s) := \frac{\partial \ln s}{\partial \ln \mu}, \tag{1}$$

[1] 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 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.

Second, instead of $\eta_\mu(s)$, empirical estimates of the rebound effect are frequently based on the negative of the price elasticity of service demand, $\eta_{p_s}(s)$ (e.g. Binswanger, 2001). As is shown, e. g., by Frondel et al. (2008:161), both rebound definitions are equivalent if, first, fuel prices p_e are exogenous and, second, service demand s solely depends on the service price $p_s := p_e/\mu$, which is proportional to the fuel price p_e:

$$\text{Definition } 2: \eta_\mu(s) = -\eta_{p_s}(s). \tag{2}$$

That the rebound may be captured by $-\eta_{p_s}(s)$ reflects the fact that the direct rebound effect is, in essence, a price effect, which works through shrinking service prices p_s.

Third, empirical estimates of the rebound effect are sometimes necessarily based on the negative own-price elasticity of fuel consumption, $-\eta_{p_e}(e)$, rather than on $-\eta_{p_s}(s)$, because data on fuel consumption and fuel prices is more commonly available than on service demand and service prices.

$$\text{Definition } 3: \eta_\mu(s) = -\eta_{p_e}(e). \tag{3}$$

Definitions 2 and 3, however, are only equivalent if the energy efficiency μ is constant (Frondel et al., 2008:161). That is, the rebound definition given by $-\eta_{p_e}(e)$ is equivalent to that given by $\eta_\mu(s)$ only if three preconditions hold true: (1) fuel prices p_e are exogenous, (2) service demand s solely depends on the service price p_s, and (3) efficiency μ is constant.

To analyze the heterogeneity of the rebound effect across households exhibiting a variety of socio-economic characteristics, we focus here on a fourth definition that is given by the negative of the fuel price elasticity $\eta_{p_e}(s)$ of the demand for transport services s. This focus is warranted for several reasons. First, while the most natural definition of the direct rebound effect is based on the elasticity of transport demand to efficiency μ (see Definition 1), this definition is frequently not applicable, because in many empirical studies efficiency data is not available or the data provides only limited variation in efficiencies (Sorrell et al., 2009:1359).

Even more disconcerting is that observed efficiency increases may be endogenous, rather than reflecting autonomous efficiency improvements. This is the case, for instance, if a more efficient car is purchased in response to a job change that results in a longer commute. Hence, due to the likely endogeneity of fuel efficiency (see e. g. Sorrell et al., 2009:1361), it would be wise to refrain from including this variable in any model specification aiming at estimating the response to fuel price effects, as fuel efficiency may be a bad control (Angrist and Pischke, 2009:63).[2]

Rather than excluding μ from the analysis, alternative approaches are to estimate simultaneous equations systems that explain vehicle miles traveled, fuel efficiency, and vehicle numbers at once or instrument variable (IV) estimations. As we have no instrument at hand, we are unable to employ IV methods to cope with the endogeneity of μ, nor are we able to estimate simultaneous equations systems due to data unavailability. In effect, we instead pursue the reduced form of such a simultaneous equations system.

Another problem emerging from the likely endogeneity of the efficiency μ is that it contaminates the rebound definition based on the negative of the service demand elasticity $\eta_{p_s}(s)$ with respect to service price p_s, which is given by $p_s = p_e/\mu$. This highlights a handicap of Definition 2, namely that service prices represent a conglomerate of

[2] Equally important with respect to fuel price responses is to note that if technical fuel efficiency were to be included in the estimation specification, the analysis is conditional on being locked to the same vehicle, thereby holding technical efficiency constant. This implies that only one scenario of responses to fuel prices is all that is allowed, that of driving the same car, whereas driving behavior will change for numerous reasons in case of fuel price increases, most importantly due to the purchase of a new, more efficient car.

efficiency and fuel prices, while more meaningful estimates of the rebound are based on estimations in which fuel-price and efficiency effects are strictly separated.

The rebound definition that is based on the own-price elasticity of fuel consumption, $\eta_{p_e}(e)$, is the most restrictive of these three definitions, as it requires the validity of three preconditions, rather than merely two of them, as is the case with rebound definition $-\eta_{p_s}(s)$. Furthermore, in contrast to transport service demand s, the dependent variable e underlying definition $-\eta_{p_e}(e)$ explicitly depends on efficiency μ. For example, fuel consumption e would *ceteris paribus* reduce to half if efficiency μ were to be doubled. This example illustrates that the likely endogenous variable μ needs to be included in any model specification for estimating $\eta_{p_e}(e)$, thereby potentially biasing the empirical results.

For these reasons, we focus here on a fourth rebound definition that is based on the negative of the fuel price elasticity of transport demand, $\eta_{p_e}(s)$:

$$\text{Definition 4}: \eta_{\mu}(s) = -\eta_{p_e}(s). \tag{4}$$

It can be shown that $-\eta_{p_e}(s)$ is equivalent to $\eta_{\mu}(s)$ under the same assumptions as the rebound definition given by $-\eta_{p_e}(e)$.

In sum, although theory would favor estimating the efficiency elasticity $\eta_{\mu}(s)$ to capture the rebound, the most promising empirical, but indirect way to elicit the rebound effect is based on the estimation of fuel price elasticities, as fuel prices typically exhibit sufficient variation and, in contrast to fuel efficiency, can be regarded as parameters that are largely exogenous to individual households. Among these fuel price elasticities, the discussion provided in this section suggests selecting the fuel price elasticity of transport demand, $\eta_{p_e}(s)$, that is, Definition 4 for estimating the rebound effect. In contrast to the other definitions, fuel efficiency μ is not necessarily relevant for estimation the rebound according to Definition 4, so that it cannot be undermined by μ's likely endogeneity.

3. Methodology

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

$$ln(s_{it}) = \alpha_0 + \alpha_{p_e} \cdot ln(p_{eit}) + \alpha_{\mathbf{x}}^T \cdot \mathbf{x}_{it} + \xi_i + \nu_{it}. \tag{5}$$

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, Definition 4 tells us that the rebound effect is obtained by the negative estimate of the coefficient α_{p_e} of the logged fuel price. For the sake of comparison, Section 5 also presents the results of those specifications that pertain to the Definitions 1–3, differing from (5) in either the dependent variable (Definition 3) or the inclusion of efficiency μ (Definition 1), or the inclusion of service price p_s (Definition 2), rather than the fuel price p_e.

To provide a reference point for the results obtained from the quantile regression approach, we estimate specification (5) using panel estimation methods (see e. g. Frondel and Vance, 2010b, for a discussion). While the fixed-effects estimator may be a potential alternative, we choose to employ random-effects methods, as the fixed-effects estimator fails to efficiently estimate the coefficients of time-persistent variables, i. e. , variables that do not vary much within a household over time (Wadud et al., 2010:55). Not least, random-effects methods also allow for the estimation of coefficients of time-invariant variables, which is precluded by the fixed-effects estimator.

One potentially restrictive feature of both OLS and panel estimation methods is that they focus on the conditional expectation function (CEF),

$$E(ln(s_{it}|p_e, \mathbf{x}_{it})) = \alpha_0 + \alpha_{p_e} \cdot ln(p_{eit}) + \alpha_{\mathbf{x}}^T \cdot \mathbf{x}_{it}, \tag{6}$$

thereby yielding a uniform rebound effect given by the negative of the coefficient α_{p_e}. Quantile regression approaches, by contrast, aim at providing a more complete picture of the relationship between the dependent variable and the regressors at different points in the conditional distribution of the dependent variable, which allows for more flexibility in the estimation of rebound effects:

$$Q_{\tau}(ln(s_{it}|p_e, \mathbf{x}_{it})) = \alpha(\tau) + \alpha_{p_e}(\tau) \cdot ln(p_{eit}) + \alpha_{\mathbf{x}}^T(\tau) \cdot \mathbf{x}_{it} + F_{\varepsilon_{it}}^{-1}(\tau), \tag{7}$$

where τ may take on values between zero and unity and specifies the percentile in the distribution of distance traveled. $Q_{\tau}(.|.)$ denotes the conditional quantile function (CQF), $F_{\varepsilon_{it}}{}^{-1}(.)$ is the inverse of the distribution function of ε_{it}, and $\alpha_{p_e}(\tau)$ indicates the variability in the households' responses to fuel price changes, depending upon the level of distance traveled. In short, the most attractive feature of quantile regression methods is that they generally provide for a richer characterization of the data, as these methods allow us to study the impact of a regressor such as fuel prices on the full distribution of the dependent variable or any particular percentile, not just the conditional mean.

For $\tau = 0.5$, for instance, $Q_{0.5}(ln(s|p_e, \mathbf{x})$ designates the median of the logged distance traveled conditional on fuel prices p_e and covariates $\mathbf{x}$. In this special case of a median regression, estimates of the parameters of quantile regression model (7) result from the minimization of the sum of the absolute deviations, $\left|Q_{0.5} - \hat{Q}_{0.5}\right|$, where $\hat{Q}_{0.5}$ denotes the prediction for the dependent variable based on the median regression. This is perfectly in line with the well-known statistical result that it is the median that minimizes the sum of the absolute deviations of a variable, whereas it is the mean that minimizes the sum of squared residuals, being a special case of OLS estimation. It is also well-known that the median is more robust to outliers than the mean. This property translates to both median and quantile regressions in general, which have the advantage that they are more robust to outliers than OLS regression methods. In fact, OLS regressions can be inefficient when the dependent variable has a highly non-normal distribution.[3]

More generally, for arbitrary $\tau \in (0,1)$, the parameter estimates are obtained by solving the following weighted minimization problem:

$$\min_{\alpha(\tau), \alpha_{p_e}(\tau), \alpha_{\mathbf{x}}^T(\tau)} \sum_{r_i > 0} \tau \cdot |r_i| + \sum_{r_i < 0} (1 - \tau) \cdot |r_i|, \tag{8}$$

where underpredictions $r_i := Q_{\tau}(y_i|\mathbf{x}_i) - \hat{Q}_{\tau}(y_i|\mathbf{x}_i) > 0$ are penalized by τ and overpredictions $r_i < 0$ by $1 - \tau$. This is reasonable, as for large τ one would not expect low estimates $\hat{Q}_{\tau}$ and vice versa, so that these incidences have to be penalized accordingly. Just as OLS fits a linear function to the dependent variable by minimizing the expected squared error, quantile regression fits a linear model using the generally asymmetric loss function $\rho_{\tau}(r) := 1(r > 0) \cdot \tau \cdot |r| + 1(r \le 0) \cdot (1 - \tau) \cdot |r|)$, where $r := Q_{\tau} - \hat{Q}_{\tau}$ and the indicator function $1(r > 0)$ indicates positive residuals r and $1(r \le 0)$ non-positive residuals, respectively. Loss function $\rho_{\tau}(r)$ is also called a "check function", as its graph looks like a check-mark. Minimization problem (8) is set

[3] Further, rather theoretical advantages of quantile regression methods are, first, that, unlike OLS, quantile regression estimators do not require the existence of the conditional expected value for consistency. Second, quantile regression is equivariant to monotone transformations. That is, the quantiles of any monotone transformation $h(y)$ of y equal the transformed quantiles of y: $Q_{\tau}(h(y)) = h(Q_{\tau}(y))$. This property generally does not hold for the mean: $E(h(y)) \neq h(E(y))$.

up as a linear programming problem and can thus be solved by linear programming techniques (Koenker, 2005). Variances can be estimated using a method suggested by Koenker and Bassett (1982), but bootstrap methods are often preferred and are used here.

Conditional on p_e and $\mathbf{x}$, the CQFs given by Eq. (7) depend on the distribution of ε_{it} via $F_{\varepsilon_{it}}{}^{-1}(\tau)$. In the special case that errors are independent and identically distributed, that is, if $F_{\varepsilon_{it}}{}^{-1}(\tau)=F_{\varepsilon}^{-1}(\tau)$ and, hence, the inverse distribution function does not vary across observations, the CQFs exhibit common slopes, $\alpha_{p_e}(\tau)=\alpha_{p_e}$ and $\alpha_{\mathbf{x}}(\tau)=\alpha_{\mathbf{x}}$, differing only in the intercepts: $\alpha(\tau)+F_{\varepsilon}^{-1}(\tau)$. In this case, there is no need for quantile regression methods if the focus is on marginal effects, as these are given by the invariant slope parameters. In general, however, the CQFs Q_τ will differ at different values τ in more than just the intercept and may well be even non-linear in $\mathbf{x}$. This may be the case if, for example, errors are heteroscedastic, which will be tested for our empirical example presented in Section 5.

4. Data

The data used in this research is drawn from the MOP (German Mobility Panel, 2011), an ongoing travel survey that was initiated in 1994. The panel is organized in overlapping waves, each comprising a group of households surveyed for a period of six weeks in the spring for three consecutive years. All households that participate in the survey are requested to fill out a questionnaire eliciting general household information, person-related characteristics, and relevant aspects of everyday travel behavior. In addition, respondents record the price paid for fuel, the liters of fuel consumed, and the kilometers driven with each visit to a gas station and for every car in the household.

The data used in this paper cover thirteen years, spanning 1997 through 2009, a period during which real fuel prices rose 1.97% per annum on average. The resulting sample includes 2165 households, 962 of which appear one year in the data, 474 of which appear two years and 729 of which appear three consecutive years. Altogether, we are faced with 4097 observations. We use the travel survey information, which is recorded at the level of the automobile, to derive the dependent and explanatory variables required for estimating each of the four variants of the rebound effect. The two dependent variables, which are converted into monthly figures to adjust for minor variations in the survey duration, are the total monthly distance driven in kilometers (Definitions 1, 2 and 4) and the total monthly liters of fuel consumed (Definition 3). The three explanatory variables for identifying the direct rebound effect are the kilometers traveled per liter (Definition 1), the price paid for fuel per kilometer traveled (Definition 2), and the fuel price per liter (Definitions 3 and 4).[4]

The suite of control variables selected for inclusion in the model measure the socio-economic attributes that are hypothesized to influence the extent of motorized travel. These capture the demographic composition of the household, its income, the surrounding population density, and dummies indicating the availability of multiple cars, whether the household undertook a vacation with the car during the survey period, and whether any employed member of the household changed jobs in the preceding year. Table 1 contains the definitions and descriptive statistics of all the variables used in the modeling.

Table 1
Variable definitions and descriptive statistics.

Variable name	Variable definition	Mean	Std. Dev.
s	Monthly kilometers driven	1546	1146
e	Monthly fuel consumption in liters	94.01	62.86
μ	Kilometers driven per liter	12.97	2.99
p_s	Real fuel price in € per kilometer	0.08	0.02
p_e	Real fuel price in € per liter	1.01	0.15
# driving licences	Number of driving licences in a household	1.76	0.75
# employed	Number of employed household members	1.03	0.86
vacation with car	Dummy: 1 if household undertook vacation with car during the survey period	0.20	–
children	Dummy: 1 if children younger than 18 live in a household	0.33	–
job change	Dummy: 1 if an employed household member changed jobs within the preceding year	0.13	–
income	Real Household income in 1,000 €	2,500	803
multi-car households	Dummy: 1 if an household has more than one car	0.35	–
population density	People in 1,000 per square km in the county in which the household is situated	0.834	1.004

5. Empirical results

To provide for a reference point for the results obtained from a quantile regression, we first report in Table 2 the random-effects estimates of the model specifications corresponding to the four rebound definitions presented in Section 2. In line with our reasoning in Section 3, we refrain from reporting the fixed-effects estimates, which are largely similar to the estimated random effects for the fuel prices, but are statistically insignificant for almost all other variables included; this is clearly the result of very low variability of time-persistent variables, such as the presence of children or the number of licensed drivers. Not surprisingly, a Hausman test rejects the equality of the random- and fixed-effects coefficients.[5]

Moreover, we perform the classical Breusch and Pagan (1979) test to examine the superiority of the random-effects model over an OLS estimation using pooled data. The test statistic $\chi^2(1)=45.1$ of this Lagrange multiplier test clearly rejects the null hypothesis of no heterogeneity among households, $H_0: Var(\xi_i)=0$, which is also confirmed by the test statistics that result if the normality assumption underlying the Breusch–Pagan test is dropped. According to the discussion of Section 3, these test results of heterogeneity also indicate that quantile regression methods may provide for insights that go beyond those given by both the OLS and random-effects estimates (Koenker and Hallock, 2001:152).

Several features of the results presented in Table 2 bear highlighting. First, while we prefer the model specification related to Definition 4 for reasons presented in Section 2, its estimated rebound effect of 57% is similar to that of Definitions 1 and 2, suggesting that some 57% of the potential energy savings due to an efficiency improvement is lost to increased driving. Particularly small is the difference in the estimated coefficient of $ln(p_e)$ for the model specifications pertaining to Definition 1 and 4, which solely differ in the inclusion of the likely endogenous variable efficiency.

Second, also of note is that the estimates fit to the range of 58% to 59% estimated by Frondel et al. (2008) for the sub-sample of single-vehicle German households observed between 1997 and 2005. Not least, it bears noting that the estimated rebound effects and fuel price elasticities are considerably higher than many estimates reported elsewhere in the literature. A key reason for this outcome is that the elasticities from household-level data are generally larger than those from aggregate time-series data (Wadud et al., 2010:65). In fact, the fuel price elasticity of travel demand of −0.57 fits well to the results of numerous household-level studies reported by Wadud et al. (2010:69).

Third, with a magnitude of about −0.9, the elasticity estimate of fuel consumption with respect to fuel price changes, and hence

[4] The price series was deflated using a consumer price index for Germany obtained from DESTATIS (2010).

[5] Following the method presented in Frondel and Vance (2010b), we also implemented a modified Hausman test that allows comparison of individual coefficients between the fixed- and random effects estimators. Using this test, we failed to reject the equality of the coefficients of the variables $ln(p_e)$, $ln(p_s)$, and $ln(\mu)$.

Table 2
Random-effects estimates for the rebound based on Definitions 1 to 4[a].

Dependent variable	Definition 1		Definition 2		Definition 3		Definition 4	
	$ln(s)$		$ln(s)$		$ln(e)$		$ln(s)$	
	Coefficients	Std. Errors	Coefficients	Std. Errors	Coefficients	Std. Errors	Coefficients	Std. Errors
ln(p_e)	**−0.555	(0.062)	–	–	**−0.903	(0.067)	**−0.574	(0.063)
ln(p_s)	–	–	**−0.459	(0.040)	–	–	–	–
ln(μ)	**0.418	(0.051)	–	–	**−0.529	(0.057)	–	–
children	**0.077	(0.027)	** 0.080	(0.027)	** 0.084	(0.028)	*0.065	(0.027)
logged income	**0.094	(0.032)	** 0.101	(0.032)	*0.082	(0.034)	*0.077	(0.032)
# driving licenses	**0.084	(0.019)	** 0.085	(0.019)	*0.035	(0.017)	** 0.079	(0.019)
# employed	**0.125	(0.016)	** 0.125	(0.016)	** 0.108	(0.016)	** 0.128	(0.016)
job change	0.044	(0.028)	0.044	(0.028)	0.050	(0.030)	0.051	(0.029)
vacation with car	**0.248	(0.020)	** 0.249	(0.020)	** 0.340	(0.021)	**0.252	(0.020)
population density	**−0.068	(0.013)	**−0.068	(0.013)	**−0.055	(0.013)	**−0.073	(0.013)
multi-car households	**0.444	(0.028)	** 0.444	(0.028)	**−0.091	(0.028)	** 0.456	(0.028)
constants	**6.782	(0.246)	** 6.819	(0.245)	** 2.423	(0.259)	** 6.059	(0.235)
Observations used	4,097		4,097		4,097		4,097	

*denotes significance at the 5%-level and ** at the 1%-level, respectively.

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

rebound Definition 3, is much larger than the respective elasticity estimates of kilometers traveled. This estimate replicates a result commonly found in the literature: that the fuel price has a much stronger influence on fuel consumption than on the number of kilometers driven (Graham and Glaister, 2004:272).

Fourth, from estimating the specification associated with Definition 1, it follows that the impact of efficiency improvements on traveled distance is of the same order as the effect of lowered fuel prices. In fact, with a test statistic of $\chi^2(1)=2.77$, we cannot reject the null hypothesis $H_0: \alpha_\mu = -\alpha_{p_e}$ for a significance level of 5%. The assumption underlying H_0 is intuitive and frequently invoked in the literature, but rarely tested (Sorrell et al., 2009:1360): for constant fuel prices p_e, *raising* 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 efficiency μ. Hence, there is no reason, neither on a theoretical nor an empirical basis, to assume that Definitions 1 and 2 yield divergent results for the rebound effect.

Ultimately, while Definition 1 would suggest a rebound effect of 42%, from a statistical point of view provided by testing H_0, it is equally warranted to take the negative of the fuel price elasticity estimate, i. e. 0.56, as an estimate of the rebound effect, indicating that the rebound estimates are of a similar magnitude across all definitions except for Definition 3. As the comparison of the estimates from Definitions 1 and 4 reveals, omitting the likely endogenous variable μ has hardly any effect on the estimation results, particularly on the fuel price coefficient estimates. The empirical reason for this outcome is that efficiency μ and contemporaneous real fuel prices p_e are virtually uncorrelated, with an empirical correlation coefficient of -0.015.

To further analyze the robustness of our results and accommodate potential sources of heterogeneity in the estimated fuel price elasticities and rebound effects, several additional models were explored. We began by estimating the same specifications, but limiting the sample to single-car households. The estimation results reported in Table 3 indicate that the travel demand responsiveness of single-car households to fuel prices is somewhat more pronounced than that for the whole sample including multi-car households. The lower responsiveness of multi-car households may be explained by the fact that their household members are able to choose among the most efficient cars for their traveling purposes, thereby largely maintaining their travel intensity. This explanation is consistent with our finding that the fuel consumption responsiveness to fuel prices is somewhat reduced, from -0.9 to -0.8, when the sample is limited to single-car households.

There are additional discrepancies emerging from the single-car sample: While the presence of children, for example, positively affects both travel demand and fuel consumption for the whole sample, this variable does not play a significant role in determining the travel behavior of single-car households. This may be due to the fact that these households prioritize car use for commuting, requiring children to use public transport systems more frequently. Conversely, the dummy variable indicating a job change in the previous year has a

Table 3
Random-effects estimates for single-car households.

Dependent variable	Definition 1		Definition 2		Definition 3		Definition 4	
	$ln(s)$		$ln(s)$		$ln(e)$		$ln(s)$	
	Coefficients	Std. errors	Coefficients	Std. errors	Coefficients	Std. errors	Coefficients	Std. errors
ln(p_e)	**−0.676	(0.079)	–	–	**−0.810	(0.078)	**−0.711	(0.082)
ln(p_s)	–	–	**−0.620	(0.050)	–	–	–	–
ln(μ)	**0.594	(0.067)	–	–	**−0.467	(0.072)	–	–
children	0.061	(0.037)	0.062	(0.037)	0.068	(0.036)	0.054	(0.038)
logged income	0.015	(0.035)	0.018	(0.034)	0.007	(0.034)	−0.005	(0.035)
# driving licenses	**0.073	(0.022)	** 0.074	(0.022)	** 0.060	(0.023)	** 0.062	(0.023)
# employed	**0.142	(0.021)	** 0.142	(0.021)	** 0.137	(0.020)	** 0.143	(0.021)
job change	*0.097	(0.040)	* 0.097	(0.040)	** 0.112	(0.039)	*0.107	(0.042)
vacation with car	**0.312	(0.024)	** 0.311	(0.024)	** 0.321	(0.025)	**0.326	(0.026)
population density	**−0.058	(0.015)	**−0.057	(0.015)	**−0.059	(0.015)	**−0.063	(0.015)
constants	**7.711	(0.265)	** 7.737	(0.262)	** 3.064	(0.271)	** 6.645	(0.258)
Observations used	2,660		2,661		2,660		2,660	

* denotes significance at the 5%-level and ** at the 1%-level, respectively.

statistically significant effect only for the single-car households, which substantiates the logic that such households use the car primarily for commuting purposes.

Aside from exploring differences across single- and multi-car households, we followed the lead of Wadud et al. (2010) in investigating heterogeneity of fuel price elasticities by analyzing the heterogeneity of the rebound effect with respect to income, the existence of multiple cars within a household, and residence in rural or urban areas. To this end, each of these variables was interacted with fuel prices to allow for differential elasticities. After exploring several specifications that included the interactions individually and jointly, we found no evidence for statistically significant effects on the interaction terms.

This contrasts with the findings of studies that allow for heterogeneous responses using US data, which have generally uncovered statistically significant differential effects. Kayser (2000), for example, finds that the price elasticity is greater at higher income levels, while West (2004) and Wadud et al. (2010) find greater price responsiveness among low-income households. The absence of heterogeneity found here suggests that poorer households bear a relatively higher burden from fuel price increases than wealthy households.

Yet another source of heterogeneity may relate to driving-intensity itself: to the extent that those who drive more are more dependent on car travel, we would expect them to exhibit less responsiveness to changes in the cost of driving than those who drive less. Drawing on Definition 4, this hypothesis can be tested by referencing the results of a quantile regression, reported in Table 4. In fact, as Table 4 illustrates, there is some substanial heterogeneity in the rebound depending on the households' travel intensity. The fuel price elasticity of about −0.90 in the lowest decile is 61% lower than the estimate of −0.56 in the most upper decile, confirming that the magnitude of the rebound is substantially larger for households that drive less. In this example, an F-test statistic of $F(1;4{,}087)=6.51$ confirms significantly different coefficients at the 5% level.

Moreover, as the F-Test results in Table 5 show, the estimated rebound at the 10%-quantile is significantly different from the respective coefficient estimates from the 40% quantile onwards. Further insight into this pattern can be gleaned from Fig. 1, which shows the quantile regression estimates along with the estimate obtained from a pooled OLS regression. While the lower responsiveness of more car-reliant households to fuel prices changes is clearly evident from the plot of quantile estimates, in statistical terms the degree of heterogeneity appears rather moderate: With some exceptions at the upper and lower ends, most of the point estimates from the quantile regressions fall within the 95% confidence interval of the OLS estimate.

6. Summary and conclusion

Because increases in fuel efficiency effectively decrease the unit cost of driving, their effectiveness in reducing emissions may be offset by increased demand for car travel. Although the existence of this so-called rebound effect has been recognized for some time (Crandall, 1992), there still remains much debate as to its magnitude. With the European Union increasingly relying on efficiency standards as a climate protection tool in the transport sector, this debate has taken on increased relevancy.

Drawing on household-level data from Germany, the present study employs panel and quantile regression techniques to estimate the magnitude of the rebound effect, as well as to explore the degree of its heterogeneity across households. Contrasting with Wadud et al.'s (2010) analysis of US-based data, we find no evidence for differential rebound effects by income level, geographical location, or the number of cars owned. Results from the quantile regression, however, do suggest some heterogeneity according to driving intensity, with the estimated rebound ranging from a low of 50% in the 80%-quantile to a high of 90% in the 10%-quantile. Evidently, reduced travel cost causes households with an already high demand for automotive service to extend their demand to a lesser degree than households with low automotive mobility.

From a policy perspective, the fact that the estimated rebound is relatively high irrespective of driving intensity calls into question the effectiveness of efficiency standards as a pollution control instrument. Specifically, the median regression rebound estimate amounts to 62%, which is just slightly higher in magnitude than the estimate of 57% from the corresponding random-effects specification. Moreover, these rebound estimates are virtually of the same order as those obtained by Frondel et al. (2008), who used an abridged version of the current data set that extended to the year 2005. Since that time, annually averaged fuel prices climbed another 9% to reach a peak in 2008, followed by a drop of 9% in the following year (ARAL, 2011). These fluctuations appear to have had no bearing on a key conclusion emerging from the data, namely that some 60% of the potential energy saving from efficiency improvements in Germany is lost to increased driving.

Table 5
F-tests for identical decile coefficients for the rebound effect.

Quantiles	10%	20%	30%	40%	50%	60%	70%	80%	90%
10%	–	–	–	–	–	–	–	–	–
20%	1.47	–	–	–	–	–	–	–	–
30%	3.54	1.34	–	–	–	–	–	–	–
40%	* 4.01	1.78	0.37	–	–	–	–	–	–
50%	** 6.66	* 4.06	2.51	1.63	–	–	–	–	–
60%	** 8.58	* 5.87	* 4.22	3.21	1.22	–	–	–	–
70%	** 8.18	* 5.44	* 4.03	3.04	1.12	0.13	–	–	–
80%	**11.15	** 8.00	* 6.58	* 5.12	3.26	1.60	1.26	–	–
90%	* 6.51	3.73	2.27	1.42	0.42	0.01	0.02	0.93	–

* denotes significance at the 5%-level and ** at the 1%-level, respectively. The critical values are $F(1;4{,}087)=3.84$ and $F(1;4{,}087)=6.66$, respectively.

Table 4
Quantile regression results for the specification related to Definition 4.

	$Q_{10}(ln(s))$		$Q_{30}(ln(s))$		$Q_{70}(ln(s))$		$Q_{90}(ln(s))$	
	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors
$ln(p_e)$	**−0.898	(0.116)	**−0.714	(0.076)	**−0.551	(0.080)	**−0.561	(0.088)
children	** 0.129	(0.045)	* 0.060	(0.029)	−0.015	(0.032)	−0.048	(0.033)
logged income	0.050	(0.068)	** 0.183	(0.042)	** 0.170	(0.045)	0.071	(0.049)
# driving licenses	**0.197	(0.035)	** 0.103	(0.018)	0.024	(0.019)	0.032	(0.021)
# employed	**0.208	(0.031)	** 0.160	(0.016)	** 0.149	(0.018)	** 0.129	(0.021)
job change	−0.053	(0.055)	** 0.079	(0.035)	** 0.107	(0.031)	** 0.099	(0.042)
vacation with car	**0.380	(0.044)	** 0.332	(0.026)	** 0.249	(0.027)	** 0.152	(0.030)
inhabitant density	**−0.081	(0.015)	**−0.078	(0.011)	**−0.060	(0.015)	**−0.043	(0.013)
multi-car households	**0.377	(0.046)	** 0.465	(0.029)	** 0.478	(0.032)	** 0.539	(0.038)
constants	**5.203	(0.478)	** 4.902	(0.307)	** 5.746	(0.330)	** 6.880	(0.358)

* denotes significance at the 5%-level and ** at the 1%-level, respectively. Standard errors are calculated using bootstrap methods. The panel structure of the data is not exploited, as panel quantile methods are fairly new. Observations used: 4,097.

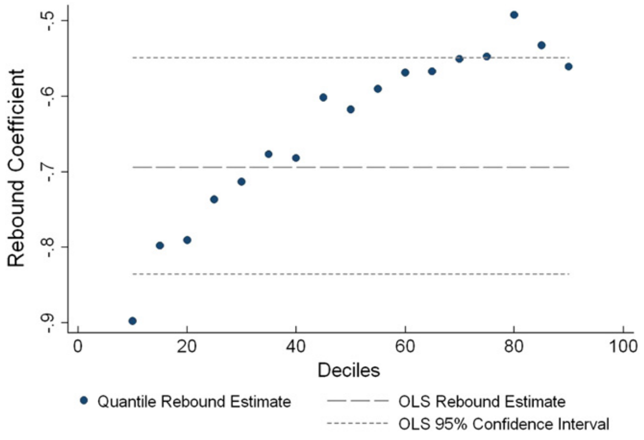

Fig. 1. Comparison of the OLS and quantile regression results for the rebound effect according to Definition 4.

On the basis of these findings, the European Commission's expressed reservations with reliance on fuel excise taxes (COM, 2007) coupled with a corresponding emphasis on per-kilometer emissions reductions as a key instrument for reducing total emissions from transport should be met with skepticism. We would instead concur with Sterner (2007) that fuel taxes should continue to play an important role in climate policy, but should potentially be coupled with other measures that reduce the burden to the poor, such as lower payroll taxes. Unlike fuel efficiency standards, fuel taxes directly confront motorists with the cost of driving, which not only encourages the purchase of more fuel-efficient vehicles, but also has an immediate impact on driving behavior.

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