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# Do High Oil Prices Matter?

## Evidence on the Mobility Behavior of German Households

#72

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# Do High Oil Prices Matter? – Evidence on the Mobility Behavior of German Households

Abstract
Focusing on travel survey data from Germany, this paper investigates the determinants of automobile travel, with the specific aim of quantifying the effects of fuel prices and fuel economy. The analysis is predicated on the notion that car mileage is a two-stage decision process, comprising the discrete choice of whether to own a car and the continuous choice of distance traveled. To capture this process, we employ censored regression models consisting of Probit and OLS estimators, which allows us to gauge the extent to which sample selectivity may bias the results. Our elasticity estimates indicate a significant positive association between increased fuel economy and increased driving, and a significantly negative fuel-price elasticity, which ranges between –35% and –41%. Taken together, these results suggest that fuel taxes are likely to be a more effective policy measure in reducing emissions than fuel-efficiency standards.

JEL Classification: D13, Q41

Keywords: Automobile travel, rebound effect, two-part model

October 2008

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# 1 Introduction

In Europe, as elsewhere in the industrialized world, the question of how motorists respond to oil prices is a priority concern of environmental policy. Private automobiles not only account for 12% of the European Union's CO2 emissions (EC 2007), but are also responsible for a range of other negative externalities, including noise pollution, congestion, and accidents. For several decades, European governments have relied heavily on fuel taxation both for raising revenues and as a disincentive to drive, with fuel taxes accounting for upwards of 75% of the price that Europeans pay at the pump. More recently, the European Commission (EC) has turned its attention to efficiency standards to lessen the environmental impact of cars, and is currently considering a legislative framework that would reduce average emissions to 120g CO2/km by 2012.

A critical question in gauging the merits of such policy measures concerns how consumers adjust to the unit costs of energy services such as 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. This demand increase is referred to as the rebound effect, as it offsets the original 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.

A survey by GOODWIN, DARGAY, and HANLY (2004), for example, cites fuel-price elasticities - from which rebound effects can be derived - varying between 4% and 89% based on both short- and long-run estimates from studies using pooled cross-section/time series data. More recent work by WEST (2004) and FRONDEL, PETERS, and VANCE (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. At the other end, SMALL and VAN DENDER (2007) uncover rebound effects varying between 2.2% and 15.3%, using a pooled cross-section of U. S. states for 1966-2001.

To date, the empirical literature on vehicle use has identified the rebound effect almost exclusively via fuel-price elasticities, thereby relying on the assumption that both rebound and price effects are simply two sides of the same coin: behavioral changes due to varied unit costs of energy services such as car traveling. Furthermore, the majority of empirical attempts to estimate price and, hence, rebound effects have drawn on country-level data or data aggregated at sub-national administrative districts, with a smaller pool of studies relying on household data.

The present study seeks to advance this line of inquiry by estimating econometric models of car use on a panel of travel-diary data collected in Germany between 1997 and 2006. The study completes a recent analysis of elasticity estimates by FRONDEL, PETERS, and VANCE (2008) in two distinct respects. First, two dimensions of car use are considered: the discrete decision to own a car and the continuous decision of distance traveled. Because these decisions are related and, moreover, may be influenced by factors unobservable to the researcher, we explore alternative specifications using censored regression techniques to assess whether the results are subject to biases emerging from sample selectivity. Second, expanding on the single-car focus of FRONDEL, PETERS, and VANCE (2008), the data set analyzed here includes multiple-car-owning households, thereby allowing us to explore the sensitivity of the estimates to their inclusion.

Our results, which range between 35% and 52%, indicate rebound and price effects that are substantially larger than the typical effects obtained from U.S. based studies, but that are lower than the 57% to 67% range identified by FRONDEL, PETERS, and VANCE (2008). Given the magnitude of the estimates, we conclude that our findings call into question the efficacy of policies targeted at reducing energy consumption via technological efficiency. Instead, these results suggest raising prices via fuel taxes to be a promising energy conservation and climate protection measure.

The following section describes the data base used in the estimation. Section 3 presents the definitions of the key variables and draws on BECKER's household production framework to prove the direct rebound effect. Section 4 describes the econometric models specified for estimating both mobility behavior as well as the rebound effect, followed by the presentation and interpretation of the results in Section 5. The last section summarizes and concludes.

## 2 The Data

The data employed in this research are drawn from the German Mobility Panel (MOP 2007), an ongoing publicly available travel survey[1]. We use ten years of data from the survey, spanning 1997 through 2006, a period during which real fuel prices in Germany rose 3% per annum. Households that participate in the survey are requested to fill out a questionnaire eliciting general socioeconomic information, such as residential location, as well as person-related characteristics, including gender, age, and employment status.

Our focus in the present analysis is on a subset of this data, referred to as the tank survey, which covers vehicle travel among randomly selected car-owning households from the larger sample. This survey takes place over a roughly six-week period in each of three consecutive years, during which time respondents record the price paid for fuel with each visit to the gas station, the distance traveled, and vehicle attributes such as fuel economy and fuel type for each car driven during the survey. The unit of observation in this data is the car, so that households owning multiple cars occupy several rows of data. As the models estimated in this analysis draw on panel methods in which the cross-sectional unit is defined as the household, the inclusion of such multi-car households preclude the unique identification of an observation based on the interaction of the panel- and time variables. Consequently, we randomly select one of these cars for inclusion in the final data set, though we also explore the robustness of the results when the multi-car households are omitted from the sample.

The data is augmented by merging in socioeconomic characteristics from the general survey, which is also carried out over three years for each household. As the tank

[1] Contact information on obtaining the data is available at http://www.dlr.de/cs/de/.

survey includes only car-owning households, we additionally append randomly selected no-car households from the general survey, such that they comprise roughly 20% of the observations in a given year.[2] The resulting data set contains 940 car-owning households. Of these, 402 participated in two years of the survey and 538 in all three years, yielding a total of 2,418 observations.[3]

In addition to fuel prices and fuel economy, several other automobile attributes and household characteristics are specified as control variables in the analysis, the descriptive statistics for which are presented in Table 1. To capture the effects of automobile quality, the age of the car and two dummy variables indicating luxury and diesel models are included. Demographic influences are measured by the number of adults, the percentage of those who are female, and the number of children under 18 years of age. Wealth effects are captured by a dummy indicating multiple car ownership, the number of employed residents, the number with a college preparatory degree, and a categorical variable measuring household income.[4]

To control for events that may disrupt the normal pattern of travel, dummies are included indicating whether any employed member changed jobs in the preceding year and whether the household undertook a vacation with the car during the survey period. Finally, to capture fixed costs incurred with owning a car but not with driving, we include an insurance cost index compiled by the German Insurance Association. This index takes an integer value between 1 and 12 and measures the average insurance cost of car ownership at the provincial level. Because the approximately 445 provinces in the data set are delineated at a slightly higher level of spatial aggregation than the

[2]Roughly 80% of cars in Germany own at least one car (MiD 2008).

[3]To assess the possibility of attrition bias, we also explored specifications of the Two-Part Model that included a dummy variable indicating the two-year participating households. As the dummy was insignificant and had a negligible impact on the remaining coefficients, it was left out of the final specifications.

[4]As is typical for survey data, information on income is missing for a large share of the households. To impute the missing values, we employ the expectation-maximization algorithm recommended by King et al. (2001). The employed algorithm can be implemented using a program compatible with the statistical software R, and is downloadable from http://gking.harvard.edu.

**Table 1:** Variable Definitions and Descriptive Statistics

| Variable Name | Variable Definition | Mean | Std. Dev. |
|---|---|---|---|
| $s$ | Monthly kilometers driven | 1185.90 | 771.79 |
| $e$ | Monthly fuel consumption in liters | 96.21 | 64.13 |
| $\mu$ | Kilometers driven per liter | 12.68 | 2.88 |
| $p_s$ | Real fuel price in € per kilometer | 0.08 | 0.02 |
| $p_e$ | Real fuel price in € per liter | 0.97 | 0.14 |
| *car age* | Age of the car | 6.23 | 4.34 |
| *premium car* | Dummy: 1 if car is a sports- or luxury model | 0.22 | 0.41 |
| *diesel car* | Dummy: 1 if car uses diesel | 0.13 | 0.34 |
| *car vacation* | Dummy: 1 if household undertook car vacation during the survey period | 0.22 | 0.42 |
| *multiple car* | Dummy: 1 if Household has more than 1 car | 0.28 | 0.45 |
| *# employed* | Number of employed household members | 0.98 | 0.84 |
| *# college preparatory degree* | Number of household members with a college preparatory degree | 0.60 | 0.76 |
| *income* | Household income class (1-8) | 5.06 | 1.38 |
| *new job* | Dummy: 1 if person changed the job last year | 0.12 | 0.32 |
| *# adults* | Number of adult household members | 1.82 | 0.70 |
| *% female* | Share of female household members | 0.51 | 0.30 |
| *# children* | Number of children younger than 17 | 0.47 | 0.84 |
| *city* | Dummy: 1 if household resides in a city | 0.43 | 0.49 |
| *insurance cost* | Car insurance cost class (1-12) | 6.12 | 2.49 |

zip code delineation of the MOP data, a Geographic Information System was used to merge in the insurance cost variable.

# 3 Key Definitions and the Rebound Effect

In this section, we present the definitions of the key variables of our analysis, the price of mobility services and energy efficiency, and provide a theoretical derivation of the direct[5] rebound effect that is due to efficiency improvements. The definition of energy efficiency typically employed in the economic literature, see e. g. BINSWANGER (2001:121) is given by:

$$\mu_i = \frac{s_i}{e_i} > 0, \tag{1}$$

where the efficiency parameter $\mu_i$ characterizes the technology with which an amount $s_i$ of service $i$ is provided and $e_i$ denotes the energy input employed for a service such as mobility. For the specific example of individual conveyance, parameter $\mu_i$ designates fuel efficiency, which can be measured in terms of vehicle kilometers per liter of fuel input.

Efficiency definition (1) reflects the fact that the higher the efficiency $\mu_i$ of a given technology, the less energy $e_i = s_i/\mu_i$ is required for the provision of service $i$ and, hence, the lower is the amount of greenhouse gases that are emitted if fossil fuels are used. Hence, the concept of energy efficiency is perfectly in line with BECKER's (1965) seminal work on household production, according to which households are, ultimately, not interested in the amount of energy required for a certain amount of service, but in the energy service itself:

$$s_i = f_i(e_i, t_i, k_i, o_i), \tag{2}$$

where production function $f_i$ describes how households "produce" service $i$ in the

[5]The literature distinguishes between direct and indirect rebound effects (e. g. GREENING and GREENE 1997, GREENE *et al.* 1999). The latter arises from an income effect: lower per-unit cost of an energy service implies - *ceteris paribus* - that real income grows. Given that indirect effects are difficult to quantify, the overwhelming majority of empirical studies are confined to analyzing the direct rebound effect.

amount of $s_i$ by using time, $t_i$, capital, $k_i$, other market goods $o_i$, and energy, $e_i$. Based on efficiency definition (1), it follows that the price $p_{s_i}$ per unit of the energy service, given by the ratio of service cost to service amount, is smaller the higher the efficiency $\mu_i$ is:

$$p_{s_i} = \frac{e_i \cdot p_{e_i}}{s_i} = \frac{e_i}{s_i} \cdot p_{e_i} = \frac{p_{e_i}}{\mu_i} \; . \tag{3}$$

Along the lines of BECKER (1965), it is assumed that any households's utility depends solely on the amounts $s_1, ..., s_n$ of services:

$$U = u(s_1, s_2, ..., s_n) \quad \text{with} \quad \frac{\partial u}{\partial s_i} > 0 \quad \text{and} \quad \frac{\partial^2 u}{\partial s_i^2} < 0 \quad \text{for } i = 1, ..., n. \tag{4}$$

The household's available time budget $T$ is split up into the hours $t_w$ spent on working and the time necessary to produce services:

$$T = t_w + \sum_{i=1}^{n} t_i. \tag{5}$$

With $w$ denoting the wage rate, households face the budget constraint

$$t_w w = \sum_{i=1}^{n} p_e e_i + p_k k_i + p_o o_i, \tag{6}$$

if the non-wage income is zero. $p_e$ and $p_o$ indicate the prices of energy and other market good inputs, respectively, while $p_k$ captures the annualized investment cost required for service $i$.

The Lagrangian $L$ for the utility maximization problem subject to budget constraint (6) and time restriction (5) reads

$$L := u(s_1, s_2, ..., s_n) - \lambda \left[ \sum_{i=1}^{n} (p_e e_i + p_k k_i + p_o o_i + w t_i) - wT \right]. \tag{7}$$

If joint production is ruled out, the first-order condition with respect to service $j$ is given by

$$\frac{\partial u}{\partial s_j} = \lambda \left[ p_e \frac{\partial e_j}{\partial s_j} + p_k \frac{\partial k_j}{\partial s_j} + p_o \frac{\partial o_j}{\partial s_j} + w \frac{\partial t_j}{\partial s_j} \right]. \tag{8}$$

If efficiency improvements increase service demand $s_j$, but do not alter the input of time $t_j$, capital $k_j$, and other market goods $o_j$, that is, if $\frac{\partial t_j}{\partial s_j} = 0$, $\frac{\partial k_j}{\partial s_j} = 0$, and $\frac{\partial o_j}{\partial s_j} = 0$, it follows that the first-order condition (8) simplifies to

$$\frac{\partial u}{\partial s_j} = \lambda \left[ \; p_{s_j} \; \right], \tag{9}$$

where we have employed price relationship (3), i. e. $p_{s_i} = p_e/\mu_i$, and $\partial e_j/\partial s_j = 1/\mu_j$, thereby exploiting efficiency definition (1).

Using this framework, the direct rebound effect, describing the increase in service demand due to the improvement in the efficiency of providing service $j$, can be proved as follows if the utility function $U$ exhibits the typical properties given by (4).

**Proposition**:

$$\eta_{\mu_j}(s_j) = \frac{\partial \ln s_j}{\partial \ln \mu_j} = \frac{\mu_j}{s_j} \cdot \frac{\partial s_j}{\partial \mu_j} > 0,$$

if $\frac{\partial u}{\partial s_j} > 0$ and $\frac{\partial^2 u}{\partial s_j^2} < 0$ and if efficiency improvements do not alter the input of time $t_j$, capital $k_j$, and market goods $o_j$ other than energy, that is, if $\frac{\partial t_j}{\partial s_j} = 0$, $\frac{\partial k_j}{\partial s_j} = 0$, and $\frac{\partial o_j}{\partial s_j} = 0$.

**Proof**: The first-order condition (9) can be solved for $s_j$, since $\frac{\partial u}{\partial s_j}$ is invertible due to $\frac{\partial^2 u}{\partial s_j^2} < 0$. Hence, the amount of service $j$ is given by

$$s_j = (\frac{\partial u}{\partial s_j})^{-1}(\lambda \frac{p_e}{\mu_j}),$$

where $(\frac{\partial u}{\partial s_j})^{-1}$ is the inverse of $\frac{\partial u}{\partial s_j}$. Using the differentiation rule for inverse functions, it follows that

$$\frac{\partial s_j}{\partial \mu_j} = \frac{\partial}{\partial \mu_j}[(\frac{\partial u}{\partial s_j})^{-1}(\lambda \frac{p_e}{\mu_j})] = \frac{1}{\frac{\partial}{\partial \mu_j}[\frac{\partial u(\lambda \frac{p_e}{\mu_j})}{\partial s_j}]} = -\frac{1}{\frac{\partial^2 u}{\partial s^2}} \cdot \lambda \frac{p_e}{\mu_j^2} > 0,$$

since $\frac{\partial^2 u}{\partial s_j^2} < 0$ and $\lambda > 0$, which results from $\frac{\partial u}{\partial s_j} > 0$ and first-order condition (8). The positivity of $\eta_{\mu_j}(s_j)$ then holds due to $\frac{\partial s_j}{\partial \mu_j} > 0$. This theoretical hypothesis is intuitive: Households will usually demand more of a service when it becomes cheaper due to an efficiency improvement.

# 4 Methodology

The reliance on household-level panel data to test this hypothesis raises several conceptual and empirical issues, the most fundamental of which is the presence of null values in the data. As 20% of the households do not own a car, the observation on distance driven is consequently recorded as zero. To accommodate this feature of the data, we employ two censored regression procedures – the Two-Part and Heckit models – that order observations into two regimes defined by whether the household owns a car.

### 4.1 The Models

The first stage of both procedures, referred to as the selector equation, defines a dichotomous variable indicating the regime into which the observation falls:

$$S = 1, \text{if} \quad S^* = \mathbf{X_1}\boldsymbol{\tau} + \varepsilon_1 > 0 \quad \text{and} \quad S = 0, \text{if} \quad S^* \leq 0 \tag{10}$$

where $S^*$ is a latent variable indicating the utility from car ownership, $S$ is an indicator for car ownership status, matrix $\mathbf{X_1}$ includes the determinants of this status, $\boldsymbol{\tau}$ is a vector of associated parameter estimates, and $\varepsilon_1$ is an error term assumed to have a standard normal distribution.

In addition to estimating $\boldsymbol{\tau}$ using the probit maximum likelihood method, the second stage of the models, referred to as the outcome equation, involves estimating the parameters $\boldsymbol{\beta}$ via an OLS regression conditional on care use, $S = 1$:

$$E[y|S = 1, \mathbf{X_2}] = \mathbf{X_2}\boldsymbol{\beta} + E(\varepsilon_2|y > 0, \mathbf{X_2}), \tag{11}$$

where $y$ is the dependent variable, measured here either as the kilometers of vehicle travel or fuel consumption over the six week survey, $\mathbf{X_2}$ includes the determinants of $y$, and $\varepsilon_2$ is the error term, assumed to be normally distributed.

The key distinction between the Two-Part Model (2PM) and HECKMAN's two-stage sample selection model, frequently called the Heckit model, is the inclusion of an additional regressor - the inverse Mill's ratio (IVM) - in the second stage regression to control for potential selectivity bias (HECKMAN 1979). In omitting this regressor, the 2PM imposes the assumption that $E(\varepsilon_2|y > 0, \mathbf{X_2}) = 0$. The relative merits of this simplification has been the subject of a vigorous debate in the literature (HAY and OLSON, 1984; DUAN et al. 1984; LUENG and YU 1996; DOW and NORTON, 2003), with much of the discussion focusing on their underlying assumptions and numerical properties.

Although we explore the use of both models, two considerations led us to select the 2PM as the superior alternative for this analysis. First, the estimated coefficient on the IVM, presented in the Appendix, is insignificant, suggesting that sample selectivity may not be an issue with these data. Second, as discussed by DOW and NORTON (2003), a more substantive consideration in choosing between the two models is whether interest centers on the actual or potential outcome of the phenomena under study.

In the present context, the potential outcome $y^*$ addresses the distance a household would drive were it to own a car, irrespective of actual ownership, while the actual outcome $y$ addresses the observed distance driven, equaling zero if no car is owned ($y = 0$). Whereas the actual outcome $y$ is a fully-observed variable, the potential outcome $y^*$ is a latent variable that is only partially observed, namely for those who have chosen to own a car: $y^* = y$ if $y > 0$, but $y^*$ is unidentified if $y = 0$, i. e. for those who have refrained from car ownership. While the Heckit estimator was designed to address selection bias for analyzing potential outcomes, it incorporates features that make it often perform worse than the 2PM when analyzing actual outcomes (DOW and NORTON 2003:6). Accordingly, the 2PM is deemed here the more appropriate modeling specification to estimate the effect of fuel prices and socioeconomic traits on *actual* distance driven or *actual* fuel consumption, whereas estimating the impact on potential distances or consumption does not conceptually fit to the goal of our study.

## 4.2 Calculation of Elasticities

For estimating the marginal effects of socioeconomic determinants on *actual* distances or *actual* fuel consumption, it is necessary to take account of the likelihood that a household refrains from owning a car, $P(y = 0)$. Hence, the prediction of the dependent variable consists of *two parts*, with the first part being the probability of owning the car, $P(y > 0) = \Phi(\mathbf{X_1}\boldsymbol{\tau})$, which results from the first stage (10) of the 2PM, and the second part being the conditional expectation $E[y|y>0] = \mathbf{X_2}\boldsymbol{\beta}$ from the second stage (11):

$$\begin{aligned} E[y] &= P(y>0) \cdot E[y|y>0] + P(y=0) \cdot E[y|y=0] \\ &= P(y>0) \cdot E[y|y>0] + 0 = \Phi(\mathbf{X_1}\boldsymbol{\tau}) \cdot \mathbf{X_2}\boldsymbol{\beta}. \end{aligned} \tag{12}$$

As our interest centers on elasticities, we now present the required formulae for the corresponding 2PM with a logged dependent variable $z = \ln(y)$ and normal homoskedastic errors $\boldsymbol{\varepsilon}_2$ with constant variance $\mathrm{Var}(\boldsymbol{\varepsilon}_2) = \sigma^2$, following DOW and NORTON (2003:11). Rather than by (12), actual outcomes are in this case predicted by[6] :

$$E[y] = \Phi(\mathbf{X_1}\boldsymbol{\tau}) \cdot \exp\{\mathbf{X_2}\boldsymbol{\beta} + 0.5 \cdot \sigma^2\}. \tag{13}$$

Using the product and chain rules of differentiation and the fact that the derivative of the cumulative normal function $\Phi$ equals the normal density function $\phi$, the marginal effect can be derived as follows:

$$\begin{aligned} \frac{\partial E[y]}{\partial x_k} &= \beta_k \cdot E[y] + \tau_k \cdot \phi(\mathbf{X_1}\boldsymbol{\tau}) \cdot \exp\{\mathbf{X_2}\boldsymbol{\beta} + .5 \cdot \sigma^2\} \\ &= \beta_k \cdot E[y] + \tau_k \cdot \frac{\phi(\mathbf{X_1}\boldsymbol{\tau})}{\Phi(\mathbf{X_1}\boldsymbol{\tau})} \cdot E[y] \end{aligned} \tag{14}$$

By dividing expression (14) by $E(y)$, the elasticity formula for logged explanatory variables ($z_k = \ln x_k$) follows immediately:

$$\eta_{x_k} = \frac{\partial \ln E[y]}{\partial \ln x_k} = \frac{\partial \ln E[y]}{\partial z_k} = \frac{\partial E[y]}{\partial z_k} \cdot \frac{1}{E[y]} = \beta_k + \tau_k \cdot \frac{\phi(\mathbf{X_1}\boldsymbol{\tau})}{\Phi(\mathbf{X_1}\boldsymbol{\tau})}. \tag{15}$$

If the explanatory variable is in levels, the respective elasticity can be obtained from (15):

$$\eta_{x_j} = \frac{\partial \ln E[y]}{\partial \ln x_j} = \frac{\partial \ln E[y]}{\partial x_j} \cdot x_j = [\beta_j + \tau_j \cdot \frac{\phi(\mathbf{X_1}\boldsymbol{\tau})}{\Phi(\mathbf{X_1}\boldsymbol{\tau})}] \cdot x_j \tag{16}$$

To handle the case of dummy variables $D_k$, we employ the following relative differences, thereby using the formula of the expected value (13):

$$(E[y|D_k = 1] - E[y|D_k = 0])/E[y]. \tag{17}$$

[6]If $z = ln(y)$ has a normal distribution with an expected value of $E(z) = \mu$ and variance $\sigma^2$, then $y$ has a lognormal distribution and an expected value of $E(y) = \exp\{\mu + 0.5 \cdot \sigma^2\}$.

## 4.3 Model Specifications

The model specifications presented here are based on the logged version (13) of the 2PM and are intimately connected with the definitions of the rebound effect catalogued by FRONDEL, PETERS, and VANCE (2008:148, 149). Referring to their Definition 1, i. e. the elasticity of service demand with respect to efficiency, $\eta_{\mu}(s) = \frac{\partial \ln s}{\partial \ln \mu}$, the dependent variable of our **Model 1** is the log of kilometers traveled, $\ln(s)$:

$$E[\ln(s)] = \Phi(\mathbf{X_1}\boldsymbol{\tau}) \cdot \exp\{\beta_{p_e} \ln(p_e) + \beta_{\mu} \ln(\mu) + \mathbf{X_2}\boldsymbol{\beta} + 0.5 \cdot \sigma^2\}. \tag{18}$$

where the set of explanatory variables specifically includes the logged price of fuel per liter, $\ln(p_e)$, as well as the log of kilometers traveled per liter, $\ln(\mu)$.

A particular feature of Model 1 bears noting: It is to be expected that the elasticity of service demand with respect to efficiency estimated from this model is of the same order as the elasticity of service demand with respect to fuel prices:

$$H_0 : \eta_{\mu}(s) = -\eta_{p_e}(s). \tag{19}$$

This null hypothesis is intuitive: for constant fuel prices $p_e$, *raising* the energy efficiency $\mu$ should have the same effect on service demand, i. e. the distance traveled, as *falling* fuel prices $p_e$ given a constant energy efficiency $\mu$. It is precisely the validity of $H_0$ that gives rise to the assumption that both price and rebound effects, identified here by $\eta_{\mu}(s)$, are just responses of the same order to changes in the unit costs of energy services, yet going into opposite directions.

Since Definition 2 of the rebound effect is based on the negative own-price elasticity of service demand, $\eta_{p_s}(s)$, the dependent variable of the corresponding **Model 2** is the same as in Model 1, but rather than the logged price of fuel per liter, the set of explanatory variables includes the logged price of service demand, $\ln(p_s)$:

$$E[\ln(s)] = \Phi(\mathbf{X_1}\boldsymbol{\tau}) \cdot \exp\{\beta_{p_s} \ln(p_s) + \mathbf{X_2}\boldsymbol{\beta} + 0.5 \cdot \sigma^2\}, \tag{20}$$

Recognizing that $p_s = \frac{p_e}{\mu}$, and that $\ln(p_s) = \ln(p_e) - \ln(\mu)$, it can be seen that this specification is functionally equivalent to Model 1 if hypothesis (19) holds. In this case, it is $\beta_{p_e} = -\beta_{\mu}$.

Referring to Definition 3 of the rebound effect, which is based on the negative own-price elasticity of energy consumption, $\eta_{p_e}(e)$, the dependent variable of the corresponding **Model 3** is the logged liters of fuel consumed:

$$E[\ln(e)] = \Phi(\mathbf{X_1}\boldsymbol{\tau}) \cdot \exp\{\beta_{p_e} \ln(p_e) + \mathbf{X_2}\boldsymbol{\beta} + 0.5 \cdot \sigma^2\}, \tag{21}$$

where the set of explanatory variables specifically includes the logged price of fuel per liter, $\ln(p_e)$. The remaining suite of variables included in these models measure the individual, household, and automobile attributes that are hypothesized to influence the extent of motorized travel.

Finally, it bears noting that it is possible to examine whether Model 3 differs from Model 2 by testing the hypothesis

$$H_0 : \beta_{p_e} = -1 \tag{22}$$

on the basis of the estimates of Model 3 and, additionally, by testing the hypothesis

$$H_0 : \beta_{p_s} = -1 \tag{23}$$

on the basis of the estimates of Model 2. Only if both hypotheses were to hold would Model 2 be identical to Model 3 (see FRONDEL, PETERS, and VANCE (2008:151)).

To exploit the panel dimension of the data, we employ the fixed-effects estimator in the analysis of distance traveled. The random-effects estimator was also explored, but, while many of the coefficients were similar to the fixed effects, this model was rejected by a standard HAUSMAN test. A key virtue of the fixed-effects model is to control for the influence of time-invariant unobservable variables that could otherwise bias the estimated coefficients. This is a particularly useful feature in the present application given that the measures of fuel efficiency used in Definitions 1 and 2 of the rebound effect may be vulnerable to endogeneity bias.[7]

Households that drive longer distances because they live in rural areas, for example, may select more efficient cars, thereby leading to an inflated estimate of the

[7]This source of bias does not afflict the estimates corresponding to Definition 3, as Model 3 does not include fuel efficiency.

rebound effect. To the extent that the unobserved characteristics that affect both fuel economy and vehicle mileage remain constant over time, the fixed effects model will control for this source of bias. Although it is not possible to exclude the possibility of relevant time-variant unobservables, we believe that the range of explanatory variables – including the number of children, the number of employed, and job changes – provides reasonably good coverage of temporal changes whose absence could induce biases.

# 5 Empirical Results

Table 2 presents elasticity estimates corresponding to each of the three definitions of the rebound effect, conditional on car ownership. To focus on the salient results, we refrain here from reporting the coefficients of the first-stage Probit models and instead present these in the appendix. It bears noting, however, that the Probit results are reflected in both the estimated coefficients and standard errors presented in Table 2 via the application of Equations (15) - (17). Because these equations comprise multiple parameters that make analytical computation of the variance impossible, we apply the Delta method to calculate statistical significance. This approach uses a first-order Taylor expansion to create a linear approximation of a non-linear function, after which the variance and measures of statistical significance can be computed.

Turning first to the coefficients on $\ln(\mu)$, $\ln(p_e)$, $\ln(p_s)$, the estimated rebound effects are all seen to be highly significant, ranging from 0.35 in Model 3 to 0.52 in Model 1. Although these estimates are somewhat lower than those of FRONDEL, PETERS, and VANCE (2008), they are nevertheless substantial, and suggest that between 35% and 52% of the potential energy savings due to an efficiency improvement is lost to increased driving.

**Table 2:** Estimation Results of the Two-Part-Model.

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Dependent Variable | $\ln(s)$ | | $\ln(s)$ | | $\ln(e)$ | |
| | Elast.s | Std. Errors | Elast.s | Std. Errors | Elast.s | Std. Errors |
| $\ln(\mu)$ | ** 0.515 | (0.090) | – | – | – | – |
| $\ln(p_e)$ | **-0.406 | (0.134) | – | – | ** -0.348 | (0.134) |
| $\ln(p_s)$ | – | – | **-0.490 | (0.073) | – | – |
| *car age* | **-0.027 | (0.005) | **-0.027 | (0.005) | ** -0.026 | (0.005) |
| *diesel car* | 0.164 | (0.097) | 0.151 | (0.095) | 0.085 | (0.052) |
| *premium car* | ** 0.360 | (0.073) | ** 0.354 | (0.072) | ** 0.451 | (0.043) |
| *multiple car* | ** -0.187 | (0.059) | **-0.186 | (0.059) | ** -0.190 | (0.038) |
| *vacation with car* | ** 0.291 | (0.033) | ** 0.292 | (0.033) | ** 0.284 | (0.023) |
| *# adults* | * 0.197 | (0.088) | *0.200 | (0.085) | *0.205 | (0.089) |
| *% females* | -0.024 | (0.050) | -0.023 | (0.049) | -0.026 | (0.051) |
| *# children* | -0.022 | (0.021) | -0.022 | (0.021) | -0.015 | (0.020) |
| *# college preparatory degree* | *-0.050 | (0.025) | * -0.050 | (0.024) | -0.045 | (0.025) |
| *# employed* | -0.007 | (0.034) | -0.008 | (0.034) | 0.003 | (0.033) |
| *new job* | 0.021 | (0.019) | 0.021 | (0.018) | 0.019 | (0.018) |
| *income* | ** 0.455 | (0.071) | ** 0.456 | (0.061) | ** 0.434 | (0.061) |
| $H_0 : \beta_{p_e} = -1$ | | | | | F(1, 2.403) = ** 23.47 | |
| $H_0 : \beta_{p_s} = -1$ | | | F(1, 2.403) = ** 48.13 | | | |
| $H_0 : \beta_\mu = -\beta_{p_e}$ | F(1, 2.403) = 0.81 | | | | | |

**Note**: * denotes significance at the 5 %-level and ** at the 1 %-level, respectively. Number of observations used for estimation: 2,418.

Focusing specifically on the estimates from Model 1, we can additionally test whether the impact of efficiency improvements on traveled distance is of the same order as the effect of fuel prices: As reported in the ultimate row of the table, we cannot reject this hypothesis, which translates into $H_0 : \beta_\mu = -\beta_{p_e}$. Hence, there is no reason, neither on a theoretical nor an empirical basis, to assume that the estimates corresponding to Definitions 1 and 2 of the rebound effect as well as Models 1 and

2 are principally different, a conclusion that is validated by the close estimates of the whole range of regressors. Despite this closeness, Model 3 is not identical to Models 1 or 2, as is confirmed by the rejection of the null hypotheses that the price coefficients in Models 3 and 2 are both -1.

With respect to the remaining control variables, most have either intuitive effects or are statistically insignificant. Referencing the estimates from Model 1, older cars are seen to be driven less while premium cars are driven more. Another important determinant is whether a vacation with the car was undertaken over the survey period, which results in a roughly 34% (=exp(0.29)-1) increase in distance traveled. Among the significant sociodemographic variables, the number of adults and household income both have positive effects, whereas the dummy indicating a multi-car household has a negative effect, a likely reflection of the household's ability to use cars other than the one under observation. With respect to income, it bears noting that the (unreported) unadjusted coefficient estimate that takes no account of the probability of a positive outcome of car ownership is insignificant. That this distinction can result in qualitatively different conclusions suggests the importance of correctly dealing with a censored dependent variable when calculating elasticities.

To further explore the robustness of the results to the inclusion of the multi-car households, we removed them from the data and re-estimated the model. As can be gleaned from the results presented in Table 3, this omission has little bearing on the conclusions drawn from the analysis. The most notable change is that the fuel-price elasticity estimates become smaller in magnitude when multi-car households are included in the sample. While the difference between the estimates is statistically minor and should not be over-interpreted, one possible explanation is that a higher sensitivity to fuel prices prevails among households that cannot substitute between cars.

We thus conclude that our estimates, be they based on Definition 1, 2, or 3 of the rebound effect, are substantially larger than the typical effects obtained from the U.S. transport sector. Using household survey data, GREENE, KAHN, and GIBSON(1999:1), for instance, find a long-run "take back" of about 20% of potential energy savings, con-

**Table 3:** Comparison of Rebound Effects with and without Multi-Car Households.

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Dependent Variable | $\ln(s)$ | | $\ln(s)$ | | $\ln(e)$ | |
| | Elast.s | Std. Errors | Elast.s | Std. Errors | Elast.s | Std. Errors |
| | Without Multi-Car Households, Number of observations: 1,732 | | | | | |
| $\ln(\mu)$ | * 0.518 | (0.107) | – | – | – | – |
| $\ln(p_e)$ | **-0.528 | (0.136) | – | – | ** -0.486 | (0.135) |
| $\ln(p_s)$ | – | – | **-0.521 | (0.084) | – | – |
| | With Multi-Car Households, Number of observations: 2,418 | | | | | |
| $\ln(\mu)$ | ** 0.515 | (0.090) | – | – | – | – |
| $\ln(p_e)$ | **-0.406 | (0.134) | – | – | ** -0.348 | (0.107) |
| $\ln(p_s)$ | – | – | **-0.490 | (0.073) | – | – |

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

firming the results of other U. S. studies using national and or state-level data. While this issue has received relatively less scrutiny in the European context, our results fall at the upper-end of those of WALKER and WIRL (1993), who estimate a long-run rebound effect of 36% for Germany using aggregate time-series data.

# 6 Summary and Conclusion

While energy policy in Europe has traditionally relied heavily on fuel taxation, it is currently undergoing a process of bifurcation, with an increasing reliance on fuel-efficiency standards to reduce emissions. This shift is evidenced by the voluntary agreement negotiated in 1998 between the EC and the European Automobile Manufacturers Association stipulating the reduction of average emissions to 140g CO2/km by 2008, in addition to subsequent legislation that would set additional targets for 2012. Although such standards undoubtedly confer economic benefits in their own right, their associated implications for emissions depends fundamentally on the behavioral response to cheaper per-unit energy prices. To the extent that motorists drive more when costs of driving are reduced, we would expect policies based on fuel taxation and those based on fuel efficiency standards to have opposing effects on vehicle kilometers traveled, a seeming incongruity that has largely escaped the notice of policy-makers.

The analysis pursued in this paper has attempted to inform the policy discussion on this issue by estimating the magnitude of both fuel-price and fuel-efficiency elasticities, using panel household data from Germany. Our most conservative estimate of fuel-price elasticities amounts to -0.35, indicating that fuel taxation may have a substantial impact in lowering fuel consumption and, hence, greenhouse gas emissions. Of a similar magnitude, but opposite sign is our conservative estimate of the fuel-efficiency elasticity of +0.52, suggesting a sizeable leakage in the potential emissions reductions from efficiency improvements commonly called rebound effect. Equally noteworthy, we confirm the hypothesis that fuel-efficiency and price effects are simply two sides of the same coin: behavioral changes due to varied unit cost of energy services. In fact, the order of the effect of a change in the fuel price on driving turns out to be statistically non-distinguishable from the impact of a change in fuel economy, a circumstance that serves to highlight the inverse relationship between the effectiveness of fuel taxes in reducing driving and the effect of efficiency standards in increasing it.

Taken together, these findings suggest that the current emphasis in Europe on efficiency as a principle means to address environmental challenges (*e.g.* EC 2007) may be misplaced. While such an emphasis has been a mainstay of energy policy in the U.S. ever since the creation of the so-called CAFE standards in 1975, the fuel efficiency of the passenger car fleet in the U.S. has long lagged behind that of Europe. Given the divergent trajectories of automotive technologies on the European and American markets, the different respective policy emphases with respect to fuel tax taxation, and the evidence presented in this paper that driving costs and, hence, oil prices matter for driving behavior, we conclude that the logic of introducing fuel efficiency standards to reduce emissions is dubious.

# Appendix: Probit Estimation Results

**Table A1:** Probit Estimation Results for Car Ownership

| | Coeff.s | Errors | Elast.s | Errors |
|---|---|---|---|---|
| *# adults* | ** .576 | (.068) | ** .091 | (.011) |
| *% female* | ** -.448 | (.082) | ** -.071 | (.014) |
| *# children* | .028 | (.063) | .005 | (.010) |
| *# college preparatory degree* | * -.144 | (.060) | *-.023 | (.010) |
| *# employed* | .100 | (.061) | .016 | (.009) |
| *new job* | .005 | (.119) | .001 | (.019) |
| *income* | ** .594 | (.035) | ** .094 | (.006) |
| *city* | ** -.308 | (.074) | ** -.050 | (.013) |
| *insurance cost* | ** -.056 | (.012) | ** -.009 | (.002) |

**Note**: * denotes significance at the 5 %-level and ** at the 1 %-level, respectively. Number of observations used for estimation: 3,022.

The key distinction between the Two-Part and Heckit model is the inclusion of the inverse Mill's ratio (IVM) in the second stage to control for potential selectivity bias. To effectively identify the Heckit model requires the inclusion of at least one variable that uniquely determines the discrete choice of car ownership but not the continuous choice of distance traveled. In the present example, this selection can be informed by consideration of the fixed costs incurred with owning a car but not with driving. As an identifying variable, we include the cost insurance index compiled by the German Insurance Association. Consistent with expectations, Table A1 shows that this variable has a negative effect on the probability of car ownership, as increases in the index measure higher insurance costs. Table A2 indicates, however, that the estimated coefficient on the IVM is insignificant, suggesting that sample selectivity may not be an issue with these data. The remaining results in Table A2 are of approximately the same magnitude as those in Table 2.

**Table A2:** Estimation Results of the Heckit-Model.

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Dependent Variable | $\ln(s)$ | | $\ln(s)$ | | $\ln(e)$ | |
| | Elast.s | Std. Errors | Elast.s | Std. Errors | Elast.s | Std. Errors |
| $\ln(\mu)$ | ** 0.515 | (0.090) | – | – | – | – |
| $\ln(p_e)$ | **-0.410 | (0.135) | – | – | ** -0.470 | (0.138) |
| $\ln(p_s)$ | – | – | ** -0.491 | (0.048) | – | – |
| *car age* | **-0.027 | (0.005) | ** -0.027 | (0.003) | ** -0.029 | (0.005) |
| *diesel car* | 0.163 | (0.010) | 0.150 | (0.050) | * 0.248 | (0.097) |
| *premium car* | ** 0.361 | (0.073) | ** 0.355 | (0.043) | ** 0.263 | (0.075) |
| *multiple car* | ** -0.189 | (0.060) | ** -0.188 | (0.037) | ** -0.186 | (0.059) |
| *vacation with car* | ** 0.291 | (0.033) | ** 0.291 | (0.022) | ** 0.299 | (0.034) |
| *# adults* | ** 0.278 | (0.100) | ** 0.281 | (0.096) | ** 0.271 | (0.097) |
| *% females* | -0.046 | (0.051) | -0.045 | (0.051) | -0.044 | (0.051) |
| *# children* | *-0.020 | (0.022) | -0.020 | (0.022) | -0.026 | (0.023) |
| *# college preparatory degree* | *-0.057 | (0.026) | * -0.057 | (0.026) | * -0.062 | (0.027) |
| *# employed* | 0.001 | (0.036) | -0.001 | (0.036) | -0.010 | (0.037) |
| *new job* | 0.021 | (0.020) | 0.021 | (0.019) | 0.022 | (0.019) |
| *income* | ** 0.716 | (0.137) | ** 0.720 | (0.137) | ** 0.740 | (0.140) |
| *inverse Mill's ratio* | 0.066 | (0.106) | 0.069 | (0.082) | ** 0.068 | (0.110) |

**Note**: * denotes significance at the 5 %-level and ** at the 1 %-level, respectively. Number of observations used for estimation: 2,418.

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