

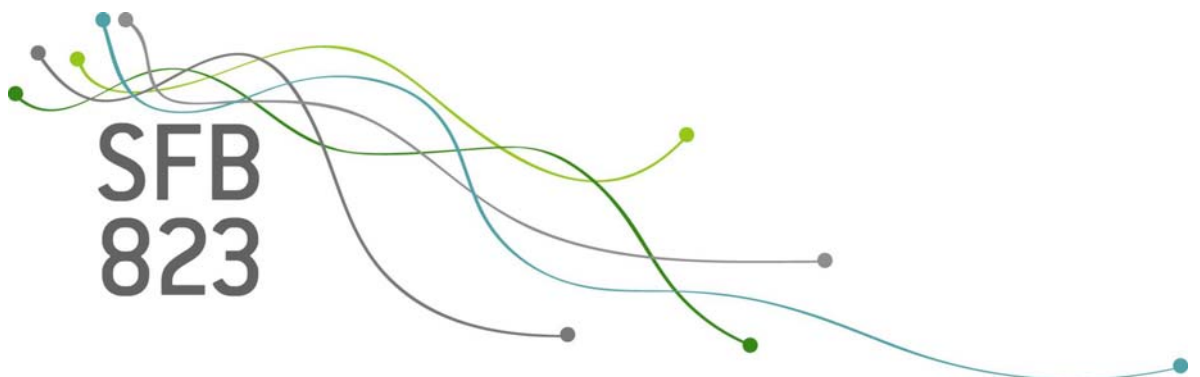
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# Re-identifying the rebound: What about asymmetry?

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## Re-Identifying the Rebound: What About Asymmetry?

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**Abstract.** Rebound effects measure the behaviorally induced offset in the reduction of energy consumption following efficiency improvements. Using panel estimation methods and household travel diary data collected in Germany between 1997 and 2009, this study identifies the rebound effect in private transport by allowing for the possibility that fuel price elasticities – from which rebound effects can be derived – are asymmetric. This approach rests on evidence that has emerged from the empirical literature suggesting that the response in individual travel demand to price increases is stronger than to decreases. With a rebound effect estimate for single-vehicle households of 58%, our result is in line with a recent German study by FRONDEL, PETERS, and VANCE (2008), but is substantially larger than those obtained from other studies. Moreover, we fail to reject the hypothesis that the magnitude of the response to a price increase is equal to that of a price decrease.

**JEL classification:** D13, Q41.

**Key words:** Automobile travel, panel estimation models.

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# 1 Introduction

Energy efficiency standards are highly in fashion as an instrument of climate protection policy in the European Union (EU), covering such diverse items as light bulbs (FRONDEL, LOHMANN, 2011) and automotive technology. These measures are seen as a cornerstone in efforts to meet the EU's international commitments to reduce greenhouse gases and achieve energy security. In the transport sector, which accounts for roughly 20% of the EU's CO<sub>2</sub> emissions, regulation 443/2009 sets limits on the allowable per-kilometer CO<sub>2</sub> emissions of newly registered automobiles, and includes legally codified targets for the maximum CO<sub>2</sub> discharges per kilometer that increase with the mass of vehicles. As non-compliance with the allowable emissions will result in heavy fines starting in 2012, the European Commission expects that this measure will induce considerable incentives for the development of fuel-saving technologies (FRONDEL, SCHMIDT, and VANCE, 2011).

Irrespective of the directive's effectiveness in increasing the average fuel efficiency of Europe's automobile fleet, a critical issue in gauging its merits concerns how consumers adjust to altered unit costs of car travel. Presuming that mobility is a conventional good, then a decrease in these costs 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 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). A survey by GOODWIN, DARGAY, and HANLY (2004), for example, cites mean fuel demand elasticities – from which rebound effects can be derived – varying between -0.1 in the short-run and -1.1 in the long-run. 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.

Several factors may account for the wide range in estimates, including differences

in the level of data aggregation, in the estimation methods employed, and in the definition of the rebound effect. A further issue that has complicated efforts to estimate fuel price elasticities relates to the possibility that motorists respond asymmetrically to fuel price increases and decreases. In particular, several studies have emerged suggesting that the response to price increases is stronger than the response to price decreases. As GATELY (1992) and others have argued, asset fixity provides one explanation for this so-called hysteresis<sup>1</sup>: improved auto design features that emerge in response to higher fuel prices are unlikely to be abandoned after prices fall, giving rise to a muted demand response. Numerous empirical studies by DARGAY (1992), GATELY (1992), HOGAN (1993), DARGAY and GATELY (1994, 1997), GATELY and HUNTINGTON (2002), and HUNTINGTON (2006) lend support to this view.

GRIFFEN and SCHULMAN (2005) have countered that the plausibility of asset fixity notwithstanding, it is incorrect to associate this with an asymmetric price response. Rather, these authors suggest that energy-saving technical change yields the spurious appearance of differing consumer reactions to price increases and decreases. When GRIFFEN and SCHULMAN include time dummies to account for technical change in their panel model of oil and energy consumption in the OECD, they conclude that a symmetric price response cannot be rejected. In an earlier analysis that takes into account inter-fuel substitution for residential energy demand, RYAN, WANG, and PLOURDE (1996) also find no evidence for asymmetric price responses.

The absence of a clear consensus on the existence of an asymmetric fuel response has important implications for policy analysis, not only with respect to projections of gasoline demand (GATELY 1992), but also with respect to assessments of fuel taxation as a transport demand management tool. As DARGAY (1993:89) has noted, were an asymmetry to exist, then at least part of the demand reduction generated by fuel price increases would be maintained even following a return to lower prices. This logic carries directly over to the analysis of the efficiency standards and the rebound effect: If the response to increases in the per kilometer cost of driving is measurably stronger

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<sup>1</sup>The notion of hysteresis originates from the physics of magnetism and refers to an effect that persists after its cause has been removed (DARGAY, GATELY, 1997:71).

than the response to decreases, then naive calculations of the rebound effect based on reversibility would be overestimated.

Using data from the German Mobility Panel, the present study advances understanding of fuel price asymmetries in several respects. First, contrasting with the typical reliance on time-series or aggregated country-level panel data, the data used here is drawn from individual households whose mobility behavior is surveyed for up to three consecutive years. This focus circumvents many of the identification challenges that confront studies using more aggregate data. Our data structure effectively allows isolation of the short-run behavioral response to changes in fuel prices by focusing on households that have not changed their cars over the three years they are surveyed, thereby reducing the possibility that technical change is driving the result.

Second, for empirical reasons, we suggest an alternate definition of the rebound effect that is based on the fuel price elasticity of travel demand. Contrary to conventional definitions that are based on potentially endogenous measures of efficiency, this rebound definition readily lends itself to an asymmetric modeling of fuel price responses. Presuming that the asymmetry assumption is found to be correct, it would imply that the rebound effect is consequently identified by an elasticity estimate that reflects changes in traveling demand due to decreases in fuel prices, as the rebound effect occurs in response to a decrease in unit cost for car travel due to improved fuel efficiency.

Finally, expanding on the single-car focus of FRONDEL, PETERS, and VANCE (2008), the data set analyzed here includes multiple-vehicle households, thereby allowing us to explore the sensitivity of the estimates to their inclusion. In addition, 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.

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 the panel data set, building the basis for the empirical estimation. Section 4 describes our estimation method, 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  $\mu$ :<sup>2</sup>

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

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, PETERS, and VANCE (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  $p_e$  for given efficiency  $\mu$ :

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

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<sup>2</sup>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  $\mu$  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  $\mu$  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  $\mu$  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  $e$ .

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.

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

Definitions 2 and 3, however, are only equivalent if the energy efficiency  $\mu$  is constant (FRONDEL, PETERS, and VANCE, 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  $\mu$  is constant.

To analyze asymmetric responses to changing driving costs, we focus here on a fourth definition of the rebound effect 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 with respect to efficiency  $\mu$ , Definition 1 is frequently not applicable, because in many empirical studies efficiency data is not available or the data provides only limited variation in efficiencies (SORRELL, DIMITROUPOULOS, SOMMERVILLE, 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, DIMITROUPOULOS, SOMMERVILLE, 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). Rather than excluding  $\mu$  from the analysis, alternative approaches are instrument variable (IV) estimations or simultaneous equations systems that explain vehicle



miles traveled, fuel efficiency, and vehicle numbers at once. As we have no instrument at hand, we are unable to employ IV methods to cope with the endogeneity of  $\mu$ , 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  $\mu$  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 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  $\mu$ . For example, fuel consumption  $e$  would *ceteris paribus* reduce to half if efficiency  $\mu$  were to be doubled. This example illustrates that the likely endogenous variable  $\mu$  needs to be included in any model specification for estimating  $\eta_{p_e}(e)$ , thereby potentially biasing the empirical results.

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

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

It is shown in the Appendix 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 suggest estimating the efficiency elasticity  $\eta_{\mu}(s)$  to capture the rebound, the most promising empirical, yet 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,  $\eta_{pe}(s)$ , for estimating the rebound effect, rather than employing other fuel- or service price elasticities that have been applied in the literature.

### 3 Data

The data used in this research is drawn from the German Mobility Panel (MOP 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 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 2,165 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 4,097 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 Definition 4 of the rebound effect. The dependent variable, which is converted into monthly figures to adjust for minor variations in the survey duration, is the total monthly distance driven in kilometers. The key explanatory variable for identifying the direct rebound effect is the price paid for fuel per liter.<sup>3</sup> Table 1 contains the definitions and descriptive statistics of all the variables used in the

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<sup>3</sup>The price series was deflated using a consumer price index for Germany obtained from DESTATIS (2010).

modeling.

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

Variable Name	Variable Definition	Mean	Std. Dev.
$s$	Monthly kilometers driven	1,110	689
$p_e$	Real fuel price in Euros per liter	1.03	0.15
$\# \text{ employed}$	Number of employed household members	1.03	0.86
$\text{vacation with car}$	Dummy: 1 if household undertook vacation with car during the survey period	0.22	–
$\text{children}$	Dummy: 1 if children younger than 19 live in household	0.35	–
$\text{job change}$	Dummy: 1 if an employed household member changed jobs within the preceding year	0.11	–
$\text{multi-car households}$	Dummy: 1 if an household has more than one car	0.35	–
$\text{income}$	Real Household income in 1,000 Euros	2.11	0.66
$\text{population density}$	People per square km in the county in which the household is situated	953	1,072

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.

## 4 Methodology

Focusing on Definition 4 and additionally allowing for asymmetric fuel price responses, we estimate the following model specification, where the logged monthly vehicle-kilometers traveled,  $\ln(s)$ , is regressed on those logged fuel prices  $\ln(p^+)$  that are ob-

served after a price increase from year  $t - 1$  to  $t$ , and those logged fuel prices  $\ln(p^-)$  that are observed after a price decrease from year  $t - 1$  to  $t$ , as well as a vector of control variables  $\mathbf{x}$  described in the previous section:

$$\ln(s_{it}) = \alpha_0 + \alpha_{p^+} \cdot \ln(p^+_{it}) + \alpha_{p^-} \cdot \ln(p^-_{it}) + \alpha_{\mathbf{x}}^T \cdot \mathbf{x}_{it} + \zeta_i + v_{it} . \quad (5)$$

Subscripts  $i$  and  $t$  are used to denote the observation and time period, respectively, and the superscript  $T$  designates the transposition of a vector.  $\zeta_i$  denotes an unknown individual-specific term, and  $v_{it}$  is a random component that varies over individuals and time.

To distinguish between the response to rising and falling prices, two price variables,  $p^+$  and  $p^-$ , are included in specification (5), with price variable  $p^+$  being defined as  $p^+_{it} = p_{it}$ , if  $p_{it} > p_{i(t-1)}$ , and  $p^+_{it} = 0$  otherwise, while  $p^-$  is generated from falling prices in a similar way. Since travel demand shrinks with increasing fuel prices, the coefficients of both price variables,  $p^-$  and  $p^+$ , should be negative, as is confirmed by our estimation results presented below.

Given this specification of asymmetric fuel price responses, where *a priori*  $\alpha_{p^+}$  can be assumed to differ from  $\alpha_{p^-}$ , we argue that the rebound is to be identified by the negative coefficient estimate of  $\ln(p^-)$ , as the rebound effect occurs in response to a decrease in unit cost for car travel due to improved fuel efficiency. The case where  $\alpha_{p^+} \neq \alpha_{p^-}$  and, hence, demand responses to price increases differ in magnitude from those to price decreases could be visualized by demand curves kinked at the current price, so that demand is related to increasing and decreasing prices in an asymmetric way (DARGAY, 1992:168). For single-vehicle households that do not change their car within the survey period, as in our case, the intuition behind such kinked demand curves may be that these households react to price rises with a fuel-saving driving behavior that they maintain even when prices fall to original levels. DARGAY and GATELY (1997:72) have referred to this behavior as “addiction asymmetry”, reflecting the proclivity of consumers to more readily adapt new habits than abandon them.

Whether this is actually the case can be examined by testing the following null

hypothesis:

$$H_0 : \alpha_{p^+} = \alpha_{p^-} , \quad (6)$$

which, if correct, implies that model (5) reduces to the reversible specifications that are typically employed to estimate the rebound effect (see e. g. FRONDEL, PETERS, and VANCE, 2008). If, however,  $H_0$  is rejected, we have reason to believe that the rebound effect should be identified by the negative of the estimate of  $\alpha_{p^-}$ .

While choosing specification (5), we deliberately refrain from employing classical models, such as the jagged ratchet model proposed by WOLFFRAM (1971), the ratchet specification of TRAILL et al. (1978), and the price decomposition approach employed by GATELY (1992), that have been suggested in the literature in order to capture potentially different responses to rising and falling prices. The reason for abstaining from the application of these models is that they are highly dependent on the starting point of the data (GRIFFIN, SCHULMAN, 2005:7). As is further illustrated by GRIFFIN, SCHULMAN (2005:7), a second troubling aspect of the price decomposition approach, which includes the ratchet models as special cases, is that the demand curve can shift inward purely due to price volatility, although the average price level remains fixed.

Finally, our data base does not allow for the application of the price decomposition approach, nor for error-correction models, so that we cannot account for some sort of dynamic adjustment mechanisms to long-run relationships, as is done by DARGAY (1992), for instance. Instead, we employ a quasi-static approach in which the inward shift of the demand function is captured by year dummies, thereby leaving the form and curvature of the demand function unchanged. In fact, in our empirical example we have reason to believe that there are only moderate shifts of the demand function, as we focus on households that have not changed their cars over the three years they are surveyed. This belief is confirmed by the fact that the year dummies included in the estimation specification are statistically insignificant both individually and as a whole, and have therefore been left out in our final estimations presented in the subsequent section.

To provide for a reference point for the results obtained from panel estimation

methods (see e. g. FRONDEL and VANCE, 2010, for a discussion), we also estimate specification (5) using pooled Ordinary Least Squares (OLS). While the fixed-effects estimator may be a potentially superior alternative, we ultimately focus on 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. Furthermore, the random-effects estimator is particularly attractive when the cross-section information, here determined by the number of households, is much larger than the number of time-series observations (HSIAO, 2003), as is the case for our database. Not least, random-effects methods also allow for the estimation of coefficients of time-invariant variables, which is precluded by the fixed-effects estimator.

## 5 Empirical Results

In line with our reasoning of the previous section, the fixed-effects estimates reported in Table 2 are statistically insignificant for almost all 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. Moreover, we perform the classical test of BREUSCH and PAGAN (1979) to examine the superiority of the random-effects model over an OLS estimation using pooled data. The test statistic of this Lagrange multiplier test of  $\chi^2(1) = 176.03$  clearly rejects the null hypothesis of no heterogeneity among households:  $Var(\xi_i) = 0$ .

In our discussion of the empirical results, we therefore focus on the random-effects estimates. Several features of the results reported in the right-hand panel of Table 2 bear highlighting. First, while we prefer the model specification related to Definition 4 for reasons presented in Section 2 and identify the rebound by the negative estimate of the coefficient of  $\ln(p^-)$ , the estimated rebound effect of 58% suggests that some 58% of the potential energy savings due to an efficiency improvement is lost to increased driving. Also of note is that this estimate perfectly fits to the rebound range of 58% to 59% estimated by FRONDEL, PETERS, and VANCE (2008) for the sub-sample

of single-vehicle German households observed between 1997 and 2005.

**Table 2:** Estimation Results for Travel Demand of Single-Vehicle Households.<sup>4</sup>

	Pooled OLS		Fixed Effects		Random Effects	
	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors
$\ln(p^+)$	** -0.663	(0.166)	0.258	(0.244)	** -0.560	(0.149)
$\ln(p^-)$	** -0.689	(0.157)	0.186	(0.294)	** -0.584	(0.168)
<i>children</i>	0.005	(0.024)	0.026	(0.090)	0.028	(0.031)
<i>income</i>	** 0.088	(0.034)	0.034	(0.053)	* 0.065	(0.031)
<i># employed</i>	** 0.177	(0.030)	0.106	(0.060)	** 0.117	(0.030)
<i>job change</i>	** 0.168	(0.053)	** 0.179	(0.066)	** 0.179	(0.048)
<i>vacation with car</i>	** 0.448	(0.042)	** 0.314	(0.051)	** 0.374	(0.039)
<i>population density</i>	* -0.054	(0.026)	0.303	(0.298)	* -0.049	(0.021)
<i>constants</i>	** 6.440	(0.076)	** 6.596	(0.306)	** 6.532	(0.069)

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

Observations used: 1,125. Number of households: 744.

Second, even without performing any tests, a superficial inspection of the coefficient estimates of  $\ln(p^-)$  and  $\ln(p^+)$  tells us that the null hypothesis  $H_0 : \alpha_{p^+} = \alpha_{p^-}$  cannot be rejected. While this impression is confirmed by a very low  $\chi^2$ -statistic of  $\chi^2(1) = 0.02$ , the very close estimates of -0.560 and -0.584 may indicate that changes in driving behavior that are potentially induced by price peaks are entirely reversed when prices fall back to original levels. In our example, therefore, the issue of whether to identify the rebound via distinguishing between demand responses due to fuel price increases or decreases appears to be moot.<sup>5</sup>

<sup>4</sup>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 OLS standard errors are robust to this survey design feature.

<sup>5</sup>If we estimate the restrictive reversible specification, with no allowance made for price increases and decreases, more plausible results are obtained from a fixed-effects estimation. The estimate of -0.46 for the logged fuel price as the key explanatory variable, presented in Table A1 in the appendix, is statistically significant and of roughly the same magnitude as the elasticities received from the random-effects model presented in Table 2.

These results, however, may not be surprising given the fact that we deliberately focus here on single-vehicle households that do not change their car during the survey period. We thus augment our sample by including multi-vehicle households. Fundamental differences, though, cannot be observed from Table 3, possibly due to the fact that multi-vehicle households comprise a relatively small share, 36%, of the entire sample. Most notably, there is again no empirical evidence for asymmetric fuel price responses, suggesting the validity of the reversible specification.<sup>6</sup>

**Table 3:** Estimation Results for Travel Demand if Multi-Car Households are included.

	Pooled OLS		Fixed Effects		Random Effects	
	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors
$\ln(p^+)$	** -0.590	(0.145)	-0.018	(0.189)	** -0.448	(0.127)
$\ln(p^-)$	** -0.589	(0.142)	0.027	(0.233)	** -0.480	(0.131)
<i>children</i>	0.030	(0.021)	0.007	(0.072)	* 0.053	(0.021)
<i>income</i>	** 0.128	(0.030)	-0.034	(0.042)	** 0.096	(0.026)
<i># employed</i>	** 0.150	(0.026)	-0.087	(0.053)	** 0.109	(0.026)
<i>job change</i>	** 0.118	(0.040)	** 0.111	(0.047)	** 0.113	(0.036)
<i>vacation with car</i>	** 0.406	(0.036)	** 0.275	(0.048)	** 0.341	(0.033)
<i>multi-car households</i>	** 0.442	(0.045)	0.148	(0.130)	** 0.472	(0.045)
<i>population density</i>	** -0.059	(0.023)	0.080	(0.227)	* -0.052	(0.021)
<i>constants</i>	** 6.385	(0.066)	** 6.960	(0.230)	** 6.482	(0.060)

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

Observations used: 1,470. Number of households: 994.

Yet, a comparison of the estimation results reported in Tables 2 and 3 and in the appendix indicates that the travel demand responsiveness of single-car households to fuel prices is somewhat more pronounced than that of multi-car households – although the discrepancies are not statistically significant. This may be due the fact that in multi-car households drivers are able to choose among the most efficient cars for

<sup>6</sup>As presented in the appendix, the fixed-effects model using the reversible specification yields a statistically significant elasticity estimate of -0.21.



their traveling purposes. This difference would also explain why the elasticity estimates reported by FRONDEL, PETERS, and VANCE (2008), which were based exclusively on single car households, are on the high side of those appearing in the literature. Finally, it 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.

There are additional discrepancies emerging from the multiple-vehicle sample: While the presence of children, for example, positively affects travel demand 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 single-car 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 larger effect for the single-car households, which substantiates the logic that such households use the car primarily for commuting purposes.

## 6 Summary and Conclusion

Drawing on household level mobility data from Germany, the principal aim of this paper has been to test for evidence of an asymmetric response to fluctuations in fuel prices. Although several studies have shown that the negative demand response to fuel price increases is higher in magnitude than the positive response to fuel price decreases, the question as to whether this reflects a behavioral reaction or a manifestation of technical change continues to stimulate discussion. Our interest in this question relates to its implications for the estimation of the rebound effect, the behaviorally induced offset in the reduction of energy consumption following efficiency improvements (CRANDALL, 1992).

By using panel data comprised of households who did not change their automobile during the survey period, our econometric analysis was structured to allow for asymmetric price responses while at the same time ruling out the possibility that these

arise from technical change. We argue that were an asymmetry to be detected, it would require us to specifically reference the fuel price elasticity derived from price decreases in order to identify the rebound effect. Failure to do so would result in an upwardly biased estimate of the rebound, presuming that the response to price increases was indeed greater than to decreases.

Our empirical estimates suggest that concerns about such bias are unsubstantiated. We have failed to reject the null hypothesis that the magnitude of the response to a price increase is equal to that of a price decrease. One implication emerging from this finding may be that the price asymmetry observed in many other studies is largely the result of the sunk-cost nature of energy-saving capital equipment, rather than behavioral inertia on the part of consumers. Even so, our symmetry finding also maintains when we expand the sample to include households owning multiple cars.

From a policy perspective, the fact that the estimated rebound is relatively high calls into question the effectiveness of the European Union's current emphasis on efficiency standards as a pollution control instrument. The random-effects estimate of the rebound amounts to 58%, which is virtually the same as that obtained by FRONDEL, PETERS, and VANCE (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 nearly 60% of the potential energy saving from efficiency improvements in Germany is lost to increased driving. Given this response, we would argue that fuel taxes should continue to play an important role in climate policy. Unlike fuel efficiency standards, fuel taxes directly confront motorists with the costs of driving, thereby encouraging the purchase of more fuel efficient vehicles and having an immediate impact on driving behavior.

# Appendix

**Proposition:** If service demand  $s$  solely depends on  $p_s$ , fuel prices  $p_e$  are exogenous, and energy efficiency  $\mu$  is constant, then

$$\eta_{p_e}(s) = \eta_{p_s}(s).$$

**Proof:** Using price relation  $p_s = p_e/\mu$ , the chain rule, and the assumption that the service amount  $s$  solely depends on the price  $p_s$ , we obtain

$$\begin{aligned} \eta_{p_e}(s) &= \frac{\partial \ln s}{\partial \ln p_e} = \frac{\partial \ln s}{\partial \ln p_s} \cdot \frac{\partial \ln p_s}{\partial \ln p_e} = \eta_{p_s}(s) \cdot \frac{\partial \ln(p_e/\mu)}{\partial \ln p_e} \\ &= \eta_{p_s}(s) \cdot \left[ \frac{\partial \ln p_e}{\partial \ln p_e} - \frac{\partial \ln \mu}{\partial \ln p_e} \right] = \eta_{p_s}(s) \cdot \left[ 1 - \frac{\partial \ln \mu}{\partial \ln p_e} \right] = \eta_{p_s}(s), \end{aligned}$$

where the last term in the most right bracket vanishes if efficiency  $\mu$  is constant, i. e. , if  $\frac{\partial \ln \mu}{\partial \ln p_e} = 0$ .

**Table A1:** Fixed-Effects Estimation Results for Reversible Specifications.

	Single-Vehicle		Multi-Vehicle	
	Households		Households	
	Coeff.s	Std. Errors	Coeff.s	Std. Errors
$\ln(p)$	** -0.458	(0.111)	** -0.206	(0.095)
<i>children</i>	0.014	(0.056)	0.005	(0.033)
<i>income</i>	0.001	(0.025)	0.003	(0.021)
<i># employed</i>	0.066	(0.035)	0.018	(0.031)
<i>job change</i>	0.049	(0.037)	0.030	(0.026)
<i>vacation with car</i>	** 0.306	(0.031)	** 0.250	(0.024)
<i>multi-car households</i>	–	–	** 0.337	(0.053)
<i>population density</i>	* 0.167	(0.084)	* 0.128	(0.010)
<i>constants</i>	** 6.674	(0.100)	** 6.821	(0.104)
Observations used:	2,969		4,104	
Number of households:	1,668		2,166	

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

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