RUHR
ECONOMIC PAPERS

Manuel Frondel
Colin Vance

Re-Identifying the Rebound – What About Asymmetry?

RUHR UNIVERSITÄT BOCHUM RUB rwi

#276

Imprint

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI)
Hohenzollernstr. 1-3, 45128 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #276

Responsible Editor: Christoph M. Schmidt

ISSN 1864-4872 (online) – ISBN 978-3-86788-321-4

Ruhr Economic Papers #276

Manuel Frondel and Colin Vance

Re-Identifying the Rebound – What About Asymmetry?

RUHR UNIVERSITÄT BOCHUM RUB
rwi

Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

ISSN 1864-4872 (online)
ISBN 978-3-86788-321-4

Manuel Frondel and Colin Vance[1]

Re-Identifying the Rebound – What About Asymmetry?

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. Such an asymmetric response would necessitate reference to the fuel price elasticity derived from price decreases in order to identify the rebound effect, as the rebound occurs in response to a decrease in unit cost for car travel due to improved fuel efficiency. While we fail to reject the hypothesis that the magnitude of the response to a price increase is equal to that of a price decrease, our rebound effect estimate for single-vehicle households of 58% is in line with a recent German study by Frondel, Peters, and Vance (2008).

JEL Classification: D13, Q41

Keywords: Automobile travel; panel estimation models

August 2011

---

1 Manuel Frondel, RWI and RUB; Colin Vance, RWI and Jacobs University Bremen. *– We are grateful for invaluable comments and suggestions by Christoph M. Schmidt, as well as two anonymous reviewers, and the editor, Lester HUNT. This work has been partly supported by the German Federal Ministry of Education and Research (BMBF) within the framework of the project "Social Dimensions of the Rebound Effect".* *– All correspondence to Manuel Frondel, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, E-Mail: manuel.frondel@rwi-essen.de..*

1 Introduction

Energy efficiency standards are seen as a cornerstone in the efforts to meet the European Commission's international commitments to reduce greenhouse gases. In the transport sector, for instance, which accounts for roughly 20% of the EU's CO2 emissions, regulation 443/2009 sets limits on the allowable per-kilometer carbon dioxide (CO2) emissions of newly registered automobiles. 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 cost of car travel. Presuming that mobility is a conventional good, a decrease in this cost 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 58-59%, 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[1]: 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.

GRIFFIN 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 GRIFFIN 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, a claim that is challenged by HUNTINGTON (2006). 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 than the response to decreases, then naive calculations of the rebound effect based on reversibility would be overestimated.

[1]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).

Using data from a German household panel, the present study advances understanding of fuel price asymmetries and the rebound effect in several respects. First, and contrary to previous studies, we suggest a novel definition of the direct[2] rebound effect that lends itself to an asymmetric modeling of fuel price responses. Presuming that the asymmetry assumption is found to be correct, we argue that the rebound effect is consequently identified by an elasticity estimate that reflects changes in travel demand due to *decreases* in fuel prices, as the rebound effect occurs in response to a decrease in the unit cost for car travel due to improved fuel efficiency.

Second, 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 mainly technical change is driving the result.

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, so that the number of households of our database almost doubled.

The following section provides for a household production model of private mo-

[2]The indirect rebound effect and general equilibrium effects have also been distinguished in the literature (see, e. g. , SORRELL, DIMITROUPOULOS, SOMMERVILLE, 2009:1356). The indirect rebound effect arises from an income effect: lower per-unit cost of an energy service implies – *ceteris paribus* – that disposable income grows. General equilibrium effects arise from innovations, such as James WATT's famous steam engine, that increase society's aggregate income potential. Given that both indirect and general equilibrium effects are difficult to quantify, the overwhelming majority of empirical studies confines itself to analyzing the direct rebound effect.

bility demand. 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 Theoretical Model

Using BECKER's (1965) household production framework, we develop a theoretical model to illustrate that symmetric demand responses to fuel price changes are plausible only under very restrictive assumptions, so that, generally, asymmetry should prevail. Taking account of asymmetric effects is important for numerous reasons. First, with respect to the direct rebound effect, for which we present the common rebound definitions in the appendix, this effect might be mis-measured if asymmetry is ignored. Second, if there are asymmetries, for instance, because motorists learn to drive more efficiently due to price increases, but do not stop driving efficiently when prices go down, price volatility might be a conservation measure and, hence, an effective means to reduce greenhouse gas emissions.

To formally explain the plausibility of asymmetric demand responses, we draw on BECKER's seminal work on household production and assume that households are, ultimately, not interested in the amount of energy required for a certain amount of service, but in the energy service, such as mobility and home heating, itself:

$$s_i = f_i(e_i, t_i, k_i, o_i), \tag{1}$$

where production function f_i describes how households "produce" service i in the amount of s_i by using time, t_i, capital, k_i, other market goods o_i, and energy, e_i. The higher the efficiency μ_i of a given technology, the less energy $e_i = s_i/\mu_i$ is required for the provision of service i, which reflects the definition of energy efficiency typically employed in the economic literature (see e. g. BINSWANGER, 2001:121):[3]

$$\mu_i = \frac{s_i}{e_i} > 0. \tag{2}$$

For the specific example of individual conveyance, parameter μ_i can be measured in terms of vehicle kilometers per liter of fuel input. Based on efficiency definition (2), 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 is:

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

It is further assumed that any household's utility depends solely on the amounts $s_1, ..., s_n$ of services:

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

Any 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

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

if the non-wage income is assumed to be zero for the sake of simplicity. p_{e_i} and p_{o_i} indicate the prices of energy and other market good inputs, respectively, while p_{k_i} captures the annualized investment cost required for satisfying the demand s_i for service i.

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

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

[3] This 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 the service level with respect to the energy input.

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

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

If price alterations merely change the service demand s_j, but do not alter the input of time t_j, capital k_j, and other market goods o_j, the first-order condition (8) further simplifies to

$$\frac{\partial u}{\partial s_j} = \lambda \cdot p_{s_j}, \tag{9}$$

where we have employed price relationship (3), i. e. $p_{s_j} = p_e/\mu_j$, and $\partial e_j/\partial s_j = 1/\mu_j$, thereby exploiting efficiency definition (2). The following proposition demonstrates that for this special case, one would expect a symmetric effect of rising and falling prices on service demand.

Proposition: If $\frac{\partial u}{\partial s_j} > 0$ and $\frac{\partial^2 u}{\partial s_j^2} < 0$ and if price changes 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 $\frac{\partial o_j}{\partial s_j} = 0$, then service demand s_j solely depends on p_{s_j}, and

$$\frac{\partial s_j}{\partial p_{s_j}} < 0,$$

and, finally, for $\Delta^+ p_{s_j} = -\Delta^- p_{s_j}$, where $\Delta^+ p_{s_j} := \Delta p_{s_j} > 0, \Delta^- p_{s_j} := -\Delta p_{s_j} < 0$, it is:

$$\Delta^+ s_j = -\Delta^- s_j, \tag{10}$$

with $\Delta^+ s_j := \frac{\partial s_j}{\partial p_{s_j}} \cdot \Delta^+ p_{s_j}$ and $\Delta^- s_j := \frac{\partial s_j}{\partial p_{s_j}} \cdot \Delta^- p_{s_j}$.

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,

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

where $(\frac{\partial u}{\partial s_j})^{-1}$ designates the inverse of $\frac{\partial u}{\partial s_j}$, which solely depends on p_{s_j}, as the argument of $(\frac{\partial u}{\partial s_j})^{-1}$ is $\lambda \cdot p_{s_j}$ with λ being constant. Using the differentiation rule for inverse functions, it follows that

$$\frac{\partial s_j}{\partial p_{s_j}} = \frac{\partial}{\partial p_{s_j}} [(\frac{\partial u}{\partial s_j})^{-1}(\lambda \cdot p_{s_j})] = \frac{1}{\frac{\partial}{\partial p_{s_j}}[\frac{\partial u(\lambda \cdot p_{s_j})}{\partial s_j}]} = \frac{1}{\frac{\partial^2 u}{\partial s^2}} \cdot \lambda < 0, \tag{11}$$

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 (9).

Finally, for $\Delta^+ p_{s_j} = -\Delta^- p_{s_j}$, the symmetry in demand responses given by (10) results immediately from the fact that, in this special case, demand s_j solely depends on price p_{s_j}, from which $\Delta^+ s_j := \frac{\partial s_j}{\partial p_{s_j}} \cdot \Delta^+ p_{s_j}$ and $\Delta^- s_j := \frac{\partial s_j}{\partial p_{s_j}} \cdot \Delta^- p_{s_j}$ follow. It bears noting that for any given price $p^0_{s_j}$, the second derivative $\frac{\partial^2 u}{\partial s^2}$ on the right-hand-side of equation (11) is well-defined, and so are $\frac{\partial s_j}{\partial p_{s_j}}$, $\Delta^+ s_j$, and $\Delta^- s_j$, as utility $u(s_1, s_2, ..., s_n)$ is a twice differentiable function, for which the demand curves exhibit no kinks. Among other assumptions, it is thus the well-behavedness of the utility function that provides for the proposed symmetry result. $\square$

In general, however, the preconditions of this proposition are not given, because energy price changes may also alter the input of time t_j or of capital k_j, rather than only affect service demand s_j and, hence, energy input e_j. For instance, as a consequence of a fuel price shock, a household may buy a new, more fuel-efficient automobile so that $\frac{\partial k_j}{\partial s_j} \neq 0$ and, hence, service demand would be different even when prices would return to the original level, yielding the hysteresis effect described above. In short, as this section's household production model illustrates, one would generally expect asymmetric mobility demand responses due to either rising and falling fuel prices.

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 some 2 % per annum on average. Our primary focus is on single-car households that did not change their car over the three years of the survey, thereby abstracting from complexities associated with the influence of technological change. The resulting sample comprises a total of 1,125 observations covering 744 households. We also explore the inclusion of multi-car households, which results in a sample size of 1,470 observations across 994 households.

The travel survey information, which is recorded at the level of the automobile, is used to derive the dependent and explanatory variables required for estimating the rebound effect. To this end, for empirical reasons explained in the appendix, we prefer Definition 4 of the rebound definitions presented there, which is based on the fuel price elasticity of mobility demand. Hence, 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.[4] To distinguish between the response to rising and falling prices, two price variables, p^+ and p^-, are employed, whose definition is given in Table 1 and explained in detail in the next section.

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. As a proxy for the availability of public transit, we expect the variable *population density*, which is measured in thousand people per square kilometer, to have a negative impact on the dependent variable, the distance driven, whereas *income* should have a positive effect. As we believe that undertaking a vacation trip with the car crucially depends on factors other than current fuel prices, such as preferences for

[4]The price series was deflated using a consumer price index for Germany obtained from DESTATIS (2011).

the vacation destination and the cost of alternative modes, such as the flight cost for the whole family, we have included the variable *vacation with car* in the model specification.

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 € per liter	1.03	0.15
p^+	Equals p_e if $p_{it} > p_{i(t-1)}$ and 0 otherwise	1.07	0.14
p^-	Equals p_e if $p_{it} \leq p_{i(t-1)}$ and 0 otherwise	0.98	0.14
# children	Number of children younger than 18 in the household	0.35	0.76
# employed	Number of employed household members	0.73	0.76
income	Real Household income in 1,000 €	2.11	0.66
job change	Dummy: 1 if an employed household member changed jobs within the preceding year	0.11	–
vacation with car	Dummy: 1 if household undertook vacation with car during the survey period	0.22	–
multi-car households	Dummy: 1 if a 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	0.95	1.07

Note: The means reported for p^+ and p^- are the means of the non-vanishing values.

4 Methodology

To capture potentially different responses to rising and falling prices, several price decomposition approaches have been suggested in the literature that have been frequently used in empirical studies. These include 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). In detail, along with price variable p, to capture the potentially asymmetric effects of prices rises above the previous maximum, TRAILL et al. (1978) include the variable p_{max}, which is defined as follows: $p_{max}(0) = p(0)$, $p_{max}(t) = p(t)$ if $p(t) > p(t-\tau)$ for $\tau = 1, ..., t$ and $p_{max}(t) = p(t-1)$ otherwise. GATELY's price decomposition approach decomposes the price variable p into three components: p_{cut}, $p_{recovery}$, and p_{max}, where p_{max} is defined as in the ratchet model of TRAILL, COLMAN, and YOUNG (1978), while p_{cut} and $p_{recovery}$ capture price cuts and recoveries, respectively, and are defined accordingly. For example, p_{cut} is defined by $p_{cut}(0) = 0$, $p_{cut}(t) = p_{cut}(t-1) + p(t) - p(t-1)$ if $p(t) < p(t-1)$, and $p_{cut}(t) = p_{cut}(t-1)$ otherwise.

In what follows, we deliberately refrain from employing such classical models for several reasons: First, GRIFFIN and SCHULMAN (2005:7) criticize these models for being highly dependent on the starting point of the data. In fact, while choosing the first year of the sampling period as starting point, for which p_{max} is set to the price $p(0)$ observed in this year, seems natural from the perspective of an empiricist, it appears to be quite arbitrary from a theoretical point of view. A second troubling aspect of the price decomposition approach, which includes the ratchet models as special cases, may be seen in the fact that the demand curve can shift inward purely due to price volatility, although the average price level remains fixed, an issue illustrated by GRIFFIN and SCHULMAN (2005:7) by a simple example. While, formally, this inward shift is due to the inclusion of the price cut and recovery variables p_{cut} and $p_{recovery}$, such an inward shift of demand curve may be plausible, however, if price volatility is an effective energy conservation measure indeed (see the discussion at the outset of Section 2).

Third, while abstaining from the application of such classical approaches that capture long-run demand relationships and potential shifts of the corresponding demand curve in the long term (DARGAY, 1992:169), we choose a model specification that allows for identifying possible asymmetric fuel price responses in the short term, as we deliberately confine our investigation to households that have not changed their cars over the three years they are surveyed. Focusing on the last of the four definitions of the rebound effects presented in the appendix, we regress the logged monthly vehicle-kilometers traveled, $\ln(s)$, on those logged fuel prices $\ln(p^+)$ that are observed after a price increase from year $t-1$ to t, and on 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:

$$\ln(s_{it}) = \alpha_0 + \alpha_{p^+} \cdot \ln({p^+}_{it}) + \alpha_{p^-} \cdot \ln({p^-}_{it}) + \alpha_{\mathbf{x}}^T \cdot \mathbf{x}_{it} + \xi_i + \nu_{it} \,. \tag{12}$$

Subscripts i and t are used to denote the observation and time period, respectively, and the superscript T designates the transposition of a vector. ξ_i denotes an unknown individual-specific term, and ν_{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 (12), with price variable p^+ being defined as

$${p^+}_{it} = p_{it}, \quad \text{if} \quad p_{it} > p_{i(t-1)}, \tag{13}$$

and ${p^+}_{it} = 0$ otherwise, while p^- is generated from falling prices in a similar way (see Table 1). 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. It bears noting that our approach is less restrictive than the classical ratchet specification of TRAILL, COLMAN, and YOUNG (1978), which assumes that only prices rises above the previous maximum have asymmetric effects (DARGAY, 1992:168). In contrast, our approach is based on the assumption that each price rise, as well as each price fall, may affect demand, albeit in a potentially different way.

While this also holds true for GATELY's price decomposition approach, a final reason for choosing specification (12) is that the temporal restrictiveness of our data base does not allow for the application of price decomposition approaches, 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 potential inward shifts of the demand function are captured by year dummies, thereby leaving the form and curvature of the demand function unchanged. In fact, for our empirical example, we have reason to believe that these time dummies would turn out to be statistically insignificant, reflecting moderate or even vanishing shifts of the demand function, as we focus on households that did not change their cars over the maximum of 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.

Given specification (12), for which *a priori* α_{p^+} can be assumed to differ from α_{p^-}, we argue that the rebound effect has to be identified by the negative coefficient estimate of $\ln(p^-)$, as the rebound occurs in response to a decrease in unit cost for car travel due to improved fuel efficiency. To our knowledge, the issue of asymmetry of fuel price elasticities has never been addressed in the literature on the rebound effect, but it is highly relevant for its correct definition and identification if one is willing to identify the rebound on the basis of price elasticities (for a discussion on this issue, see the appendix).

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:

$$H_0 : \alpha_{p^+} = \alpha_{p^-} , \tag{14}$$

which, if correct, implies that model (12) reduces to the reversible specifications that are typically employed to estimate the rebound effect (see e. g. FRONDEL, PETERS, and

VANCE, 2008).[5] If, however, H_0 is rejected, we argue that the rebound effect should be identified by the negative of the estimate of α_{p^-}.

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 (12) using pooled Ordinary Least Squares (OLS), although applying OLS methods generally yields neither consistent nor efficient estimation outcomes. 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 number of children or the number of employed household members. 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: $Var(\xi_i) = 0$.[6]

[5] Instead of including p^+ and p^-, an equivalent way of testing asymmetry would have been to include p and p^+ or p and p^- (DARGAY, 1992:168) and to test for $H_0 : \alpha_{p^+} = 0$ or $H_0 : \alpha_{p^-} = 0$, respectively.

[6] Nevertheless, in the results tables we also present the OLS outcomes to demonstrate the improvements in the estimation results if heteroskedasticity is taken into account by employing GLS methods,

In our discussion of the empirical results, we therefore focus on the random-effects estimates. Several features of the results reported in Table 2 bear highlighting. First, noting from the discussion in the previous section that the rebound effect is identified by the negative estimate of the coefficient of $\ln(p^-)$, the estimated coefficients suggest that 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 subsample of single-vehicle German households observed between 1997 and 2005.

Table 2: Estimation Results for Travel Demand of Single-Vehicle Households.[7]

	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)
# children	0.005	(0.024)	0.026	(0.090)	0.028	(0.031)
income	**0.088	(0.034)	0.034	(0.053)	*0.065	(0.031)
# employed	**0.177	(0.030)	0.106	(0.060)	** 0.117	(0.030)
job change	**0.168	(0.053)	** 0.179	(0.066)	** 0.179	(0.048)
vacation with car	**0.448	(0.042)	** 0.314	(0.051)	** 0.374	(0.039)
population density	*-0.054	(0.026)	0.303	(0.298)	*-0.049	(0.021)
constant	**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 at any conventional level. This impression is confirmed by a low χ^2-statistic of $\chi^2(1) = 0.02$. The very close estimates of -0.560 and -0.584 thus indicate that

as is done by the random-effects estimator.

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

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.[8]

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. As presented in Table 3, we thus augment our sample by including multi-vehicle households. Fundamental differences, though, cannot be observed from the estimates, possibly due to the fact that multi-vehicle households comprise a relatively small share – about 25% – of the sample. Most notably, there is again no empirical evidence for asymmetric fuel price responses. The χ^2-statistic obtained from the test of $H_0 : \alpha_{p^+} = \alpha_{p^-}$ from the random-effects model is $\chi^2(1) = 0.04$, suggesting the validity of the reversible specification.

Yet, a comparison of the estimation results reported in Tables 2 and 3 indicates that the travel demand elasticity obtained from the sample limited to single-car households is somewhat more pronounced than that received from the sample that includes multi-car households – although the discrepancies are not statistically significant. If price responses of single-car households were actually stronger than those of multi-vehicle households, this may be due the fact that in multi-car households drivers are able to choose among the most efficient cars for their traveling purposes. To some degree, this difference may 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. Another key reason for the high elasticities obtained here and by FRONDEL, PETERS, and VANCE (2008) might be that the elasticities from household-level data are generally larger than those from aggregate time-series data. Finally, it bears noting that much of the research on this

[8]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 is statistically significant and of roughly the same magnitude as the elasticities obtained from the random-effects model presented in Table 2.

topic, particularly that using household level data, is drawn from the US, where elasticity estimates may be lower because of longer driving distances and fewer alternative modes.

Table 3: Estimation Results for Travel Demand if Multi-Vehicle 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)
# children	0.030	(0.021)	0.007	(0.072)	* 0.053	(0.021)
income	**0.128	(0.030)	-0.034	(0.042)	** 0.096	(0.026)
# employed	**0.150	(0.026)	-0.087	(0.053)	** 0.109	(0.026)
job change	**0.118	(0.040)	** 0.111	(0.047)	** 0.113	(0.036)
vacation with car	**0.406	(0.036)	** 0.275	(0.048)	** 0.341	(0.033)
multi-car households	**0.442	(0.045)	0.148	(0.130)	** 0.472	(0.045)
population density	**-0.059	(0.023)	0.080	(0.227)	*-0.052	(0.021)
constant	**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.

There are additional discrepancies emerging from the sample of households with multiple vehicles: While the number 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

Although several empirical 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 (GRIFFIN and SCHULMAN, 2005). Our principal interest in this asymmetry 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). We argue that if the responses to increasing and decreasing fuel prices are asymmetric, it would require us to reference the fuel price elasticity derived from price *decreases* in order to identify the rebound effect, as the rebound occurs in response to a decrease in unit cost for car travel due to improved fuel efficiency.

Drawing on household-level mobility data from Germany, we have tested for evidence of an asymmetric response to fluctuations in fuel prices. 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 minimizing the possibility that these arise from technical change. Failure to control for asymmetry 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, at least for our empirical example, concerns about such a 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. Our symmetry finding also maintains when we expand the sample to include households owning multiple cars. 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.

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 resulting from both the asymmetric and the reversible specification amounts to 58% for single-car households, 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 merely 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 between about 50% to 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 cost of driving, thereby encouraging the purchase of more fuel efficient vehicles and having an immediate impact on driving behavior.

Appendix: A Variety of Rebound Definitions

Along the lines of SORRELL and DIMITROUPOULOS (2008), we 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, and add a fourth definition that we believe is superior for empirical reasons. 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:

Definition 1:
$$\eta_\mu(s) := \frac{\partial \ln s}{\partial \ln \mu}\,, \tag{15}$$

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 μ:

Definition 2:
$$\eta_\mu(s) = -\eta_{p_s}(s)\,. \tag{16}$$

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:
$$\eta_\mu(s) = -\eta_{p_e}(e)\,. \tag{17}$$

Definitions 2 and 3, however, are only equivalent if the energy efficiency μ 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 μ is constant.

To analyze asymmetric responses to changing driving cost, 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 μ, 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 μ from the analysis, alternative approaches are instrumental 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 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 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 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:
$$\eta_\mu(s) = -\eta_{p_e}(s) \; . \tag{18}$$

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

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

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

Proof: Using price relation $p_s = p_e/\mu$ derived in Section 2, the chain rule, and the assumption that the service amount s solely depends on the price p_s, we obtain

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

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

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 appendix suggests selecting the fuel price elasticity of transport demand, $\eta_{p_e}(s)$, for estimating the rebound effect, rather than employing other fuel- or service price elasticities that have been applied in the literature.

References

ANGRIST, J. D. , PISCHKE, J.-S. (2009) *Mostly Harmless Econometrics – An Empiricists Companion*. Princeton University Press.

ARAL (2011) http://www.aral.de/.

BECKER, G. S. (1965) A Theory of the Allocation of Time. *Economic Journal* **75**, 493-517.

BERKHOUT, P. H. G. , MUSKENS, J. C. , VELTHUISJEN, J. W. (2000) Defining the Rebound Effect. *Energy Policy* **28**, 425-432.

BINSWANGER, M. (2001) Technological Progress and Sustainable Development: What About the Rebound Effect? *Ecological Economics* **36**, 119-132.

BREUSCH, T., PAGAN, A. (1979) A simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica* **47**, 1287-1294.

BROOKES, L. (2000) Energy Efficiency Fallacies Revisited. *Energy Policy* **28**, 355-367.

CRANDALL, R. W. (1992) Corporate Average Fuel Economy Standards. *Journal of Economic Perspectives*, 6(2), 171-180.

DARGAY, J. M. (1992) *The Irreversible Effects of High Oil Prices: Empirical Evidence for the Demand for Motor Fuels in France, Germany, and the UK*, in Energy Demand: Evidence and Expectations, ed. D. Hawdon, London: Academic Press, 165-182.

DARGAY, J. M. (1993) Demand Elasticities. A Comment. Journal of Transport Economics and Policy 27 (1), 87-90.

DARGAY, J. M. , GATELY, D. (1994) Oil Demand in the Industrialized Countries. *The Energy Journal*, Special Issue on the Changing World Petroleum Market, 39-67.

DARGAY, J. M. , GATELY, D. (1997) The Demand for Transportation Fuels: Imperfect Price-Reversibility. *Transportation Research Part B: Methodological*, 31 (1), 71-82.

DESTATIS (Federal Statistical Office Germany) (2011) http://www.destatis.de/.

FRONDEL, M., SCHMIDT, C. M. , VANCE, C. (2011) A Regression on Climate Policy: The European Commission's Legislation to Reduce CO2 Emissions from Automobiles. *Transportation Research Part A: Policy and Practice*, forthcoming.

FRONDEL, M., VANCE, C. (2010) Fixed, Random, or Something in Between? A Variant of Hausman's Specification Test for Panel Data Estimators. *Economics Letters*, 107, 327-329.

FRONDEL, M., PETERS, J., VANCE, C. (2008) Identifying the Rebound: Evidence from a German Household Panel. *The Energy Journal*, 29 (4), 154-163.

GATELY, D. (1992) Imperfect Price-Reversibility of U. S. Gasoline Demand: Asymmetric Responses to Price Increases and Decreases. *The Energy Journal* 13(4), 179-207.

GATELY, D. , HUNTINGTON, H. G. (2002) The Asymmetric Effects of Changes in Price and Income on Energy and Oil Demand. *The Energy Journal* 23(1), 19-55.

GOODWIN, P., DARGAY, J., HANLY, M. (2004) Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review . *Transport Reviews* **24 (3)**, 275-292.

GRIFFIN, J. M. SCHULMAN, T. C. (2005) Price Asymmetry: A Proxy for Energy Saving Technical Change. *The Energy Journal* 26(2), 1-21.

HOGAN, W. W. (1993) OECD Oil Demand Dynamics: Trends and Asymmetries, *The Energy Journal* **14 (1)**, 125-157.

HSIAO, C. (2003) *Analysis of Panel Data.* Cambridge, Cambridge University Press.

HUNTINGTON, H. G. (2006) A Note on Price Asymmetry As Induced Technical Change. *The Energy Journal* 27(3), 1-7.

KHAZZOOM, D. J. (1980) Economic Implications of Mandated Efficiency Standards for Household Appliances. *The Energy Journal* **1**, 21-40.

MOP (German Mobility Panel) (2011) http://www.ifv.uni-karlsruhe.de/MOP.html.

RYAN, D. L. , WANG, Y., PLOUDRE, A. (1996) Asymmetric Price Responses of Residential Energy Demand in Ontario. *Canadian Journal of Economics*, 29 (Special Issue Part 1), S317-S323.

SORRELL, S., DIMITROUPOULOS, J. , SOMMERVILLE, M. (2009) Empirical Estimates of the Direct Rebound Effect: A Review. *Energy Policy* **37**, 1356-1371.

SORRELL, S. , DIMITROUPOULOS, J. (2008) The Rebound Effect: Microeconomic Definitions, Limitations, and Extensions. *Ecological Economics* **65 (3)**, 636-649.

TRAILL, B. , COLMAN, D. , YOUNG, T. (1978) Estimating Irreversible Supply Elasticities. *American Journal of Agricultural Economics* **60**, 528-531.

WEST, S. E. (2004) Distributional Effects of Alternative Vehicle Pollution Control Policies. *Journal of Public Economics* **88 (3-4)**, 735-757.

WOLFFRAM, R. (1971) Positivistic Measures of Aggregate Supply Elasticities: Some New Approaches – Some Critical Notes. *American Journal of Agricultural Economics* **53**, 356-359.