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Theoretical Issues and Empirical Evidence from a German Household Panel

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Manuel Frondel, Jörg Peters, and Colin Vance*

Identifying the Rebound: Theoretical Issues and Empirical Evidence from a German Household Panel

Abstract

Using a panel of household travel diary data collected in Germany between 1997 and 2005, this study assesses the effectiveness of fuel efficiency improvements by econometrically estimating the rebound effect, describing the extent to which higher efficiency causes additional travel. Following a theoretical discussion outlining three alternative definitions of the rebound effect, the econometric analysis generates corresponding estimates using panel methods to control for the effects of unobservables that could otherwise produce spurious results. Our results, which range between 56% and 66%, indicate a rebound that is substantially larger than obtained in other studies, calling into question the efficacy of recently implemented measures in the European Union targeted at technological innovations in the automotive sector.

JEL Classification: D13, Q41

Keywords: Household production, rebound effect, panel models

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1 Introduction

The improvement of energy efficiency is often asserted to be one of the most promising options to reduce both the usage of energy and associated negative externalities, such as carbon dioxide emissions (CO_2). Ever since the creation of the Corporate Average Fuel Economy (CAFE) standards in 1975, this assertion has been a mainstay of energy policy in the United States. In recent years, it has also found increasing currency in Europe, as attested to by the voluntary agreement negotiated in 1999 between the European Commission and the European Automobile Manufacturers Association, stipulating the reduction of average emissions to a target level of 140g CO_2/km by 2008.

Although such technological standards undoubtedly confer benefits via reduced per-unit prices of energy services, the extent to which they reduce energy consumption, and hence pollution, remains controversial. It is plausible, for instance, that the owner of a more fuel-efficient car will *ceteris paribus* drive more in response to lower per-kilometer traveling costs relative to other modes. This increase in service demand from reduced energy prices is called the "rebound effect", alternatively referred to as "take back" of efficiency improvements. KHAZZOOM (1980) was among the first to study the rebound effect at the microeconomic level of households, focusing on the effects of increases in the energy efficiency of a single energy service, such as space heating and individual conveyance. The "rebound", however, is a general economic phenomenon, diminishing potential gains of time-saving technologies (e. g. BINSWANGER 2001) as well as of innovations that may reduce the usage of resources such as water.

The significance of the "rebound", whose principle mechanisms are based on price and income effects embedded in economic theory, has been hotly debated among energy economists ever since then – see e. g. BINSWANGER (2001), BROOKES (2000), and GREENING *et al.* (2000) for surveys of the relevant literature. Part of the controversy is due to the fact that there are several mechanisms at work that may offset potential energy savings triggered by efficiency improvements. Accordingly, three types of rebound effects have been identified and distinguished in the economic literature: the direct and indirect rebound effect, as well as general equilibrium effects (GREENING and GREENE 1997, and GREENE *et al.* 1999:2).

The *direct rebound effect* describes the increased demand for an energy service whose price shrinks due to improved efficiency. This substitution mechanism in favor of the energy service works exactly as would the price reduction of any commodity other than energy and suggests that price elasticities are at issue when it comes to the estimation of the direct rebound effect. The *indirect rebound effect* arises from an income effect: lower per-unit cost of an energy service *ceteris paribus* imply that real income grows. To the extent that more money can then be spent on other goods and services that also require energy, the respective use of energy rises. Finally, innovations, such as James WATT's famous steam engine, that increase society's income potential may cause substantial *general equilibrium effects*. 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.

Though the basic mechanism is widely accepted, the core of the controversy lies in the identification of the magnitude of the direct rebound effect. Some analysts, most notably LOVINS (1988), maintain that rebound effects are so insignificant that they can safely be ignored, see e. g. GREENE (1992) and SCHIPPER and GRUBB (2000). Other authors argue that these effects might be so large as to completely defeat the purpose of energy efficiency improvements (BROOKES 1990, SAUNDERS 1992). Support for both views are found in the available empirical evidence. A survey by GOODWIN, DARGAY, and HANLY (2004), for example, cites rebound effects varying between 4 % and 89 % from studies using pooled cross-section/time-series data. Results from subsequent studies are equally wide-ranging. Using cross-sectional micro data from the 1997 Consumer Expenditure Survey, WEST (2004) finds a rebound effect that is 87 % on average, while SMALL and VAN DENDER (2007), who use a pooled cross-section of US states for 1966-2001, uncover rebound effects varying between 2.2 % and 15.3 %.

Aside from differences in the level of data aggregation, one major reason for the diverging results of the empirical studies is that there is no unanimous definition of the direct rebound effect. Instead, several definitions have been employed as determined by the availability of price and efficiency data, making comparisons across studies difficult. The resulting variety of definitions used in the economic literature is summarized and analyzed in an illuminating way by DIMITROUPOULOS and SORRELL (2006), who argue that it is particularly due to the omission of potentially relevant factors, such as capital cost, that the size of the direct rebound effect might be frequently overestimated in empirical studies. GREENE, KAHN; and GIBSON (1999) and SMALL, and VAN DENDER (2007) express similar reservations, noting in particular the shortcomings of cross-sectional or pooled approaches that fail to control for the time-invariant effects of neighborhood design, infrastructure and other geographical features, which are likely to be strongly correlated with fuel economy and travel.

Departing from the theoretical grounds provided by BECKER's (1965) classical household production function approach and drawing on a panel of household travel data, this paper focuses on estimating the rebound effect from variation in the fuel economy of household vehicles. Several features distinguish our analysis. In the theoretical section of the paper, we catalogue three commonly employed definitions of the direct rebound effect and derive propositions therefrom that are the basis for the empirical estimation of the "rebound". The empirical section of the paper builds directly on the theoretical discussion by presenting econometric estimates corresponding to each of the three definitions of the rebound effect. These estimates are generated from panel models of micro-level data, thereby bypassing aggregation problems with direct measures of how households respond to variations in fuel efficiency while at the same time controlling for omitted variables.

Our results, which range between 56 % and 66 %, indicate a "rebound" that is substantially larger than the typical effects obtained for the U.S. Based on household survey data, GREENE, KAHN, and GIBSON(1999:1), for instance, find a long-run "take back" of about 20 % of potential energy savings, confirming 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 are also substantially larger than those of WALKER and WIRL (1993), who estimate a long-run rebound effect of 36 %

for Germany using aggregate time-series data.

The following section presents three definitions of the direct rebound effect, building the basis for the empirical estimation. Section 3 describes the econometric specifications and estimators. Section 4 describes the panel data base used in the estimation, followed by the presentation and interpretation of the results in Section 5. The last section summarizes and concludes.

2 Energy Services and Direct Rebound Effects

Along the lines of BECKER's seminal work on 'household production', we assume that an individual household derives utility from energy services, such as mobility or comfortable room temperature. These services are taken to be the output of a production function f_i:

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

where f_i describes how households "produce" an amount s_i of service i by using time, t_i, energy, e_i, capital, k_i, and other market goods o_i.

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

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

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:

$$T = t_W + \sum_{i=1}^{n} t_i. \tag{3}$$

Note that t_W does not enter utility function (2).

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

$$t_W w = \sum_{i=1}^{n} p_e e_i + p_k k_i + p_o o_i, \tag{4}$$

if the household's 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 capital cost required for the service i. Time restriction (3) and budget constraint (4) can be combined to a single resource constraint involving the household's "full income" S, a concept introduced by Becker (1965):

$$S := wT = \sum_{i=1}^{n} p_e e_i + p_k k_i + p_o o_i + wt_i. \tag{5}$$

The "full income" S is the maximum labor income that a household could achieve if all available time were to be spent working at the wage rate w.

The Lagrangian L for the utility maximization problem subject to budget constraint (5) reads

$$L := u(s_1, s_2, ..., s_n) - \lambda \left[\sum_{i=1}^{n} (p_e e_i + p_k k_i + p_o o_i + wt_i) - S \right]. \tag{6}$$

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

$$\frac{\partial u}{\partial s_j} = \lambda \left[p_e \frac{\partial e_j}{\partial s_j} + \frac{\partial k_j}{\partial s_j} + \frac{\partial o_j}{\partial s_j} + w \frac{\partial t_j}{\partial s_j} \right]. \tag{7}$$

2.1 Energy Efficiency and the Direct Rebound Effect

Using the above framework to illustrate the rebound effect, we begin by drawing on the definition of energy efficiency typically employed in the economic literature, see e. g. WIRL (1997),

$$\mu_j := \frac{s_j}{e_j} > 0, \tag{8}$$

from which it follows:

$$\frac{\partial e_j}{\partial s_j} = 1/\mu_j. \tag{9}$$

Definition (8) reflects the fact that the higher the efficiency μ_j of a given technology, the less energy $e_j = s_j/\mu_j$ is required for the provision of a certain amount s_j of energy service j. For the specific example of individual conveyance, for instance, the fuel efficiency μ_j can be measured in terms of vehicle kilometers per liter of fuel input. The price p_{s_j} per unit of energy service j results from relationship (8) and is smaller the higher efficiency μ_j is:

$$p_{s_j} = \frac{p_e}{\mu_j} \ . \tag{10}$$

The concept of energy efficiency is perfectly in line with BECKER's idea of 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.

In practice, more energy efficient appliances frequently have higher fixed costs, but simultaneously reduce operating costs through lower fuel and time requirements. Commonly, however, it is assumed that energy efficiency μ_j and, hence, energy use e_j and the amount s_j of service j are uncorrelated with all other input factors of the household production function (1) such as time t_j and capital k_j. Based on this assumption, which we will relax later on, and the relationships (9) and (10), the first-order condition (7) simplifies to

$$\frac{\partial u}{\partial s_j} = \lambda \left[\, p_{s_j} \, \right]. \tag{11}$$

In principle, first-order condition (11) may 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 only a function g of service price p_{s_j} alone:

$$s_j = g(p_{s_j}). \tag{12}$$

Using this framework, the direct rebound effect of an energy efficiency improvement with respect to a single service j can be proved as follows: An efficiency improvement, causing an increase in μ_j, will yield a decline in the per-unit price $p_{s_j} = p_e/\mu_j$ of service j and, hence, of the marginal utility $\frac{\partial u}{\partial s_j}$ appearing on the left-hand side of first-order condition (11). If service j is of the usual kind, for which the derived marginal utility is decreasing when demand is increasing, that is, if $\frac{\partial^2 u}{\partial s_j^2} < 0$, as assumed by definition (2), a decrease in marginal utility will be accompanied by an increase in service demand. In short, households will usually demand more of service j as j becomes cheaper through the efficiency gains, causing a rebound partially offsetting the energy savings potential due to the efficiency improvement.

2.2 A Variety of Definitions of the Direct Rebound Effect

We now provide a concise summary of three widely known definitions of the direct rebound effect that are based on either efficiency, service price, or energy price elasticities. Using these definitions and data on fuel efficiency, fuel prices, and distance driven for household vehicles originating from German household data, we will estimate each of the three rebound effects. In what follows, subscripts will be dropped for expositional purposes.

Definition 1: An immediate and most general measure of the direct rebound effect – see e. g. BERKHOUT *et al.* (2000) – is given by $\eta_\mu(s) := \frac{\partial \ln s}{\partial \ln \mu}$, the elasticity of service demand with respect to efficiency, reflecting the relative change in service demand due to a percentage increase in efficiency.

Proposition 1: Having $\eta_\mu(s)$ in hand, we obtain the relative reduction in energy use due to a percentage change of efficiency:

$$\eta_\mu(e) = \eta_\mu(s) - 1 \, . \tag{13}$$

Only if $\eta_\mu(s)$ equals zero, that is, only if there is no rebound, $\eta_\mu(e)$ amounts to -1, indicating that 100 % of the potential energy savings due to an efficiency improvement can actually be realized. But if there is a rebound effect, i. e. if $\eta_\mu(s) > 0$, increases in energy efficiency would not completely translate to a reduction in energy usage of the same order: $\eta_\mu(e) > -1$.

Proof of Proposition 1: Employing efficiency definition (8) and taking logarithms, we get $\ln e = \ln s - \ln \mu$. Logarithmic differentiation with respect to μ yields the claim:

$$\eta_\mu(e) = \frac{\partial \ln e}{\partial \ln \mu} = \frac{\partial \ln s}{\partial \ln \mu} - \frac{\partial \ln \mu}{\partial \ln \mu} = \frac{\partial \ln e}{\partial \ln \mu} - 1 = \eta_\mu(s) - 1 \, .$$

The following two definitions are restrictive in that energy efficiency is assumed to be neither correlated with time efficiency nor capital cost, nor any other commodity. That is, it is assumed that service demand only depends on service prices, as in (12).

Definition 2: Instead of $\eta_\mu(s)$, empirical estimates of the rebound effect are frequently based on $-\eta_{p_s}(s)$, the negative price elasticity of service demand – see e.g. BINSWANGER (2001) and GREENE *et al.* (1999). Major reasons for this preference are that data on energy efficiency is often unavailable or data provides only limited variation in efficiencies.

Proposition 2: If energy prices p_e are exogenous and demand solely depends on p_s, as in (12),

$$\eta_\mu(s) = -\eta_{p_s}(s) \; . \tag{14}$$

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, that is, works through shrinking service prices p_s.

Proof of Proposition 2: Using (10), (12), and the chain rule, we obtain

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

If energy prices p_e are exogenous, $\frac{\partial \ln p_e}{\partial \ln \mu} = 0$, so that $\eta_\mu(s)$ equals $-\eta_{p_s}(s)$.

Definition 3: Empirical estimates of the rebound effect are sometimes necessarily based on $-\eta_{p_e}(e)$, the negative energy price elasticity of energy consumption, rather than on $-\eta_{p_s}(s)$, because data on energy consumption and prices is more commonly available than on energy services and service prices. It was this definition of the rebound that was originally introduced by KHAZZOOM (1980:38) and is also employed by, e. g. , WIRL (1997:30).

Proposition 3: If the energy efficiency μ is constant,

$$\eta_{p_e}(e) = \eta_{p_s}(s) \; . \tag{15}$$

Proof of Proposition 3: Using the chain rule and the definition (8) of energy efficiency as well as of service prices, (10), we get

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

Hence, only if $\frac{\partial \ln \mu}{\partial \ln p_s} = 0$ and $\frac{\partial \ln \mu}{\partial \ln p_e} = 0$, which holds true if the energy efficiency μ is constant, both elasticities are equal: $\eta_{p_e}(e) = \eta_{p_s}(s)$.

Definitions 1 - 3 of the rebound effect are based on the assumption that changes in energy efficiency trigger an increase in the demand for an energy service by reducing its price, but not because efficiency improvements may also vary other factors such as the time usage required by an energy service. In other words, correlations of energy and time efficiency have been ignored thus far, as well as the possibility that more energy efficient appliances may imply higher capital cost than less efficient alternatives. We now present a definition of the direct rebound that controls for possible correlations between energy efficiency and capital cost and, hence, assume that service demand is not only a function of service prices, but of both service prices p_s and annualized capital cost p_k: $s = h(p_s(\mu), p_k(\mu))$.

2.3 Capital Cost and the Direct Rebound Effect

Proposition 4: If efficiency changes not only imply alterations of service prices, but also of capital cost, and furthermore energy prices p_e are exogenous,

$$\eta_\mu(s) = -\eta_{p_s}(s) + \eta_{p_k}(s) \cdot \eta_\mu(p_k) \; . \tag{16}$$

In this case, the rebound $\eta_\mu(s)$ generally differs from $-\eta_{p_s}(s)$ and is determined by two impact factors, the service price effect captured by $-\eta_{p_s}(s)$ and the change in capital cost due to an efficiency improvement.

Proof of Proposition 4: Using $s = h(p_s(\mu), p_k(\mu))$ and the chain rule, we readily obtain

$$\eta_\mu(s) = \frac{\partial \ln s}{\partial \ln \mu} = \frac{\partial \ln s}{\partial \ln p_s} \cdot \frac{\partial \ln p_s}{\partial \ln \mu} + \frac{\partial \ln s}{\partial \ln p_k} \cdot \frac{\partial \ln p_k}{\partial \ln \mu} = -\eta_{p_s}(s) + \eta_{p_k}(s) \cdot \eta_\mu(p_k),$$

if energy prices p_e are exogenous, and thus $\frac{\partial \ln p_e}{\partial \ln \mu} = 0$, so that $\frac{\partial \ln p_s}{\partial \ln \mu}$ equals -1.

In case that efficiency increases imply higher annualized capital cost, i. e. if $\eta_\mu(p_k) > 0$, the rebound $\eta_\mu(s)$ is lower than otherwise if, additionally, $\eta_{p_k}(s) < 0$. Several authors, such as HENLEY *et al.* (1988), therefore argue that under these circumstances neglecting capital cost would lead to an overestimation of the rebound when relying on Definitions 2 and 3, that is, when calculating the rebound effect by estimating $-\eta_{p_s}(s)$. Since our data set in fact does not include annualized capital cost, our estimation results may be biased for this reason.

3 Methodology

Our empirical methodology proceeds with two principle aims: (1) to compare alternative model specifications that yield estimates corresponding to each of the three definitions of the rebound effect explicated in the theoretical discussion; (2) to generate these estimates using various panel data estimators that control for the omission of potentially relevant factors varying across observations and over time.

Referring to Definition 1, the first specification regresses the log of monthly kilometers traveled, $ln(km)$, on the log of kilometers traveled per liter, $ln(\mu)$, the coefficient of which is the rebound effect. As control variables, we additionally include the logged price of fuel per liter, $ln(p_e)$, and a set of household- and car-level variables designated by the vector $\mathbf{x}$.

Model 1:

$$\ln(km_{it}) = \alpha_0 + \alpha_\mu \cdot \ln(\mu_{it}) + \alpha_{p_e} \cdot \ln(p_{eit}) + \alpha_{\mathbf{x}} \cdot \mathbf{x}_{it} + \xi_i + \nu_{it} \ , \tag{17}$$

Subscripts i and t are used to denote the observation and time period, respectively. ξ_i denotes an unknown individual-specific term, and ν_{it} is a random component that varies over individuals and time.

The second model generates estimates of the rebound corresponding to Definition 2, which involves regressing $ln(km)$ on the logged price of fuel per kilometer, $ln(p_s)$, and the vector of control variables $\mathbf{x}$. In this model, the rebound effect is obtained by multiplying the coefficient of $ln(p_s)$ by (-1).

Model 2:

$$\ln(km_{it}) = \alpha_0 + \alpha_{p_s} \cdot \ln(p_{s\,it}) + \alpha_{\mathbf{x}} \cdot \mathbf{x}_{it} + \xi_i + \nu_{it} \ . \tag{18}$$

Recognizing that $p_s = \frac{p_e}{\mu}$, and that $ln(p_s) = ln(p_e) - ln(\mu)$, it can be seen that the specification of Model 2 is functionally equivalent to that of Model 1. We therefore expect the coefficients of the control variables, $\alpha_{\mathbf{x}}$, to be similar across the two models. In fact, if we impose the restriction

$$H_0 : \alpha_\mu = -\alpha_{p_e}$$

on Model 1, we exactly get Model 2. Hence, testing the null-hypothesis H_0 using Model 1 allows for a simple examination of whether both models are equivalent. Moreover, the anti-symmetry reflected by H_0 is quite intuitive: for constant fuel prices p_e, *raising* the energy efficiency μ should have the same effect on the service price p_s, and hence on the distance traveled, as *falling* fuel prices p_e given a constant energy efficiency μ.

Corresponding to our third definition of the rebound effect, the final specification regresses the logged monthly liters of fuel consumed, $ln(fuel)$, on $ln(p_e)$ and the vector of control variables $\mathbf{x}$.

Model 3:

$$\ln(fuel_{it}) = \beta_0 + \beta_{p_e} \cdot \ln(p_{e\,it}) + \beta_{\mathbf{x}} \cdot \mathbf{x}_{it} + \zeta_i + \varepsilon_{it} \ . \tag{19}$$

As in Model 2, the rebound effect can be obtained by multiplying the price coefficient by (-1). The individual-specific and random components are designated now by ζ_i and ε_{it}, and the coefficients by β rather than α, reflecting the fact that Model 3 has both a different dependent variable and a different set of regressors from Models 1 and 2.

Panel data affords three principle approaches for econometric modeling: the fixed-, between-, and random effects estimators. While most analyses neglect between effects, instead focusing on the choice between fixed and random effects, we see merit in applying all three estimators to the three model specifications. For starters, our relatively short panel of three years means that some of the regressors may have insufficient variability to be precisely estimated using fixed effects, a problem that does not afflict between effects given its reliance on cross-sectional information. Beyond this, the between-effects estimator, which is equivalent to an OLS regression of averages across time, conveys valuable economic content that is not otherwise revealed by fixed effects. Specifically, while fixed effects tells us the effect of an explanatory variable as it inter-temporally changes within subjects, between effects tells us the cross-sectional effects of changes in an explanatory variable between subjects. Last but equally important, instead of employing the standard HAUSMAN test for distinguishing between between fixed and random effects, we use a modified, but equivalent, test that, in essence, is based on the comparison of the fixed- and between effects.

The key advantage of using the fixed-effects estimator is that it produces consistent estimates even in the presence of time-invariant, unobservable factors (e.g. topography and urban form) that vary across observations and are correlated with the explanatory variables. The random-effects estimator, finally, is a matrix-weighted average of the fixed- and between-effects estimators. In contrast to the fixed-effects estimator, in which dummy variables are included to capture the time-invariant, unobservable factors ξ_i and ζ_i that vary across observations, random effects treats these factors as part of the disturbances, thereby assuming that their correlation with the regressors is zero. If this assumption is met, the random-effects estimator is a viable alternative, as it confers the advantage of greater efficiency over the fixed-effects estimator. Violation of the assumption, however, implies biased estimates.

Commonly, a HAUSMAN test is employed to test the null hypothesis that the estimated coefficients of the fixed-effects estimator are equal to those of the random-effects estimator, which, if not rejected, would suggest adoption of the random-effects estimator due to its higher efficiency. Yet, the equivalence of the fixed- and the random effects also implies that the between- and fixed effects are equal – for a proof, see the appendix – and thus that the inter-temporal within-subject effects are identical to the cross-sectional effects across subjects. As there is rarely a theoretical basis for this assumption, it must not be surprising if the null hypothesis of the HAUSMAN test is not found to withstand empirical scrutiny.

Exploiting the equivalence of between- and fixed effects under the null, we implement a modified, but equivalent[1], version of the HAUSMAN test that allows us to examine the equality of the fixed- and between coefficients for individual variables, rather than that of the whole range of fixed- and random-effects coefficients. Chi square tests can then be used to determine for which variables the assumption of equivalence holds and which variables require separate specification of the fixed- and between effects. Using, say, Model 3, the modified test is based on the following specification:

$$\ln(fuel_{it}) = \beta_0 + \beta_{\bar{p}_e} \cdot \ln(\bar{p}_{ei}) + \beta_{p_{eit}-\bar{p}_e} \cdot \ln(p_{eit} - \bar{p}_{ei}) + \boldsymbol{\beta}_{\bar{\mathbf{x}}_i} \cdot \bar{\mathbf{x}}_i + \boldsymbol{\beta}_{\mathbf{x}_{it}-\bar{\mathbf{x}}_i} \cdot (\mathbf{x}_{it} - \bar{\mathbf{x}}_i) + \eta_{it}\,, \quad (20)$$

where testing the null of the HAUSMAN test translates to examining

$$H_0 : \beta_{\bar{p}_e} = \beta_{p_{eit}-\bar{p}_e}, \boldsymbol{\beta}_{\bar{\mathbf{x}}_i} = \boldsymbol{\beta}_{\mathbf{x}_{it}-\bar{\mathbf{x}}_i}. \quad (21)$$

Estimated using the random-effects estimator, specification (20) retrieves the entire set of fixed- and between-effects estimates.

4 The German Mobility Panel Data Set

The data used in this research is drawn from the German Mobility Panel (MOP, 2007), 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 one week in autumn 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 all relevant aspects of everyday travel behavior. In addition to this general survey, the MOP includes another survey focusing specifically on vehicle travel among a sub-sample of randomly selected car-owning households. This survey takes place over a roughly six-week period in the spring, during which

[1]It is intuitively clear that specification (20) yields the fixed-effects estimates of $\boldsymbol{\beta}_{\mathbf{x}_{it}-\bar{\mathbf{x}}_i}$ and $\beta_{p_{eit}-\bar{p}_e}$ when it is estimated using the fixed-effects estimator, while the variables $\ln(\bar{p}_{ei})$ and $\bar{\mathbf{x}}_i$ are dropped due to perfect collinearity. Similarly, specification (20) should provide for the between-effects estimates of $\beta_{\bar{p}_e}$ and $\boldsymbol{\beta}_{\bar{\mathbf{x}}_i}$ when it is estimated using the between-effects estimator, while the variables $\ln(p_{eit} - p_{ei})$ and $\mathbf{x}_{it} - \bar{\mathbf{x}}_i$ vanish, as the between-effects estimator takes the average over time.

time respondents record the price paid for fuel, the liters of fuel consumed, and the kilometers driven with each visit to a gas station and for every car in the household.

The data used in this paper cover nine years of the panel, spanning 1997 through 2005. To avoid complications of multiple car ownership due to substitution effects among cars, we focus on single-car households. The resulting sample includes 574 households, 254 of which appear two years in the data and 293 of which appear all three years. To correct for the non-independence of repeat observations over the years of the survey, the regression disturbance terms are clustered at the level of the household, and the presented measures of statistical significance are robust to this survey design feature.

Table 1: Variable Definitions and Descriptive Statistics

Variable Definition	Variable name	Mean	Std. Dev.
Log of monthly kilometers driven	$\ln(kms)$	6.86	0.65
Log of monthly fuel consumption in liters	$\ln(fuel)$	4.36	0.65
Log of kilometers driven per liter	$\ln(\mu)$	-2.10	0.22
Log of fuel price per kilometer	$\ln(kms)$	2.05	0.27
Log of fuel price	$\ln(p_e)$	-0.06	0.14
Age of the car	*car age*	6.13	4.04
Dummy: 1 if fuel type is diesel	*diesel car*	0.10	0.30
Dummy: 1 if car a sports- or luxury model	*premium car*	0.21	0.40
Household size	*household size*	1.98	1.04
Number of household members with a high school diploma	*high school diploma*	0.48	0.065
Number of employed household members	*# employed*	0.71	0.074
Dummy: 1 if household undertook car vacation during the survey period	*car vacation*	0.24	0.43
Dummy: 1 if children younger than 12 live in household	*children*	0.13	0.34

We used this information, which is recorded at the level of the automobile, to derive the dependent and independent variables required for estimating each of the three variants of the rebound effect. The two dependent variables, which are converted into monthly figures to adjust for minor variations in the survey duration, are the total monthly distance driven in kilometers (Definitions 1 and 2) and the total monthly liters of fuel consumed (Definition 3). The three independent variables are the kilometers traveled per liter (Definition 1), the price paid for fuel per kilometer traveled (Definition 2), and the price paid for fuel per liter (Definition 3).[2] Table 1 contains the definitions of all the variables used in the modeling.

5 Empirical Results

Our empirical analysis of the data involved the estimation of two sets of models, one in which the individual-specific component was specified at the level of the household and one in which it was specified at the level of the automobile. Noting that this distinction had little bearing on the qualitative conclusions of the analysis, the following discussion focuses on the estimates generated at the household level. This focus facilitates comparison of the three estimators as it ensures that each uses the same sample of observations. Were the individual component set at the level of the automobile, then observations in which the household changes automobiles from one year to the next would drop out in the case of the fixed-effects estimator.

Table 2 presents estimates corresponding to Definition 1 of the rebound effect, in which fuel efficiency is regressed on – among other variables – the distance driven using fixed-, between-, and random-effects estimators. Several features of the results bear highlighting. First, we confirm that the impact of efficiency improvements on traveled distance is of the same order as the effect of fuel prices: As reported in the final row of the table, upon testing the null-hypothesis $H_0 : \alpha_\mu = -\alpha_{p_e}$, we cannot reject the anti-symmetry given by H_0 for any of the estimation techniques. Second,

[2] Because the panel spans the period preceding the introduction of the Euro in 2001, exchange rate figures obtained from the Federal Reserve Statistical Release (2007) were used to convert fuel prices recorded in Deutsche Marks into Euros. The price series was additionally deflated using a consumer price index for Germany obtained from the Statistisches Bundesamt (2007).

the estimated rebound effects are considerably higher than most estimates reported elsewhere in the literature, and suggest that some 58 % of the potential energy savings due to an efficiency improvement is lost to increased driving. Finally, these effects are of a strikingly similar magnitude across the three estimators, differing by less than a percentage point.

Table 2: Estimation Results for Model 1 and the Rebound based on Definition 1.

	Fixed-Effects Estimator		Between-Group Estimator		Random-Effects Estimator		Modified Hausman Test
$\ln(kms)$	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors	χ^2 (1) Statistics
$\ln(\mu)$	** .582	(.122)	** .593	(.139)	** .584	(.105)	0.00
$\ln(p_e)$	**-.615	(.164)	**-.583	(.211)	**-.588	(.127)	0.03
car age	-.010	(.006)	**-.020	(.006)	**-.018	(.005)	0.84
diesel car	-.240	(.183)	.120	(.102)	.014	(.090)	2.98
premium car	.145	(.146)	** .253	(.062)	** .220	(.052)	0.45
household size	-.019	(.050)	.007	(.031)	*.040	(.025)	0.07
# *high school diploma*	-.013	(.056)	** .091	(.036)	*.070	(.030)	2.64
# *employed*	**-.133	(.046)	** .220	(.036)	** .092	(.029)	**36.1
vacation with car	** .270	(.036)	** .408	(.070)	** .300	(.031)	3.25
children	-.087	(.116)	.064	(.091)	.036	(.067)	0.07
constants	**8.120	(.283)	**7.800	(.284)	**7.862	(.218)	–
$H_0 : \alpha_\mu = -\alpha_{p_e}$	F(1, 545) = 0.03		F(1, 535) = 0.00		$\chi^2(1)$ = 0.00		

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

This similarity does not hold for many of the remaining coefficients. A particularly stark difference is seen for the effect of the number of employed household members, which has a counterintuitive and negative coefficient in the fixed-effects model, but is positive in the between- and random-effects models. All else equal, we would expect that a greater number of employed persons in the household would increase the dependency on the automobile. The counterintuitive negative estimate may be the result of our relatively short panel of three years, implying insufficient variability of some regressors to be precisely estimated using fixed effects.

The remaining control variables have either intuitive effects or are statistically insignificant. Referencing the random-effects coefficients, 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 30 % increase in distance traveled. Aside from the fuel price and the number of employed household members, this is the only control variable also found to be significant in the fixed-effects model. We also explored models in which time dummies were included to control for autonomous changes in the macroeconomic environment. As these were found to be jointly insignificant across all of the models estimated, they were excluded from the final specifications.

Not unexpectedly, a HAUSMAN test rejects the null hypothesis that the fixed- and random-effects coefficients are jointly equal for all significance levels (not presented). Whether this result therefore implies that equality fails to hold for each of the variables individually is, however, not immediately clear. To pursue this issue further, we estimated the model in equation (20) and proceeded to test the equality restrictions using individual chi-square tests, the results for which are presented in the final column of Table 2. These findings confirm what was already evident from casual inspection: the difference between the fixed- and between-effects estimates of the rebound effect are statistically insignificant. In fact, this conclusion applies to several of the other explanatory variables, with the one clear exception being the number of employed people in the household.

Table 3 presents estimates of the rebound effect corresponding to Definition 2, based on a regression of distance traveled on the price of fuel per kilometer. As expected, the overall pattern is similar to that of Table 2. Again, the estimated rebound effects are high, roughly on the order of 59 %. The remaining coefficient estimates are also similar to the first specification. The HAUSMAN test rejects equality of the fixed- and random-effects models for all significance levels (not presented), and the only variable for which differences are clearly evident at the 1 % level is again the number of employed household members.

Table 3: Estimation Results for Model 2 and the Rebound based on Definition 2.

	Fixed-Effects Estimator		Between-Group Estimator		Random-Effects Estimator		Modified Hausman Test
$\ln(kms)$	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors	χ^2 (1) Statistics
$\ln(p_s)$	**-.592	(.099)	**-.590	(.122)	**-.585	(.084)	0.00
car age	-.011	(.006)	**-.019	(.006)	**-.018	(.005)	0.83
diesel car	-.236	(.181)	.120	(.098)	.014	(.090)	2.93
premium car	.145	(.146)	** .253	(.061)	** .220	(.051)	0.45
household size	.018	(.050)	.006	(.031)	*.040	(.025)	0.06
# *high school diploma*	-.012	(.056)	**.091	(.036)	*.070	(.031)	2.65
# *employed*	**-.132	(.047)	** .220	(.036)	**.092	(.030)	**36.0
vacation with car	** .270	(.037)	** .408	(.070)	**.300	(.031)	3.29
children	-.086	(.115)	.064	(.091)	.036	(.067)	1.08
constants	**8.142	(.233)	**7.794	(.249)	**7.864	(.175)	–

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

Table 4 presents estimates of the rebound effect based on Definition 3, which is distinguished by the use of total fuel consumption as the dependent variable and the price of fuel per liter as the key regressor. Despite these differences, the estimates in Table 3 are remarkably similar to those of Tables 2 and 1, albeit with a larger range across the fixed- and between-effects estimators. In this instance, the estimated rebound effect is seen to vary between 56 % and 66 %; but even here we cannot reject the hypothesis that the coefficients are equal based on the chi square test. Likewise, with the exception of the number of employed household members, the other coefficients also appear to be equal despite the rejection of the HAUSMAN test for all significance levels.

We thus conclude that although our estimates of the rebound effect are high, they appear to be robust to both the estimator and the specification. Whether the model controls for time-invariant factors that vary across cases (as with the fixed effects estimator) or case-invariant factors that vary over time (as with the between effects estimator) has no substantial impact on the key results. Perhaps even more notable is the similarity of the estimates corresponding to Definition 3 with those of Definitions 1 and 2. While the latter two incorporate efficiency either directly via the kilometers per liter traveled or indirectly via the service price per kilometer, Definition 3 relies exclusively on the price mechanism, suggesting that this information can serve as a useful substitute in the absence of data on technology.

Table 4: Estimation Results for Model 3 and the Rebound based on Definition 3.

	Fixed-Effects Estimator		Between-Group Estimator		Random-Effects Estimator		Modified Hausman Test
$\ln(fuel)$	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors	χ^2 (1) Statistics
$\ln(p_e)$	**-.562	(.166)	**-.659	(.211)	** -.583	(.128)	0.13
car age	-.009	(.007)	**-.019	(.006)	** -.017	(.005)	0.84
diesel car	-.306	(.196)	.004	(.094)	-.075	(.091)	2.06
premium car	.154	(.147)	** .325	(.057)	** .285	(.050)	1.23
household size	.004	(.048)	.036	(.031)	*.052	(.024)	0.12
# high school diploma	.001	(.055)	**.078	(.036)	*.062	(.031)	1.49
# employed	**-.114	(.045)	** .228	(.036)	** .103	(.030)	**35.2
vacation with car	** .249	(.036)	** .409	(.070)	** .283	(.031)	4.34
children	-.042	(.116)	.055	(.092)	.046	(.066)	0.45
constants	**4.405	(.105)	**4.001	(.073)	** 4.095	(.063)	–

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

6 Summary and Conclusion

Industrialized countries are increasingly struggling both to ensure their security of energy supply and to reduce emissions of greenhouse gases. It is commonly asserted that efficiency-increasing technological innovations, particularly in the transport sector, are an important pillar in this process. This assertion underpins the CAFE standards in the United States and the more recently reached voluntary agreement between the European Union and the European Automobile Manufacturers Association (ACEA) stipulating the reduction of average emissions in the new car fleet.

Although increased efficiency confers economic benefits in its own right, its effectiveness in reducing fuel consumption and pollution depends on how consumers alter behavior in response to cheaper per-unit energy prices due to improved efficiency. To the extent that consumption increases via rebound effects, gains in reducing environmental impacts and energy dependency will be offset. The results presented in this paper, based on the analysis of a German household panel, suggest that the size of this offset is potentially quite large, varying between 56 % and 66 %. Stated alternatively, the relative reduction in energy use due to a percentage change in efficiency is on the order of 34 % and 44 %.

While these estimates are considerably different from those found elsewhere in the literature, with most empirical evidence originating from the U.S., they are robust to both alternative panel estimators and to alternative measures of the rebound effect. Moreover, our results are consistent with recent anecdotal evidence from Germany. Between 2004 and 2005, fuel prices increased by 5% while average road milage decreased by 3 % (MVW 2007), suggesting a sizeable price elasticity of -0.6. Taken together, this evidence suggests that policy interventions targeted at technological efficiency - be they voluntary agreements or command and control measures - may have only muted effects in reducing fuel consumption. Given the strong responses to prices found here, price-based instruments such as fuel taxes would appear to be a more effective policy measure.

Appendix

Proposition: The null hypothesis of the classical HAUSMAN test employed for the distinction of fixed versus random effects, $H_0 : \boldsymbol{\beta}_{\text{random}} = \boldsymbol{\beta}_{\text{fixed}}$, is equivalent to the hypothesis that the fixed-effects estimator equals the between-effects estimator:

$$\boldsymbol{\beta}_{\text{fixed}} = \boldsymbol{\beta}_{\text{between}}.$$

Proof of Proposition: Given that the random-effects estimator is a matrix-weighted average of the fixed- and between-effects estimators,

$$\boldsymbol{\beta}_{\text{random}} = W \cdot \boldsymbol{\beta}_{\text{fixed}} + (I - W) \cdot \boldsymbol{\beta}_{\text{between}} ,$$

where W denotes an invertible weight matrix and I the unity matrix, H_0 implies

$$\boldsymbol{\beta}_{\text{fixed}} = \boldsymbol{\beta}_{\text{random}} = W \cdot \boldsymbol{\beta}_{\text{fixed}} + (I - W) \cdot \boldsymbol{\beta}_{\text{between}} ,$$

and, hence,

$$(I - W) \cdot \boldsymbol{\beta}_{\text{fixed}} = (I - W) \cdot \boldsymbol{\beta}_{\text{between}} .$$

This yields the proposition because W and thus $(I - W)$ are assumed to be invertible.

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