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Measuring the Rebound Effect with Micro Data

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Measuring the rebound effect with micro data (*)

Bruno De Borger, Ismir Mulalic and Jan Rouwendal

Abstract

We provide estimates of the rebound effect for car transport in Denmark, using a rich data set with individual household data on car use, fuel efficiency, and car as well as household characteristics. A demand model is estimated in first differences; the availability of households in the sample that replaced their car during the period of observation combined with information on their driving behaviour before and after the car switch allows us to identify the rebound effect. Endogeneity is taken into account by using appropriate instruments. Results include the following. First, we reject the 'conventional' formulation in which only fuel cost per kilometre matters. Second, the selection equation confirms that higher fuel prices induce households to switch car. Third, the results suggest the presence of a rebound effect that is on the lower end of the estimates available in the literature. Specifically, our best estimate of the rebound effect is some 7.5%-10%. Fourth, the fuel price sensitivity of the demand for kilometres appears to be declining with household income, but we do not find a significant impact of income on the rebound effect. Finally, simulation results indicate that the small rebound effect and changes in car characteristics in response to higher fuel prices imply that -- compared to the reference scenario -- higher fuel prices lead to a substantial reduction in both the demand for kilometres and in demand for fuel.

Keywords: The rebound effect, fuel efficiency, first difference models

JEL codes: Q5, D1, R4, C2

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1. Introduction

It is well known that consumer responses to improved energy-efficiency of energy-intensive devices induce a 'rebound' effect. Better energy-efficiency reduces the unit cost of using the device, so that optimizing behaviour by users implies that some of the energy savings that would have been realized with unchanged behaviour are foregone. Of course, this diminishes the effectiveness of such improvements. The rebound effect has a long history in several energy-intensive sectors. Surveys are provided in, among others, Greening, Greene and Difiglio (2000) and Sorell, Dimitropoulos and Sommerville (2009).

Recently, environmental concerns in the transportation industries have generated widespread interest in the rebound effect for car transport, capturing the impact of improved fuel efficiency on the demand for kilometres driven. This is not surprising, as the effectiveness of the corporate average fuel efficiency (CAFE) standards in the US and the weight-based fuel efficiency standards in the EU may strongly depend on the size of this effect. Quite a few papers have therefore explicitly focused on the transport sector, and a fair number of estimates of the rebound effect for car transport – some using aggregate data, others individual household information -- are now available in the literature[1]. For example, in an early study Greene, Kahn and Gibson (1999) used US household data over the period 1979-1994 and estimated the rebound effect at 17%-28%. In a seminal paper, Small and Van Dender (2007) reconsider the rebound effect in the context of a set of aggregate simultaneous equations (demand for car stock, demand for mileage, and demand for fuel efficiency), using aggregate panel data for U.S. states over the period 1966-2001[2]. They evaluate the rebound effect at 4.5% in the short run and more than 20% in the long run. That is, 4.5% of the fuel savings implied by an increase in fuel efficiency under the *ceteris paribus* condition is retaken immediately by a change in driver behaviour, and in the course of time this increases to over 20%. The authors find substantially lower values, some 11%, for the more recent years (1997-2001) in their study period, which they attribute to higher incomes. Hymel, Small and Van Dender (2010) extend earlier results using a larger data set, further exploring the role of

[1] A few studies have attempted to estimate the rebound effect using freight transport data (see, for example, De Borger and Mulalic (2012)).

[2] Barla, Lamonde, Miranda-Moreno and Boucher (2009) use similar techniques based on aggregate data for Canadian provinces.

income and the potential importance of congestion in explaining the decline in the rebound effect[3]. Based on individual household data for the US, Linn (2013) recently relaxes several implicit assumptions in earlier studies and reports estimates in the range of 20%-40%. Remarkably, in some European countries much higher values have been reported. For example, Frondel, Peeters and Vance (2008) and Frondel and Vance (2012) estimate the rebound effect on German panel data, producing very large rebound effects of up to 60%. Finally, Weber and Farsi (2014) use Swiss data to estimate a simultaneous equation system that accounts for endogeneity of distance, fuel intensity and vehicle weight; they report rebound effects of almost 75%.

Since the rebound effect is essentially a phenomenon that occurs at the level of the individual actor it seems appropriate to evaluate the responses of car users to fuel prices and fuel efficiency using individual household data. The purpose of this paper is to contribute to the literature by studying the rebound effect of an increase in the fuel efficiency of cars, using a detailed and especially rich panel data set on individual households in Denmark for the period 2001-2011, paying careful attention to endogeneity and selection issues. Our focus is on the 'direct' rebound effect, the effect of better fuel efficiency on demand for kilometers driven. This is not to downplay the possible additional effects that can be associated with the more intensive use of cars, but it helps to focus on what we regard as the most important issue; moreover, it facilitates direct comparison with previous literature[4]. We further use the estimates to simulate the implications of fuel price increases.

Central to the analysis is a demand equation for car kilometres in which the fuel price per kilometre and fuel efficiency are the main explanatory variables of interest; the coefficients for fuel price and fuel efficiency are allowed to differ. Contrary to earlier studies based on individual data, we estimate the demand equation in first differences; this has the advantage of fully controlling for unobserved factors that remain constant over time. To do so, we use data on almost 350 000 observations on single car families, covering a period of ten years (2001-2011). To estimate the rebound effect in our first difference model, we split the sample period in three

[3] Very recently, Hymel and Small (2014) find the rebound effect to be asymmetric: it is larger in periods of fuel price increases than in years when fuel prices decline.

[4] The recent literature (see, for example, Borenstein (2013)) distinguishes direct, indirect, re-spending and transformational rebound effects. The indirect effect is defined as the increased energy consumption from changes in the use of other energy-using products than the one where the improvement occurs. A respending effect occurs when the money saved by improved fuel efficiency is spent on other goods that use fuel (for example, spend less on gasoline but buy an extra plane ticket). For more details, see Borenstein (2013). The numerical example on page 19-21 of Borenstein (2013) gives an impression of the magnitude of the wider effects of car fuel efficiency improvement. See also Gillingham, Rapson and Wagner (2014) for a discussion of the wider effects of a change in energy efficiency of a device.

subperiods. Based on odometer readings we derive information about the numbers of kilometres driven in the first and the third subperiod, allowing us to consider the change between the two periods. Moreover, by distinguishing households that replaced their car during the mid-period of observation, we can precisely measure the impact of the switch of cars and the associated change in fuel efficiency on the demand for kilometres. Of course, in such a demand analysis endogeneity of fuel efficiency (of the new car) is an important concern, because households may replace their car because they expect to drive more or less in the future. We deal with endogeneity of car characteristics by using instrumental variables; the instruments used are the characteristics of the old car relative to the average Danish car. We also model the decision to replace cars using a Heckman selection model, incorporating the occurrence of car accidents -- based on individual information – and the length of car ownership as additional identifying variables.

Results include the following. First, as expected and in line with other recent studies, the data reject the ‘conventional’ formulation in which only fuel cost per kilometre matters. Second, the selection equation confirms that higher fuel prices induce households to switch car. Third, the results suggest the presence of a rebound effect that is on the lower end of the estimates available in the literature. Specifically, our best estimate of the rebound effect is some 7.5%-10%. Fourth, we find that the fuel price sensitivity of the demand for kilometres is declining with household income, but we are unable to confirm earlier suggestions in the literature that the rebound effect decreases with household income. Finally, simulation results suggest that the small pure rebound effect and the impact of adaptations in all car attributes jointly imply that, compared to the reference scenario, higher fuel prices lead to a substantial reduction in both the demand for kilometres and in demand for fuel.

The remainder of this paper is organized as follows. In the next section we briefly discuss the rebound effect and review the literature that is most relevant for our purposes. Section 3 describes the data. In Section 4 we discuss our empirical strategy and explain how we dealt with endogeneity and selection problems. Section 5 reports the estimation results and presents some robustness checks. In Section 6 we analyse in more detail the effect of income on households’ responses to higher fuel prices and better fuel efficiency. We further use the estimates to simulate the short and long run response of households to a higher fuel price in Section 7. Finally, Section 8 concludes.

2. Literature review

The basic idea of the rebound effect is easy. An improvement in fuel efficiency reduces the unit cost of driving, hence it raises the demand for driving. As a consequence, improved fuel efficiency leads to less than proportional reductions in fuel consumption, as driving increases and partially compensates the fuel-saving effect of better fuel efficiency. This is the direct rebound effect that we attempt to measure in this paper[5].

As argued by, among others, Gillingham et al. (2014), Sorell et al. (2009) and Weber and Farsi (2014), several early studies estimated the rebound effect by the price elasticity of demand for kilometres with respect to the fuel cost per kilometre. The argument can be illustrated as follows. Consider the definition of fuel consumption *F* as the traffic volume *q* divided by realized fuel efficiency *E*:

$$F = \frac{q\left(P^{KM}\right)}{E}; \quad P^{KM} = \frac{P^F}{E} \tag{1}$$

In this expression, P^{KM} is the fuel cost per kilometre and P^F is the fuel price. Note that this specification assumes that the effect of the fuel price and fuel efficiency on demand is, in absolute value, the same; only the fuel price per kilometre matters. This is the standard assumption in the early literature; for a recent study, see Gillingham (2012). Differentiating (1) with respect to E, multiplying by fuel efficiency and dividing by fuel use *F*, we find after simple algebra:

$$\varepsilon_{F,E} = -(1+\varepsilon_{q,P^{KM}}) \tag{2}$$

In this formula (and in those that follow below), the $\varepsilon_{i,j}$ refer to elasticities of variable *i* with respect to *j*. It follows that an increase in fuel efficiency reduces fuel use less than proportionately if the number of kilometres driven rises as a consequence of the lower fuel cost per kilometre. The rebound effect that is the focus of this paper is the difference between the actual effect and the proportional change, which equals the size of the elasticity of demand with respect to the fuel cost per kilometre $\varepsilon_{q,P^{KM}}$.

[5] The recent literature has focused on the microeconomics underlying the rebound effect. For instance, Borenstein (2013) studies the implications of an energy efficiency upgrade at the end-use consumer level in a model with multiple energy-intensive goods, showing that the rebound effect can be interpreted in terms of an income and substitution effect. Chan and Gillingham (2014) further show that, when fuel is used for multiple energy services, the direct effect is poorly approximated by the fuel price elasticity of demand. Moreover, the welfare effects depend on whether the costs are based on fuel use or on service use. Finally, Gillingham, Rapson and Wagner (2014) compare the rebound effect when it is induced by a costless and exogenous increase in fuel efficiency and when it comes from a change in fuel efficiency together with changes in other product attributes. The former leads to a clean estimate of the direct rebound effect, but it is less useful for energy policy evaluations.

The rebound effect has potentially important consequences for the long run implications of a change in fuel prices for fuel demand. An increase in fuel prices raises the benefits of driving a more fuel efficient car and makes it more attractive for producers to develop such cars. This suggests that in the long run fuel efficiency is enhanced by rising fuel prices:

$$E = E(P^F); \quad \frac{\partial E\left(P^F\right)}{\partial P^F} > 0 \tag{3}$$

It is then straightforward to show (using (1) and (3)) that

$$\varepsilon_{F,P^F} = \varepsilon_{F,P^F}\Big|_E + \varepsilon_{F,E}\varepsilon_{E,P^F} \tag{4}$$

The elasticity of fuel use with respect to the fuel price equals the same elasticity evaluated at constant fuel efficiency times a correction term that captures the impact of the fuel price on better fuel efficiency, which in turn affects fuel consumption. Using (2), we can rewrite (4) as

$$\varepsilon_{F,P^F} = \varepsilon_{F,P^F}\Big|_E - \varepsilon_{E,P^F}(1+\varepsilon_{q,P^{KM}}) \tag{5}$$

Fuel savings after a fuel price increase induce drivers to switch to more fuel efficient cars. In itself this switch contributes to the negative impact of the fuel price increase on demand for fuel. However, since the increased fuel efficiency lowers the fuel cost per kilometre, it evokes a countereffect that partly offsets it the initial stimulus (assuming the rebound effect is less than one, an assumption confirmed by all empirical evidence, see e.g. Gillingham et al. (2013)).[6]

Moreover, differentiating the demand for driving with respect to the fuel price we easily show

$$\varepsilon_{q,P^F} = \varepsilon_{q,P^F}\Big|_E - \varepsilon_{q,P^{KM}}\varepsilon_{E,P^F} \tag{6}$$

This equation shows that demand for driving is affected less by a fuel price increase due to the rebound effect of better fuel efficiency.

The discussion above assumes, in line with ‘conventional’ economic theory, that the fuel cost per kilometre is the relevant variable in the demand function for kilometres, implying that fuel efficiency and fuel prices have, in absolute value, an equal impact on demand. However, it has recently been convincingly argued – and to some extent empirically been confirmed -- that the effects of fuel price and fuel efficiency on the demand for car kilometers may in fact be quite different. On the one hand, Gillingham et al. (2014) discuss the possibility that consumers react comparatively less to changes in fuel efficiency; for instance, they may be less aware of the fuel

[6] A rebound effect larger than 1 is usually referred to as ‘backfire.’

efficiency of the car they drive than about fuel prices, which they observe regularly. On the other hand, Linn (2013) argues that fixed costs involved in the adjustment of demand may drive a wedge between the impact of changes in fuel prices and fuel efficiency on demand: price changes may be viewed as temporary while fuel efficiency improvements are unlikely to be reversed. This would make the effect of fuel efficiency larger than that associated with a fuel price increase. Still another argument for different responses arises if demand is estimated using panel data when some respondents switch car during the period of observation. Heterogeneity in the sensitivity of demand with respect to fuel cost per kilometre may then interact with differences in the propensity to switch car. This may generate a difference in the average impact of changes in fuel prices and fuel efficiency, even if no such differences occur at the individual level.

Interestingly, the equality (in absolute value) of the effects of fuel efficiency and fuel prices has been rejected in some, but not all, recent empirical work. For example, Greene (2012) convincingly rejects equality of the two coefficients[7]. Linn's (2013) analysis of cross-section data suggests that the impact of fuel efficiency is substantially larger than that of the fuel price. The rebound effect is estimated to be smaller when equality of the effects of gasoline prices and fuel efficiency is imposed. However, Frondel, Peeters and Vance (2008) and Frondel and Vance (2012) explicitly compare specifications that impose equality with a specification that does not, and they are unable to reject the null hypothesis that only the fuel price per kilometre matters[8].

Adaptation of the framework developed above (see (1)-(6)) for the case where the effects of the fuel price and fuel efficiency are not equal in absolute value is straightforward. We then specify demand as a function of the fuel price and fuel efficiency separately and have

$$F = \frac{q\left(P^F, E\right)}{E} \tag{1bis}$$

Similar derivations as before then show

$$\varepsilon_{F,E} = -(1 - \varepsilon_{q,E}) \tag{2bis}$$

The rebound effect is directly captured by the elasticity of the demand for driving with respect to a change in fuel efficiency. We further find

[7] Interestingly, in line with predictions from the behavioral economics literature, Li, Linn and Muehlegger (2012) also find that consumers respond more strongly to a gasoline tax increase than to an increase in the tax-inclusive price of gasoline.
[8] In the second study they instrument fuel efficiency by the tax rate per 100 cm^3 cubic capacity. The tax rate depends on carbon dioxide emissions, and the authors argue that it should not affect distance driven nor the error term of the demand equation. Note that, since Frondel and Vance's (2012) coefficients of fuel efficiency become insignificant when they attempt to deal with the possible endogeneity of the fuel efficiency variable, the evidence they provide cannot be regarded as conclusive.

$$\varepsilon_{F,P^F} = \varepsilon_{F,P^F}\Big|_E - \varepsilon_{E,P^F}(1-\varepsilon_{q,E}) \tag{5bis}$$

and

$$\varepsilon_{q,P^F} = \varepsilon_{q,P^F}\Big|_E + \varepsilon_{q,E}\varepsilon_{E,P^F} \tag{6bis}$$

Interpretation is analogous to that of (5)-(6).

3. The data

In this paper we reconsider the issue of measuring the rebound effect for passenger cars, using a rich panel data and giving careful attention to endogeneity and selection issues. As the empirical strategy makes intensive use of the characteristics of the data, it will be instructive to first take a look at the nature of our data. The empirical model itself is discussed in the next section.

3.1. Data sources

We use Danish register-data for the period 2001-2011. The database contains information on *car attributes* of all model variants supplied on the car market in Denmark including, e.g., car brand/model/type, car weight, car vintage, and engine horsepower. We also observe *household characteristics* in our dataset, i.e., information on household's socio-economic characteristics (including, e.g., income, education, presence of children, etc.). We focus on all one-car-households[9]. Importantly, for reasons explained below, we will estimate a demand function in first differences to derive estimates of the rebound effect. As this requires observations on the change in fuel efficiency over time, it is crucial that our sample not only consists of households that used the same car throughout the period but that it also contains households that replaced their car. We therefore proceeded as follows: we consider three periods: 2001-2005, 2005-2007 and 2007-2011. We then use observed demand for kilometers in two periods, viz. 2001-2005 and 2007-2011 by comparing subsequent odometer readings of cars that have been used by a single household in the time interval between these readings. Some households replaced their car during the mid-period 2005-2007, so that for this group we observe demand at two different values of fuel efficiency of their cars. More details are given below[10].

[9] In Denmark, only about 8% of households own two cars.
[10] Moreover, we distinguish between cars that were in use for more than four years in the sample period and those that were not (see below; also see figure 1).

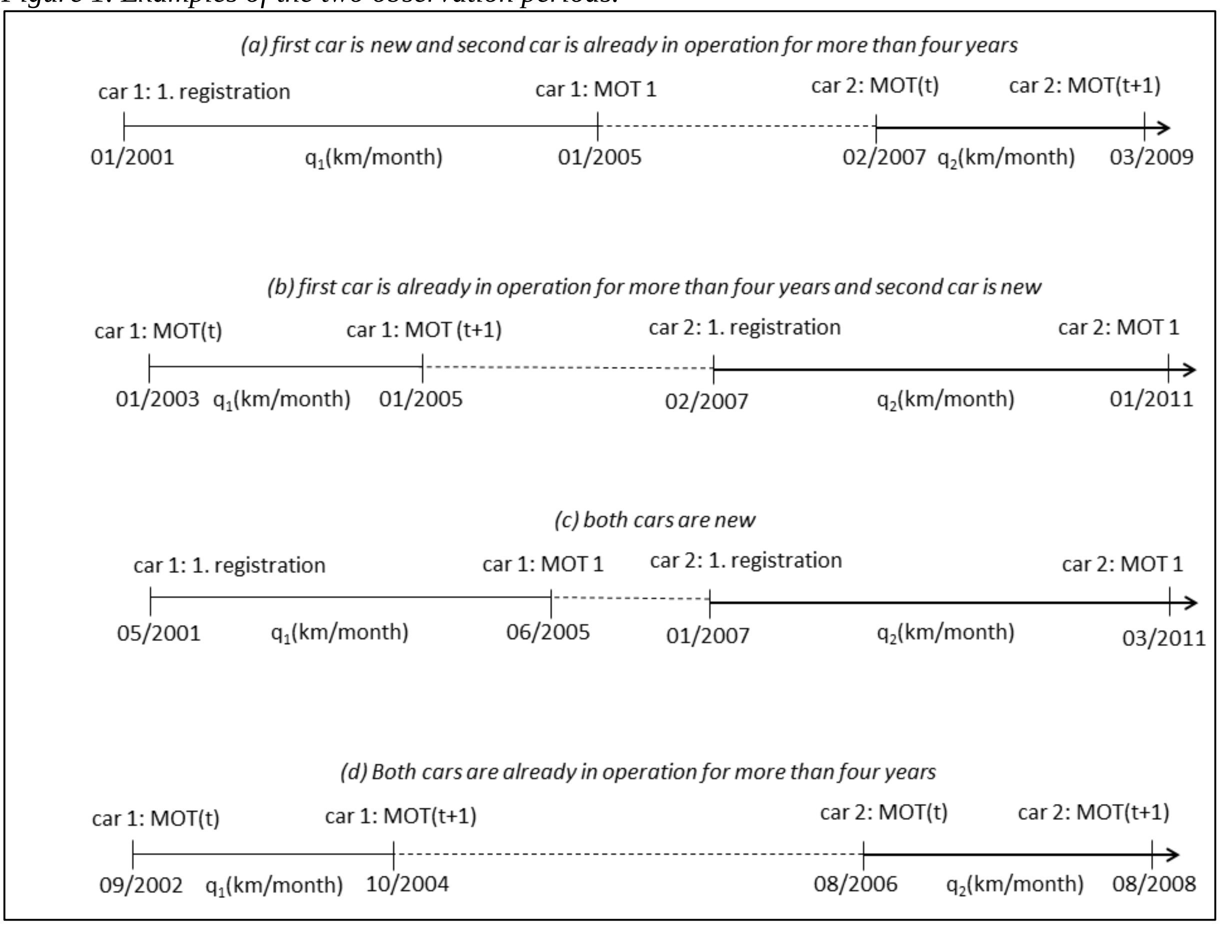
The number of kilometres driven in a given period has been calculated for each car in the sample using information on exact odometer readings from the Ministry of Transport (MOT)-tests. These are compulsory tests that take place every two years, starting after a new car has been in use for four years. We use two odometer readings for each period in which we want to observe demand (i.e. 2001-2005 and 2007-2011) and for each car in the sample. The exact dates when the car passed its MOT-tests were registered, which allows us to make a fairly accurate estimate of the number of kilometres driven during the time interval between tests (see Figure 1). However, because drivers are allowed some flexibility for submitting their car to the test, the intervals between two successive tests is not exactly two years or four years, but it may be a few months more or less[11]. We are able to recover the average monthly number of kilometres driven for each car in the sample in two sub-periods, i.e. $\mathrm{q} = (\Delta\ \mathrm{odometer\ reading}) / \mathrm{months}$, where the Δ refers to the difference between the odometer readings at the beginning and end of the observation period.

Figure 1 illustrates the use of the MOT-test data to derive information on the number of kilometers driven by each car in the sample. We distinguished between cars that were in use for more than four years in the sample period and those that were not. Consider the examples of Figure 1. First, consider panel (a). This is the case where the first car has been new and was registered for the first time in January 2001. For new cars we have information from the first MOT-test after the car has been four years in operation (in the example of Figure 1 this is assumed to be in January 2005). The household replaced this car early 2007 by a second-hand car that was in operation for more than four years. It was subject to MOT-tests in February 2007 and March 2009. As the exact dates when the cars passed their MOT-tests were registered, this gives fairly accurate information about the number of kilometres driven during the time interval between different MOT-tests. From this information, we are able to recover the average monthly number of kilometres driven in two non-successive periods (see figure 1). Panels (b), (c) and (d) show other possible combinations. For example, panel (b) shows the case where the first car has already been in operation for more than four years and the car that replaces it is new. Panel (c) shows the case where both cars are new cars. Finally, panel (d) shows an example in which both cars were already in operation for more than four years. The number of kilometres driven by the first car corresponds to year 2003 and the number of kilometres driven by the second car corresponds to year 2008. The car's age and household characteristics were recorded for the years 2003 and 2008.

[11] This timing problem raises issues similar to the seasonality problem discussed in detail in Gillingham (2012). We deal with the issue in the empirical section, see below.

Summarizing, we use only observations for which we can compute the number of kilometres driven in two time periods. Given data availability and, in the case of a switch to another car, the need to have two odometer readings before and two after the switch, we selected the sample such that the first measurement of the number of kilometres was contained in the time interval 2001-2005, the second in the interval 2007-2011. For new cars the time intervals refer to the period between buying the car and the first MOT-test, for existing cars it is the period between two subsequent MOT-tests. As will become clear below, some households replaced their car by another one in-between the two periods. We dropped 39,496 observations (about 11%) for which two such intervals did not exist. This was the case when there were frequent changes of cars, when the number of cars differed between periods, etc.

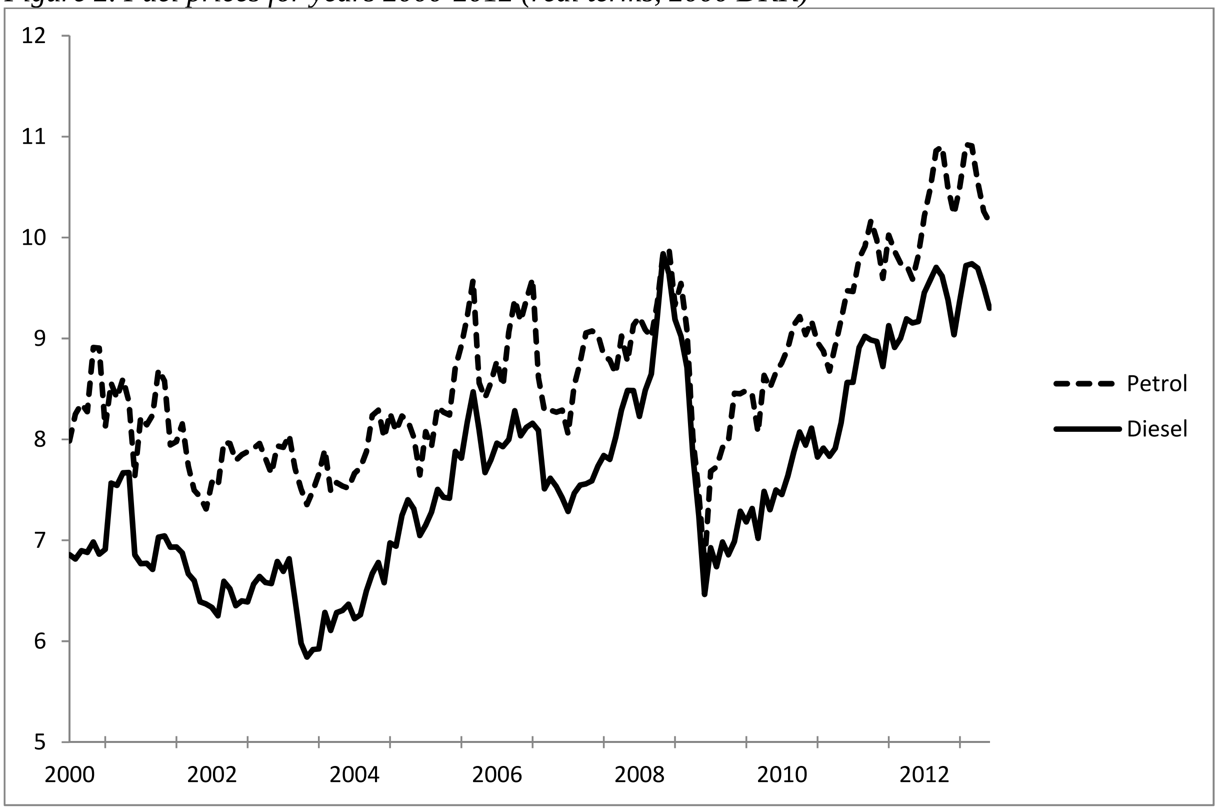
Figure 1. Examples of the two observation periods.



Note: the figure shows a possible outcome of periods between the considered MOTs.

Fuel prices are from The Danish Petroleum Association web page (http://oliebranchen.dk/da-DK/Service/English.aspx); they are also averaged over the interval between MOT-tests. Figure 2 shows the evolution of real fuel prices for the period 2000-2012. The car's fuel efficiency is derived from annual register data from Statistics Denmark. The specific (brand/model/make) car's fuel efficiency provided in the annual register data is based on the New European Driving Cycle (NEDC); this is a driving cycle designed to assess the emission levels of car engines and fuel economy in passenger cars (excluding light trucks and commercial vehicles)[12].

Figure 2. Fuel prices for years 2000-2012 (real terms, 2000 DKK)



3.2. Selection of sample and descriptive statistics

Table 1 shows summary statistics of the variables of interest for three subsamples. The first two columns refer to the data that were actually used. Total sample size was 349,763 one-car-households. The first column refers to households that did not replace their car by another one in-between the two periods of observation -- identified before -- in which kilometre demand was

[12] For a detailed documentation of the NEDC see Directive 98/69/EC of the European parliament and of the council of 13 October 1998 (http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CONSLEG:1998L0069:19981228:EN:PDF).

recorded. The second column gives information on the 110,788 households that did replace their car (this amounts to about 31 percent of all observations). The third column provides summary data on the subsample that was not used in our empirical work, for the reason discussed above. Note that Table 1 consists of two parts. The upper part refers to information about the cars. The lower part contains socio economic information on the household.

Table 1. Summary statistics

	Households that did not replace their car	Households that replaced their car	Households not used for estimation
Car total weight of the first car (t)	1.586	1.571	1.593
	(0.178)	(0.175)	(0.179)
Engine horse-power of the first car	104.585	104.630	105.953
	(25.849)	(24.362)	(24.969)
Car age of the first car in 2003 (years)	5.926	7.588	6.229
	(3.620)	(4.134)	(4.429)
Fuel efficiency of the first car (km/l)	13.794	13.724	13.773
	(1.569)	(1.504)	(1.537)
Car total weight of the second car (t)		1.698	
		(0.194)	
Engine horse-power of the second car		114.21	
		(29.97)	
Car age of the second car in 2007 (years)		4.667	
		(4.052)	
Fuel efficiency of the second car (km/l)		13.914	
		(1.774)	
Fuel price (DKK/l)	8.269	8.257	
	(0.272)	(0.283)	
Number of driven kilometres (1000 km/month)	1.086	1.258	
	(0.573)	(0.547)	
Change in number of driven kilometres (1000 km/month)	*-0.087*	*-0.023*	
	(0.351)	*(0.499)*	
Change in fuel price (DKK/km)	*0.232*	*0.252*	
	(0.131)	*(0.176)*	
Difference in car age between the first and the second car (years)		*-2.921*	
		(4.027)	
Difference in fuel efficiency between the first and the second car (km/l)		*0.190*	
		(1.837)	
Difference in car total weight between the first and the second car (t)		*0.127*	
		(0.182)	
Difference in engine horse power between the first and the second car		*9.582*	
		(27.368)	
Household's income (1000 DKK)	451.065	504.273	511.772
	(224.877)	(216.994)	(215.523)
Household's labour supply (1000 hours)	1.141	1.541	1.604
	(1.550)	(1.684)	(1.714)
Number of children in household	0.365	0.564	0.594
	(0.789)	(0.914)	(0.928)
Number of persons in household	2.139	2.438	2.486
	(1.027)	(1.100)	(1.105)
Car owners commuting distance (km)	7.996	10.239	10.721
	(21.457)	(23.243)	(23.286)
Vocational education	0.399	0.444	0.455
	(0.490)	(0.497)	(0.498)
Short-cycle higher education	0.043	0.044	0.045
	(0.202)	(0.206)	(0.207)
Medium-cycle higher education	0.138	0.134	0.123
	(0.345)	(0.340)	(0.329)
Bachelor	0.004	0.005	0.006
	(0.064)	(0.072)	(0.075)
Long-cycle higher education	0.062	0.055	0.050
	(0.241)	(0.229)	(0.217)
PhD-degree	0.003	0.003	0.002
	(0.059)	(0.055)	(0.048)
Change in number of persons in household	*-0.042*	*-0.005*	0.014
	(0.442)	*(0.538)*	(0.573)
Change in car owners commuting distance (km)	*-0.747*	*-0.565*	-0.281

	(23.017)	*(25.781)*	(26.444)
Change in household's income (1000 DKK)	*38.418*	*59.792*	68.829
	(139.026)	*(147.038)*	(153.356)
Change in household's labour supply (1000 hours)	*-0.081*	*-0.020*	0.018
	(1.291)	*(1.541)*	(1.573)
Number of obs.	238,975	110,788	39,494

Notes: standard deviations are in parentheses. Difference in car age between the first and the second car has been calculated as the difference between the car age of the second car in 2007 and the car age of the first car in 2003.

The cars in the two subsamples used for estimation purposes are comparable in terms of fuel prices, fuel efficiency, engine horse-power and total weight, but (as expected) not in terms of the car's age. Differences in the car owner's level of education, the number of persons and children in household are negligible, but household income, household labour supply, and the changes in these variables are slightly higher for households that replaced their car.

4. Empirical strategy

To estimate the rebound effect we start from a standard log-linear demand equation:

$$\log(q_h) = \alpha_0 + \alpha_1 \log\left(P_h^f\right) - \alpha_2 \log\left(E_h\right) + \beta' X_h^H + \delta' X_h^C + \varepsilon_h \qquad \textbf{(7)}$$

In this equation, q_h denotes the number of kilometers driven by household *h*. The fuel price faced by this household and the car's fuel efficiency are denoted by P_h^f and E_h, respectively. We further distinguish between the vector of household characteristics X^H **(**including income) and the vector of car characteristics X^C. Finally, ε_h is an error term. Note that we allow $\alpha_1 \neq \alpha_2$: the coefficient of fuel economy can differ from the coefficient of the fuel price. Although the evidence reported in Section 2 only partially supports this hypothesis, we should at least allow for this possibility and test whether $\alpha_1 = \alpha_2$.

In line with the recent literature we define the rebound effect as the impact of an exogenous change in fuel efficiency on demand. Provided the model is estimated properly, the coefficient α_2 therefore captures the effect we are interested in: if significant and positive, it indicates that an exogenous increase in fuel efficiency (conditional on a given fuel price) raises demand.

Our econometric work takes (7) as starting point. Writing this equation in first differences, we have:

$$\Delta\log(q_h) = \alpha_1 \Delta\, log(P_h^f) - \alpha_2 \Delta \log(E_h) + \beta' \Delta X_h^H + \delta' \Delta X_h^C + v_h \qquad (8)$$

where Δ denotes the time-difference operator; for example (similar for the other variables) $\Delta \log(q_h) = \log(q_{h,t}) - \log(q_{h,t-1})$, and $v_h = \varepsilon_{h,t} - \varepsilon_{h,t-1}$. As discussed in the previous section, the difference in kilometers driven refers to two periods between MOT-tests for cars of the same household. The cars of this household may be the same, or they may differ. The changes in household and car characteristics refer to the same two periods.

Estimating the model in first differences has the important advantage that we tacitly control for all household and car characteristics that remain constant over time. For households who do not replace their car, this includes fuel efficiency. The implication is that changes in car characteristics (engine power, fuel efficiency, etc.) are zero for all households who did not replace their car. Hence, the coefficient α_2 is identified through the presence of observations on people that changed to another car during the period of observation.

The setup of our empirical model implies that endogeneity and (self) selection are potentially important concerns. First, since replacing the car is, in most cases, a decision deliberately taken by the household, we should care about endogeneity. For example, one can easily imagine that a household replacing it's car and anticipating to drive less in the future, may care somewhat less about fuel efficiency, ceteris paribus. Alternatively, a household expecting to be driving more in the future may attach more value to car attributes (such as horse power) that make driving more convenient, although a more powerful car has lower fuel efficiency. To deal with these concerns, we instrument the characteristics of the new car. Our instrument is the difference between the characteristic of the old car of the household and the average value of that characteristic for new registered cars in Denmark in the year when the car was purchased. We expect households to be inclined to maintain their relative position in the distribution of car characteristics, which will lead to a positive correlation between the instrument and the change in car characteristics if the variation in car characteristics increases over time, as appears to be the case in Denmark. The number of available car brand/model/type combinations increased from 9084 in 2003 to 14699 in 2007, so by 62% (see Arnberg et al. (2008) and Mabit (2014)). We observe many new varieties of city (small) cars, while at the opposite side of the market vans and MPV's are an active segment. The increasing variation in car characteristics is confirmed by, for example, the increase in the standard deviation of car total weight (for the Danish car stock) from 262 in 2003 to 315 in 2007 (a 20% increase). The mean of the car's total weight increased in the same period from 1578 kg to 1643 kg.

Of course, the instrument is only valid if the differences between the characteristics of the old car and their average for the new registered cars in the year when the car was purchased are uncorrelated with the error term in (8). A household driving a very fuel efficient car in the first period should therefore – on average – not be inclined to drive much more or less in the second period of observation for reasons that are not covered by the explanatory variables in the equation. This seems a plausible assumption. The argument for the validity of the instruments of the other car characteristics is similar. We will argue below, based on the empirical results, that the instruments used are indeed strong.

Second, a somewhat different concern related to equation (8) is selection bias. Households replacing their car may not be a random sample of the population of one-car households. Although we control for unobserved individual (household) effects through our first difference formulation, and we do include a number of changes in observed household characteristics, selection issues may still play a role. For instance, some households may be more inclined to avoid the consequences of higher fuel prices by replacing their cars than others. To deal with this issue, we re-estimate equation (8) on the subsample of households who replaced their car, using the Heckman correction for sample selectivity. This implied estimating a car replacement equation as a preliminary step. In this equation we used two additional variables: a dummy variable that indicates whether or not the household was involved in a car accident between the two periods of observation, and the length of car ownership (in essence, how long the household owned the car). Being involved in a car accident increases the probability of car replacement, and it will usually not have an impact on the changes in household or car characteristics[13]. The probability of car replacement increases with the length of car ownership.

5. Empirical results

Estimation results are reported in Table 2. Column [1] reports the OLS estimates of equation (8). Column [2] reports the results of the instrumental variable (IV) regression in which the three car characteristics have been instrumented. First stage results are reported in Table A1 in Appendix. They show that the instruments have a strongly significant impact on the changes in car characteristics. For example, the robust regression-based F-test rejects the null hypothesis that the three car characteristics are exogenous ($F = 52.10$ and $p < 0.0001$). Moreover, both the Durbin (score) test ($\chi^2 = 168.74$, $p < 0.0001$) and the Wu-Hausman test ($F = 56.32$, $p < 0.0001$) reject the hypothesis of exogeneity. In columns [3] and [4] of Table 2 we further report the results of repeating the OLS and IV analyses for the subsample of households who replaced their car between

[13] The important exception is the case in which the car driver is permanently injured by the accident, e.g. loses his job or is only able drive in an adapted car type.

the two observation periods. Finally, column [5] gives the estimates of correcting for selection bias using the Heckman selection model. Indeed, car switchers may not be random subsample. We therefore estimated a Heckman selection model using the familiar two-stage procedure. The results of estimating the first stage selection equation are reported in Table A.2 in the Appendix. The fuel price change included as an explanatory variable in that equation is the change in the fuel price between the beginning and the end of the first time interval. The estimates of the equation explaining households' decision to switch cars show that changes in fuel prices, being involved in an accident, and how long the car has been owned are all important explanatory variables that positively affect this decision, as are income and changes in labour supply.

Turning to the results, several general observations can be made that hold across all estimated equations. First, the coefficients of the fuel price and of fuel efficiency are significantly negative and positive, respectively. Second, F-tests show that both coefficients differ significantly in absolute value in all equations, confirming some (but not all) recent empirical work in other countries (and derived using different methods), see our earlier discussion in Section 2. Third, taking all equations at face value, the rebound effect ranges between 5.4% and 12.4% (but see below for more details). Fourth, the coefficient of fuel efficiency is systematically smaller than the fuel price effect. This contradicts the findings of several other studies (see, for example, Linn (2013), who report the opposite, and Frondel and Vance (2012), who are unable to reject the equality hypothesis). However, our results are in line with Gillingham et al. (2014). A plausible explanation is that an increase in fuel prices is directly observable and immediately brought to the attention of drivers, whereas they may be less aware of the fuel efficiency of the car they drive. Finally, we find in almost all cases significant positive coefficients for horse power and weight. The estimated effects of household characteristics are all plausible as well: changes in the number of children raise the demand for driving unless there is a new-born child. A longer commuting distance, an increase in labour supply and a residential move all significantly raise the demand for kilometres as well.

If we reconsider the results to focus on differences between specifications, several findings stand out. First, moving from OLS to the preferred IV estimates, we see that the rebound effect is estimated to be slightly smaller when estimated on the full sample, and slightly larger when based on the subsample of car switchers. To understand this, note that the effect of a higher fuel price on fuel efficiency in the first stage regressions (see Table A1 in Appendix) is significantly positive: as expected, higher fuel prices raise fuel efficiency of the new car. Second, comparing the estimates of the full sample with those for car replacers only (compare columns [2] and [4]), we observe that moving to the subsample of people that switch car reduces the coefficient of the fuel price (in absolute terms) and increases the coefficient of fuel efficiency. This may point at the fact that consumers with inelastic kilometre demands are more inclined to respond to fuel price changes by switching to a more fuel efficient car. Interestingly, when correcting for selection bias (see column [5] in Table 2), the rebound effect is estimated to be the same, whether based on the full sample or on the subsample of car switchers; it amounts to 7.6%. Note that this figure is close to what Frondel and Vance (2012) reported for German data. The coefficients for the changes in household characteristics are qualitatively similar to those in the regressions referring to the full sample.

Table 2. First-difference models

	[1]	[2]	[3]	[4]	[5]
	all households OLS	all households IV	car switchers OLS	car switchers IV	car switchers IV
Change in logarithm of fuel price (DKK/l)	-0.928***	-0.856***	-0.524***	-0.565***	-0.562***
	(0.037)	(0.039)	(0.059)	(0.059)	(0.061)
Change in logarithm of fuel efficiency	*0.124****	*0.076**	*0.054****	*0.093****	*0.076****
	(0.012)	*(0.039)*	*(0.013)*	*(0.025)*	*(0.025)*
Change in logarithm of car total weight	*0.718****	*-0.007*	*0.584****	*0.370 ****	*0.374****
	(0.016)	*(0.048)*	*(0.020)*	*(0.035)*	*(0.036)*
Change in logarithm of engine horse-power	*0.055****	*0.046**	*0.061****	*0.031***	*0.019*
	(0.008)	*(0.026)*	*(0.008)*	*(0.016)*	*(0.016)*
Change in logarithm of household's income (1000 DKK)	0.080***	0.096***	0.107***	0.122***	0.167***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.008)
Change in number of adults in household	0.018***	0.015***	0.022***	0.020***	0.013***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Change in presence of a baby in household	-0.042***	-0.037***	-0.036***	-0.032***	-0.031***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
Change in presence of a children in household	0.028***	0.037***	0.028***	0.034***	0.051***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Change in commuting distance (km)	0.761***	0.755***	0.655***	0.649***	0.632***
	(0.031)	(0.031)	(0.053)	(0.053)	(0.054)
Change in household's labour supply (1000 hours)	0.003***	0.003***	0.003***	0.003***	0.004***
	(0.0005)	(0.0005)	(0.001)	(0.001)	(0.001)
Residential move (dummy)	0.007***	0.007***	0.019***	0.018***	0.025***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Mills ratio					0.230***
					(0.022)
R-squared	0.030		0.040		
No. of observations	349,763	349,763	110,788	110,788	110,788

Notes: the dependent variable is log travel demand (1000 km/month); the car attributes are instrumented using the characteristic of the old car relative to the average new Danish car; for the first step of model [4] see Table A.2 in the Appendix; for the first step of the Heckman selection model [5] see Table A.3 in Appendix; standard errors (clustered by the interval between MOTs used to compile the demand for kilometer and the fuel prices) are in parentheses; ***,** indicate that estimates are significantly different from zero at the 0.01 and the 0.05 level, respectively.

In columns [1]-[4] of Table 3 we report the results of a number of sensitivity and robustness checks. In all cases, we focus on the model for car switchers only, estimated using instrumental variables. First, in columns [1]-[3] of Table 3 we control for i) differences in the length of the time interval between the different MOT-tests that we used to compute the demand for kilometres in both the first and the second period of observation, ii) the length of the periods, and iii) seasonality. Second, in column [4] of Table 3 we report the result of re-estimating the model, using a dummy indicating whether or not the individual has been involved in an accident, as an additional instrument[14]. Comparing with column [4] of Table 2 we note no important changes worth mentioning. It appears that our results are robust.

Table 3. Robustness check, first-difference IV models for car switchers

	[1]	[2]	[3]	[4] car accident as an additional IV	[5] model with interaction terms
Change in logarithm of fuel price (DKK/l)	-0.500***	-0.598***	-0.496***	-0.566***	-9.289***
	(0.060)	(0.060)	(0.061)	(0.059)	(0.499)
Change in (logarithm of fuel price) * logarithm of household's income in 2003 (1000 DKK)					1.403***
					(0.079)
Change in logarithm of fuel efficiency	*0.096****	*0.077****	*0.094****	*0.095****	0.561*
	(0.025)	*(0.023)*	*(0.025)*	*(0.025)*	(0.298)
Change in (logarithm of fuel efficiency) * logarithm of household's income in 2003 (1000 DKK)					-0.074
					(0.047)
Change in logarithm of car total weight	*0.373****	*0.346****	*0.371****	*0.372****	0.485***
	(0.035)	*(0.032)*	*(0.034)*	*(0.035)*	(0.034)
Change in logarithm of engine horse-power	*0.029**	*0.039***	*0.030**	*0.032***	0.035**
	(0.016)	*(0.015)*	*(0.016)*	*(0.016)*	(0.016)
Change in logarithm of household's income (1000 DKK)	0.123***	0.121***	0.122***	0.122***	0.083***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Change in number of adults in household	0.020***	0.020***	0.020***	0.020***	0.024***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Change in presence of a baby in household	-0.032***	-0.032***	-0.032***	-0.032***	-0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Change in presence of a children in household	0.034***	0.033***	0.034***	0.034***	0.032***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Change in commuting distance (km)	0.650***	0.647***	0.649***	0.649***	0.657***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
Change in household's labour supply (1000 hours)	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Residential move (dummy)	0.018***	0.017***	0.018***	0.018***	0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Control for the lengths between the considered periods	Yes	no	no	no	no
Control for the lengths of the periods	No	yes	no	no	no
Control for seasonality	No	no	yes	no	no
No. of observations	110,788	110,788	110,788	110,788	110,788

Notes: the dependent variable is log travel demand (1000 km/month); the car attributes are instrumented using the characteristic of the old car relative to the average new Danish car; standard errors (clustered by the interval between MOTs used to compile the demand for kilometer and the fuel prices) are in parentheses; ***,** indicate that estimates are significantly different from zero at the 0.01 and the 0.05 level, respectively.

6. The impact of income

[14] We also estimated models in which we included only the observations on households that changed car after being involved in an accident. The advantage of limiting the analysis to this sample is that a change in fuel efficiency is more plausibly exogenous in this case; the disadvantages are that the sample size (fortunately!) drops substantially (from roughly 110 800 to 2 100) and that many of these households may be inclined to buy the same car as has been damaged in the accident, which results in limited variation in fuel efficiency. Estimation results show that the disadvantages are important: we hardly find any significant coefficient.

Several earlier studies (see, e.g., Small and Van Dender (2007) and Hymel et al. (2010)) found a substantial decline in the size of the rebound effect over time, and they attributed it mostly to income changes[15]. However, they note as a caveat that their results rely on the imposed restriction that people react identically to changes in the cost per mile caused by changes in fuel price and fuel efficiency. In the previous section we argued that this restriction is not supported by our data. It is therefore of some interest to see what our data can tell us about the impact of income on the rebound effect. Unfortunately, unlike these previous studies, we do not have data that refer to an extensive period with substantial income growth. Although we use panel data, the number of MOT-tests observed in a 10-year period is too small to carry out a panel data analysis of the impact of changes in income on the coefficients for fuel price and fuel efficiency in our demand equation. However, what we can do is carry out a cross-sectional analysis and analyse whether the sensitivity of kilometre demand for changes in the fuel price and in fuel efficiency depend on a household's place in the income distribution.

To investigate this, we re-estimate the IV-model for car switchers after including interaction terms with household income for both the fuel price and fuel efficiency. The results are presented in column [5] of Table 3. They suggest that the sensitivity for changes in the fuel price reduces markedly with income, which is in line with earlier results in the literature (also see West (2004)). However, we do not find a significant coefficient for the cross term of the fuel efficiency variable, and we are unable to reject the hypothesis that the size of the rebound effect is independent of a household's position in the income distribution. This conclusion is confirmed by a further analysis in which we estimate different coefficients for the changes in fuel price and fuel efficiency for each quartile of the income distribution. Estimation results are reported in Table A.3 in Appendix. The null hypothesis of equality of all coefficients for the change in fuel efficiency for the quartiles of household income cannot be rejected ($\mathrm{F} = 1.20$, $\mathrm{p} = 0.50$).

Although it has to be corroborated by other studies, this seems to suggest that the results about the declining rebound effect reported in the previous literature were primarily driven by declining sensitivity with respect to fuel prices, whereas the pure rebound effect may have been constant over time.

7. Simulating the impact of higher fuel prices

[15] Another part is attributed to falling fuel prices.

In this section we use the estimated models to describe the short- and the long-run effects of increasing fuel prices, taking into account the rebound effect identified above. Of course, the equations we estimated do not constitute a complete structural model of demand for cars, car characteristics and car kilometres. However, they do allow us to describe the various implications of an exogenous increase in the fuel price. In the remainder of this section, we focus on the annual effects of a 10% fuel price increase on the demand for kilometres and fuel use under three scenarios:

i) Scenario 1 assumes no changes in car characteristics. This is the short-run effect; it implies, among others, that we simply ignore the rebound effect that operates via adjustments of fuel efficiency.
ii) Scenario 2 assumes that the higher fuel price induces a change in fuel efficiency but not in other car characteristics. This is, of course, a purely hypothetical response of consumers, but it comes as close as we can get to capturing the 'pure' rebound (see Gillingham, Rapson and Wagner (2014)). The idea is to estimate the effect of higher fuel prices when this leads consumers to shift towards more fuel efficient cars, hypothetically assuming that the other characteristics of the car remain the same.
iii) Finally, Scenario 3 assumes the higher fuel price leads consumers, when replacing their cars in the longer run, to adjust both fuel efficiency and other car characteristics.

For purposes of comparison, we start from a baseline scenario, determined by using the observed demand for kilometres and observed fuel efficiency to generate fuel use. The baseline demand for kilometres so obtained was, on average over the sample, 15099 kilometres per year; fuel use was estimated at 1122 litres per year on average.

In the first scenario**,** we then consider a 10% fuel price increase and calculate the immediate effect on car kilometres when no adjustment takes place in neither fuel efficiency nor other car characteristics. To do so, we use our estimates reported in Table 2, model [4]. More precisely, demand for kilometres is determined as $Q_1 = \exp(\log(Q_0) + (-0.565) * 0.1)$, where Q_0 is demand under the baseline scenario, -0.565 is the estimated effect of the fuel price on demand, and $\Delta \ln(P^f) = 0.1$. Fuel use is then predicted using this calculated demand and the baseline fuel efficiency.

In the second scenario we consider a 10% fuel price increase, taking into account that -- in the longer run -- this leads consumers to switch to more fuel efficient cars but, to isolate the pure effect of fuel efficiency, other car characteristics are hypothetically assumed to be unchanged. To calculate the relevant effects on demand and fuel use, we combine the direct effect of the fuel price increase (as in scenario 1) with the indirect long run effect when higher fuel prices induce people to buy more fuel efficient cars. The latter effect can be determined by using the coefficient of the fuel price in the fuel efficiency equation of the first stage IV regressions (see Table A1 in Appendix); these relations describe the impact of (among others) higher fuel prices on fuel efficiency and other car characteristics when consumers replace their car. This change in fuel efficiency then has a further effect on the demand for kilometres, captured by the relevant coefficient of Table 2, model [4].

To be very specific, the demand for kilometres in this second scenario is given as

$$Q_2 = \exp(\log(Q_0) + (-0.565 * 0.1) + (0.093 * (0.1 * 0.373))$$

In this expression, -0.565 and 0.093 are estimated coefficients from Table 2 model [4] (the effects of the fuel price and the fuel efficiency on the demand for kilometres) and 0.373 is the fuel price effect on fuel efficiency, as given in Table A1. Finally, the corresponding fuel use is calculated using predicted improved fuel efficiency. This is given by (E_0 is the reference fuel efficiency)

$$E_2 = \exp(log(E_0) + (0.1 * 0.373))$$

Predicted fuel use is then $\frac{Q_2}{E_2}$.

Finally, in scenario 3 we adjust -- following the same procedure as in scenario 2 -- all the observed car characteristics, i.e. we include the effect of the fuel price increase on the type of car chosen, assuming that fuel efficiency, weight and horse power are simultaneously adapted. We therefore also use the coefficient of the fuel price on the other car characteristics (Table A1) and the effect the changes in these other characteristics have on kilometre demand (Table 2).

The results of the simulation exercise described above are summarized in Table 5. The immediate short-run effect of a 10% fuel price increase (scenario 1) is that demand for kilometres drops from 15099 to 14270 kilometres on average; fuel consumption declines accordingly, from 1122 to 1060 on average.

Under scenario 2, the rebound effect implies that part of the reduction in kilometre demand disappears; more fuel efficient cars are cheaper per kilometre and are used more. As indicated in Table 5, the 10% increase in fuel price raises fuel efficiency by 3.73%. The result is that demand for kilometres rises again, from 14270 to 14319. Note, however, that the impact of the rebound effect on demand is quite small: the rebound effect was estimated at less than 10%, and the impact of better fuel efficiency on demand was estimated to be much less than proportional. Finally, despite the slight increase in demand from scenario 1 to scenario 2, fuel consumption declines (from 1060 to 1025) as a result of better fuel efficiency.

Finally, Scenario 3 shows the overall effects when we take into account that high fuel prices lead consumers to buy cars with better fuel efficiency but also with different other characteristics such as horse power and weight: the estimates from Table A1 suggest that a 10% increase in fuel prices leads consumers to buy a car with 4.03% less horsepower and 0.48% lower weight. As a consequence, demand for kilometres slightly declines and comes down from 14319 to 14276, extremely close to what we found under scenario 1 (no change in car characteristics). Fuel consumption further marginally declines to 1022.

Table 5. The effect of 10% fuel price increase

	Reference scenario	Scenario 1 No chg. in car characteristics	Scenario 2 Chg. in fuel eff. but not in other car characteristics	Scenario 3 All car characteristics adjust
Change in fuel price		*10.00%*	*10.00%*	*10.00%*
Change in fuel efficiency		*0*	*3.73%*	*3.73%*
Change in car weight		*0*	*0*	*-0.48%*
Change in car engine horse-power		*0*	*0*	*-4.03%*
Kilometers per year	15,099	14,270	14,319	14,276
	(6,562)	(6,201)	(6,201)	(6,204)
Fuel use (liters per year)	1,122	1.060	1,025	1,022
	(522)	(493)	(477)	(475)

Notes: standard deviations are in parentheses.

The exercise reported in Table 5 is obviously quite mechanical, but it does suggest the following. First, the impact of the estimated rebound effect on the demand for kilometres is obviously quite small, so that higher fuel prices do substantially reduce fuel consumption after accounting for the shift towards more fuel efficient cars. Second, taking into account that the shift towards more fuel efficient cars also implies slight changes in other car characteristics that affect demand, the combined impact of adaptations in all car attributes is such that it largely neutralizes the effect of the pure rebound effect on kilometre demand. Compared to the reference scenario, higher fuel prices therefore lead to a substantial reduction in both the demand for kilometres and in demand for fuel.

8. Conclusion

This paper has analysed the rebound effect for car transport based on a demand model specified in first differences and estimated using a rich data set on individual households and cars. The rebound effect was identified by combining data on households that replaced their car during the period of observation with information on their driving behaviour before and after the car switch. Endogeneity was taken into account by using appropriate instrumental variables.

Similar to some other recent studies, the data reject the 'conventional' formulation in which only fuel cost per kilometre matters, focusing on separate effects of fuel prices and fuel efficiency. Our estimated rebound effect is on the lower end of the estimates available in the literature: our best estimate is 7.5%-10%. We further find that the fuel price sensitivity of the demand for kilometres is declining with household income, but we are unable to confirm earlier suggestions in the literature that the rebound effect decreases with household income. This may be due to the fact that several of these earlier studies that found a 'declining' rebound effect were based on specifications of the demand function that did not distinguish between the impact of fuel prices and fuel efficiency. Our results may therefore suggest that earlier statements may in fact refer mainly to a changing impact of fuel prices. Finally, simulation results suggest that the small pure rebound effect and the impact of adaptations in all car attributes jointly imply that, compared to the status quo reference scenario, higher fuel prices lead to a substantial reduction in both the demand for kilometres and in demand for fuel.

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Appendix

Table A1. First Stage of model [4] (Table 2)

	Change in logarithm of fuel efficiency	*Change in logarithm of car total weight*	*Change in logarithm of engine horse-power*
Fuel efficiency of the old car relative to the fuel efficiency of the average new Danish car (instrument)	*0.052**** *(0.0004)*	*-0.001**** *(0.0003)*	*0.005**** *(0.001)*
Car total weight of the old car relative to the car total weight of the average new Danish car (instrument)	*0.00004**** *(3.91e-06)*	*0.0004**** *(3.34e-06)*	*-0.0002**** *(7.54e-06)*
Engine horse-power of the old car relative to the engine horse-power of the average new Danish car (instrument)	*0.001**** *(0.00003)*	*-0.0005**** *(.00002)*	*0.005**** *(0.0001)*
Change in logarithm of fuel price (DKK/l)	0.373*** (.016)	-0.048*** (0.014)	-0.403*** (0.031)
Change in logarithm of household's income (1000 DKK)	-0.055*** (0.002)	0.044*** (0.001)	0.092*** (0.003)
Change in number of adults in household	0.006*** (0.001)	-0.006*** (0.001)	-0.012*** (0.002)
Change in presence of a baby in household	-0.002 (0.002)	0.006*** (0.002)	0.008*** (0.003)
Change in presence of a children in household	-0.025*** (0.001)	0.022*** (0.001)	0.032*** (0.002)
Change in commuting distance (km)	0.010 (0.014)	-0.031*** (0.012)	-0.029 (0.026)
Change in household's labour supply (1000 hours)	-0.002*** (0.0002)	0.001*** (0.0002)	0.002*** (0.0004)
Residential move (dummy)	-0.002*** (0.001)	-0.007*** (0.001)	-0.012*** (0.001)
Number of observations	110,788	110,788	110,788
Shea's adj. partial R-squared	0.2824	0.3130	0.2611

Notes: standard errors (clustered by the interval between MOTs) are in parentheses; ***,** indicate that estimates are significantly different from zero at the 0.01 and the 0.05 level, respectively.

Table A2. First stage of the Heckman selection model [5] (Table 2)

	[5]
Car accident (individual/personal information), instrument	***0.296****
	(0.018)
Length of the car ownership (years)	***0.026****
	(0.001)
Change in logarithm of fuel price between the beginning and end of the first time interval (DKK/l)	0.516***
	(0.032)
Change in logarithm of household's income (1000 DKK)	0.283***
	(0.010)
Change in number of adults in household	-0.043***
	(0.008)
Change in presence of a baby in household	0.021
	(0.014)
Change in presence of a children in household	0.112***
	(0.009)
Change in commuting distance (km)	-0.0001
	(0.0001)
Change in household's labour supply	0.009***
	(0.002)
Residential move (dummy)	0.050***
	(0.005)
Constant	-0.534***
	(0.006)
Rho	0.623
	(0.016)
Sigma	0.503
	(0.005)
Lambda	0.313
	(0.012)
Wald test of indep. eqns. (rho = 0)	733.34
Uncensored observations	110,788
Number of observations	349,763

Notes: model accounts for selection regarding car switchers; standard errors are in parentheses; *** indicates that estimates are significantly different from zero at the 0.01 level.

Table A.3. First-difference IV model for car switchers: fuel price and fuel efficiency effects for quartiles of household income in year 2003

	Change in log travel demand (1000 km/month)
Change in logarithm of fuel price (DKK/l), q1	-1.785***
	(0.106)
Change in logarithm of fuel price (DKK/l), q2	-1.026***
	(0.086)
Change in logarithm of fuel price (DKK/l), q3	-0.205***
	(0.075)
Change in logarithm of fuel price (DKK/l), q4	0.184**
	(0.074)
Change in logarithm of fuel efficiency, q1	0.174***
	(0.059)
Change in logarithm of fuel efficiency, q2	0.064
	(0.048)
Change in logarithm of fuel efficiency, q3	0.086**
	(0.041)
Change in logarithm of fuel efficiency, q4	0.102***
	(0.039)
Change in logarithm of car total weight	0.496***
	(0.034)
Change in logarithm of engine horse-power	0.035**
	(0.016)
Change in logarithm of household's income (1000 DKK)	0.123***
	(0.006)
Change in number of adults in household	0.023***
	(0.004)
Change in presence of a baby in household	-0.032***
	(0.006)
Change in presence of a children in household	0.032***
	(0.004)
Change in commuting distance (km)	0.660***
	(0.053)
Change in household's labour supply (1000 hours)	0.003***
	(0.001)
Residential move (dummy)	0.023***
	(0.003)
No. of observations	110,788

Notes: standard errors (clustered by the interval between MOTs) are in parentheses; the car attributes are instrumented using the characteristic of the old car relative to the average new Danish car; *** indicates that estimates are significantly different from zero at the 0.01 level.