Travel Distance and Fuel Efficiency: An Estimation of the Rebound Effect using Micro-Data in Switzerland*

Sylvain Weber† Mehdi Farsi‡

July 25, 2014

PRELIMINARY DRAFT PREPARED FOR THE EMEE 2014
(7^{th} International Workshop on Empirical Methods in Energy Economics)
PLEASE DO NOT CITE WITHOUT AUTHORS' PERMISSION

Abstract

We estimate the rebound effect for private cars using cross-section micro-level data in Switzerland for 2010. Our simultaneous equations model accounts for endogeneity of travel distance, vehicle fuel intensity and vehicle weight. Compared to the literature, our paper provides an important contribution as micro-level data and simultaneous equations models have seldom been used before to estimate the rebound effect. Moreover, among the distance measures we use, one is highly reliable as it was recorded using GIS (Geographical Information System) software. Our results, obtained via 3SLS, point to substantial direct rebound effects between 75% and 81%, which lie at the higher end of the estimates found in the literature. OLS estimates of the rebound effect are however much lower.

JEL Classification: C31, D12, Q41, R41.

Keywords: rebound effect, travel demand, simultaneous equations model.

*We thank Arnaud Blaser for valuable research assistance. This research was financially supported by Swiss National Science Foundation (SNSF) grant N° 100018-144310.

†Corresponding author. University of Neuchâtel, Institute of Economic Research, A.-L. Breguet 2, 2000 Neuchâtel, Switzerland. sylvain.weber@unine.ch.

‡University of Neuchâtel. mehdi.farsi@unine.ch.

1 Introduction

Thanks to technological progress, a given distance can be traveled using less fuel. At the same time, technological progress fosters the use of cars made more efficient. The latter reaction is called a rebound or takeback effect, and it partially offsets the benefits of technological improvements. While the principle of the rebound effect is widely accepted, its magnitude remains a debated question, with empirical estimates ranging from negative rebound effects, also called superconservation, to rebound effects larger than 100%, also called backfire effects.[1]

In this paper, we investigate the rebound effect for the private transportation sector in Switzerland, using data from wave 2010 of the *Microcensus on Mobility and Travel*, which contains information on almost 60,000 households, more than 140,000 individuals, and more than 70,000 private cars. Because investigations on rebound effect in private transport, and more generally on fuel consumption, are traditionally conducted using aggregate data, our use of micro-level data constitute an important asset. Moreover, this literature is heavily skewed towards the US, so that it seems important to study these aspects in other countries. The case for analyses outside the US is made stronger by the fact that non-US households are likely to have very different driving habits than US households and it is highly plausible that they react differently. For example, a meta-analysis by Brons et al. (2008) shows that the price elasticity of gasoline demand is significantly lower in the US, Canada and Australia than in the rest of the world. Studies directly concerned with the estimation of rebound effects also appear to bring different results whether they are conducted using US data or not (see Section 2).

An important feature of our study is that we estimate the rebound effect from its most basic definition, i.e., consumers' reaction to a change in energy efficiency. Our database provides the characteristics of each single car, so that we are able to measure (among others) the effect of fuel efficiency on the traveled distance. Contrary to most of the literature, constrained by data availability, we do not assume that the rebound effect is given by the price elasticity of fuel demand (in absolute value). Such an assumption is a clear

[1]See Chakravarty et al. (2013) for a recent literature overview. However, we draw the reader's attention on the fact that this article contains several mistakes. In particular, the links between rebound effect and energy price elasticity shown in Table 1 (p. 217) are completely wrong. More in general, rebound effects seem to be misunderstood, as many papers in this literature describe or report them approximately. For example, many authors simply report the fuel price or cost elasticity of vehicle miles traveled and assimilate this coefficient to a rebound effect, while in fact the signs of these two parameters should be opposite. Turner (2013) highlights some of the problems of the literature on rebound effects.

shortcoming, as equivalence between price elasticity and rebound effect holds if energy efficiency is *constant* (Sorrell & Dimitropoulos, 2008, see Definition 4). Said otherwise, the equivalence holds, because "*in principle*, rational consumers should respond in the same way to a decrease in energy prices as they do to an improvement in energy efficiency (and vice versa), since these should have an identical effect on the energy cost of energy services" (Sorrell et al., 2009, p. 1359). In our opinion, this is a serious caveat on which most of this literature is built. In fact, there is evidence showing that consumers' reaction depends on the source of the cost variation. For instance, Li et al. (2012) find that consumers respond more strongly to gasoline tax changes than to equal-sized changes in tax-inclusive gasoline prices, and Baranzini & Weber (2013) show that oil shocks and gasoline tax increases have further impacts on top of their direct effect due to price increase.

In this paper, we further treat several cars' characteristics as endogenous. Indeed, we believe that individuals who purchase a car have in mind the distance they intend to drive with this car in the future. Therefore, expected distance might have an impact on the characteristics of the chosen car. In particular, we expect distance to have an effect on the fuel efficiency of the car and its weight, which we view as a proxy for correlated valuable attributes such as car size, comfort, social signaling value and security feeling. Rational individuals should opt for a more fuel efficient car if longer distances are planned. Also, heavier (i.e., larger and/or more comfortable) cars might be chosen by those who drive a lot. Finally, one may expect complex links between fuel efficiency and weight, as for example an improvement in fuel efficiency might free some budget that may be allocated to the purchase of a larger car (Blaser et al., 2014).

Because distance, fuel efficiency and weight are simultaneously determined, these three variables are endogenous and running OLS estimations might yield biased coefficients. Our estimation strategy therefore relies on a simultaneous equations model that we estimate using three stage least squares (3SLS). Such a setting has been seldom used in the literature on rebound effect. To our knowledge, only Greene et al. (1999) modelize a simultaneous equations model using micro-level data to identify rebound effects.

The interest of our research is further enhanced by the current political context in Switzerland. First, when ratifying the Kyoto Protocol, the country committed to reducing its greenhouse gas emissions by 8% between 2008 and 2012 compared to 1990 levels. A new CO_2 Ordinance, which became effective in 2013, also states that domestic greenhouse gas emissions must be reduced by 20% compared to 1990 levels by year 2020. Such an ambitious target will be difficult to achieve, so that knowledge of the size of the rebound effect appears crucial. Second, on the 24^{th} November 2013, the Swiss voted on a price increase of the motorway vignette from 40 to 100 Swiss Francs.[2] More than 60% of the voters rejected this price increase, which is a sign that people are not ready to change the legislation regarding transportation and that additional taxes will not be easily implemented. Hence, alternative solutions to decrease emissions, and in particular improvements in efficiency, must be investigated.

The remainder of the paper is organized as follows. Section 2 provides an overview of the literature on the rebound effect in the private transportation sector. Section 3 develops the estimation model. Section 4 describes the data, and section 5 discusses the empirical estimates. Conclusions are provided in section 6.

2 Rebound effects in transport

An extensive discussion of rebound effects and their definitions is provided in Sorrell & Dimitropoulos (2008). Most naturally, the direct rebound effect (RE) is defined as the elasticity of the service demand (S) with respect to efficiency (ε):[3]

$$RE = \eta_{\varepsilon}(S) = \frac{\partial \ln S}{\partial \ln \varepsilon} \tag{1}$$

Due to data availability, the literature mostly relies on alternative definitions of the rebound effect, such as the elasticity of service demand with respect to energy cost or even as the own price elasticity of energy demand (both in absolute value). However, such definitions of the rebound effect imply a symmetry argument (Sorrell & Dimitropoulos, 2008), which assumes that raising energy efficiency has the same effect as falling energy prices. Moreover, for the own price elasticity of energy demand to be interpretable as a rebound effect, one has to assume that energy efficiency is *constant*. This is in total contradiction with the basics of the rebound effect, which originates in the behavioral response to a *change* in energy efficiency. In our view, the rebound effect should therefore not be estimated as a price elasticity. The results obtained by Greene (2012) indeed reject the hypothesis of equal and opposite effects of fuel economy and the price of gasoline.

In the present paper, we estimate the rebound effect using variability in cars fuel efficiency across households. It is assumed that the price of fuel

[2] The vignette gives the right to drive on Swiss motorways during one year.

[3] Energy efficiency is defined as $\varepsilon = \frac{S}{E}$, that is the service demand (S) divided by the energy input (E). In our setting, S would be a travel distance while E would be a quantity of fuel. Efficiency would thus be defined (using standard units in Europe) as a number of kilometers traveled using 1 liter of fuel.

applies similarly to every households. Because our data is a cross-section, the assumption of a single fuel price for every household does not seem too strong. Even though prices might differ across gas stations, differences are likely compensated over time as drivers refill at different places. Moreover, canton (i.e., state) fixed effects included in our estimations will capture most of the spatial variations in price.

An empirical difficulty is that energy efficiency is likely to be endogenous and correlated with energy services. In our context, one can indeed expect that drivers who plan to drive much will choose an energy efficient car in order to minimize the running costs. This positive correlation would therefore strengthen the link between energy services and efficiency, and the identified rebound effect would be over-estimated. In order to correct for this problem, we will use a simultaneous equations model, where energy efficiency is endogenous and depends on the distance traveled.

Table 1 displays the main characteristics of the studies where the direct rebound effect in the private transportation was explicitly investigated (i.e., we do not consider studies that estimate price elasticities of fuel). The range of rebound effect estimates in the literature is wide, but seems to be relatively narrow inside each country. For instance, in the US (the most studied country), long run direct rebound effects seem to revolve around 20%, whatever the econometric technique and the data used. Outside the US, rebound effect estimates are larger. These differences tend to confirm that American and non-American households behave differently with respect to car usage, so that it is important to conduct investigations on different countries.

Another point to mention based on Table 1 is that micro-level data The present paper is at the intersection of two branches of the literature, as it uses simultaneous equations models and micro-level data, a combination that has been implemented only by Greene et al. (1999) before.

To our knowledge, de Haan et al. (2006) and de Haan et al. (2007) are the only previous studies about rebound effects in the transport sector in Switzerland. They do, however, not study the rebound effect as we understand it in the present paper, but what they call socio-psychological rebound effects. In particular, they investigate whether buyers of Toyota Prius did tend to switch from small and/or already fuel-efficient cars, and if the purchase of the new vehicle did increase average vehicle ownership. Their analysis is based on 303 buyers (representing 82.6% of all buyers) of the Toyota Prius in Switzerland in the first nine months after market entry. Our study is thus the first to conduct an analysis of the rebound effect in Switzerland using a sample representative of the entire population.

Table 1: Studies (explicitly) on the direct rebound effect in private transport

Study (in alphabetic order)	Country	Data		Econometric technique	Rebound effect	
		Period	Level		SR[a]	LR[a]
Ajanovic & Haas (2012)	6 EU countries[b]	1970-2007	Country	Cointegration		44%
Frondel et al. (2008)	Germany	1997-2005	Household	Panel estimations		57-67%
Frondel et al. (2012)	Germany	1997-2009	Household	Panel estimations + Quantile regressions		57-62%
Greene (2012)	US	1966-2007	National	OLS + IV	3-6%[c]	12-24%[c]
Greene et al. (1999)	US	1979-1994	Household	3SLS		17-28%
Hymel et al. (2010)	US	1966-2004	State	3SLS	4.7%	24.1%
Small & Van Dender (2007)	US	1966-2001	State	3SLS	4.5%	22.2%
Su (2012)	US	2009	Household	Quantile regressions		10.6%-19.3%
Wang et al. (2012b)	China	1994-2009	Province (State)	LA-AIDS[d]		96%
Wang et al. (2012a)	Hong Kong	1993-2009	National	SUR		45%

The estimates reported in this table are the authors' mean evaluations.

All estimates based on cross-sections of households are considered as long run estimates, even though the authors did not explicitly state it explicitly.

[a]: SR = short run, LR = long run.

[b]: Austria, Germany, Denmark, France, Sweden, and Italy.

[c]: Deduced from Figure 10, p. 26.

[d]: LA-AIDS = linear approximation of the almost ideal demand system.

3 Model

Following some authors already mentioned in previous section, we build a system of simultaneous equations. The variables we consider as simultaneously determined are distance traveled (D), fuel intensity (FI) (in liters per 100 kilometers; i.e., the inverse of the efficiency) of the vehicle,[4] and its weight (W). Contrary to Greene et al. (1999), who also estimate a system of equations based on household data, we do not consider an equation for fuel price because our dataset is a single cross section and prices are not collected at a regional level. Said otherwise, we consider fuel price to be similar for each individual and exogenous. In spirit, our system is similar to that of Small & Van Dender (2007), who consider vehicle-miles traveled, fuel efficiency, and stock of vehicles as being simultaneously determined at the macroeconomic level. In our model, the first two endogenous variables are identical, and vehicle weight plays a similar role as vehicle stock at the microeconomic level.

Our model is thus given by the following set of equations:

$$\begin{cases} \ln D_i = \ln FI_i \cdot \alpha^{d,fi} + \ln W_i \cdot \alpha^{d,w} + X_i \cdot \beta^d + Z_i^d \cdot \gamma^d + u_i^d \\ \ln FI_i = \ln D_i \cdot \alpha^{fi,d} + X_i \cdot \beta^{fi} + Z_i^{fi} \cdot \gamma^{fi} + u_i^{fi} \\ \ln W_i = \ln D_i \cdot \alpha^{w,d} + X_i \cdot \beta^w + Z_i^w \cdot \gamma_i^w + u_i^w \end{cases} \tag{2}$$

where D_i is a measure of distance traveled by individual i, FI_i is vehicle's fuel intensity, W_i is vehicle's weight, X_i is a row vector of characteristics expected to affect distance, fuel intensity and weight, and Z_i^j ($j = d, fi, w$) is a row vector of characteristics expected to affect only one dependent variable but not the other two. Parameters to be estimated are denoted α, β, and γ. Error terms are denoted u. The system will be estimated by 3SLS (Zellner & Theil, 1962).

In this specification, the rebound effect is given by $-\alpha^{d,fi}$, i.e., the negative of the elasticity of distance with respect to fuel intensity. Because our dataset is a cross-section of individuals, the coefficients must be interpreted as long-run effects.

It is important to emphasize that we do not include weight in the fuel intensity equation and vice versa. We do so in order to avoid capturing mechanically any technical link between fuel intensity and weight. What we want to explain is how individuals make their choice, which presupposes

[4] 1 mile $\cong$ 1.609 kilometers and 1 gallon $\cong$ 3.785 liters, so that 1 MPG $\cong$ 0.425 km/l. So, for example, 20 MPG correspond to a consumption of around 12 liters per 100 km. For more on these relationships and the misperception induced by the usage of MPG, see Larrick & Soll (2008).

that they do have an influence. It seems legitimate to assume individuals can choose the distance they drive and the fuel efficiency of their vehicle independently, even though both influence each other, so that they are simultaneously chosen. Similarly, individuals can make a decision about the distance traveled and car's weight. However, the individual cannot choose fuel efficiency independently of vehicle's weight, as these two dimensions are linked for technical reasons. Said otherwise, one cannot choose a very fuel efficient car that is large and heavy at the same time.

4 Data

We use data from the *Microcensus on Mobility and Transport* (MMT), which is carried out by the Swiss Federal Statistical Office every five years since 1974.[5] In this paper, we only use the most recent wave of the survey, which was conducted in 2010. In addition to individual and household characteristics, the MMT gives detailed information about the vehicles owned by the households, and about distance traveled by transportation mean and travel behavior of households.

The 2010 MMT contains data about a total of 70,294 private cars. Among those, administrative data is available for 51,895 cars, Owners of these vehicles indeed accepted that information was retrieved from the MOFIS system, the official inventory of motor vehicles in Switzerland managed by the Federal Roads Office. For those 51,895 cars, we have information on vehicle weight, efficiency label, transmission type, number of cylinders, and registration date (year and month). We can also link the car to its primary user inside the household.

A detailed overview of the distance measures collected in the MMT is provided in Table 2. Several of those are interesting for our purposes. First, an estimation by the respondents of the mileage (in km) over the last 12 months is available for each vehicle. Both total mileage and mileage inside Switzerland are provided. Second, distance traveled during a specific reference day (i.e., one of the two days that predate the interview) is available for a subsample of the respondents. This daily distance is broken down by transportation mean (private, public, light or other). In 2010, for the first time, the actual routes traveled were recorded using GIS (Geographical Information System) software, and thus provide very accurate information on the distances covered.[6]

[5]The survey was conducted in years ending 4 and 9 until 1994, and in years ending 0 and 5 since 2000.

[6]Deviations between georouting distances and distances estimated by the respondents are sometimes substantial, and almost 20% of respondents make a mistake of at least

Table 2: Description of the distance measures available in the MMT

Variable	Description
mileage_last12m	Mileage over the last 12 months
mileageCH_last12m	Mileage over the last 12 months in Switzerland
dist_estim[a]	Estimated distance in a specific reference day
distCH_estim[a]	Estimated distance in Switzerland in a specific reference day
dist[a]	Georouting distance in a specific reference day
distCH[a]	Georouting distance in Switzerland in a specific reference day
distCH decomposes into:	
distCH_priv	private transport
distCH_pub	public transport
distCH_light	light transport
distCH_other	other transport

[a]: measure that cumulates all transportation means.

In this paper, as we are interested in private transportation, we will focus on two variables: mileage_last12m and distCH_priv. Both of these variables are appealing to us. On the one hand, mileage_last12m is the most common measure of travel distance available in surveys and therefore it is the one used in virtually all studies. Results obtained using this variable will allow direct comparisons with the literature. The drawback of this variable is that it is based on self-declared travel distances which might turn out to be largely erroneous. On the other hand, distCH_priv provides a very accurate measure of distance traveled. Its drawback is that it concerns a single (reference) day, which may be an exception for some respondents. However, reference days are evenly distributed across days of the week over all respondents, such that exceptional days in terms of travel should cancel out.

Interestingly, the correlation coefficient between these two distance measures amounts to 0.20.[7] Even though positive, this correlation is weak. Hence, the different distance measures probably relate to different types of mobility: the individuals who drive a lot on a particular day (presumably to go to work) are not necessarily those who drive the most over the year, where vacation travels are likely to represent a substantial share of total

10 kilometers, which is large compared to an average traveled distance of less than 50 kilometers.

[7]This result is based on 22'255 observations that have positive distances recorded driven with a car and using individual survey weights. When computed on the 8'090 observations remaining in the final sample, the correlation coefficient is 0.21.

traveling. We will consider these two distance measures alternatively in our estimations, as they could turn out to be differentially sensitive.

Because our goal is to measure a rebound effect based on definition (1), we need a fuel efficiency measure. In the MMT, the only measure directly available is given by efficiency labels, from A (most efficient) to G (least efficient). These labels are obtained by a formula based on vehicle weight and fuel consumption of the vehicle, which allows us to backward compute a continuous fuel efficiency measure.[8]

Note that, in theory, combining information about fuel, transmission, efficiency labels, weight, and engine displacement should allow us to identify almost exactly any vehicle and thus merge the MMT data with technical data provided by the Touring Club Switzerland (TCS). However, it appears that the weight and engine displacement variables of these two databases do not perfectly match. Removing these continuous variables to perform the merge

[8]The formula is adapted every other year. In the 2010 MMT, the 2007 energy label scale was used. Concretely, the following formula was used to compute an index I:

$$I = 7,267 \cdot \frac{FI}{600 + W^{0.9}}$$

where FI is fuel intensity in kg/100km and W is car's weight. Efficiency labels were then assigned according to the following scale:

A if $I \leq 26.54$
B if $26.54 < I \leq 29.45$
C if $29.45 < I \leq 32.36$
D if $32.36 < I \leq 35.27$
E if $35.27 < I \leq 38.18$
F if $38.18 < I \leq 41.09$
G if $I > 41.09$

In order to retrieve a measure of consumption, we extract FI from the above formula:

$$FI = \frac{(600 + W^{0.9}) \cdot I}{7,267}$$

Car's weight (W) is available in the data. However, since we do not know the index I values, we set them to the mid-point of each class. For the open categories A and G, we use the average between the threshold value and the minimal (for category A) and maximal (for category G) values observed in the 2007 database of the Touring Club Switzerland (TCS), considering only gasoline and diesel cars, and removing cars with prices above 100,000 CHF, which are obvious outliers.

Finally, we obtain a measure of fuel intensity in l/100km by dividing the values of FI in kg/100km by gasoline and diesel densities, i.e., 0.745 kg/l and 0.829 kg/l respectively. Simulating this methodology using the TCS data and comparing the estimated values and the actual values differ by less than 0.5 l/100km for almost all vehicles. This difference is negligible, as it corresponds to the additional consumption that would be induced by an additional passenger.

Table 3: Descriptive statistics of the endogenous variables

Variable	Mean (sd)	# Obs.
Distance distCH_priv (km)	49.93 (60.23)	24,619
Distance mileage_last12m (km)	$11,988.30$ $(10,311.82)$	31,191
Fuel intensity (l/100km)	9.10 (2.56)	14,535
Vehicle weight (kg)	$1,845.20$ (398.43)	26,969

Statistics based on all non-missing observations for each variable.
Individual survey weights are used.
Distances recorded at 0 were removed.

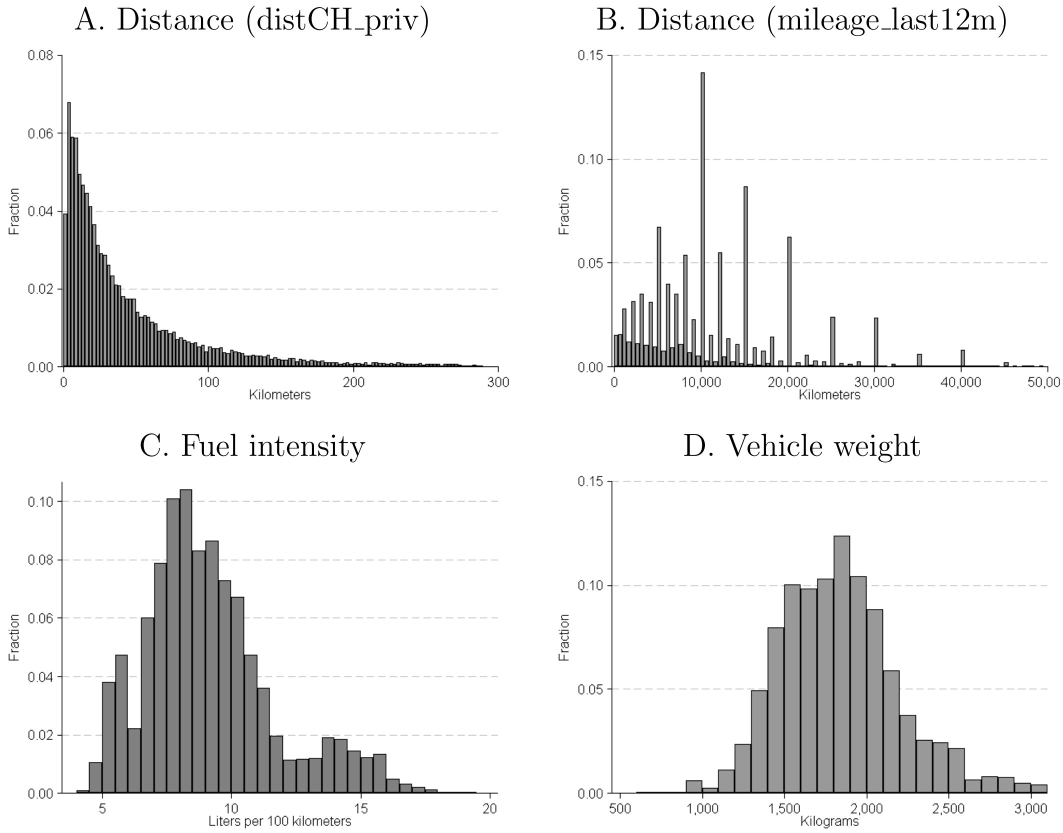
leads to numerous multiple matches, which imposes to make choices on how to eventually assign a single car to each observation and makes this process hardly defendable. The backward computation of consumption is not perfect either, but more straightforward.

Table 3 provide descriptive statistics of the endogenous variables and Figure 1 shows their distribution.[9] We observe that distances traveled daily (panel A) are strongly right skewed, with a mode below 5 kilometers, and a median around 22 kilometers. The distribution of this variable distCH_priv is perfectly smooth, as could be expected because it was computed using GIS software. On the contrary, the variable reporting self-declared mileage over the last 12 months (panel B) shows spikes at round numbers, especially for large values. Such phenomenon is known as heaping and obviously arises because of rounding with regard to the distance traveled.

In order to make our estimations comparable when using different distance measures, we restrict the sample to the observations that have non-missing values in both cases. Our final sample is composed of 8'090 observations.

[9]Table A.1 in Appendix provides descriptive statistics for the final sample.

Figure 1: Distributions of the endogenous variables



Statistics based on all non-missing observations for each variable.

Distances recorded at 0 were removed.

Distributions of the distance variables and the vehicle weight are truncated at their 99$^{\text{th}}$ percentile to make the graphs more readable.

5 Empirical Results

Empirical estimations of model (2) are displayed in Table 4 using the distance traveled in a single reference day (distCH_priv) and in Table 5 using the annual mileage of the car (mileage_last12m).[10] Even though the distance variables differ widely, it is interesting to note that the two sets of estimations are very similar. The rebound effect is estimated at 81% and 75% in the 3SLS estimations. Such values clearly lie in the higher end of the estimates found in the literature (see section 2, and for example Greening, Greene, & Difiglio,

[10] As a robustness check, we also run our model excluding the weight equation. The results are displayed in Appendix Table A.2. We do not report OLS results there, as they would obviously be identical to those displayed in Tables 4 and 5.

2000). However, as mentioned before, most of the studies are based on US data, which traditionally yield low estimates of the rebound effect. Moreover, most of the references cited by Greening et al. (2000) use OLS (and are not necessarily explicitly after the estimation of a rebound effect). In fact, our OLS estimates of the rebound effect are much lower (19% and 37%). Based on our results, one should therefore conclude that OLS estimates of the rebound effect are biased downwards, which goes against the usual assumption that OLS estimates are *upward* biased because individuals who intend to drive long distances will choose high fuel efficiency (Sorrell & Dimitropoulos, 2008).

It is important to emphasize at this point that our measure of fuel intensity is derived from manufacturers tests, and it might differ from the true on-road consumption. Mock et al. (2013) in fact reveal that there is a divergence between manufacturers and on-road fuel consumption, and this divergence has increased over time, especially rapidly since 2007. For this reason, we included vehicle age in the fuel intensity equation. This control variable turns out positive but weak in the 3SLS estimations (and even insignificant when using distCH_priv), but larger in the OLS estimations. Such results might indicate why OLS estimates of the rebound effect are biased downward. Fuel consumption provided by manufacturers has rapidly decreased over time, while true on-road consumption has also decreased, but less so. If the manufacturers measure is directly used to estimate a rebound effect, it may only show a weak effect on distance given that its variation is large. However, when instrumented through the 3SLS procedure, fuel intensity will show less variations so that its (true) effect on distance turns out stronger.

Weight does not appear to have a significant effect on travel distance. However, the converse is not true, with distance influencing positively car's weight. This might be interpreted by considering that vehicle weight proxies comfort and safety, so that heavier cars are preferred for driving long distances. Income elasticity of distance traveled is found to be in the magnitude of 0.2-0.3.[11] Traveling by car might thus be classified as a first-necessity good. Women appear to drive significantly less than men, so as parents compared to people without children. We also find that travel distances decrease with age, while education level increases traveling. Finally, population density has a negative impact on distance: in urban areas more activities are within reach without a private vehicle. Contrarily, people living in rural areas might be forced to use their car as they face few transportation alternatives.

Results for the fuel intensity and the weight equations are mostly as

[11] A continuous income variable has been constructed based on a variable that was originally categorical. The mean point of every bracket has been assigned to each household inside the bracket. For the lowest (highest) category, we assigned the upper (lower) bound.

Table 4: 3SLS and OLS estimations, Distance = distCH_priv

	3SLS			OLS		
	ln(Distance)	ln(Fuel intensity)	ln(Weight)	ln(Distance)	ln(Fuel intensity)	ln(Weight)
ln(Fuel intensity)	−0.814***	—	—	−0.187**	—	—
	(0.267)			(0.091)		
ln(Vehicle weight)	0.093	—	—	0.287**	—	—
	(0.928)			(0.126)		
ln(Distance)	—	−1.253***	0.222	—	−0.003	0.003*
		(0.207)	(0.168)		(0.002)	(0.002)
Diesel	−0.121	—	—	0.049	—	—
	(0.143)			(0.053)		
Automatic	−0.557***	—	—	−0.013	—	—
	(0.212)			(0.038)		
Vehicle age	—	0.003	−0.004	—	0.023***	−0.007***
		(0.006)	(0.004)		(0.001)	(0.001)
Household size: 2 persons	—	—	−0.059***	—	—	0.013**
			(0.012)			(0.005)
Household size: 3+ persons	—	—	−0.071***	—	—	0.061***
			(0.026)			(0.011)
ln(income)	0.316***	0.340***	0.022	0.226***	0.062***	0.047***
	(0.053)	(0.060)	(0.048)	(0.030)	(0.006)	(0.005)
Women	−0.301***	−0.327***	−0.052	−0.179***	−0.085***	−0.086***
	(0.079)	(0.053)	(0.042)	(0.028)	(0.006)	(0.004)
Children	−0.098*	−0.132***	0.120***	−0.139***	0.021***	0.010
	(0.059)	(0.046)	(0.037)	(0.030)	(0.006)	(0.010)
Driver age/10	−0.099***	−0.165***	0.037	−0.139***	0.013***	0.005***
	(0.013)	(0.032)	(0.026)	(0.010)	(0.002)	(0.002)
Education: medium	0.115*	0.142**	−0.020	0.113**	0.005	0.009
	(0.059)	(0.067)	(0.051)	(0.049)	(0.010)	(0.007)
Education: high	0.248***	0.307***	−0.054	0.247***	0.006	0.012
	(0.063)	(0.085)	(0.066)	(0.053)	(0.011)	(0.008)
Urban region	−0.267***	−0.333***	0.037	−0.258***	−0.003	−0.014**
	(0.051)	(0.077)	(0.061)	(0.042)	(0.009)	(0.006)
Constant	2.271	4.101***	6.488***	0.203	1.473***	7.110***
	(6.892)	(0.569)	(0.448)	(0.822)	(0.061)	(0.044)
# Obs.	8,090			8,090		

Standard errors in parentheses. ***/**/*: significant at the 0.01/0.05/0.10 level. Additional controls not reported: canton (i.e., state) fixed effects (all equations). Distance in this table is distCH_priv.

Table 5: 3SLS and OLS estimations, Distance = mileage_last12m

	3SLS			OLS		
	ln(Distance)	ln(Fuel intensity)	ln(Weight)	ln(Distance)	ln(Fuel intensity)	ln(Weight)
ln(Fuel intensity)	-0.745^{***}	—	—	-0.365^{***}	—	—
	(0.158)			(0.060)		
ln(Vehicle weight)	-0.338	—	—	0.924^{***}	—	—
	(0.378)			(0.083)		
ln(Distance)	—	-0.635^{***}	0.671^{***}	—	0.003	0.032^{***}
		(0.056)	(0.058)		(0.004)	(0.002)
Diesel	0.248^{***}	—	—	0.036	—	—
	(0.077)			(0.035)		
Automatic	-0.226^{**}	—	—	-0.004	—	—
	(0.091)			(0.025)		
Vehicle age	—	0.010^{***}	0.006^{***}	—	0.023^{***}	-0.007^{***}
		(0.002)	(0.002)		(0.001)	(0.001)
Household size: 2 persons	—	—	0.026^{**}	—	—	0.014^{***}
			(0.011)			(0.005)
Household size: 3+ persons	—	—	0.082^{***}	—	—	0.064^{***}
			(0.023)			(0.011)
ln(income)	0.206^{***}	0.144^{***}	-0.043^{***}	0.106^{***}	0.061^{***}	0.043^{***}
	(0.028)	(0.016)	(0.016)	(0.020)	(0.006)	(0.005)
Women	-0.325^{***}	-0.239^{***}	0.077^{***}	-0.187^{***}	-0.084^{***}	-0.079^{***}
	(0.036)	(0.019)	(0.019)	(0.018)	(0.006)	(0.004)
Children	-0.019	-0.005	0.024	-0.089^{***}	0.021^{***}	0.009
	(0.030)	(0.015)	(0.023)	(0.020)	(0.006)	(0.010)
Driver age/10	-0.094^{***}	-0.065^{***}	0.087^{***}	-0.122^{***}	0.014^{***}	0.008^{***}
	(0.008)	(0.009)	(0.009)	(0.007)	(0.002)	(0.002)
Education: medium	0.088^{**}	0.054^{**}	-0.042^{*}	0.075^{**}	0.004	0.007
	(0.039)	(0.024)	(0.023)	(0.032)	(0.010)	(0.007)
Education: high	0.158^{***}	0.101^{***}	-0.086^{***}	0.147^{***}	0.004	0.008
	(0.042)	(0.027)	(0.026)	(0.035)	(0.011)	(0.008)
Urban region	-0.090^{***}	-0.062^{***}	0.049^{**}	-0.078^{***}	-0.002	-0.012^{*}
	(0.034)	(0.021)	(0.021)	(0.028)	(0.009)	(0.006)
Constant	12.068^{***}	7.052^{***}	1.244^{**}	2.719^{***}	1.441^{***}	6.839^{***}
	(2.779)	(0.514)	(0.520)	(0.541)	(0.068)	(0.049)
# Obs.	8,090			8,090		

Standard errors in parentheses. $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level. Additional controls not reported: canton (i.e., state) fixed effects (all equations). Distance in this table is mileage_last12m.

expected. The only counter-intuitive result concerns household size in the 3SLS estimation of Table 4, where it apparently exerts a negative impact on vehicle's weight. However, it is to note that our estimations also control for the presence of children in the household, and this variable is obviously closely related to household size. Having children has a positive effect on vehicle weight, which more than offsets the negative effect of household size. Moreover, it is interesting to note that the weight equation displays very few significant coefficients when using the distance traveled during a single day (Table 4), while more coefficients are significant and in line with expectations when using annual distance traveled (Table 5). This could indicate that people using a car for daily trips (for example to commute to work) put less emphasis on weight than for traveling over the year (for example for holidays).

6 Conclusions

This paper investigates travel demand in Switzerland, using a cross-section of households in 2010. We build a system of simultaneous equations where travel distance, fuel efficiency, and weight are jointly determined. This setting allows to correct for potential biases encountered by OLS estimations. An important feature of our study is that we use micro-level data, whereas most of the literature is based on aggregate data. In fact, the combination of micro-level data and simultaneous equations model in the literature on rebound effect in private transport has only been used once before, by Greene et al. (1999). Moreover, among the distance measures available to us, one is highly reliable as it was recorded using GIS (Geographical Information System) software. On the contrary, most micro-data studies on travel demand are based on distances self-reported by the respondents, which are likely to suffer from recollection and rounding biases.

Our model, estimated by three-stage least squares (3SLS), gives large rebound effects between 75% and 81%. Such estimates are high compared to the rest of the literature. However, the difference between our estimates and those based on data from outside the US is less pronounced. Our results thus tend to confirm a difference between the US and other countries, in particular European countries, where the rebound effects in transportation appear to be relatively strong. In this situation, it appears that a substantial share of technological improvements would not be passed to energy savings. In terms of energy policy, this indicates a need to look for alternative solutions in order to curb CO_2 emissions, given that technology improvements would not be particularly effective. The problem becomes especially acute in Switzerland, where the universal direct democracy allows the people to contradict the government on almost any subject, and it seems (based on the outcome of a recent vote) that people are not ready to accept taxes increases in the private transportation sector.

An important extension to this work that could be considered is to include previous waves of the *Microcensus on Mobility and Transport* in the analysis. This survey has been conducted every 5 years since 1974, and 8 waves are now available. Even though several changes preclude a perfect comparison across the different waves, it should be possible to investigate the evolution of the parameters of interest by using repeated cross-section and pseudo-panel techniques.

Appendix

Table A.1: Descriptive statistics for the final sample

Variable	Mean (sd)	Min	Max
Distance distCH_priv (km)	50.56 (59.93)	0.02	712.35
Distance mileage_last12m (km)	13,708.85 (9,959.51)	4.00	200,000.00
Fuel intensity (l/100km)	9.02 (2.58)	4.07	19.44
Vehicle weight (kg)	1,868.63 (369.43)	980.00	3,500.00
Diesel	0.23 (0.42)	0.00	1.00
Automatic	0.21 (0.40)	0.00	1.00
Vehicle age	5.92 (3.77)	0.00	17.00
Income	8,586.48 (3,799.18)	2,000.00	16,000.00
Women	0.41 (0.49)	0.00	1.00
Children	0.46 (0.50)	0.00	1.00
Driver age	47.82 (14.05)	18.00	94.00
Education: low	0.08 (0.28)	0.00	1.00
Education: medium	0.56 (0.50)	0.00	1.00
Education: high	0.35 (0.48)	0.00	1.00
Household size	2.66 (1.27)	1.00	12.00
Household size: 1 person	0.17 (0.38)	0.00	1.00
Household size: 2 persons	0.37 (0.48)	0.00	1.00
Household size: 3+ persons	0.45 (0.50)	0.00	1.00
Urban region (population density > 2,000 persons per km^2)	0.14 (0.34)	0.00	1.00
# Obs.	8,090		

Individual survey weights are used.

Table A.2: 3SLS estimations, Model with only 2 equations

	distCH_priv		mileage_last12m	
	ln(Distance)	ln(Fuel intensity)	ln(Distance)	ln(Fuel intensity)
ln(Fuel intensity)	-0.674^{***}	—	-0.798^{***}	—
	(0.168)		(0.111)	
ln(Vehicle weight)	-0.023	—	2.653^{***}	—
	(0.173)		(0.119)	
ln(Distance)	—	-1.413^{***}	—	0.364^{***}
		(0.382)		(0.032)
Diesel	0.011	—	-0.825^{***}	—
	(0.078)		(0.050)	
Automatic	-0.003	—	0.253^{***}	—
	(0.024)		(0.022)	
Vehicle age	—	0.001	—	0.030^{***}
		(0.008)		(0.001)
ln(income)	0.265^{***}	0.375^{***}	0.037^{*}	0.015
	(0.030)	(0.095)	(0.020)	(0.011)
Women	-0.252^{***}	-0.358^{***}	-0.140^{***}	0.004
	(0.028)	(0.083)	(0.019)	(0.012)
Children	-0.107^{***}	-0.151^{**}	-0.129^{***}	0.036^{***}
	(0.030)	(0.063)	(0.020)	(0.010)
Driver age/10	-0.133^{***}	-0.187^{***}	-0.155^{***}	0.058^{***}
	(0.010)	(0.056)	(0.007)	(0.005)
Education: medium	0.113^{**}	0.159^{**}	0.050	-0.024
	(0.049)	(0.081)	(0.032)	(0.016)
Education: high	0.245^{***}	0.346^{***}	0.132^{***}	-0.050^{***}
	(0.053)	(0.119)	(0.035)	(0.018)
Urban region	-0.266^{***}	-0.376^{***}	-0.087^{***}	0.032^{**}
	(0.042)	(0.118)	(0.028)	(0.014)
Constant	3.246^{***}	4.437^{***}	-8.468^{***}	-1.734^{***}
	(0.942)	(0.900)	(0.674)	(0.299)
# Obs.	8,090		8,090	

Standard errors in parentheses. $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level. Additional controls not reported: canton (i.e., state) fixed effects (all equations).

References

Ajanovic, A. & Haas, R. (2012). 'The Role of Efficiency Improvements vs. Price Effects for Modeling Passenger Car Transport Demand and Energy Demand – Lessons from European Countries', *Energy Policy*, *41*, 36–46.

Baranzini, A. & Weber, S. (2013). 'Elasticities of gasoline demand in Switzerland', *Energy Policy*, *63*, 674–680.

Blaser, A., Farsi, M. & Weber, S. (2014). 'An Analysis of Willingness-to-Pay for Fuel Economy in the Swiss Car Market', Working Paper.

Brons, M., Nijkamp, P., Pels, E. & Rietveld, P. (2008). 'A Meta-Analysis of the Price Elasticity of Gasoline Demand. A SUR Approach', *Energy Economics*, *30*(5), 2105–2122.

Chakravarty, D., Dasgupta, S. & Roy, J. (2013). 'Rebound Effect: How much to Worry?', *Current Opinion in Environmental Sustainability*, *5*(2), 216–228.

de Haan, P., Mueller, M. G. & Peters, A. (2006). 'Does the Hybrid Toyota Prius Lead to Rebound Effects? Analysis of Size and Number of Cars Previously Owned by Swiss Prius buyers', *Ecological Economics*, *58*(3), 592–605.

de Haan, P., Peters, A. & Scholz, R. W. (2007). 'Reducing Energy Consumption in Road Transport through Hybrid Vehicles: Investigation of Rebound Effects, and Possible Effects of Tax Rebates', *Journal of Cleaner Production*, *15*(11-12), 1076–1084.

Frondel, M., Peters, J. & Vance, C. (2008). 'Identifying the Rebound: Evidence from a German Household Panel', *The Energy Journal*, *29*(4), 145–163.

Frondel, M., Ritter, N. & Vance, C. (2012). 'Heterogeneity in the Rebound Effect: Further Evidence for Germany', *Energy Economics*, *34*(2), 461–467.

Greene, D. L. (2012). 'Rebound 2007: Analysis of U.S. Light-Duty Vehicle Travel Statistics', *Energy Policy*, *41*, 14–28.

Greene, D. L., Kahn, J. R. & Gibson, R. C. (1999). 'Fuel Economy Rebound Effect for U.S. Household Vehicles', *The Energy Journal*, *20*(3), 1.

Greening, L. A., Greene, D. L. & Difiglio, C. (2000). 'Energy Efficiency and Consumption – The Rebound Effect – A Survey', *Energy Policy*, *28*(6-7), 389–401.

Hymel, K. M., Small, K. A. & Van Dender, K. (2010). 'Induced Demand and Rebound Effects in Road Transport', *Transportation Research Part B: Methodological*, *44*(10), 1220–1241.

Larrick, R. P. & Soll, J. B. (2008). 'The MPG Illusion', *Science*, *320*(5883), 1593–1594.

Li, S., Linn, J. & Muehlegger, E. (2012). 'Gasoline Taxes and Consumer Behavior', Working paper 17891, National Bureau of Economic Research.

Mock, P., German, J., Bandivadekar, A., Riemersma, I., Ligterink, N. & Lambrecht, U. (2013). 'From Laboratory to Road – A Comparison of Official and 'Real-World' Fuel Consumption and CO_2 Values for Cars in Europe and the United States', Tech. rep., International Council on Clean Transportation.

Small, K. A. & Van Dender, K. (2007). 'Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect', *The Energy Journal*, *28*(1), 25–52.

Sorrell, S. & Dimitropoulos, J. (2008). 'The Rebound Effect: Microeconomic Definitions, Limitations and Extensions', *Ecological Economics*, *65*(3), 636–649.

Sorrell, S., Dimitropoulos, J. & Sommerville, M. (2009). 'Empirical Estimates of the Direct Rebound Effect: A Review', *Energy Policy*, *37*(4), 1356–1371.

Su, Q. (2012). 'A Quantile Regression Analysis of the Rebound Effect: Evidence from the 2009 National Household Transportation Survey in the United States', *Energy Policy*, *45*, 368–377.

Turner, K. (2013). '"Rebound" Effects from Increased Energy Efficiency: A Time to Pause and Reflect', *Energy Journal*, *34*(4), 25–42.

Wang, H., Zhou, D., Zhou, P. & Zha, D. (2012a). 'Direct Rebound Effect for Passenger Transport: Empirical Evidence from Hong Kong', *Applied Energy*, *92*, 162–167.

Wang, H., Zhou, P. & Zhou, D. Q. (2012b). 'An Empirical Study of Direct Rebound Effect for Passenger Transport in Urban China', *Energy Economics*, *34*(2), 452–460.

Zellner, A. & Theil, H. (1962). 'Three-Stage Least Squares: Simultaneous Estimation of Simultaneous Equations', *Econometrica*, *30*(1), 54–78.