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Travel distance, fuel efficiency, and vehicle weight: An estimation of the rebound effect using individual data in Switzerland

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Abstract

Improvements in cars' fuel efficiency may induce people to travel more, taking back some of the potential fuel savings. This behavior, known as the (direct) rebound effect, has received much attention in the literature. However, no consensus has been reached regarding its size or the methodology to measure it. In this paper, we estimate the rebound effect for private vehicle transportation in Switzerland using individual household data. We estimate a system of equations that explain travel distance, fuel efficiency, and vehicle weight using seemingly unrelated regressions. Our results point to substantial rebound effects ranging from 57% to 82%, which lie at the higher end of the estimates obtained in the literature, but concur with findings in other European countries. Importantly, our results also indicate that OLS estimates of the rebound tend to be under-estimated rather than over-estimated as usually assumed.

JEL Classification: C31, D12, Q41, R41.

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

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1 Introduction

Following an improvement in fuel efficiency, a given distance can be traveled using less fuel. However, because driving becomes cheaper, such an improvement also fosters utilization. This response, known as the rebound (or take-back) effect, offsets part of potential fuel savings.[1] While the principle of the rebound effect is widely accepted, its magnitude remains a debated question, with empirical estimates for personal transportation ranging from negligible to almost 100%. These discrepancies are partly due to various assumptions across studies. Price elasticities are occasionally used to estimate the rebound effect. As we discuss later, this requires a quite restrictive assumption. Many studies do not account for interrelations between the individual travel behavior and their choice of car, that is, its fuel efficiency but also other attributes such as size and power.

In this paper, we investigate the rebound effect in the context of personal automotive transportation using data from the 2010 *Mobility and Transport Microcensus* (*MTMC*), a large-scale survey representative of the travel behavior of Switzerland's population. We investigate the rebound effect by estimating the sensitivity of service demand to energy efficiency. The *MTMC* data indeed enclose precise vehicle characteristics, allowing to measure the effect of fuel efficiency on distance traveled. Moreover, we account for the

[1] More precisely, what we discuss here is the *direct* rebound effect. For a general discussion of rebound effects (direct, indirect, and economy-wide) and a recent literature overview, see e.g., Azevedo (2014).

interrelations between travel behavior and the decisions about the car's fuel efficiency and size, at the micro level. The micro-level dataset represents as well an important contribution to the bulk of studies that have used aggregate data. Moreover, this literature – heavily skewed toward the United States – could mislead policy makers in other countries as to the extent of real rebound effects in driving.[2]

In our empirical model, we assume that individuals who purchase a car envisage their car usage and the distance they intend to drive in the future. Therefore, (expected) distance will have an impact on the characteristics of the chosen car. In particular, we assume distance to have an impact 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, power, and safety. Rational individuals should opt for a more efficient car if longer distances are planned. The very same drivers might also end up with heavier cars due to their greater power, comfort, and safety. Finally, one may expect complex links between efficiency and weight, for example because an improved fuel efficiency might free some budget that may be allocated to the purchase of a larger car, or because of technical relationships that connect multiple car attributes.

[2] American households are likely to have very different driving habits from other households, and it is thus expected to observe differences across countries in response to changes in price or fuel efficiency. Indeed, a meta-analysis by Brons et al. (2008) shows that price elasticity of gasoline demand is significantly lower in the US, Canada and Australia than in the rest of the world. Likewise, Dimitropoulos et al. (2016) conduct a meta-analysis of the direct rebound effect in road transport and note that rebound effect estimates for the US are on the lower side, whereas estimates for European countries tend to be higher.

Henceforth, distance, fuel efficiency, and weight appear as simultaneously determined, and running OLS regressions would yield biased estimates. Our empirical strategy therefore relies on a system of equations. Small & Van Dender (2007), Hymel et al. (2010), and Hymel & Small (2015) estimate such models using aggregate data at the state-level in the United States. This paper is in line with Greene et al. (1999), Linn (2013), and De Borger et al. (2016) that applied simultaneous equations models to micro-level data in order to identify fuel efficiency rebound effects in the US and Denmark. Our main contribution compared to these studies is the inclusion of a third equation for car's weight.

This paper is a first of its kind applied to Switzerland. Given the ambitious emission targets from one hand and the lack of public acceptance of other policy measures such as taxes, efficiency improvements remain one of the few solutions for reducing emissions in passenger transport.[3] Therefore, the knowledge of the size of the rebound in private transportation, which accounts for 22% of total emissions (see FOEN, 2017), appears crucial.

The remainder of the paper is organized as follows. Section 2 provides an overview of the literature on the rebound effect in the context of personal automotive transport. Section 3 develops the estimation model. Section 4

[3]After its ambitious commitment (20% GHG reduction compared to 1990, by 2020), Switzerland communicated an intended nationally determined contribution of 50% emission reduction by 2030. In 2013, however, 60% of the Swiss voters rejected a price increase of the motorway vignette (which gives the right to drive on motorways during one year) from 40 to 100 Swiss Francs (currency roughly equivalent to US dollar). This is a sign that people are not ready to change the legislation regarding transportation and that additional taxes will not be easily implemented.

describes the data, and Section 5 discusses the empirical estimates. Conclusions and policy recommendations are provided in Section 6.

2 Rebound effects in transport

A general and extensive discussion of rebound effects and their definitions is provided in Sorrell & Dimitropoulos (2008). Here, we focus on the direct rebound effect (RE), which is defined as the elasticity of the service demand (S) with respect to fuel efficiency (ε):[4]

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

Due to data (un)availability, many studies rely on alternative definitions of the rebound effect, such as the elasticity of service demand with respect to energy cost or even the own price elasticity of energy demand. However, such definitions of the rebound effect imply a symmetry argument, i.e., that a one percent increase in energy efficiency has the same effect as a one percent decrease in energy price.

Hence, contrary to many studies constrained by the lack of data on efficiency, we do not rely on alternative definitions of the rebound effect such as the own price elasticity of energy demand. The equivalence between price

[4]In our context, energy efficiency is measured using standard European units as the number of kilometers traveled using 1 liter of fuel. Its opposite – fuel intensity – is measured as the amount of fuel (in liters) required to travel a given distance (usually 100 kilometers).

elasticity and rebound effect in fact 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 part of this literature is built, as there exists theoretical reasons and empirical evidence showing that consumers' reaction depends on the source of the cost variation.

For instance, Li et al. (2014) show that consumers respond more strongly to gasoline tax changes than to equal-sized changes in tax-inclusive gasoline prices, and Baranzini & Weber (2013) find that oil shocks and gasoline tax increases have further impacts on top of their direct effect due to price increase. Linn (2013) argues that price variations might be viewed as temporary while efficiency improvements are unlikely to be reversed, therefore causing consumers to react more to efficiency than to price changes. Conversely, Gillingham et al. (2016) highlight that because fuel prices are more salient than energy efficiency, consumers might respond more to price than to efficiency changes.

Recent empirical evidence related to the hypothesis of symmetric effects of efficiency and fuel prices is mixed. Linn (2013) obtains a stronger impact for efficiency than for fuel prices. Frondel & Vance (2013) fail to reject the null hypothesis that the magnitude of the demand response to a price increase is equal to that of a price decrease. Finally, Greene (2012), De Borger et al. (2016), and Stapleton et al. (2016) find that household travel demand is significantly more sensitive to fuel prices than to fuel efficiency.

Furthermore, for the own price elasticity of energy demand to be interpretable as a rebound effect, one has to assume that energy efficiency is *constant* (see Definition 4 in Sorrell & Dimitropoulos, 2008). This appears in total contradiction with the basic principle of the rebound effect, which originates in the behavioral response to an improved energy efficiency.

Several papers moreover emphasize theoretical non-equivalences between price elasticities and rebound effects. For instance, Hunt & Ryan (2014) show that fuel price elasticities do not appropriately identify rebound effects, unless one makes the following two assumptions: (i) there is a one-to-one correspondence between energy services and energy sources (i.e., each energy service can be produced with only one energy source and each energy source can produce only one energy service), and (ii) within each energy service, there is a single uniform energy efficiency. In the same vein, Chan & Gillingham (2015) demonstrate how elasticity identities are biased when a single fuel provides multiple energy services or when multiple fuels can provide the same energy service. Finally, West et al. (2015) argue that a decrease in price exerts a different effect on driving compared to an equivalent increase in efficiency because a change in fuel price leaves everything else constant while fuel efficiency is typically correlated with vehicle attributes (like weight and power), which alters the value of driving.

An important empirical issue arises when estimating the rebound effect: Energy efficiency is likely to be endogenous and correlated with energy services. In our context, one can indeed expect drivers with high usage rates will choose an energy efficient car in order to minimize running costs. This positive correlation could bias the link between energy services and efficiency, and the rebound effect obtained without correction would be over-estimated. However, those who intend to drive more may also decide to purchase larger and more comfortable vehicles (West, 2004; Gillingham, 2012), or intensive drivers may simply like high-performance cars, which happen to be fuel intensive as well (Linn, 2013). Such individuals would cause the rebound effect to be under-estimated. In the end, whether the selection between distance and fuel efficiency is positive or negative is not obvious and the resulting bias of OLS estimates is ambiguous.

Table 1 displays the main characteristics of the empirical studies focusing on direct rebound effects in the personal automotive transport.[5] As already noticed in former literature reviews and meta-analyzes (e.g., Azevedo, 2014; Dimitropoulos et al., 2016), the range of estimates is wide, which is to be expected considering the variety in regions, time periods, data types, and econometric techniques. An explanation usually put forward to explain differences in magnitude is that aggregate data tend to yield lower rebound estimates than household level data (e.g., Moshiri & Aliyev, 2017).

It moreover appears from Table 1 that estimates are relatively close within countries. In the United States for instance, where a good number of estimations are available, long run direct rebound effect estimates revolve around

[5]Studies that estimate price elasticities of fuel demand are not considered.

20%, regardless of the econometric technique and the data. By contrast, several estimates of the rebound effect for European countries have been obtained in the vicinity of 70%. Overall, estimates tend to be larger outside North America, suggesting that American and non-American households behave differently with respect to car usage, which calls for further investigation in alternative countries.

Another important point highlighted by Table 1 is that the present paper is located at the intersection of two branches of the literature: it uses micro-level data and multiple equation models, an approach that has been implemented by only few papers before (Greene et al., 1999; Linn, 2013; De Borger et al., 2016).

Table 1: Rebound effect in personal automotive 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	5-36	19-88
Barla et al. (2009)	Canada	1990-2004	Province	FE-2SLS	8	20
De Borger et al. (2016)	Denmark	2001-2011	Household	IV		7.5-10
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
Frondel & Vance (2013)	Germany	1997-2009	Household	Panel estimations		46-70
Greene (2012)	US	1966-2007	National	OLS + IV	3-6	12-24
Greene et al. (1999)	US	1979-1994	Household	3SLS		17-28
Hymel et al. (2010)	US	1966-2004	State	3SLS	4.7	24.1
Hymel & Small (2015)	US	2000-2009	State	3SLS	2.6-4.2	14.8-25.5
Linn (2013)	US	2009	Household	OLS + IV		20-40
Moshiri & Aliyev (2017)	Canada	1997-2009	Household	AIDS		82-88
Small & Van Dender (2007)	US	1966-2001	State	3SLS	4.5	22.2
Stapleton et al. (2016)	Great Britain	1970-2011	Country	OLS + Cointegration		9-36
Su (2012)	US	2009	Household	Quantile regressions		10.6-19.3
Wang et al. (2012a)	Hong Kong	1993-2009	National	SURE		45
Wang et al. (2012b)	China	1994-2009	Province (State)	AIDS		96
West et al. (2015)	US	2009	Household	RDD		0

Authors' preferred estimates are reported. All estimates based on cross-sections of households are reported as long run estimates.

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

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

To our knowledge, de Haan et al. (2006, 2007) are the only previous studies about rebound effects in the transport sector in Switzerland. They focus however, on a particular kind of rebound behavior, namely: the impact of hybrid technology on car ownership and replacement of small and efficient vehicles.[6] Our study is thus the first conducting an analysis of the rebound effect in private transportation using a sample representative of the entire Swiss population.

3 Econometric methodology

Our model intends to identify the structural relationship between distance traveled and fuel efficiency in order to estimate the direct rebound effect. We distinguish between structural and causal relationships in the context of rebound behavior. In our data, as in virtually all realistic set-ups, fuel efficiency and distance are decided upon by the same individual. Even though the choice of a car precedes the decision about its usage, we can assume that the consumer plans usage at the time of purchase of the car. In other words, it is likely that decisions about travel behavior and car attributes such as fuel efficiency and size are simultaneous. In this context, there is no direction of causality from one variable to the other. Our estimations represent therefore,

[6] Their analysis is based on 303 buyers (representing 82.6% of all buyers) of Toyota Prius in the first nine months after market entry of this model in Switzerland. They find no evidence for the two rebound effects investigated: The purchase of an hybrid car did not increase vehicle size, nor did it increase average household vehicle ownership.

the structural relationships based on a given equilibrium, to the extent that individuals keep their cars and driving habits at a given year.

A policy-relevant situation in which a causal relationship appear from efficiency to traveled distance is when consumers change their cars, merely because of a newly imposed regulation on efficiency standards, and the existing equilibrium will change to a new equilibrium. Such cases are rarely observed in real data. In all other cases, in order to make causal inference, we need to assume that the structural relationships are invariant to policy changes.

Given the above discussion, we use a simultaneous structural model with three equations for traveled distance (D) and two car attributes namely, fuel intensity (FI, i.e. the inverse or fuel efficiency) and car's weight (W). Our structural system is in some way similar to those used by Greene et al. (1999), Small & Van Dender (2007), Hymel et al. (2010) with US data. The main difference is that we estimate the rebound effect using variability across households at a cross-sectional equilibrium, without temporal variations.[7] Moreover, in contrast with those studies, we use SURE rather than 3SLS.

[7]Other differences also exist: Greene et al. (1999) consider a separate equation for regional fuel prices, but we rely on canton (i.e., state) fixed effects to capture spatial price variability. In comparison with Small & Van Dender (2007) and Hymel et al. (2010), we use an equation for the car's weight rather than the vehicle stock at the state level.

Our model is given by the following set of equations:[8]

$$\begin{cases} \ln D_i = \alpha_0 + \alpha_2 \cdot \ln FI_i + \alpha_3 \cdot \ln W_i + \alpha_4 Z_i^d + \alpha_5 X_i + u_i^d & \text{(2a)} \\ \ln FI_i = \beta_0 + \beta_1 \cdot \ln D_i + \beta_3 \cdot \ln W_i + \beta_4 Z_i^{fi} + \beta_5 X_i + u_i^{fi} & \text{(2b)} \\ \ln W_i = \gamma_0 + \gamma_1 \cdot \ln D_i + \gamma_2 \cdot \ln FI_i + \gamma_4 Z_i^w + \gamma_5 X_i + u_i^w & \text{(2c)} \end{cases}$$

where D_i is distance traveled by individual i, FI_i is engine's fuel intensity, W_i is vehicle's weight, Z_i^j $(j = d, fi, w)$ is a vector of personal and household characteristics expected to affect only the corresponding dependent variable but not the other two, and X_i is a vector of characteristics expected to affect distance, fuel intensity and weight. Error terms are denoted u_i^j.

Because the three dependent variables are inter-related, we here assume that the residuals u_i^j are correlated and estimate the model using seemingly unrelated regressions (SURE, see Zellner, 1962). This model allows us to avoid critical problems we faced with instrumental variables (as in Crown et al., 2011), while inferring about the correlation between unobservables and their likely impact on the direction of potential biases in our estimates.[9]

By definition, the rebound effect is the negative of the elasticity of distance with respect to fuel intensity. In this specification, the rebound effect is thus estimated by $-\alpha_2$. Given that the dataset used to conduct the estimations is a cross-section of households, the coefficients should be interpreted

[8]Parameters α_1, β_2, and γ_3 are intentionally unused.

[9]We have also tried to estimate the model by three-stage least squares (3SLS, see Zellner & Theil, 1962). However, even when using strong instruments, our results were extremely sensitive and often not plausible. We therefore do not pursue this route here.

as long-run effects.

In the empirical estimations, we highlight that we use engine fuel intensity, defined as the amount of fuel needed to move a given mass over a given distance (measured in $\frac{\text{L}}{100\text{km}\times 1{,}000\text{kg}}$), instead of the more standard fuel intensity (measured in $\frac{\text{L}}{100\text{km}}$). We do so because there is a strong mechanical correlation between fuel intensity and weight. However, engine fuel intensity is almost uncorrelated to weight, confirming our assumption that they represent two independent features of the car.[10]

On a more conceptual level, another reason for using this variable is that we want to avoid capturing any mechanical relationship between fuel intensity and weight. Our objective is indeed to explain how individuals form their choices, which presupposes that they do actually have a choice. Namely, they do have the choice of making separate but interdependent choices for distance, engine's efficiency and car's weight. That is, they can freely choose the degree of interdependence among these three features. This is not valid for fuel efficiency and weight, because the two features are strongly connected for technical reasons. Said otherwise, one cannot find a car that is very efficient and heavy at the same time. Considering engine fuel intensity instead provides us with a space of variables in which freedom of choice is restored: One can indeed find a heavy vehicle with an efficient engine.

As a specific variable in the distance equation (Z_i^d), we include a dummy

[10]In our final sample, the correlation is +0.57 between fuel intensity and weight while it is −0.16 between engine fuel intensity and weight. See Weber (2016) for more details on these relationships.

accounting for the working status of the driver. Workers can indeed be expected to drive more than non-workers, since many of the former commute from home to their work place by car.[11] In the fuel intensity equation, we use elevation of the home place as a specific variable (Z_i^{fi}). Elevation should impact fuel intensity positively given that mountainous regions imply the need for a more powerful, hence more fuel intensive, vehicle.[12] In the weight equation, the specific variables (Z_i^w) we use are a dummy for the presence of children in the household and the number of adults. Our expectation is that both variables influence positively the size of cars, henceforth their weight. A similar argument has been used by De Borger et al. (2016).

Finally, all equations encompass several personal and household characteristics, namely household income, gender, age, and education level of the main driver of the car to control for possible systematic differences along these dimensions. We also include a set of cantonal fixed effects, in order to control for spatial effects, such as differences in fuel price and in the road infrastructures and public transport networks across cantons.

[11]As an alternative, we also used travel distance from home to work, obtained using the software command developed by Weber & Péclat (2016). It turns out the results (available on request) are similar. However, some observations are obviously lost in the process, and we therefore report results using the simple working status dummy.

[12]Concerning the relationship between horsepower and fuel consumption, see for instance Autosmart (2014).

4 Data

We use data from wave 2010 of the *Mobility and Transport Microcensus* (*MTMC*).[13] In addition to individual and household characteristics, the *MTMC* provides detailed information about the vehicles, distance traveled by transportation mean, and travel behavior.

The 2010 *MTMC* contains information on a total of 70,294 private cars, with administrative data being available for 51,895 of these. For the latter, attributes such as weight, efficiency label, transmission type, and registration date (year and month) are provided, and these technical data are complete for a subsample of 26,596 cars. When matching vehicle data with household characteristics and travel distance measures, additional observations are lost because of missing values. Our estimations are thus based on samples ranging from 6,800 to 11,400 observations, depending on the specification and variables considered.

Several distance variables collected in the *MTMC* are relevant to our analysis. First, mileage over the last 12 months is available for most vehicles. This measure corresponds to the travel distance commonly recorded in mobility surveys and it is comparable to what is used in most studies in the field. Results obtained using this variable will thus allow direct comparisons with the literature. One weakness of this measure is it is self-stated, so

[13] *MTMC* is a survey carried out by the *Swiss Federal Statistical Office* every five years. The 2010 wave is the largest wave conducted so far and the last wave available to us. Each wave is an independent cross sectional sample. Because of substantial evolution related to question types and data quality, successive waves are hardly reconciled.

that it might contain rough approximations. Also, annual distance is fully attributed to the main driver of the car as stated in the survey.[14] Moreover, for vehicles registered within the last 12 months before the interview, we had to extrapolate recorded mileage to obtain a yearly-equivalent measure.

A second distance measure is available for a subsample of selected individuals, namely distance traveled in a specific reference day (i.e., one of the two days that predate the interview). These daily distances are provided both as estimations by the respondents and (for the first time in 2010) as measured by Geographical Information System (GIS) software.[15] Distances recorded by GIS appear very precise, and thus constitute an important asset of the database. Moreover, the car driver is personally identified for the daily distances. The drawback is that these measures concern a single day, which may be exceptional for some respondents. Nevertheless, reference days are evenly distributed across days of the week over all respondents, such that special days should cancel out.

Sample size depends on the distance measure used. About 8,500 observations are available for the daily distances, while there are a little more than 11,400 observations for the yearly distances. The difference in sample size is mainly because some cars were not used in the reference day considered

[14]Mileage is provided at the car-level and might obviously be shared by several drivers. However, there is no means to attribute mileage to a specific person in the case of multiple drivers for a single car.

[15]Deviations between georouting distances and distances estimated by the respondents are substantial: More than one fourth of respondents make a mistake of at least 10 kilometers, which is large considering the average traveled distance of less than 50 kilometers.

for the interview. Also, some individuals used a car in the reference day for which they are not registered as the main driver. Such individuals are enclosed in both daily and yearly estimations, but with two different cars. The "common subsample", composed by individuals who appear in both samples with the same car, contains 6,851 observations.

Interestingly, the correlation coefficient between the daily and yearly distance measures amounts to 0.24.[16] Even though positive, this correlation is weak. Hence, the different distance measures probably relate to different types of mobility: Individuals who drive a lot on a particular day (most often for commuting or leisure activities) are not necessarily those who drive the most over the year, where vacation trips are likely to represent a substantial share of total traveling. We will consider these two distance measures alternatively in our estimations.

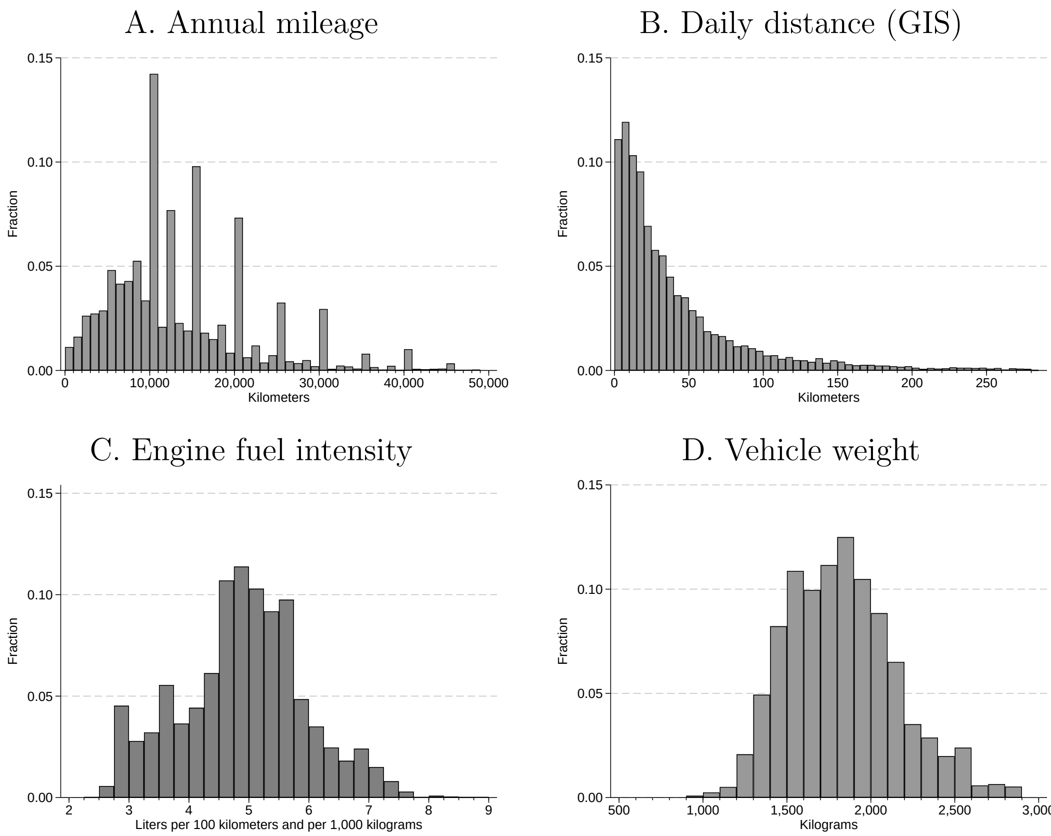
Our goal being to measure a rebound effect based on equation (1), we need a fuel efficiency measure. In the *MTMC*, the only related measure is given by efficiency labels, from A (most efficient) to G (least efficient). These labels are obtained by a formula based on vehicle weight and fuel consumption. Knowing weight and efficiency label thus allows to backward compute fuel consumption and hence retrieve a continuous fuel efficiency measure that is relatively accurate. The details of the procedure are explained in Appendix A.

[16]This correlation is based on the common subsample and calculated using individual survey weights.

Figure 1 displays the distribution of the endogenous variables.[17] We observe that self-stated mileages over the last 12 months (panel A) show spikes at round numbers, in particular for large values. Such phenomenon is known as heaping and obviously arises because respondents are not able to give a precise answer. On the contrary, daily distances (panel B) are smoothly distributed thanks to the use of the GIS software. This variable is heavily right skewed, with a mode below 5 km and a median around 25 km. The technical attributes engine fuel intensity (panel C) and weight (panel D) are relatively smoothly and symmetrically distributed, and their values appear reasonable.

[17] Table B.1 in Appendix B provides further descriptive statistics.

Figure 1: Distributions of the endogenous variables



Statistics based on the common subsample.
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 the system of equations (2) using annual mileage of the car and distance traveled in a single day are respectively displayed in Tables 2 and 3. In the estimations using annual mileage, the estimated rebound effect is larger than 80% when using SURE. Such a value lies among the highest estimates found in the literature (see Section 2, and for example Greening et al., 2000). However, as mentioned before, most existing studies are based on US data, which traditionally yield relatively low rebound effect estimates. Rebound effects of almost 70% were for instance estimated in Germany by Frondel et al. (2008, 2012) and Frondel & Vance (2013).

When using OLS to estimate our model, the rebound effect is 46%, which is still high compared to the results in the literature, but much lower than the one obtained with SURE. Based on our results, one should therefore conclude that OLS estimates of the rebound effect are biased downwards, which goes against the usual assumption of an upward bias due to individuals who intend to drive long distances and therefore choose high fuel efficiency (Sorrell & Dimitropoulos, 2008). However, as mentioned before, there are also reasons to think that the rebound effect could be under-estimated in OLS estimations, for instance if long-distance drivers tend to purchase larger and more powerful vehicles. In fact, our estimates show that weight exerts a positive and significant effect on travel distance. Owners of heavier (or more comfortable, safer, ...) cars tend to drive more.

Tables 4 and 5 show the correlations between the residuals of the equations estimated by OLS in Tables 2 and 3. These residuals are significantly correlated, and as shown by the high χ^2 values, independence is strongly rejected across the three equations. SURE thus provides a significant improvement over OLS estimations. Also, the fact that the correlation between errors of the distance equation with the fuel intensity equation is positive is

Table 2: Empirical estimations with annual mileage

	SURE			OLS		
	ln(distance)	ln(engine FI)	ln(weight)	ln(distance)	ln(engine FI)	ln(weight)
ln(distance)	—	-0.064^{***}	0.053^{***}	—	-0.036^{***}	0.031^{***}
		(0.003)	(0.002)		(0.003)	(0.002)
ln(engine FI)	-0.816^{***}	—	-0.215^{***}	-0.456^{***}	—	-0.116^{***}
	(0.033)		(0.007)	(0.033)		(0.007)
ln(weight)	1.102^{***}	-0.357^{***}	—	0.633^{***}	-0.199^{***}	—
	(0.042)	(0.012)		(0.042)	(0.012)	
Worker	0.184^{***}	—	—	0.197^{***}	—	—
	(0.020)			(0.020)		
Elevation (1,000 m)	—	0.025^{*}	—	—	0.025^{*}	—
		(0.014)			(0.015)	
Children in HH	—	—	0.046^{***}	—	—	0.051^{***}
			(0.004)			(0.004)
Number of adults in HH	—	—	0.019^{***}	—	—	0.020^{***}
			(0.003)			(0.003)
ln(income)	0.063^{***}	0.010^{**}	0.039^{***}	0.103^{***}	-0.006	0.044^{***}
	(0.017)	(0.005)	(0.004)	(0.017)	(0.005)	(0.004)
Women	-0.128^{***}	-0.045^{***}	-0.073^{***}	-0.169^{***}	-0.024^{***}	-0.079^{***}
	(0.016)	(0.004)	(0.003)	(0.016)	(0.004)	(0.003)
Driver's age/10	-0.078^{***}	0.006^{***}	0.011^{***}	-0.083^{***}	0.010^{***}	0.007^{***}
	(0.006)	(0.002)	(0.001)	(0.006)	(0.002)	(0.001)
Education: medium	0.082^{***}	0.002	0.004	0.088^{***}	-0.002	0.007
	(0.027)	(0.007)	(0.006)	(0.027)	(0.008)	(0.006)
Education: high	0.145^{***}	-0.005	0.002	0.155^{***}	-0.011	0.008
	(0.029)	(0.008)	(0.006)	(0.029)	(0.008)	(0.006)
Constant	1.793^{***}	4.734^{***}	6.960^{***}	4.421^{***}	3.417^{***}	6.973^{***}
	(0.343)	(0.091)	(0.040)	(0.346)	(0.092)	(0.040)
Canton FE	YES	YES	YES	YES	YES	YES
Rebound effect		81.6%			45.6%	
# Obs.		11,439			11,439	
R^2	0.140	0.048	0.151	0.161	0.076	0.178

Standard errors in parentheses. $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level.

Table 3: Empirical estimations with daily distance (GIS)

	SURE			OLS		
	ln(distance)	ln(engine FI)	ln(weight)	ln(distance)	ln(engine FI)	ln(weight)
ln(distance)	—	-0.020^{***}	0.006^{***}	—	-0.011^{***}	0.005^{***}
		(0.002)	(0.002)		(0.002)	(0.002)
ln(engine FI)	-0.592^{***}	—	-0.255^{***}	-0.305^{***}	—	-0.129^{***}
	(0.059)		(0.008)	(0.059)		(0.008)
ln(weight)	0.199^{***}	-0.419^{***}	—	0.141^{*}	-0.220^{***}	—
	(0.074)	(0.013)		(0.074)	(0.013)	
Worker	0.223^{***}	—	—	0.224^{***}	—	—
	(0.036)			(0.036)		
Elevation (1,000 m)	—	0.019	—	—	0.018	—
		(0.017)			(0.017)	
Children in HH	—	—	0.051^{***}	—	—	0.054^{***}
			(0.004)			(0.004)
Number of adults in HH	—	—	0.020^{***}	—	—	0.021^{***}
			(0.004)			(0.004)
ln(income)	0.114^{***}	0.004	0.044^{***}	0.126^{***}	-0.011^{**}	0.046^{***}
	(0.030)	(0.005)	(0.004)	(0.030)	(0.005)	(0.004)
Women	-0.205^{***}	-0.028^{***}	-0.068^{***}	-0.211^{***}	-0.012^{**}	-0.069^{***}
	(0.027)	(0.005)	(0.004)	(0.027)	(0.005)	(0.004)
Driver's age/10	-0.072^{***}	0.009^{***}	0.008^{***}	-0.075^{***}	0.010^{***}	0.007^{***}
	(0.011)	(0.002)	(0.001)	(0.011)	(0.002)	(0.001)
Education: medium	0.143^{***}	-0.003	0.022^{***}	0.149^{***}	-0.010	0.025^{***}
	(0.047)	(0.009)	(0.007)	(0.047)	(0.009)	(0.007)
Education: high	0.287^{***}	-0.012	0.028^{***}	0.298^{***}	-0.021^{**}	0.033^{***}
	(0.051)	(0.009)	(0.007)	(0.051)	(0.009)	(0.007)
Constant	1.608^{***}	4.726^{***}	7.433^{***}	1.490^{**}	3.324^{***}	7.213^{***}
	(0.609)	(0.105)	(0.042)	(0.610)	(0.106)	(0.042)
Canton FE	YES	YES	YES	YES	YES	YES
Rebound effect		59.2%			30.5%	
# Obs.		8,561			8,561	
R^2	0.061	0.036	0.130	0.064	0.064	0.152

Standard errors in parentheses. $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level.

an interesting result. Consistent with the selection bias based on comparing OLS and SURE, this positive correlation indicates that selection issues are opposite to the usual expectation of longer distances inducing more efficient cars to be chosen. The selection might instead run through alternative characteristics. For instance, individuals with a greater affluence are likely to travel more and have more fuel intensive vehicles, which could explain this result.

Interestingly, comparing the OLS and SURE results points to a downward bias in the OLS estimate of the effect of weight on distance. Given that the coefficient of weight is positive on distance, the contrasting potential downward selection bias suggests that there is a third unobserved factor with a negative effect on weight but a positive effect on distance. This might be explained by other categories of individuals, e.g., those with environmentally friendly attitudes, that prefer lighter cars and less usage.

Overall, these results confirm that the OLS biases in the distance equation are upward for weight and downward for efficiency. The residual correlations are consistent with these directions, suggesting that if the SURE estimates

Table 4: Correlation of residuals between equations with annual mileage

	Dist	Engine FI	Weight
Dist	1.000		
Engine FI	0.129^{***}	1.000	
Weight	-0.134^{***}	0.155^{***}	1.000
χ^2	672.653		

Notes: $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level. The χ^2 statistic is the outcome of a Breusch-Pagan test for independence.

Table 5: Correlation of residuals between equations with daily distance (GIS)

	Dist	Engine FI	Weight
Dist	1.000		
Engine FI	0.058^{***}	1.000	
Weight	-0.019^{*}	0.172^{***}	1.000
χ^2	284.578		

Notes: $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level. The χ^2 statistic is the outcome of a Breusch-Pagan test for independence.

are biased, it is likely that the bias should be in the same direction.[18]

All specific controls included in distance, fuel intensity, and weight equations turn out as significant and with the expected signs. In the distance equation, we observe that workers drive 18% more than non-employed individuals. Elevation has a small but positive impact on engine fuel intensity. We also find that weight increases by around 5% when children are present in a household and by almost 2% with every additional adult.

The additional controls included in all three equations also show the expected signs. For instance, income elasticity of distance is found to be positive but close to zero.[19] Traveling by car can thus be classified as a first-necessity good. As expected, wealthier people select more powerful and heavier cars. Women appear to drive significantly less than men, and to opt for more efficient and smaller cars. Older individuals are found to travel less, but to drive cars with larger fuel intensity and weight. Finally, the level of education

[18]The SURE estimates would be potentially biased if there is a correlation between error terms and the explanatory variables of interest, in particular, efficiency and weight.

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

exerts a positive impact on travel distance, but not on the car attributes.

Turning to the results obtained with the daily distances (Table 3), we first note that almost all coefficients keep the same sign and remain of the same magnitude as in previous set of estimations. Still, a major difference is related to the size of the rebound: While we obtain an 82% rebound using annual distances, a 59% rebound effect obtained using daily distances. The difference between our two estimates could arise for various reasons. First, it could be due to differences in the samples used in both estimations. In order to investigate this possibility, we run our models on a common subsample containing exactly the same individuals and the same cars (see Tables C.1 and C.2 in Appendix C). It turns out that the gap narrows a little with the yearly rebound decreasing to 74% and the daily rebound growing to 66%, but a substantial spread remains.

A second plausible explanation could be that drivers are differently sensitive to fuel efficiency on a particular day and over the year. Within a day, flexibility of transportation is relatively small and some trips cannot be avoided, while it is easier to adjust traveling over the year. In that sense, households with more than one car might take advantage of using their more efficient car(s) for long distances, but be less careful for daily trips. In order to test this hypothesis, we estimate our model on single-car households (Tables C.3 and C.4).[20] The coefficients indicate a rebound effect of 69%

[20]According to the *MTMC* 2010 data, 21% of the Swiss households do not have a car, 49% have a single car, and 30% have two or more. This structure is very different to what is observed in the US, where a large majority of households own two or more cars (see

using the annual distance and of 57% using the daily distance. As could be expected, single-car households rebound less than those with more than one car. Multiple-car households have the opportunity to shift among vehicles, which yields larger rebound estimates. These results are however opposed to Greene et al. (1999) who obtain rebound effects of 28%, 25% and 17% for US households with respectively 1, 2 and 3 cars.[21]

6 Conclusions

This paper investigates the rebound effect in private transportation using a cross-section of households from Switzerland. In order to account for potential biases encountered in OLS estimations, we build a system of equations where travel distance, fuel efficiency, and vehicle weight are dependent variables. Our contention is that these three dimensions are taken into account by a household at the time of purchasing a car. Compared to the literature, which has mostly focused on the endogeneity of fuel efficiency and distance traveled, we thus add vehicle weight in the model.

Another 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 com-

for example the statistics in the National Household Travel Survey (NHTS) of the Federal Highway Administration (FHWA) at `https://nhts.ornl.gov`).

[21] As another robustness check, we have also run the models excluding the weight equation. Such a model is closer to what is usually done in the literature, where the focus is on the endogeneity of fuel efficiency but other car attributes are in general not considered. The rebound effects estimated in these two-equation systems are very similar to those obtained with the three-equation systems (results available on request).

bination of micro-level data and multiple-equation models in the literature on rebound effect in private transportation has seldom been used before. Moreover, among the distance measures available to us, one is highly reliable as it was recorded by Geographical Information System (GIS) software. On the contrary, most micro-data studies on travel demand are based on self-reported distances, which are likely to suffer from recollection and rounding biases.

Our model, estimated by seemingly unrelated regressions (SURE), gives relatively large rebound effects ranging from 57% to 82%, depending mostly on how distance is measured. When annual distance is considered, very high rebound effect around 70-80% are obtained. When daily distance is used, smaller but still substantial rebound effects around 55-65% are found. This gap is likely explained by differences in daily and yearly mobility patterns. People are less flexible in a particular day than over the year.

Our estimates are thus 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, which tends to confirm a difference between the US and other countries, in particular European countries where the rebound effect in transportation appears to be relatively strong. These results imply that a substantial share of fuel efficiency improvements would not be translated into fuel savings but taken back by increased car usage.

Another important result from our research is that OLS estimates are under-estimating rather than over-estimating the rebound effect. OLS estimates are most often expected to be upward biased because of endogeneity between distance traveled and fuel efficiency, people intending to drive longer distances being those who should opt for more efficient cars. However, distance traveled might also be interdependent with other car attributes, such as weight or size: Buying a larger and more comfortable car seems reasonable when planning to drive a lot. This pattern, indeed confirmed by our analysis, would cause a downward bias in OLS estimates.

In terms of energy policy, our findings indicate that curbing CO_2 emissions from the transportation sector could be an even more challenging task than expected. As political measures relying on taxation appear unpopular, as evidenced by the Swiss voters' rejection of an increase in highway access price, political efforts are being devoted to increasing energy efficiency. Energy efficiency is indeed one of the key ingredient in the Energy Strategy 2050. Our estimates of high rebound effects however cast doubts on the possibility to radically curb CO_2 emissions by merely relying on efficiency improvements. Yet further alternative solutions might be explored in order to reach the reduction targets.

Appendix A From energy labels to fuel intensity

The formula used to assign efficiency labels (A to G) to cars is adjusted every second year in Switzerland. In the 2010 *MTMC*, the 2007 energy label scale is used. Concretely, labels are based on the values of an index I calculated as follows:

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

where FI is fuel intensity in kg of fuel per 100km and W is car's weight in kg. Efficiency labels are then assigned as follows:

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 category A (G), we use the average between the threshold value and the minimal (maximal) value 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 luxury cars considered here as 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, we find estimated and actual values to differ by less than 0.5 L/100km for almost all vehicles. This difference corresponds to the additional consumption that would be induced by an additional passenger, so that we argue it can be considered as negligible and this strategy gives satisfactory measures of fuel intensity.

Note that, in theory, detailed information from the *MTMC* (fuel, transmission, efficiency labels, weight, engine displacement, ...) should allow us to identify almost exactly any vehicle and thus find additional technical data such as fuel economy in *Touring Club Switzerland* (*TCS*) databases, which provide information for most car models marketed in Switzerland (see `http://www.verbrauchskatalog.ch/`). It turns out, however, that weight and engine displacement do not correspond perfectly in the two databases. Removing these continuous variables to perform the merge leads to numerous multiple matches, which makes this process hardly defensible. The backward computation of consumption is not perfect either, but more straightforward.

Appendix B Descriptive statistics

Table B.1: Descriptive statistics for the final common subsample

Variable	Mean (sd)	Min	Max
Annual mileage [km]	14,607.89 (10,341.57)	6.00	200,000.00
Daily distance (GIS) [km]	46.89 (68.45)	0.02	1,736.15
Fuel intensity [L/100km]	8.99 (2.49)	4.07	19.44
Engine fuel intensity [L/(100km × 1,000kg)]	4.86 (1.06)	2.36	8.90
Vehicle weight [kg]	1,862.05 (357.29)	980.00	3,500.00
Worker	0.79 (0.41)	0.00	1.00
Elevation (1,000 m)	0.51 (0.18)	0.20	1.96
Children in HH	0.45 (0.50)	0.00	1.00
Number of adults in HH	1.79 (0.55)	1.00	7.00
Income	8,477.87 (3,795.10)	2,000.00	16,000.00
Women	0.41 (0.49)	0.00	1.00
Driver's age	48.27 (14.21)	18.00	92.00
Education: low	0.08 (0.27)	0.00	1.00
Education: medium	0.56 (0.50)	0.00	1.00
Education: high	0.36 (0.48)	0.00	1.00
# Obs.		6,851	

Individual survey weights are used.

Appendix C Additional results

Table C.1: Empirical estimations with annual mileage, Common subsample

	SURE			OLS		
	ln(distance)	ln(engine FI)	ln(weight)	ln(distance)	ln(engine FI)	ln(weight)
ln(distance)	—	-0.064^{***}	0.061^{***}	—	-0.037^{***}	0.035^{***}
		(0.003)	(0.003)		(0.004)	(0.003)
ln(engine FI)	-0.736^{***}	—	-0.205^{***}	-0.414^{***}	—	-0.111^{***}
	(0.040)		(0.009)	(0.041)		(0.009)
ln(weight)	1.158^{***}	-0.351^{***}	—	0.659^{***}	-0.197^{***}	—
	(0.051)	(0.015)		(0.052)	(0.015)	
Worker	0.167^{***}	—	—	0.179^{***}	—	—
	(0.025)			(0.025)		
Elevation (1,000 m)	—	0.033^{*}	—	—	0.034^{*}	—
		(0.019)			(0.019)	
Children in HH	—	—	0.044^{***}	—	—	0.048^{***}
			(0.005)			(0.005)
Number of adults in HH	—	—	0.017^{***}	—	—	0.018^{***}
			(0.004)			(0.004)
ln(income)	0.052^{**}	0.008	0.042^{***}	0.097^{***}	−0.009	0.048^{***}
	(0.021)	(0.006)	(0.005)	(0.021)	(0.006)	(0.005)
Women	-0.167^{***}	-0.044^{***}	-0.071^{***}	-0.214^{***}	-0.022^{***}	-0.079^{***}
	(0.019)	(0.006)	(0.004)	(0.019)	(0.006)	(0.004)
Driver's age/10	-0.074^{***}	0.005^{**}	0.013^{***}	-0.077^{***}	0.008^{***}	0.009^{***}
	(0.008)	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)
Education: medium	0.093^{***}	0.003	0.010	0.105^{***}	−0.003	0.015^{*}
	(0.033)	(0.010)	(0.008)	(0.033)	(0.010)	(0.008)
Education: high	0.173^{***}	−0.002	0.010	0.190^{***}	−0.011	0.018^{**}
	(0.036)	(0.011)	(0.008)	(0.036)	(0.011)	(0.008)
Constant	1.453^{***}	4.721^{***}	6.817^{***}	4.302^{***}	3.439^{***}	6.864^{***}
	(0.419)	(0.117)	(0.052)	(0.423)	(0.118)	(0.052)
Canton FE	YES	YES	YES	YES	YES	YES
Rebound effect		73.6%			41.4%	
# Obs.		6,851			6,851	
R^2	0.149	0.047	0.163	0.171	0.073	0.191

Standard errors in parentheses. $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level.

Table C.2: Empirical estimations with daily distance (GIS), Common subsample

	SURE			OLS		
	ln(distance)	ln(engine FI)	ln(weight)	ln(distance)	ln(engine FI)	ln(weight)
ln(distance)	—	-0.024^{***}	0.008^{***}	—	-0.013^{***}	0.005^{***}
		(0.002)	(0.002)		(0.002)	(0.002)
ln(engine FI)	-0.664^{***}	—	-0.251^{***}	-0.343^{***}	—	-0.127^{***}
	(0.064)		(0.009)	(0.064)		(0.009)
ln(weight)	0.314^{***}	-0.420^{***}	—	0.208^{**}	-0.221^{***}	—
	(0.082)	(0.015)		(0.082)	(0.015)	
Worker	0.235^{***}	—	—	0.237^{***}	—	—
	(0.040)			(0.040)		
Elevation (1,000 m)	—	0.034^{*}	—	—	0.035^{*}	—
		(0.019)			(0.019)	
Children in HH	—	—	0.045^{***}	—	—	0.047^{***}
			(0.005)			(0.005)
Number of adults in HH	—	—	0.016^{***}	—	—	0.017^{***}
			(0.004)			(0.004)
ln(income)	0.119^{***}	0.006	0.051^{***}	0.136^{***}	-0.011^{*}	0.054^{***}
	(0.032)	(0.006)	(0.005)	(0.032)	(0.006)	(0.005)
Women	-0.164^{***}	-0.037^{***}	-0.086^{***}	-0.175^{***}	-0.016^{***}	-0.087^{***}
	(0.030)	(0.006)	(0.004)	(0.030)	(0.006)	(0.004)
Driver's age/10	-0.081^{***}	0.009^{***}	0.007^{***}	-0.085^{***}	0.010^{***}	0.006^{***}
	(0.012)	(0.002)	(0.002)	(0.012)	(0.002)	(0.002)
Education: medium	0.139^{***}	0.000	0.016^{**}	0.144^{***}	-0.005	0.018^{**}
	(0.052)	(0.010)	(0.008)	(0.052)	(0.010)	(0.008)
Education: high	0.299^{***}	-0.007	0.019^{**}	0.308^{***}	-0.015	0.023^{***}
	(0.056)	(0.011)	(0.008)	(0.056)	(0.011)	(0.008)
Constant	0.907	4.723^{***}	7.382^{***}	1.053	3.327^{***}	7.167^{***}
	(0.663)	(0.117)	(0.047)	(0.665)	(0.119)	(0.047)
Canton FE	YES	YES	YES	YES	YES	YES
Rebound effect		66.4%			34.3%	
# Obs.		6,851			6,851	
R^2	0.072	0.035	0.150	0.076	0.063	0.172

Standard errors in parentheses. $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level.

Table C.3: Empirical estimations with annual mileage, Single-car households

	SURE			OLS		
	ln(distance)	ln(engine FI)	ln(weight)	ln(distance)	ln(engine FI)	ln(weight)
ln(distance)	—	-0.049^{***}	0.044^{***}	—	-0.028^{***}	0.026^{***}
		(0.003)	(0.002)		(0.003)	(0.002)
ln(engine FI)	-0.687^{***}	—	-0.199^{***}	-0.387^{***}	—	-0.104^{***}
	(0.047)		(0.009)	(0.047)		(0.009)
ln(weight)	1.165^{***}	-0.397^{***}	—	0.673^{***}	-0.221^{***}	—
	(0.064)	(0.017)		(0.064)	(0.017)	
Worker	0.192^{***}	—	—	0.201^{***}	—	—
	(0.027)			(0.028)		
Elevation (1,000 m)	—	0.034^{*}	—	—	0.035^{*}	—
		(0.019)			(0.019)	
Children in HH	—	—	0.065^{***}	—	—	0.071^{***}
			(0.005)			(0.005)
Number of adults in HH	—	—	0.027^{***}	—	—	0.029^{***}
			(0.004)			(0.004)
ln(income)	0.068^{***}	0.003	0.048^{***}	0.121^{***}	-0.017^{***}	0.055^{***}
	(0.024)	(0.006)	(0.005)	(0.024)	(0.006)	(0.005)
Women	-0.105^{***}	-0.033^{***}	-0.065^{***}	-0.148^{***}	-0.014^{**}	-0.069^{***}
	(0.021)	(0.006)	(0.004)	(0.021)	(0.006)	(0.004)
Driver's age/10	-0.086^{***}	0.005^{***}	0.006^{***}	-0.093^{***}	0.010^{***}	0.003^{**}
	(0.009)	(0.002)	(0.001)	(0.009)	(0.002)	(0.001)
Education: medium	0.084^{**}	−0.009	−0.006	0.084^{**}	−0.010	−0.003
	(0.034)	(0.009)	(0.006)	(0.034)	(0.009)	(0.006)
Education: high	0.128^{***}	-0.021^{**}	−0.011	0.127^{***}	-0.022^{**}	−0.005
	(0.038)	(0.010)	(0.007)	(0.038)	(0.010)	(0.007)
Constant	1.129^{**}	4.972^{***}	6.948^{***}	3.938^{***}	3.597^{***}	6.918^{***}
	(0.509)	(0.128)	(0.048)	(0.513)	(0.129)	(0.049)
Canton FE	YES	YES	YES	YES	YES	YES
Rebound effect		68.7%			38.7%	
# Obs.		6,395			6,395	
R^2	0.161	0.062	0.218	0.176	0.087	0.242

Standard errors in parentheses. $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level.

Table C.4: Empirical estimations with daily distance (GIS), Single-car households

	SURE			OLS		
	ln(distance)	ln(engine FI)	ln(weight)	ln(distance)	ln(engine FI)	ln(weight)
ln(distance)	—	-0.017^{***}	-0.001	—	-0.009^{***}	0.002
		(0.003)	(0.002)		(0.003)	(0.002)
ln(engine FI)	-0.566^{***}	—	-0.243^{***}	-0.277^{***}	—	-0.121^{***}
	(0.083)		(0.010)	(0.083)		(0.010)
ln(weight)	-0.260^{**}	-0.489^{***}	—	-0.088	-0.260^{***}	—
	(0.114)	(0.019)		(0.114)	(0.020)	
Worker	0.237^{***}	—	—	0.238^{***}	—	—
	(0.049)			(0.049)		
Elevation (1,000 m)	—	0.021	—	—	0.020	—
		(0.022)			(0.022)	
Children in HH	—	—	0.067^{***}	—	—	0.072^{***}
			(0.005)			(0.006)
Number of adults in HH	—	—	0.030^{***}	—	—	0.032^{***}
			(0.004)			(0.005)
ln(income)	0.070	0.001	0.056^{***}	0.068	-0.019^{***}	0.060^{***}
	(0.043)	(0.007)	(0.005)	(0.043)	(0.007)	(0.005)
Women	-0.171^{***}	-0.030^{***}	-0.064^{***}	-0.161^{***}	-0.012^{*}	-0.064^{***}
	(0.037)	(0.006)	(0.005)	(0.037)	(0.006)	(0.005)
Driver's age/10	-0.070^{***}	0.008^{***}	0.003^{*}	-0.072^{***}	0.010^{***}	0.002
	(0.015)	(0.002)	(0.002)	(0.015)	(0.002)	(0.002)
Education: medium	0.102^{*}	-0.015	0.005	0.107^{*}	-0.016	0.007
	(0.060)	(0.010)	(0.007)	(0.060)	(0.010)	(0.007)
Education: high	0.277^{***}	-0.036^{***}	0.002	0.289^{***}	-0.037^{***}	0.007
	(0.066)	(0.012)	(0.008)	(0.066)	(0.012)	(0.008)
Constant	5.407^{***}	5.287^{***}	7.357^{***}	3.676^{***}	3.702^{***}	7.119^{***}
	(0.908)	(0.148)	(0.051)	(0.912)	(0.150)	(0.052)
Canton FE	YES	YES	YES	YES	YES	YES
Rebound effect		56.6%			27.7%	
# Obs.		4,798			4,798	
R^2	0.056	0.054	0.201	0.058	0.082	0.225

Standard errors in parentheses. $^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level.

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