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

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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 a novelty regarding the data used. Micro-level data and simultaneous equations models have not 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 preferred results, obtained via 3SLS, point to a substantial rebound effect of 60%, which lies 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.

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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. This latter effect is called the rebound or takeback effect, and it partially offsets the benefits of technological improvements. A consensual estimate of the long run rebound effect is 20 to 30%.

In this paper, we estimate the rebound effect in Switzerland, using 2010 data from 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 our estimates are derived from cross-section data, they must be interpreted as long-run effects. Only few papers have analyzed micro-level data in this literature.[1] None of these studies, however, use data after 2000. In recent years, driving habits and the types of cars bought have changed rapidly. Hence, the use of recent data might yield very different results than older data. Moreover, estimations outside the US are few. Nevertheless, non-American households have very different driving habits and it seems likely that they react differently.

Given the current political context in Switzerland, the interest of this research is enhanced. First, when ratifying the Kyoto Protocol, Switzerland committed to reducing its greenhouse gas emissions by 8% between 2008 and 2012 compared with 1990 levels. A new CO_2 Ordinance, which became effective in 2013, states that domestic greenhouse gas emissions must be reduced by 20% compared to 1990 levels by year 2020. Such a target will be difficult to achieve, so that precise knowledge of the size of the rebound effect appears crucial. Second, on the 24th November 2013, the Swiss voted on a price increase of the motorway vignette from 40 to 100 Swiss Francs. More than 60% of the voters rejected this price increase. Even though this measure was not crucial for drivers' incentives, this is a sign that people are not willing to change the legislation regarding transportation. Hence, alternative solutions to decrease emissions must be investigated.

The remainder of the paper is organized as follows. Section 2 develops the model. Section 3 describes the data, and section 4 discusses the empirical estimates. Conclusions are provided in section 5.

[1] See Mannering & Winston (1985), Train (1986), Goldberg (1998), Berkowitz, Gallini, Miller, & Wolfe (1990), Hensher, Smith, Milthorpe, & Bernard (1992), Pickrell & Schimek (1999), West (2004).

2 Model

Following Small & Van Dender (2007), we build a system of simultaneous equations. The variables we consider as simultaneously determined are the distance traveled (D) and the fuel intensity (FI) (in liters per 100 kilometers; i.e., the inverse of the efficiency) of the vehicle.[2] Contrary to Greene, Kahn, & Gibson (1999), we do not consider an equation for the price of fuel, 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. The model is given by the following two equations:

$$\begin{cases} \ln(D) = \ln(FI)\alpha^{D,FI} + \ln(W)\alpha^{D,W} + X\beta^{D} + Z^{D}\gamma^{D} + \varepsilon^{D} \\ \ln(FI) = \ln(D)\alpha^{FI,D} + \ln(W)\alpha^{FI,W} + X\beta^{FI} + Z^{FI}\gamma^{FI} + \varepsilon^{FI} \\ \ln(W) = \ln(D)\alpha^{W,D} + \ln(FI)\alpha^{W,FI} + X\beta^{W} + Z^{W}\gamma^{W} + \varepsilon^{W} \end{cases} \tag{1}$$

where D is a measure of distance traveled, FI is vehicle's fuel intensity, W is vehicle's weight, X is a row vector of characteristics expected to affect both distance and fuel intensity, and Z^j is a row vector of characteristics expected to affect only variable $j = D, FI, W$. Parameters to be estimated are denoted α, β, and γ. Error terms are denoted ε. 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.

3 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. In this paper, we only use the most recent wave of the survey, which way conducted in 2010. Among other, the MMT gives information about distance traveled by transportation mean and travel behavior of households, in addition to basic individual characteristics.

The 2010 MMT contains data about 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 system MOFIS, the

[2] 1 mile ≅ 1.609 kilometers and 1 gallon ≅ 3.785 liters, so that 1 MPG ≅ 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).

Table 1: Description of 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.

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.

A detailed overview of distance measures collected in the MMT is provided in Table 1. 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 accurate information on the distances covered. Deviations between georouting distances and distances estimated by the respondents are sometimes substantial, and almost 20% of respondents make a mistake of at least 10 kilometers, which is large compared to an average traveled distance of less than 50 kilometers.

In this paper, as we are interested in private transportation, we will focus on the three variables mileage_last12m, mileage_last12mCH, and distCH_priv. Table 2 provides pairwise correlations between these different distance measures. It is interesting to note that even though the correlations are all positive, they are very weak. Hence, it appears that the different distance

Table 2: Correlation between distance variables

	distCH_priv	mileage_last12m	mileageCH_last12m
distCH_priv	1.00		
mileage_last12m	0.20^{***}	1.00	
mileageCH_last12m	0.06^{***}	0.46^{***}	1.00

Pairwise correlations.

Survey individual weights are used.

$^{***}/^{**}/^{*}$: significant at the 0.01/0.05/0.10 level.

measures indicate different types of mobility: the individuals who drive a lot on a typical 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 traveling. It seems interesting to consider alternatively these three distance measures in our estimations, as we could expect them to be differentially sensitive.

Because our goal is to measure a rebound effect, 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 consumption of the vehicle, which allows us to recompute a continuous fuel efficiency measure.[3]

Note that, in theory, combining information about fuel, transmission, efficiency labels, weight, and engine displacement should have allowed 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 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 (distance measures in panels A to C, and consumption measure in panel D).[4] From panel A, we observe that distances

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[3]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 C from the above formula:

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

Since we do not know the index values I, 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.

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

Table 3: Descriptive statistics of the endogenous variables

Variable	Mean (sd)	# Obs.
distCH_priv	45.37 (58.94)	35,363
mileage_last12m	11,988.23 (10,311.64)	31,192
mileageCH_last12m	2,868.26 (4,511.10)	15,106
Fuel intensity (l/100km)	9.10 (2.56)	14,535
Vehicle weight (kg)	1,845.12 (398.61)	26,970

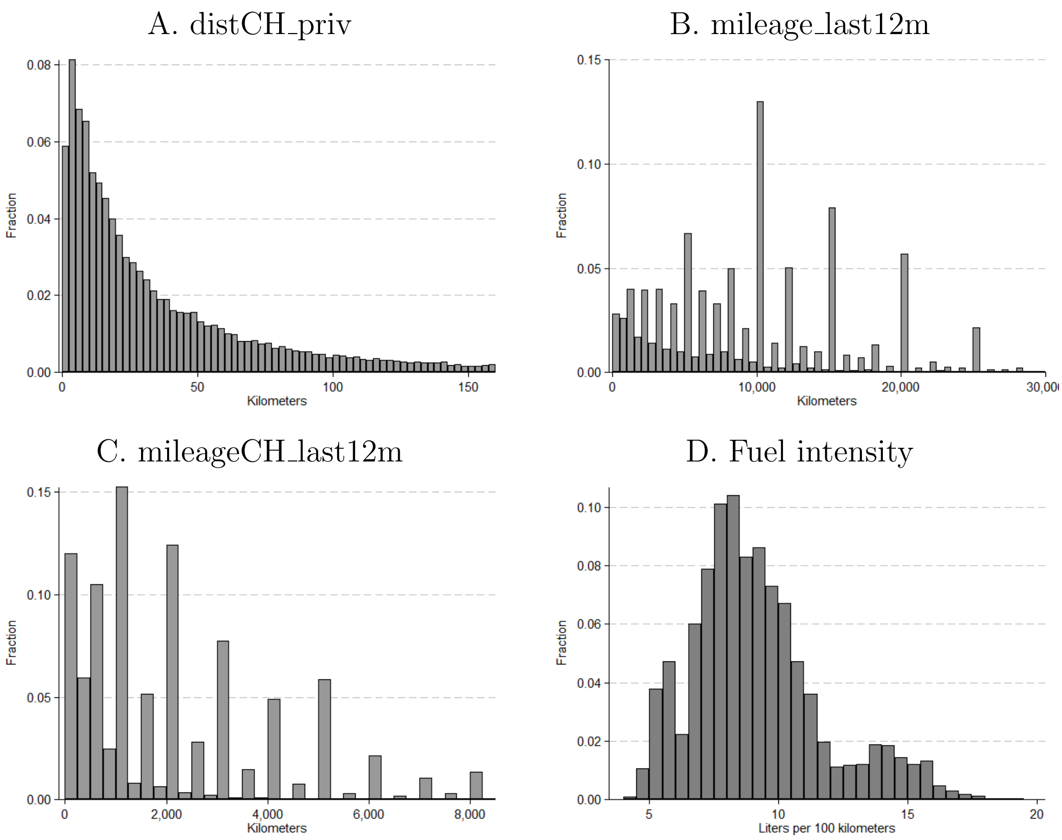
Statistics based on all non-missing observations for each variable.
Survey individual weights are used.
Distances recorded at 0 were removed.
Distances in kilometers.

traveled daily 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 two variables reporting estimated mileage covered in the last 12 months show spikes at round numbers, especially for large values. Such phenomenon is known under the name of heaping and presumably arises because of rounding with regard to the distance traveled.

Even though characterized by heaping, we still observe that the distributions of total mileage over the last 12 months and mileage inside Switzerland are right skewed. The large difference between these two distances probably stems from vacation trips.

estimations of Table 4.

Figure 1: Distributions of the endogenous variables



Statistics based on all non-missing observations for each variable.
Distances recorded at 0 were removed.
Distance distributions are cut at the 95^{th} percentile.

4 Empirical Results

Tables 4 to 6 display the results obtained using different estimations techniques (3SLS, 2SLS, and OLS) and the three distance variables discussed before. Even though the distance variables differ widely, it is interesting to note that the three sets of estimations are very similar. All the coefficients have the expected sign, and most of them are significant.

With the most reliable distance measure we have at hand (Table 4), the rebound effect is estimated at 60% in the 3SLS estimation. This rebound effect lies in the higher end of the estimates found in the literature (see for example Greening, Greene, & Difiglio, 2000). However, most of the studies use OLS, and in fact our OLS estimate is much lower and closer to what is found elsewhere. It therefore seems that OLS estimates of the rebound effect are biased downwards. Using the other distance measures (Tables 5 and 6), we find rebound effect estimates slightly larger than 60%. In this case as well, OLS estimates are lower or even non-significant.

In the distance equations, we observe that weight appears to have a positive effect on travel distance (even though not significant in Tables 4 and 5). This might be interpreted by considering that vehicle weight proxies comfort and safety, so that heavier cars are preferred for driving long distances. Women drive less than men, parents travel less than people without children, and travel distances decrease with age. 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 from the fuel intensity equations show that distance and fuel intensity are jointly determined. Individuals who plan to drive long distances choose more fuel efficient cars, so that we find a strong negative effect of distance on fuel intensity. Unsurprisingly, vehicle weight increases fuel consumption per kilometer. Vehicle age has a positive sign as expected, but it is not significant.

In the weight equations, both distance and fuel intensity play a significant and positive role. Long distance travelers prefer to drive heavy (safer and more comfortable) cars. Household size shows a positive (but non-significant) effect. Interestingly, women, older drivers and people with children have heavier cars, which brings credit to our interpretation of weight in terms of safety and comfort. Overall, our results are largely in line with expectations.

Table 4: Estimations with Distance = distCH_priv

	3SLS	2SLS	OLS
Distance equation, depvar: ln(Distance)			
ln(Fuel intensity)	-0.605^{***}	-0.828^{***}	-0.161^{*}
	(0.127)	(0.207)	(0.090)
ln(Vehicle weight)	0.377	-0.771	0.263^{**}
	(0.370)	(0.745)	(0.125)
Diesel	0.040	0.071	0.071
	(0.053)	(0.120)	(0.053)
Automatic	-0.042	0.341^{**}	-0.038
	(0.079)	(0.167)	(0.038)
Urban area (pop density > 2,000 persons per km^2)	-0.231^{***}	-0.257^{***}	-0.229^{***}
	(0.039)	(0.040)	(0.037)
Women	-0.241^{***}	-0.333^{***}	-0.210^{***}
	(0.039)	(0.061)	(0.027)
Driver age/10	-0.139^{***}	-0.155^{***}	-0.143^{***}
	(0.011)	(0.012)	(0.010)
Children	-0.147^{***}	-0.083^{*}	-0.152^{***}
	(0.035)	(0.047)	(0.030)
Constant	2.594	11.701^{**}	2.493^{***}
	(2.837)	(5.747)	(0.797)
Fuel intensity equation, depvar: ln(Fuel intensity)			
ln(Distance)	-1.320^{***}	-1.320^{***}	-0.005^{**}
	(0.090)	(0.248)	(0.002)
ln(Vehicle weight)	0.535^{***}	0.586^{***}	0.852^{***}
	(0.136)	(0.195)	(0.012)
Vehicle age	0.004	0.005	0.029^{***}
	(0.003)	(0.006)	(0.001)
Women	-0.333^{***}	-0.327^{***}	-0.011^{**}
	(0.040)	(0.064)	(0.005)
Driver age/10	-0.185^{***}	-0.184^{***}	0.007^{***}
	(0.019)	(0.039)	(0.002)
Children	-0.190^{***}	-0.196^{***}	-0.028^{***}
	(0.042)	(0.055)	(0.005)
o.GL	0.000	0.000	0.000
	(.)	(.)	(.)
Urban area (pop density > 2,000 persons per km^2)	-0.308^{***}	-0.314^{***}	0.011
	(0.054)	(0.081)	(0.007)
Constant	3.568^{***}	3.168^{**}	-4.411^{***}
	(0.966)	(1.574)	(0.093)
Weight equation, depvar: ln(Vehicle weight)			
ln(Distance)	2.551^{***}	1.829^{***}	0.006^{***}
	(0.492)	(0.513)	(0.001)
ln(Fuel intensity)	1.598^{***}	0.703^{***}	0.360^{***}
	(0.159)	(0.239)	(0.006)
Household size: 2 persons	0.095	0.238^{***}	0.008^{*}
	(0.067)	(0.091)	(0.005)
Household size: 3+ persons	0.190	0.491^{***}	0.058^{***}
	(0.132)	(0.182)	(0.010)
Urban area (pop density > 2,000 persons per km^2)	0.608^{***}	0.454^{***}	-0.014^{***}
	(0.144)	(0.152)	(0.005)
Women	0.629^{***}	0.406^{***}	-0.052^{***}
	(0.138)	(0.146)	(0.004)
Driver age/10	0.359^{***}	0.258^{***}	0.001
	(0.071)	(0.074)	(0.001)
Children	0.249^{***}	-0.027	-0.003
	(0.061)	(0.123)	(0.009)
o.GL	0.000	0.000	0.000
	(.)	(.)	(.)
Constant	-6.512^{***}	-1.668	6.712^{***}
	(2.397)	(2.587)	(0.018)
# Obs	[illegible]	[illegible]	[illegible]

Table 5: Estimations with Distance = mileage_last12m

	3SLS	2SLS	OLS
Distance equation, depvar: ln(Distance)			
ln(Fuel intensity)	-0.656^{***}	-0.913^{***}	-0.368^{***}
	(0.089)	(0.124)	(0.053)
ln(Vehicle weight)	0.462	-0.697	0.993^{***}
	(0.309)	(0.449)	(0.074)
Diesel	0.066	0.144^{**}	0.013
	(0.040)	(0.073)	(0.031)
Automatic	0.121^{*}	0.442^{***}	-0.005
	(0.067)	(0.097)	(0.022)
Urban area (pop density > 2,000 persons per km^2)	-0.131^{***}	-0.147^{***}	-0.123^{***}
	(0.023)	(0.024)	(0.021)
Women	-0.244^{***}	-0.339^{***}	-0.187^{***}
	(0.030)	(0.037)	(0.016)
Driver age/10	-0.131^{***}	-0.144^{***}	-0.128^{***}
	(0.007)	(0.007)	(0.006)
Children	-0.043^{*}	0.025	-0.077^{***}
	(0.026)	(0.030)	(0.018)
Constant	7.875^{***}	17.125^{***}	3.291^{***}
	(2.438)	(3.455)	(0.475)
Fuel intensity equation, depvar: ln(Fuel intensity)			
ln(Distance)	-1.686^{***}	-1.946^{***}	-0.020^{***}
	(0.167)	(0.232)	(0.002)
ln(Vehicle weight)	1.735^{***}	1.999^{***}	0.873^{***}
	(0.222)	(0.261)	(0.011)
Vehicle age	0.002^{*}	-0.003	0.028^{***}
	(0.001)	(0.005)	(0.001)
Women	-0.343^{***}	-0.388^{***}	-0.010^{**}
	(0.043)	(0.052)	(0.004)
Driver age/10	-0.213^{***}	-0.243^{***}	0.007^{***}
	(0.025)	(0.032)	(0.001)
Children	-0.123^{***}	-0.153^{***}	-0.029^{***}
	(0.039)	(0.041)	(0.004)
o.GL	0.000	0.000	0.000
	(.)	(.)	(.)
Urban area (pop density > 2,000 persons per km^2)	-0.211^{***}	-0.183^{***}	0.009
	(0.044)	(0.051)	(0.006)
Constant	5.880^{***}	6.419^{***}	-4.392^{***}
	(1.213)	(1.515)	(0.083)
Weight equation, depvar: ln(Vehicle weight)			
ln(Distance)	0.971^{***}	0.909^{***}	0.036^{***}
	(0.068)	(0.070)	(0.002)
ln(Fuel intensity)	0.538^{***}	0.395^{***}	0.354^{***}
	(0.039)	(0.050)	(0.005)
Household size: 2 persons	0.013^{*}	0.062^{***}	0.015^{***}
	(0.007)	(0.019)	(0.004)
Household size: 3+ persons	0.031^{*}	0.159^{***}	0.068^{***}
	(0.017)	(0.042)	(0.008)
Urban area (pop density > 2,000 persons per km^2)	0.116^{***}	0.091^{***}	-0.008^{*}
	(0.021)	(0.023)	(0.004)
Women	0.196^{***}	0.178^{***}	-0.048^{***}
	(0.024)	(0.025)	(0.003)
Driver age/10	0.122^{***}	0.114^{***}	0.002^{*}
	(0.010)	(0.010)	(0.001)
Children	0.051^{**}	-0.034	-0.006
	(0.020)	(0.037)	(0.008)
o.GL	0.000	0.000	0.000
	(.)	(.)	(.)
Constant	-3.303^{***}	-2.375^{***}	6.406^{***}
	(0.736)	(0.762)	(0.022)

Table 6: Estimations with Distance = mileageCH_last12m

	3SLS	2SLS	OLS
Distance equation, depvar: ln(Distance)			
ln(Fuel intensity)	-0.617^{***}	-0.326	-0.130
	(0.115)	(0.243)	(0.120)
ln(Vehicle weight)	1.966^{***}	0.773	1.448^{***}
	(0.239)	(0.718)	(0.173)
Diesel	-0.006	0.249^{**}	0.215^{***}
	(0.031)	(0.125)	(0.067)
Automatic	0.005	0.110	-0.053
	(0.040)	(0.142)	(0.048)
Urban area (pop density > 2,000 persons per km^2)	0.200^{***}	0.184^{***}	0.203^{***}
	(0.045)	(0.048)	(0.045)
Women	-0.237^{***}	-0.278^{***}	-0.225^{***}
	(0.042)	(0.058)	(0.037)
Driver age/10	-0.063^{***}	-0.064^{***}	-0.060^{***}
	(0.014)	(0.014)	(0.014)
Children	-0.088^{**}	-0.025	-0.081^{**}
	(0.044)	(0.064)	(0.040)
Constant	-5.948^{***}	2.319	-3.166^{***}
	(1.976)	(5.410)	(1.117)
Fuel intensity equation, depvar: ln(Fuel intensity)			
ln(Distance)	-1.682^{***}	-1.664^{***}	-0.011^{***}
	(0.242)	(0.299)	(0.002)
ln(Vehicle weight)	3.296^{***}	3.418^{***}	0.885^{***}
	(0.552)	(0.658)	(0.017)
Vehicle age	-0.001	0.017^{**}	0.029^{***}
	(0.003)	(0.008)	(0.001)
Women	-0.396^{***}	-0.387^{***}	-0.004
	(0.081)	(0.089)	(0.006)
Driver age/10	-0.106^{***}	-0.111^{***}	0.009^{***}
	(0.029)	(0.032)	(0.002)
Children	-0.150^{**}	-0.190^{**}	-0.035^{***}
	(0.075)	(0.079)	(0.006)
o.GL	0.000	0.000	0.000
	(.)	(.)	(.)
Urban area (pop density > 2,000 persons per km^2)	0.335^{***}	0.270^{***}	0.013
	(0.085)	(0.098)	(0.008)
Constant	-10.001^{***}	-11.132^{***}	-4.607^{***}
	(2.894)	(3.243)	(0.129)
Weight equation, depvar: ln(Vehicle weight)			
ln(Distance)	0.509^{***}	0.488^{***}	0.022^{***}
	(0.046)	(0.049)	(0.001)
ln(Fuel intensity)	0.302^{***}	0.240^{***}	0.297^{***}
	(0.045)	(0.051)	(0.007)
Household size: 2 persons	0.000	0.006	0.022^{***}
	(0.001)	(0.023)	(0.005)
Household size: 3+ persons	0.002	0.050	0.097^{***}
	(0.009)	(0.052)	(0.011)
Urban area (pop density > 2,000 persons per km^2)	-0.101^{***}	-0.079^{***}	-0.023^{***}
	(0.022)	(0.025)	(0.006)
Women	0.120^{***}	0.112^{***}	-0.045^{***}
	(0.025)	(0.026)	(0.004)
Driver age/10	0.032^{***}	0.033^{***}	0.002
	(0.007)	(0.007)	(0.002)
Children	0.044^{**}	0.014	-0.011
	(0.021)	(0.047)	(0.011)
o.GL	0.000	0.000	0.000
	(.)	(.)	(.)
Constant	3.045^{***}	3.323^{***}	6.715^{***}
	(0.401)	(0.433)	(0.021)
# Obs	5,720	5,720	5,720

5 Conclusions

This paper investigates travel demand in Switzerland, using a cross-section of individuals in 2010. An important feature of our study is that we use micro-level data, whereas most of the literature is based on aggregate data. Moreover, among the distance measures that are 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 reported by respondents, which are likely to suffer from recollection and rounding biases.

We use a simultaneous equations model, where we consider travel distance, vehicle fuel intensity and vehicle weight to be endogenous. Estimations by three-stage least squares (3SLS) yield results which are largely consistent with expectations. In particular, we find a rebound effect of 60%, indicating that a substantial share of technological improvements would not be passed to energy savings.

An important extension that must 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

Variable	Mean (sd)	Min	Max
Distance distCH_priv (km)	50.30 (59.88)	0.02	712.35
Fuel intensity (l/100km)	9.04 (2.58)	4.07	19.44
Vehicle weight (kg)	1,868.13 (369.86)	980.00	3,500.00
Diesel	0.22 (0.42)	0.00	1.00
Automatic	0.21 (0.41)	0.00	1.00
Vehicle age	5.98 (3.81)	0.00	39.00
Women	0.41 (0.49)	0.00	1.00
Driver age	47.83 (14.03)	18.00	94.00
Children	0.47 (0.50)	0.00	1.00
Household size	2.68 (1.28)	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	0.46 (0.50)	0.00	1.00
Urban area (pop density > 2,000 persons per km^2)	0.14 (0.35)	0.00	1.00
# Obs.	8,296		

Statistics based on the final sample used in Table 4.
Survey individual weights are used.

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