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The more kilometers, the merrier? The rebound effect and its welfare implications in private mobility☆

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ABSTRACT

Tighter fuel economy standards came into force in the EU in 2020. Such standards reduce the usage cost of cars, encouraging people to drive more, a reaction known as the rebound effect. Whether and how to prevent the rebound is an ongoing policy debate – since the rebound eliminates parts of the expected fuel savings – yet the economic analysis of the rebound welfare implications is very scarce. To fill this gap, first the direct rebound for private vehicles in Switzerland is estimated and is found to be between 30% and 40%. Second, the utility surplus from the extra kilometers is estimated for each household, at 7 cents per kilometer on average. This is half the external costs of driving in Switzerland (15 cents per km). This gap supports a rebound mitigation, for instance through an internalization of external costs with a tax on the distance driven.

1. Introduction

The European Union enacted a massive progression in fuel economy standard in 2020, with the new car fleet average set to 95 g of CO_2 per kilometer.[1] Following the EU, Switzerland has fixed the same limit. Compared to the 2019 new car fleet average of 138.1 g of CO_2 per km (SFOE, 2019), these standards represent a 31% efficiency improvement in Switzerland.

Such standards reduce the cost per km driven, which encourages people to drive more, a reaction known as the direct rebound effect. The direct rebound effect eliminates parts of the expected fuel savings, and delays the fulfillment of the CO_2 reduction commitments of the governments. Hence, a debate about whether and how to offset this rebound effect is growing at the political level (Maxwell et al., 2011), especially for mobility, where the CO_2 reduction targets are far from being met. In Switzerland for instance, the target for transport was −10% of GHGs in 2020 compared to 1990, but in 2019 it was still at +2.9%,[2] while the reduction target for industry has been met, and the target for buildings partially met.

The debate is also at the scientific level, with several papers discussing approaches to address the rebound (Herring and Roy, 2007; Ouyang et al., 2010; Van den Bergh, 2011). Yet, the empirical analysis of the welfare impacts of the rebound is very scarce. To our knowledge, only one empirical article on the subject exists (Alfawzan and Gasim, 2019). In a recent review on the rebound literature, Font Vivanco et al. (2022) highlight the need of research on the negative and positive outcomes of rebound effects that may arise simultaneously. This article contributes to fill this gap and provides a cost–benefit analysis of the rebound in the context of private transportation based on welfare economics. The consumer surplus[3] gained from the direct rebound (additional driving) is compared to the increase in negative externalities. On the one hand, people adapt to the more efficient and hence cheaper – in terms of running costs – vehicles and consumes more of the energy service, so their utility increases. On the other hand, consuming more of the energy service generates external costs, such as congestion, noise, accident and pollution costs. If these external costs outweigh the utility gains, the net welfare diminishes. It is important

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[1] Regulation 2019/631 of the European Parliament.

[2] Swiss Federal Office for the Environment, CO_2 Statistics. In 2020, a slight decrease compared to 1990 happened, due to the pandemic.

[3] For readers who are not familiar with consumers' surplus calculation, I suggest the reading of Frank and Cartwright (2010).

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to highlight that only the welfare consequences of the direct rebound are assessed here, it is out of the scope of this article to provide a cost-benefits analysis of vehicle fuel efficiency improvements.

To quantify the private gains, the first step is to estimate the direct rebound. I estimate it in Section 4 through the fuel intensity elasticity using panel data at the household level from an online survey. The fuel intensity elasticity is defined as the percent change in kilometer driven caused by a 1 percent decrease in fuel intensity (fuel intensity being the amount of gas consumed for 1 km). I find a direct rebound between 30% and 40%, meaning that about a third of the expected energy savings after a fuel efficiency improvement is lost due to an increase in the distance driven.

One asset of the data used is that it contains the self-estimated vehicle fuel consumption and not solely car manufacturers' estimations which are known to be severely underestimated in Europe (Tietge et al., 2017c). I show that using data from manufacturers brings a downward bias in the rebound estimation.

Once the rebound is estimated, I quantify in Section 5 the additional utility from induced travel by using Hausman's method to calculate the consumers' surplus (Hausman, 1981). While the rebound is kept constant across individuals, the efficiency improvement is different for each household and is based on the new 2020 EU fuel standards. On average, this additional utility is 7 cents per km. This surplus varies by household, from 0 cent to more than 20 cents, depending mainly on the level of efficiency improvement.

Although the extra km driven are beneficial at an individual level, they are costly for the whole society through air pollution, accident and congestion costs, more noise, etc. These costs are precisely estimated in Switzerland by the government. They amounted to about 15 cents per km in 2017, as detailed in Section 5.3. Therefore, they are on average twice of the extra utility from the rebound, supporting measures for a rebound "mitigation" in the mobility sector. Such measures should focus on the external costs, because the direct rebound itself is welfare improving. Indeed, if external costs diminish, the rebound could turn beneficial. Two sets of potential measures exist: (a) a decrease in external costs, for instance with a shift to electric vehicles which emit no harmful particles, and (b) an internalization of external costs, for instance through an increase of the fuel tax or a new tax on the distance driven, or even through a new bonus/penalty mechanism on car insurance linked to the car usage. These different measures are discussed in Section 5.4.

2. Related literature

The rebound literature for private mobility is abundant, focusing mostly on the US. Dimitropoulos et al. (2018) provide a review of 74 studies about the direct rebound in road transport, and 64% of them concern the US. Thus, one contribution of the paper is to provide a direct rebound estimation for a European country. Moreover, stricter new regulations for vehicle emissions came into force in 2020 in the EU and Switzerland, highlighting the need of rebound estimations in these countries. Another contribution of the paper is to estimate the direct rebound with the fuel intensity elasticity based on self-stated fuel consumption rather than based on car manufacturers statements. Data from manufacturers are indeed heavily biased downward in Europe (Tietge et al., 2017c). Few papers use the fuel intensity or fuel efficiency elasticity to estimate the rebound, and even fewer use real-world fuel consumption (Frondel et al., 2008; Ruzzenenti and Basosi, 2017). For instance, among the 255 preferred rebound estimates of Dimitropoulos et al. (2018), only 22% employed the fuel efficiency elasticity; the most popular rebound measures being the fuel cost and fuel price elasticities.

The fuel efficiency elasticity is nonetheless the closest to the original direct rebound definition in road transport: a change in travel demand following an increase in fuel efficiency. Yet, efficiency elasticity is the least employed because of data constraints, and fuel cost/price elasticities prevail. However, some assumptions are needed to consider them as measures of the direct rebound effect, and it is unclear if these assumptions hold.[4] Sorrell and Dimitropoulos (2008) detail these assumptions, one of them being that consumers must react in a symmetric way to an increase in efficiency or to a decrease in fuel price. Another key assumption is whether the rebound relates to a "single-fuel multiple- energy service" type of market or a "multiple-fuel single-energy service" type of market (Chan and Gillingham, 2015). Because of these necessary assumptions and the availability of fuel intensity in my data, I prefer to use the fuel intensity elasticity to estimate the direct rebound.

Dimitropoulos et al. (2018) compare in their meta-analysis the results of these three different elasticities. Overall, an average short run rebound of 10%–12% and an average long-run rebound of 26%–29% are found, with the fuel price elasticities giving the highest estimates (30% on average). These results are in line with the review of Sorrell et al. (2009), who find a likely long-run rebound between 10% and 30%. Some studies for European countries find notably higher rebound, up to 60%–80% (Frondel et al., 2008; Frondel and Vance, 2013) – including the only other paper estimating a rebound effect for private mobility in Switzerland (Weber and Farsi, 2018). This gap between Europe and the US is possibly explained because Europeans, driving less than Americans, are further away from their satiation point and hence rebound more. However, other estimates for European countries are lower, for instance De Borger et al. (2016) find a rebound of 7.5%–10% for Denmark.

Contrary to an abundant rebound literature, studies about the welfare implications of the rebound are almost nonexistent. Some authors argue that the rebound is likely to be welfare improving by providing cheaper energy services (Borenstein, 2015; Gillingham et al., 2016), while others are in favor of a rebound mitigation (Herring and Roy, 2007; Ouyang et al., 2010; Van den Bergh, 2011). Chan and Gillingham (2015) provide the only theoretical contribution about the welfare implications of the rebound. They highlight that the rebound is beneficial if the individual surplus associated to it is larger than the external costs. On the empirical side, only one article about the welfare implications of the rebound exists to my knowledge: also focused on private transportation, Alfawzan and Gasim (2019) show that the direct rebound is in most cases welfare reducing. Using price elasticites and aggregated data at the country level, they study many different countries. Although our methods are different, their results for Switzerland are very close to my results: the ratio of the additional surplus from the rebound over the external costs generated by the extra km driven is 0.4. If I apply the same ratio to this article, it would be 0.47 on average (7 cents/15 cents).

This article fills a gap in the literature by providing a welfare analysis of the direct rebound based on welfare economics. To study empirically the welfare consequences of the rebound, we need to estimate (i) the individual utility surplus coming from the extra km driven, and (ii) the external costs of induced travel. Utility is a central concept in economics and can be described as a numerical score that represents the satisfaction, happiness, benefit, or welfare that a consumer gets from a given market. Here, two situations after a vehicle fuel efficiency improvement are compared: the situation with no direct rebound (the consumer drives exactly the same number of km before and after the efficiency improvement) and the situation with a positive direct rebound (the consumer drives more km than previously). The difference in utility between these two situations gives the utility surplus from additional driving.

To estimate part (i), I apply the surplus calculation method from Hausman seminal paper (Hausman, 1981) on consumers' surplus. Hausman provides exact expressions to estimate the compensating variation,

[4] Some authors argue they do hold (Greene et al., 1999; Frondel and Vance, 2013), others argue they do not (Sorrell et al., 2009; Greene, 2012; Hymel and Small, 2015; De Borger et al., 2016).

which can be seen as the amount of money that needs to be taken away from consumers to cancel the utility gain from additional driving. The main asset of this method is its accuracy compared to the simple Marshallian surplus calculation. Araar and Verme (2019) showed that when the price variation is medium (over 20%) or large (over 50%), the Marshallian surplus differs from the true surplus value. They strongly suggest the Breslaw and Smith (1995) method for medium and large price variations, a method almost identical to the Hausman's method. The price variations considered later in this article are indeed medium (33% on average).

For part (ii), the external costs, I rely on the Swiss government estimations (Swiss Federal Office for Spatial Development, 2020, 2018). A tax per km exists for trucks in Switzerland, and precise estimations are carried out regularly to ensure that the tax is aligned with trucks' external costs. No such tax per km exists for cars, but their external costs are nonetheless estimated. Compared to the literature, these Swiss estimations are extremely comprehensive and include as many externalities as possible, while usually only three main externalities are considered (air pollution, congestion costs and accident costs). The Swiss estimations include, on top of these three main externalities, indirect emissions from car making and scrapping, damages to buildings, forests and harvests due to pollution, biodiversity losses, etc. According to these official Swiss estimations, the external costs for private cars amounted to 15 cents per km[5] in Switzerland in 2017.

Santos (2017) collected the external costs of road transport for 22 European countries, taking into account local air pollution, climate change, congestion, accident and noise costs. She finds an average cost between 11 and 14 cents per km, and a slightly lower average cost for Switzerland of 9 to 10 cents per km. Because the official Swiss estimations are more comprehensive, they are logically larger. Another estimation largely used in the literature is the one by Small et al. (2007). They estimate the external costs for the US in urban and rural contexts. When adjusted to 2013 dollars (Langer et al., 2017), the external costs are 13.5 cents per km in the urban context, and 2.4 cents per km in the rural context. Although the noise costs are not included, these US urban costs are close to the European values found by Santos (2017). The urban context is comparable to Switzerland, a very dense country. In light of these different estimations, the official estimation of 15 cents per km looks adequate for Switzerland.

Once both individual surplus and external costs are estimated, the microeconomic welfare implications of the direct rebound can be determined.[6]

3. Data

3.1. Data sources

The data come from an annual online survey focusing on Swiss households energy consumption (more information in Weber et al., 2017). Five waves of the survey are available (2015–2019), and 5000 households answered annually.[7] As many households as possible were kept each year to create a panel. In this paper, I keep only households with at least one gasoline- or diesel-powered vehicle to ensure comparable fuel efficiency measures. Thus, hybrid or electric cars are dropped (3.9% of the observations). On top of the survey data, data from manufacturers about vehicle weight and vehicle fuel consumption are added. These data were gathered by the Touring Club Suisse (TCS), the largest motor club in Switzerland. The matching between the household survey data and the data from manufacturers is done on six characteristics and is described in Appendix A.

The two key variables related to the direct rebound are the annual kilometers driven and the vehicle fuel consumption. Because both of them are self-reported in the survey, they contain implausible answers. To eliminate these unreasonable answers, both variables are trimmed at the 1% and 99% levels. All graphs and statistics in this paper are presented with the trimmed variables.

The assets of the data are three-fold: (1) The fuel intensity elasticity is used to estimate the direct rebound effect, instead of the fuel price elasticity as in most of the papers in the literature. (2) A panel with micro-data is rare and allows to control for households' characteristics which do not vary over time and which could influence the distance driven (for instance a strong preference for driving instead of taking public transportation). Furthermore, the control variables at the household level are numerous. (3) Real-world fuel consumption is used, and not the estimations from manufacturers, who systematically underestimate it in Europe (Tietge et al., 2017c). One disadvantage of self-stated data is that they contain more errors, however their accuracy appears to be high enough, as shown in the next part about summary statistics.

Finally, I integrate data about monthly fuel price in Switzerland from the Federal Statistical Office. Prices are aggregated over the 12 months prior to respondents' answers, to match the time lapse of the distance driven. Fuel price is needed to estimate the consumers' surplus. I also tried to include the fuel price on top of fuel intensity in the regressions estimating the rebound effect, but since the variation in fuel price was limited over the survey years, the coefficient turned insignificant.[8]

3.2. Summary statistics

The full sample – containing 13,637 observations (households with at least one gasoline or diesel car) – is only employed for descriptive graphs. For regressions, only households who changed their vehicle at least once are kept, as the identification strategy of the rebound relies on variations in fuel intensity and in kilometers driven after a vehicle change. This sub-sample of households with a vehicle change consists of 3235 observations (1065 households).

Table 1 displays the sub-sample summary statistics. The annual kilometers driven are calculated as the difference between the current odometer reading of the car and the number of kilometers when the car was purchased, then averaged over 365 days, that is:

$$km_{driven} = \frac{km_{current} - km_{purchase}}{\#\text{days owned}} * 365.25$$

The kilometers are therefore averaged annually over the car lifetime. Another option was to take the difference of km between two survey waves, but the sample would have been much smaller since at least two observations before the car change were needed to calculate the km driven (two-third of the observations would have been lost).

Since odometer readings are self-reported, their accuracy may be an issue. To check their quality, I compare the km driven distribution from the survey data (Fig. B.1), with the 2010 Swiss Mobility Microcensus distribution, reported in Weber and Farsi (2018). The Microcensus provides a precise measure of the distance driven on a specific day, recorded with Geographical Information System software. Thus, we can compare self-reported data with geocoded data. As a result, both distributions are similar: 70% of the observations are below 50 km per day – or 18,250 km annually – and the means are commensurate: 41

[5] All the numbers presented are in CHF. For a reference, 15 cents per km [CHF] is equal to 24.2 cents per mile [$], when the exchange rate of 1 CHF = 1 $ is used, because 1 km equals 0.62 mile.

[6] For simplicity, the producers' surplus is assumed to be zero in the long-run.

[7] The first wave in 2015 was smaller, with 3500 participants.

[8] The minimum price was 1.32 CHF per liter of gasoline in February 2016, and the maximum was 1.69 CHF in October 2018, with an average of 1.52 CHF over the 5 survey waves. Diesel price is 5–15 cents higher.

Table 1
Summary statistics for the final sub-sample.

	Mean	Std. dev.	Min.	Max.	Median
Km driven (annually)	15,032	9944	714	91,875	12,766
Fuel intensity [L/100 km]	7.17	1.77	2.50	14.70	7.0
Fuel intensity (from car manuf.)	6.41	1.68	3.10	19.55	6.1
Car weight [kg]	1503	306	809	2767	1487
Car 1st registration year	2011	5.38	1989	2019	2012
Diesel	0.31	–	0	1	–
Automatic transmission	0.47	–	0	1	–
# Car doors	4.74	0.72	2	5	5
Fuel price [CHF per liter]	1.53	0.09	1.40	1.77	1.54
Implicit price [CHF per km]	0.11	0.03	0.04	0.23	0.11
Ownership length [year]	4.14	3.90	1	30	3
# Car	1.45	0.60	1	3	1
# Car change	1.21	0.45	1	3	1
Commute by car (no/yes)	0.46	–	0	1	–
Commute distance [km]	8.92	20.60	0	264	0
Income (monthly)					
<4500 CHF	0.10	–	0	1	–
4500–5999 CHF	0.14	–	0	1	–
6000–8999 CHF	0.30	–	0	1	–
9000–12,000 CHF	0.26	–	0	1	–
>12,000 CHF	0.20	–	0	1	–
Education					
Compulsory school or less	0.02	–	0	1	–
Apprenticeship	0.39	–	0	1	–
High school	0.13	–	0	1	–
University	0.46	–	0	1	–
Age	50.24	14.76	18	86	51
Female	0.40	–	0	1	–
Household size	2.46	1.21	1	9	2
Children in HH (no/yes)	0.37	–	0	1	–
Rail passes (no/yes)	0.77	–	0	1	–
City (versus rural area)	0.69	–	0	1	-

Notes: N = 3235 for all variables. Only households with at least one vehicle change are kept in this sub-sample. The distance driven annually and the fuel intensity (self-reported variables) are trimmed at the 1% and 99% to eliminate implausible answers. For readers used to American standards, a maximum of about 92,000 km driven annually could seem low but is reasonable for a small European country.

daily km in the survey data, 46.9 daily km in the Microcensus.[9] Hence, data quality of the distance driven looks satisfactory.

3.3. Real-world fuel consumption versus manufacturers' estimations

Besides the distance driven, the other key variable for the analysis is the fuel intensity (FI). Table 1 shows two FI measures: the self-reported one and the one from manufacturers. The self-reported FI is measured in (Liter/100 km) since it is the typical measure in Europe, versus the fuel efficiency (FE) in (km/Liter) or miles per gallon in the US. The use of FI instead of FE is also relevant in view of the so called "MPG illusion": the amount of gas consumed by a vehicle decreases non linearly when the fuel efficiency is considered, while it is linear with the fuel intensity. Thus, the fuel intensity is more transparent and more easily understood by people (Larrick and Soll, 2008).

The mean FI is 7.2 l/100 km, or 32.7 miles per gallon. Fig. B.2 displays the distribution of fuel intensity. Because the fuel intensity is self-reported, respondents are expected either to calculate how much fuel their vehicle consumes, or to report, if available, the fuel consumption display of their vehicle. Since precise information about the vehicle model is asked in the survey, each vehicle can be matched with data from manufacturers. The matching is detailed in Appendix A.

Thanks to these two different measures, we can investigate how far data from manufacturers are from real-world driving. Fig. 1 displays this gap. The divergence has increased substantially since 2009 – following the application of more stringent CO_2 emissions standards in the EU and Switzerland – going from no difference in 2004 to more than one liter in 2016. Tietge et al. (2017c) indicate that most of this difference is explained by car manufacturers optimizing test cycles and exploiting loopholes in test procedures to comply with the new standards.

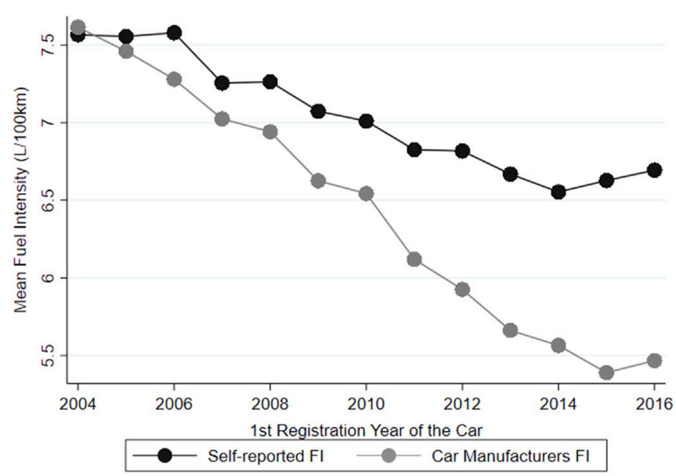

Fig. 1. Divergence in fuel intensity: Manufacturers vs. self-stated estimations. *Notes:* The gap between the two lines dramatically increased since 2009, following more stringent regulations. In 2016, the fuel consumption of new cars was for the first time higher than the previous year. This increasing trend continued in 2017, 2018 and 2019, and is explained by the Swiss government (SFOE, 2020) by a growing number of SUVs, an increased car weight average and the fall in diesel engines with respect to gasoline engines (N = 12,034).

The track of this divergence is useful to check the accuracy of self-reported fuel consumption answers. Indeed, we can compare the gap

[9] The means would even be closer if the highest observations were dropped in the Microcensus as in the survey sample. The maximum daily km in the Microcensus is indeed 1736 km, while it is only 252 km in the sample.

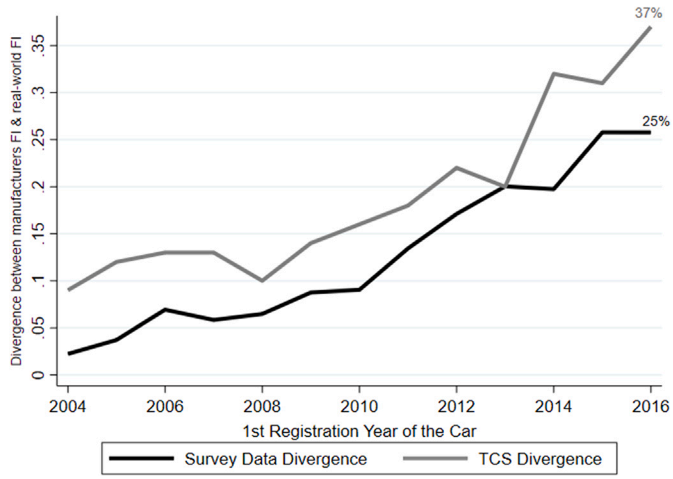

Fig. 2. Divergence in fuel intensity: Comparison with TCS data. *Note:* The TCS divergence is calculated each year on the 15 to 20 most popular vehicle models in Switzerland. For cars of 2016, the TCS estimated a 37% higher fuel consumption in real-world conditions compared to data from manufacturers. The divergence found in the survey data is somewhat lower, but the trend is comparable, with a surge after 2009 (N = 12,034).

found in the survey to the gap found in other data sources. Fig. 2 plots the divergences from the survey data and from the TCS (the largest motor-club in Switzerland). The TCS compares each year real-world fuel consumption and manufacturers' claims of 15 to 20 of the most popular vehicle models in the Swiss market.[10] The gap found by the TCS progresses similarly to the survey gap, with a rapid growth since 2008–2009. The TCS gap is even larger than in the survey sample, going from a 10% higher fuel consumption in real-world conditions in 2004, to 37% in 2016; versus 25% in 2016 in the sample.

This systematic fuel intensity underestimation by car manufacturers is an issue for the rebound calculation as it introduces a measurement error. De Borger et al. (2016), who use data from manufacturers, discuss this caveat and conclude it is not an issue as long as people believe this gap is stable over time. However, their analysis misses a crucial point: the gap varies with the fuel efficiency level of the car. The divergence is indeed larger for more efficient cars, as found by Tietge et al. (2017b). I also find clear evidence of a higher gap for more efficient cars. In Fig. C.1, the sample is divided into low and high FI cars, the threshold being each year the median manufacturers FI.[11] The divergence is always larger for the efficient cars, reaching 35% in 2016 versus only 15% for the less efficient cars.

This greater underestimation for more efficient cars biases the rebound downward if data from car manufacturers are used. To know the bias direction, an experiment was made in this paper: the self-reported fuel consumption of the 50% most efficient cars was artificially decreased[12] – to get closer to manufacturers' values – and then the rebound was estimated. The rebound diminished in that experiment. The results are presented in Table C.1.

This rebound underestimation is also found when data from manufacturers are used in the regressions directly instead of the self-stated fuel intensity. In this case, the rebound falls to almost zero. This is no surprise, since the efficiency improvement between the old car and the new car is smaller in reality compared to what is on paper. Moreover this gap was not stable but worsening over time (see Fig. 2). Hence, in reality, drivers are experiencing a smaller fuel efficiency improvement than expected; they therefore react to this small improvement by driving only a little more. If data from manufacturers are used in the regressions, large efficiency improvements exist on paper, but people adapt by driving only a little more. As a consequence, the rebound effect tends to zero.

In view of this underestimation bias, the use of the self-reported fuel consumption instead of manufacturers' measures is an important asset of the paper.[13]

4. Rebound calculation: Empirical strategy & results

4.1. Empirical strategy

As defined in the Literature section, the fuel efficiency rebound is the effect on the distance driven of a 1 percent increase in fuel efficiency. Since fuel intensity (FI) is more common in Europe, I will use it instead of fuel efficiency (FE). As a consequence, the rebound effect becomes the fuel intensity rebound which describes the effect on the distance driven of a 1 percent *decrease* in fuel intensity. Both measures are identical since FI and FE are linked as follow:

Fuel Intensity (FI) = Liter/km

Fuel Efficiency (FE) = km/Liter

$FI = 1/FE$

An example showing that the FI and FE rebound measures are identical is provided in Appendix D.

The rebound identification strategy relies on a fuel intensity variation, that is, after a vehicle change. Thus, only individuals who change their vehicle at least once are kept in the sample, to compare their driving behavior before and after the car change. I assume that individual i's number of kilometer driven in period t has a generalized Cobb–Douglas functional form given by:

$$km_{i,t} = f_{i,t} O^{\gamma}_{i,t} W^{\phi}_{i,t} FI^{\beta}_{i,t} \tag{1}$$

where O is the ownership length of the vehicle in years, W the car weight in kilos, FI the self-stated fuel intensity in liter per 100 km, and where $f_{i,t}$ has the following form:

$$f_{i,t} = exp(\alpha_0 + \lambda_i + \lambda_c + \theta' Z_{i,t})$$

λ_i is the time-invariant individual effect that captures individual's unobserved characteristics affecting car usage, λ_c the state fixed-effect, and $\theta' Z$ a vector of socio-economic characteristics and vehicle characteristics.

To estimate the parameters in (1), the following log-linear equation is used:

$$\begin{aligned} Ln(km_{i,t}) = {} & \alpha_0 + \lambda_i + \lambda_c + \theta' Z_{i,t} + \gamma ln(O_{i,t}) + \phi ln(W_{i,t}) \\ & + \beta ln(FI_{i,t}) + \epsilon_{i,t} \end{aligned} \tag{2}$$

Coefficient β is the fuel intensity rebound effect, that is $\partial Ln(km)/\partial Ln(FI)$. Eq. (2) is estimated with fixed-effects at the household level to account for individual heterogeneity.[14] The logs of ownership length

[10] TCS values are reported in Tietge et al. (2017c), page 43, available at https://theicct.org/publications/laboratory-road-2017-update.

[11] The results are the same if the median of the self-reported FI is used.

[12] The self-reported fuel consumption of the less efficient cars was kept unchanged since they are closer to data from manufacturers.

[13] The vast majority of the rebound literature relies on data from car manufacturers. While I show it brings a downward bias for European countries, the problem is less acute for the US, because the gap between manufacturers FI and real-world FI is less pronounced than in Europe (Tietge et al., 2017a). This gap is even non-existent in the US if the fuel consumption values of the Environmental Protection Agency are used, as they are designed to match real-world driving conditions (Tietge et al., 2017a).

[14] A Hausman test was performed to check whether random- or fixed-effects should be used, pointing to fixed-effects model. Moreover, tests were performed to check whether time fixed-effects were needed, but year dummies were not different from zero. Finally, robust standard errors are used in all regressions, to obtain heteroskedasticity-robust standard errors.

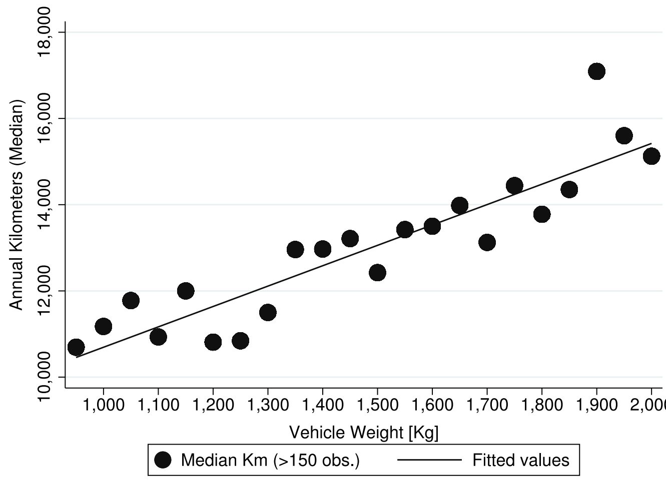

Fig. 3. Vehicle weight & distance driven. *Notes:* Vehicle weight is rounded in bins of 50 kg. The median of the distance driven is calculated for each bin. Vehicles lighter than 950 kg or heavier than 2000 kg are too few (less than 150 observations) and are not shown in the graph (N = 13,045).

and car weight are used because both variables are not normally distributed (both are skewed to the right).

Concerns about the potential endogeneity of fuel intensity are raised in the literature. Do the expected km driven have an impact on the fuel intensity of the car, in other words, do people who expect to drive a lot buy more efficient cars? If yes, an endogeneity bias exists and instruments are needed to overcome this issue. However, many signs show this is probably not the case. First, the bias direction is ambiguous: People who expect to drive a lot may purchase an economical car, but they could also wish to purchase a comfortable car, hence a heavier and less efficient car. In Switzerland, this last option seems the be accurate in view of Fig. 3: heavier vehicles are driven more. Secondly, the expected car usage has only a limited impact on the car choice, according to the vehicle-choice literature (Baltas and Saridakis, 2013). Thirdly, half of the respondents of the first wave of the survey rated the fuel efficiency as “not important” in their car choice, a result confirmed by the European Barometer on climate change in which only 9% of the European consumers rated the fuel efficiency as “an important factor” in the choice of their new car.[15]

These arguments may explain why two recent papers estimating the rebound effect with fuel efficiency elasticity and instruments find no significant difference with or without instruments: De Borger et al. (2016) for Denmark, and Linn (2016) for the US. The latter does not find any difference when vehicle-model fixed effects are added. Nevertheless, different instruments were tested with these survey data, but none was satisfactory. In view of the bias direction ambiguity and of Linn and De Borger results, there is no reason to believe that endogeneity strongly affects the results.

Another concern exists for multi-vehicle households. In the dataset, the distance driven is known only for one car (the most used by the responding person). I thus assume that the km driven of one vehicle is independent of the km driven of other vehicles belonging to the same household. To test whether this hypothesis brings a bias to the rebound estimation, all regressions were also performed solely with one-car households. As 55% of the households in the sample own only one vehicle, the sub-sample is large enough for analysis. The rebound is slightly lower with single vehicle households, but remains very close to the estimation with the full sample. Linn (2016) also finds evidence that the rebound is larger when one assumes that the km driven of the households’ vehicles are uncorrelated, but the difference is not statistically significant. Overall, using the full sample with the multi-vehicle households does not strongly alter the results.

Variations in self-stated fuel consumption

In each survey wave, the fuel consumption is self-stated by the respondents. As a consequence, fuel intensity fluctuates even if the vehicle is the same. For instance, some respondents stated in 2016 that their vehicle consumed 7 liter per 100 km, and 7.5 liter in 2017. This is no mistake, real-world fuel consumption depends on weather, car load, driving-style, etc. However, we are not interested in such ordinary variations to calculate the rebound, but on variations due to a real efficiency improvement in motorization after a car change.

To eliminate these superfluous variations, two solutions are applied:

- Solution 1: *The mean fuel intensity of the two vehicles*
  The fuel intensity is averaged for the old and the new vehicle. For instance, if the vehicle change happened in 2017, the fuel intensity is first averaged over 2015 and 2016 (old car), and secondly over 2017–2018–2019 (new car).
- Solution 2: *Before/after a car change*
  Only the year before and the year after the car change are kept in regressions. In the above example, it would be 2016 (old car) and 2017 (new car).

The rebound estimations for these two solutions are presented in the next section. Within the sample, about half of the households changed their vehicle for a more efficient one, and the other half changed for a less efficient one.

4.2. Results for the rebound effect

Overall, the rebound effect is estimated between 29% and 42%, meaning that about a third of the expected energy savings is lost due to more kilometers driven. These values are at the upper end of the average long-run rebound found by Dimitropoulos et al. (2018) in their meta-analysis (26%–29%).

Solutions 1 and 2 are presented in each table for comparison. The mean fuel intensity (solution 1) gives a rebound around 30%, and the before/after car change (solution 2) a rebound around 40%. Table 2 displays Eq. (2) estimation for all households with at least a car change. Table 3 keeps only single vehicle households. All estimations have been performed with Stata by using the xtreg commad.

Three variables are essential in the regressions, because they are correlated to both distance driven and to fuel intensity: vehicle weight, engine type (diesel/gasoline) and ownership length. Vehicle age can alternatively be used instead of ownership length, but years of ownership better suit households buying second-hand vehicles. Fig. 4 shows the strong negative relation between ownership length and the distance driven, also reported in Caserini et al. (2013). Since ownership length is also correlated to fuel intensity (older vehicles are less efficient), omitting this variable would bring a serious bias in the results. The same problem would arise if the engine type or the vehicle weight were not included. Vehicle weight is negatively correlated to efficiency, and, as expected in view of Fig. 3, has a positive effect on the distance driven. It strengthens the argument that people who drive a lot buy bigger and more comfortable vehicles. Weber and Farsi (2018) found a similar result for car weight in Switzerland. Finally, the coefficient of diesel cars is expected to be positive, because diesel cars are known to be more economical over long distances and are hence more often chosen by people driving a lot. The coefficient of ownership length is more difficult to interpret, because ownership length varies every year. Since fixed-effects are used, the positive coefficient indicates that the higher variation in ownership length between the two different vehicles, the larger increase in kilometers. Indeed, if someone has owned a car for 10 years and then buys a new vehicle, the variation

[15] ec.europa.eu/clima/sites/clima/files/support/docs/report_2017_en.pdf, p.98.

Table 2
Rebound estimation (Fixed-effects at the household level).

	Solution 1 Mean fuel intensity	Solution 2 Before/After car change
Ln(Fuel intensity)	−0.306** (0.122, 0.012)	−0.424*** (0.142, 0.003)
Ln(Car weight)	0.331** (0.147, 0.025)	0.427** (0.176, 0.015)
Diesel	0.155*** (0.057, 0.007)	0.133** (0.066, 0.044)
Automatic transmission	0.008 (0.048, 0.870)	0.012 (0.058, 0.835)
Number of doors	0.036 (0.031, 0.247)	0.015 (0.040, 0.698)
Ln(Nmb years car owned)	0.044*** (0.017, 0.009)	0.069*** (0.020, 0.001)
Commute by car	0.082** (0.039, 0.033)	0.057 (0.059, 0.331)
Income	0.043** (0.018, 0.020)	0.047 (0.033, 0.149)
Education	0.012 (0.021, 0.563)	−0.013 (0.045, 0.767)
Children	0.069 (0.054, 0.205)	−0.082 (0.133, 0.537)
HH size	−0.043** (0.022, 0.047)	−0.011 (0.037, 0.759)
Rail pass	−0.051 (0.058, 0.381)	−0.260** (0.131, 0.047)
Constant	7.307*** (1.016, 0.000)	7.302*** (1.174, 0.000)
County FE	YES	YES
# Observations	3235	1580
# Individuals	1065	790

Notes: In parentheses: robust standard errors, p-values. *p < 0.10, **p < 0.05, ***p < 0.01. For solution 1, the mean fuel intensity (FI) is averaged for each vehicle (the one before and the one after the vehicle change) over the multiple years of the survey. Each household appears at least twice and maximum five times. For solution 2, the FI of each vehicle is kept only the year before and the year after the vehicle change. Consequently, each household appears twice.

in ownership length is higher (from 10 to 0) than for someone who has owned it for only 5 years (from 5 to 0); and since the distance driven decreases with ownership length, the variation in kilometers will be larger for the first person in the above example, all other things being equal. In other words, the greater ownership length variation, the larger variation in the distance driven. Thus the coefficient of ownership is expected to be positive.

On top of these three variables, other control variables display the expected sign, such as income (more affluent households drive more) or rail pass (households with a train pass drive less), although most of the control variables turned insignificant. In addition, the commuting distance was also included, to control for the fact that people might buy more efficient vehicles if their commuting distance increases, for instance if they move further away from their workplace. Since the coefficient of commuting distance was almost zero and that the inclusion of it had no influence on the fuel intensity coefficient – unlike vehicle weight, engine type and ownership length – I dropped it.

Until now, households with one or several vehicles were studied. To avoid any potential bias in the rebound estimation for multi-vehicle households, the same regression is performed keeping only single vehicle households. Results are presented in Table 3. The rebound magnitude is only slightly smaller than for the whole sample: 29% vs. 31% for solution 1, and 37% vs. 42% for solution 2. In view of these similar results and since the rebound estimation main purpose in this paper is to be used in the welfare calculations, multi-vehicle households will be held in the analysis.

In Table C.1, a third result is presented: Here the fuel intensity of efficient vehicles is decreased, to get closer to manufacturers' values.

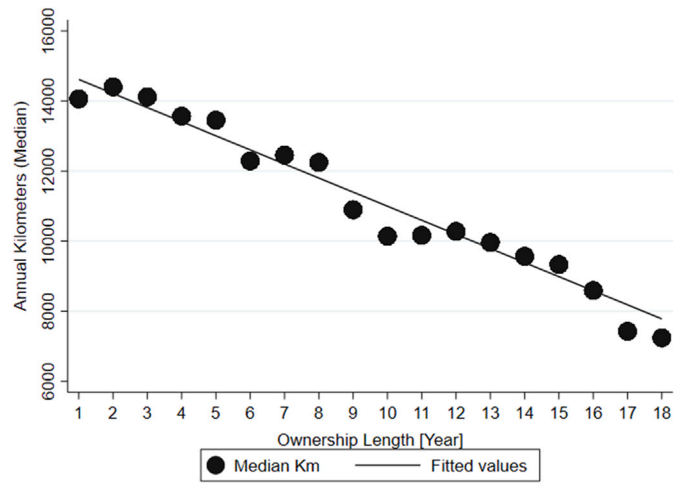

Fig. 4. Ownership length & kilometers driven annually. *Notes:* The median distance driven is reported for each year of vehicle ownership (N = 12,673).

Table 3
Rebound estimation: Single vehicle households (Fixed-effects at the household level).

	Solution 1 Mean fuel intensity	Solution 2 Before/After car change
Ln(Fuel intensity)	−0.285* (0.168, 0.089)	−0.372** (0.173, 0.033)
Ln(Car weight)	0.226 (0.221, 0.305)	0.312 (0.254, 0.221)
Diesel	0.073 (0.085, 0.393)	0.040 (0.105, 0.701)
Automatic transmission	−0.030 (0.063, 0.633)	−0.023 (0.086, 0.786)
Number of doors	−0.073 (0.045, 0.104)	−0.093* (0.055, 0.091)
Ln(Nmb years car owned)	0.045** (0.022, 0.045)	0.061** (0.027, 0.026)
Commute by car	0.047 (0.049, 0.333)	0.061 (0.074, 0.409)
Income	0.082*** (0.024, 0.001)	0.152*** (0.039, 0.000)
Education	0.037 (0.030, 0.220)	0.066 (0.068, 0.331)
Children	−0.056 (0.060, 0.359)	−0.145 (0.194, 0.455)
HH size	−0.068** (0.030, 0.022)	−0.083* (0.048, 0.084)
Rail pass	−0.074 (0.093, 0.424)	−0.291 (0.196, 0.137)
Constant	8.189*** (1.546, 0.000)	7.555*** (1.825, 0.000)
County FE	YES	YES
# Observations	1796	846
# Individuals	607	423

Notes: In parentheses: robust standard errors, p-values. *p < 0.10, **p < 0.05, ***p < 0.01. Only households with one vehicle are kept in this Table. For solution 1, the mean fuel intensity (FI) is averaged for each vehicle (the one before and the one after the vehicle change) over the multiple years of the survey. Each household appears at least twice and maximum five times. For solution 2, the FI of each vehicle is kept only the year before and the year after the vehicle change. Consequently, each household appears twice.

The aim is to study the impact on the rebound estimation of the greater fuel consumption underestimation of the more efficient vehicles by car manufacturers. To do so, the self-stated fuel intensity of the 50% most efficient cars[16] was decreased by 20% (the average gap between

[16] The median was calculated for each car registration year.

real-world and theoretical fuel consumption found in Fig. C.1). The fuel intensity of the other vehicles remained the same, because their efficiency is fairly in line with car manufacturers' values. Results in Table C.1 depict a smaller rebound (19% and 34% versus 31% and 42% with no FI decrease). Therefore, by using data from manufacturers, we may underestimate the rebound.

In the next part of the paper, these rebound estimates are used for welfare calculations. The rebound magnitude is necessary to calculate the surplus gains from induced travel.

5. Welfare calculations: Empirical strategy & results

In this second part, the welfare consequences of the direct rebound are estimated based on welfare economics. The question is: Will there be overall welfare gains or welfare losses from the rebound? On the one hand, drivers benefit from a price decrease and gain some utility by driving more kilometers, but, on the other hand, driving produces external costs supported by the whole society. Overall, there could be net gains or net losses from the direct rebound. To get an answer, we need to compare the utility gains and the external costs from the rebound effect. I first described in Section 5.1 how the utility gains from the rebound are calculated, and then in Section 5.3 how external costs are computed. For simplicity, only the consumers' side is studied here and the producers' surplus is assumed to be zero (a standard assumption in economics in the long-run).

5.1. Surplus calculation: Empirical strategy

To estimate the utility surplus stemming from additional driving due to the rebound effect, an efficiency improvement is needed for each vehicle of the sample, that is, a vehicle change for each household. Instead of taking a random and homogeneous improvement for each household, I apply the 2020 European fuel standards to each vehicle. These standards give a good indication on how fuel efficiency will evolve in the future. According to these standards, each new car has from 2020 a cap on the CO_2 it emits per kilometer.[17] The cap is determined as follows:

$$CO_2 \text{ [g/km]} = 95 + a * (M - M_0)$$

where M is the car weight in kg, M_0 = 1379.88 [kg] and a = 0.033. M_0 is the average mass of all new passenger cars in the EU of the past years and will be adjusted in the future. According to this equation, the average weighted car cannot emit more than 95 g of CO_2 per km, lighter vehicles must emit less and heavier ones can emit more.

I apply this cap to each car of the sample. Overall, the average efficiency improvement with this cap is 33%, ranging from 0 to 76%. By doing this, each vehicle gets its own future CO_2 emissions based on its weight and, therefore, gets its own future fuel efficiency (95 g of CO_2 per km corresponds to 4.1 l/100 km for gasoline cars, and to 3.6 l/100 km for diesel cars). These individual efficiency improvements are then used in the utility surplus calculation to depict variations in the price of driving: price at time zero is before the efficiency improvement, and price at time one is after the efficiency improvement, so when the new 2020 fuel standards are applied.

The utility surplus is calculated by using the compensating variation (CV) from Hausman seminal method. The compensating variation is often used to capture individual surplus after a price decrease (recently by Langer et al., 2017 for automobile travel), and can be seen as the "maximum willingness to pay" to obtain such price decrease (Markandya, 2014). In our case, it is the amount of money that needs to be taken away from drivers to cancel the utility increase from additional driving. An alternative way to calculate the surplus is to use the equivalent variation (EV). The EV corresponds to "the minimum willingness to accept as compensation for giving up the price decrease". In our case, the EV is extremely close to the CV, because the income elasticity is small (Markandya, 2014).

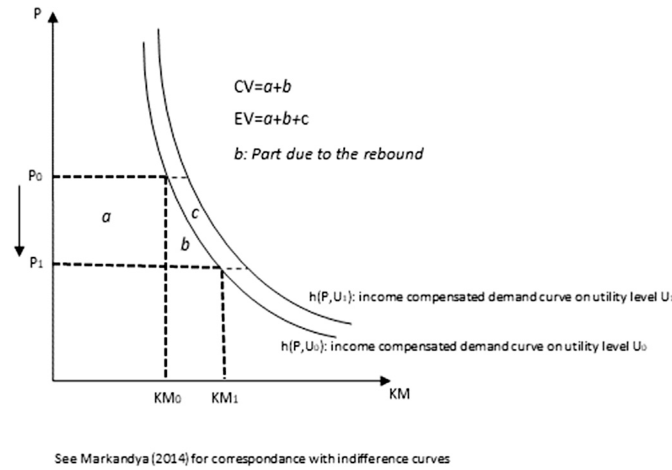

Fig. 5. Compensating & equivalent variation.

The CV and EV are illustrated in Fig. 5: After an efficiency improvement, the price per km decreases from P_0 to P_1 and the kilometers driven increase (rebound effect). Only the part of the CV due to the rebound, part *b*, is kept in this article. The extra surplus from the price decrease (part *a*) is removed, since this part is not caused by the rebound and would still exist if the rebound was zero.

Another simple way to measure the surplus would be to compute the Marshallian consumer surplus. For small efficiency improvements (up to 10%), the Marshallian surplus and the CV (or EV) are very similar, as shown by Araar and Verme (2019). As soon as the improvements are larger, the Marshallian consumer surplus is unfortunately not a precise measure of the true consumers' surplus. On the contrary, CV is a very precise measure, even in the case of large efficiency improvements (Araar and Verme, 2019). Since efficiency improvements – and consequently the price variations – are between 0 and 76% in our case, with an average of 33%, the CV is a better measure than the Marshallian surplus.

To apply Hausman's method, a price variable is necessary in the CV equation to depict the cost of one kilometer driven. So, instead of the fuel intensity, I use the variable P in Eq. (1). P is the implicit price of one km driven, that is, the fuel price multiplied by the fuel intensity.[18] 1.54 CHF is used for the fuel price; it is the mean fuel price of gasoline in Switzerland for the sample.

Eq. (1) then becomes:

$$km_{i,t} = f_{i,t} O^{\gamma}_{i,t} W^{\phi}_{i,t} P^{\beta}_{i,t} Y^{\delta}_{i,t} \quad (3)$$

β, which was the rebound effect, is now the implicit price elasticity of one km driven. As in Eq. (2), logarithms are used in the regression and the log of income (Y) instead of income is used to derive δ, needed in the CV equation. Results are given in Appendix E. β is slightly lower than in Table 2 (26% for solution 1 and 35% for solution 2). δ, the income elasticity of distance driven, is once 0.13 and once 0.20. In the following equations, an average of 0.17 is kept. The impact on the surplus calculation of using 0.13 of 0.20 is very limited.

[17] Regulation 2019/631 of the European Parliament and of the Council of 17 April 2019 setting CO_2 emission performance standards for new passenger cars.

[18] Only using the fuel price instead of the implicit price of one km driven would not be sufficient in the CV equation.

Table 4
Surplus from additional driving.

Rebound level	Average surplus	Range
25%	6.3 cents per km	0.1–19.7 cents per km
30%	6.8 cents per km	0.1–21.1 cents per km
40%	7.9 cents per km	0.1–24.7 cents per km

Notes: The surplus calculated is part b in Fig. 5. N = 3217.

To estimate the compensating variation according to Hausman's method, we need first to describe the indirect utility function, which is given by:

$$v(P,Y) = c = f_{i,t}O^{\gamma}_{i,t}W^{\phi}_{i,t}\frac{P^{1+\beta}_{i,t}}{1+\beta} + \frac{Y^{1-\delta}_{i,t}}{1-\delta} \tag{4}$$

where c, the constant of integration, is chosen as $c = u_0$ (the initial utility level). Inverting the indirect utility function gives the expenditure function:

$$e(P,\bar{u}) = \left\{(1-\delta)(\bar{u} + e^{\omega}\frac{P^{1+\beta}_{i,t}}{1+\beta})\right\}^{1/(1-\delta)} \tag{5}$$

ω standing for $f_{i,t}O^{\gamma}_{i,t}W^{\phi}_{i,t}$ and $\bar{u}$ for the pre-defined utility level.

Following Hausman, the compensating variation is then computed as:

$$\begin{aligned} CV_i &= e(P_{1,i}, u_{0,i}) - Y_i \\ &= \left\{ \frac{(1-\delta)}{(1+\beta)Y_i^{\delta}}[P_{1,i}km_{1,i} - P_{0,i}km_{0,i}] + Y_i^{(1-\delta)} \right\}^{1/(1-\delta)} - Y_i \end{aligned} \tag{6}$$

The CV is calculated for three rebound levels (β) in the range found in this article: 25, 30 or 40%. P_0 and P_1 are the prices per km before and after the efficiency improvement[19], km_0 is reported in the survey, km_1 is simulated for each household according to their new car fuel efficiency and to the rebound level, Y is given in the survey, and the income elasticity (δ) is 0.17.

The CV is therefore different for each household and depends in large part on the efficiency improvement faced by each of them. A variation in income or in income elasticity has only a very small impact on the CV. The surplus from the rebound (part b in Fig. 5) is then calculated from this CV by subtracting the part of the surplus coming from the implicit price decrease (part a).

5.2. Surplus calculation: Results

The utility surplus from additional driving is calculated as the compensating variation (CV) minus its price decrease part. The average surplus is between 6 and 8 cents per extra km, depending on the rebound level. The surplus can exceed 20 cents per extra km for some households. Results are shown in Table 4 and a histogram of the surplus is provided in Appendix F (for a rebound level of 30%). The heterogeneity across households is explained in a large part by the different efficiency variations faced by each of them. For instance, households experiencing an improvement between 10% and 20% have an average surplus due to the rebound of 1.6 cents per km, while those experiencing an improvement between 50% and 60% display an average surplus of 11 cents per km (using a rebound level of 30%).

[19] P_1 varies only because fuel efficiency improves since the fuel price is kept constant. The level of the improvement is tailored to each household and is given by new 2020 EU fuel standards.

5.3. External costs

Besides the utility gains, external costs need to be estimated. To measure driving externalities, the Swiss government estimations are used (Swiss Federal Office for Spatial Development, 2020, 2018). They are very exhaustive, as explained in the review of literature. The estimations of passenger cars' external costs are available for 2017 (except 2015 for congestion costs). Table 5 shows them.

Divided by the number of kilometers driven in Switzerland in 2017[20], the external costs represent 15 cents per km. For a comparison, the tax per km that trucks pay in Switzerland – the tax should cover their external costs – was on average 98 cents per km in 2019, and the minimal tax for the least pollutant mid-sized truck was about 40 cents per km.[21] 15 cents per km for passenger cars seems therefore reasonable.

5.4. Conclusion and policy implications

In the next years, a massive efficiency improvement in vehicles is expected in the European Union and in Switzerland, with the new car fleet emissions set on average to 95 g of CO_2 per km. For Switzerland, it represents a 31% efficiency improvement compared to the 2019 average. Such fuel efficiency improvements reduce the cost of driving, encouraging people to drive more. Therefore, a portion of the expected energy savings is lost, a phenomenon known as the direct rebound effect.

A debate exists at the political level about how to reduce or prevent this effect. However, before planning a rebound mitigation, it is necessary to understand the welfare implications of the rebound: On the one hand, people driving more benefit from a utility increase, but on the other hand, driving more generates external costs such as air pollution, congestion, noise, accidents, etc. This is one of the first paper to quantify the surplus gains from additional driving due to the direct rebound and to compare these gains to the external costs of driving.

To undertake this welfare analysis, a rebound estimation is first carried out with panel data and with household fixed-effects regressions. The vehicle fuel intensity elasticity is used, and a rebound between 30% and 40% is found. A novelty is brought by the use of self-stated vehicle fuel consumption, which is very rare in the rebound literature. Usually, car manufacturers data are employed. In Europe, these values are known to be heavily downward biased. This gap between real-world and theoretical fuel consumption is investigated in this paper, as well as its impact on the rebound estimation. I find that the gap is larger for the more efficient vehicles (32% in 2017) than for the less efficient ones (only 15% in 2017). This difference brings a downward bias in the rebound estimation when manufacturers data are employed, as tested in this paper.

Once the direct rebound is estimated, the additional surplus stemming from it can be calculated for each household. The seminal Hausman method for consumer's surplus estimation is applied, and an average of 7 cents per extra km is found. The same average direct rebound was applied to all households, this is one limitation of the paper. A heterogeneous rebound could be estimated and then applied to each household in future research. This will probably not modify the average surplus of 7 cents per km, but it would bring more heterogeneity in the surplus gains.

In opposition to the surplus gains, external costs – taken from government estimations – are twice higher, on average 15 cents per km.

[20] Source for the number of km in 2017: Federal Statistical Office, "Transport de personnes: prestations kilométriques et mouvements des véhicules". Total km driven in the country in 2017 with passenger cars: 58,735 million.

[21] The tax depends on the truck's emission level and weight. More information here: www.ezv.admin.ch/ezv/en/home/information-companies/transport--travel-documents--road-taxes/heavy-vehicle-charges--performance-related-and-lump-sum-/hvc---general---rates.html.

Table 5
External costs in Switzerland in 2017 [CHF per year].
Source: Swiss Federal Office for Spatial Development (2020, 2018).

Health costs due to air pollution	≈2.2 billion or 4 cents per km [CHF]
Congestion costs	≈1.4 billion or 2 cents per km [CHF]
Climate costs	≈1.3 billion or 2 cents per km [CHF]
Noise costs	≈1.3 billion or 2 cents per km [CHF]
Accident costs	≈0.7 billion or 1 cent per km [CHF]
Nature & Landscapes damages	≈0.8 billion or 1 cent per km [CHF]
Other costs (indirect emissions from car making/scrapping, damages to buildings due to pollution, biodiversity losses, etc.)	≈1.3 billion or 2 cents per km [CHF]

They include a wide range of driving externalities, with the major ones being air pollution damages, climate costs, congestion costs and noise costs. The evolution of external costs with more efficient vehicles was not examined in this article, and further research could be conducted on this, especially with the soar in electric vehicles which emit no harmful particles.

In the case of Switzerland, one might argue that fuel is highly taxed and that the external costs from driving are already internalized by consumers. The gasoline tax in Switzerland was in 2021 76.82 cents per liter. For an average car consuming 7.2 liters for 100 km, this translates to 5.5 cents per km. If those 5.5 cents were redirected to pay for the external costs, 9.5 cents per km would still be needed to fully internalize the external costs, so more than the 7 cents of surplus gains. Moreover, redirecting the entire 5.5 cents to pay for external costs is not judicious, because half of them (2.75 cents per km) is already earmarked for tasks related to road traffic (road maintenance for instance). If drivers stop paying for these tasks through the fuel tax, the whole society will be asked to pay for them, creating new costs that are not internalized by drivers.

This gap between the private surplus from the rebound and its societal costs supports policies to “mitigate” the rebound effect. Nevertheless, policymakers should first consider policies to address these external costs. Indeed, if they diminish, the rebound could turn beneficial. In the future, external costs (in cents per km driven) are likely to decrease as vehicles become more efficient or electric. Only congestion and accident costs will presumably increase (more vehicles and more km driven)[22]; the other major external costs – being associated with the polluting emissions of vehicles – will diminish with the shift to more efficient/electric vehicles. The gap between the private surplus and the external costs will then probably be reduced in the future.

Another set of policies to consider should be policies to internalize external costs. A considerable part of them are not supported by those who cause them, but are supported by the community or future generations. Since drivers do not support these costs themselves, they travel more often and further than if they had to. By internalizing these costs, the rebound would mechanically be mitigated as the price per km would increase. One option is to increase the fuel tax, however it is politically difficult to do so, particularly in Switzerland where such decisions need to be approved by the majority of the population by vote. Other new taxes or new mechanisms could promise better results and acceptance: a tax per km driven, a bonus mechanism on the car insurance when the car is used less than a threshold, or a penalty if the car is driven more for instance.

Given that a tax per km driven already exists for trucks in Switzerland, an extension of it to private cars seems conceivable. However, for acceptance, such policies should take into account that households would be affected differently by it: rural areas will be more affected than urban areas, lower-level income households would face a greater burden than affluent households, etc. A well-designed redistribution scheme could be a solution, and rebound effect studies can contribute to this redistribution discussion. Individuals who rebound the most are those gaining the most from efficiency improvements, and they are also likely to be those losing the most if the price of the energy service increases. Hence, understanding better rebound heterogeneity will allow to design better redistribution plans.

Finally, policies that tackle directly the level of energy consumption could be investigated, for example by informing consumers that driving fuel-efficient cars is not enough, but that an absolute reduction in fuel/energy usage is needed. Such policies would be more efficient if high energy consumption groups are targeted rather than high rebound groups, as suggested by Galvin (2015).

The results of this article are comparable only to the results of Alfawzan and Gasim (2019), since they provide the only other empirical analysis of the direct rebound welfare implications. Their results for Switzerland, among many other countries, are very close to the results found in this paper. They also calculate the consumer surplus gained from additional driving and compare it to external costs. The ratio is 0.4 for Switzerland, and is, for most countries, below one, pointing to a welfare reduction from the direct rebound. In this analysis, the ratio found is 0.47 (7 cents/15 cents), hence also pointing to a welfare reduction. The closeness of the two ratios is striking, knowing that the methods used in each article are very different (Alfawzan and Gasim, 2019 use aggregated data at the country level for 2010). They also find, as in this paper, that the level of the direct rebound considered in the calculations does not strongly alter their conclusions on the welfare implications of the rebound.

This work thus provides one of the first empirical estimation on the net welfare change from the rebound in private mobility. Additional work on this topic is needed to gather results from different methods and different countries. An interesting point would be to study further the heterogeneity of individual surplus gained from the rebound. For some households, the surplus is indeed larger than the external costs, i.e. the rebound is welfare-enhancing. What are the characteristics of such households? Do less affluent households benefit more from the rebound? Is the surplus distribution linked to the share of the gasoline expenses in the consumption basket of households? These questions should be the next step of research on the welfare implications of the rebound effect in private mobility. Future research on the negative and the positive outcomes of the rebound effect could also be undertaken outside of an economic perspective, for instance by studying the impacts of driving more on the health, if less cycling or walking is undertook as a consequence, or by studying the rationales of driving more (is it to go more often to the gym, or to visit relatives, which are supposed to be good for the health?)

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data and code can be shared only on request. The person must sign a contract with the data curator, the Swiss Household Energy Demand Survey (SHEDS).

[22] Although it is unclear for accident costs because smarter vehicles could decrease the number and the severity of accidents.

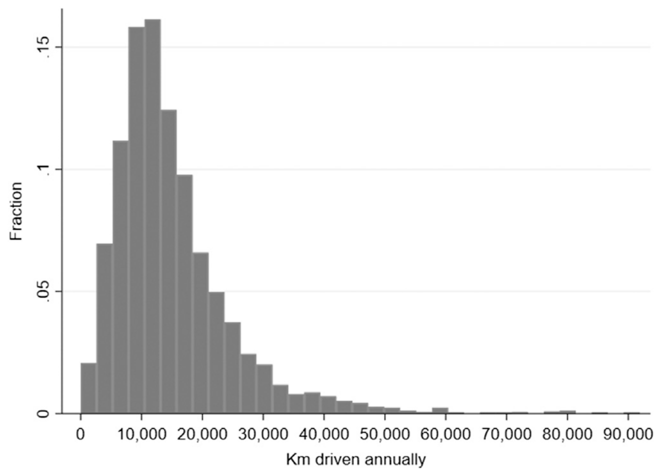

Fig. B.1. Distribution of km driven. *Notes:* N = 3235.

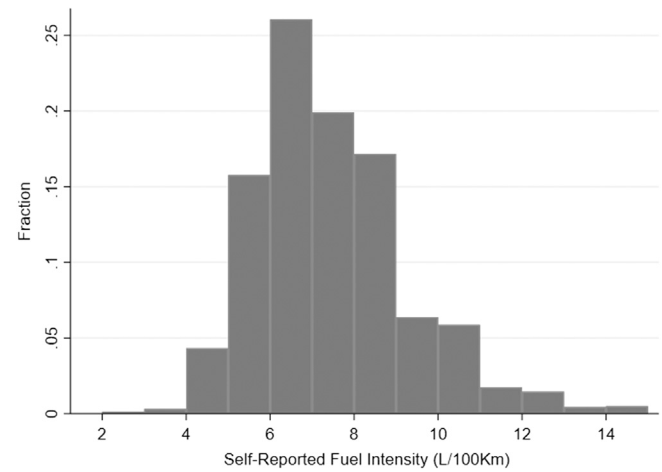

Fig. B.2. Distribution of fuel intensity. *Notes:* N = 3235.

Appendix A

Matching each car with data from manufacturers

In this article, the purpose of the data from manufacturers is to collect the weight and the fuel consumption of each car. The most refined matching level would be the exact car model *version*. However, the version was not asked in the survey because very few respondents would have known it. Instead, the matching was done on six characteristics known by the respondents: the car manufacturer, the car model, the first registration year, the fuel type, the transmission type (manual or automatic) and the number of doors. Then, the weight and the fuel consumption were averaged over all the versions with these six identical characteristics. Here is an example:

- All VW Golf from 2012, powered by gasoline, with 5 doors, and automatic transmission have the same manufacturer fuel consumption of 6.1 L/100 km.
- All VW Golf from 2012, powered by gasoline, with 5 doors, but manual transmission, have a manufacturer fuel consumption of 6.2 L/100 km.

The car weight was averaged the same way.

Appendix B

See Figs. B.1 and B.2.

Appendix C

See Fig. C.1 and Table C.1.

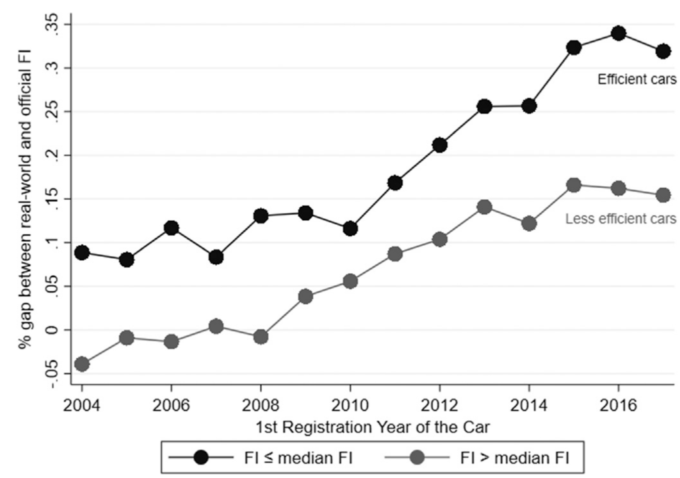

Fig. C.1. Divergence in fuel intensity (FI) for cars below or above the FI median. *Notes:* The median FI is calculated for each first registration year. For cars below or at the median ("efficient" cars), real-world fuel consumption was on average 20% higher than data from manufacturers between 2004 and 2017. For cars above the median (less efficient cars), the divergence was on average only 5.5% (N = 12,034).

Appendix D

Fuel efficiency & fuel intensity rebound

Fuel Intensity (FI) = Liter/km Fuel Efficiency (FE) = km/Liter FI = 1/FE

In this example, the direct rebound based on the fuel intensity is shown to be the same as the rebound based on the fuel efficiency. The rebound effect can be measured by the difference between potential and actual energy savings following an efficiency improvement, or directly as the lost part of the expected energy savings. Fig. D.2 summarizes the example given here:

Let us assume an initial fuel intensity of 7 liters per 100 km, that is, a fuel efficiency of 14,29 km per liter. After an efficiency improvement following a car change, the same individual is now driving a car of 5 liters per 100 km, or 20 km per liter. The potential energy savings (PES) are:

- with FI: 28.6% [(7 − 5)/7]
- with FE: 40% [(20 − 14.29)/14.29]

Rebound Calculus with Fuel Intensity:

If 12,000 km are driven per year:

- with 7 l/100 km: 840 l used per year
- with 5 l/100 km: 600 l used per year

Hence, with no direct rebound, 240 l are saved (28.6% = PES).
If a 30% direct rebound is assumed:

- 30% of the saved 240 l are lost: $0.3 * 240 = 72$ l. 72 l over 840 l = 0.086% (=Lost ES)
- Only 168 l are finally saved (20% = AES)

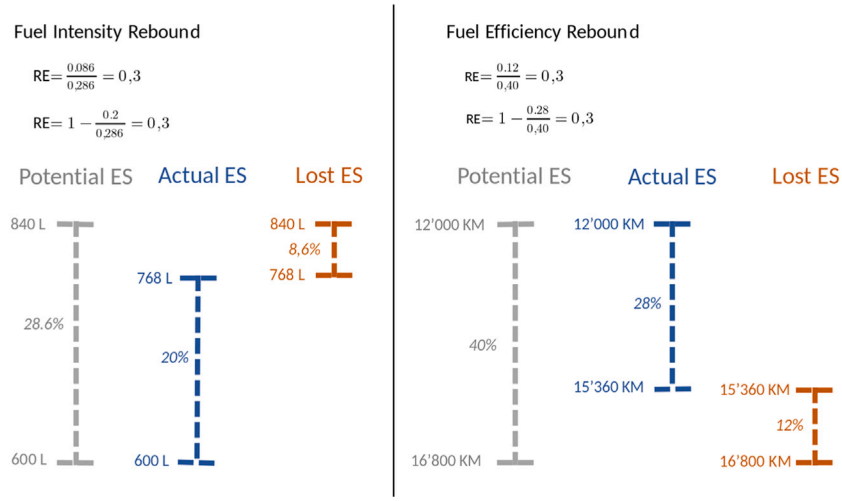

Fig. D.2. Fuel intensity & fuel efficiency rebound. *Note:* ES = Energy Savings. The direct rebound can be estimated directly as the ratio of the Lost ES over the Potential ES, or as 1 - (Actual ES/Potential ES).

Table C.1
Bias direction test: Underestimation of the rebound (Fixed-effects at the household level).

	Solution 1 Mean fuel intensity	Solution 2 Before/After car change
Ln(Fuel intensity)	−0.195*	−0.337***
	(0.102, 0.057)	(0.127, 0.008)
Ln(Car weight)	0.335**	0.492**
	(0.160, 0.036)	(0.197, 0.013)
Diesel	0.147**	0.105
	(0.062, 0.017)	(0.073, 0.148)
Automatic transmission	0.010	0.016
	(0.049, 0.834)	(0.058, 0.782)
Number of doors	0.035	0.015
	(0.031, 0.266)	(0.040, 0.705)
Ln(Nmb years car owned)	0.040**	0.066***
	(0.016, 0.016)	(0.020, 0.001)
Commute by car	0.081**	0.056
	(0.039, 0.035)	(0.059, 0.344)
Income	0.042**	0.045
	(0.018, 0.022)	(0.033, 0.175)
Education	0.012	−0.016
	(0.021, 0.576)	(0.046, 0.726)
Children	0.070	−0.076
	(0.055, 0.202)	(0.132, 0.565)
HH size	−0.041*	−0.010
	(0.022, 0.056)	(0.037, 0.788)
Rail pass	−0.052	−0.265**
	(0.058, 0.373)	(0.134, 0.048)
Constant	7.055***	6.669***
	(1.073) (0.000)	(1.272) (0.000)
County FE	YES	YES
# Observations	3235	1580
# Individuals	1065	790

Notes: In parentheses: robust standard errors, p-values. *p < 0.10, **p < 0.05, ***p < 0.01. Fixed-effects are used. For each car registration year, the 50% most efficient vehicles had a 20% decrease in their fuel intensity (FI), to better match car manufacturers values. The goal is to test the bias direction of underestimating more the FI of the most efficient cars, as it exists in manufacturers' data. The rebound found here is lower than in Table 2. Thus, using manufacturers' data may bias the rebound downward.

$\Rightarrow RE = 1 - (AES/PES) = 1 - (0.2/0.286) = 0.3$

$\Rightarrow RE = LES/PES = 0.086/0.286 = 0.3$

Rebound Calculus with Fuel Efficiency:

If 840 l are consumed over one year:

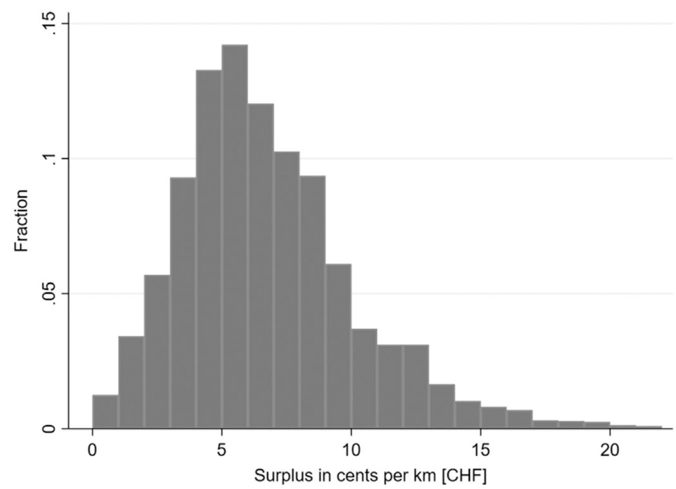

Fig. F.3. Individual surplus. *Notes:* Individual surplus from the rebound (part b from Fig. 5) for a rebound level of 30% (N = 3217).

- with 14,29 km per liter: 12,000 km driven per year
- with 20 km per liter: 16,800 km driven per year

Hence, with no direct rebound, a 40% (=PES) increase in the km driven are possible (+4800 km) thanks to the efficiency improvement.

If a 30% direct rebound is assumed:

- 30% of the extra 4800 km are lost: $0.3 * 4800 = 1440$ km
- Total km driven per year = 15'360 km

Hence, the increase in driving is +3360 km (28%), which is also the actual energy savings (AES).

$\Rightarrow RE = 1 - (AES/PES) = 1 - (0.28/0.40) = 0.3$

$\Rightarrow RE = LES/PES = 0.12/0.4 = 0.3$

In terms of elasticities, this example translates to:

$$\boxed{RE = -\frac{\partial Ln(km)}{\partial Ln(FI)} = 1 - \frac{\partial Ln(l)}{\partial Ln(FI)} = \frac{\partial Ln(km)}{\partial Ln(FE)} = 1 + \frac{\partial Ln(l)}{\partial Ln(FE)}}$$

In this paper, I use the first elasticity, as described in Eq. (2), but all the other three elasticites could be used instead, with the same results.

Table E.1
Implicit price (Fixed-effects at the household level).

	Solution 1 Mean fuel intensity	Solution 2 Before/After car change
Ln(Implicit price)	−0.262** (0.115, 0.023)	−0.345*** (0.132, 0.009)
Ln(Car weight)	0.310** (0.147, 0.035)	0.371** (0.170, 0.029)
Diesel	0.171*** (0.056, 0.002)	0.159** (0.063, 0.012)
Automatic transmission	0.010 (0.048, 0.830)	0.012 (0.058, 0.841)
Number of doors	0.034 (0.031, 0.269)	0.011 (0.040, 0.787)
Ln(Nmb years car owned)	0.037** (0.016, 0.021)	0.061*** (0.020, 0.002)
Commute by car	0.084** (0.039, 0.029)	0.072 (0.059, 0.225)
Ln(Income)	0.135*** (0.047, 0.004)	0.202** (0.081, 0.013)
Education	0.015 (0.021, 0.476)	−0.002 (0.046, 0.964)
Children	0.072 (0.054, 0.183)	−0.077 (0.132, 0.558)
HH size	−0.045** (0.022, 0.038)	−0.021 (0.038, 0.585)
Rail pass	−0.050 (0.058, 0.394)	−0.256* (0.133, 0.055)
Constant	4.867*** (1.339, 0.000)	3.875** (1.606, 0.016)
County FE	YES	YES
# Observations	3235	1580
# Individuals	1065	790

Notes: In parentheses: robust standard errors, p-values. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Fixed-effects are used. For solution 1, each household appears at least twice and maximum five times. For solution 2, each household appears twice.

Appendix E

See Table E.1.

Appendix F

See Fig. F.3.

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