Université de Neuchâtel
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AN EMPIRICAL ANALYSIS OF HOUSEHOLD DIRECT AND INDIRECT REBOUND EFFECTS

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An empirical analysis of household direct and indirect rebound effects

Cécile HEDIGER

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Abstract

This thesis investigates how households react to improved energy efficiency in residential heating (Chapters 1 and 2) and in private transportation (Chapter 3). Since efficiency gains may lead to a price decrease of the energy service in question, households could decide to consume more of this service. Households may also decide to consume more of other goods or services thanks to the savings made after the efficiency improvement. Both effects offset parts of the initial potential energy savings.

The data used in the three chapters comes from an annual survey on household energy demand in Switzerland. The survey spans seven years and builds a rich and novel panel dataset for Switzerland. About 5000 households were surveyed each year, and as many households as possible were kept in all the survey waves. This thesis was written at the same time the survey was running, so not all survey years were already existing and available for each chapter. Thus, while Chapter 1 is based only on the first wave, Chapter 2 and Chapter 3 use respectively six and five waves (Chapter 2 was written the last) and can therefore take advantage of the panel dataset.

The first chapter is based on the stated preference approach with an innovative choice experiment. The design includes questions to quantify both the direct and indirect rebound effects. Overall, relatively low direct rebound effects are found for heating in the residential sector. However, after accounting for the indirect rebound, the average total rebound is estimated at about one third, meaning that one third of the expected energy savings after an efficiency improvement are lost.

The second chapter also explores households' adjustments to efficiency gains in heating, but revealed preferences are used instead of stated preferences. First, an increase in temperature for households living in more efficient dwellings is studied (direct rebound). Second, the energy embodied in the re-spending of the efficiency gains savings on other goods and services than heating is assessed (indirect rebound). Overall, about 20% of the potential energy savings are taken back by those households adjustments, with a direct rebound estimated between 4% and 8%, and an indirect rebound of 15%. In addition, low income households are found to increase more their heating usage than affluent households, indicating that buildings retrofits have the potential to substantially improve the living conditions of the poorest households.

The third chapter analyses households' reactions to an efficiency improvement of their private vehicle. In the European Union and in Switzerland, much tighter fuel economy standards for new vehicles came into force in 2020. Such standards reduce the vehicle usage cost, encouraging people to drive more. Whether and how to prevent this rebound effect is an ongoing policy debate, yet almost no economic analysis of the welfare implications of the rebound exists. To fill this gap, the direct rebound effect for private vehicles in Switzerland is calculated first, and is found to be around 30% to 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 an internalization of external costs, for instance with a tax on the distance driven, or an insurance penalty when a certain limit of kilometer is exceeded.

Keywords: Energy efficiency, energy policies, rebound effects, households energy consumption, residential heating demand, private mobility, panel data.

JEL Classification : D12, D61, D62, D90, Q40, Q47 Q48, R22, R41

Résumé

Cette thèse aborde la question de la manière dont les ménages réagissent à l'amélioration de l'efficacité énergétique dans deux domaines: le chauffage (chapitres 1 et 2) et la mobilité privée (chapitre 3). Etant donné que des gains en termes d'efficacité énergétique entraînent une baisse du prix du service énergétique en question, les ménages pourraient décider de consommer davantage de ce service. En outre, grâce aux économies financières réalisées après ce gain d'efficience, les ménages pourraient également consommer davantage d'autres biens ou services. Ces deux effets vont contrebalancer une partie des économies d'énergie prévues initialement.

Les données utilisées dans les trois chapitres de cette thèse proviennent d'une enquête annuelle portant sur la consommation d'énergie des ménages en Suisse. L'enquête, s'étendant sur sept ans, constitue un ensemble riche et nouveau de données longitudinales. Environ 5000 ménages ont été interrogés chaque année et tout a été mis en oeuvre pour qu'un maximum d'entre eux soient conservés lors des différentes vagues de l'enquête. Comme cette thèse a été rédigée durant la période de l'enquête, le nombre de vagues disponibles diffère selon les chapitres. Ainsi, alors que le chapitre 1 ne se base que sur la première année d'enquête, les données longitudinales de respectivement six et cinq vagues d'enquête sont utilisées dans les chapitres 2 et 3 (le chapitre 2 ayant été écrit en dernier, une vague supplémentaire par rapport au chapitre 3 était disponible).

En détail, le premier chapitre est basé sur l'approche des "préférences déclarées" (stated preferences) et comprend une expérience innovante concernant la consommation d'énergie des ménages pour le chauffage. Le questionnaire inclut des questions pour mesurer l'effet rebond direct ainsi que l'effet rebond indirect dans le domaine du chauffage des ménages. Dans l'ensemble, des effets de rebond directs relativement faibles sont constatés. Cependant, après la prise en compte du rebond indirect, le rebond total moyen est estimé à environ un tiers, signifiant qu'un tiers des économies d'énergie attendues après une amélioration de l'efficacité énergétique du système de chauffage est perdu.

La réaction des ménages à un gain d'efficacité dans le domaine du chauffage est également étudiée dans le deuxième chapitre de cette thèse. Cette fois-ci, la méthode des "préférences révélées" (revelead preferences) est utilisée. Dans la première partie, une augmentation de la température intérieure (effet rebond direct) pour les ménages vivant dans des logements peu gourmands en énergie est étudiée, par rapport à des ménages vivant dans des logements moins efficients. Dans la deuxième partie, l'énergie contenue dans les biens et services acquis suite aux économies d'énergie est mesurée (effet rebond indirect). Dans l'ensemble, environ 20% des économies d'énergie potentielles sont contrebalancées par ces deux effets: le rebond direct est estimé entre 4% et 8% et le rebond indirect à environ 15%. En outre, on constate que les ménages à faibles revenus augmentent davantage leur consommation de chauffage que les ménages aisés après une rénovation énergétique, indiquant que la rénovation des bâtiments peut considérablement améliorer les conditions de vie des ménages les plus pauvres.

Le troisième chapitre de cette thèse analyse les réactions des ménages à une amélioration de l'efficacité de leur véhicule privé. En 2020, de nouvelles normes concernant la consommation de carburants des voitures neuves sont entrées en vigueur en Suisse et dans l'Union européenne, réduisant le coût d'utilisation des véhicules pour les individus. Cette réduction de coût peut encourager les individus à conduire davantage. Cet effet rebond amène un débat pour savoir s'il faut le limiter et par quel moyen. Pourtant, il n'existe pratiquement aucune analyse économique des conséquences de cet effet rebond sur le bien-être des individus et de la société. Ce chapitre comble en partie cette lacune. En premier, l'effet rebond direct est calculé pour les véhicules privés en Suisse. Un rebond entre 30% et 40% est mesuré. Ensuite, l'utilité additionnelle de conduire davantage est estimée pour chaque ménage, une estimation en moyenne de 7 centimes par kilomètre supplémentaire. Finalement, ce montant est comparé aux coûts externes de la conduite en Suisse, qui sont d'environ 15 centimes par kilomètre. Cet écart plaide en faveur d'une internalisation des coûts externes, par exemple en élaborant une taxe sur la distance parcourue ou en introduisant une pénalité lorsqu'une certaine limite de kilométrage est dépassée.

Mots-clés : Efficacité énergétique, politiques énergétiques, effets rebonds, consommation d'énergie des ménages, chauffage résidentiel, mobilité privée, données longitudinales.

Classification JEL : D12, D61, D62, D90, Q40, Q47 Q48, R22, R41

Acknowledgments

Success is a journey, not a destination. The doing is often more important than the outcome. Arthur Ashe

This quote perfectly applies to a PhD thesis. Obviously, to finish it and publish articles is a rather appreciated outcome, but the most precious gift is what you learn during the journey. Science is truly unique to human beings, and to understand what it is, how it is made, and how to be a good scientist is an invaluable accomplishment. This will change the way you think for the rest of your life. And for that, I am infinitely grateful to my mentor, Mehdi Farsi, who trusted me since day one. I would probably not have embarked on this journey if he had not encouraged me to. His scientific guidance was excellent, and he always gave me the freedom to pursue my own ideas. Thanks to him, I had the chance to design an entire survey for the needs of our project, survey that spanned over many years and that provided the substantial core of this thesis.

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Introduction

Energy is by far the largest source of greenhouse gases (GHGs), accounting for two-thirds of global GHGs emissions in the world. Many countries have started their energy transition to reduce their fossil fuels dependence and curb their GHGs emissions. One core element of their transition, alongside clean energy, is energy efficiency. In Switzerland, the largest potential efficiency gains stand in buildings, transports, and industry (SwissEnergy, 2019). However, effective energy savings might be lower than predicted savings, due to rebound effects. Indeed, when an energy service, such as heating or traveling by car, becomes more efficient, the price per unit of service decreases since less energy is needed. Consumers may adjust to this price diminution by consuming more of the energy service. This increased consumption offsets parts of the anticipated energy savings and constitutes *the direct rebound effect.* The direct rebound is calculated as the percentage of energy savings which is lost due to behavioral adaptations.

The concept of rebound dates back to 1866, when Jevons (1866) described how industrial efficiency gains would generate an increase in resource consumption rather than a decrease. Over time, research on rebound effects has flourished in different sectors; in particular to investigate whether energy efficiency could lead to *greater* energy consumption instead of fewer, as described by Jevons and coined backfire. Although backfire has often been ruled out, research shows that a non-negligible part of expected energy savings might still disappear due to rebound effects (Gillingham et al., 2013).

Households, accounting for 32% in final energy consumption in Switzerland (FSO, Environmental accounting), will play a key role in the energy transition. As they mostly consume energy for heating and transport, energy efficiency improvements for these two sectors are fundamental for the energy transition. In this thesis, I study rebound effects at the household level for these two sectors. Some of the questions I try to answer are the following: Do rebound effects exist in these sectors at the household level, and if yes, what is their magnitude? Are we at risk of backfire? Is there a rationale to limit the rebound effect in some ways? What happens with the remaining savings that are made thanks to the efficiency improvements? How much of them are spent on energy intensive goods and services?

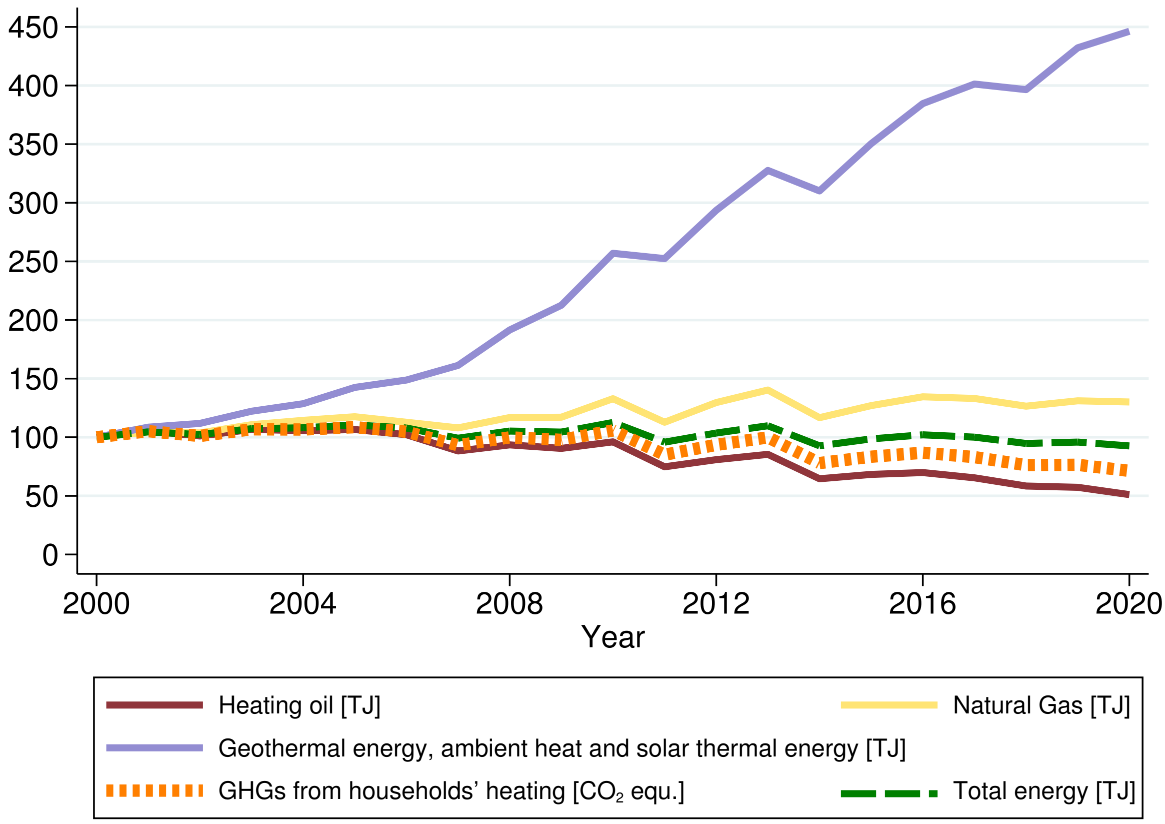
These last two questions refer to another type of rebound: *the indirect rebound effect.* While the direct rebound relates to increased consumption of the good or service directly impacted by the efficiency improvement, the indirect rebound concerns increased consumption of all other goods and services. If only some savings are reinvested in the same good after the efficiency improvement (direct rebound), some savings will indeed remain and will be spent on other goods or kept on a bank account. In case of a zero direct rebound, all savings from the efficiency gain will compose the indirect rebound. While the direct and indirect rebound effects, studied in this dissertation, appear at the household level, a macroeconomic rebound effect also exists and relates to economic-wide effects after a fall in real price of energy services. As this dissertation focuses on households, the macroeconomic rebound effect is not studied here, but the reading of Greening et al. (2000); Barker et al. (2007); Saunders (2013) are suggested.

The study and comparison of rebound effects in the heating and transport sectors is of particular interest, because energy used in both sectors evolved quite differently in the past years in Switzerland: while energy for heating decreased between 2000 and 2018 (-16.6%), energy for transports slightly increased (+3.1%) according to estimations of Infras et al. (2019). Despite an overall decrease of 3.8% in energy consumption between 2000 and 2018, the 2020 CO_2 emissions reduction targets have been missed. The next decade will therefore be crucial to meet the Swiss Energy Strategy target of 43% reduction of energy consumed per person by 2035 compared to 2000, and energy efficiency is expected to play a key role.

For buildings, the next target is a reduction of 20% of the energy used by 2030 compared to 2015 (SwissEnergy, 2019). The main tool is a large subsidy program (Programme Bâtiments) promoting energy efficient refurbishments and renewable energy. In the past years, energy used for heating has diminished in Switzerland, but the pace of the reduction needs to accelerate to meet the 2030 goals. Figure 1 shows the trends from 2000 for the total energy used by households for heating, GHGs (in CO_2 equivalent) from this sector and the evolution of different heating energy sources. Between 2000 and 2020, GHGs decreased by 29%, which is more than the decrease in total energy (-7%). This decoupling effect happened thanks to the diminution of heating oil usage and the increase of renewable energy, mainly solar and geothermal energy.

In private mobility, the objectives are much less ambitious than in buildings. No specific energy reduction target is set for 2030 in Switzerland, but different objectives are outlined; among them, a reduction of 37.5% of CO_2 emitted by new vehicles between 2021 and 2030, and a vehicle fleet composed at 38% by electrical vehicles by 2030. The difficulty of reducing energy and GHGs emissions from private transport is a worldwide challenge, and despite improvements in vehicle efficiency, GHGs emissions from this sector are stable in many countries, including Switzerland. Trends in efficiency, CO_2 emissions, vehicle weight and traveled kilometers are sketched in Figure 2, showing that (parts of) efficiency gains have been offset by more kilometers traveled and heavier vehicles in the past years.

Figure 1: Trends in Households' Heating Energy in Switzerland

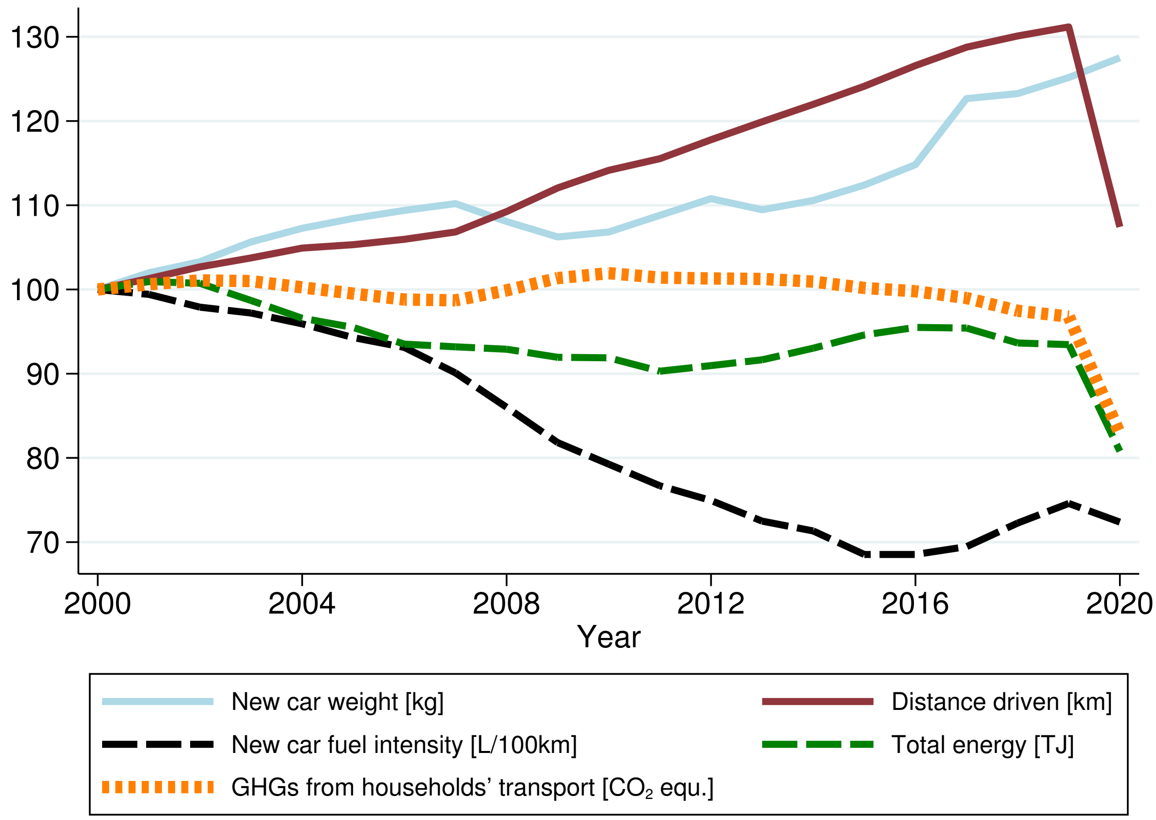


Notes: 2000 values are set to 100 for all variables. All data refers to households' heating. Data on total energy and energy sources comes from the Physical Energy Flow Account and are different from the estimations made by Infras et al. (2019) who use different aggregation rules. *Source*: Federal Statistical Office: Physical Energy Flow Account, Household Air Emissions Accounts

To anticipate the effectiveness of these efficiency programs, rebound effects in residential heating and private transportation need to be known. Chapters 1 and 2 of this thesis deal with space heating direct and indirect rebounds, while Chapter 3 is devoted to the study of the direct rebound for private vehicles. The data used in all chapters comes from a large novel survey on energy consumption of Swiss households (SHEDS – Swiss Households Energy Demand Survey). The survey started in 2015 and lasted 7 years, with about 5,000 households surveyed each year. From one year to another, as many households as possible were kept in order to benefit from panel data.

More specifically, in Chapter 1, direct and indirect rebounds for heating are investigated using a choice experiment based on stated preferences. First, respondents answered to a series of questions about their potential reactions to an efficiency improvement of their heating system, such as setting the thermostat higher or extending their heating usage earlier/later in the season. Second, they were asked to estimate their increased heating usage quantitatively. Finally, a re-spending task was performed. Our main finding is a total rebound of about one-third, meaning that a third of predicted savings from heating

Figure 2: Trends for Passenger Cars in Switzerland



Notes: 1996 values are set to 100 for all variables. Data on new car fuel intensity comes from car manufacturers and does not necessarily reflect real-world driving conditions. The drop in 2020 is linked to the restrictive measures to fight against the Covid-19 pandemic, but 2021 data will be back to levels close to 2019. *Source*: Federal Statistical Office: New vehicle fleet statistics, Passenger transport services statistic, Greenhouse gas inventory

efficiency improvements are canceled out. The direct rebound is found to be around 12%, and the indirect rebound around 24%. Our results also indicate a strong heterogeneity across households, for both direct and indirect rebounds. For instance, almost one out of three people would not react to heating efficiency gains (zero direct rebound). This variation in rebound is partly explained by observable characteristics such as income, education and house ownership status. In particular, lower-level income households rebound the most, consistent with the fact that heating, as a basic need, is associated with low rebound once a sufficient level of comfort is achieved.

In Chapter 2, panel data are taken advantage of, with the use of six survey waves. A partial direct rebound is identified in two steps. First, I examine whether households in efficient buildings heat their dwelling at a higher temperature, with building construction date and accommodation type used as instruments for building efficiency. Second, the indoor temperature increase is translated into energy using the heating degree days method. This engineering method is conventional in the building field, and assumes that a one degree decrease in outdoor temperature requires the same heating energy as a one degree increase in indoor temperature. Although only one specific part of the direct rebound is studied with this identification strategy (the increase in indoor temperature), this action is likely the one asking for the most energy compared to other actions such as extending the heating season or airing more (Palmer et al., 2012). Thus, this temperature rebound makes up a substantial part of the total direct rebound. A partial direct rebound between 4% and 8% is found with a maximum of 11% for poorer households, in line with Chapter 1 estimations. The indirect rebound is also estimated, on average at 15%, using spending shares and energy intensities of 11 categories of goods and services.

In Chapter 3, the direct rebound for private transportation is studied, as well as its welfare consequences. Panel data are again exploited; the rebound identification relies on households changing their vehicle and on variations in kilometers traveled after that change. Here, a larger direct rebound is found, between 30% and 40%. In light of this large rebound and the difficulty of achieving emissions reductions in this sector, I study the welfare costs and benefits of additional driving in the second part. If costs outweigh the benefits, a rationale exists to limit the rebound. However, although different articles discuss how to limit the rebound, very little work has been done on the welfare analysis of the rebound and this Chapter fills this gap. My analysis shows that welfare costs of additional driving are about twice of the private gains, and that the core of the problem are the large driving external costs that are not borne by the drivers. So, instead of directly looking at some ways to restrict the rebound, a more adequate response relies in incorporating these external costs in the price of driving.

To conclude, a limited direct rebound is found for heating (around 10%), but the indirect rebound is non negligible in this sector (between 15% and 20%)[1]. Heterogeneity in rebound levels is also outlined for space heating, with less affluent households displaying higher rebound levels. For passengers cars, a larger direct rebound is estimated, around 30% to 40%, partly explaining why energy reductions are difficult in this sector.

In addition, this thesis sheds light on future paths of research: (i) a deeper analysis of heterogeneity in rebound levels and (ii) more studies on the utility gained from the direct rebound, and the heterogeneity of this surplus among individuals. Determining who benefits the most from efficiency gains and from the rebound is indeed valuable to understand the large heterogeneity in rebound estimations and to understand who will be the most opposed to measures that increase the price of the energy service in question. For instance, in the case of a fuel tax increase, individuals who will be the most opposed to this measure are also probably those who benefit the most from an

[1] The idea that a small direct rebound is accompanied by a large indirect rebound is discussed by Chan and Gillingham (2015) and holds when two (or more) energy services are compared (it might not be true when energy service and nonenergy services are considered).

efficiency improvement of their vehicle. If their utility surplus from additional driving after an efficiency improvement is high compared to other individuals, their utility loss will probably also be high if they need to drive less in case of increasing fuel prices. Thus, understanding who are those individuals is useful to design better policies, for instance implementing a redistribution scheme in their favor if the fuel tax increases.

Another path for future research it the so-called "green" rebound, also known more broadly as moral licensing (if I do something good in one area, I am entitled to behave badly in another area) (Effron and Conway, 2015). The green rebound relates to an increased usage of the energy service because this service is now fueled by clean energy, for instance, feeling entitled to drive longer distances with an electric vehicle than with a gasoline one. Signs of it are found in Chapter 1 (Appendix G); some individuals displayed a higher direct rebound if the energy source of their heating system was renewable rather than non-renewable. Literature on moral licensing applied to energy economics is growing (Jacobsen et al., 2012; Tiefenbeck et al., 2013, for instance). Dütschke et al. (2018) highlight the need to incorporate this psychological aspect to the rebound analysis.

From a public policy perspective, this thesis shows that efficiency improvements will deliver energy savings in the residential heating sector, because the comfort threshold where the direct rebound is zero has already been reached by many people in Switzerland. In addition to dwellings' refurbishments, other policies are needed in the residential sector, for instance a boost of renewable energy, which participates to the decoupling of total energy and GHGs emissions in this sector. We start to see this decoupling in Switzerland in the residential sector: it is the difference between total energy in green and GHGs from heating in orange in Figure 1. Different measures exist to boost renewable energy, such as subsidies, the current CO_2 tax on heating fuel, etc. Forthcoming measures are probably a ban on heating oil, and later on natural gas.

For private transportation, it is a different story. The direct rebound is at least three times larger than for buildings, and only one rebound aspect was investigated here (the increase in traveled distance). Other studies show that purchasing heavier vehicles is also a consequence of efficiency gains (Weber, 2019). Hence, to curb emissions from private transportation, efficiency improvements are not sufficient, and a price increase on combustion car usage seems inevitable. It could be a new tax, for instance on the distance traveled, an increase in existing taxes, or new schemes to tax the most polluting vehicles. Electric vehicles are part of the solution, but combustion cars still compose the vast majority of the vehicle fleet, and will do so for a long time. Large investments in public transportation will also be part of the solution, and could diminish the number of kilometers driven individually.

CHAPTER 1

Turn it up and open the window: On the rebound effects in residential heating

This chapter is co-authored with Sylvain Weber and Mehdi Farsi, and has been published in *Ecological Economics* in 2018, volume 149. This research was supported by the Swiss National Science Foundation Grant 100018-144310. It is also part of the activities of SCCER CREST, which is financially supported by the Swiss Commission for Technology and Innovation (CTI). The authors thank Benjamin Volland, Valéry Bezençon, Ivan Tilov, and participants of the Spring Meeting of Young Economists 2016 and of the Swiss Society of Economics and Statistics Congress 2016 for their helpful suggestions. This paper was previously circulated under the title "Measuring the Direct and Indirect Rebound Effects for Residential Heating in Switzerland".

JEL Classification: D12, Q41, Q47, R22.

Keywords: Rebound effects, energy efficiency, residential heating, double hurdle model, stated preferences, contingent behaviour model, online experiment.

1 Introduction

Energy efficiency is often considered as the "invisible fuel" of the energy transition.[1] In Switzerland, like in many other industrialized countries, large efficiency gains remain feasible in buildings and heating systems. According to SFOE (2016), 37% of Switzerland's final energy consumption is attributable to heating and warm water, promising an important potential for energy savings. Yet, setting ambitious efficiency standards might not be sufficient to achieve the targeted energy conservation level, because a significant part of the expected energy savings could be lost due to behavioural adaptations known as rebound effects.

In this article, we investigate how households adjust heating usage and re-spend potential savings following an efficiency improvement of their heating system. The heating adjustment corresponds to a direct rebound (Sorrell and Dimitropoulos, 2008), whereas the re-spending leads to an indirect rebound. Our experimental design allows a simultaneous observation of both effects.

As a first of its kind, this paper relies on the contingent behaviour method, a type of stated preference approach. Respondents were presented with an exogenous efficiency improvement in their heating system, and were requested to use a sliding bar to represent their change of heating usage in reference to their current heating level. In addition to scripts describing the scenarios, potential behavioural reactions were suggested to prime respondents and cross-validate the results. A subsequent choice task was designed to identify the re-spending preferences for the remaining net savings, and hence the indirect rebound. This design constitutes the first attempt to identify underlying mechanisms of the rebound in heating, which could be due to an increase in temperature, but also to other reactions such as further airing or expansion of heating usage on space and time dimensions. Furthermore, this paper is among the few that seek to explain heterogeneity of rebound responses among individuals, in particular with regard to socio-economic variables, environmental concerns, and energy intensity usage.

Another important feature of this study is our particular effort in identifying respondents who have genuinely negligible or zero direct rebound. While this behaviour is not explicable for a utility-maximizing person with unlimited substitution, the outcome of our survey indicates that zero-rebound phenomenon deserves more attention. The wide range of rebound estimations observed in the empirical literature and the focus on average estimates may have hidden no-rebound individuals. In fact, we observe that a substantial share of respondents did not feel any appeal in increasing their heating usage only because it becomes cheaper. This observation points to hierarchical preferences (see e.g., Drakopoulos,

[1] See for instance *The Economist* (15$^{\text{th}}$ January 2015): "Energy efficiency: The invisible fuel".

1994): Once a given level of thermal comfort is reached, efficiency improvements would not lead to more usage.

While recognizing that stated preference data face potential shortcomings, we contend that this approach deserves special attention in the rebound context. In our view, a choice experiment presents three important advantages over revealed data. First, the experiment design allows to eliminate the potential endogeneity bias encountered in the analysis of revealed data. Correcting for such selection bias would require valid instruments that are not readily available. In our experiment, efficiency improvements are randomly and exogenously assigned, hence preventing the possibility that intensive energy users systematically opt for higher efficiency. Second, stated data allow a better identification and validation strategy for zero-rebound individuals. Finally, the stated preference approach overcomes an important challenge in analysing the indirect rebound: In revealed data, it is practically impossible to link savings arising from a particular efficiency investment to a change in individual consumption pattern. In general, such savings become available over time in conjunction with a variety of other likely changes in income and savings. Identifying various rebound effects for the same individual would therefore require a prohibitively large amount of information. On the other hand, the experiment allows respondents to report their re-spending plan in a hypothetical context.

In our empirical analysis, we obtain an average direct rebound of 12% and an average indirect rebound of 24%. Combining both rebounds leads to a total micro-level rebound of around 33%. Moreover, our results indicate a strong heterogeneity among households, both for direct and indirect rebound effects, with about one third of the households displaying no direct rebound. Income is the main driver explaining the zero-rebound, showing that heating, as a basic need, calls for little rebound in high-income groups and those with a sufficient level of thermal comfort.

Policy makers in charge of the energy transition rely primarily on energy efficiency improvements to reach their targets of energy conservation, and in turn mitigate CO_2 emissions. Reliable estimations of direct and indirect rebound effects in the residential sector, as well as an overview of variations in households' responses to efficiency improvements, are therefore of crucial importance. The proposed analysis of the determinants of rebound responses is also relevant from a policy point of view, since it makes it possible to design customized measures targeted to specific population segments.

The remainder of the article is structured as follows. In section 2, we provide an overview on how the rebound effects are defined and measured in the literature and in our experiment. Section 3 presents our survey and the data collected, while section 4 reports our empirical estimations of the direct and indirect rebound effects. Section 5 investigates the determinants of rebound effects, relying on variations across households. Conclusions and policy implications are discussed in section 6.

2 Rebound Effects in Residential Heating

Rebound effects (direct or indirect) can be measured through the difference, following an efficiency improvement, between potential and actual energy savings (e.g., Azevedo, 2014):

$$\text{Rebound effect} = 1 - \frac{\text{Actual energy savings (AES)}}{\text{Potential energy savings (PES)}} \tag{1.1}$$

The direct rebound is more precisely described as an increase in the consumption of an energy service following a decrease in the effective price of that service caused by an efficiency improvement (Sorrell and Dimitropoulos, 2008).

Energy efficiency is defined as $\varepsilon = \frac{S}{E}$, where E represents energy input and S energy services (or useful work). In our study, S represents the services provided by heating, and we emphasize that S is not only the indoor temperature, but it also encompasses several additional dimensions of thermal comfort such as airing frequency or whether all rooms are heated or not. The direct rebound can then be defined as the elasticity of the demand for energy services (S) with respect to efficiency (ε):[1]

$$\eta_\varepsilon(S) = \frac{\partial S}{\partial \varepsilon} \cdot \frac{\varepsilon}{S} \approx \frac{\Delta S}{\Delta \varepsilon} \cdot \frac{\varepsilon}{S} \tag{1.2}$$

For data-driven reasons, however, this definition is seldom used in empirical studies, and authors usually rely on alternative definitions such as the elasticity of service demand with respect to energy price. The latter is commonly used to approximate the direct rebound in the context of residential heating (Madlener and Hauertmann, 2011; Haas and Biermayr, 2000). Yet, strong assumptions have then to be invoked: people have to react symmetrically to a change in price and to a change in efficiency, a hypothesis rejected by Greene (2012) in the context of private mobility. Chan and Gillingham (2015) moreover demonstrate that fuel price elasticity is not equivalent to the rebound effect when multiple fuels can be used to provide a single energy service, which is the case for heating.

Some studies rely on engineering calculations to estimate potential energy savings. For instance, Aydin et al. (2017) study a large number of households in the Netherlands,

[1] Recognizing that AES $= \frac{\Delta\varepsilon}{\varepsilon} - \frac{\Delta S}{S}$ and PES $= \frac{\Delta\varepsilon}{\varepsilon}$, we observe that definitions (1.1) and (1.2) are equivalent for the direct rebound:

$$\text{Direct RE} = 1 - \frac{\text{AES}}{\text{PES}} = 1 - \frac{\frac{\Delta\varepsilon}{\varepsilon} - \frac{\Delta S}{S}}{\frac{\Delta\varepsilon}{\varepsilon}} \approx \eta_\varepsilon(\text{S})$$

comparing energy labels of dwellings with their actual energy consumption. They find a direct rebound of 28% for owners and 42% for tenants. This identification strategy has sometimes been criticised, mostly because it relies on engineering predictions that often over-estimate potential energy savings of efficiency improvements. As an example, Fowlie et al. (2018) study 30,000 households participating in an energy efficiency program in the US. They find that savings projected by engineers are roughly 2.5 times higher than actual savings. Attributing all this discrepancy to engineering over-estimation of savings, they conclude that there is no evidence of a direct rebound. One drawback is however that their definition of rebound effect is very narrow, considering only indoor temperature changes. In this article, we argue that the direct rebound is not only due to higher temperatures, but also to other heating-related behavioural adaptations. For instance, in their study of Danish households who installed a heat pump, Gram-Hanssen et al. (2012) observe various possible adaptations in addition to a temperature increase, such as extended heating areas and a longer heating season.

The literature provides a wide range of rebound estimates, suggesting that a variety of factors could characterize individual rebound behaviours. For residential space heating, Sorrell et al. (2009) review the literature and collect estimates of the direct rebound ranging from 10 to 58% in the short run, and from 1.4 to 60% in the long run. They propose a mean value of 20%. Nadel (2012) suggests a plausible range from 1 to 12% and questions studies claiming higher direct rebound because they are mostly based on price elasticity. More recently, Nadel (2016) summarizes the findings of studies looking at both direct and indirect rebounds. For residential space heating, he observes a direct rebound around 10% and an indirect rebound around 10-20%, leading to a total rebound of 20 to 30%.

Most of the literature focuses on the direct rebound, yet the indirect appears as much (if not more) important for energy policies. This paper is among the few exceptions analysing both rebound effects empirically. Other examples are Druckman et al. (2011) and Chitnis et al. (2013), who conduct similar analyses in terms of GHG emissions, finding a total rebound respectively between 12 and 34% and between 5 and 15%. Most studies on the indirect rebound are based on income elasticities for specific categories of goods and services (for instance Chitnis et al., 2013) or input-output tables (Thomas and Azevedo, 2013; Lenzen and Dey, 2002). Combining such data with information on energy intensity allows to compute the overall variation in energy consumption and to provide an average estimate of the indirect rebound. As for the direct rebound, such an average estimate hides variations across individuals. On the contrary, our micro-level analysis provides individual estimates of the indirect rebound.

In our online survey, we present the respondents with various $\frac{\Delta\varepsilon}{\varepsilon}$ randomly selected in a predetermined range. Respondents subsequently choose how they would adapt their behaviour, that is $\frac{\Delta S}{S}$. The way we measure the direct rebound, through scenarios and questioning respondents about their potential reactions, is innovative. It is the first time such an experiment is used to assess rebound effects in residential heating. Only few former studies implemented surveys to investigate the rebound effect: Schleich et al. (2014) in Germany for lightning, and Yu et al. (2013) in Japan for transportation.

Our measure of the indirect rebound is, like for the direct rebound, based on definition (1.1). Potential energy savings (PES) stem from a decrease in heating expenses transformed in energy terms using the energy intensity in this sector, while actual energy savings (AES) are the difference between PES and the energy content of goods and services purchased with the savings made on heating. The energy intensities of PES and AES are based on life-cycle assessment data and include embodied energy.

Both our direct and indirect rebound measures incorporate income and substitution effects. Indeed, respondents were free to take any factor into account while making decisions about their reactions. Disentangling the substitution and income effects in each response is however beyond the scope of our choice experiment and requires further research. For detailed accounts about income and substitution effects, see Chitnis and Sorrell (2015) and Thomas and Azevedo (2013).

3 Survey and Data

We collected data using an online survey carried out in 2015 with 3,555 respondents representative of the Swiss population. The key questions of the survey, dedicated to elicit the rebound effects, were formulated as scenarios with hypothetical efficiency improvements of the heating system. These scenarios were presented as savings in running costs of heating.[1] Each respondent was faced with three successive scenarios: 1) a relatively small efficiency improvement of 10, 15 or 20%; 2) a large improvement of 40, 50 or 60%; 3) an intermediate improvement of 25 or 30% stemming from a CO_2-neutral heating technology. The improvement levels were randomly selected in each scenario.[2]

Under each scenario, the respondents were requested to state whether the efficiency improvement would trigger changes in their heating habits formulated in qualitative no/maybe/yes choices (see Appendix A.2). These questions served a twofold objective: First, they provide qualitative information about various rebound responses such as higher temperature, more airing, starting the heater earlier in the season and paying less attention to heaters. Second, they were intended to help respondents think about potential

[1] An example is displayed in Appendix A.1.

[2] We note that the upper bound of 60% is realistic and was also used by Alberini et al. (2013) for Switzerland. According to Streicher et al. (2017b), with the most stringent refurbishment standard, efficiency improvement may reach more than 80% for some buildings in Switzerland.

actions which positively impact their heating usage, thus priming them for the following choice task that needed more thinking. Namely, the respondents, who have responded yes or maybe to at least one of the qualitative changes, were faced with a slider choice task (see Appendix A.3). The choice consists of moving a slider representing how much of their potential savings would be allocated to increase their heating usage.

We presented the efficiency improvement as a percentage decrease in heating costs on the premise that respondents understand relative savings on their heating bills better than the technical aspects. Later in our analysis, we consider the relative reduction in heating costs and efficiency improvement as equivalent. For respondents who could not provide their heating costs during the survey, we provided an indication of annual heating costs for an average household (as shown in Appendix A.1).

From the definition of efficiency $\varepsilon = \frac{S}{E}$, we observe that any efficiency improvement translates into an exactly proportional reduction of energy consumption if services are kept constant (zero rebound). At the other extreme, energy services could increase exactly proportionally while keeping energy consumption unchanged (full rebound). The efficiency improvement ($\frac{\Delta\varepsilon}{\varepsilon}$) is exogenously provided and defines the maximum possible increase of energy services. Using the slider, respondents choose their desired energy service increase ($\frac{\Delta S}{S}$). We thus rule out super-conservation (negative rebound) and backfire (rebound greater than 100%). This choice was guided by the direct rebound estimates available in the literature, most of which being around 10 to 20% and none outside the range of 0 to 100%.

In order to elicit the indirect rebound, we requested respondents to state how they would re-spend an annual net saving of CHF 1,000 resulting from the heating efficiency improvements (see Appendix A.4). The CHF 1,000 amount is constant across all respondents, regardless of their response to the direct rebound question. We selected this amount because it provides sufficient flexibility for respondents to distribute savings across different categories of goods and it is realistic in most situations. CHF 1,000 roughly correspond to 65% of average annual heating costs in Switzerland, which were CHF 1,560 in 2011 according to the Swiss household budget survey (SFSO, 2013). 65% efficiency improvement is on the upper-end of what can be expected, but it is plausible in Switzerland.[1]

The objective of the re-spending question is to capture an individual marginal consumption bundle, as opposed to an average consumption bundle which can be obtained using typical monthly spending. We implicitly assume that the marginal bundle is constant with regard to the savings actually realized. This assumption is standard in studies using marginal bundles to estimate the indirect rebound (Chitnis et al., 2013, 2014; Thomas

[1]See footnote 2.

and Azevedo, 2013). Under this assumption, the magnitude of the direct rebound plays no role in determining the marginal consumption bundle.

Respondents were free to split the CHF 1,000 between 8 categories of goods and services: vehicle fuel, public transport, air travel, food and beverages, leisure, clothes and shoes, electrical appliances, and all other goods and services. Savings were also available to respondents as a 9th category. These categories were built such that the goods and services classified together are comparable in terms of energy intensity. Energy intensities indicate how much energy (kWh) is used for every CHF spent in a given sector and contain both direct and embodied energy.[1,2] These figures were provided by Tilov et al. (2019), who use a combination of Life-Cycle Assessment (LCA) and Environmentally-Extended Input-Output Tables (EEIOT) for Switzerland to estimate energy intensities for 281 commodities.[3]

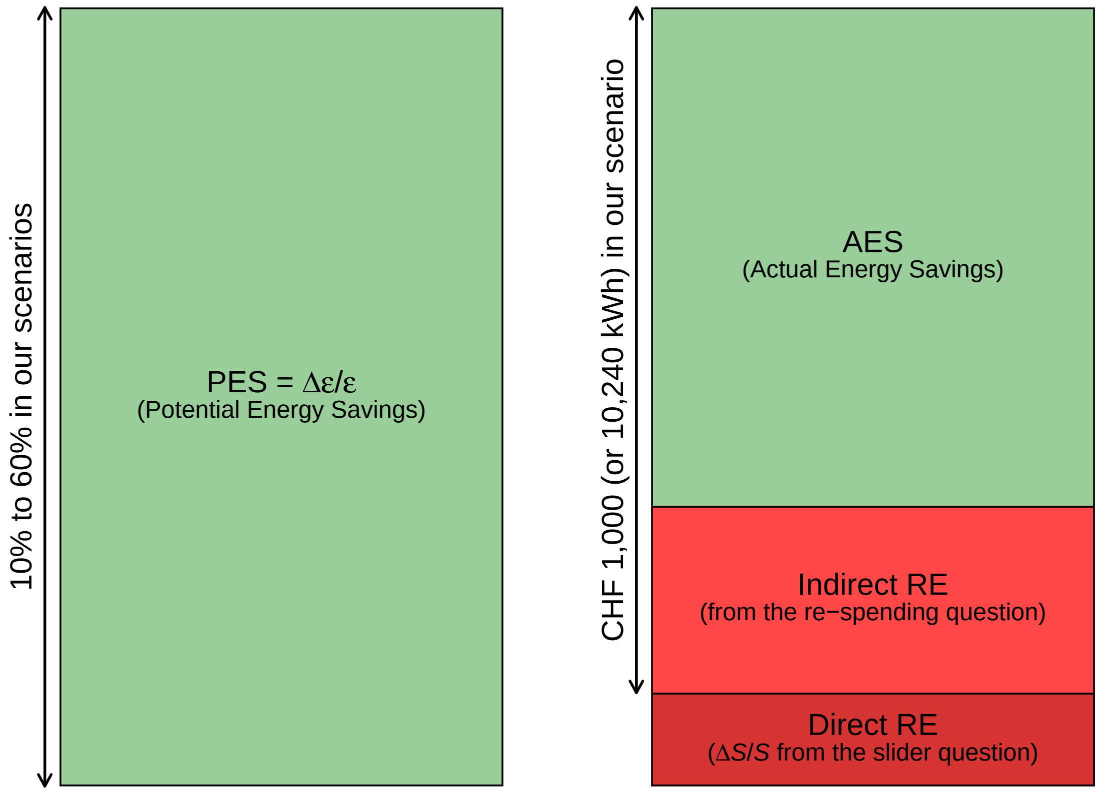
The energy intensity of each category along with average re-spending shares are displayed in Appendix B.1. For savings, energy intensity is set equal to the overall average energy intensity of CHF 1 spent, that is 2.54 kWh/CHF. When doing this, our underlying assumption is that savings will be spent in the future according to current spending pattern.

Figure 1.1 summarises our strategy to quantify direct and indirect rebounds. The left bar indicates potential energy savings (PES) arising from the efficiency improvements, which ranged from 10 to 60% depending on the scenarios. In the slider question, respondents indicated their subsequent increase in heating usage ($\frac{\Delta S}{S}$). Combining these two elements using definition (1.1), we determine individual direct rebound effects. The indirect rebound effect is determined thereafter, by allocating to each respondent CHF 1,000 to re-spend in different categories of goods and services. This monetary amount is identical for every respondent in our design, regardless of the efficiency improvement and of the direct rebound. In energy terms, following Tilov et al. (2019), CHF 1,000 spent in the heating sector correspond to 10,240 kWh, which therefore constitute the energy savings that could be obtained without any indirect rebound effect. The upper part of the right bar finally shows the energy savings left (AES) once direct and indirect rebounds have taken back some of the potential savings. The direct and indirect rebounds combined give rise to the total micro-level rebound effect.

Our survey also collected a series of household characteristics which we use to investigate the determinants of rebound responses. The variables considered are described in Appendix C. Out of the 3,555 respondents, 2,637 have no missing values and constitute our final sample.

[1]Currently, CHF 1 is almost equivalent to USD 1.
[2]Embodied energy is based on a cradle-to-grave approach.
[3]Ecoinvent life-cycle inventory, version 2.2, ESU-services Ltd. & N. Jungbluth, 2015.

Figure 1.1: Links between the survey and theoretical concepts



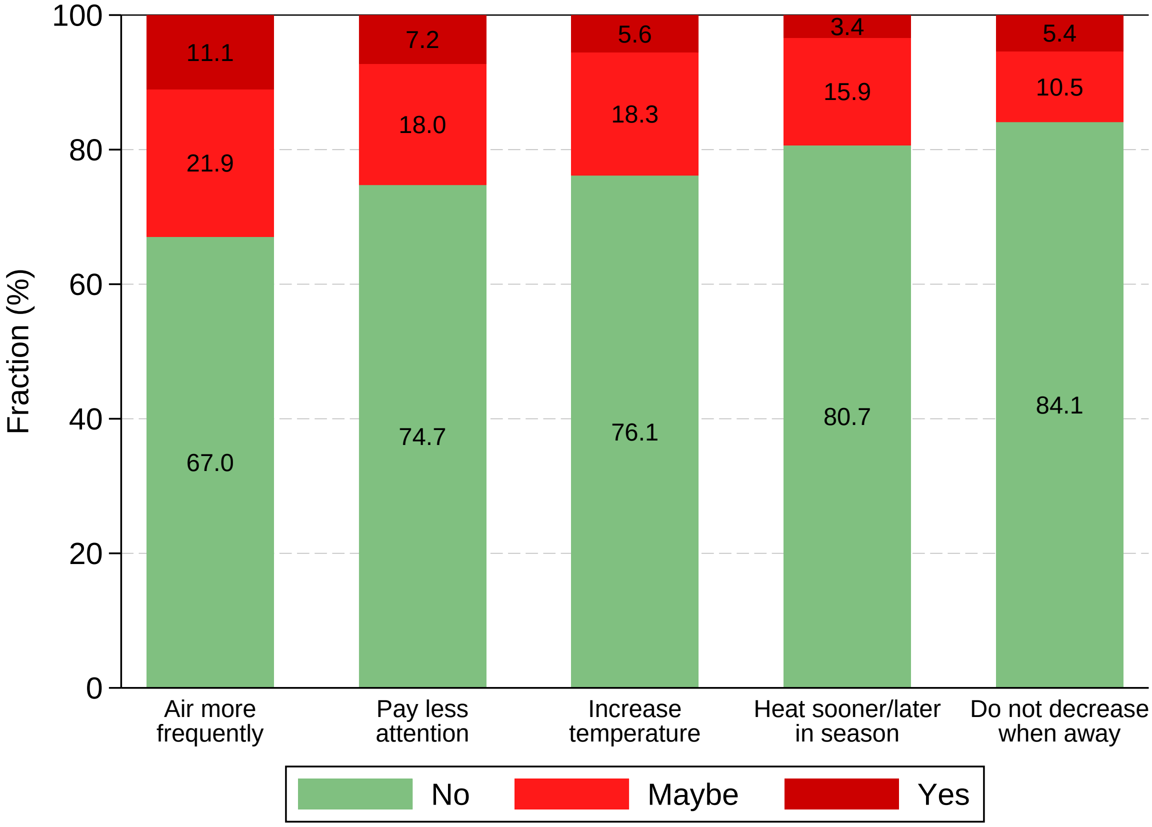
4 Estimation of the Rebound Effects

4.1 Direct Rebound Effect

Our definition of the direct rebound encompasses several possible behavioural adjustments in addition to commonly studied manifestations as higher indoor temperature. Other reactions, such as airing more frequently, or starting to heat earlier in the season, appear equally plausible especially in advanced countries, where indoor temperature might not be an issue. In fact, responses to our qualitative questions, plotted in Figure 1.2, indicate that airing longer or more frequently is what respondents chose the most, before paying less attention to heating in general. Increasing temperature comes as the third most popular choice, with 24% of maybe or yes. Galassi and Madlener (2017) find similar results in a survey conducted in Germany, with air quality being the preferred way to improve thermal comfort, and only one third of the respondents stating a preference for higher temperature. These findings show that considering only temperature changes would result in an underestimation of the direct rebound (see also Volland, 2016).

The quantitative question (slider) provides the necessary data to apply definition (1.1) in order to estimate a rebound effect specific to every individual in each scenario. To

Figure 1.2: Behavioural adaptations following efficiency improvements



Notes: There are between 7,859 and 7,867 observations by item, except the fourth one (5,805) which was only displayed to respondents having previously stated that they decrease heating when away from home. On top of these five behavioural proposed changes, respondents could also state any other change in an open text field.

gauge the consistency and plausibility of respondents' answers to that quantitative question, we regress the stated heating service variation, $\frac{\Delta S}{S}$, on the qualitative indicators. Results (displayed in Appendix D) indicate that all coefficients are positive and (with one exception) statistically significant. Moreover, in 4 cases out of 5, the magnitude of the coefficient is commensurate with the affirmative scale, "yes" responses showing a greater effect than "maybe" responses. These results suggest broad consistency among our respondents: When they qualitatively indicated changes in their heating behaviour, they also quantitatively stated a sensible corresponding variation of their service demand.

The individual direct rebound estimates are displayed in Table 1.1. The global average direct rebound is 11.9%, with scenario-specific averages ranging from 10 to 15%.[1] Our estimates are thus consistent with the reviews by Sorrell et al. (2009) and Nadel (2016). Nevertheless, we find a strong heterogeneity across individuals, which is often overlooked

[1]Calculating the direct rebound on the entire sample without excluding individuals with missing values (10,665 respondents) leads to very similar results (the rebound increases by 0.3 percentage point on average).

in the literature. A direct rebound of zero is found for 55% of the observations. Figure 1.3 (Panel A) displays the distribution of the positive direct rebounds. Most of these observations (65%) show a direct rebound below 30%.

Table 1.1: Estimations of rebound effects

	Mean	Std dev.	Min.	Max.	N
Direct rebound:					
Small eff. improvement	0.144	0.0043	0	1	2,637
Large eff. improvement	0.102	0.0036	0	1	2,637
Middle eff. improv.+ CO_2-neutral	0.110	0.0037	0	1	2,637
All scenarios pooled	**0.119**	0.0023	0	1	7,911
Indirect rebound	**0.243**	0.0047	0.028	1.357	2,637
Total micro-level rebound	**0.329**	0.0030	0.028	1.357	7,911

Notes: The direct rebound is calculated using definition (1.1). The indirect and total rebounds are calculated using respectively equations (3.7) and (3.9).

4.2 Indirect Rebound Effect

If positive savings remain after the direct rebound occurred, individuals will purchase further goods and services. Hence, due to the energy embodied in these goods and services, an indirect rebound will arise. To calculate the additional energy used in this process, we multiply the energy intensities of the goods' categories with their respective share in the individual marginal consumption bundle. In addition, potential energy savings still feasible after the direct rebound are obtained by multiplying the energy intensity in the heating sector (10.24 kWh/CHF) by the saving amount remaining after the direct rebound. The details of the indirect rebound calculation are provided in Appendix E.

Using this strategy, we obtain an average indirect rebound of 24.3% (Table 1.1). Thus, beside the direct rebound, about a quarter of potential energy savings are lost due to the re-spending of savings made on heating. The median indirect rebound effect is 14.4%, and a few of the largest values are above 100% (62 respondents, i.e., 2.3% of the sample), which corresponds to a backfire situation. Such a situation is possible if most of the savings made on heating are used for additional air travel. In our setup, the maximum possible indirect rebound (136%) indeed occurs if all savings are re-spent on air travel.

4.3 Total Micro-level Rebound Effect

The total micro-level rebound effect is obtained as a combination of the direct and indirect rebound effects. Appendix E provides a detailed explanation of how the total rebound is calculated. In particular, we observe that an individual's total rebound is obtained by a weighted sum of the direct and indirect rebound effects, in which the indirect rebound estimated from the re-spending question needs to be re-weighted by a factor (1 − direct rebound).

Applying equation (3.10), we obtain an average total micro-level rebound of 32.9%, when pooling all scenarios for the direct rebound. Figure 1.3 (Panel B) shows the distribution of the individual total rebound effects. Backfire happens for 178 observations (2.2% of all observations), with a maximum total rebound of 136%.[1] The mode of the distribution occurs between 10 and 15% because more than 20% of the respondents decided to allocate all their CHF 1,000 to other goods or services, which yields an indirect rebound of 10.4%.

Our main findings about the magnitude of the rebound effects can be summarised as follows: in the domain of residential heating, about one third of the energy savings initially expected after an efficiency improvement are lost due to the direct and indirect rebound effects. The direct rebound is less important in magnitude than the indirect rebound (12% versus 24%). While very few studies use the same dataset to estimate direct and indirect rebounds together, one comparable result is obtained by Chitnis et al. (2014) for the UK. Using expenditure elasticities, they find a total rebound effect (direct and indirect) between 0 and 32% in terms of GHG. Moreover, we observe that heterogeneity across individuals is substantial, with a total rebound ranging from 3% to 136%. This heterogeneity is the topic of the next section.

5 Determinants of Rebound Effects

5.1 Methods

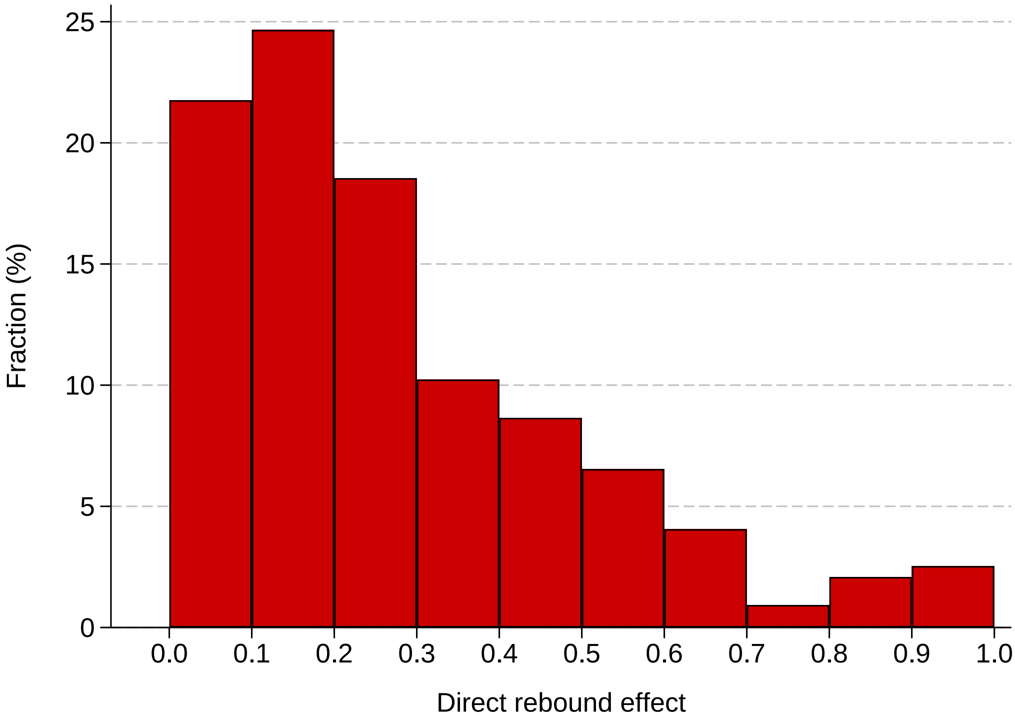
From an econometric perspective, our measure of the direct rebound exhibits two specific attributes. First, a lower bound at zero, with a cluster of individuals stating they would not change anything in their heating-related behaviour. Second, those who consider behavioural changes go through a two-stage process while deciding their rebound. Indeed, we note that the responses in each scenario, hence the direct rebound, could change for the same respondent. While 32% of the respondents never rebound and 42% show always a positive rebound, the remaining 26% change from zero to a positive rebound across scenarios.

A hurdle model is therefore appropriate to our experimental design, since respondents need to pass a first "threshold" to have the possibility to display a positive rebound (the qualitative rebound question). Yet, a single hurdle model is not suitable in the case of individuals with a mix of zero and nonzero direct rebound over different scenarios.

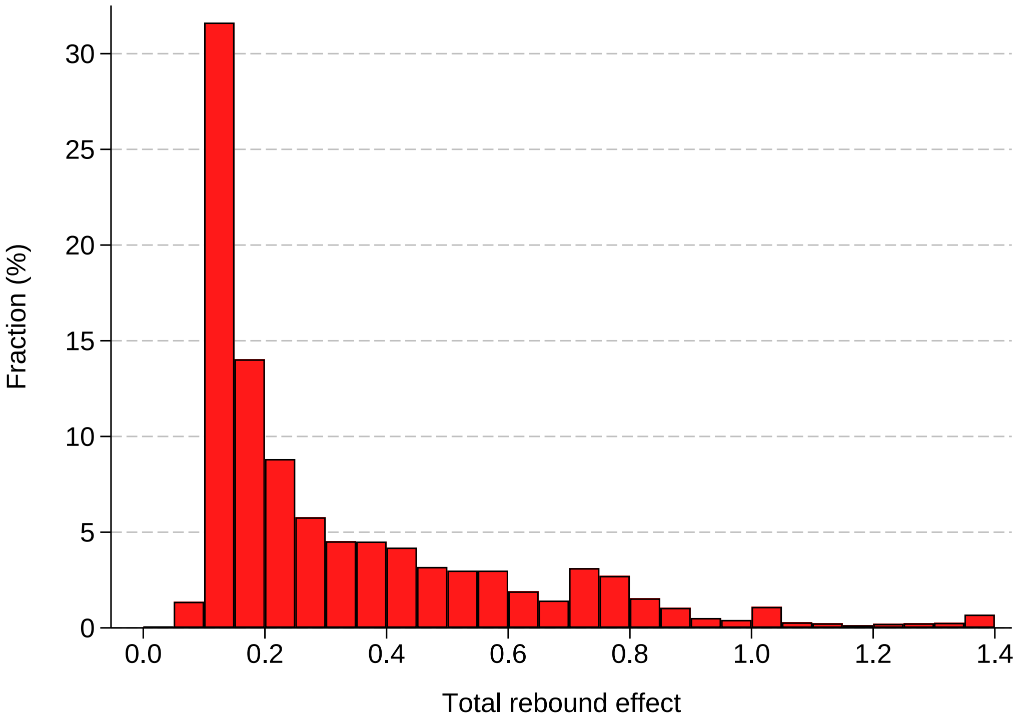
[1] This maximum is attained by respondents showing no direct rebound and re-spending everything on air travel.

Figure 1.3: Distribution of individual rebound effects

A. Direct rebound



B. Total rebound



Notes: Panel A is based on 3,548 non-zero observations. The 4,363 observations with a direct rebound of zero (representing 55% of the final sample) are excluded. Panel B is based on 7,911 observations (final sample).

We hence opt for a double hurdle model (Cragg, 1971) which was adapted to panel data by Dong and Kaiser (2008). The two hurdles refer to: a) whether the individual is a zero-rebound individual, and b) for the nonzero-type, whether the specific circumstances call for a rebound. Therefore people with a positive rebound in a specific scenario would have crossed two hurdles, an individual-specific hurdle separating them from zero-type respondents, and a second hurdle depending on the scenario.

Denoting $y_{i,t}$ the observed rebound of individual i, $d_i^\star$ a latent (unobserved) variable related to the individual's (zero or nonzero) type, $y_{i,t}^\star$ a latent variable for the desired rebound of individual i, we can specify the double hurdle model as follows:

Selection (first hurdle):

$$d_i^\star = \mathbf{z_i'}\boldsymbol{\alpha} + \varepsilon_{1,i} \tag{1.3}$$

Rebound intensity (second hurdle):

$$y_{i,t}^\star = \mathbf{x_{i,t}'}\boldsymbol{\beta} + u_i + \varepsilon_{2,it} \tag{1.4}$$

Observation:

$$y_{i,t} = \begin{cases} y_{i,t}^\star & \text{if } d_i^\star > 0 \text{ and } y_{i,t}^\star > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1.5}$$

where i denotes the individual, t $(= 1, 2, 3)$ denotes the scenario, $\mathbf{z_i}$ is a vector of time-invariant covariates, $\mathbf{x_{i,t}}$ is a vector of covariates encompassing $\mathbf{z_i}$ plus additional time-varying covariates, and u is a random intercept representing individual heterogeneity.

The zero-type individuals can be considered as perfectly satisfied with their current thermal comfort, and as having reached a satiety point similar to what Davis (2017) considers for the current state of electricity demand in most American households. Yet, this threshold cannot be explained in the usual economic context of unlimited substitutability.

An alternative explanation is provided by the theory of hierarchical choices (Drakopoulos, 1994), in which preferences are structured in *necessities* that require to be satisfied first, and *non-necessary desires* that are considered only after necessities are fulfilled. Extremely limited substitution between the two groups of consumption could explain a satiation point, at which the marginal utility of increasing demand for heating is zero. On the other hand, the households below the satiation point, lacking their maximum thermal comfort, increase their heating demand should the price of heating service falls.

5.2 Determinants of the Direct Rebound

We run the double hurdle model described in equations (1.3) to (1.5) to investigate the impact of individual characteristics on the direct rebound magnitude. The covariates include socio-economic characteristics, indoor temperature, heating satisfaction, owner/tenant status in conjunction with their heating bill features, environmental concerns, and scenario dummies.[1] Descriptive statistics and some explanations of these variables are available in Appendix C.

The output is composed by two equations: the selection (first hurdle), and the rebound intensity (second hurdle) based only on individuals who passed the first hurdle. The scenarios' dummies enter only the second equation, because by definition the distinction between zero- and nonzero-type individuals is made on characteristics which do not vary through the treatments.

We expect a negative effect of education, income, heating satisfaction, and environmental concerns, both on the likelihood of the rebound and on its intensity. The effect of income has been analysed by Chitnis et al. (2014) and Madlener and Hauertmann (2011), both reporting a negative effect. An explanation is that wealthy households have reached a satisfying level of comfort, so that any efficiency improvement will not affect their usage. Income should thus play a role in the first hurdle differentiating zero- and nonzero-type individuals. Similarly, education, capturing certain wealth effects not observed by the income variable, should have a negative effect.

The usual assumption concerning temperature is that people with lower temperature rebound more. However, it supposes that they have low temperature because of budget constraints, and it rules out people with low temperature for comfort reasons or environmental concerns. In Switzerland, the hypothesis of low temperature because of budget constraints does not appear particularly relevant, because fuel poverty is virtually nonexistent. According to Eurostat (EU-SILC survey), less than 1% of people were "unable to keep home adequately warm" in 2014. In comparison, this share is around 8% in the UK, 4% in Germany, and 9% on average in the EU. Furthermore, our definition of direct rebound is broader than only a temperature increase, so people with high indoor temperature could still rebound by airing more, turning the heating on earlier in the season, asf. For these reasons, we do not make any assumption on the sign of the coefficient for temperature.

The literature (e.g., Madlener and Hauertmann, 2011) suggests that tenants tend to rebound more than owners. Yet, whether heating costs are paid individually or shared across

[1] We also tested for the impact of additional variables: age, region, heating fuel, housing type, dwelling size, household size, number of children, rural or urban area, and attitudes toward risk. None of them was significant.

all dwellers of a building is often omitted, and could play a key role in this difference. Indeed, the proportion of dwellers in each regime is very different among the two groups: only 15% of the owners share heating costs with co-dwellers, but almost 50% of the tenants do so. When costs are shared, the free-riding incentives could induce households to reach a high level of heating usage, and hence lower rebound effects. To investigate whether tenants with shared or individual costs behave differently from each other, we use a dummy variable with four categories (owners/tenants with shared/individual costs), the base category being owners with individual costs.

The scenario dummies allow us to test whether the direct rebound is influenced by the efficiency improvement, e.g., whether larger improvements induce a larger direct rebound. The CO_2-neutral technology in the third scenario is additionally used to assess whether people react more (have a larger direct rebound) when efficiency improvements arise from a green technology. Our hypothesis is that people would react more because they get rid of the guilt of consuming more of a polluting service.

Our estimation results are displayed in Table 1.2. For the selection equation, we report the marginal effects at the means. Income, heating satisfaction, gender and owner/tenant status turn out as significant to distinguish zero- from nonzero-type individuals. As income increases, the probability to cross the first hurdle (i.e., to be in the pool of individuals that do positively rebound in some situations) diminishes, in line with our expectations. The probability of rebound decreases respectively by 9.5% and 11.9% for the middle- and high-income categories. Moreover, the difference between these two categories is not significant (formally checked by a Wald test), showing that only the most deprived households behave differently, which is consistent with the hierarchical preference framework. The negative effect of heating satisfaction is also consistent with this framework, respondents with the lowest satisfaction level having a higher probability of rebound.

Female respondents appear less likely to rebound than their male counterparts. Yet, the coefficient is low and weakly significant, and it becomes insignificant in the robustness check performed later (Appendix Table H). Concerning the owner/tenant status, we find contrarily to most studies that tenants have a lower probability of rebound, especially those with shared costs.[1] This finding highlights the importance of taking the heating bill structure into account when investigating whether owners or tenants rebound differently, because the structure implies different free-riding incentives for the heating usage and as a consequence different direct rebounds.

In the intensity equation, which describes the impacts of the covariates on the magnitude of the direct rebound, the coefficients are to be interpreted as in a linear regression. As

[1]Owners with shared costs appear not different from those with individual costs probably because they share their costs with much fewer households than tenants, and hence have fewer incentives for free-riding.

Table 1.2: **Determinants of the direct rebound**

	Selection (ME)	Intensity
Vocational school	−0.018	−0.079
	(0.115)	(0.070)
High school	−0.003	-0.138^{*}
	(0.120)	(0.072)
University	−0.000	-0.147^{**}
	(0.116)	(0.070)
Income CHF 4500-9000	-0.095^{**}	0.028
	(0.046)	(0.021)
Income CHF >9000	-0.119^{***}	0.016
	(0.045)	(0.021)
Moderate heating satisf.	-0.130^{*}	−0.029
	(0.076)	(0.025)
High heating satisf.	-0.147^{*}	-0.125^{***}
	(0.077)	(0.026)
20-20.9 degrees	−0.015	0.054^{*}
	(0.050)	(0.030)
21-21.9 degrees	−0.035	0.066^{**}
	(0.046)	(0.028)
≥22 degrees	0.006	0.074^{***}
	(0.044)	(0.026)
Environmental concerns	−0.000	-0.003^{**}
	(0.002)	(0.001)
Female	-0.037^{*}	-0.026^{*}
	(0.021)	(0.014)
Owners with shared costs	0.024	0.015
	(0.056)	(0.029)
Tenants with shared costs	-0.080^{***}	0.008
	(0.027)	(0.018)
Tenant with individual costs	−0.023	−0.006
	(0.030)	(0.018)
Large efficiency improv.	–	-0.077^{***}
		(0.007)
Middle eff. improv and CO_2-neutral	–	-0.022^{***}
		(0.002)
Constant	–	0.263^{***}
		(0.088)
N	7,911	7,911

Notes: Standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01. The dependent variable is the direct rebound. Marginal effects (ME) at the means are presented in column Selection.

the dependent variable ranges from 0 to 1, coefficients need to be multiplied by 100 to get variations in percentage points. The impact of education is negative as expected and significant (the last two categories of education), while income plays no role. Heating satisfaction and environmental concerns exert a negative effect. There is again a difference between men and women, the latter having a slightly lower rebound.

The positive coefficients of the temperature variables show that the hypothesis of fuel poverty and low temperature because of budget constraints does not hold in Switzerland. The three coefficients are not statistically different from each other, but they reveal a significant difference with the omitted category (< 20 degrees). Aydin et al. (2017) find similar results, with households using more energy than the average displaying a higher direct rebound. Looking at the different dimensions of the direct rebound (airing, temperature, asf.) reveals no difference between the temperature groups. To investigate what determines indoor temperature, we regress temperature on various characteristics (Appendix Table F). Interestingly, income has no effect, strengthening the rejection of the fuel poverty hypothesis, while environmental concerns are strongly significant and negative. It thus seems that a low indoor temperature is explained by environmental concerns or comfort preferences, both implying a low direct rebound.

From the scenario dummies, we obtain that larger efficiency improvements lead to lower direct rebounds. This finding can again be explained in the framework of hierarchical choices and non-infinite substitution. People do not rebound proportionally to efficiency improvements: Once they reach an optimal comfort level, they stop. In the perspective of policy implications, it implies that one-shot large efficiency improvements should be favoured, because less energy savings would be lost through the direct rebound. The last scenario dummy also included a CO_2-neutral heating technology. We discuss in Appendix G the possibility of a green rebound based on this scenario. We find evidence in this direction only for a limited number of respondents.

In Appendix H we perform some robustness checks to overcome issues inherent to stated preference data. We identify inconsistent respondents, and we exclude them or limit their influence in the regressions through weights. Overall, the results are very similar and we conclude that our findings are robust.

5.3 Determinants of the Indirect Rebound

To analyse the determinants of the indirect rebound, we use both an OLS model and an ordered probit model.[1] We consider similar determinants as in Table 1.2. We present the results of both models in Appendix Table I. Our main interest is on the effect of income, which could drive down both direct and indirect rebound effects. In particular, this effect

[1]More information can be obtained on ordered probit for instance in Baltagi (2011) (chapter 13.10).

could be expected if non-heating embodied energy-intensive goods are characterized by a satiation effect, as in the heating domain.

In the OLS regression, the dependent variable is our indirect rebound measure. For the ordered probit, we constructed four categories of energy intensity: air travel, car fuel, food and beverages, and "other", where the latter aggregates the lowest five energy intensity categories (below average) and savings.[1] The order in the probit goes from the least ("other") to the most energy intensive category (air travel). The results are consistent across the two models, with the coefficients' signs and their significance levels being mostly comparable.

Only a few variables display a significant effect. In particular, age seems to matter, with younger people having a higher indirect rebound. Environmental concerns have a negative impact as expected. The effect of income appears negative, but the related coefficients are only significant in the probit model. Our results thus provide only weak evidence in favour of a satiation effect applying to all energy-intensive goods and services.

Two important features of the indirect rebound could explain the lack of significant associations with observed characteristics. First, due to the diversity of tastes and consumption patterns across various groups, there are many unobserved factors that dominate the effects of usual socio-economic characteristics. Second, the indirect rebound is driven by embodied energy that is less salient than primary energy for most consumers. While possibly aware of the high energy intensity of traveling by plane or driving a car, most people probably ignore how eating out compares to buying clothes.

6 Conclusion

The rebound effect is a behavioural reaction causing energy savings to be smaller than expected under engineering calculations. If not correctly accounted for, the rebound effect may induce policy makers to underestimate the necessary measures to achieve their energy conservation targets. In this paper, we investigate direct and indirect rebound effects in residential heating using stated preferences at the household-level elicited through an innovative choice experiment. The experiment describes different scenarios with exogenous efficiency improvements of the heating system.

We obtain an average direct rebound of 12%, and an average indirect rebound of 24%. Once combined, they constitute a total micro-level rebound of about 33%. Said otherwise,

[1] Strictly speaking, the estimation conducted is a weighted ordered probit, where the weights are proportional to the amounts spent in each category. For instance, if a respondent decided to re-spend CHF 400 on car fuel and CHF 600 on other, he appears twice in the probit: once in the car fuel category with a weight of 0.4, and once in the other category with a weight of 0.6. We also performed an unweighted ordered probit by considering only the modal category of re-spending for each respondent, and it yields very similar results.

rebound effects take back about one third of potential energy savings, which is considerable but well below 100%. Backfire situations, a rebound of more than 100%, only happen for a very limited number of people (about 2% of the respondents in our sample).

Beyond these averages, our results indicate strong heterogeneity across households, both for the direct and indirect rebounds. An important finding hardly ever raised in the literature is that a substantial share of the households (almost one third in our sample) displays no direct rebound, regardless of the magnitude of the efficiency improvement. The traditional framework of unlimited substitution cannot explain such no-rebound behaviours. We therefore resort to hierarchical choices models, which support alternative predictions. In the context of heating, it indeed makes sense to consider the existence of some thermal comfort threshold, beyond which the direct rebound effect should be negligible or zero.

Thanks to our experiment design, we are able to investigate the determinants of rebound effects – both direct and indirect – at the individual level. This constitutes a major contribution of our paper, since most rebound studies are based on specific samples and leave aside between-individual variability, which may be one explanation for the lack of estimates' convergence in the literature. Using a double hurdle model for panel data, we show that the substantial variation in direct rebounds is partly explained by observed characteristics such as income, education and ownership status. Our results are consistent with the conjunction that heating, as a basic need, calls for little rebound in high-income groups and those with a sufficient level of heating comfort.

In addition, we are able to characterize the underlying mechanisms of the direct rebound. The most popular adaptation is further ventilation, in line with findings from Galassi and Madlener (2017). Yet, studies in the field generally focus only on temperature increases (see for instance Fowlie et al., 2018), and are thus prone to underestimating the direct rebound.

Several important policy implications can be formulated on the basis of our study. First, the extremely low incidence of backfire suggests that the promotion of efficiency would bring energy conservation, and in turn reductions in CO_2 emissions. It is important to note however that our analysis focuses on relatively short-term responses. Including possible long-term rebound responses, such as moving to a larger house, is beyond the scope of this study, but could significantly increase the demand for heating services from certain households.

Second, the strong variation in individual rebound responses indicates that one-size-fits-all policies are not adequate when it comes to promoting efficiency. In particular, zero-rebound households could be targeted in priority to achieve the best results in terms of energy savings. Because these households are concentrated in high-income groups, imposing high efficiency standards in expensive dwellings may prove especially effective for reducing energy consumption.

On the other hand, subsidies targeted at low-income group would be less efficient in terms of energy saved, because of the higher rebound this group displays. However, subsidies would increase the welfare of low-income individuals, since the direct rebound leads to an improvement of thermal comfort. Such subsidies exist (for instance the Weatherization Assistance Program in the US), and even though their net welfare gains are not clear (Fowlie et al., 2018), their non-energy benefits such as reduction of thermal stress and improved sleep could be important.

Third, considering that the indirect rebound accounts for about two thirds of the total rebound in our results, we claim that it deserves more attention in future research and policy measures. A tax on embodied energy could be one way to mitigate the indirect rebound. Another way would be to make embodied energy more salient, for instance via labels and information campaigns.

Finally, our findings point to the importance of a heating comfort threshold. To mitigate rebound effects, policies could therefore aim at reducing the perceived optimal comfort level, for instance by education campaigns highlighting the undesired health effects of excessive heating.

CHAPTER 2

Residential heating rebound effects: How much does an extra degree matter?

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1 Introduction

Ambitious efficiency gains targets have been set in many countries to reach their greenhouse gases (GHGs) emissions reduction goals. In Switzerland, one of the most promising sector in terms of energy savings and GHGs reductions is the heating sector (SwissEnergy, 2019), responsible of 38% of final energy consumption in 2018 (Infras et al., 2019). Thus, to meet the national objective of a 43% reduction of energy consumed per person by 2035 compared to 2000 (SwissEnergy, 2019), a substantial decrease of energy used for heating is anticipated in the next years. Currently, the main tool to achieve this decrease is a large subsidy program promoting energy efficient retrofits and renewable energy ("Programme bâtiments").

Take-back effects after such energy retrofits are outlined in the literature and are called rebound effects. Some of the energy saved might indeed be offset by behavioral adjustments of individuals who may decide to increase their heating usage after retrofits, thanks to a price decrease. Individuals will also re-spend the savings from efficiency gains on other goods and services. The *direct* rebound effect relates to an increased consumption of the energy service targeted by the efficiency improvement, while the *indirect* rebound depicts an increased consumption of all other products.

Rebound estimates for the heating sector are rather scarce, due to data constraints. It is indeed challenging to obtain data on heating usage and building efficiency. To overcome this issue, aggregated data on energy usage and energy prices are often used to identify the rebound effect in the heating sector (Brännlund et al., 2007; Madlener and Hauertmann, 2011; Chitnis et al., 2020; Schmitz and Madlener, 2020). On the opposite, we rely on micro-level data from a large scale survey on households energy consumption. Indoor temperature is used as a proxy for heating usage, and heating costs per square meter as a proxy for building efficiency. To prevent an endogenous issue arising from a potential measurement bias in efficiency, heating costs are instrumented by building age and accommodation type.

The direct rebound estimation is carried out in two steps: First, we investigate whether households living in a more efficient dwelling set higher indoor temperature. Second, we convert the increased temperature into energy by using the heating degree days method. According to this method, a one-degree decrease in outdoor temperature requires the same amount of energy than increasing the indoor temperature by one degree. Our findings point to a minimal direct rebound – the portion of the potential energy savings that is lost – between 4% and 8%. This rebound estimation is a lower limit, since a single heating behavior adjustment is considered here (an increase in indoor temperature), while other adjustments exist, such as airing more often, starting sooner to heat one's dwelling, etc. (Hediger et al., 2018; Galassi and Madlener, 2018)

In a second part, we estimate the indirect rebound effect in order to obtain a full picture of the micro-level rebound. Expenditures shares of 11 categories of goods and services are available in the survey, and information on the energy intensity of these goods and services are appended. The energy intensity represents the total embodied energy (also called grey energy) in these products. We investigate how total energy embodied in households consumption bundles vary after a decrease in heating costs, keeping total spending constant. We find an average indirect rebound of 15%, contributing to a minimal total micro-level rebound of 19% to 23%.

Overall, these findings show that efficiency improvements in buildings will deliver energy savings, but not as large as anticipated if no rebound effects are taken into account in the predictions. A correct assessment of energy take-backs in heating is valuable for energy policies which need to anticipate correctly future energy consumption and future renovations rates to meet their GHGs reduction plans. In addition, we highlight that the lowest income group displays a larger direct rebound level (11%), consistent with prior literature. Buildings retrofits for this group would hence improve their living conditions along energy savings, as they are further away from their satiety point in terms of heating level than more affluent households.

The article is structured as follows: Section 2 presents the rebound literature, in particular the different identification methods employed for the heating sector. Section 3 gives an overview of the data used. Section 4 and Section 5 describes the empirical strategy and the results for the direct and indirect rebounds. Finally, Section 6 concludes.

2 Related Literature on Direct & Indirect Rebounds

The rebound effect is most commonly measured as an elasticity of demand (Berkhout et al., 2000; Sorrell and Dimitropoulos, 2008). More precisely, the direct rebound is the elasticity of the demand for energy services (S) with respect to efficiency (ϵ):

$$\eta_\varepsilon(S) = \frac{\partial S}{\partial \varepsilon} \cdot \frac{\varepsilon}{S} \tag{2.1}$$

This definition is however difficult to implement, because a measure for energy services and a measure for efficiency are needed. To circumvent this issue, most rebound studies rely on alternative elasticities definitions, for instance the elasticity of energy demand with respect to energy price. Sorrell and Dimitropoulos (2008) provide rigorous definitions of these different elasticites and assumptions underlying their use.

Direct rebound studies for space heating can be broadly divided into four categories according to the method used:

a) The use of the own-price elasticity of demand of the relevant energy service. Here, individuals are assumed to be indifferent to the source of the price change, i.e. they should react symmetrically to efficiency improvements and to price diminutions. Formally, the rebound effect is in this case:

$$\eta_{\varepsilon}(S) = -\eta_{p_q}(q) = -[\frac{\partial q}{\partial P_q} \cdot \frac{P_q}{q}] \tag{2.2}$$

Where q is the energy consumption for the relevant energy service, and P_q its price. This method requires data on household expenditures – usually taken from national survey data or input-output databases – prices and energy intensities to estimate the energy use associated to each expenditure categories. Studies using this method are the most numerous (Brännlund et al., 2007; Kratena and Wüger, 2010; Madlener and Hauertmann, 2011; Chitnis and Sorrell, 2015; Chitnis et al., 2020; Schmitz and Madlener, 2020) and provide various rebound estimates in the heating sector, from very limited rebounds to rebounds larger than 100%. One popular method is to employ the (linearized) Almost Ideal Demand System (AIDS or LAIDS) from Deaton and Muellbauer (1980).

One pivotal aspect is the aggregation level of households' expenditures, as the number of categories is limited by the number of degrees of freedom in the model. Hence, how goods and services are aggregated can vary greatly from one study to another, and results can be sensitive to this aggregation scale (Chitnis et al., 2020). The time-frame is also diversified across the studies, usually spanning over a few decades. Moreover, disputable key assumptions behind this method exist (Haas and Biermayr, 2000; Sorrell and Dimitropoulos, 2008; Hunt et al., 2014): (i) the aforementioned symmetrical reaction to efficiency improvements and to price diminutions; (ii) the assumption that energy efficiency is constant; (iii) the fact that price elasticities are the same for falling and rising prices. Some studies address some of these issues; for instance Schmitz and Madlener (2020) include energy efficiency in different ways to their econometric specifications. Yet, some authors remain very critical of this approach (Nadel, 2012; Hunt et al., 2014).

b) Estimations of energy consumption before and after building retrofits. Here, heating energy consumption must be monitored before and after home refurbishments, and estimated savings are calculated by engineering predictions. The gap between predicted and realised energy savings constitutes the direct rebound effect. Obviously, the critical point is the engineering predictions which must be extremely reliable, otherwise the rebound will be under- or over-estimated. It is now acknowledged that those predictions generally largely overestimate the expected savings (Fowlie et al., 2018), threatening the rebound identification. Studies applying this method find indeed rather large rebound estimates, as 27%-41% by Aydin et al. (2017), 30% by Haas and Biermayr (2000), and 26% or 100% by Gram-Hanssen et al. (2012) (depending on the dwelling occupancy).

A similar method is to compare actual energy consumption to theoretically calculated energy demand, for instance through energy performance ratings. Different studies (Heesen and Madlener, 2018; Galvin and Sunikka-Blank, 2016; Hens et al., 2010) find a discrepancy between upfront-calculated building energy performance and actual heat energy consumption. When households consume more energy than expected in the ratings, the gap is identified as a direct rebound effect. The opposite situation exists when energy consumption is less than expected from the ratings, a situation coined “prebound” by Sunikka-Blank and Galvin (2012). The key aspect is again how accurate the theoretically calculated energy demand is. Heesen and Madlener (2018) show for instance that energy performance ratings rely on hypothetical heating behaviors that are rarely met in real world and are far from the average household’s heating behavior.

c) The use of the elasticity of the energy demand. As $S = \epsilon \cdot q$, equation 2.1 can be written as:

$$\eta_{\varepsilon}(S) = \frac{\partial q}{\partial \varepsilon} \cdot \frac{\varepsilon}{q} + 1 \tag{2.3}$$

If energy demand q is perfectly elastic with respect to variations in ε, that is, a 1% increase in efficiency diminishes energy demand by 1%, the rebound effect is zero. Hence, a deviation from an elasticity of -1 constitutes the direct rebound. Yet, this equation is difficult to implement for heating demand since reliable measures of q and ε are needed, and ε is not readily available in conventional household surveys. One solution applied by Volland (2016) is to estimate ε based on q, as q is easily known (it is for instance the annual energy consumed for heating in kWh). However, a major issue appears since q is used both as the explained and explaining variable in the model.

d) Energy demand frontier analysis. With this recent approach proposed by Orea et al. (2015), frontier analysis is used to estimate energy efficiency, and the rebound is directly estimated from equation 2.3. Large rebound estimates are found, between 56 to 80% for the US (Orea et al., 2015).

In this analysis, we rely on the elasticity of energy service with respect to efficiency level, that is, on equation 2.1. The energy service (S) considered is indoor temperature, and heating costs per square meter, instrumented by building construction date and accommodation type, are used as a proxy for building efficiency. In a second step, variations in S are converted in energy following the heating degree days (HDDs) method, which assumes that a one-degree decrease in outdoor temperature requires the same amount of energy that a one-degree increase in indoor temperature. The HDDs method is conventional in the building field and is used for instance by Dyson et al. (2014) or Fowlie et al. (2018) to estimate variations in heating demand. Heating degree days have also been used for a long time in energy economics as explanatory variables to model residential energy demand[1], for instance by Berndt and Watkins (1977, 1986).

The advantages of this method are (i) to apply directly the initial rebound definition, (ii) to rely on two separate measures of heating service and heating efficiency, and (iii) to be directly comparable with similar studies for other countries. The drawback is that indoor temperature is only one part of the heating energy service, so the rebound estimate in this study is only a partial assessment. But as shown later, this partial temperature rebound likely constitutes a substantial part of the total rebound, because setting a higher temperature requires more energy than other adaptations such as airing more or extending the heating period (Palmer et al., 2012; Scheer et al., 2015).

To our knowledge, only one other recent study (Fowlie et al., 2018) focuses on this partial rebound, but without estimating the rebound per se, and our findings are similar, although the country studied is different. The other studies calculating a temperature take-back are older (Dubin et al., 1986; Schwarz and Taylor, 1995) or do not provide an estimation of the rebound (Oreszczyn et al., 2006). They are furthermore limited to the US or the UK. Sorrell et al. (2009) provide a review of these studies, pointing to a rebound of 20% on average for space heating. Often, technical data on insulation are needed to translate the increased temperature into energy (Dubin et al., 1986; Schwarz and Taylor, 1995). Such information is rarely available in common surveys on energy consumption. Instead, by using the HDDs method, we only need to know households' zip code and to merge this information with data on heating degree days. Thus, one of the main contribution of this article is to propose a robust way to estimate the direct rebound in residential heating with data that are commonly available in energy consumption surveys.

A second contribution of the article is the study of the indirect rebound effect with micro-level data. This type of rebound is also of great importance; previous works show that the indirect rebound might be larger[2] than the direct rebound for space heating (Hediger et al., 2018). A recent review by Reimers et al. (2021) lists the studies estimating both direct and indirect rebounds in different sectors, including residential heating. They point out that magnitudes of both rebounds vary considerably across studies. Most of the studies rely on aggregated consumption data, and fewer on household-level data. To estimate the indirect rebound, income elasticities or input-output tables are the most often used, in

[1]For further information on early residential energy demand modeling methods, we advise the reading of Madlener (1996) extensive review.

[2]Others studies found low indirect rebounds for space heating (Cellura et al., 2013; Chitnis et al., 2020), or of similar size to the direct rebound (Thomas and Azevedo, 2013), using however aggregated data.

conjunction with energy intensity data. Some studies estimate indirect carbon emissions, and other studies indirect energy consumption, explaining partly the great variations in results.

For this indirect rebound analysis, we use cross-sectional household expenditures data and energy intensity for 11 goods and services categories. The variation of the embodied kWh of the overall households' consumption bundle is estimated following a variation in heating costs, keeping total spending constant. If an indirect rebound between 0% and 100% exists, this variation should be lower than the average energy intensity of heating. If the variation exceeds it, an indirect rebound larger than 100% appears.

3 Data

The dataset compiles data from three different sources. The main source is the Swiss Household Energy Demand Survey (SHEDS), which is an annual online panel survey on Swiss households energy consumption (more details in Weber et al. (2017)). Six waves are used in this article (2015-2020), with 5,000 households per wave, except in 2015 where 3,500 households were surveyed. Each respondent was invited to answer the survey again each year, but not all came back. Overall, the sample used for this analysis encompasses 28,664 observations and 12,537 households, with 4,445 households who answered at least three times.

This survey contains many questions about the households' energy consumption, including their annual heating and hot water costs. As two-third of the households cannot differentiate hot water costs from heating costs, regressions are performed twice in this paper: once for heating costs alone, and once for heating and hot water costs. The survey also collects additional information on heating fuels and whether the heating bill is paid individually or collectively. In this last case, heating costs are shared among all the inhabitants of the building, usually proportionally on the dwelling size. When costs are shared among all inhabitants, the incentive to save energy is obviously reduced. Information on buildings renovations are also at disposal. One notable concept for building efficiency in Switzerland is the Minergie certification (`www.minergie.ch`). This certification is granted after refurbishments or for new buildings, and imposes strict rules to limit energy and fossil fuel consumption.

Table C shows the summary statistics of the variables used in this article. A key variable is the indoor temperature. This variable is at the center of the rebound identification strategy. The question was: "At what average temperature (°C) do you heat your living room during the day in winter ?"

Table 2.1: Summary Statistics

	Mean	Std. dev.	Min-Max	Median	N
*Heating & hot water costs (CHF per year)	1,260	927	[2 – 5,141]	1,070	18,019
*Heating costs (CHF per year)	943	814	[2 – 5,250]	780	5,924
*kWh (heating and hot water)	13,590	11,279	[21 – 61,831]	10,982	14,810
*kWh (only heating)	10,275	9861	[4 – 60,827]	7,765	4,893
HDD (per year)	3,055	391	[2,001 – 7,232]	3,048	28,127
Building construction year	1971	46	[1396 – 2020]	1980	27,411
Heating fuel:					
Oil	0.40	–	[0 – 1]	–	24,911
Gas	0.22	–	[0 – 1]	–	24,911
Electricity	0.07	–	[0 – 1]	–	24,911
Wood	0.06	–	[0 – 1]	–	24,911
Heat pump	0.16	–	[0 – 1]	–	24,911
District heating	0.07	–	[0 – 1]	–	24,911
Other	0.02	–	[0 – 1]	–	24,911
Individual heating costs	0.59	–	[0 – 1]	–	23,874
Isolation renovation	0.46	–	[0 – 1]	–	26,007
Windows renovation	0.53	–	[0 – 1]	–	26,557
Heating system renovation	0.50	–	[0 – 1]	–	25,809
Minergie	0.18	–	[0 – 1]	–	22,934
Accomodation Type:					
Detached house	0.29	–	[0 – 1]	–	28,656
Flat (in building with <5 flats)	0.14	–	[0 – 1]	–	28,656
Flat (in building with 5-10 flats)	0.31	–	[0 – 1]	–	28,656
Flat (in building with >10 flats)	0.21	–	[0 – 1]	–	28,656
Terraced house	0.06	–	[0 – 1]	–	28,656
*Indoor temperature (Celsius)	20.8	1.3	[18 – 23]	20.9	26,008
Tenant (no/yes)	0.61	–	[0 – 1]	–	28,655
*Dwelling square meters	116.9	80.4	[20 – 360]	100	28,014
Household size	2.3	1.2	[1 – 15]	2	28,644
Income:					
<3,000 CHF	0.06	–	[0 – 1]	–	26,884
3,000-4,499 CHF	0.10	–	[0 – 1]	–	26,884
4,500-5,999 CHF	0.16	–	[0 – 1]	–	26,884
6,000-8,999 CHF	0.29	–	[0 – 1]	–	26,884
9,000-12,000 CHF	0.22	–	[0 – 1]	–	26,884
>12,000 CHF	0.17	–	[0 – 1]	–	26,884
Education:					
Compulsory school or less	0.02	–	[0 – 1]	–	28,644
Apprenticeship	0.38	–	[0 – 1]	–	28,644
High school	0.14	–	[0 – 1]	–	28,644
University	0.46	–	[0 – 1]	–	28,644
Age	46.4	15.5	[18 – 94]	46	28,664
Female	0.51	–	[0 – 1]	–	28,664

* Trimmed variables at the 1% and 99% levels.

One shortcoming of such surveys are the unreasonable responses that might appear. To correct for this bias, four variables are trimmed at the 1% and 99% levels: heating and water costs, heating costs, indoor temperature and dwelling size. These variables are marked with a star in Table C. To diminish as much as possible the unreasonable answers, respondents could also answer "I don't know" to most of the questions, explaining the different number of observations per variable.

Two supplementary data sources are used, the first one to add heating degree days (HDDs), and the second one to add heating fuel prices. HDDs come from cantonal sources[1] and MeteoSwiss. HDDs are the difference between 20°C and the average outdoor temperature when this average is <12°C. If the average is >=12°C, then HDDs=0. Households living too far from a measurement point or at a much higher altitude were dropped (about 700 observations). HDDs are available on a monthly basis and have been summed up over 12 months (from July to June) to represent the winter prior to the survey answers.

Heating energy prices come from the Federal Statistical Office[2]. They are available on a monthly basis and are an average for the whole country. To depict one winter, like for HDDs, prices are aggregated over 12 months (from July to June) and the mean price is kept. Prices per kWh are given for oil, gas, wood and electricity, covering 91% of the households. Only prices for district heating are missing. Prices have been relatively stable over the survey years, as shown in Figure 2.1. By dividing heating costs [CHF] by the fuel price [CHF per kWh], the energy consumed for heating in kWh is obtained. As heating costs need to be trimmed at the 1% and 99% level, so are the kWh consumed.

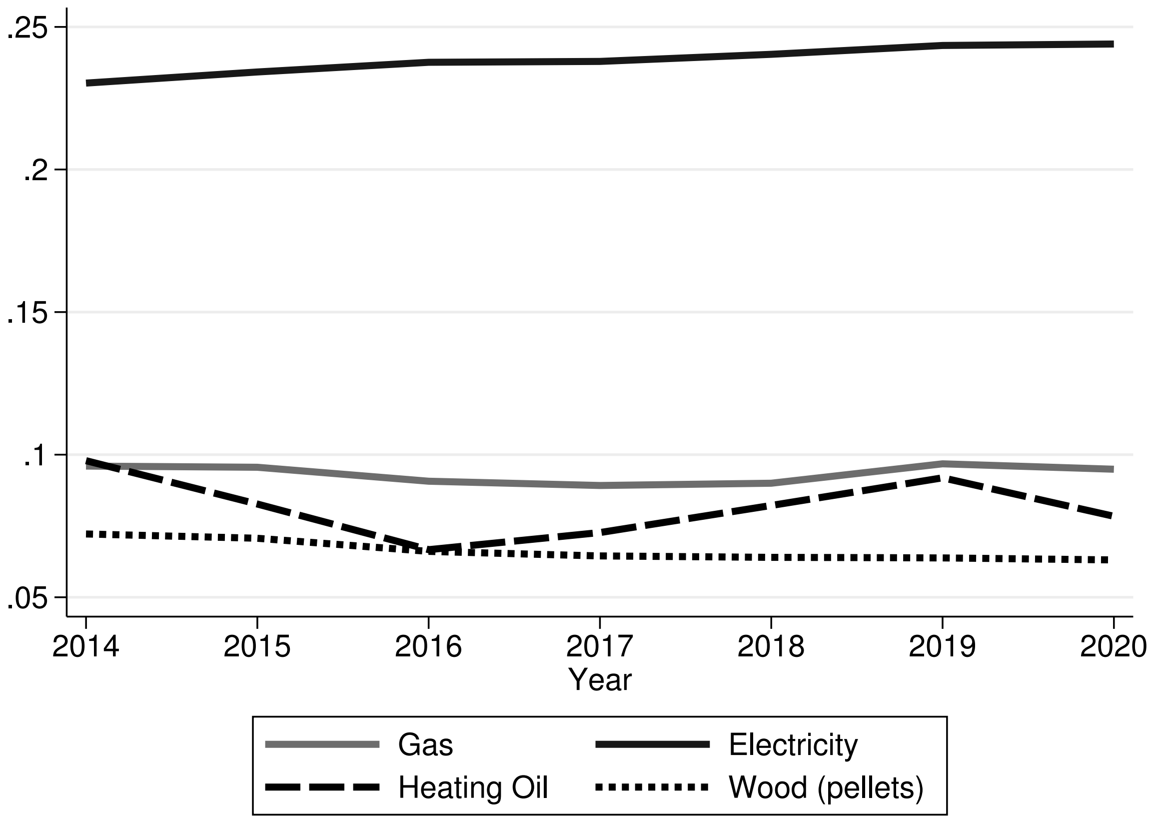
4 Direct Rebound Effect

4.1 Empirical Strategy

The direct rebound effect estimated in this article is a partial direct rebound as it encompasses only one behavioral adjustment to an efficiency improvement: an increase in temperature. Nevertheless, this is the most cited adjustment in the literature, and some articles consider it as the total direct rebound (Fowlie et al., 2018). In a previous paper (Hediger et al., 2018), we investigated these different behavioral adaptations, and we found that a quarter of households would (for sure or maybe) set up their thermostat higher if their heating costs were to diminish after an efficiency improvement. The only adjustment which more households would undertake was airing more frequently (one third of the households), but this adjustment requires less energy than setting the thermostat higher. Palmer et al. (2012) compared energy savings from 44 different actions that any household can undertake; decreasing the indoor temperature by one degree was on the top, saving about two times more energy than delaying the heating period by one month,

[1]For the cantons of Geneva, Valais, Fribourg, Neuchâtel and Jura.
[2]Consumer Price Index: Average price of fuel and energy

Figure 2.1: Heating Fuel Price [CHF per kWh]



Notes: Fuel prices are aggregated from July to June to depict one winter prior to respondents' answers, for instance 2014 prices are from July 2013 to June 2014.
Source: Federal Statistical Office, Consumer Price Index

and almost four times more than closing the bedroom window at night. Hence, this partial temperature rebound likely makes up a substantial part of the direct rebound.

In order to empirically identify this temperature rebound, we proceed in two steps:

1. Indoor temperature is regressed on heating costs per m^2 to observe whether indoor temperature increases when heating costs diminish. In an ideal world, we would be able to regress indoor temperature on the dwelling efficiency. However, efficiency is not directly observable, and we need to approximate it as best as we can. One straightforward method is to use the heating costs per m^2 as a proxy for efficiency. Because the true value of efficiency can not be recorded and is instead observed with errors, a typical measurement error bias occurs. To prevent a bias in our estimates, we instrument the heating costs per m^2 with the building construction date and the accommodation type. Both variables have a significant influence on efficiency (Streicher et al., 2018), but should not influence the indoor temperature choice, except through the variations in heating costs.

We could alternatively use heating consumption in kWh instead of heating costs per m^2, but since we control for the fuel type, counties and years, price variations are almost completely erased, and both specifications give comparable results.

2. Once the increase in indoor temperature is known, we still need to translate it into an increase in energy consumption (kWh). To do so, we use the relationship between HDDs and heating energy consumption, presuming that heating energy demand is directly proportional to the indoor to outdoor temperature difference. This is a standard method in residential heating to model the energy consumption of a building[1]. The central assumption is, that for a given building, a one-degree increase in indoor temperature needs the same heating energy as a one-degree decrease in outdoor temperature. Thus, a model estimating the impact of outside air temperature on heating energy consumption can also be interpreted as estimating the impact of a change in indoor temperature. Another available method is the popular rule of thumb that an extra degree of indoor temperature (°C) increases your heating bill by about 6-7%[2]. We verify later that this rule holds and what rebound results this rule gives compared to the HDDs method.

The equation for the first step is:

$$Indoor\ Temperature_{i,t} = \alpha_0 + \alpha_1 ln(Heating\ Costs\ per\ m^2{}_{i,t}) + \theta' Z_{i,t} + \lambda_c + \lambda_t + \epsilon_{i,t} \tag{2.4}$$

$\theta' Z$ is a vector of buildings' characteristics and socio-economic variables of the households, λ_c the state fixed-effect, λ_t the year fixed-effect and $\epsilon_{i,t}$ the error term.

As building efficiency is not directly observed but approximated, causing a measurement bias, building construction dates and accommodation types are used as instruments for heating costs, and equation 2.4 is estimated with a two-stage least squares estimator. Building age is strongly correlated to heating costs since building efficiency has greatly improved over time with stricter regulatory insulation norms. This is a standard instrument for heating costs (also used by Aydin et al. (2017); Volland (2016)). In Switzerland, Dettli et al. (2003) showed that building age has a significant influence on heating energy use. Accommodation types are also strongly related to heating costs, since efficiency depends on buildings' compactness. For instance, Streicher et al. (2018) define various archetypes of the energy performance for the Swiss residential building stock. To do so, they rely on building age, accommodation type (single- or multiple-family house), and area type (urban, suburban or rural). Therefore, we are confident that building age and accommodation types are valid instruments for dwellings' efficiency.

[1] See chapter 3.1 of CIBSE (2006) for examples of calculation.

[2] See for instance "tips and advice" on `www.suisseenergie.ch/menage/chauffer`. This is equivalent to a 3% increase in heating bill for an extra Fahrenheit degree.

By using these two instrumental variables, we assume that building age and accommodation types have no influence on the choice of internal temperature, except through the variation in heating costs due to variation in efficiency. A potential concern may arise if these two variables are correlated with unobserved preferences that influence the choice of indoor temperature (for instance elderly people sorting to more recent dwellings because they like to be warm). Thanks to the rich dataset, we are able to control for many households' characteristics and dwellings' features. All control variables are directly presented in the table of results. We assume that these controls are likely to capture a large part of the unobserved preferences (for instance by controlling for age), and thus address the potential sorting issue. Moreover, as explained in the next paragraph, the choice of the dwelling is limited in Switzerland, due to an acute shortage of flats and houses.

Another potential source of endogeneity is that high-end energy users would opt for more efficient dwellings. If it is true, the direct rebound will be over-estimated. We believe this source of endogeneity is not an issue in Switzerland, as the housing market is very tight. The vacancy rate has indeed been very low for decades, especially in urban centers[1]. Moreover, 60% of households rent their dwelling and do not own it. Being a tenant in a very tight housing market do not provide many choices to people. Hence, it seems implausible that tenants take into account the energy efficiency of a flat in conjunction of their own energy consumption on top of all other criteria. However, it may be more plausible for house owners to take energy efficiency into account, even though the market is very tight. To control for the existence of such a bias, we perform later the regressions for tenants and home owners separately. Results for both groups are almost identical, confirming that such an endogenous bias may exist in theory, but will be very limited in the Swiss context.

Once this first step of estimating the effect of heating efficiency on indoor temperature is completed, we turn to the second step. The equation for the second step, the HDDs method, is estimated with fixed-effects at the household level. The yearly variation in heating energy consumption in kWh is explained by the variation in heating degree days, controlling for different home renovations and the household size. Only households who stayed in the same dwelling are kept, in order to identify solely the effect of variation in outdoor temperature on energy consumption, and not the effect of variation in building efficiency. This second-step equation is:

$$\begin{aligned} kWh_{i,t} = \beta_0 + \beta_1 HDD_{i,t} + \beta_2 HDD^2_{i,t} + \theta' W_{i,t} + \beta_3 Minergie_{i,t} \\ + \beta_4 HHsize_{i,t} + \lambda_i + \lambda_c + \epsilon_{i,t} \end{aligned} \tag{2.5}$$

[1]The vacancy rate has always been below 2% since the statistic began, and is frequently below 1% in urban centers (www.bfs.admin.ch/bfs/en/home/statistics/construction-housing/dwellings.html)

HDD and HDD squared are included to allow for a non-linear relationship between energy consumption and outdoor temperature. Houses where winter conditions are harsh are indeed likely to be better insulated, therefore we expect a negative coefficient on HDD^2. $\theta' W$ is a vector of building renovations, Minergie is a dummy variable to capture the effect of the certification, λ_i is the time-invariant individual effect that captures individual's unobserved characteristics affecting heating energy consumption, λ_c the state fixed-effect and $\epsilon_{i,t}$ the error term.

β_1 is not constant for all households, and will vary by dwelling size since the energy needed when HDD increase by 1 is proportional to the heated square meters. Thus, the β_1 coefficient found is true for the average household. To express equation 2.5 directly in terms of percentage variation, we also estimate the following equation:

$$
\begin{aligned}
ln(kWh_{i,t}) = \beta_5 + \beta_6 ln(HDD_{i,t}) + \theta' W_{i,t} + \beta_7 Minergie_{i,t} \\
+ \beta_8 HHsize_{i,t} + \lambda_i + \lambda_c + \epsilon_{i,t}
\end{aligned}
\tag{2.6}
$$

The expected β_6 coefficient is 1, based on prior literature (CIBSE, 2006). Here we dropped HDD^2 to get a β_6 coefficient comparable to other articles. Both β_1 and β_6 can be used in the rebound estimate.

From equation 2.4, we learn that when heating costs decrease by 1%, indoor temperature increases by $(\alpha_1/100)$ per day. To translate this rise into energy, we need to multiply it by the number of heated days. The average length of winter, based on HDDs, is 6.9 months in the survey sample (more details in Appendix J on the calculation), so the average heated days are $30 * 6.9 = 207$[1]. By multiplying $(\alpha_1/100)$ by 207, we obtain the total rise in HDDs per year due to increased indoor temperature. Then, we must multiply this number by β_1 to get the corresponding increase in kWh. Finally, to estimate the temperature rebound effect, those extra kWhs need to be divided by the potential energy savings (PES) in kWh (a 1% decrease was assumed). Hence, the temperature rebound is:

$$
\textit{Temperature Rebound} = \frac{(\alpha_1/100) * 207 * \beta_1}{0.01 * \overline{kWh}} \tag{2.7}
$$

In this example, we assumed a 1% decrease in heating costs. If we assume a 5% decrease in heating costs, then we need to multiply $(\alpha_1/100)$ by 5, and take $(0.05 * \overline{kWh})$ for the PES. The result for the rebound would be exactly the same.

[1]In the Results section, we also compute the rebound with ±5% heated days. There is no point in testing a larger range around 207 while keeping the same heating costs, because in real conditions, when winters are harsher, HDDs increase and heating costs increase as well, so there is no impact on rebound estimations.

Alternatively, if we use equation 2.6, the temperature rebound is:

$$Temperature\ Rebound = \frac{(\alpha_1/100) * 207 * \beta_6}{0.01 * \overline{HDD}} \tag{2.8}$$

These two rebound equations assume the same rebound definition, that is:

$$Temperature\ Rebound = \frac{Potential\ energy\ savings - Realised\ energy\ savings}{Potential\ energy\ savings} \tag{2.9}$$

As *Potential energy savings* equals $\frac{\triangle\epsilon}{\epsilon}$ and *Realised energy savings* equals $(\frac{\triangle\epsilon}{\epsilon} - \frac{\triangle S}{S})$, equation 2.9 is similar to equation 2.1.

4.2 Results

Determinants of heating and hot water costs

Before turning to the rebound results, we looked at the determinants of heating and hot water costs. We simply regressed by OLS various buildings and households characteristics known to affect energy consumption on the logarithm of heating and hot water costs. We do not include fuel prices since we already control for the year and for the heating fuel type, so almost no variation in prices remains. Results are presented in Table 2.2. Accommodation type has an effect, with detached house consuming the most energy for heating and hot water (the same conclusion was found by Dettli et al. (2003) for Switzerland). Construction date, here grouped by decade, has a strong impact on heating energy consumption. These two variables are later used as instruments for heating costs. Also of interest, households paying individually for their heating consumption experience almost a 10% decrease in their bill (13% if heating costs are kept alone as the explained variable). However, 41% of the households in the sample do not pay individually their heating bill, so installing individual metering would be an easy and cheap way to save energy, consistent with the findings of Lang and Lanz (2021). Finally, an extra degree increases the bill by 5.1% (8.9% for heating costs alone), similar to the popular rule of thumb. This coefficient is nevertheless to take with caution, because the causality between indoor temperature and heating costs goes in both direction[1]. When only water costs are kept as the explained variable, few explaining variables are significant, as expected, with only dwelling size and household size being significant at the 1% level, dwelling size picking up perhaps the effect of the number of bathrooms in the house. Detailed results are available on demand.

[1] An instrumental variable was searched for internal temperature, to correct for the bias, but without success.

Table 2.2: **Determinants of Heating & Hot Water Costs**

	Ln(Heating and Hot Water Costs per m^2)	
Accommodation Type:		
(Detached house as base category)		
Flat (in building with <5 flats)	-0.106***	(0.038)
Flat (in building with 5-10 flats)	-0.104***	(0.033)
Flat (in building with >10 flats)	-0.128***	(0.038)
Terraced house	-0.141***	(0.040)
Heating Fuel: (Oil as base category)		
Gas	-0.021	(0.024)
Electricity	-0.061	(0.046)
Wood	-0.296***	(0.050)
Heat pump	-0.248***	(0.031)
District heating	0.028	(0.037)
Other	-0.185***	(0.067)
Construction decade:		
(Before 1960 as base category)		
1960-1969	-0.088**	(0.036)
1970-1769	-0.148***	(0.033)
1980-1989	-0.124***	(0.035)
1990-1999	-0.276***	(0.039)
2000-2010	-0.318***	(0.043)
After 2010	-0.402***	(0.050)
Indoor temperature	0.051***	(0.010)
Tenant (0/1)	-0.090***	(0.026)
Dwelling m^2	-0.004***	(0.000)
Household size	0.018*	(0.009)
Income	0.047***	(0.008)
Education	0.010	(0.009)
Age	0.008***	(0.001)
Individual heating costs (0/1)	-0.093***	(0.022)
Insulation renovation (0/1)	-0.042*	(0.025)
Windows renovation (0/1)	-0.027	(0.028)
Heating renovation (0/1)	-0.020	(0.025)
Minergie (0/1)	-0.138***	(0.029)
Constant	1.385***	(0.234)
County FE	YES	
Year FE	YES	
N	10,232	

Notes: Clustered standard errors at the household level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Step 1: Indoor temperature regression

Concerning the rebound effect, results for equation 2.4, estimated by 2SLS, are given in Table 2.3. We find that when heating and hot water costs decrease by 1%, indoor temperature increases by 0.01 unit, and by 0.009 unit when heating costs are considered alone. Without the instrumental variables, these coefficients are positive, whereas we expect and find negative coefficients with 2SLS. Results for the OLS regression are shown in Appendix K. Not surprisingly, the Durbin-Wu-Hausmann test strongly rejects exogeneity. Moreover, in all 2SLS regressions, the first-stage F-statistics exceed the critical value of 10, while first-stage coefficients of the instruments are highly significant, showing that the instruments are strong[1].

Although +0.01 to +0.009 °C might seem small, we must keep in mind that not all households are concerned by a potential direct rebound effect. In a previous paper (Hediger et al., 2018), we found that 24% of the households would perhaps or for sure increase the indoor temperature after an efficiency improvement. To provide an example, assume a refurbishment that diminish heating energy usage by 10%, which means an increase of about 0.1°C according to our results. Out of 100 households, 85 households will for instance not adjust their internal temperature, 5 households by one degree, and 10 households by half a degree. The mean temperature increase is hence 0.1°C ($0.05 * 1 + 0.1 * 0.5 = 0.1$).

We should note that the cost decrease hypothesized here is the outcome of an energy efficiency improvement rather than the outcome of a decrease in price, because since we control for the state, the year, and the heating fuel, little variation in price remains. Indeed, when the same regression is performed with the energy consumed in kWh instead of heating costs, the coefficients are very close (-1.18 and -0.77). Nevertheless, we believe that these results can also be interpreted in case of a price variation, because households are rarely aware of their exact energy consumption (Fell and King, 2012), but they are aware of their monthly or yearly heating bill. Hence, it should not strongly matter for households whether their bill diminution comes from an energy price decrease or an efficiency improvement. As a consequence, we can also interpret the coefficient on indoor temperature in case of increasing heating fuel prices, as happening for the 2022 winter. In other words, if heating prices rise by 10%, we expect an average diminution of the indoor temperature by 0.1°C.

A recent comparable study measuring the effect on internal temperature of a variation in heating costs is Fowlie et al. (2018). They found an increase of +0.67 F after weatherization, although not significantly different from 0, possibly due to the restricted number of observations (349 households with recorded temperature data after weatherization). As

[1] In regressions with heating costs alone, because the number of observations are much lower, we needed to define accommodation type in three categories instead of five: detached house, flat, terraced house. With five categories, not all categories were significant in the first-stage regression.

Table 2.3: 2SLS: Indoor Temperature & Heating Costs

	Heating & Hot Water: Indoor temp. (°C)		Only Heating: Indoor temp. (°C)	
Ln(Heating (& hot water) costs per m^2)	-1.22***	(0.17)	-0.91***	(0.32)
Tenant (0/1)	-0.08**	(0.04)	-0.13	(0.09)
Dwelling m^2	-0.004***	(0.00)	-0.003**	(0.00)
Heating Fuel: (Oil as base category)				
Gas	-0.02	(0.04)	-0.11	(0.08)
Electricity	-0.07	(0.06)	-0.05	(0.14)
Wood	-0.51***	(0.09)	-0.52***	(0.16)
Heat pump	-0.26***	(0.07)	-0.27*	(0.15)
District heating	0.04	(0.06)	-0.05	(0.11)
Other	-0.35***	(0.12)	-0.57**	(0.25)
Household size	0.01	(0.01)	-0.00	(0.03)
Income: (<3,000 CHF as base category)				
3,000-4,499 CHF	0.26***	(0.09)	0.46**	(0.18)
4,500-5,999 CHF	0.35***	(0.09)	0.41**	(0.17)
6,000-8,999 CHF	0.47***	(0.09)	0.60***	(0.18)
9,000-12,000 CHF	0.56***	(0.09)	0.57***	(0.18)
>12,000 CHF	0.60***	(0.10)	0.72***	(0.19)
Education	-0.07***	(0.01)	-0.02	(0.03)
Age	0.02***	(0.00)	0.03***	(0.00)
Individual heating costs (0/1)	-0.28***	(0.03)	-0.39***	(0.08)
Minergie (0/1)	-0.20***	(0.06)	-0.21*	(0.13)
Constant	23.69***	(0.38)	21.57***	(0.40)
County FE	YES		YES	
Year FE	YES		YES	
N	11,056		2,634	

Notes: Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Building construction date and accommodation type are used as instruments for heating costs. The first stage F-statistic is 40.0 (13.8 in the equation with heating costs only) and the first stage instrument coefficient is significant at the 99% level (95% level in the equation with heating costs alone).

weatherization diminished energy consumption by 10%-20% on average according to their estimations, we can directly compare +0.67 F to our result[1]. As +0.67 F corresponds to +0.372°C, we can estimate the coefficient α_1 in their case. It gives a coefficient a little larger than the one found in this study (between 1.5 and 2).

[1]Nosperger et al. (2017) also reports rather large increases in average temperature in French households after home refurbishments, with data on indoor temperature before and after various efficiency programs. However, they do not provide estimation of percentage energy savings of these programs, hence we cannot compare our findings.

We also performed the same regressions for tenants and owners separately. The aim is to check whether a potential endogenous bias exists in the case of high-end energy users choosing efficient dwellings. As described in the empirical strategy part, it seems unlikely that such a bias arises for tenants, because of the extremely tight housing market in Switzerland. Yet, such a bias may still arise for home owners. The results for both groups, presented in Appendix L, are extremely close and not statistically different. The regression with heating and hot water costs was used, because of the higher number of observations. The coefficient for tenants is 1.17 and 1.21 for owners. Thus, although an endogenous bias may exist in theory, this bias seems to be very limited or non existing in the Swiss context, probably because of the very tight housing market.

From Table 2.3, we also learn that high income households heat their home at a higher temperature than low income households. The difference is about 0.5 °C between the poorest and the richest households. It is the sign that poorer households limit their heating energy consumption to save money. They are hence unlikely to be at their satiety point in terms of thermal comfort, and the rebound effect is expected to be larger for them. It is also interesting to note that households with a renewable fuel (wood, heat pump, or other fuels which are mainly solar systems), mainly home owners, opt for a temperature up to half a degree less than households with oil as heating fuel. Those households are probably more environmentally conscious and are likely to display a preference for lower indoor temperature.

In the next part, we investigate further the impact of income on the variation in internal temperature. To do so, we add interaction terms between income and heating costs. These results will be used later to estimate a rebound effect per income categories.

The impact of income

One feature of the rebound described in the literature in space heating and in other sectors is that the direct rebound effect is larger for low income households (Milne and Boardman, 2000; Sorrell et al., 2009; Madlener and Hauertmann, 2011; Reimers et al., 2021). To test for the impact of income on the rebound, we add in equation 2.4 the interaction terms [Ln(Heating and hot water cost)*income]. As income is a categorical variable, one interaction term per categories is added. We expect that low income households react more to a decrease in heating costs than high income households, because poorer households are more likely to restrict their heating usage. We already observed in Table 2.3 that when income rises, internal temperature rises as well.

As heating costs are endogenous, but not income (higher internal temperature does not increase your income), the interaction term between both is also an endogenous regressor. We thus add as instrumental variables the product of building construction age and income categories, following Wooldridge (2010), in addition to building age and accommodation types. We also tested with the addition of the product of accommodation types and income categories as instruments, but they were rarely significant in the first stage of the 2SLS. Furthermore, the results were very similar to the one presented here.

Results are given in Table 2.4. Income indeed displays a substantial effect on the coefficient of interest, although the interaction terms are not significant. We are nevertheless confident that with more observations, interaction terms would be significant. We do not present the regression with heating costs alone, because with four times less observations, the coefficients of interest are not distinguishable from zero. We learn from Table 2.4 that as income rises, the variation in internal temperature becomes smaller. For the first income categories (less than 3,000 CHF per month), indoor temperature increases by 0.0176°C when heating and hot water costs per m^2 diminish by 1%. For the richest households (more than 12,000 CHF per month, the omitted category), the increase is only of 0.0097°C. To translate these increases into a rebound effect, we need to transform the additional temperature into energy consumption (kWh), which is done in the next part.

Step 2: Heating degree days (HDDs) method

To estimate the rebound, it is necessary to convert the indoor temperature increase we found in step 1 into energy. We use the HDDs method to do so, with the main assumption being that a one-degree increase in indoor temperature consumes the same heating energy as a one-degree decrease in outdoor temperature.

Results of equation 2.5 are shown in Table 2.5. Fixed-effects at the household level are used, and only households who did not move are kept in the sample. Hence, we control for heating habits that do not vary over time and for variations in building efficiency. We furthermore added four dummy variables (Minergie and three types of renovations) to control if home refurbishments took place over the survey years.

We find that an additional unit of heating degree day augments on average the kWh consumed by 3.54 units when heating and hot water consumption is considered, and by 2.05 units on average for heating alone. $HDDs^2$ is negative, as expected, showing that the relationship between HDDs and energy consumption is not perfectly linear, likely because houses where HDDs are more numerous are better insulated. The diverse retrofits diminished the energy consumption, except for windows renovations. As it is not the topic of this paper, we will not discuss them further (they require a deeper analysis such as when did the renovation took place, of which kind, etc.), but we refer to Lang and Lanz (2021) who provide an analysis of realised energy savings after different building retrofits in Switzerland.

Table 2.4: 2SLS: The impact of income

	Indoor Temperature (°C)	
Ln(Heating & hot water costs per m^2)	-0.97***	(0.22)
Ln(Heating & hot w. costs per m^2)*income1	-0.79	(0.72)
Ln(Heating & hot w. costs per m^2)*income2	-0.56	(0.56)
Ln(Heating & hot w. costs per m^2)*income3	-0.42	(0.42)
Ln(Heating & hot w. costs per m^2)*income4	-0.27	(0.29)
Ln(Heating & hot w. costs per m^2)*income5	-0.13	(0.15)
Ln(Heating & hot w. costs per m^2)*income6	*omitted*	(.)
Tenant (0/1)	-0.08**	(0.04)
Dwelling m^2	-0.004***	(0.00)
Heating Fuel: (Oil as base category)		
Gas	-0.03	(0.04)
Electricity	-0.08	(0.07)
Wood	-0.52***	(0.10)
Heat pump	-0.24***	(0.07)
District heating	0.04	(0.06)
Other	-0.31**	(0.13)
Household size	0.00	(0.01)
Income	-0.22	(0.30)
Education	-0.07***	(0.02)
Age	0.02***	(0.00)
Individual heating costs (0/1)	-0.28***	(0.04)
Minergie (0/1)	-0.21***	(0.07)
Constant	25.06***	(1.52)
County FE	YES	
Year FE	YES	
N	11,056	

Notes: Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Income 1 is the first income bracket (less than 3000 CHF per month) and income 6, the omitted category, the last income bracket (more than 12,000 CHF per month). Building construction date, accommodation types and (building construction date * income categories) are used as instruments. The first stage F-statistics range from 40.8 to 540.7, and the first stage instruments are significant at the 99% level, except in the first stage of the first income category, where interaction terms instruments are significant at the 90% level. This income category is smaller than the other categories.

3.54 and 2.05 kWh are averaged estimations, and will vary for instance with the dwelling size. To provide estimations in percentage variations directly comparable between households and between different articles of the literature, we estimate equation 2.6 with the natural logarithm of HDDs. The drawback is that the relationship is constrained to be linear[1]. Table 2.6 displays the results. The coefficients found are very close to 1, which is the expected theoretical value (CIBSE, 2006).

[1] In the literature, HDDs^2 is rarely mentioned, and by definition, the HDDs method assumes a linear relationship between HDDs and heating energy consumption. We nevertheless tried to add ln(HDDs)^2 in the regression, but the coefficients turned insignificant.

Table 2.5: **HDDs & energy consumption [kWh]**

	Heating & Hot Water: kWh	Only Heating: kWh
HDD	3.54^{***}	2.05^{**}
	(0.64)	(0.93)
HDD^2	-0.0003^{***}	-0.0001
	(0.0001)	(0.0002)
Minergie (0/1)	-2636.2^{***}	-1520.5
	(636.8)	(1100.5)
Insulation renovation (0/1)	-1169.7^{***}	850.4
	(411.3)	(732.1)
Windows renovation (0/1)	85.2	829.4
	(537.4)	(993.6)
Heating renovation (0/1)	-725.7^{**}	862.6
	(368.7)	(583.9)
Household size	471.4	-309.5
	(362.1)	(726.0)
Constant	7746.6^{***}	10946.3^{***}
	(2555.2)	(3602.1)
County FE	YES	YES
# Observations	8,084	1,252
# Households	2,842	522

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Fixed-effects at the household level are used. The sample is restricted to households with no accommodation change.

We are now able to convert an increase in indoor temperature into energy. We present these calculations and the rebound computations in the next part.

Computing the temperature rebound

With steps 1 and 2 completed, we know all coefficients needed to compute the temperature rebound following equation 2.7 and equation 2.8. Results are summarized in Table 2.7. In the first column, the coefficients used to compute the temperature rebound comes from the regressions with heating and hot water costs, while in column 2 they refer to regressions with heating costs alone. Results with a small variation (plus or minus 5%) around the number of heated days are also presented. For the different income levels, coefficients from Table 2.4 are used in the rebound equation 2.8. For using equation 2.7, we needed six different coefficients (one per income level) instead of α_1, which appears not possible due to the limited number of observations per income level. All averages needed to compute the rebound (average heating costs, average HDDs, etc.) are available in Table C.

Overall, the temperature rebound ranges from 4% to 8%. It means that only a small portion of the expected energy savings after a heating efficiency improvement is lost due

Table 2.6: Linear relationship HDD-kWh

	Heating & Hot Water: Ln(kWh)	Only Heating: Ln(kWh)
Ln(HDD)	0.892***	0.918**
	(0.137)	(0.438)
Minergie (0/1)	-0.263***	-0.061
	(0.075)	(0.190)
Insulation renovation (0/1)	-0.045	0.121
	(0.039)	(0.113)
Windows renovation (0/1)	0.041	0.213
	(0.054)	(0.163)
Heating renovation (0/1)	-0.027	0.138
	(0.034)	(0.118)
Household size	0.007	-0.096
	(0.031)	(0.091)
Constant	2.190*	2.003
	(1.124)	(3.500)
County FE	YES	YES
# Observations	8,088	1,255
# Households	2,842	523

Notes: Standard errors in parentheses. *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01. Fixed-effects at the household level are used. The sample is restricted to households with no accommodation change.

to higher internal temperature. Here, only results using the HDDs method are presented, but we could also have transformed the increase in indoor temperature using the rule of thumb that an extra degree increases your heating bill by 6 to 7% (we take 6.5% in the following calculation): +0.0122°C translates to +0.079% of the annual bill, that is, +1 CHF on average. We initially assumed a decrease of 1% in heating and hot water costs (12.6 CHF). Thus, the temperature rebound is given by $1/12.6 = 0.079$. 7.9% is in the upper limit of what we find with the HDDs method.

When the rebound is investigated for different income levels, we find the expected amplified rebound for poorer households. For the lowest income level, the temperature rebound reaches 11%, while it ranges from 6% to 9% for the other income categories. It is a sign that poorest households limit voluntarily their heating energy consumption and that building retrofits, in addition of bringing energy savings, will improve their living conditions by restricting less their heating consumption.

Our rebound findings are similar to those of Fowlie et al. (2018). Although they do not estimate a temperature rebound, we can do it with the information they provide. A rebound of 9.4% is found, the detailed calculations are provided in Appendix M.

To obtain a full picture of the micro-level rebound, estimating the direct rebound is not sufficient, the indirect rebound needs consideration as well. What happens with the

Table 2.7: Temperature Rebound Results

	Heating & hot water coefficients	Heating coefficients
With equation 2.7:		
207 heating days	6.6%	3.8%
217 heating days (+5%)	6.9%	3.9%
197 heating days (-5%)	6.3%	3.6%
With equation 2.8:		
207 heating days	7.4%	5.7%
217 heating days (+5%)	7.7%	5.9%
197 heating days (-5%)	7.0%	5.4%
For income levels: (with equation 2.8):		
Income 1	10.6%	-
Income 2	9.2%	-
Income 3	8.4%	-
Income 4	7.5%	-
Income 5	6.6%	-
Income 6	5.9%	-

Notes: From Table C, we know that the average number of HDDs is 3055, the average annual heating and hot water consumption is 13,590 kWh and the average annual heating consumption is 10,275 kWh.

remaining savings from an efficiency improvement? If most of the savings are spent on energy intensive goods, like air travel, a large part of the initial energy savings will be offset. We study this indirect rebound effect in the next section.

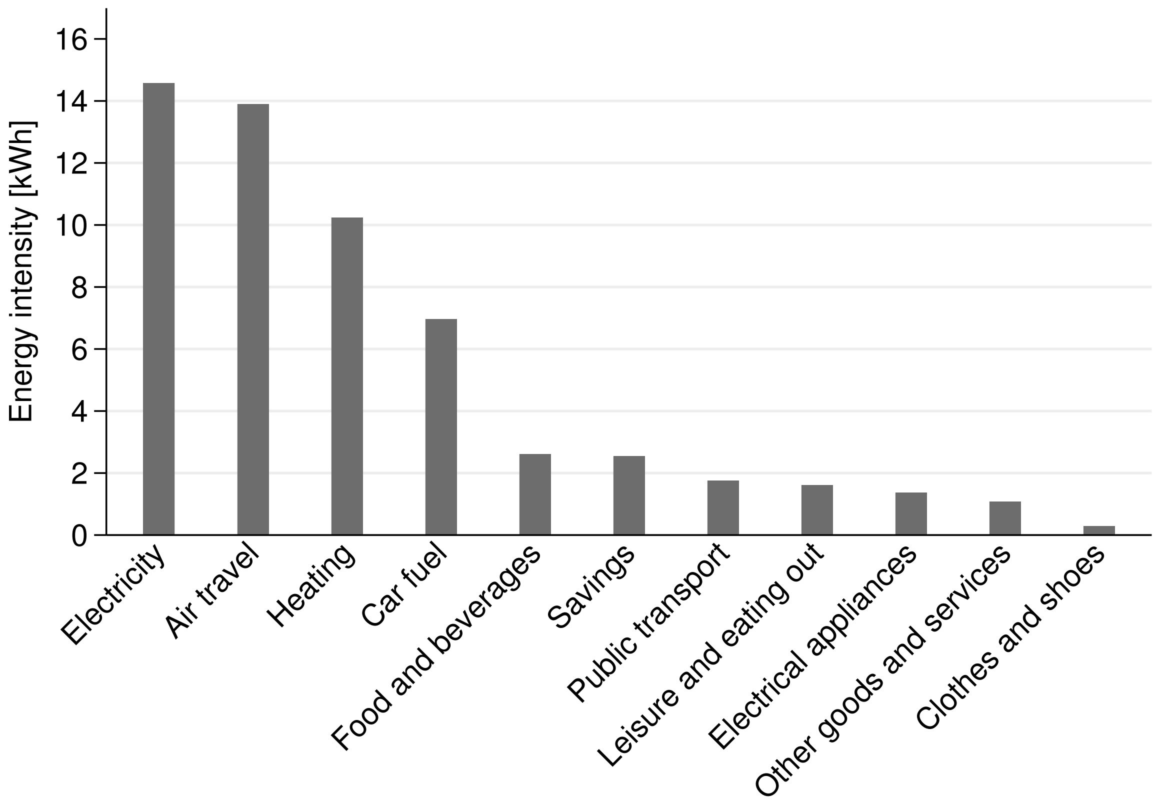
5 Indirect rebound

5.1 Empirical strategy

If positive savings remain after that the efficiency improvement and the direct rebound occurred, households will spend those savings on other goods or services, or they will keep those savings at the bank. All these actions involve energy to manufacture, provide and use the good or service in question. Even savings at banks carry embodied energy, as they are either invested by the bank or used later by households.

To estimate the indirect rebound, we need (i) data on consumption habits, and (ii) data on the embodied energy in goods and services. For (i), we make use of the 2015 SHEDS wave, where households had to report their usual monthly spending on 11 categories of goods and services. Those categories were chosen according to the available data on embodied energy. Data for (ii) comes from Tilov et al. (2019), who use a combination of Life-cycle assessment and Environmentally-extended input–output tables for Switzerland to estimate energy intensities for 281 commodities. Energy intensities in kWh per CHF are depicted in Figure 2.2. We treat savings as carrying the average energy intensity of all goods and services.

Figure 2.2: Energy Intensities [kWh per CHF]

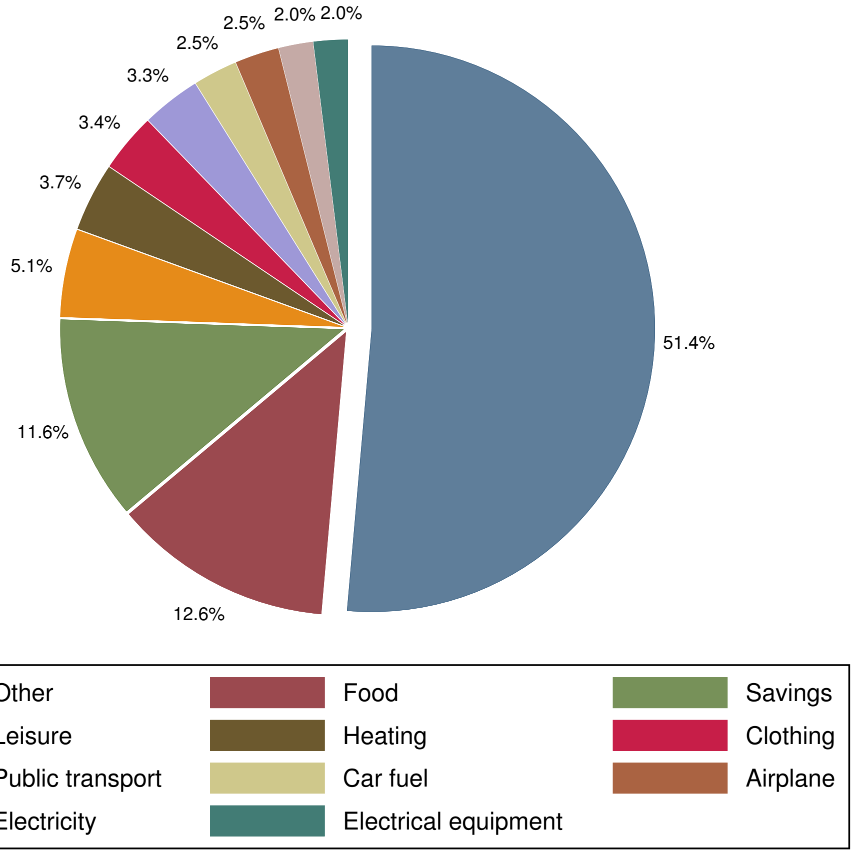


Notes: For savings, the average energy intensity of all goods and services is taken.
Source: Tilov et al. (2019)

The monthly spending shares are shown in Figure 2.3. Appendix N provides a comparison of spending shares from the survey and from the Federal Office of Statistics (Household budget survey). The categories are less numerous to adapt to the available categories at the national level. We can see that the survey spending shares are close to the national data, with only spending shares on food and leisure being somewhat divergent. As the energy intensity of these two categories are similar, we do not see this difference as an issue in the indirect rebound estimation.

To estimate the indirect rebound, we first compute the total embodied kWh of households' consumption bundles by multiplying the monthly spending by their respective energy intensity. The kWh from heating and hot water are subtracted from the total kWh, since we aim to study the indirect rebound. Then, total embodied kWh is regressed on spending for heating, keeping total spending constant. In this way, if there is no re-spending at all on other goods or services (for instance if the direct rebound=100%), total embodied kWh

Figure 2.3: Monthly Spending Shares



Notes: From 2015 wave of SHEDS. The average total monthly spending is 5,362 CHF, consistent with the 2014 median gross salary of 6,427 CHF per month in Switzerland (Federal Office of Statistics), as social contributions are in the range of 15%-20% of the gross salary.
"Other" groups rent, insurances, taxes, etc.
N=2,327

should not vary since the kWh from heating were subtracted. On the opposite, if the direct rebound is zero and all savings are spent on other goods and services displaying a zero energy intensity, total embodied kWh should decrease by (10.24 * savings in CHF), 10.24 being the average energy intensity of heating in kWh per CHF. This is hypothetical, since nothing displays an energy intensity of zero. As we expect some re-spending on various goods and services with a positive embodied energy, the coefficient of interest should be positive and lower than 10.24. For some households, this coefficient could be larger than 10.24, for instance if they re-spend all savings on air travel. For them, when heating costs decrease, the total embodied kWh would increase, and the indirect rebound would be larger than 100%.

The estimated equation for the indirect rebound is thus given by:

$$Total\ embodied\ kWh_i = \gamma_0 + \gamma_1 Heating\ Cost_i + \gamma_2 Total\ Spending_i + \theta' W_i + \epsilon_i \quad (2.10)$$

Where $\theta'W$ is a vector of socio-economic characteristics. It is crucial to control for total spending, as we are interested in knowing how the efficiency gains savings are reallocated between different consumption categories, keeping the total amount of money spent constant. Otherwise, the effect would be mixed with an increase in total spending, following for instance an income increase. γ_2 is thus expected to reflect the average energy intensity of 1 CHF spent by Swiss households.

Based on equation 2.10, the indirect rebound is:

$$Indirect\ Rebound = \frac{|\gamma_1|}{10.24} = \frac{Increase\ in\ kWh}{Potential\ Energy\ Savings} \tag{2.11}$$

Results are provided in the next section. In absolute value, we expect a γ_1 larger than zero and smaller than 10.24, that is, an indirect rebound in the range of 0% and 100%. We also expect a negative coefficient: when heating costs diminish, households will re-spend those savings in some way and the total energy embodied in their consumption bundle will increase (excluding the embodied energy of heating from the total embodied energy).

5.2 Results

Table 2.8 displays the results of equation 2.10 estimated by cross-section. γ_1 equals 1.56 in absolute value, smaller as expected than 10.24, the average energy intensity of 1 CHF spent on heating in Switzerland. It means that, when heating costs diminish by one franc, keeping total spending constant, the total embodied energy in a household consumption bundle (without heating) increases by 1.56 units. γ_2, the marginal effect of one extra franc of total spending on the embodied energy, presents a realistic value of 1.76. It is half way between the average energy intensity (2.5 kWh per CHF) and the energy intensity of all other goods and services (1.1 kWh per CHF).

Once γ_1 is estimated, equation 2.11 can be applied to calculate the indirect rebound. The result is an indirect rebound of 15.2%. Here, this indirect rebound happens after the direct rebound occurred, because the embodied energy of heating is excluded from the total embodied energy. 15.2% is slightly smaller than the previous 21% found by Hediger et al. (2018) (the magnitude of the indirect rebound once the direct rebound is accounted for). It is meaningful to compare them, because they are based on the same energy intensity data.

This indirect rebound can be added to the direct rebound to evaluate the total micro-level rebound. In view of a partial direct rebound between 4% and 8%, the total micro-level rebound is estimated at a minimum of 19%-23%. It is a minimum, because only a partial direct rebound (the temperature rebound) was taken into account. These estimates fall in the typical range of 20%-30% found by Nadel (2016) for the total micro-level rebound.

Table 2.8: Indirect Rebound

	Total embodied kWh (except for heating)
Heating and hot water costs	-1.56***
	(0.49)
Total spending	1.76***
	(0.02)
Accomodation type: (Detached house as base category)	
Flat (in building with <5 flats)	-137.80
	(173.73)
Flat (in building with 5-10 flats)	-114.99
	(160.94)
Flat (in building with >10 flats)	-235.48
	(174.93)
Tenant (0/1)	-763.40***
	(145.76)
Dwelling m^2	6.00***
	(1.34)
Household size	70.97
	(50.79)
Age	-22.61***
	(3.81)
Female	-137.79
	(105.89)
Education	30.64
	(50.63)
Constant	2084.11***
	(539.10)
# Observations	1,914

Notes: Clustered standard errors at the household level in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

6 Conclusion

This paper discusses rebound effects at the household level for residential space heating. A robust way to estimate the direct rebound with micro-level data is employed, avoiding many issues raised in prior literature, as how to estimate heating usage and heating efficiency separately, or how to estimate the direct rebound without resorting to own-price elasticites. One recent paper (Fowlie et al., 2018) uses this method to evaluate behavioral adaptations after buildings retrofits, but does not estimate the rebound effect per se. Panel data from an online large scale survey on energy consumption of Swiss households is used for the analysis, complemented with information on energy prices and heating degree days.

The direct rebound estimation is performed in two steps: 1) An increase in indoor temperature of about 0.01°C on average is found when building efficiency improves by 10%. Heating costs per square meters, instrumented by building construction date and accommodation type, are used as a proxy for efficiency. 2) The increase in indoor temperature is translated to energy using the heating degree days method. Trying diverse specifications, our findings point to a minimal direct rebound between 4% and 8%. It is a minimum, because the rebound estimated in this way is only a partial rebound, as only the increase in indoor temperature is considered after efficiency gains, and no other behavioral adaptations such as an extended heating period or a larger heated area. Nevertheless, this temperature rebound covers a substantial part of the total direct rebound, because an increase in indoor thermostat requires more energy than most of the other individuals' potential adjustments (Palmer et al., 2012). This estimation of the temperature rebound is robust for different subsets of households. We tested the tenants versus the owners, and households providing estimations of their heating costs alone versus households providing heating and hot water costs together. We also tested the robustness of our coefficients when kWh were used for energy consumption instead of monetary estimates [CHF].

Another important finding, consistent with prior studies (Milne and Boardman, 2000; Madlener and Hauertmann, 2011; Aydin et al., 2017), is that low income households rebound more. In our study, the lowest income group (with less than 3,000 CHF per month) displays a direct rebound of 11%. Thus, efficiency measures will benefit more to less affluent households, by improving their living conditions along with energy savings.

To draw a complete picture of the micro-level rebound, the indirect rebound is assessed in addition to the direct rebound. Embodied energy intensities for 11 goods and services categories and monthly expenditure data are employed. On average, 15% of energy savings in the heating sector are taken back by re-spending on other goods and services. The total micro-level rebound is therefore estimated at a lower limit of 19% to 23%.

Different policy implications can be drawn from this study. First, a cheap and simple way to reduce rapidly energy consumption of heating is the installation of individual metering. Indeed, about 40% of the Swiss households do not pay individually for their heating usage, the global heating bill being divided among the building's inhabitants, giving little incentive to an economical use of energy. Our finding points to an average 10% energy savings when individual billing is in place, consistent with findings of Lang and Lanz (2021) on smart meters. 10% is a non-negligible potential reduction given the simplicity of the measure. It is for instance more than the 4% average savings from windows replacements (Lang and Lanz, 2021).

Second, building efficiency improvements are a good target for environmental policies aiming at decreasing energy usage, since the direct rebound is limited in this sector. Even if the indirect rebound is added to it, about 80% of energy savings are still achieved, far from the worrying situation of backfire when more energy rather than less energy is used after the efficiency gains. However, not all the expected saving will be realised, and this gap needs to be taken into account in energy policies to anticipate correctly future energy consumption.

Third, the indirect rebound calls for more attention, both from research and from environmental policies. Embodied energy is actually often overlooked, for instance national energy accounts in Switzerland[1] look at the final energy consumed in the country, but not at the energy embodied in all imported goods. A first step would be a better accounting of this embodied energy. Another step could be to make it more salient to individuals, through energy labeling for instance. A global carbon tax would also be a powerful tool to mitigate the indirect rebound, as carbon-intensive goods and products are also the most energy-intensive products.

A few limitations of the study and scope for future research can also be highlighted: The scope of this article was limited to one feature of the rebound, the temperature rebound, because of data availability. However, other features of the direct rebound could be assessed with the same method, as an extension of the heating period or an extension of the heated area. Concerning the indirect rebound, no test was made on the sensitivity of the results to the energy intensities magnitudes. If different sources of energy intensities are available, such tests could be performed. Finally, it would also be of interest to compare indirect rebound estimates based on embodied carbon emissions and embodied energy for the same country.

[1] Physical Energy Flow Accounts:
`www.bfs.admin.ch/bfs/en/home/statistics/territory-environment/environmental-accounting/energy.html`

CHAPTER 3

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

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JEL Classification: D12, D61, D62, Q41, Q47, R22.

Keywords: Rebound effects, energy efficiency, private mobility, welfare analysis, cost-benefit analysis, online survey.

1 Introduction

The European Union enacted a massive progression in fuel economy standard in 2020, with the new car fleet average set to 95 grams 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 grams 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, empirical analysis of the welfare impacts of the rebound are very scarce. To our knowledge, only one empirical article on the subject exists (Alfawzan and Gasim, 2019). This article contributes thus to fill this gap and provides a cost-benefit analysis of the rebound in the context of private transportation. The consumer surplus gained from the direct rebound (additional driving) is compared to the increase in negative externalities. On the one hand, people adapts 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 it generates external costs, such as pollution. For private transportation, external costs may be particularly large, with accident, noise, and congestion costs on top of air pollution costs. If these external costs outweigh the utility gains, the net welfare diminishes.

To quantify these private gains, the first step is to estimate the 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 kilometer). I find a direct rebound between 30 and 40%, meaning

[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.

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 is that it contains the self-estimated car fuel consumption, not only car manufacturers' estimations which are known to be severely underestimated in Europe (Tietge et al., 2017c). I show that using the official fuel consumption data brings a downward bias in the rebound estimation, because the underestimation of fuel consumption by manufacturers is not homogeneous: the more efficient vehicles are more severely affected than the less efficient ones. The bias direction was tested in this article, and is found to underestimate the rebound.

Once the rebound is estimated, I quantify in section 5 the additional utility from induced travel by using Hausman's method to calculate 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 subsection 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 that pollute less, and b) an internalization of external costs, for instance through an increase of the fuel tax or a new tax on km driven, or even through a new bonus/ penalty mechanism on car insurance linked to the car usage. These different measures are discussed in subsection 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 (the only other paper found is Frondel et al. (2008)). 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[1]. 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 made when the price elasticity is used, 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; Weber and Farsi, 2018); possibly explained because Europeans, driving less than Americans, are further away from their satiation point and hence rebound more. But 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

[1]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).

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 our 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 we apply the same ratio to this article, it would be 0.47 on average (7 cents / 15 cents).

In detail, to study empirically the welfare consequences of the rebound, we need i) to estimate the individual surplus coming from the extra km driven, and ii) to asses the external costs of induced travel. For 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 tax per km exist for cars, but their external costs are nonetheless estimated at the same time. Compared to the literature, these 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 in addition indirect emissions from car making and scrapping, damages to buildings, forests and harvests due to pollution, biodiversity losses, etc. According to these official estimations, the external costs for private cars amounted to 15 cents per km[1] 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 (except for the mountainous parts). In light of these different estimations, the official estimation of 15 cents per km looks adequate for Switzerland.

[1] 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.

Concerning the individual surplus from induced travel, I apply the surplus calculation method from Hausman seminal paper (Hausman, 1981). He provides exact expressions to estimate the compensating variation, 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 or large, the Marhsallian surplus differs from the true surplus value. They strongly suggest the Breslaw and Smith (1995) method for large price variations, a method almost identical to the Hausman's method. The price variations considered later in this article are indeed medium, defined by Araar and Verme (2019) respectively as over 20% and over 50%. On average, these variations are 40% in this article and come from the efficiency improvements needed to reach the new EU fuel standards.

Once both individual surplus and external costs are estimated, the microeconomic welfare implications of the rebound can be determined[1].

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 5,000 households answered annually[2]. As many households as possible were kept each year to create a panel. In this paper, only households with at least one gasoline or diesel car are kept, to ensure comparable fuel efficiency measures. 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 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

[1]For simplicity, the producers' surplus is assumed to be zero in the long-run.
[2]The first wave in 2015 was smaller, with 3,500 participants.

(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 official estimations from manufacturers, who systematically underestimate it (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 included in some models, but since the variation of it was limited over the survey years, it does not bring significant difference to the results[1].

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 after a vehicle change. This sub-sample of households with a car change consists of 3,235 observations (1,065 households).

Table C 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 observation 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 (Figure O.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:

[1]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 3.1: Summary Statistics for the Final Sub-Sample

	Mean	Std. dev.	Min.	Max.	Median
Km driven (annually)	15,032	9,944	714	91,875	12,766
Fuel Intensity [l/100km]	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]	1,503	306	809	2,767	1,487
Car 1^{st} 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)					
<4,500 CHF	0.10	–	0	1	–
4,500-5,999 CHF	0.14	–	0	1	–
6,000-8,999 CHF	0.30	–	0	1	–
9,000-12,000 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=3,235 for all variables. Only households with at least one vehicle change are kept in this sub-sample.

41 daily km in the survey data, 46.9 daily km in the Microcensus[1]. Hence, data quality of the distance driven looks satisfactory.

[1]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 1,736 km, while it is only 252 km in the sample.

3.3 Real-World Fuel Consumption versus Official Estimations

Besides the distance driven, the other key variable for the analysis is the fuel intensity (FI). Table C shows two FI measures: the self-reported one and the official one from manufacturers. The self-reported FI is measured in $\frac{\mathrm{l}}{100\ \mathrm{km}}$ since it is the typical measure in Europe, versus the fuel efficiency (FE) in km/l 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. Figure O.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. By contrast, the official fuel intensity comes directly from car manufacturers. 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 P.

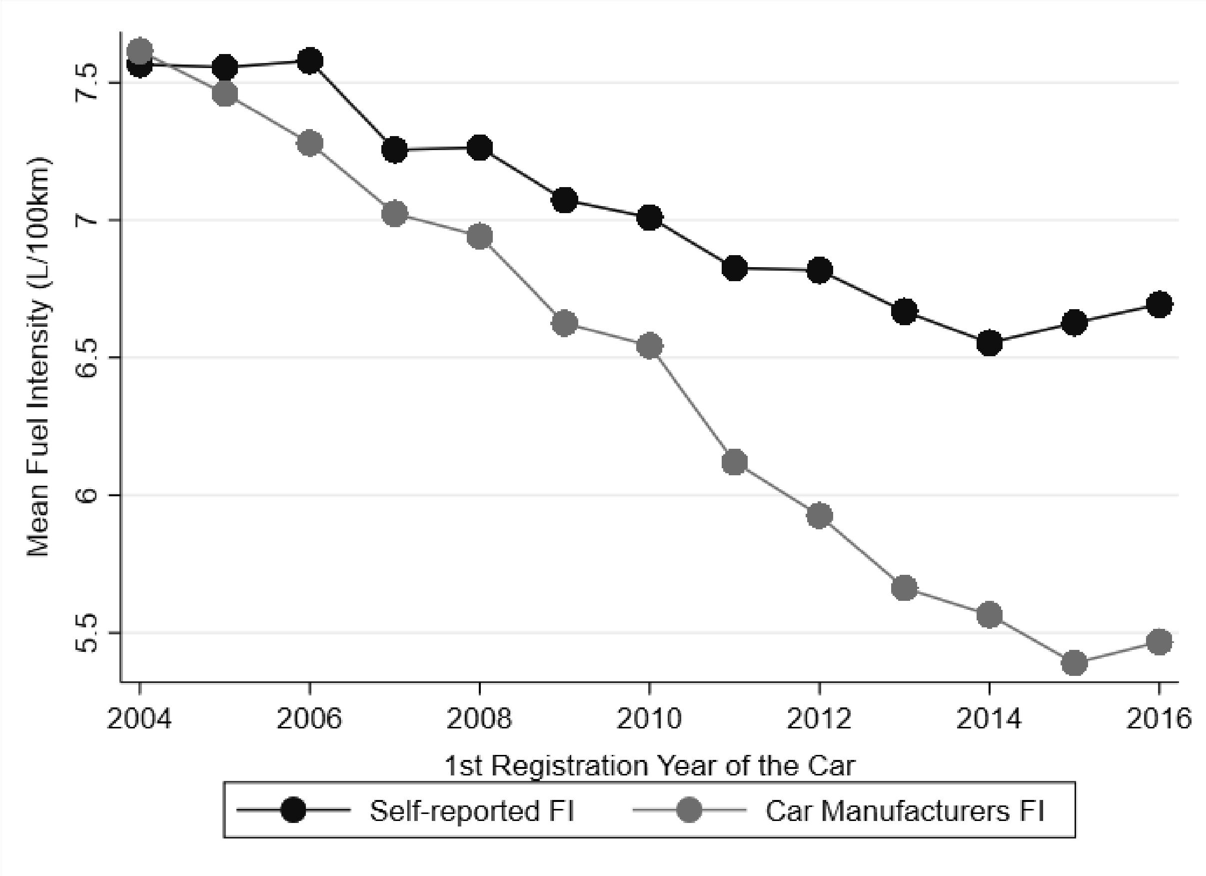
Thanks to the two different measures, we can investigate how far official measures are from real-world driving. Figure 3.1 displays this gap. The divergence has increased substantially since 2009 – following the application of more stringent CO_2 emissions standards in the EU and Switzerland – going 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.

The track of this divergence is useful to check the accuracy of self-reported fuel consumption answers. Indeed, we can compare the gap found in the survey to the gap found in other data sources. Figure 3.2 plots the divergences from the survey data and from the TCS (the largest motor-club in Switzerland). The TCS compares each year real-world and official fuel consumption of 15 to 20 of the most popular vehicle models in the Swiss market[1]. 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 form manufacturers, discuss this caveat and conclude it is not an issue as long

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

Figure 3.1: 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 a growing number of SUVs in Switzerland. (N=12,034)

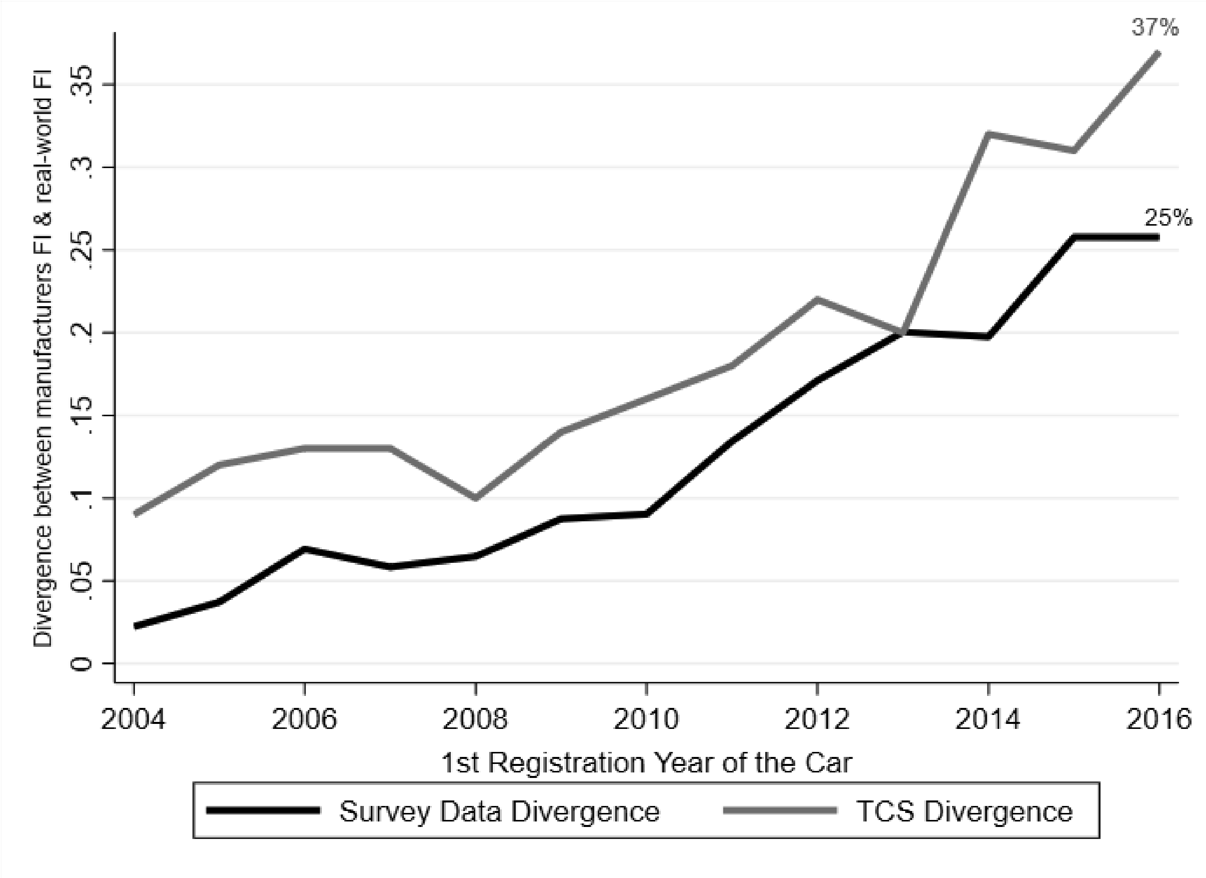
as people believe this gap is stable over time. However, their analysis misses a crucial point: the gap varies with the fuel efficiency level of the car. The divergence is indeed larger for more efficient cars, as found by Tietge et al. (2017b). I also find clear evidence of a higher gap for more efficient cars. In Figure Q.1, the sample is divided into low and high FI cars, the threshold being each year the median manufacturers FI[1]. 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[2] – to get closer to official values – and then the rebound was estimated. The

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

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

Figure 3.2: Divergence in Fuel Intensity: Comparison with TCS Data



Notes: 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)

rebound diminished in that experiment. The results are presented in Table Q. 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. In view of this bias, the use of the self-reported fuel consumption instead of official measures is an important asset of the paper[1].

[1]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).

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 R.

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:

$$km_{i,t} = f_{i,t} O_{i,t}^{\gamma} W_{i,t}^{\phi} FI_{i,t}^{\beta} \tag{3.1}$$

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 (3.1), the following log-linear equation is used:

$$\begin{aligned} Ln(km_{i,t}) = {} & \alpha_0 + \lambda_i + \lambda_c + \theta' Z_{i,t} + \gamma ln(O_{i,t}) + \phi ln(W_{i,t}) \\ & + \beta ln(FI_{i,t}) + \epsilon_{i,t} \end{aligned} \tag{3.2}$$

Coefficient β is the fuel intensity rebound effect, that is $\partial Ln(km)/\partial Ln(FI)$. Equation (3.2) is estimated with fixed-effects at the households level to account for individual heterogeneity. The logs of ownership length and car weight are used because both variables are not normally distributed (both are skewed to the right).

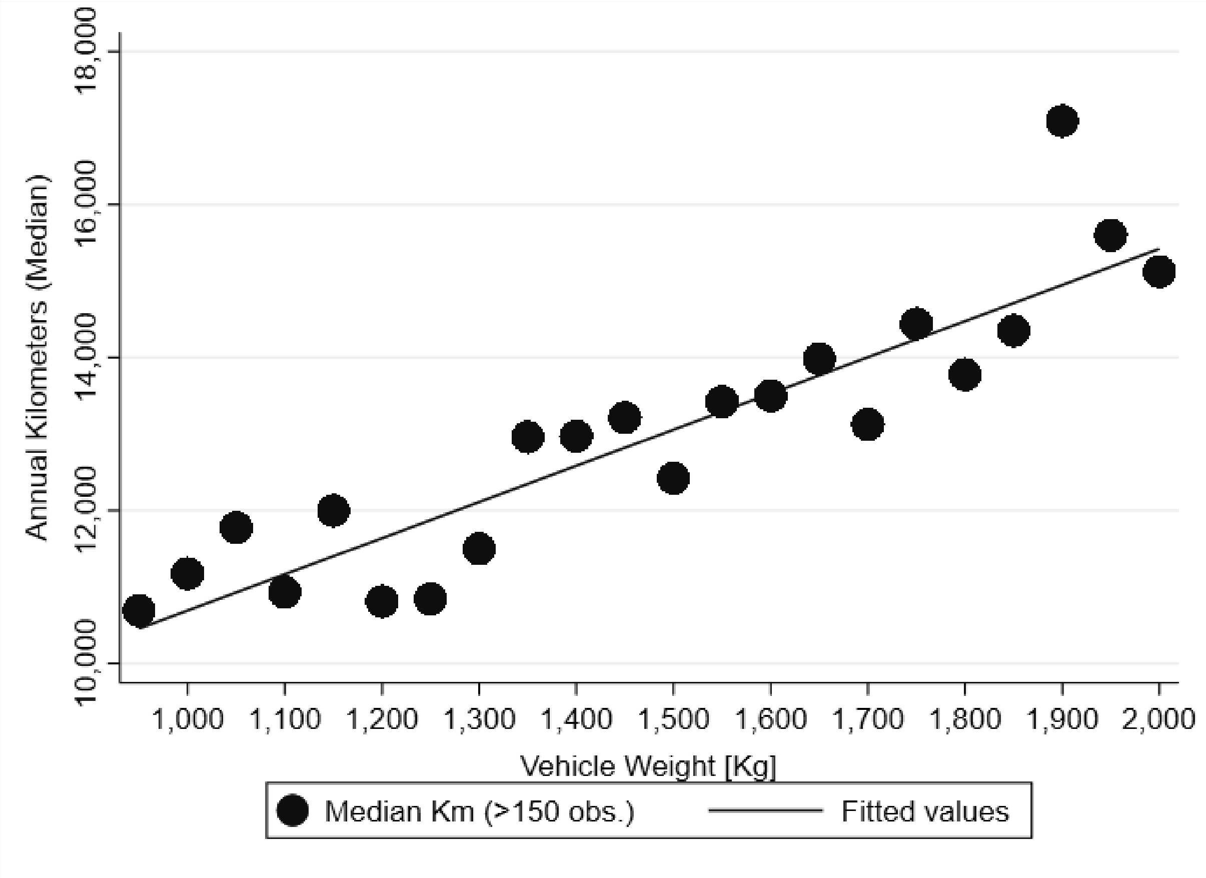
Concerns about the potential endogeneity of fuel intensity are raised in the literature. Do the expected km driven have an impact on the fuel intensity of the car, in other words, do people who expect to drive a lot buy more efficient cars? If yes, an endogeneity bias exists and instruments are needed 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 Figure 3.3: 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[1].

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 affect 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). We 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. Thus, using the full sample with the multi-vehicle households does not seem not an issue and does not strongly alter the results.

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

Figure 3.3: Vehicle Weight & Km



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 2,000 kg are too few (less than 150 observations) and are not shown in the graph. (N= 13,045)

Variations in self-stated fuel consumption

In each survey wave, the fuel consumption is self-stated by respondents. As a consequence, fuel intensity fluctuates even if the vehicle is the same. For instance, a respondent stated in 2016 that his car 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).

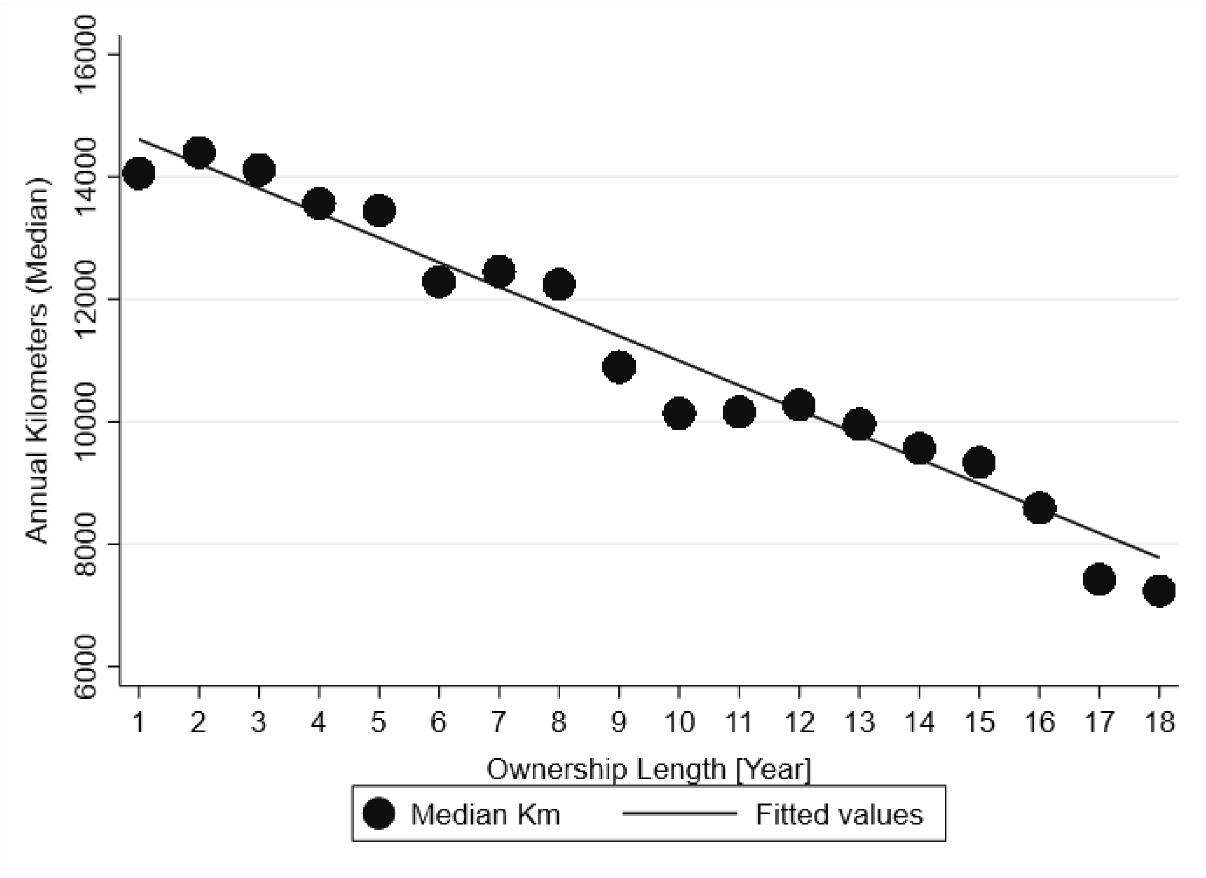
- Solution 2: *Before/after a car change*
  Only the year before and the year after the car change are kept in regressions. In the above example, it would be 2016 (old car) and 2017 (new car).

The rebound estimations for these two solutions are presented in the next section.

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. 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 3.2 displays equation 3.2 estimation for all households with at least a car change. Table 3.3 keeps only single vehicle households.

Figure 3.4: Ownership Length & Km



Notes: The median distance driven is reported for each year of vehicle ownership. (N= 12,673)

Three variables are essential in the regression, 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. Figure 3.4 shows the

Table 3.2: Rebound Estimation (Fixed-Effects at the Household Level)

	Solution 1 Mean Fuel Intensity	Solution 2 Before/After Car Change
Ln(Fuel intensity)	-0.306^{***}	-0.424^{***}
	(0.091)	(0.126)
Ln(Car weight)	0.331^{***}	0.427^{***}
	(0.111)	(0.163)
Diesel	0.155^{***}	0.133^{**}
	(0.044)	(0.066)
Automatic transmission	0.008	0.012
	(0.039)	(0.057)
Number of doors	0.036	0.015
	(0.022)	(0.035)
Ln(Nmb years car owned)	0.044^{***}	0.069^{***}
	(0.013)	(0.019)
Commute by car	0.082^{**}	0.057
	(0.032)	(0.059)
Income	0.043^{**}	0.047
	(0.018)	(0.035)
Education	0.012	−0.013
	(0.023)	(0.050)
Children	0.069	−0.082
	(0.054)	(0.144)
HH size	-0.043^{**}	−0.011
	(0.021)	(0.042)
Rail pass	−0.051	−0.260
	(0.055)	(0.166)
Constant	7.307^{***}	7.302^{***}
	(0.750)	(1.168)
County FE	YES	YES
# Observations	3,235	1,580
# Individuals	1,065	790

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. For solution 1, the mean 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.

strong negative relation between ownership length and the distance driven, also reported in Caserini et al. (2013).

These three variables are significant in all regressions. As expected in view of Figure 3.3, vehicle weight has a positive effect on 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. The positive coefficient on diesel vehicles was also expected, because diesel cars are known to be more economical over long distances and are hence more often chosen by people driving a lot. Finally, ownership length also displays the expected positive sign. This coefficient 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 his car for 10 years and then buys a new car, the variation 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 decrease 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 distance driven.

Other control variables also display the expected sign (such as income or rail pass), although most of them are not significant. The commuting distance was also added, to control for the fact that people might buy a more efficient cars if their commuting distance increases, for instance if they move, but the coefficient was almost zero and the inclusion of the variable had no influence on the rebound coefficient, and hence was dropped.

Table 3.3 displays the results for single vehicle households. 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. Some variables turned insignificant because the number of observations diminished. In view of these similar results and as 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 Q, a third result is presented: Here the fuel intensity of efficient vehicles is decreased, to get closer to manufacturers' values. 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[1] was decreased by 20% (the average gap between real-world and theoretical fuel consumption found in Figure Q.1). The fuel intensity of the other vehicles remained the same, because their efficiency is fairly in line with car maufacturers' values. Results in Table Q 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.

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

Table 3.3: 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^{**}	-0.372^{**}
	(0.127)	(0.166)
Ln(Car weight)	0.226	0.312
	(0.160)	(0.244)
Diesel	0.073	0.040
	(0.066)	(0.104)
Automatic transmission	−0.030	−0.023
	(0.053)	(0.082)
Number of doors	-0.073^{**}	-0.093^{*}
	(0.032)	(0.053)
Ln(Nmb years car owned)	0.045^{***}	0.061^{**}
	(0.016)	(0.025)
Commute by car	0.047	0.061
	(0.042)	(0.079)
Income	0.082^{***}	0.152^{***}
	(0.023)	(0.049)
Education	0.037	0.066
	(0.032)	(0.069)
Children	−0.056	−0.145
	(0.070)	(0.201)
HH size	-0.068^{**}	−0.083
	(0.030)	(0.062)
Rail pass	−0.074	−0.291
	(0.080)	(0.232)
Constant	8.189^{***}	7.555^{***}
	(1.137)	(1.827)
County FE	YES	YES
# Observations	1,796	846
# Individuals	607	423

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Only households with one vehicle are kept in Table 3.3. For solution 1, the mean 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.

5 Welfare Calculations: Empirical Strategy & Results

In this second part, the welfare consequences of the direct rebound are estimated. 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 rebound. To get an answer, we need to compare the utility gains and the external costs from the rebound effect. I first described how the utility surplus from the rebound is calculated, and then how external costs are computed. For simplicity, producers' surplus is assumed to be zero in the long-run.

5.1 Surplus Calculation: Empirical Strategy

To estimate the utility surplus from the rebound, an efficiency improvement is needed for each vehicle of the sample, that is, a car change for each household. Instead of 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[1]. The cap is determined as follows:

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

Where M is the car weight in kg, $M_0 = 1'379.88[kg]$ 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 2022. According to this equation, the average weighted car cannot emit more than 95 grams 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, i.e. each car gets its own future CO_2 emissions based on its weight and, therefore, each car gets its own future fuel consumption (95 grams 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). Overall, the average efficiency improvement is 33% in the sample. The range goes from 0 to 76%.

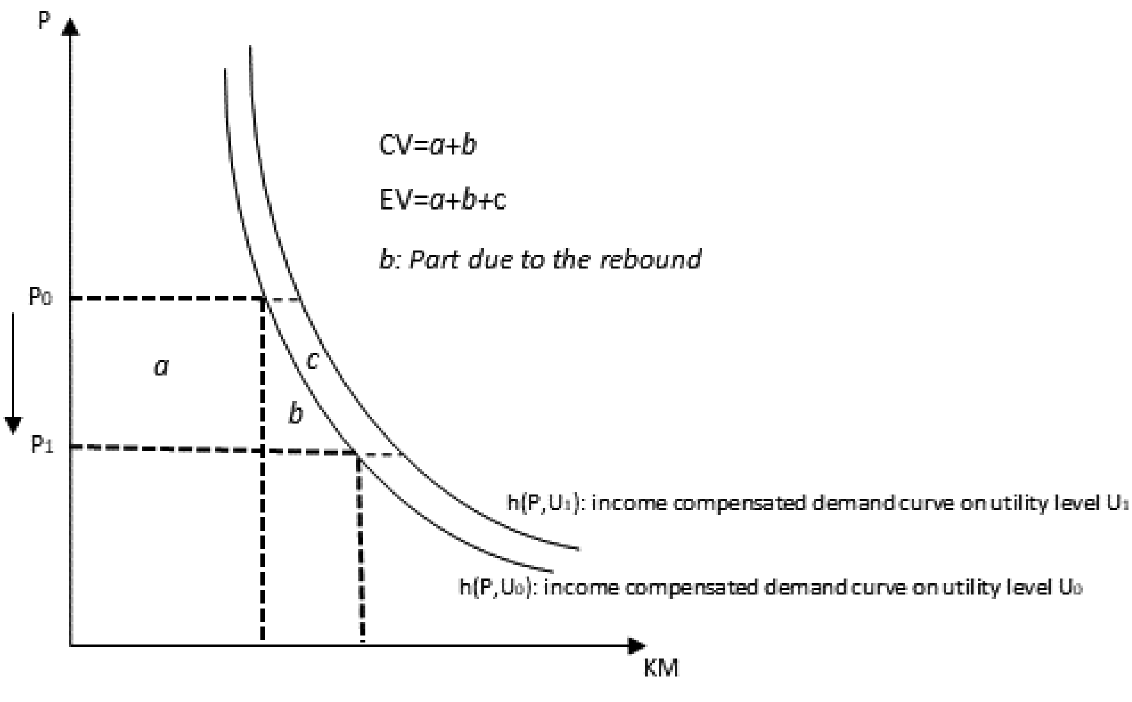
These individual efficiency improvements are then used in the utility surplus calculation. The surplus is calculated with the compensating variation (CV) from Hausman seminal method. The compensating variation is often used to capture individual surplus after a price decrease (recently by Langer et al. (2017) for automobile travel), and can be seen as

[1]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.

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).

The CV and EV are illustrated in Figure 3.5: 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.

Figure 3.5: Compensating & Equivalent Variation



See Markandya (2014) for correspondance with indifference curves

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 40%, CV is a better measure than the Marshallian surplus.

A price variable is necessary in the CV equation to depict the cost of one kilometer driven. So, instead of fuel intensity, I use the variable P in equation (3.1). P is the implicit price of one km driven, that is, the fuel price multiplied by the fuel intensity. 1.54 CHF is used for the fuel price, as it is the mean fuel price of gasoline in Switzerland for the sample.

Equation (3.1) becomes:

$$km_{i,t} = f_{i,t} O_{i,t}^{\gamma} W_{i,t}^{\phi} P_{i,t}^{\beta} Y_{i,t}^{\delta} \tag{3.3}$$

β, which was the rebound effect, is now the implicit price elasticity of one km driven. As in equation 3.2, logarithms are used in the regression and the log of income (Y) instead of income is used to derive δ. Results are given in Appendix S. β is slightly lower than in Table 3.2 (26% for solution 1 and 35% for solution 2). δ, the income elasticity of distance driven, is once 0.135 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.

Similar to Hausman (1981), the indirect utility function is given by:

$$v(P, Y) = c = f_{i,t} O_{i,t}^{\gamma} W_{i,t}^{\phi} \frac{P_{i,t}^{1+\beta}}{1+\beta} + \frac{Y_{i,t}^{1-\delta}}{1-\delta} \tag{3.4}$$

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:

$$e(P, \overline{u}) = \left\{ (1-\delta)(\overline{u} + e^{\omega} \frac{P_{i,t}^{1+\beta)}}{1+\beta}) \right\}^{1/(1-\delta)} \tag{3.5}$$

ω standing for $f_{i,t} O_{i,t}^{\gamma} W_{i,t}^{\phi}$ and $\overline{u}$ for the pre-defined utility level.

Following Hausman, the Compensating Variation is computed as:

$$\begin{aligned} CV_i &= e(P_{1,i}, u_{0,i}) - Y_i \\ &= \left\{ \frac{(1-\delta)}{(1+\beta) Y_i^{\delta}} [P_{1,i} km_{1,i} - P_{0,i} km_{0,i}] + Y_i^{(1-\delta)} \right\}^{1/(1-\delta)} - Y_i \end{aligned} \tag{3.6}$$

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[1], km_0 is reported in the survey, km_1 is simulated for each household according to his new car fuel efficiency and the rebound level, Y is given in the survey, and the income elasticity (δ) is 0.17.

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 CV. The surplus from the rebound (part b in Figure 3.5) is then calculated from this CV by subtracting 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 km, depending on the rebound level (variation in income elasticity hardly changes the results). The surplus can exceed 20 cents per km for some households. Results are shown in Table 3.4 and a histogram of the surplus is provided in Appendix T (for a rebound 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%).

Table 3.4: 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 Figure 3.5. N=3,217

5.3 External Costs

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 3.5 shows them.

[1] P_1 varies only because fuel efficiency improves as the fuel price is kept constant.

Table 3.5: External Costs in Switzerland in 2017 [CHF per year]

Health costs due to air pollution	≈ 2.2 billion
Congestion costs (2015 data)	≈ 1.4 billion
Climate costs	≈ 1.3 billion
Noise costs	≈ 1.3 billion
Accident costs	≈ 0.7 billion
Nature & Landscapes damages	≈ 0.8 billion
Other costs (indirect emissions from car making/scrapping, damages to buildings due to pollution, biodiversity losses, etc.)	≈ 1.3 billion

Source: Swiss Federal Office for Spatial Development (2020, 2018)

Divided by the number of kilometers driven in Switzerland in 2017[1], 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[2]. 15 cents per km for passenger cars seems therefore reasonable.

5.4 Discussion

The initial question was whether the rebound would overall bring welfare gains or welfare losses. The rebound itself, in the absence of externalities, is welfare improving. But once external costs are accounted for, some of these welfare gains will be offset. The critical point is to know whether all the welfare gains will be canceled, or just a portion of them. This question has been raised in the literature (Chan and Gillingham (2015) for example), but very little empirical work has been done in this area.

The results show that the external costs, 15 cents per km, outweigh the surplus from additional driving (7 cents per km on average). The rebound effect is thus more costly for the society than beneficial. Only for a handful of households (2-6% of the households, depending on the rebound level) was the surplus greater than the external costs.

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 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

[1] Source for the number of km in 2017: Federal Statistical Office, "Transport de personnes: prestations kilométriques et mouvements des véhicules"

[2] 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`

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.

These results are comparable only to the results of Alfawzan and Gasim (2019), since they provide the only other empirical analysis of the direct rebound welfare impacts. Their results for Switzerland, among many other countries, is 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 of both 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.

This gap between the private surplus from the rebound and its societal costs supports policies to “mitigate” the rebound effect. Nevertheless, we 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)[1]; the other major external costs – being associated with the polluting emissions of vehicles – will diminish with the shift to more efficient or 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. One option is to increase the fuel tax, however it is politically difficult to do so. 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.

Finally, policies to tackle directly the rebound effect could be investigated, for example by informing consumers that driving fuel-efficient cars in itself is not enough, but that an absolute reduction in fuel/ energy usage is needed.

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

6 Conclusion

In the next years, a massive efficiency improvement in vehicles is expected in the EU and in Switzerland, with the new car fleet emissions set on average to 95 grams of CO_2 per km from 2020. For Switzerland, this 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. But before planning a rebound mitigation, it is necessary to understand the welfare implications of the rebound: On the one hand, people driving more benefits from a utility increase, but on the other hand, it generates external costs such as air pollution costs, congestion costs or noise costs that are borne by everyone. 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 households fixed-effects. The fuel intensity elasticity is used, and a rebound between 30 and 40% is found. A novelty is brought by the use of self-stated car fuel consumption, which is very rare in the rebound literature. Usually, data from car manufacturers are employed. In Europe, these values are known to be heavily downward biased because the test cycles imposed to car manufacturers do not reflect real-world drvingin conditions. 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 data from manufacturers are employed, as tested in this paper.

Once the 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 rebound was applied to all households, which 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 surplus gains, external costs – taken from government estimations – are about the double, on average 15 cents per km. They include a wide range of driving externalities; 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: Will the decrease in pollution costs be large enough to compensate a hypothetical increase of other external costs if more km are driven ?

This gap between additional surplus and external costs support policies to prevent or mitigate the rebound. First, policies that diminish external costs should be considered, because the rebound itself increases social welfare. For instance, policies that accelerate the transition to electric vehicles diminishing air pollution and noise, or a push for smarter vehicles reducing the risk of accidents should be examined.

Secondly, policies aiming to internalize external costs should be looked at. One way to prevent the rebound when efficiency improves would be to increase the fuel tax in parallel. However, other new taxes or new mechanisms might be easier to implement: a tax per km driven, a bonus mechanism on the car insurance linked to the distance driven, etc.

This work provides one of the first empirical estimation on the net welfare change from the rebound in private mobility, and additional work on this is needed to gather results from different methods and different countries. An interesting point would be to study further the distribution of individual welfare effects, to investigate for instance whether less affluent households benefit more from the rebound, or whether the welfare distribution is linked to the share of the gasoline expenses in the consumption basket of individuals.

Conclusion

This thesis discusses the existence and magnitude of rebound effects for residential space heating and private transportation. These two sectors are indeed crucial for the energy transition in terms of potential energy savings, since space heating accounts for 38% of final energy consumption in Switzerland, and mobility for 41% (Infras et al., 2019). Energy efficiency programs exist for these two sectors, promising substantial efficiency gains for many individuals in the country over the next years. However, reactions of these individuals to efficiency improvements need to be studied. Individuals can increase their consumption of the service in question (direct rebound), because its price falls, or increase their consumption of other goods or services (indirect rebound) with the remaining savings. In both cases, these newly consumed goods or services require energy, either directly (a more intensive usage of cars), or indirectly (the embodied, or "grey" energy used to manufacture, transport and eliminate the product). Hence, a portion of the anticipated energy savings will be offset by these behavioral adaptations. How much exactly? This thesis proposes different ways to estimate it.

A worrisome situation for policy makers would be if more energy is consumed after efficiency improvements rather than less, a situation called backfire. No sign of backfire is found in my analysis, with limited rebound effects in the heating sector. Nevertheless, a larger rebound is found for private transportation, calling for more diversified actions by policy makers than solely relying on vehicle efficiency improvements in order to diminish the CO_2 emissions from this sector.

Chapters 1 and 2 investigate rebound effects for space heating. While the same subject is studied, the methods applied are completely different, with stated preferences used in Chapter 1 and revealed preferences in Chapter 2. The results outlined in both chapters are very much alike, with direct rebounds in the range of 5%-15%, and indirect rebounds in the range of 15%-20%. Thus, about a quarter of the expected savings from building retrofits will be offset by rebound effects in space heating. Chapter 3 examines another sector, private transportation, also targeted by ambitious efficiency improvements in the next decade. Here, a higher direct rebound effect is found, between 30% and 40%. No indirect rebound is calculated, but if we refer to the average value presented by Nadel (2016) of 10%-20%, the total micro-level rebound would be 40%-60% for private transportation. This larger rebound questions the effectiveness of vehicle efficiency improvements programs.

Chapter 1 more specifically details the mechanisms behind the direct rebound. Using an innovative choice experiment, we find that the most frequent adaptation after an efficiency improvement of the heating system is airing more, ahead of setting the thermostat higher or extending the heating period. We also find strong heterogeneity across households, both for the direct and indirect rebounds: a substantial share of the households (almost one third) displays no direct rebound. Although these no-rebound behaviors make sense in the context of heating, in which a maximal thermal comfort threshold likely exists, the traditional framework of unlimited substitution cannot explain these behaviors. We therefore resort to hierarchical preferences to interpret them. Moreover, we demonstrate that variations in direct rebounds are partly explained by observed characteristics such as income, education or ownership status.

Chapter 2 focuses on one mechanism of the direct rebound in space heating, the increase in temperature. Among the different behavioral adjustments outlined in Chapter 1, the temperature increase is the one requiring the most energy (Palmer et al., 2012). Thus, this adaptation will constitute the major part of the total direct rebound. Using six waves of the Swiss households energy demand survey (SHEDS), I show that households living in more efficient dwellings set a higher indoor temperature on average. Then, this increased temperature is converted to energy using the heating degree days (HDDs) method. This method presumes that heating energy demand is directly proportional to the indoor to outdoor temperature difference. Thus, by knowing variations in HDDs and variations in heating costs for the same household over multiple years, the energy needed for a 1°C increase in indoor temperature can be deducted and used to calculate the direct rebound. Overall, a direct rebound of 4% to 8% is found, with a peak at 11% for the lowest level income households. The major contribution of this chapter is on the method used to estimate the direct rebound, which could be expanded to others dimensions of the rebound in future research, such as an extension of heated areas or an extension in the heating period. Another contribution is the use of micro-level data for rebound estimates in space heating, which is indeed scarce in the literature, with most studies using aggregated data.

Chapters 1 and 2 are also relevant to compare the stated preference approach to the revealed preference approach. Indeed, it is rare to be able to compare these two methods as directly as in this dissertation: the same research question is investigated with data from the same survey, but with two different methods. Revealed preferences are usually seen as superior to stated preferences in terms of accuracy. Yet, the results found in both chapters are consistent, and different robustness checks performed in Chapter 1, where stated preferences are used, highlight the coherence of the answers. Hence, we cannot conclude to the superiority of revealed preferences in view of this dissertation. Both methods have assets and weaknesses; one major difference is the cost between the two methods. The stated preference method asks for less resources in time and money, here for instance only one survey wave was needed for this method, while six waves are used to apply the revealed preference method.

Chapter 3 looks at rebound effects in private transportation and addresses one gap in the literature: an empirical estimation on the net welfare change from the rebound. As greenhouse gases (GHGs) emissions from mobility are stable or increasing in developed countries (Lamb et al., 2021), and as the direct rebound is relatively large, discussions around the rationale to restrict the rebound have flourished. However, before planning any rebound mitigation, it is necessary to understand the welfare implications of it. On the one hand, individuals driving more benefit from a utility increase, but on the other hand, it generates external costs such as air pollution, congestion, noise, accidents, etc. This chapter compares the surplus gains from additional driving, stemming from the rebound, and the external costs of driving. Using panel data over five years from SHEDS, the direct rebound is first estimated between 30% and 40%. The identification strategy relies on comparisons of the same household before and after the purchase of a new vehicle. Second, the utility from additional driving is assessed, based on the seminal Hausman (1981) method of surplus calculations. This increase in utility is then compared to the external costs generated by additional driving. Globally, external costs are about twice of the private gains, calling for a better internalization of external costs. Indeed, if the price paid to drive one kilometer increases, for instance through an increase of the fuel tax, additional driving would be reduced. Another novelty brought by that chapter is the use of self-stated car fuel consumption instead of data from car manufacturers. In Europe, these values are known to be heavily downward biased. This large gap is detected in the analysis, and its impact on the rebound estimations is investigated. This gap is found to produce a downward bias on rebound estimations.

This thesis allows to draw additional conclusions and opens up new paths of research. First, the limited direct rebound for heating shows that energy efficiency improvements of dwellings will deliver energy savings. That is good news for policy makers, because the building stock has a huge potential for energy savings, still largely untapped in Switzerland. Streicher et al. (2017b) estimate that large-scale retrofits of the residential building stock could bring up to 84% of energy savings for this entire sector (no rebound effect is considered here), but that the renovation rate is still too little, below 1% per year. Considering that the demand for space heating should diminish by 64% to reach the Energy Strategy 2050 targets (SFOE, 2012), the renovation rate needs to increase rapidly. An important feature of the rebound in this sector, when it happens, is that it concerns most often the poorest households, who improve their thermal comfort this way. For these different reasons, investments in buildings efficiency should be one of the most, if not the most, important focus of energy policies.

Second, additional policies on top of fuel efficiency improvements are needed to substantially diminish energy and GHGs emissions from the transport sector. The large direct rebound for private transportation and the different other rebounds not studied here, such as efficiency gains offset by the purchase of heavier and more powerful vehicles, are counteracting the efficiency improvements of the last two decades. Indeed, we are currently unable to curb GHGs emissions from the private transport sector. Policies that seriously encourage public transportation should be envisaged, like free public transportation, instead of relying solely on efficiency gains and cleaner vehicles. Moreover, as shown in Chapter 3, the external costs of driving are far from being internalized by drivers, thus a new tax on the distance driven should also be considered. Such a tax already exists for trucks in Switzerland, but there is no discussion to broaden it to passenger cars. Another sensible policy would be the extension of the current carbon tax (applied only to heating oil and gas) to gasoline.

Yet, the political feasibility of taxing more gasoline is an important challenge, particularly in Switzerland where such decisions need to be approved by the majority of the population by vote. A possible way to acceptance would be a clear redistribution scheme of the tax. Taxing more vehicle fuels is indeed unpopular partly because it affects individuals differently: rural areas feel more affected, lower-level income households face a greater burden than affluent households, etc. Thus, a well-designed redistribution scheme could increase acceptance, and rebound effect studies can contribute to this redistribution discussion. In the future, further research is needed on the heterogeneity in rebound magnitudes across individuals and on the private welfare gains from the rebound. 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.

Another path for future research is on what I called the green rebound in Chapter 1. How will individuals who switch to a green technology – for instance switching from oil to a heat pump for space heating or to an electric vehicle for mobility – change their usage habits, because the technology is perceived as green? Psychological aspects, such as a mental accounting of good/bad behaviors related to global warming, need to be included along economic rationality to investigate these questions. Individuals, for instance, can feel entitled to use their electric vehicle more and abandon public transports as a consequence, a phenomenon called "moral licensing". How individuals will use their electric vehicle is indeed a hot topic, with still a lot of interrogations (see e.g., Davis, 2019, 2022), such as how the distance driven will change, how the atmospheric pollution will be affected, how multi-vehicles households will use their electric car versus their gasoline-powered vehicle, etc. Research linking psychological mechanisms of the green rebound to electric vehicle usage would contribute greatly to this discussion.

More studies are also needed on the indirect rebound. It is at least as important in its size as the direct rebound, yet no environmental policies tackle this issue. Indirect rebound mitigation is embedded in a broader discussion on how to make individuals aware of their direct and indirect energy consumption. The target of a 2000-watt society in Switzerland is laudable, but how many people can assess what does it mean for their own consumption? Measures to make energy more salient could be taken, for instance a better metering of its own heating energy consumption. As stated in Chapter 2, 40% of Swiss households still do not have access to this information and pay collectively with neighbors for heating. Smart meters for heating, and also for electricity, should be installed at a large scale. Concerning the embodied energy, new labels with information on it or on embodied emissions could be introduced on the most energy intensive goods. Better accounting of embodied energy at the national level could also be targeted. Once more data is available, new paths of research can be developed.

Appendices

Appendix A

Figure A.1: Scenario

According to the Energy Strategy of the Confederation, the energy consumption per person must be reduced by 40% by 2035 compared to our current consumption.

A significant part of this reduction can be achieved by improving the energy efficiency of buildings.

The next questions consist of 3 hypothetical scenarios. Please answer as if you really had to make these decisions.

Suppose the building you are living in no longer meets energy efficiency standards. The owner will soon have to improve the heating system and insulation.

Even if, as a result of the renovations, the rents will be slightly increased, you will benefit from it because your heating costs will be significantly reduced.

Scenario 1: Now, heating your home is 20% cheaper.

For information, a household pays on average CHF 1,600 per year for its heating.

Notes: This screen and the following are extracted from the online survey (originally available in French and German). The above scenario was presented to the tenants, and was slightly adapted for the owners. Average heating costs were given only for respondents who were not able to provide any information on their heating costs in a previous question.

Figure A.2: Qualitative questions related to the direct rebound

Will you modify the way you heat your place in order to improve heating comfort?

Compare to last winter for instance.

	No	Maybe	Yes
I will increase the temperature (in all or only some rooms).	O	O	O
I will heat earlier or later in the year.	O	O	O
I will air longer/ more often.	O	O	O
I will pay less attention to heating in general.	O	O	O
I will decrease less or not at all the temperature when the home is empty for a few days.	O	O	O

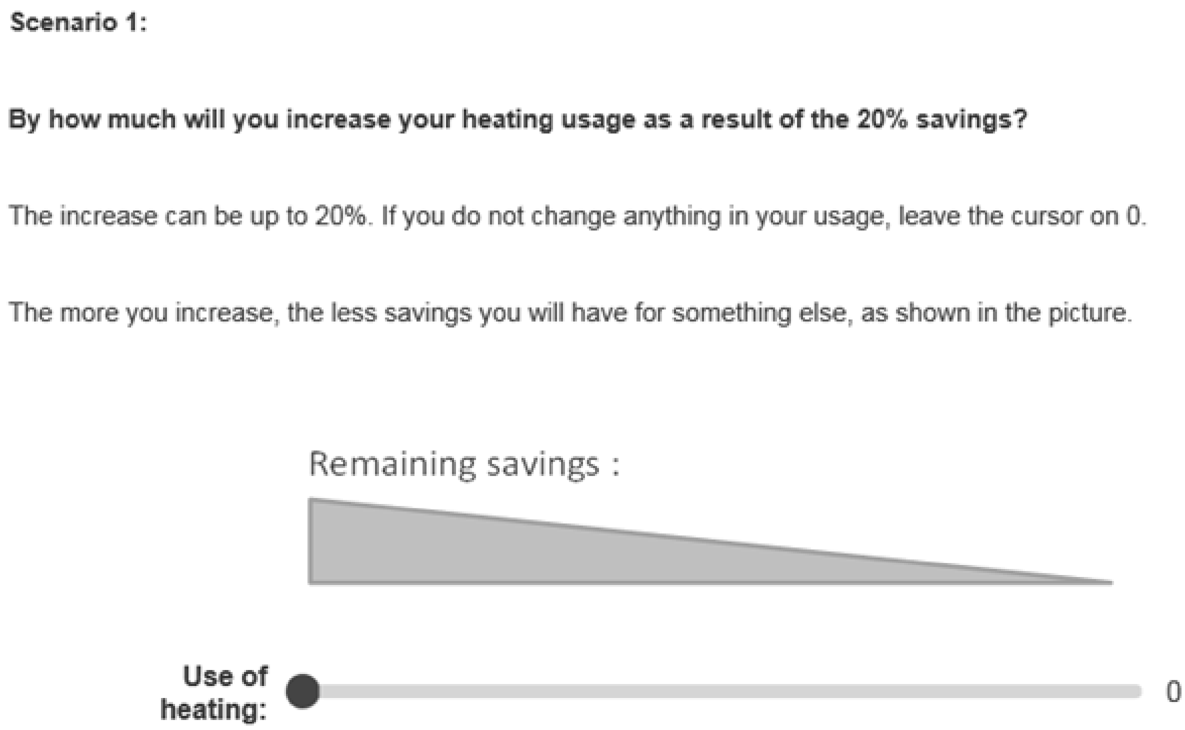
Would you change something else in the way you heat your place?

O Yes: __________

O No

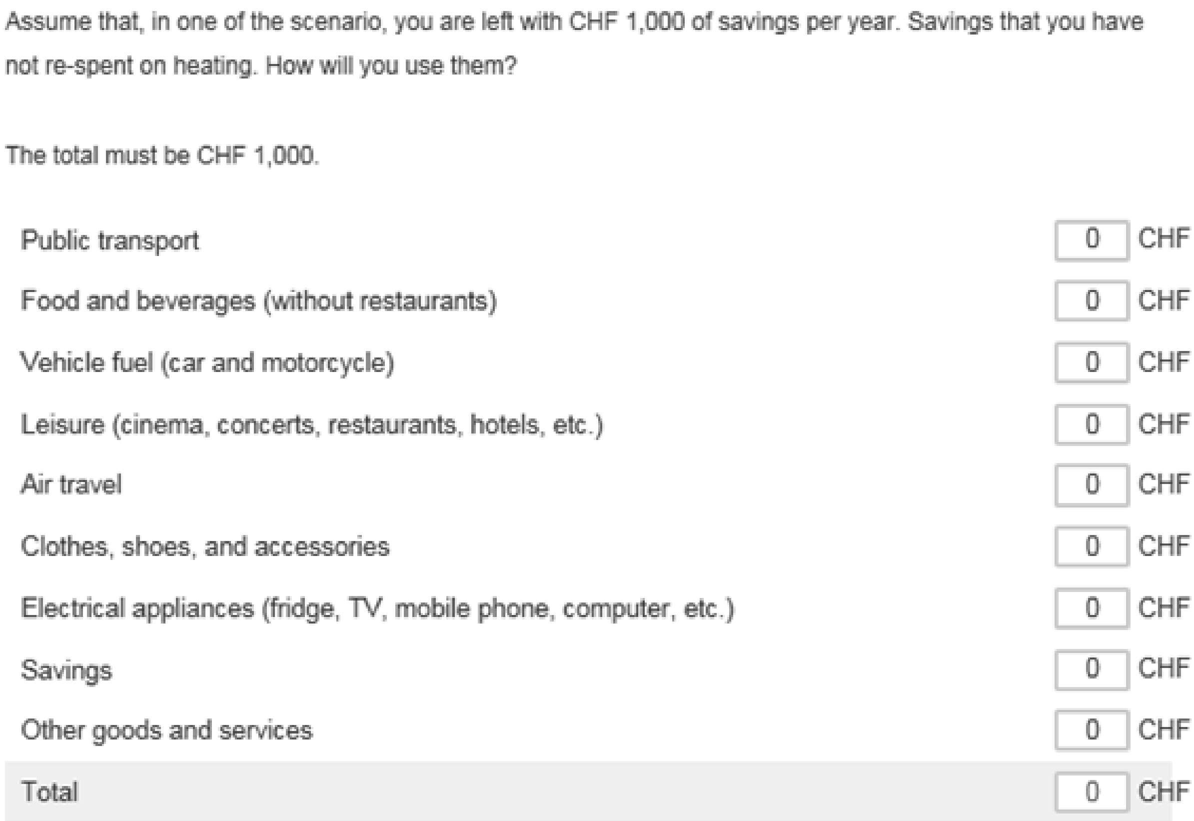
Notes: The scenario was presented before this question, with the efficiency improvement presented as a percentage decrease of current heating costs.

Figure A.3: Quantitative question related to the direct rebound



Notes: The slider is constrained to be at most equal to the efficiency improvement in percentage.

Figure A.4: Re-spending question related to the indirect rebound



Assume that, in one of the scenario, you are left with CHF 1,000 of savings per year. Savings that you have not re-spent on heating. How will you use them?

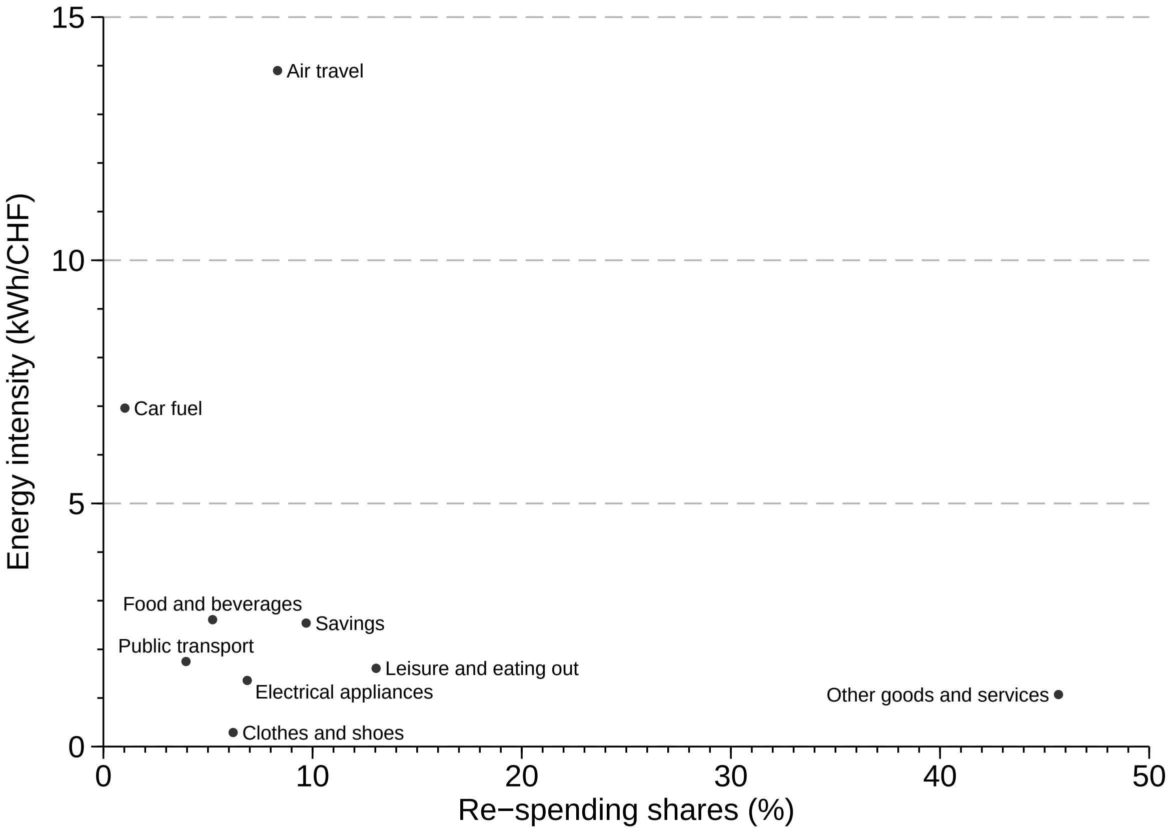
The total must be CHF 1,000.

Public transport	0	CHF
Food and beverages (without restaurants)	0	CHF
Vehicle fuel (car and motorcycle)	0	CHF
Leisure (cinema, concerts, restaurants, hotels, etc.)	0	CHF
Air travel	0	CHF
Clothes, shoes, and accessories	0	CHF
Electrical appliances (fridge, TV, mobile phone, computer, etc.)	0	CHF
Savings	0	CHF
Other goods and services	0	CHF
Total	0	CHF

Notes: The 9 categories were randomly presented, with the exception of other goods and services that always remained at the bottom.

Appendix B

Figure B.1: Re-spending shares and energy intensity



Notes: Re-spending shares of the CHF 1,000 are from the re-spending question and are used to estimate the indirect rebound. Energy intensities are from LCA data. *Source:* ESU-services (Zürich), and Tilov et al. (2019).

Appendix C

Table C: Summary statistics

	Mean	Std. dev.	Min.	Median	Max.
Education					
Compulsory school	0.012	–	0	–	1
Vocational school	0.382	–	0	–	1
High school	0.109	–	0	–	1
University	0.497	–	0	–	1
Income					
<4,500 CHF	0.160	–	0	–	1
4,500-9,000 CHF	0.457	–	0	–	1
>9,000 CHF	0.383	–	0	–	1
Owners/Tenants Status					
Owners with individual costs	0.378	–	0	–	1
Owners with shared costs	0.066	–	0	–	1
Tenants with shared costs	0.272	–	0	–	1
Tenants with individual costs	0.283	–	0	–	1
Age	49.174	15.965	19	50	89
Female	0.483	–	0	–	1
Dwelling size (m^2)	123.597	154.439	0	110	7000
Household size	2.242	1.161	1	2	7
Indoor temperature	21.189	1.577	9	21	30
Heating satisfaction	10.488	3.201	0	10	15
Environmental concerns	22.051	5.403	4	22	36
Heating Fuel					
Oil	0.424	–	0	–	1
Gas	0.231	–	0	–	1
Wood (logs)	0.035	–	0	–	1
Wood (pellets)	0.030	–	0	–	1
Heat pump	0.147	–	0	–	1
Electricity	0.059	–	0	–	1
District heating	0.059	–	0	–	1
Other	0.015	–	0	–	1

Notes: N=2,637 for all variables, except for heating fuel for which n=2,439.

Environmental concerns is a nine-item index, conceptualized by Maloney and Ward (1973), and used by Best and Mayerl (2013).[1] Respondents indicate to which extent they agree/disagree on a five-point scale. Their answers are then transformed into scores from 0 (completely disagree) to 4 (completely agree) and summed over the nine items. Hence, the index ranges from 0 to 36 and increases with the level of environmental concerns.

[1]See the general environmental attitude scale in Table 3.

Heating satisfaction is an index based on five items: internal temperature in winter, uniformity of temperature, quality of ventilation, ease to modify the temperature, and number of days with the heating on. Respondents indicate their satisfaction for each item on a four-point scale. The index thus ranges from 0 to 15 and increases with heating satisfaction. We constructed three categories from this index, for an easier interpretation: from 0 to 5 points (low satisfaction), from 6 to 10 points (moderate satisfaction), and from 11 to 15 points (high satisfaction).

The (stated) *indoor temperature* goes from 9 to 30 degrees, but 96% of the answers lie between 18 and 25 degrees, a more reasonable range. *Individual* versus *shared* costs indicates whether the heating bill is calculated on the individual consumption or shared among all the dwellers (calculated as a proportion of the dwelling size).

Appendix D

Table D: Relationship between stated heating service variations and stated behavioural changes

	OLS
Increase temperature	
Maybe	2.447^{***}
	(0.268)
Yes	3.778^{***}
	(0.546)
Heat sooner or later	
Maybe	1.543^{***}
	(0.303)
Yes	0.526
	(0.751)
Air more	
Maybe	1.837^{***}
	(0.257)
Yes	2.207^{***}
	(0.376)
Less attention in general	
Maybe	3.356^{***}
	(0.313)
Yes	3.403^{***}
	(0.473)
Do not decrease anymore	
Maybe	1.066^{***}
	(0.383)
Yes	2.076^{***}
	(0.682)
Other change	1.320^{***}
	(0.400)
Constant	0.768^{***}
	(0.066)
N	7,775
Adj. R-Squared	0.241

Notes: Clustered standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The dependent variable is $\frac{\Delta S}{S}$.

Appendix E

Indirect Rebound

The indirect rebound effect (RE) expressed in terms of energy is:

$$\text{Indirect RE} = \frac{\text{Additional energy from G\&S purchased}}{\text{PES after direct rebound}} \tag{3.7}$$

Using the following notation:

b	:	initial heating bill [CHF]
$\frac{\Delta\varepsilon}{\varepsilon}$	:	efficiency improvement [%]
d	:	direct rebound [%]
s_j	:	re-spending share on category j [%] (see also Figure B.1)
int_j	:	energy intensity in category j [kWh/CHF] (see also Figure B.1)
int_{heating}	:	energy intensity in the heating sector = 10.24 [kWh/CHF]

we obtain that the potential energy savings after direct rebound (denominator of (3.7)) is:

$$\begin{aligned}\text{PES after direct rebound} &= \underbrace{(1-d)\cdot\frac{\Delta\varepsilon}{\varepsilon}\cdot b}_{\substack{\text{Savings [CHF] left}\\ \text{after direct RE}}}\cdot int_{\text{heating}}\\ &= (1-d)\cdot\frac{\Delta\varepsilon}{\varepsilon}\cdot b\cdot 10.24\end{aligned}$$

and that additional energy from additional goods and services purchased (numerator of (3.7)) is:

$$\begin{aligned}\text{Additional energy from G\&S purchased} &= \sum_{j=1}^{9}\left(\underbrace{s_j\cdot(1-d)\cdot\frac{\Delta\varepsilon}{\varepsilon}\cdot b}_{\substack{\text{Money re-spent}\\ \text{on category } j}}\cdot int_j\right)\\ &= (1-d)\cdot\frac{\Delta\varepsilon}{\varepsilon}\cdot b\cdot\sum_{j=1}^{9}(s_j\cdot int_j)\end{aligned}$$

We can therefore re-write and simplify (3.7) as follows:

$$\begin{aligned}\text{Indirect RE} &= \frac{(1-d)\cdot\frac{\Delta\varepsilon}{\varepsilon}\cdot b\cdot\sum_{j=1}^{9}(s_j\cdot int_j)}{(1-d)\cdot\frac{\Delta\varepsilon}{\varepsilon}\cdot b\cdot 10.24}\\ &= \frac{1}{10.24}\sum_{j=1}^{9}(s_j\cdot int_j)\end{aligned}\tag{3.8}$$

Total Rebound

The total rebound expressed in terms of energy is:

$$\text{Total RE} = \frac{\text{Additional energy from direct RE} + \text{Additional energy from indirect RE}}{\text{PES}}\tag{3.9}$$

Using the same notation as before and adding the following:

$$\begin{aligned}\varepsilon:&\quad \text{heating efficiency [kWh/m}^2\text{/year]}\\ m:&\quad \text{dwelling size [m}^2]\end{aligned}$$

we obtain that the components of (3.9) are given by:

$$\begin{aligned}&\text{PES} = \frac{\Delta\varepsilon}{\varepsilon}\cdot\varepsilon\cdot m = \Delta\varepsilon\cdot m\\ &\text{Additional energy from direct RE} = d\cdot\frac{\Delta\varepsilon}{\varepsilon}\cdot\varepsilon\cdot m = d\cdot\Delta\varepsilon\cdot m\\ &\text{Additional energy from indirect RE} = (1-d)\cdot\frac{\Delta\varepsilon}{\varepsilon}\cdot b\cdot\sum_{j=1}^{9}(s_j\cdot int_j)\end{aligned}$$

We can therefore re-write and simplify (3.9) as follows:

$$\begin{aligned}\text{Total rebound} &= \frac{d\cdot\Delta\varepsilon\cdot m + (1-d)\cdot\frac{\Delta\varepsilon}{\varepsilon}\cdot b\cdot\sum_{j=1}^{9}(s_j\cdot int_j)}{\Delta\varepsilon\cdot m}\\ &= d + (1-d)\cdot\underbrace{\frac{b}{\varepsilon\cdot m}\cdot\sum_{j=1}^{9}(s_j\cdot int_j)}_{\text{indirect RE if } [b/(\varepsilon\cdot m)] = [1/10.24]}\end{aligned}\tag{3.10}$$

Comparing (3.8) and (3.10), we observe that the final portion of the total rebound corresponds to the indirect rebound, provided that $\frac{b}{\varepsilon\cdot m} = \frac{1}{10.24}$. Equation (3.10) therefore shows that the total rebound is given by the addition of the direct and indirect rebounds, with the latter being weighted by $(1-d)$. Intuitively, this formula indicates that the magnitude of the indirect rebound will be constrained by the amount of savings left after the direct rebound has occurred.

In our calculation of the individual total rebound, we equate $\frac{b}{\varepsilon \cdot m}$ to $\frac{1}{10.24}$ for every respondent. As an alternative, we could have used data collected in the survey to compute individual values of $\frac{b}{\varepsilon \cdot m}$: Heating bills ($b$) and dwelling size ($m$) are directly provided by the respondents, while we can approximate heating efficiency (ε) using the age of the building (also provided by the respondents) and values of energy usage in buildings provided by Streicher et al. (2017a) by decade.

Based on this alternative approach, we obtain an average indirect rebound of 27.9% instead of 24.3%. We prefer to use the constant factor $\frac{1}{10.24}$, mainly because computing individual factors implies the loss of numerous observations due to missing values, but also because the constant factor accounts for the embodied energy of heating.

Appendix F

In Table F, we regress indoor temperature on various characteristics. Income has no effect, indicating that fuel poverty is not an issue in Switzerland. Household equipped with heating systems using environmentally friendly fuels (wood pellets, heat pump, and district heating) display positive coefficients, the omitted category being heating oil. It can be a sign of a “green rebound”, people feeling entitled to heat more if they use a less polluting fuel. But it could also show that intensive heating users choose a more efficient fuel than oil or gas (the most conventional fuels in Switzerland).

Table F: Determinants of indoor temperature

	OLS
Vocational school	-0.226
	(0.304)
High school	-0.267
	(0.315)
University	-0.422
	(0.305)
Income CHF 4500-9000	0.052
	(0.094)
Income CHF >9000	0.098
	(0.101)
Environmental concerns	-0.038^{***}
	(0.006)
Female	0.119^{**}
	(0.059)
Age	0.005^{**}
	(0.002)
Tenant	0.151^{**}
	(0.070)
Individual heating costs	-0.130^{*}
	(0.071)
Dwelling size (m^2)	-0.000
	(0.000)
Household size	-0.037
	(0.028)
Heating fuel	
Gas	0.067
	(0.074)
Wood (logs)	-0.047
	(0.153)
Wood (pellets)	0.393^{**}
	(0.165)
Heat pump	0.287^{***}
	(0.083)
Electricity	-0.071
	(0.134)
District heating	0.314^{**}
	(0.135)
Other	-0.211
	(0.208)
Constant	22.003^{***}
	(0.382)
N	2,400
Adj. R-Squared	0.035

Notes: Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, *** $p < 0.01$. Respondents outside the range of 17 to 25°C were excluded.

Appendix G

A green rebound?

Will people rebound more if the efficiency improvement arises from a clean technology? In scenario 3 of our experiment, we presented the heating technology as being CO_2-neutral in order to investigate this question. Our hypothesis is that people would in this case feel free of the guilt of polluting, potentially leading to a higher increase in heating service demand, hence a higher direct rebound.

The idea of a behavioural response after purchasing a green product has been studied for instance by Jacobsen et al. (2012) and Mazar and Zhong (2010), but never in the context of rebound effects to our knowledge. Jacobsen et al. (2012) study whether households consume more electricity after voluntarily paying a fixed fee to purchase green electricity. They find that only a limited number of households consumed more electricity after paying the fee. The difference with the present paper is that our green technology comes for free, since households do not have to pay for it. Thus the behavioural response may be less salient; households did not buy the right to pollute.

For most respondents, scenario 3 did not trigger a higher rebound. In the double hurdle model, we find that scenario 3 leads to a lower rebound compared to scenario 1, but the magnitude of the efficiency improvement may have played a role in addition to the green technology. To isolate the effect of the CO_2-neutral technology, we implement a correlated random effect model explaining the direct rebound by the efficiency improvement, the mean of the efficiency improvement, and a dummy for scenario 3. People who never rebound are excluded from the regression. The coefficient of the scenario dummy turns out to be negative, but close to zero (results available on request). When inconsistent respondents are excluded, the coefficient is not different from zero. We therefore do not find any evidence that a clean technology would induce a higher direct rebound.

To investigate further the question, we focus on people who only rebound in scenario 3 (95 respondents), or who have a higher rebound in scenario 3 than in the two others scenarios (222 respondents). These people are few, representing 12% of the sample, but they display a “green rebound”, i.e., they seem to feel entitled to rebound more when the heating technology is environmentally friendly. We apply a probit model to unravel the characteristics of this group. The results are shown in Table G. People who never rebound were excluded from the regression. Quantitatively speaking, education has the strongest impact, with university graduates being 26.5% more likely to be in this group compared to people who have no further degree than compulsory school certificate. Environmental concerns have also a positive and significant impact. Thus a “green rebound” may exist, but seems to be limited to a small group of people, with more education and higher environmental concerns.

Table G: Characteristics of individuals who rebound more (or only) in scenario with CO_2-neutral technology

	MEs Probit
Vocational school	0.185
	(0.120)
High school	0.202
	(0.125)
University	0.265^{**}
	(0.121)
Income CHF 4500-9000	0.029
	(0.034)
Income CHF >9000	−0.032
	(0.037)
Moderate heating satisf.	−0.014
	(0.043)
High heating satisf.	−0.018
	(0.044)
Environmental concerns	0.004^{*}
	(0.002)
Female	−0.006
	(0.024)
Age	0.000
	(0.001)
Tenant	0.008
	(0.029)
Individual heating costs	0.015
	(0.027)
20-20.9 degrees	0.094^{*}
	(0.049)
21-21.9 degrees	0.073
	(0.049)
≥22 degrees	0.017
	(0.047)
Heating fuel	
Gas	0.024
	(0.031)
Wood (logs)	-0.118^{**}
	(0.053)
Wood (pellets)	0.020
	(0.075)
Heat pump	−0.022
	(0.037)
Electricity	0.025
	(0.050)
District heating	−0.042
	(0.047)
Other	0.079
	(0.114)
N	1,430

Notes: Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Inconsistent respondents are excluded. Marginal effects (MEs) at the means are shown.

Appendix H

Consistency weights

As robustness checks, we identify respondents whose answers are inconsistent, and we limit their influence in regressions through weights or even exclude them. Consistency tests are useful when stated preference approaches are used and allow to overcome some problems inherent to the method (such as respondents answering randomly without really thinking about their true reaction). Alolayan et al. (2017), who assess the willingness-to-pay for mortality-risk reduction, use such consistency tests to solve stated preference issues.

Two types of consistency weights can be defined: binary or continuous. Binary weights take the value 0 (for inconsistent respondents) or 1 (for consistent respondents), and the 0s are then completely excluded. One drawback is that people just below/above the cutoff defining the switch from 0 to 1, who are actually not very different from each other, are either excluded or kept. Also, among the consistent people, some differences may exist in terms of consistency, but all of them are given the same importance. Continuous weights can solve these issues. We use both types of weights to check the results of the double hurdle regression. Both weight types give results in line with the non-weighted regression presented in the paper, showing that our results are robust.

We define binary weights as follow: A respondent is inconsistent if he stated a lower variation of service demand in absolute term (i.e., $\frac{\Delta S}{S}$) in scenario 2 than in scenario 1.[1] Scenario 2 consists of a large efficiency improvement and scenario 1 a small one. The service variation in absolute terms in scenario 2 should at least be equal, or higher than the variation in scenario 1. Scenario 3 (medium efficiency improvement) is different because a CO_2-neutral technology is added. Respondents may react more or less than in other scenarios because of the green technology, and still be rational. Moreover, we do not consider a respondent as inconsistent if the difference in his answers is just equal to one in absolute value. With this definition, 217 respondents are inconsistent.

As a robustness check, we perform our double hurdle model without the inconsistent respondents. Results are presented in Table H. There is hardly any change, the most important being a decrease in the magnitude of the coefficients related to the scenarios. Coefficients are still negative, but close to zero.

Continuous weights are defined thanks to the qualitative rebound question. The weights indicate to what extent the qualitative question and the slider question were answered

[1]Note that the variation of service demand in absolute terms is not equal to the rebound effect, because the rebound is defined in relative terms with respect to the efficiency improvement. It means that a consistent respondent can still display a lower rebound in scenario 2 compared to scenario 1.

Table H: Determinants of the direct rebound excluding inconsistent respondents

	Selection (ME)	Intensity
Vocational school	-0.048	-0.073
	(0.129)	(0.058)
High school	-0.050	-0.114^{*}
	(0.133)	(0.061)
University	-0.023	-0.140^{**}
	(0.130)	(0.059)
Income CHF 4500-9000	-0.109^{**}	0.042^{**}
	(0.045)	(0.019)
Income CHF >9000	-0.133^{***}	0.018
	(0.045)	(0.019)
Moderate heating satisf.	-0.112^{*}	-0.031
	(0.066)	(0.024)
High heating satisf.	-0.134^{**}	-0.138^{***}
	(0.068)	(0.026)
20-20.9 degrees	-0.025	0.060^{**}
	(0.053)	(0.029)
21-21.9 degrees	-0.034	0.068^{**}
	(0.052)	(0.028)
≥22 degrees	0.017	0.072^{***}
	(0.050)	(0.027)
Environmental concerns	0.000	-0.004^{***}
	(0.002)	(0.001)
Female	-0.032	-0.037^{***}
	(0.024)	(0.013)
Owners with shared costs	0.014	0.019
	(0.054)	(0.027)
Tenants with shared costs	-0.090^{***}	0.011
	(0.031)	(0.017)
Tenant with individual costs	-0.035	0.000
	(0.033)	(0.018)
Large efficiency improv.	–	-0.010
		(0.007)
Middle eff. improv and CO_2-neutral	–	-0.003
		(0.002)
Constant	–	0.248^{***}
		(0.079)
N	7,260	7,260

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The dependent variable is the direct rebound. Marginal effects (ME) at the means are presented in column Selection. Inconsistent respondents are excluded.

consistently. For instance, if a respondent answers the qualitative question with only one maybe, he should not state a high service variation in the slider question. The weights range from 0 (not consistent at all) to 1 (extremely consistent). To define the weights, we estimate with a robust regression the model of the cross-validation analysis of Appendix D :

$$\frac{\Delta S_{i,t}}{S_{i,t}} = \alpha + \sum_{k=1}^{5} \sum_{j=2}^{3} \beta_k^j \text{Quali}_{i,t}^k + \beta_6 \text{Quali other}_{i,t} + u_{i,t} \tag{3.11}$$

where i denotes the individual, $t(= 1, 2, 3)$ denotes the scenario.

Respondents who stated *no* to every item of the qualitative question and who hence had automatically a service variation equal to zero are excluded from the robust regression, because they are by construction perfectly consistent. We thus attribute them automatically the maximal weight of 1.

The double hurdle model for panel data does not allow for continuous weights. Alternatively, we implement a two-part model, where the first part is a probit model (the selection model), and the second part a linear regression (the intensity equation). Panel data models impose weights to be constant within individuals, while we have three different weights per individual. Consequently, the two-part model we estimate does not account for the panel structure of our data, but simply clusters standard errors at the individual level.

Overall, the results of the weighted two-part model (available on request) are close to the results of the non-weighted double hurdle model. There are no changes in signs. The most important change is that education and temperature are now significant in the selection model, and not in the intensity equation any more. Also tenants with shared costs still display a negative coefficient, but in the intensity equation and not in the selection model.

Appendix I

Table I: Determinants of the indirect rebound

	OLS	Ordered probit
Vocational school	0.045	0.025
	(0.044)	(0.172)
High school	0.055	0.038
	(0.046)	(0.180)
University	0.034	-0.048
	(0.044)	(0.173)
Income CHF 4500-9000	-0.007	-0.095^{*}
	(0.014)	(0.055)
Income CHF >9000	-0.020	-0.171^{***}
	(0.015)	(0.060)
Age	-0.001^{***}	-0.007^{***}
	(0.000)	(0.001)
Female	0.002	-0.035
	(0.010)	(0.042)
Environmental concerns	-0.003^{***}	-0.012^{***}
	(0.001)	(0.004)
Tenant	0.013	0.064
	(0.011)	(0.045)
20-20.9 degrees	0.010	-0.001
	(0.018)	(0.074)
21-21.9 degrees	0.013	0.002
	(0.019)	(0.077)
≥22 degrees	0.034^{*}	0.098
	(0.018)	(0.071)
Constant	0.313^{***}	–
	(0.056)	–
# Observations	2,637	4,086
# Individuals	2,637	2,637

Notes: Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The dependent variable is the indirect rebound. The ordered probit is a weighted regression.

Appendix J

How to find the number of heated days per year

To estimate the rebound with equation 2.7, the number of heated days per year are needed. They correspond to the number of days where the increase in indoor temperature found from equation 2.4 happens. Heating degree days are known by month in many of the data sources, and by days for one canton (canton of Neuchâtel).

To translate these monthly HDDs to the number of heated days, we assume that heating is needed as soon the daily average external temperature drops below 12°C, that is, as soon as HDDs are positive. However, for months at the beginning of the heating season (September-October) and at the end of the season (April-May), not every days are heated according to the 12°C threshold. We thus applied the following rule to count partially these months:

- If monthly HDDs < 81, then no heating days were counted for the month,
- If 81 >= monthly HDDs <= 121.5, 10 heating days were counted for the month,
- If 121.5 > monthly HDDs <= 243, 20 heating days were counted for the month,
- If monthly HDDs > 243, 30 heating days were counted for the month.

These thresholds come from the fact that, if the daily average external temperature is 11.9°C, 8.1 HDDs are recorded for that day, as HDDs from the data source take 20°C as the comfortable internal temperature. If the external temperature is 12°C, 0 HDD are recorded. Hence, 81 HDDs would correspond to 10 heated days when the average external temperature is 11.9°C, and 121.5 HDDs to 20 heated days. Obviously these thresholds could have been chosen differently. They have the advantage to count fully the central winter months (November to March) and to count partially the other months.

By applying that counting method, a total of 207 heated days is found in the sample. To verify this number, we counted the number of days where HDDs were positive for the only canton providing daily HDDs. For the years 2015-2020, an average of 202 heated days per year are found for the main city of the canton (situated at an altitude of 480 m), 231 heated days for villages at about 800 m, and 261 heated days for a city at 1000 m. Thus, the average of 207 heated days per year seems totally acceptable since most households live in regions comparable to the main city of this canton (i.e. in the flatland and not in mountainous areas), and few of them live on higher altitude. The average altitude is indeed 510 m in the survey sample, with fewer that 10% of the households living above 700 m.

Appendix K

Table K: Indoor Temperature Regression without Instrumental Variables

	Heating & Hot Water: Indoor temp. (°C)		Only Heating: Indoor temp. (°C)	
Ln(Heating (& hot water) costs per m^2)	0.07***	(0.01)	0.10***	(0.02)
Tenant (0/1)	-0.002	(0.03)	0.049	(0.05)
Dwelling m^2	0.001***	(0.00)	0.001***	(0.00)
Construction date	0.002***	(0.00)	0.002***	(0.00)
Accommodation Type: (Detached house as base category)				
Flat (in building with <5 flats)	0.076**	(0.04)	-0.005	(0.08)
Flat (in building with 5-10 flats)	0.20***	(0.03)	0.15***	(0.06)
Flat (in building with >10 flats)	0.19***	(0.04)	0.18**	(0.07)
Terraced house	-0.004	(0.04)	-0.041	(0.08)
Heating Fuel: (Oil as base category)				
Gas	0.02	(0.03)	0.01	(0.05)
Electricity	0.04	(0.04)	0.17*	(0.09)
Wood	-0.06	(0.04)	-0.12	(0.08)
Heat pump	0.08***	(0.03)	0.09	(0.07)
District heating	0.04	(0.04)	-0.02	(0.08)
Other	-0.07	(0.08)	-0.20	(0.16)
Household size	-0.02**	(0.01)	-0.01	(0.02)
Income: (<3,000 CHF as base category)				
3,000-4,499 CHF	0.15**	(0.06)	0.22*	(0.11)
4,500-5,999 CHF	0.14***	(0.06)	0.16	(0.11)
6,000-8,999 CHF	0.20***	(0.05)	0.25**	(0.10)
9,000-12,000 CHF	0.26***	(0.05)	0.23**	(0.11)
>12,000 CHF	0.26***	(0.06)	0.33***	(0.11)
Education	-0.08***	(0.01)	-0.08***	(0.02)
Age	0.01***	(0.00)	0.01***	(0.00)
Individual heating costs (0/1)	-0.13***	(0.02)	-0.17***	(0.04)
Minergie (0/1)	0.04	(0.03)	0.05	(0.05)
Constant	16.56***	(0.51)	16.01***	(1.12)
County FE	YES		YES	
Year FE	YES		YES	
N	11,056		2,634	

Notes: An OLS regression is performed to investigate the bias if no instrumental variables are used. Standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Appendix L

Table L: 2SLS: Indoor Temperature Regression for Tenants vs Owners

	Tenants: Indoor temp. (°C)		Owners: Indoor temp. (°C)	
Ln(Heating (& hot water) costs per m^2)	-1.17***	(0.39)	-1.21***	(0.17)
Dwelling m^2	-0.005**	(0.00)	-0.004***	(0.00)
Heating Fuel: (Oil as base category)				
Gas	0.14**	(0.05)	-0.22***	(0.05)
Electricity	-0.22*	(0.12)	0.10	(0.08)
Wood	-0.30**	(0.14)	-0.69***	(0.11)
Heat pump	-0.10	(0.10)	-0.41***	(0.08)
District heating	0.15*	(0.08)	-0.12	(0.09)
Other	0.01	(0.18)	-0.70***	(0.15)
Household size	-0.00	(0.02)	0.00	(0.02)
Income: (<3,000 CHF as base category)				
3,000-4,499 CHF	0.28**	(0.11)	0.19	(0.17)
4,500-5,999 CHF	0.35***	(0.12)	0.33**	(0.16)
6,000-8,999 CHF	0.49***	(0.15)	0.40**	(0.16)
9,000-12,000 CHF	0.56***	(0.14)	0.51***	(0.16)
>12,000 CHF	0.65***	(0.16)	0.51***	(0.16)
Education	-0.06***	(0.02)	-0.08***	(0.02)
Age	0.02***	(0.00)	0.02***	(0.00)
Individual heating costs (0/1)	-0.37***	(0.07)	-0.13***	(0.05)
Minergie (0/1)	-0.22*	(0.13)	-0.17***	(0.06)
Constant	23.49***	(0.79)	23.98***	(0.47)
County FE	YES		YES	
Year FE	YES		YES	
N	5,591		5,465	

Notes: Robust standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01. Building construction date and accommodation type are used as instruments for heating costs. The first stage F-statistic is 18.5 for tenants and 26.9 for owners.

Appendix M

Temperature Rebound Calculation in Fowlie et al. (2018)

To estimate the temperature rebound in Fowlie et al. (2018), we proceed as follow:

1) +0.67 F per day = +20.1 F per month
2) From equation (3), page 1631, and Figure A.2 in the supplementary information, we deduced that: +20.1 F per month $\simeq$ 0.14 MMBtu per month
3) From Table IV, page 1622, we know that gas consumption without weatherization program is 6.39 MMBtu per month (imputed counterfactual consumption). After weatherization, gas consumption decreased by 21% according to this table (so by 1.34 MMBtu), to reach 5.048 MMBtu per month.

Gas consumption:

- without weatherization: 6.39 MMBtu
- after weatherization (with rebound): 5.048 MMBtu
- after weatherization (if no rebound): 4.908 MMBtu (6.39-1.34-0.14=4.908)

Energy savings:

- expected savings if no rebound: 1.49 MMBtu (6.39-4.908 = 1.49)
- energy savings lost due to rebound: 0.14 MMBtu

Direct rebound effect: 9.4% (0.14/1.49 = 0.094)

Appendix N

Comparison of spending shares from SHEDS and from the National Household Budget Survey

To check the accuracy of survey answers, we compare the spending shares found in our survey with the shares of the national household budget survey. The shares are fairly similar, except that food share is smaller in national data and leisure share higher. It may be due to over-represented low income households in the survey, since the share of food spending is higher for low income households. Or it might be because households tend to remember better how much they spend on food and beverages than for instance on leisure, because food is a very regular purchase. We do not expect these small variations in spending shares to affect strongly the indirect rebound results, as energy intensities for food and leisure are similar.

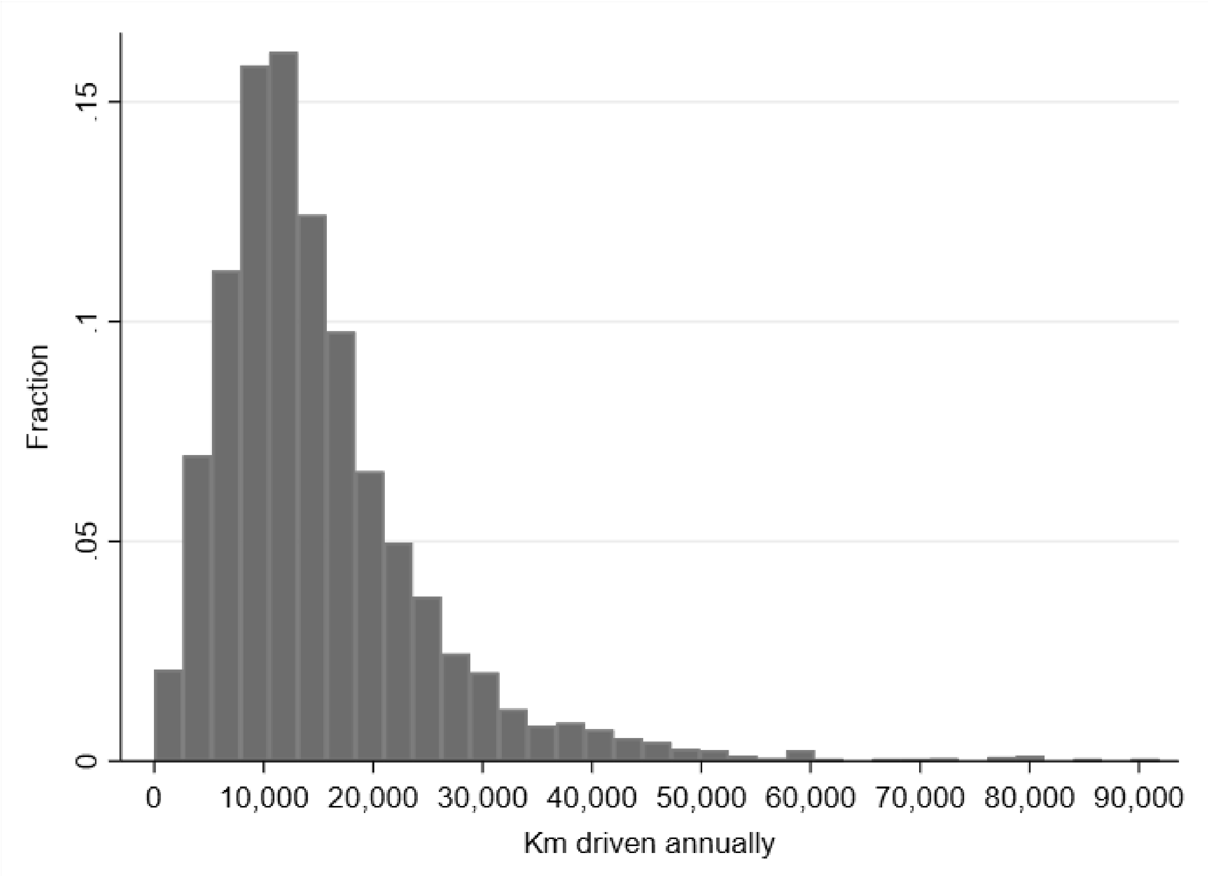
Table N: Spending Shares, SHEDS Data vs Household Budget Data

	SHEDS Data	**Household Budget Data**
Other	59.0%	58.0%
Savings	11.6%	14.2%
Food & Beverages	12.6%	7.2%
Leisure	7.6%	11.0%
Transport	5.8%	7.4%
Clothing	3.4%	2.0%

Notes: SHEDS data comes from the 2015 survey wave. Household budget data comes from the Federal Statistical Office, Household Budget Survey, for years 2015-2017.

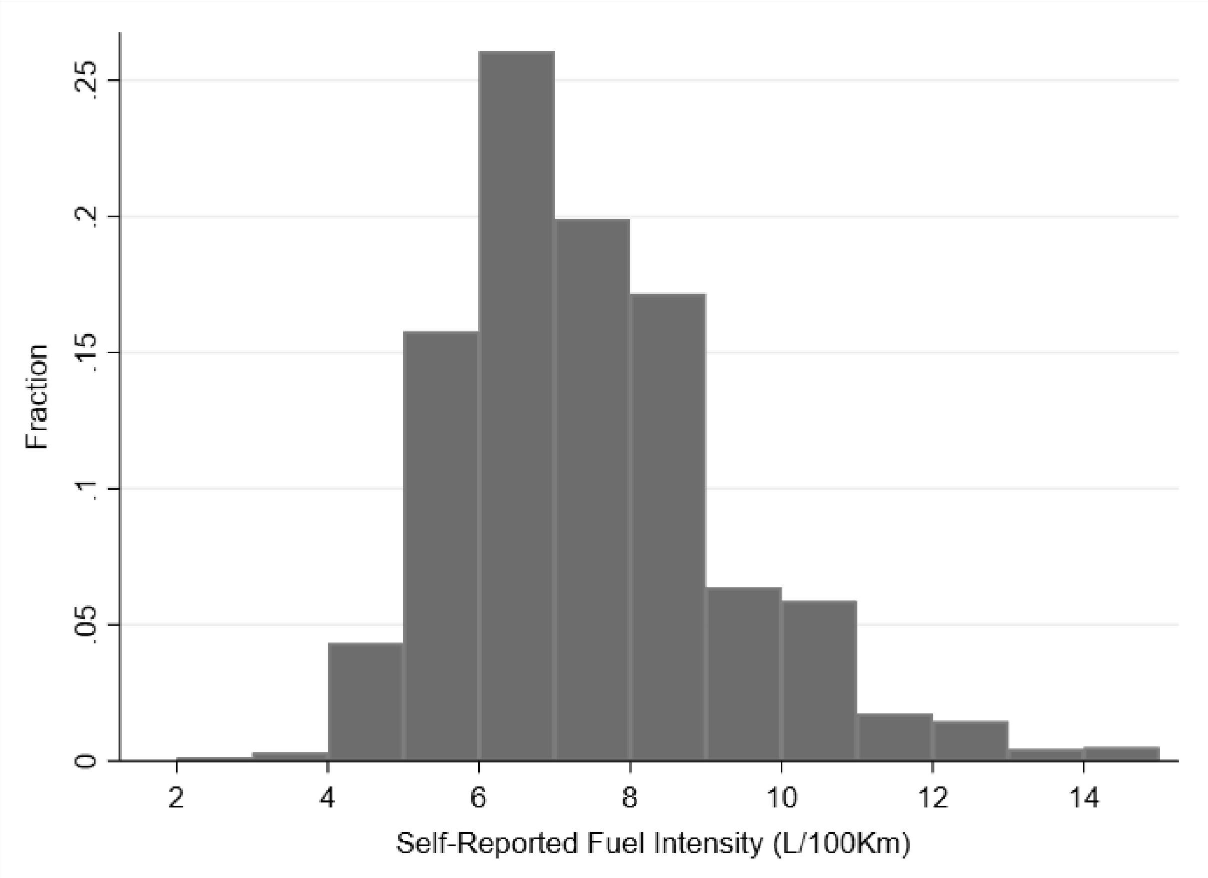
Appendix O

Figure O.1: Distribution of Km Driven



Notes: N=3,235

Figure O.2: Distribution of Fuel Intensity



Notes: N=3,235

Appendix P

Matching each car with data from vehicles manufacturers

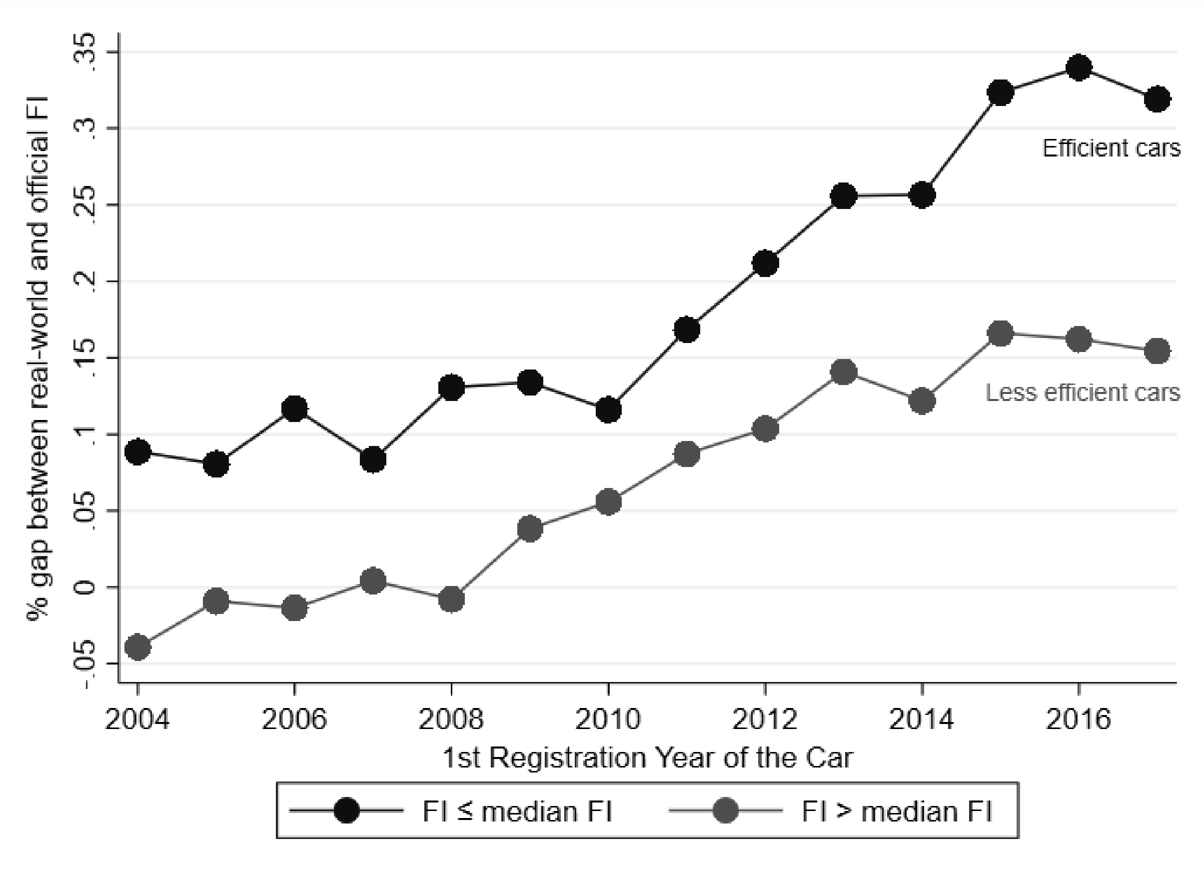
In this article, the purpose of data from manufacturers is to collect the weight and the official fuel consumption of each car. The most refined matching level would be the exact car model *version*. However, the version was not asked in the survey, because very few respondents would have known it. Instead, the matching was done on six characteristics known by the respondents: the car manufacturer, the car model, the first registration year, the fuel type, manual/automatic transmission and the number of doors. Then, the weight and the official 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 in the same way.

Appendix Q

Figure Q.1: Divergence in FI for Cars Below or Above the FI Median



Notes: The median fuel intensity (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 official data between 2004 and 2017. For cars above the median (less efficient cars), the divergence was on average only 5.5%. (N=12,034)

Table Q: 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^{***}
	(0.078)	(0.111)
Ln(Car weight)	0.335^{***}	0.492^{***}
	(0.121)	(0.179)
Diesel	0.147^{***}	0.105
	(0.048)	(0.072)
Automatic transmission	0.010	0.016
	(0.039)	(0.057)
Number of doors	0.035	0.015
	(0.022)	(0.035)
Ln(Nmb years car owned)	0.040^{***}	0.066^{***}
	(0.013)	(0.019)
Commute by car	0.081^{**}	0.056
	(0.033)	(0.059)
Income	0.042^{**}	0.045
	(0.018)	(0.035)
Education	0.012	-0.016
	(0.023)	(0.050)
Children	0.070	-0.076
	(0.054)	(0.144)
HH size	-0.041^{*}	-0.010
	(0.021)	(0.042)
Rail pass	-0.052	-0.265
	(0.055)	(0.166)
Constant	7.055^{***}	6.669^{***}
	(0.808)	(1.257)
County FE	YES	YES
# Observations	3,235	1,580
# Individuals	1,065	790

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Fixed-effects at the household level 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 data from manufacturers. The rebound found here is lower than in Table 3.2. Thus, using data from manufacturers may bias the rebound downward.

Appendix R

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 (Azevedo, 2014, for example), or directly as the lost part of the expected energy savings. Figure R.2 summarizes the example given here:

Let's 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)

$\Rightarrow RE = 1 - (AES/PES) = 1 - (0.2/0.286) = 0.3$
$\Rightarrow RE = LES/PES = 0.086/0.286 = 0.3$

Rebound Calculus with Fuel Efficiency:

If 840 l are consumed over one year:

- 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.

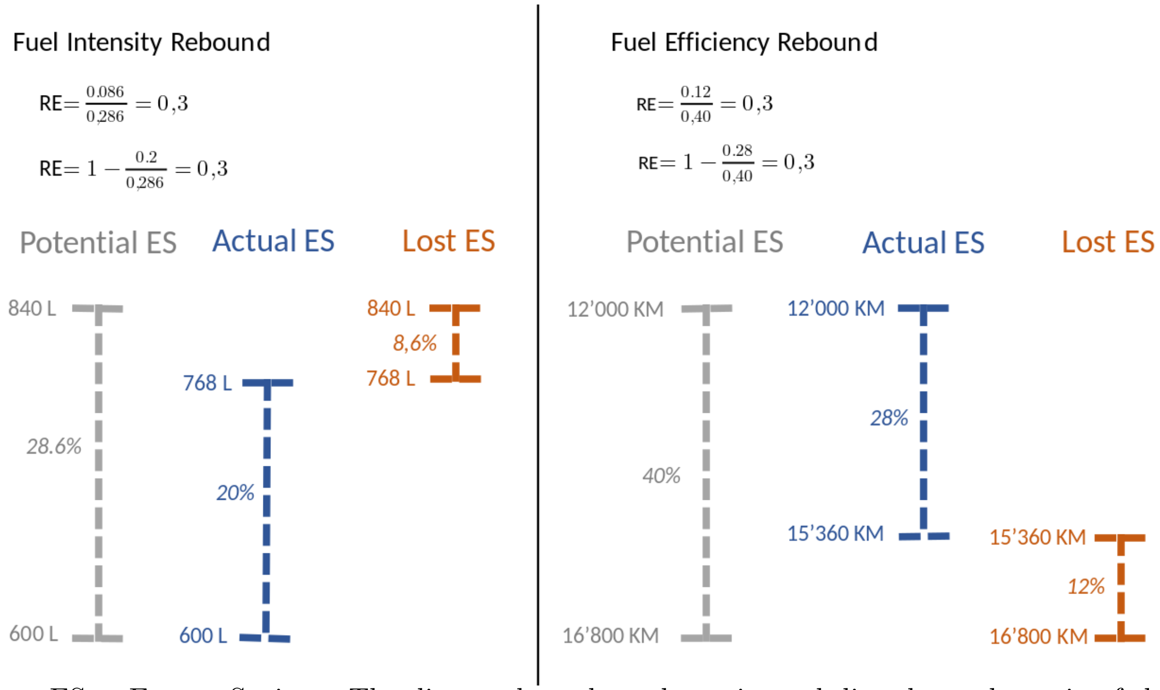
If a 30% direct rebound is assumed:

- 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).

$\Rightarrow RE = 1 - (AES/PES) = 1 - (0.28/0.40) = 0.3$
$\Rightarrow RE = LES/PES = 0.12/0.4 = 0.3$

Figure R.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).

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 equation 3.2, but all the other three elasticites could be used instead, with the same results.

Appendix S

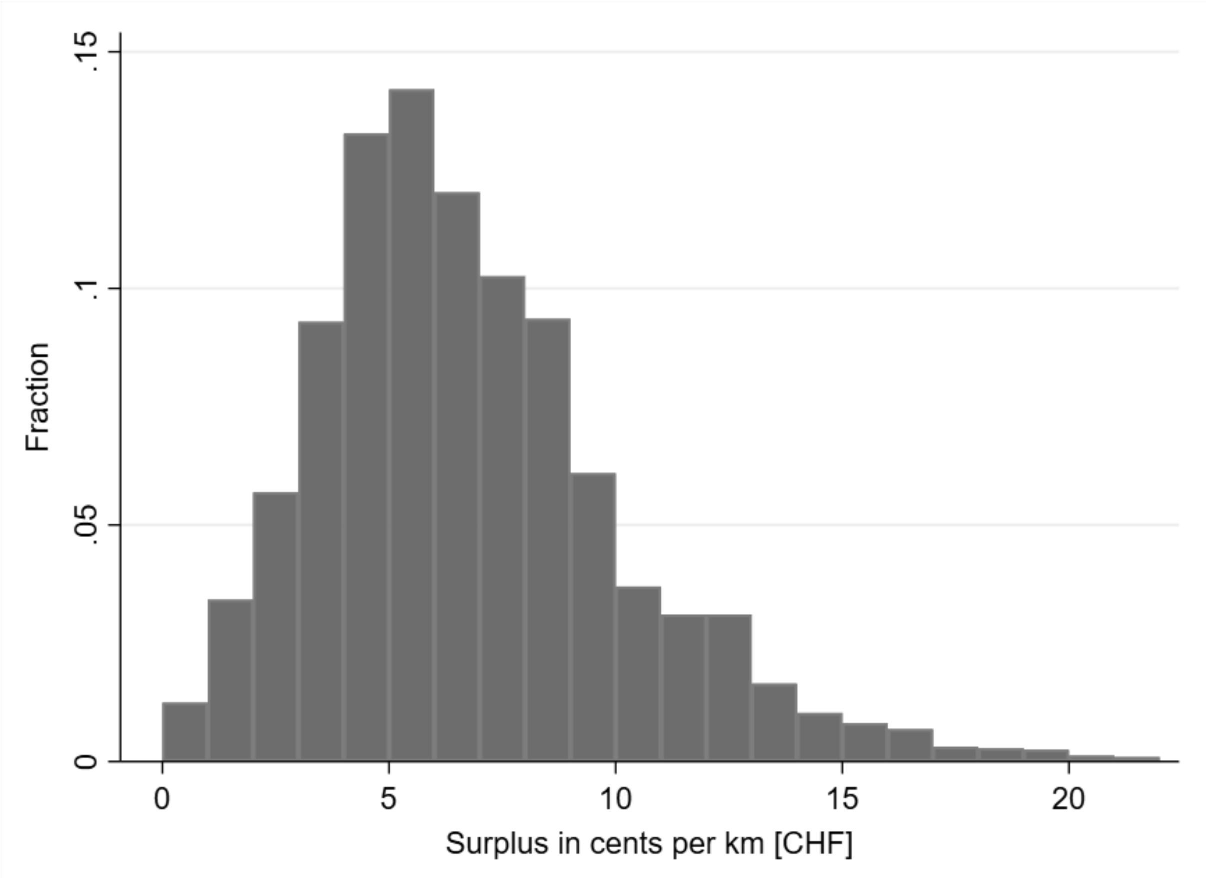
Table S: Implicit Price (Fixed-Effects at the Household Level)

	Solution 1 Mean Fuel Intensity	Solution 2 Before/After Car Change
Ln(Implicit Price)	-0.262^{***}	-0.345^{***}
	(0.086)	(0.117)
Ln(Car weight)	0.310^{***}	0.371^{**}
	(0.110)	(0.160)
Diesel	0.171^{***}	0.159^{**}
	(0.043)	(0.064)
Automatic transmission	0.010	0.012
	(0.039)	(0.057)
Number of doors	0.034	0.011
	(0.022)	(0.035)
Ln(Nmb years car owned)	0.037^{***}	0.061^{***}
	(0.013)	(0.019)
Commute by car	0.084^{***}	0.072
	(0.033)	(0.059)
Ln(Income)	0.135^{***}	0.202^{**}
	(0.041)	(0.081)
Education	0.015	−0.002
	(0.023)	(0.050)
Children	0.072	−0.077
	(0.054)	(0.143)
HH size	-0.045^{**}	−0.021
	(0.021)	(0.042)
Rail pass	−0.050	−0.256
	(0.055)	(0.166)
Constant	4.867^{***}	3.875^{**}
	(1.013)	(1.625)
County FE	YES	YES
# Observations	3,235	1,580
# Individuals	1,065	790

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Fixed-effects at the household level are used. For solution 1, each household appears at least twice and maximum five times. For solution 2, each household appears twice.

Appendix T

Figure T.3: Individual Surplus



Notes: Individual surplus from the rebound (part b from Figure 3.5) for a rebound level of 30%. (N=3,217)

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