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

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Abstract

This paper investigates how households respond to efficiency improvement of their heating system. Micro-level rebound effects are estimated using a survey with an innovative choice experiment based on the stated preference approach. The experiment design allows to identify the direct and indirect rebound effects as well as their possible trade-offs at the household level. A series of easy discrete choices have been designed to prime respondents and make them think about potential actions impacting their heating service demand. Answers to these discrete choices are moreover used to cross-validate the quantitative results. Overall, we find relatively low direct rebound effects. However, after considering indirect rebound effects calculated as embodied primary energy, we estimate a total rebound of more than one third. The econometric analysis points to substantial variation across individuals that is only partly explained by observed characteristics. The results are consistent with the conjunction that heating is a basic need that calls for little rebound in high-income groups.

JEL Classification: D12, Q41, Q47, R22.

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

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1 Introduction

Energy efficiency is often considered as the "invisible fuel" (The Economist, 2015) of the energy transition. In Switzerland, like in many other industrialized countries, large efficiency gains remain feasible in buildings and heating systems. According to SFOE (2016, Table 0-1), 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 first adjustment corresponds to a direct rebound effect (Sorrell and Dimitropoulos, 2008), whereas the re-spending leads to an indirect rebound effect.

While previous papers in that literature focus on one or the other, our experimental design allows a simultaneous observation of both rebound effects, providing insights into their potential trade-offs. If consumers consider energy as a substitutable component across goods and services, the direct and indirect rebound should be negatively correlated. On the other hand, if the consumer's energy demand is driven by a single propensity (taste) to consume energy services, the two rebound behaviors should be complementary with a positive correlation. The heating domain is especially relevant for testing the two competing hypotheses, mainly because the net savings from the efficiency investments can be considerable, and hence the indirect rebound may be sufficiently large for a reasonable identification.

As a first in its kind, this paper relies on the stated preference approach with an innovative choice experiment to elicit rebound responses in residential heating. Respondents faced an exogenous efficiency improvement in their heating system, and are exposed to a sliding bar representing their choice of heating usage in reference to their actual heating level. In addition to scripts describing the scenarios, questions on behavioral changes have been used to prime respondents and cross-validate the results. This constitutes the first attempt to identify underlying mechanisms of the heating rebound, which could be due to an increase in temperature, but also to other reactions such as more airing or expansion of heating on space and time dimensions. Subsequent choice tasks are designed to identify the re-spending preferences for the potential net savings. 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 behavior is not explicable for a utility-maximizing person with unlimited substitution, our survey convinced us that zero-rebound phenomenon deserves more attention than it has received in the empirical literature. In fact, the vast range of rebound estimations and the focus on average estimates may have hidden no-rebound individuals in aggregate estimates. We observe that a substantial share of respondents did not feel any appeal in increasing their heating usage only because it is cheaper to heat. This observation may point to hierarchical preferences (Drakopoulos, 1994), at least for some individuals for whom increasing efficiency would not lead to more usage once a given level of thermal comfort is reached.

While recognizing that revealed data do not suffer from potential shortcomings inherent to stated preference data, we contend that the latter approach deserves much 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. In fact, models with revealed data could pose serious identification problems for individuals with zero marginal effects. Finally, the stated preference approach overcomes an important challenge in analysing the trade-offs between direct and indirect rebounds: 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 the rebound trade-offs for the same individual would therefore require a prohibitively large amount of information. The experiment on the other hand, 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%, adding up to a micro-level rebound of around 36%. Overall, our results indicate a strong heterogeneity among households, for both direct and indirect rebound effects, with about one third of the households displaying no direct rebound. Income is the main factor 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 analysis of the determinants of rebound effects we perform here 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. 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., Chitnis et al., 2013; Haas and Biermayr, 2000):

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

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 particular service due to an efficiency improvement (Sorrell and Dimitropoulos, 2008).

Energy efficiency is defined as $\varepsilon = \frac{S}{E}$, where E represents energy input and S service demand. In our study, S represents the services provided by heating. We emphasize S is not only the internal temperature, but it also encompasses several additional dimensions of thermal comfort such as airing frequency, when heating is turned on/off, asf. The direct rebound can then be defined as the elasticity of service demand (S) with respect to efficiency (ε):

$$\eta_\varepsilon(S) = \frac{\partial S}{\partial \varepsilon} \cdot \frac{\varepsilon}{S} \approx \frac{\Delta S}{\Delta \varepsilon} \cdot \frac{\varepsilon}{S} \tag{2}$$

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. In the case of heating, the price elasticity of heating fuel demand is often used to approximate the direct rebound (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.

Recognizing that AES $= \frac{\Delta\varepsilon}{\varepsilon} - \frac{\Delta S}{S}$ and PES $= \frac{\Delta\varepsilon}{\varepsilon}$, we observe that definitions (1) and (2) are equivalent for the direct rebound:

$$\text{Direct RE} = 1 - \frac{\text{AES}}{\text{PES}} = 1 - \frac{\frac{\Delta\varepsilon}{\varepsilon} - \frac{\Delta S}{S}}{\frac{\Delta\varepsilon}{\varepsilon}} \approx \eta_{\varepsilon}(\text{S}) \tag{3}$$

In our online survey, we face 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 in the field. It is the first time such an experiment is designed to assess rebound effects in residential heating. Only few former studies designed surveys to investigate the rebound effect: Schleich et al. (2014) in Germany for lightning, and Yu et al. (2013) in Japan for transportation.

While the principle of rebound effect is widely accepted, there is no consensus about its magnitude. 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 suggest a mean value of 20% for the direct rebound in residential heating. 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 rebound. 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%.

In their study about the effects of global warming on energy use in Switzerland, Gonseth et al. (2015) find a direct rebound of 35% in the long run (up to 2060) using a CGE model. Madlener and Hauertmann (2011) and Haas and Biermayr (2000) investigate the direct rebound in residential heating for two neighbour countries, Germany and Austria. A direct rebound from

12 to 49% is found in Germany, with tenants having a higher rebound than owners, and from 20 to 32% in Austria. Both use price elasticity of heating fuel.

Some studies rely on engineering calculations to estimate potential energy savings. For instance, Aydin et al. (2014) study a large number of households in the Netherlands, comparing energy labels of dwellings with their actual energy consumption. They find a direct rebound of 28% for owners and 42% for tenants. This technique has sometimes been criticised, mostly because it relies on engineering predictions that often over-estimate potential energy savings of efficiency improvements. For instance, Fowlie et al. (2015) 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 actual savings. They attribute all this discrepancy to engineering calculations over-estimating savings, finding no evidence of a direct rebound. One criticism is 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.

Most of the literature focuses solely on the direct rebound, yet the indirect appears as much (if not more) important for energy policies. This paper is among the few exceptions analyzing both rebound effects empirically. Other examples are limited to Druckman et al. (2011) and Chitnis et al. (2013), who conduct similar analyses in terms of GHG emissions, finding respectively a total rebound between 12 and 34% and between 5 and 15%. Most studies on the indirect rebound are based on income elasticities for diverse categories of goods and services (Chitnis et al., 2013, for instance) or input-output tables (Thomas and Azevedo, 2013a; Lenzen and Dey, 2002). Combining such data with information on energy intensity allows to compute the overall variation in energy consumption, and provides an aggregate estimate of the indirect rebound. As for the direct rebound, these aggregate estimates mask the variations across individuals. On the contrary, our household-level analysis allows individual estimates of the indirect rebound. Our measure, based on definition (1), focuses on income effect, that is, how net savings resulting from efficiency improvement are spent. The fraction of the indirect rebound due to substitution effects is not taken into account, as it is considered as relatively small (Thomas and Azevedo, 2013a). An asset of having both direct and indirect rebound estimates at the household level, is that we can study their potential trade-offs, which is new in the field.

3 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 regarding the direct rebound were formulated as scenarios, which simulated an improvement in the efficiency of the heating system. Each respondent was faced with three successive scenarios: 1) a relatively small improvement of 10, 15 or 20% in efficiency; 2) a large improvement of 40, 50 or 60%; 3) an intermediate improvement of 25 or 30% combined with a CO_2-neutral heating technology. The improvement was randomly chosen among the 2 or 3 alternatives of each scenario.[1] The upper bound of 60% is realistic in Switzerland, and was also used by Alberini et al. (2013). According to the Model of the Swiss Residential Sector,[2] the space heating demand in the worst buildings in Switzerland is slightly higher than 200 kWh/m^2 per year. With the current most stringent refurbishment standard, the limit is 60 kWh/m^2 per year, namely an efficiency improvement of more than 70%.

Under each scenario, respondents were asked two sets of questions. First, they had to state whether the efficiency improvement would trigger changes in their heating habits, formulated in a simple qualitative way (see Figure A.1). Respondents had to make a no/maybe/yes choice about setting the thermostat higher, airing more often, or heating earlier/later in the season, asf. These qualitative questions were firstly intended to help respon-

[1]For simplicity, we presented respondents' savings on the heating bill as proportional to the efficiency improvement (implicitly assuming no fixed costs, but only variable costs).

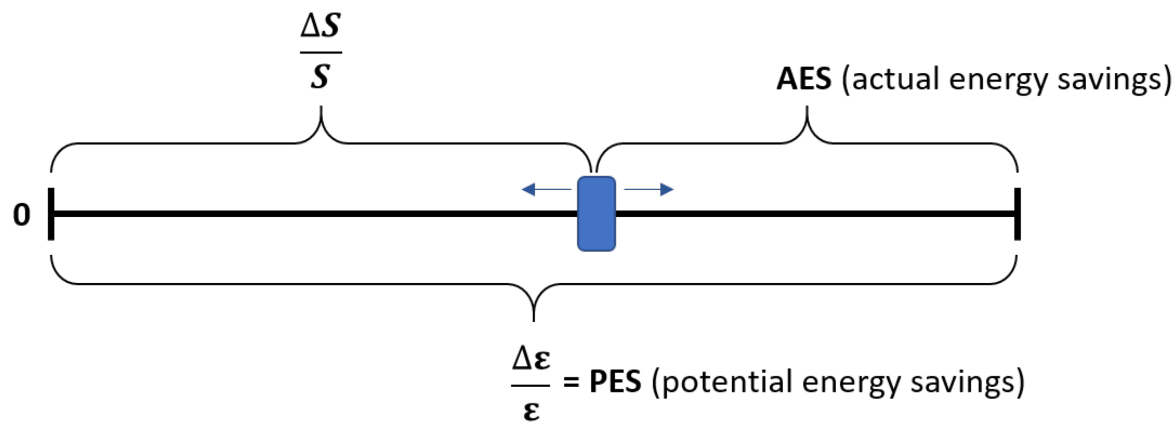
[2]Description available at `www.unige.ch/efficience/files/6414/2493/2151/SCCER-CREST_Poster_UNIGE.pdf`.

dents think about potential actions that impact heating fuel consumption. Secondly, it primes them for the next question, only asked if at least one of the possible qualitative reactions was non-negatively selected: Respondents were faced with a slider choice task (see Figure 1 and Appendix A.2), in which they had to state how much of their savings would be allocated to improve heating services.

From the definition of efficiency $\varepsilon = \frac{S}{E}$, we observe that any efficiency improvement translates in 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 (100% rebound). These two values determine how we constructed the slider to collect respondents' answers. 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 ($\frac{\Delta S}{S}$). Figure 1 schematically represents the links between the slider and the elements defining the rebound effect.

We should acknowledge that our survey rules out super-conservation (a negative rebound) and backfire (a rebound larger than 100%) by design. 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

Figure 1: The slider in detail: Variation of heating service demand



range of 0 to 100%. In addition, any extension of the bar outside the 0-100% range could have created confusion among the respondents.

This scenario- and question-based approach is called contingent behaviour method, and it belongs to the stated preference approach. This method was first coined by Chapman et al. (1993), and used for instance by Englin and Cameron (1996). *Stated* or *intended* behaviours are observed. The hypothetical nature of questions and answers can be considered as a weakness, since observed choices could differ from stated choices. Respondents may be placed in unfamiliar situations, with no certainty that their choices would reflect their real ex-post behaviour.

To assess the validity of stated preference approaches, some studies compared stated versus revealed preferences. Carson et al. (1996), in a meta-analysis of 83 studies on stated-revealed preference comparisons, find that stated preference estimates are smaller, but only slightly so. Moreover, the downward bias is not systematic, and they conclude that there is no general need to correct stated preference estimates. Grijalva et al. (2002) studied visitors' behaviour in a climbing area, finding that intended behaviour matches aggregate actual data. Loomis and Richardson (2006) examine the number of visits to a national park, and conclude that the estimates from the stated and revealed preference methods are not statistically different. In view of these results, we confidently argue that our method is appropriate to tackle our research questions.

The stated preference approach has also numerous advantages, summarised in Whitehead et al. (2008). Stated preference data are useful for the analysis of policies expected to lead to a behavioural change (such as efficiency improvements policies): In this case, hypothetical choices may be the only way to gather information and forecast the policies' impacts. Additionally, the number of observations can be expanded even with a fixed sample size, as respondents can be faced with several similar hypothetical questions. Repeating similar questions results in a panel data structure allowing for a better control of individual fixed effects. Moreover, as mentioned before, the stated preference approach presents three important advantages that we consider decisive in our study: circumvent the potential endogeneity bias between energy usage and heating technology choices, identify zero-rebound individuals and design a relevant model to explain their behavior, investigate the trade-offs between direct and indirect rebounds.

In order to strengthen the validity of our estimates, we use a cross-validation strategy by exploiting a series of questions intended to look for the specific actions households would take. Contrasting these specific decisions with quantitative rebounds indeed allows to determine which respondents are consistent and which are less so. Focusing on the most reliable respondents therefore provides a mean to check the robustness of our results.

We also collected a series of individual and household characteristics to investigate the determinants of the individual's heterogeneous responses. The variables considered are described in Appendix Table B. Out of the 3,555 respondents, 2,637 have no missing values and constitute our final sample.

To estimate the indirect rebound, we take into account the embodied energy used in the production of the good/service (cradle-to-gate approach) using life-cycle analysis (LCA) (as in Tilov et al., 2016). LCA encompasses embodied energy, that is the equivalent in kWh of primary energy consumed for each CHF spent on a given category of goods and services.[3] In the survey, we requested the respondents to state how they would re-spend an annual net saving of CHF 1,000 resulting from the heating efficiency improvements.[4] They were free to split the CHF 1,000 between eight categories of goods and services, plus savings. These categories were chosen such that the goods and services classified together are comparable in terms of embodied energy. The energy intensity (kWh/CHF) of each category is presented in Appendix Figure C, as well as the re-spending shares over the nine categories. For savings, energy intensity is set equal to the overall average energy intensity of CHF 1 spent, that is 2.54 kWh/CHF. When

[3]Currently, CHF 1 is almost equal to USD 1.

[4]CHF 1,000 roughly correspond to 65% of average annual heating costs in Switzerland, which were CHF 1,560 in 2011 according to the household budget survey. Said otherwise, an average household could expect to save CHF 1,000 every year following an efficiency improvement of 65%.

doing this, our underlying assumption is that savings will be spent in the future according to current spending pattern.

4 Estimation of the Rebound Effects

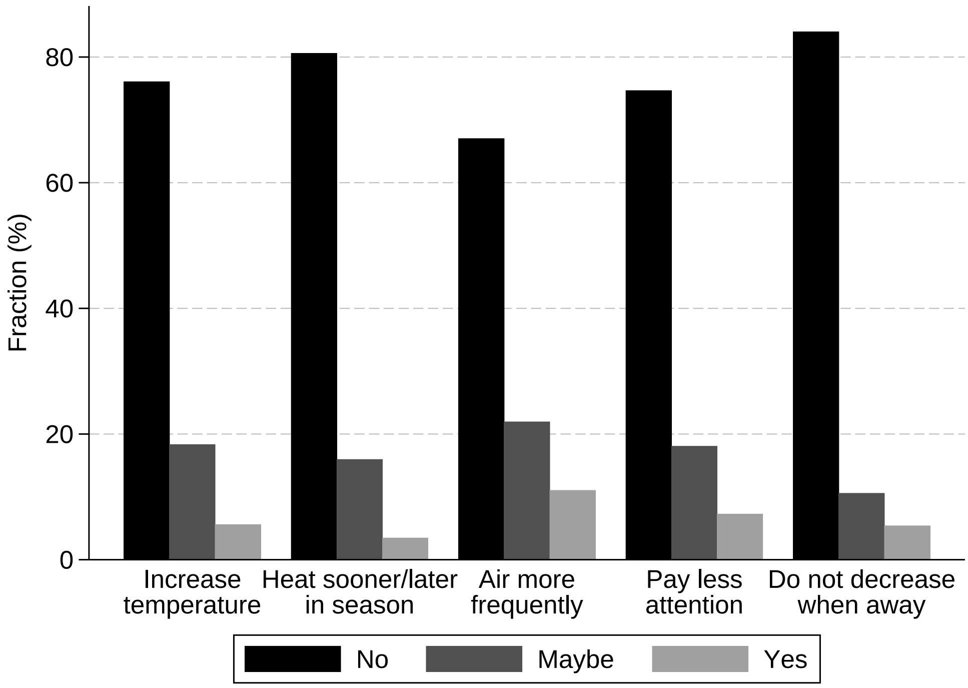
4.1 Direct Rebound Effect

Our definition of the direct rebound effect encompasses several possible behavioural adjustments. Usually only temperature increases are considered. Yet, people can react to an efficiency improvement in various ways, for instance by airing more frequently, or starting to heat earlier in the season, asf. The latter reactions in fact appear more plausible in advanced countries, where indoor temperature is generally not an issue. In that sense, allowing various responses seems more relevant.

The purpose of our qualitative no/maybe/yes questions (provided in Appendix A.1) is precisely to investigate such possibilities. Respondents' answers are plotted in Figure 2, and we observe that airing longer or more frequently is indeed what respondents chose the most, before paying less attention to heating in general. Increasing temperature only comes as the third most popular choice, with 25% of the answers being maybe or yes. Galassi and Madlener (2017) find similar results in a survey in Germany, with air quality being the preferred way to improve thermal comfort, and only 33% stating they would prefer a higher temperature. These findings show that considering only temperature changes would result in an underestimation of the direct rebound (see also Volland, 2016).

After having indicated their intended behavioral changes, respondents answered the quantitative question (slider) previously described, which provides all the necessary data to apply definition (1). Potential energy savings are given by the efficiency improvement, while actual energy savings are deduced from respondents' answers. This strategy provides a rebound effect specific to every individual in each scenario.

Figure 2: Qualitative questions: changes in behaviour



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

To gauge the consistency and plausibility of respondents' answers to the quantitative rebound question, we used an OLS model to regress the heating service variation, $\frac{\Delta S}{S}$, on the answers to the qualitative questions.

Results (displayed in Appendix Table 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 response's affirmative scale. That is, "yes" responses show a greater effect than "maybe" responses. These results suggest broad consistency among our respondents: When they indicated they would change something in their heating behaviour, they also stated a sensible corresponding variation of their service demand.

The individual direct rebound estimates we obtain are displayed in the first panel of Table 1. The global average direct rebound is 11.9%, with scenario-specific averages ranging from 10 to 15%. Our estimates are thus consistent with the reviews by Sorrell et al. (2009) and Nadel (2016). If we keep the entire sample (10,665 respondents), without dropping the individuals with missing values, the results are very similar (+0.3 percentage point on average). Figure 3 displays the distribution of the rebound effects, exhibiting wide heterogeneity across individuals.

Table 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	**0.119**	0.0023	0	1	7,911
Indirect rebound	**0.243**	0.0047	0.028	1.357	2,637
Total micro-level rebound	**0.362**	0.0037	0.028	2.357	7,911

Notes: The individual rebound effects are calculated using definition (1). The total rebound is calculated by adding the indirect rebound (measured once per respondent) and the direct rebounds (measured in three different scenarios for each respondent).

4.2 Indirect Rebound Effect

The indirect rebound is determined by exploiting the re-spending question presented in the data section. Potential energy savings are calculated as the amount of embodied energy saved when spending CHF 1,000 less on heating. The energy intensity of CHF 1 spent on heating is 10.24 (an average over all fuel types), thus 1,000 [CHF] × 10.24 [kWh/CHF] = 10,240 [kWh] potentially saved. We then compute the embodied energy consumed when re-spending CHF 1,000 on various categories of goods. These potential and actual savings for each household allow us to apply definition (1) and retrieve an estimation of the indirect rebound effect.

We obtain an average indirect rebound of 24.3% (displayed in Table 1).

Thus, on top of the direct rebound, about a quarter of the potential energy savings are lost due to the re-spending of the savings initially made on heating. The median indirect rebound effect is at 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. The maximum indirect rebound is by construction at 136%, and happens when everything is re-spent on air travel.

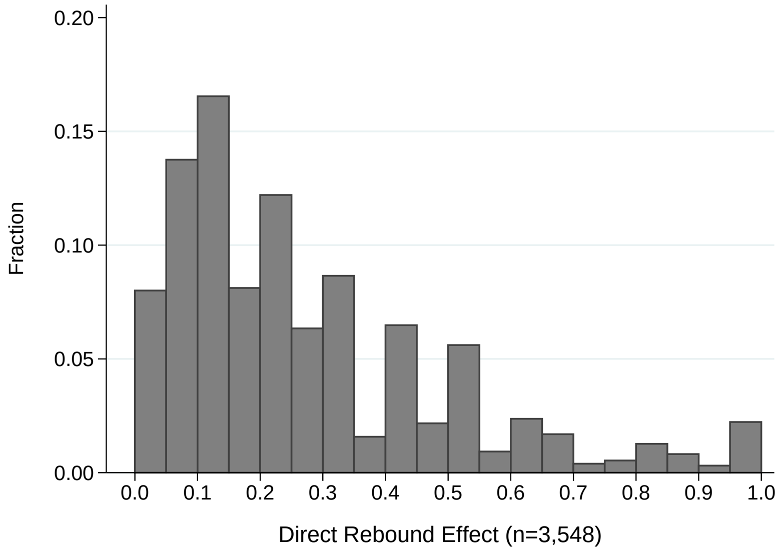
4.3 Total Micro-level Rebound Effect

Adding up the direct and indirect rebound effects yields what we call the total household rebound effect. We obtain an average total micro-level rebound of 36.2%, when using all scenarios for the direct rebound. Figure 3 shows its distribution. Depending on the scenario, backfire happens for 130 to 180 respondents (5-7% of the sample), with a maximum total rebound of 236%. The spike between 10 and 15% is explained by respondents re-spending all the CHF 1,000 on other goods or services, resulting in an indirect rebound of 10.4% (594 respondents, or 22.5% of the sample).

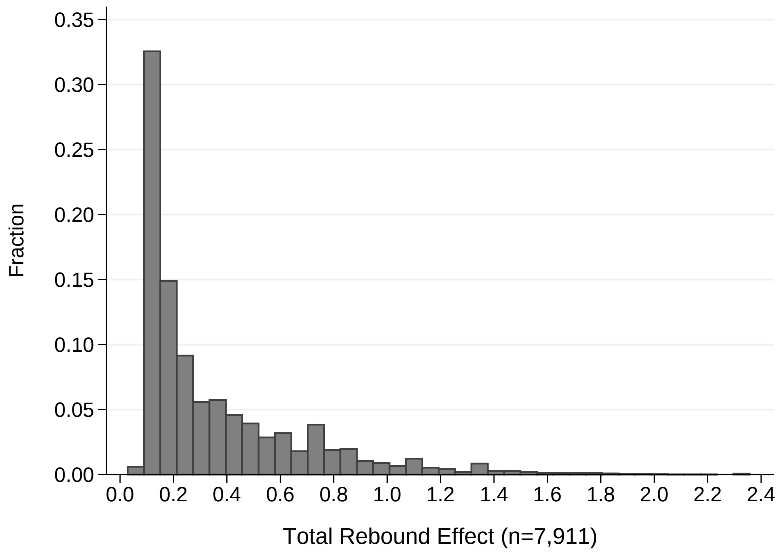
At this point, we may summarise our main findings as follows: in the domain of residential heating, about one third of the energy savings (in terms of kWh) initially expected after an efficiency improvement are lost due to the direct and indirect rebound effects. The direct rebound is less important in magnitude than the indirect rebound (12% versus 24%). While very few studies use the same dataset to estimate direct and indirect rebound together, one comparable result is obtained by Chitnis et al. (2014) for the UK. Using expenditure elasticities, they find a rebound effect (direct and indirect) between 0 and 32% in terms of GHG. Moreover, we find that heterogeneity is very large, with a total rebound ranging from 3% to 236%. We investigate what explains this heterogeneity in the next section.

Figure 3: Distribution of individual rebound effects

A. Direct rebound



B. Total rebound



Notes: The 4,363 zero-rebound observations are not displayed in the histogram of the direct rebound.

5 Determinants of Rebound Effects

5.1 Methods

In the next step of our analysis, we seek to unravel which individual characteristics influence the rebound effects, starting with the direct rebound. In order to select the most adapted estimation technique, we need to acknowledge the specific features of the direct rebound measure created by our experimental design. First, the direct rebound is constrained to be zero or positive (up to a maximum of 100%). Second, the individual starts by making a series of qualitative choices implying whether he rebounds or not, and depending on at least one answer being non-negative, he then decides the rebound magnitude.

In an econometric perspective, our setting exhibits two specific attributes: First a lower bound at zero, with a cluster of observations at this bound; second a two-stage process in the rebound determination. This first attribute corresponds to a Tobit model, and the second to a two-part model. A two-part model is usually made of a selection model to separate the 0 and the 1 people, and conditional on being a 1, a linear model constitutes the second part. Hurdle models, an extension of Tobit models, are an example of two-part models and match our dependent variable's specific features.

A hurdle model is appropriate for our experimental design, since respondents need to pass a first "obstacle" to have the possibility to display a positive rebound. Indeed, if they answer "no" at every item of the qualitative question, the slider choice was not displayed to them. Yet, a single hurdle model is not adapted for our panel data, because such a model classifies individuals as being either a 0 (no rebound) or a 1 (always a positive rebound). Individuals with a mix of 0 and 1 over different periods are ruled out. They do however exist in our experiment, since respondents were exposed to three different scenarios, and therefore can present a mix of 0 and 1. For instance, a respondent can have no rebound in one scenario, but positive rebounds in the next. It is in fact the case for 26% of the respondents, who sometimes but not always rebound, while 32% never rebound, and 42% always positively rebound.

A single hurdle would not account for the mixed category, while a double hurdle model (Cragg, 1971) would. The two hurdles refer to: a) whether the individual is a 0 (never rebound) or not; b) given he is not a 0 type, whether he rebounds or not in specific circumstances. Therefore people with a positive rebound in a specific scenario would have crossed two hurdles. 0 type individuals cross no hurdle, and will never rebound whatever the circumstances. 1 type individuals cross one or two hurdles, depending on the scenario (one hurdle when they do not rebound, two hurdles when they rebound).

Cragg's (1971) double hurdle model has been adapted to panel data by Dong and Kaiser (2008). The model includes a random variable to capture individual heterogeneity. The double hurdle model for panel data is thus perfectly adapted to our design, because each respondent answered the choice experiment three times, therefore creating a panel.

Denoting $y_{i,t}$ the observed rebound of subject i, $d_i^\star$ a latent (unobserved) variable related to the individual's (0 or 1) 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):

$$d_i^\star = \mathbf{z_i'}\boldsymbol{\alpha} + \varepsilon_{1,i} \tag{4}$$

Rebound intensity (second hurdle):

$$y_{i,t}^\star = \mathbf{x_{i,t}'}\boldsymbol{\beta} + u_i + \varepsilon_{2,it} \tag{5}$$

Observation:

$$y_{i,t} = \begin{cases} y_{i,t}^\star & \text{if } d_i^\star > 0 \text{ and } y_{i,t}^\star > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where $\mathbf{z_i}$ is a vector of time-invariant covariates, and $\mathbf{x_{i,t}}$ is a vector of covariates that encompasses $\mathbf{z_i}$ plus additional time-varying covariates. 0 type individuals are the specificity of the double hurdle model. For heating, it seems very plausible that such individuals exist. It means that, whatever the circumstances – the magnitude of efficiency improvement and consequently the implicit service price decrease – their demand for heating service will never increase. We can think of them as highly satisfied with their thermal comfort, and having reached their maximal level of heating demand. Such a satiety point is mentioned by Davis et al. (2017) for electricity. Yet, this maximum 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 the following way: First *necessary wants* have to be satisfied, and *non-necessary goods* will only be considered thereafter. For the necessary wants, very limited substitution possibilities exist. However, once a given amount of the necessary want is obtained, individuals will not consume more of it, because it would not bring anything to their utility (it may even decrease it).

The theory of hierarchical preferences seems well adapted to our context. Indeed, the need for a warm shelter can be considered as a necessary want: As long as internal temperature and thermal comfort are unacceptably low, householders have no other choices but to increase heating usage to increase their utility. Once a decent level of thermal comfort is reached however, pushing heating usage further will not increase utility, and it may even diminish it (think about a flat that is already overheated). In our setting, the threshold could thus be formally represented as follows:

$$\frac{\partial u}{\partial h} \leq 0 \qquad \text{when} \quad h > h^{\star} \tag{7}$$

where u denotes utility, h heating, and $h^{\star}$ the necessary heating level. Contrarily to a standard model with unlimited substitutability, this model can explain why some people will never rebound.

5.2 Determinants of the Direct Rebound

We run the double hurdle model described in equations (4) to (6) to investigate the impact of individual characteristics on the direct rebound magnitude. The equation, estimated by maximum of likelihood, is:

$$y_{i,t} = \alpha + \mathbf{x'_{i,t}}\boldsymbol{\beta} + u_i + \nu_{i,t} \tag{8}$$

where i denotes the individual, t $(= 1, 2, 3)$ denotes the scenario, and u is an individual random intercept. $\mathbf{x_{i,t}}$ includes socio-economic characteristics, indoor temperature, heating satisfaction, heating bill features, and scenario dummies.[5] A description of the variables is available in Appendix B.

The output is composed by two estimations: the selection (the first hurdle), and the rebound intensity, based only on individuals who have passed the first hurdle. The first equation is a binary dependent variable regression. The scenarios' dummies enter only in the second equation, because by definition the distinction between the 0 and 1 type is made on characteristics which do not vary through the treatments. Indeed, the scenario cannot explain why the 0 type individuals do not rebound, because whatever the situation, they would never rebound.

We expect a negative effect on the direct rebound of education, income, heating satisfaction and environmental concerns. Also, it seems obvious that people already satisfied with their thermal comfort will be less prone to a direct rebound, as well as people paying more attention to the environment. The effect of income has been analysed in Chitnis et al. (2014) and Madlener and Hauertmann (2011), both finding that richer people rebound less. An explanation is that wealthy households do not restrict their usage of heating and have reached a satisfying level of comfort, so that any efficiency improvement will not affect their usage. Thus, income should play a role in the first hurdle, to differentiate the 0 and 1 type. Some evidence of the impact of income can also be found in macro-level studies and in

[5]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.

various fields. For instance, Small and Van Dender (2007) find that the rebound effect for motor vehicles declined over 1966-2001 in the US, which they explain by the overall rise in incomes. In general, rebound effect estimates are larger for developing countries than for developed ones, which is also interpreted as the impact of income constraints in the former (e.g., Azevedo, 2014). Therefore an interesting contribution of our paper is that we are able to determine the effect of income on the rebound effect at the individual level.

It is less obvious why education should play a role. A possibility is that more-educated individuals might be better informed on how to limit their heating usage, thereby minimizing the effect of efficiency improvement and hence the rebound. Concerning temperature, the usual assumption is that people with lower temperature will rebound more. However, it supposes that they have low temperature because of budget constraint, and it rules out people with low temperature for comfort reasons or environmental concerns. In Switzerland, the hypotheses of low temperature because of budget constraints does not appear particularly relevant, because fuel poverty is virtually non-existent. According to Eurostat (EU-SILC survey), less than 1% of people were "unable to keep home adequately warm" in 2014. In comparison, it 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, turn 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.

Finally, in view of the literature (e.g., Madlener and Hauertmann, 2011), tenants are expected to rebound more than owners. Yet, the feature of the heating bill is never taken into account, and we argue it matters. When costs are shared among all dwellers, the incentives to refrain personal heating usage are low. Hence it would lead to a lower rebound effect, as people are already closer or even at their optimal comfort level. We therefore add a dummy variable for individual costs, and an interaction term with the tenant dummy to see whether tenants with shared or individual costs behave differently. When omitted, this bill's feature might explain part of the difference between tenants and owners given that the proportion of dwellers with shared costs is very different among the two groups: only 15% of the owners, but almost 50% of the tenants.

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 the efficiency improvement arises 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 2. For the selection equation, the marginal effects at the means are displayed. Only three variables are significant to explain the difference between the 0 and 1 type: income, gender and owner/tenant status. 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, which is in line with our expectations. The probability of rebound decreases respectively by 6.7% and 7.5% 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.

Tenants with shared costs are less likely to rebound, as well as females. Yet, the latter coefficient is low, and not significant in the robustness check performed later. The coefficient for the tenants with shared costs is of considerable magnitude, as it diminishes the likelihood of rebound by 18.1%. As argued above, tenants with shared costs have fewer incentives to limit their heating usage, hence they are more likely to be already at their thermal comfort satiety point. This finding highlights the importance of taking the heating bill structure into account when investigating whether owners or tenants rebound differently. Tenants with individual heating bills are not different from owners.

Table 2: Double hurdle model

	Selection (ME)	Intensity
Vocational school	0.040	-0.155^{***}
	(0.039)	(0.057)
High school	0.057	-0.223^{***}
	(0.044)	(0.059)
University	0.049	-0.223^{***}
	(0.040)	(0.057)
Income CHF 4500-9000	-0.067^{**}	0.024
	(0.031)	(0.019)
Income CHF >9000	-0.075^{**}	0.004
	(0.031)	(0.019)
Moderate heating satisf.	-0.055	-0.040^{*}
	(0.040)	(0.024)
High heating satisf.	-0.033	-0.164^{***}
	(0.042)	(0.026)
20.1-21 degrees	-0.025	0.041^{**}
	(0.017)	(0.018)
21.1-22 degrees	-0.024	0.068^{***}
	(0.016)	(0.018)
>22 degrees	0.007	0.039^{**}
	(0.021)	(0.019)
Environmental concerns	0.000	-0.004^{***}
	(0.001)	(0.001)
Female	-0.023^{*}	-0.029^{**}
	(0.013)	(0.013)
Tenant	-0.181^{*}	-0.005
	(0.107)	(0.024)
Individual heating costs	-0.154	0.014
	(0.112)	(0.024)
Tenant*individual costs	0.177	-0.013
	(0.110)	(0.029)
Large efficiency improv.	–	-0.080^{***}
		(0.008)
Middle eff. improv and CO2 neutral	–	-0.023^{***}
		(0.003)
Constant	–	0.376^{***}
		(0.073)
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.

In the rebound intensity equation, the coefficients are to be interpreted as in a linear regression. As the dependent variable ranges from 0 to 1, the coefficients need to be multiplied by 100 to get the variation in percentage points. The impact of education is negative as expected and significant at the 1% level, while income plays no role. Heating satisfaction and environmental concerns exert a negative effect as expected. 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 hypotheses of fuel poverty and low temperature because of budget constraint do not hold in Switzerland. The three coefficients are not statistically different from each other, but they reveal a significant difference between the indicated temperature categories and the omitted category ($\leq$ 20 degrees). Aydin et al. (2014) find similar results, with households using more energy than the average displaying a higher direct rebound. One question then arises: Why have low temperature households a lower rebound, considering that they still sometimes rebound? They may restrain themselves for environmental concerns or comfort reason (they prefer low temperature). Looking at the different dimensions of the direct rebound (airing, temperature, asf.) reveals no difference between the temperature groups. They all behave similarly, and the high temperature households still want to increase it further.

To investigate what determines indoor temperature and if environmental concerns play a role, we regress temperature on various characteristics. The results are displayed in Appendix Table E. Interestingly, income has no effect, strengthening the rejection of the fuel poverty hypothesis. Environmental concerns are highly significant: the more environmentally concerned, the lower the temperature. With no surprise, individual heating costs diminish the temperature. The effect of the heating fuels is also of interest: 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). We discuss in Appendix F the possibility of a green rebound based on our CO_2 neutral scenario. We find evidence of a green rebound only for a limited number of respondents.

Concerning the effect of the scenario dummies, i.e., of the magnitude of the efficiency improvement, we find that larger efficiency improvements lead to a lower direct rebound. 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.

Hypotheses on who will rebound the most have often been made in previous research, but very seldom tested due to the lack of data. Our findings highlight important facts: First, the magnitude of the direct rebound is very heterogeneous among households. Second, large improvements do not mechanically imply a higher rebound than smaller improvements. Third, accounting for the tenant/owner status is not sufficient, because the structure of the heating bill matters, and often differs between the two groups. Fourth, measures targeting low-income households (for instance subsidies conditional on income) will be less effective in terms of energy saved, because they are associated with larger direct rebound effects.

5.3 Determinants of the Indirect Rebound

As for the direct rebound, we can assess which personal characteristics have an impact on the magnitude of the indirect rebound. An important difference to mention at this point is that the indirect rebound is less salient and less tangible since it incorporates embodied energy. Most people are obviously aware that traveling by plane or driving a car is energy intensive, but they are much less likely to know how eating out in a restaurant compares to buying clothes in terms of energy intensity. Hence, we expect fewer coefficients to turn out significant and make few assumptions. We consider similar determinants as in equation (8).

Furthermore, to investigate the trade-offs between direct and indirect rebound effects, we include the direct rebound as a determinant of the indirect rebound. For each respondent, we use the average direct rebound from the three scenarios. In theory, a mechanical negative link should exist between the two effects, because the larger the direct rebound, the lowest the remaining savings to spend on other goods (Thomas and Azevedo, 2013b). In other words, substitution is expected between both rebound effects. However, considering that individuals might differ in their propensity to consume energy services, we would expect intensive users displaying both a high direct rebound and a high indirect rebound. Light users would display a low or no direct rebound, and re-spend their savings on non-energy intensive activities. Direct and indirect rebounds would then be complementary rather than substitutable responses.

We use both an OLS model and an ordered probit model to check the robustness of our results. For the ordered probit, we construct four categories of energy intensity: air travel, car fuel, food and beverages, and "other". "Other" aggregates the lowest five energy intensity categories (below average), and savings. The order in the probit goes from the least ("other") to the most energy intensive category (air travel). Table 3 displays the results.[6] The estimation results are consistent across the two models, with the coefficients' signs and their significance levels being comparable.

The positive coefficient of the direct rebound supports the complementarity assumption: The larger the direct rebound, the larger the indirect one. Looking at the re-spending shares of people who always rebound (intensive energy users) versus people who never rebound (light energy users) reveals

[6]Strictly speaking, the estimation conducted is a weighted ordered probit, where the weights are the amounts spent on one category divided by 1000. For instance, if a respondent re-spent 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 taking the modal category of re-spending, and very similar results were obtained.

Table 3: Indirect rebound effect

	OLS	Ordered probit
Direct rebound	0.134^{***}	0.631^{***}
	(0.028)	(0.118)
Vocational school	0.055	0.064
	(0.044)	(0.183)
High school	0.066	0.079
	(0.045)	(0.190)
University	0.046	0.007
	(0.044)	(0.184)
Income CHF 4500-9000	−0.004	−0.082
	(0.014)	(0.055)
Income CHF >9000	−0.014	-0.149^{**}
	(0.015)	(0.060)
Age	-0.001^{***}	-0.006^{***}
	(0.000)	(0.001)
Female	0.006	−0.014
	(0.010)	(0.042)
Environmental concerns	-0.003^{***}	-0.010^{***}
	(0.001)	(0.004)
Tenant	0.013	0.070
	(0.010)	(0.045)
20.1-21 degrees	0.005	−0.009
	(0.013)	(0.054)
21.1-22 degrees	0.014	0.026
	(0.012)	(0.051)
>22 degrees	0.040^{***}	0.162^{***}
	(0.014)	(0.060)
Constant	0.278^{***}	–
	(0.055)	
# 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.

that the latter save more money, and re-spend less on air travel or car fuel. It backs up the assumption of heterogeneity across individuals in their propensity to consume energy services. The ordered probit confirms this result. The marginal effects of the direct rebound (Appendix Figure G) reveal that an increase in the direct rebound lessens the probability to be in the "other" category by about 14%, but increases the probability to be in the three most energy intensive categories.

Concerning the other variables, it appears that age matters, with younger people having a higher indirect rebound. Environmental concerns have the expected negative sign. People heating at more than 22 degrees have a higher indirect rebound, again suggesting a higher propensity of such individuals to consume energy services.

Contrarily to the direct rebound, the indirect rebound is much less tangible for people, because embodied energy accounts for a significant share of many activities' energy intensity. The patterns of individual indirect rebound are therefore much less obvious than for the direct rebound, and we identify a smaller number of significant determinants. Nevertheless, we find robust evidence for a complementarity between the direct and indirect rebound, supporting the hypothesis of a higher propensity to consume energy services among some segments of the population. This taste for energy services partly explains the variability of the indirect rebound at the individual level.

6 Conclusion

The rebound effect is a behavioural reaction which causes 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. Accurate estimates are therefore essential for countries that engage in their energy transition.

In this paper, we investigate direct and indirect rebound effects in residential heating using stated preference at the household-level. We designed an innovative choice experiment: Under different scenarios describing an exogenous efficiency improvement in their heating system, respondents indicated which behavioural adjustments they would make in terms of heating usage and decided how to re-spend their savings. The heating usage adaptation identifies the direct rebound, while the re-spending allows to retrieve the indirect rebound. The direct rebound not only encompasses a potential temperature increase, but also a rise in ventilation, a heating turned on (off) earlier (later) in the season, asf. The indirect rebound encompasses energy embodied in the goods and services.

We obtain an average direct rebound of 12%, and an average indirect rebound of 24%, adding up to a total micro-level rebound of 36%. Said otherwise, rebound effects take back more than one third of potential energy savings, which is substantial, but well below 100%. Policy makers can therefore confidently rely on energy efficiency in residential heating to reduce energy consumption and in turn CO_2 emissions. Backfire situations (a micro-level rebound of more than 100%) only happen for a very limited number of people (about 6% of the respondents in our sample). At the same time, policy makers should keep in mind that energy saving estimations based only on engineering calculations could largely over-estimate the potential of efficiency measures in the residential heating sector.

Beyond these overall averages, our results indicate strong heterogeneity among households, both for the direct and the indirect rebound effects. The individual effects range from 0 to 100%, and from 3% to 136% respectively. An important finding hardly ever raised in the literature is that about one third of the households display no direct rebound, regardless of the magnitude of the efficiency improvement. These households are of particular interest to policy makers, since they could be targeted in priority to achieve the best results in terms of energy savings. Such no-rebound behaviour cannot be explained in the traditional framework of unlimited substitution. 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 experimental 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 leave aside the variations among individuals, which may be one explanation for the lack of convergence in the literature estimates. Using a double hurdle model for panel data, we show that the substantial variation in rebound effects 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 more 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., 2015), and are thus prone to underestimating the direct rebound. We are also able to characterize the trade-offs between the direct and indirect rebounds, and our results reveal complementarity between both, not substitutability as suggested in the literature. This finding points toward the existence of heterogeneity among individuals concerning their taste for energy services, which implies that the population is segmented into low and high energy users.

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 reductions of energy usage. In other words, we can expect that improvements in energy efficiency would result in energy conservation. 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 heating energy demand for certain households.

Second, the strong variability in individual rebound responses indicates that one-fits-all policies are not adequate when it comes to promoting buildings' efficiency. In particular, the finding that zero-rebound individuals are concentrated in high-income groups suggest that imposing high efficiency standards in expensive dwellings may prove especially effective for reducing energy consumption.

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 results in an improvement of thermal comfort. Such subsidies exist in the US (Weatherization Assistance Program's), and their net welfare gains are not clear (Fowlie et al., 2015), but non-energy benefits exist (reduction of thermal stress, improved sleep, asf.).

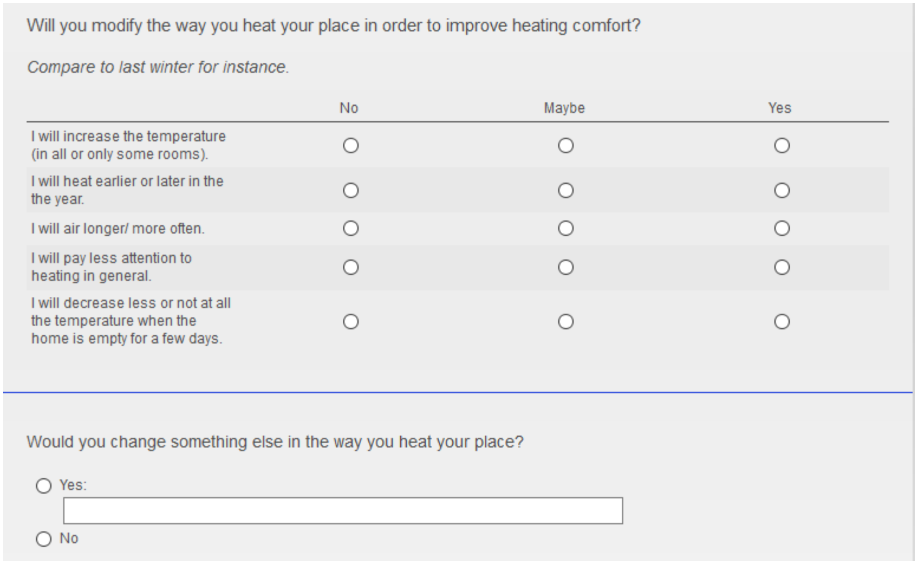
Third, considering we find that the indirect rebound accounts for about two thirds of the total rebound, we claim that it deserves more attention in terms of future research and policy measures. A tax on embodied energy could be one way to mitigate the indirect rebound. Another way would be to make embodied energy more salient for customers, as through mentions on packaging.

Fourth, the positive correlation between individual direct and indirect rebounds indicate that efficiency programs should avoid a selection of people whose total rebound response could be so large that it would offset most of the potential energy savings stemming from efficiency gains. 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.

Appendices

Appendix A

Figure A.1: 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).	○	○	○
I will heat earlier or later in the the year.	○	○	○
I will air longer/ more often.	○	○	○
I will pay less attention to heating in general.	○	○	○
I will decrease less or not at all the temperature when the home is empty for a few days.	○	○	○

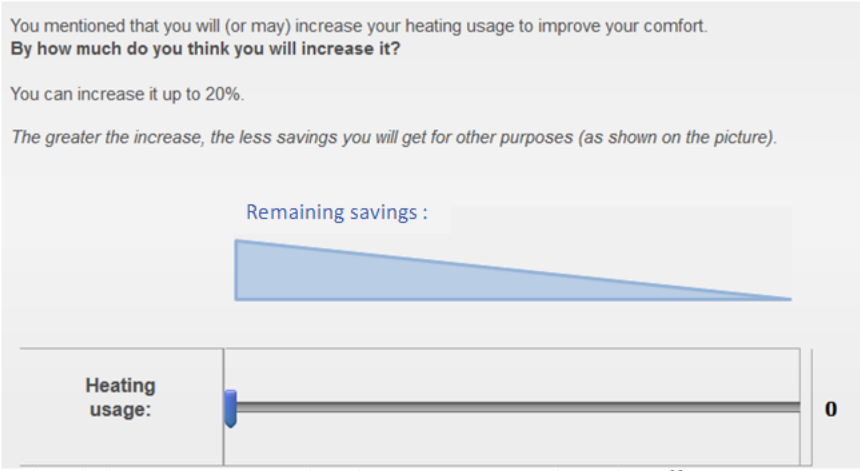
Would you change something else in the way you heat your place?

○ Yes:

○ No

Note: This question is extracted from the online survey (originally available in French and German). The scenario was presented before this question, with the efficiency improvement and the corresponding cost savings provided in percentage of current heating costs.

Figure A.2: Quantitative question related to the direct rebound



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

Appendix B

Table B: 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
Age	49.174	15.965	19	50	89
Female	0.483	–	0	–	1
Tenant	0.555	–	0	–	1
M^2	123.597	154.439	0	110	7000
Household size	2.242	1.161	1	2	7
Individual heating costs	0.661	–	0	–	1
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

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

Environmental concerns is the score on a nine-item index, conceptualized by Maloney and Ward (1973), and used by Best and Mayerl (2013).[7] Respondents indicate to which extent they disagree-agree on a five-point scale.

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

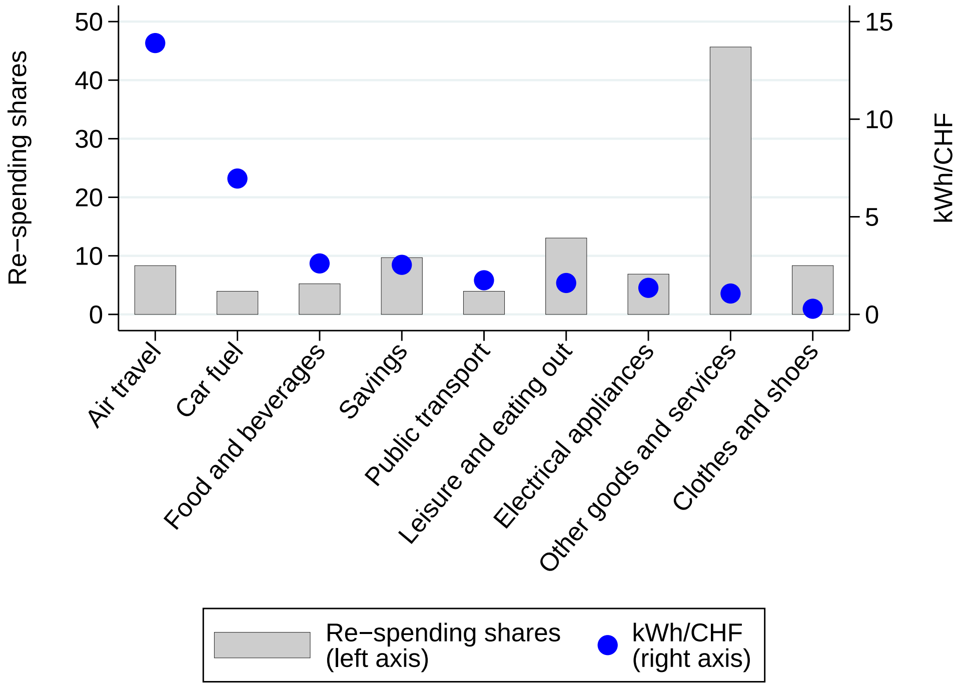
Their answers are then transformed into scores from 0 (completely disagree) to 4 (completely agree) and summed over the nine items. Hence, the index ranges from 0 to 36 and increases with the level of environmental concerns.

Heating satisfaction is the score on an index of heating satisfaction. It is 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).

Individual heating costs indicates whether the heating bill is calculated on the individual consumption or shared among all the inhabitants (calculated as a proportion of the dwelling size). 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.

Appendix C

Figure C: Re-spending shares and energy intensity



Note: Re-spending shares of CHF 1,000 from the re-spending question, used to estimate the indirect rebound. Embodied energy from LCA data. *Source:* ESU-services (Zürich), and Tilov et al. (2016).

Appendix D

Table D: Cross-validation analysis

	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

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

Appendix E

Table E: 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)
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

Note: 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 F

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 Jacobsen et al., 2012; 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 paying voluntarily 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, however, 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 F. People who never rebound were excluded from the regression. The significant variables are university degree (positive effect), environmental concerns (positive effect), high indoor temperature (negative effect), and wood logs as heating fuel (negative effect). Quantitatively speaking, education has the strongest impact, with university graduates being 27.1% more likely to be in this group compared to people who stopped after compulsory school. Thus a "green rebound" may exist, but seems to be limited to a small group of people, with more education and higher environmental concerns.

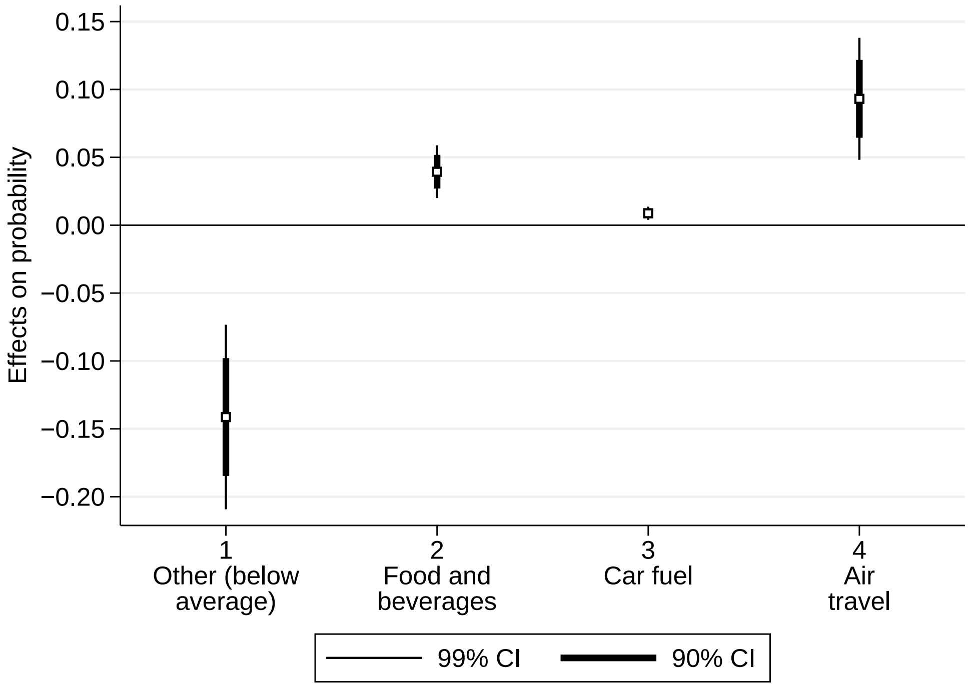
Table F: A green rebound?

	MEs Probit
Vocational school	0.191
	(0.122)
High school	0.206
	(0.126)
University	0.271^{**}
	(0.122)
Income CHF 4500-9000	0.032
	(0.034)
Income CHF >9000	−0.031
	(0.037)
Moderate heating satisf.	−0.013
	(0.043)
High heating satisf.	−0.017
	(0.045)
Environmental concerns	0.004^{*}
	(0.002)
Female	−0.003
	(0.024)
Age	0.000
	(0.001)
Tenant	0.008
	(0.029)
Individual heating costs	0.017
	(0.027)
20.1-21 degrees	0.007
	(0.033)
21.1-22 degrees	-0.052^{*}
	(0.030)
>22 degrees	−0.056
	(0.035)
Heating fuel	
Gas	0.021
	(0.031)
Wood (logs)	-0.115^{**}
	(0.053)
Wood (pellets)	0.025
	(0.076)
Heat pump	−0.022
	(0.037)
Electricity	0.028
	(0.051)
District heating	−0.044
	(0.047)
Other	0.085
	(0.114)
N	1,430

Note: 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 G

Figure G: Conditional marginal effects of direct rebound



Note: Marginal effects at the means of the direct rebound from the ordered probit.

Appendix H

Consistency weights

As robustness checks, we identify respondents whose answers are inconsistent, and we limit their influence in regressions through weights, or exclude them from our analysis. Consistency tests are appropriate when stated preference approach is used, and allows 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 (inconsistent respondents) or 1 (consistent respondents), and the 0s are then completely excluded from the analysis. One drawback is that people just below/above the threshold defining the switch from 0 to 1, who are not very different, 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[8]. Scenario 2 consists of the large efficiency improvement, and scenario 1 the small one. The service variation in absolute term 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

[8]Note that the variation of service demand in absolute term 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.

CO_2 neutral technology is added. Respondents may react more or less than in other scenarios because of the green technology, and still being rational.

Moreover we do not consider a respondent to be inconsistent if the difference in his answers is less or equal to one in absolute term. For instance, if a respondent stated an increase of 10 in his service demand in scenario 1, and an increase of 9 in scenario 2, is he really inconsistent? As 9 and 10 are so close, we consider it as an acceptable deviation. 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 coefficients of 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 respondent answered the qualitative question and the slider question consistently. For instance, if he 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 them, we apply the model used for the cross-validation analysis of Table D and presented below as a robust regression. 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 a weight of 1, the maximum.

$$\frac{\Delta S_{i,t}}{S_{i,t}} = \alpha + \sum_{k=1}^{5} \sum_{j=2}^{3} \beta_k^j \text{Quali}_{i,t}^k + \beta_6 \text{Quali other}_{i,t} + u_{i,t} \tag{9}$$

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

It is not possible to use continuous weights in the double hurdle model for panel data. Alternatively, we implement a two-part model to use weights. The first part is a probit model (the selection model), the second part a linear regression (the intensity equation). As one weight is attributed

Table H: Double hurdle model without the inconsistents

	Selection (ME)	Intensity
Vocational school	-0.002	-0.088
	(0.087)	(0.056)
High school	0.019	-0.147^{**}
	(0.093)	(0.059)
University	0.022	-0.160^{***}
	(0.088)	(0.056)
Income CHF 4500-9000	-0.101^{**}	0.043^{**}
	(0.043)	(0.020)
Income CHF >9000	-0.118^{***}	0.023
	(0.042)	(0.020)
Moderate heating satisf.	-0.078	-0.035
	(0.057)	(0.026)
High heating satisf.	-0.070	-0.155^{***}
	(0.063)	(0.029)
20.1-21 degrees	-0.032	0.040^{**}
	(0.028)	(0.020)
21.1-22 degrees	-0.001	0.041^{**}
	(0.030)	(0.021)
>22 degrees	0.021	0.040^{*}
	(0.034)	(0.021)
Environmental concerns	-0.000	-0.003^{*}
	(0.002)	(0.002)
Female	-0.023	-0.045^{***}
	(0.020)	(0.014)
Tenant	-0.102^{*}	-0.006
	(0.053)	(0.028)
Individual heating costs	-0.032	-0.015
	(0.057)	(0.029)
Tenant*individual costs	0.064	0.020
	(0.061)	(0.034)
Large efficiency improv.	–	-0.013^{*}
		(0.007)
Middle eff. improv and CO2 neutral	–	-0.004^{*}
		(0.002)
Constant	–	0.287^{***}
		(0.080)
N	7,260	7,260

Note: 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.

to each observation, i.e., three different weights per individual, panel data models cannot be used with these kind of weights. With panel data, weights must be constant within individuals. Consequently the two-part model used is cross-sectional, with a cluster on individuals.

Overall the results of the weighted two-part model (available on request) are close to the results of the non-weighted double hurdle model. The coefficients are smaller, but still significant, and there is no change in the signs. The most important change is that temperature is now significant in the selection model, and not in the intensity equation any more. It means that people with higher indoor temperature are more likely to rebound.

In conclusion, it shows that our results are robust. They do not vary when inconsistent respondents are excluded. When continuous weights are used, the coefficients get smaller, but are still significant, and the main results hold.

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