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Rebound effects in residential heating: How much does an extra degree matter?

Cécile Hediger

Rebound effects in residential heating: How much does an extra degree matter? *

Cécile Hediger†

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Abstract

Households reactions to efficiency gains in heating, known as rebound effects, are investigated in this article. First, an increase in temperature for households living in more efficient dwellings is studied (direct rebound). This increased temperature is then converted into energy following the heating degree days method. Second, the energy embodied in the re-spending of 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 7%, and an indirect rebound of 15%. As only a partial direct rebound was considered, these results represent a lower limit. In addition, we find that low income households increase more their heating usage than affluent households when efficiency improves, indicating that buildings retrofits have the potential to improve the living conditions of the poorest households.

JEL Classification: D12, D90, Q41, Q47, R22.

Keywords: rebound effects, energy efficiency, energy demand, embodied energy, micro data.

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†Corresponding author: cecile.hediger@unine.ch. University of Neuchâtel, Institute of economic research.

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 much less numerous than for the mobility sector, due to data constraint. It is indeed more challenging to obtain data on heating usage and building efficiency than on distance traveled and vehicle 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 7%. 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)

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 22%.

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):

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

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:

$$\eta_{\varepsilon}(S) = -\eta_{p_q}(q) = -[\frac{\partial q}{\partial P_q} \cdot \frac{P_q}{q}] \tag{2}$$

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 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 rebound effect. A similar method is to compare actual energy consumption to theoretically calculated energy demand. 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).

c) The use of the elasticity of the energy demand. As $S = \epsilon \cdot q$, equation 1 can be written as:

$$\eta_{\varepsilon}(S) = \frac{\partial q}{\partial \varepsilon} \cdot \frac{\varepsilon}{q} + 1 \tag{3}$$

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 rebound. Yet, if this equation is fairly easy to implement for private mobility demand, it is more challenging for heating demand. Indeed, reliable measures of q and ε are needed. For passenger cars, that could be the distance traveled and the vehicle fuel efficiency, but for heating, a measure of ε is not readily available in conventional household surveys. One solution applied by Volland (2016) is to calculate 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 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 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.

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).

To our knowledge, only one other recent study (Fowlie et al., 2018) focuses on this partial rebound, but without calculating 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 the households' zip code and 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[1] 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 conjunction with energy intensity data. Some studies calculate 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

[1] 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.

of the overall households' consumption bundle is estimated following a variation in heating costs, keeping total spending constant. If a 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 3 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 article: 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 for a household 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 1 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 our rebound identification strategy. The question was: "At what average temperature ($^{\circ}C$) do you heat your living room during the day in winter ?"

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 1. To diminish as much as possible the unreasonable answers, respondents

Table 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.

could also answer “I don’t know” to most of the questions, explaining the different number of observations per variable.

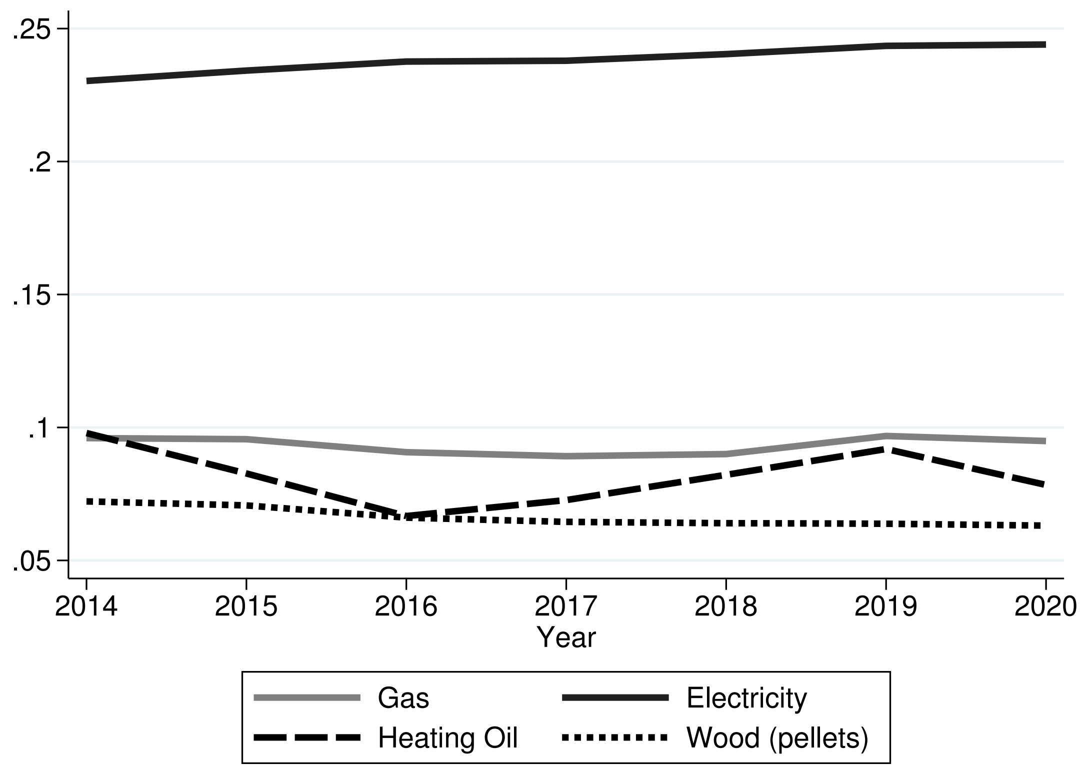
Two supplementary data sources are used, the first one to add heating degree days (HDDs), and the second one to add heating fuel prices. HDDs come from cantonal sources[2] and MeteoSwiss. HDDs are the difference between $20°C$ and the average outdoor temperature when this average is $<12°C$. If the average is $>=12°C$, then HDD=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[3]. 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 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.

[2]For the cantons of Geneva, Valais, Fribourg, Neuchâtel and Jura.

[3]Consumer Price Index: Average price of fuel and energy

Figure 1: Heating Fuel Price [CHF per kWh]



Note: 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

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 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, 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[4]. 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 ($^{\circ}C$) increases your heating bill by about 6-7%[5]. 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:

$$Indoor\ Temperature_{i,t} = \alpha_0 + \alpha_1 ln(Heating\ Costs\ per\ m^2{}_{i,t}) + \theta' Z_{i,t} + \lambda_c + \lambda_t + \epsilon_{i,t} \tag{4}$$

$\theta' Z$ 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 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.

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

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

[5] 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.

vacancy rate has indeed been very low for decades, especially in urban centers[6]. 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 compared to their own consumption use 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 similar, although the direct rebound is slightly larger for home-owners (about 1.5 percentage point higher). This difference confirms that such an endogenous bias may exist, but will be 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:

$$\begin{aligned} kWh_{i,t} &= \beta_0 + \beta_1 HDD_{i,t} + \beta_2 HDD^2_{i,t} + \theta' W_{i,t} + \beta_3 Minergie_{i,t} \\ &+ \beta_4 HHsize_{i,t} + \lambda_i + \lambda_c + \epsilon_{i,t} \end{aligned} \tag{5}$$

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 5 directly in terms of percentage

[6]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/fr/home/statistiques/construction-logement/logements.html`)

variation, we also estimate the following equation:

$$
\begin{aligned}
ln(kWh_{i,t}) = {} & \beta_5 + \beta_6 ln(HDD_{i,t}) + \theta' W_{i,t} + \beta_7 Minergie_{i,t} \\
& + \beta_8 HHsize_{i,t} + \lambda_i + \lambda_c + \epsilon_{i,t}
\end{aligned} \tag{6}
$$

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 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 A on the calculation), so the average heated days are $30 * 6.9 = 207$[7]. 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 calculate 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:

$$
Temperature\ Rebound = \frac{(\alpha_1/100) * 207 * \beta_1}{0.01 * \overline{kWh}} \tag{7}
$$

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.

Alternatively, if we use equation 6, the temperature rebound is:

$$
Temperature\ Rebound = \frac{(\alpha_1/100) * 207 * \beta_6}{0.01 * \overline{HDD}} \tag{8}
$$

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

$$
Temperature\ Rebound = \frac{Potential\ energy\ savings - Realised\ energy\ savings}{Potential\ energy\ savings} \tag{9}
$$

[7] 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 calculations.

As *Potential energy savings* equals $\frac{\triangle\epsilon}{\epsilon}$ and *Realised energy savings* equals $(\frac{\triangle\epsilon}{\epsilon} - \frac{\triangle S}{S})$, equation 9 is similar to equation 1.

4.2 Results

4.2.1 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. 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 (12% 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 6.6%, 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[8]. 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.

4.2.2 Step 1: Indoor temperature regression

Concerning the rebound effect, results for equation 4, estimated by 2SLS, are given in Table 3. We find that when heating and hot water costs decrease by 1%, indoor temperature increases by 0.01 unit, and by 0.0095 unit when heating costs are considered alone. Without the instrumental variable, these coefficients are positive, whereas we expect and find negative coefficients with 2SLS. Not surprisingly, the Durbin-Wu-Hausmann test strongly rejects

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

Table 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)	-0.102***	(0.039)
Flat (in building with 5-10 flats)	-0.100***	(0.033)
Flat (in building with >10 flats)	-0.122***	(0.038)
Terraced house	-0.142***	(0.040)
Heating Fuel:		
(Oil as base category)		
Gas	0.002	(0.024)
Electricity	-0.065	(0.047)
Wood	-0.294***	(0.050)
Heat pump	-0.248***	(0.032)
District heating	0.047	(0.038)
Other	-0.194***	(0.067)
Construction decade:		
(Before 1960 as base category)		
1960-1969	-0.086**	(0.037)
1970-1769	-0.129***	(0.033)
1980-1989	-0.119***	(0.035)
1990-1999	-0.294***	(0.039)
2000-2010	-0.357***	(0.044)
After 2010	-0.479***	(0.050)
Indoor temperature	0.066***	(0.010)
Tenant (0/1)	-0.175***	(0.025)
Dwelling m^2	-0.004***	(0.000)
Household size	-0.005	(0.009)
Income	0.035***	(0.008)
Education	-0.000	(0.009)
Individual heating costs (0/1)	-0.097***	(0.023)
Insulation renovation (0/1)	-0.037	(0.025)
Windows renovation (0/1)	-0.051*	(0.029)
Heating renovation (0/1)	-0.017	(0.025)
Minergie (0/1)	-0.115***	(0.029)
Constant	1.740***	(0.236)
County FE	YES	
Year FE	YES	
N	10, 232	

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

exogeneity. Moreover, in all 2SLS regressions, 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[9].

Table 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)	-1.13***	(0.16)		
Ln(Heating costs per m^2)			-0.95***	(0.33)
Tenant (0/1)	-0.29***	(0.04)	-0.37***	(0.12)
Dwelling m^2	-0.003***	(0.00)	-0.003*	(0.00)
Heating Fuel: (Oil as base category)				
Gas	0.03	(0.03)	-0.03	(0.08)
Electricity	-0.10	(0.06)	-0.17	(0.15)
Wood	-0.50***	(0.08)	-0.56***	(0.17)
Heat pump	-0.28***	(0.07)	-0.35**	(0.16)
District heating	0.06	(0.06)	-0.07	(0.12)
Other	-0.40***	(0.12)	-0.67**	(0.26)
Household size	-0.06***	(0.01)	-0.08***	(0.03)
Income: (<3,000 CHF as base category)				
3,000-4,499 CHF	0.30***	(0.09)	0.50***	(0.19)
4,500-5,999 CHF	0.36***	(0.09)	0.41**	(0.18)
6,000-8,999 CHF	0.44***	(0.09)	0.57***	(0.19)
9,000-12,000 CHF	0.47***	(0.09)	0.47***	(0.18)
>12,000 CHF	0.48***	(0.09)	0.54***	(0.19)
Education	-0.10***	(0.01)	-0.05	(0.03)
Individual heating costs (0/1)	-0.30***	(0.03)	-0.41***	(0.09)
Minergie (0/1)	-0.18***	(0.06)	-0.22*	(0.13)
Constant	25.13***	(0.46)	23.48***	(0.66)
County FE	YES		YES	
Year FE	YES		YES	
N	11,056		2,634	

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 35.9 (11.5 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).

Although +0.0113 to +0.0095 $°C$ 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

[9]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.

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 rather the outcome of an energy efficiency improvement than 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 results are very close (+1.11 and +0.80). 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 weatherization diminished energy consumption by 10%-20% on average according to their estimations, we can directly compare +0.67 F to our result[10]. 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).

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 are similar and are presented in Appendix B. The regression with heating and hot water costs was used, because of the higher number of observations. The coefficient for tenants is 0.94, and 1.17 for owners.

[10] 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.

This will translates later to a difference in the direct rebound of 1.5 percentage point. Thus, although an endogenous bias may exist in view of this difference, the bias will be limited in the Swiss context, probably because of the very tight housing market.

From Table 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) 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.

4.2.3 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 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 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 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 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 increase is only of $0.0086°C$. 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.

4.2.4 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 5 are shown in Table 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. HDD^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 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.

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 6 with the natural logarithm

Table 4: 2SLS: The impact of income

	Indoor Temperature ($^\circ C$)	
Ln(Heating & hot water costs per m^2)	-0.86***	(0.22)
Ln(Heating & hot w. costs per m^2)*income1	-0.90	(0.73)
Ln(Heating & hot w. costs per m^2)*income2	-0.62	(0.57)
Ln(Heating & hot w. costs per m^2)*income3	-0.46	(0.43)
Ln(Heating & hot w. costs per m^2)*income4	-0.30	(0.29)
Ln(Heating & hot w. costs per m^2)*income5	-0.15	(0.15)
Ln(Heating & hot w. costs per m^2)*income6	*omitted*	(.)
Tenant (0/1)	-0.29***	(0.05)
Dwelling m^2	-0.003***	(0.00)
Heating Fuel: (Oil as base category)		
Gas	0.02	(0.04)
Electricity	-0.11*	(0.07)
Wood	-0.52***	(0.10)
Heat pump	-0.25***	(0.07)
District heating	0.07	(0.06)
Other	-0.35***	(0.12)
Household size	-0.06***	(0.01)
Income	-0.29	(0.31)
Education	-0.10***	(0.01)
Individual heating costs (0/1)	-0.30***	(0.04)
Minergie (0/1)	-0.19***	(0.07)
Constant	26.83***	(1.67)
County FE	YES	
Year FE	YES	
N	11,056	

Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Building construction date, accommodation types and (building construction date * income categories) are used as instruments. The first stage F-statistics range from 36.7 to 529.3, 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.

Table 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

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.

of HDDs. The drawback is that the relationship is constrained to be linear[11]. Table 6 displays the results. The coefficients found are very close to 1, which is the expected theoretical value (CIBSE, 2006).

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.

Table 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

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.

4.2.5 Computing the temperature rebound

With steps 1 and 2 completed, we know all coefficients needed to compute the temperature rebound following equation 7 and equation 8. Results are summarized in Table 7. In the first column, the coefficients used to compute the temperature rebound apply to regressions with heating and hot water costs, while in column 2 they refer to regressions with heating

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

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 4 are used in the rebound equation 8. For using equation 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 1.

Table 7: Temperature Rebound Results

	Heating & Hot Water coefficients	Heating coefficients
With equation 7:		
207 heating days	6.1%	3.9%
217 heating days (+5%)	6.4%	4.1%
197 heating days (-5%)	5.8%	3.7%
With equation 8:		
207 heating days	6.8%	5.9%
217 heating days (+5%)	7.2%	6.2%
197 heating days (-5%)	6.5%	5.6%
For income levels:		
(with equation 8):		
Income 1	10.6%	-
Income 2	8.9%	-
Income 3	8.0%	-
Income 4	7.0%	-
Income 5	6.1%	-
Income 6	5.2%	-

Notes: From Table 1, we know that the average number of HDD is 3055, the average annual heating and hot water consumption is 13,590 kWh and the average annual heating consumption is 10,275 kWh.

Overall, the temperature rebound ranges from 4% to 7%. It means that only a small portion of the expected energy savings after a heating efficiency improvement are lost due 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 information that an extra degree increases your heating bill by 6.6% (from Table 2): $+0.0113°C$ translates to +0.075% of the annual bill, that is, +0.94 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 0.94/12.6 = 0.075. 7.5% 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 5% 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 calculate 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 C.

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 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

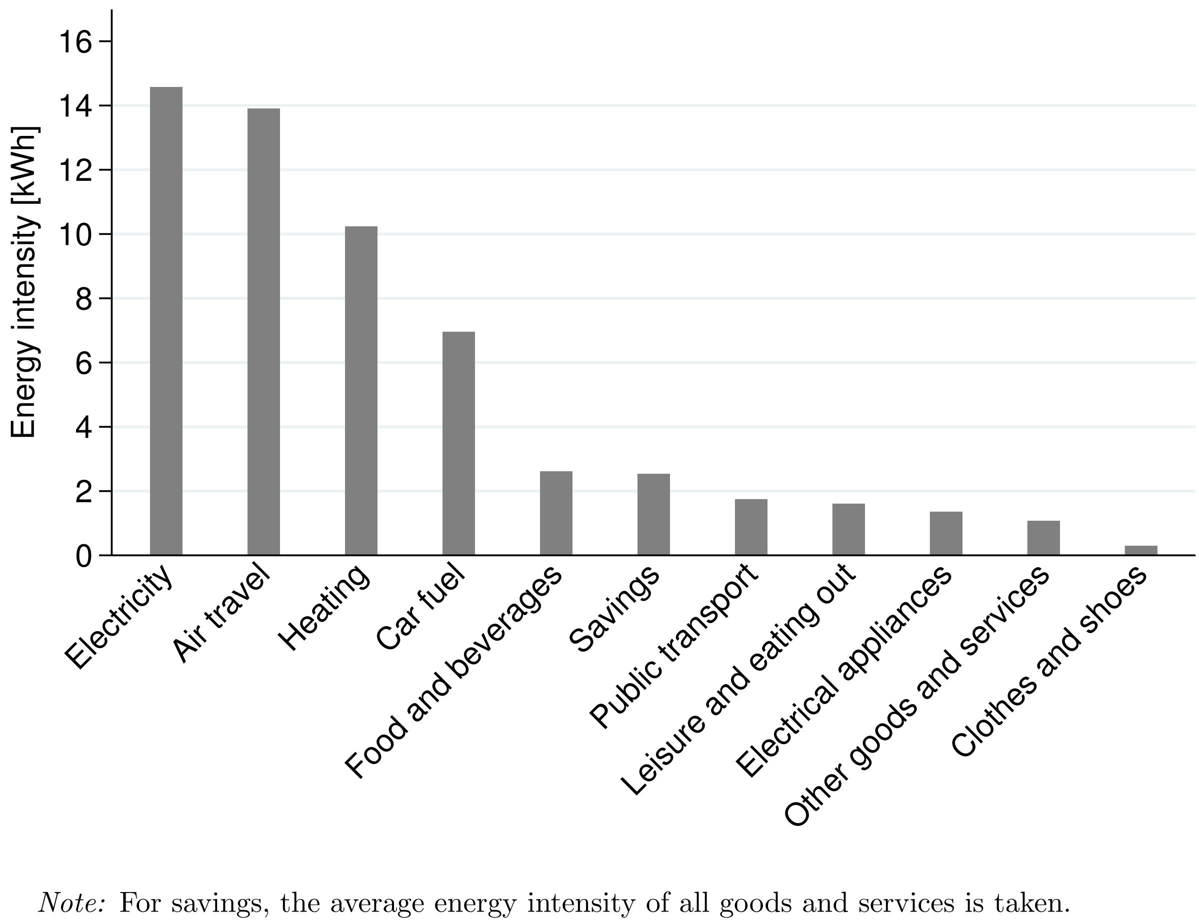
5.1 Empirical strategy

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. We treat savings as carrying the average energy intensity of all goods and services.

The monthly spending shares are shown in Figure 3. Appendix D 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

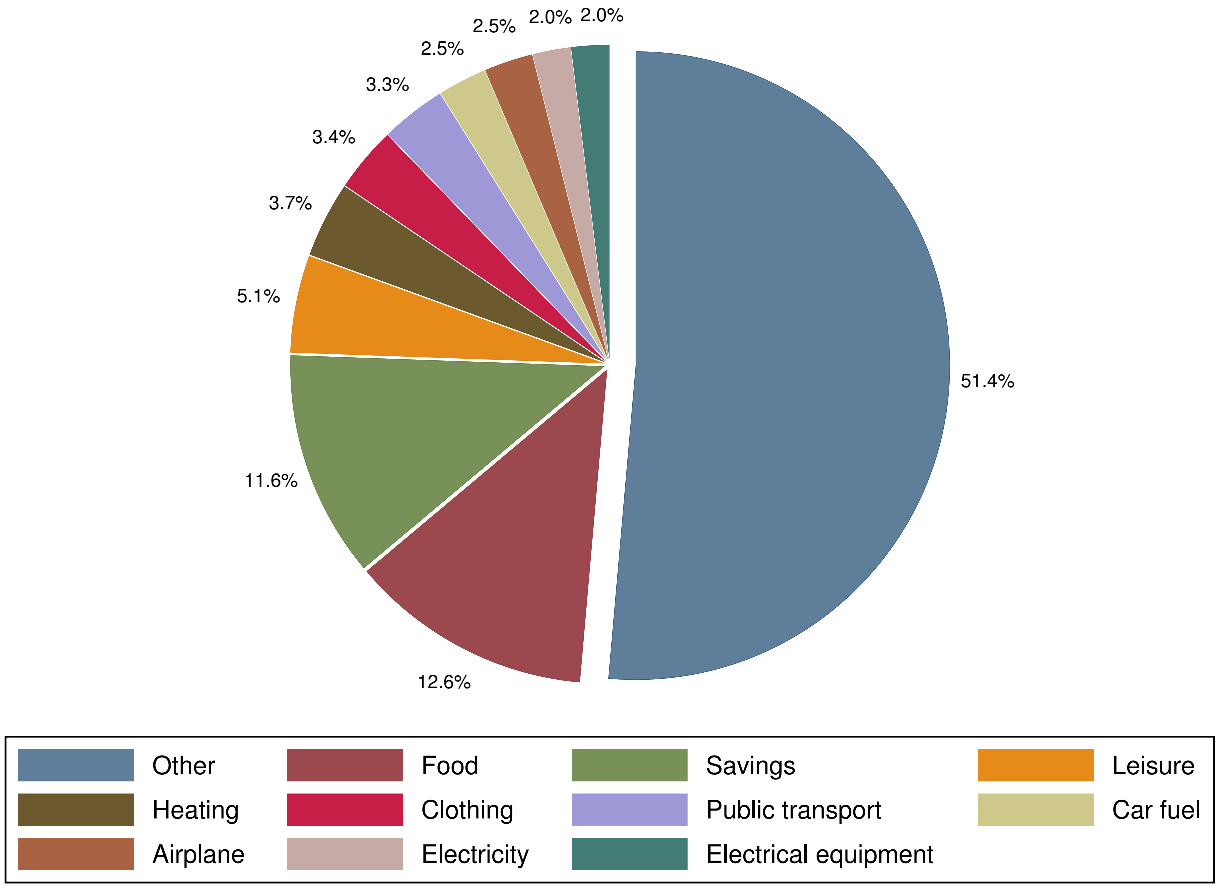
Figure 2: Energy Intensities [kWh per CHF]



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

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.

Figure 3: Monthly Spending Shares



Note: 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

To calculate 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 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:

$$Total\ embodied\ kWh_i = \gamma_0 + \gamma_1 Heating\ Cost_i + \gamma_2 Total\ Spending_i + \theta' W_i + \epsilon_i \tag{10}$$

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 10, the indirect rebound is:

$$Indirect\ Rebound = \frac{|\gamma_1|}{10.24} = \frac{Increase\ in\ kWh}{Potential\ Energy\ Savings} \tag{11}$$

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 8 displays the results of equation 10 estimated by cross-section. γ_1 equals -1.56, 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 also a realistic value of 1.76. It is half way between the average energy intensity (2.54 kWh per CHF) and the energy intensity of all other goods and services (1.1 kWh per CHF).

Table 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

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

Once γ_1 is estimated, equation 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) and 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 7%, the total micro-level rebound is estimated at a minimum of 19%-22%. 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.

6 Conclusion

This article 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 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 calculate 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 between $+0.0095°C$ and $+0.0113°C$ is found when building efficiency improves by 1%. 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 7%. 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).

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 22%.

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[12] 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

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

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. It would also be interesting to compare indirect rebound estimates based on embodied carbon emissions and embodied energy for the same country.

Appendices

Appendix A

How to find the number of heated days per year

To estimate the rebound with equation 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 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 (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.

Those 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 confortable internal temperature. If the external temperature is $12°C$, 0 HDD are recorded. So 81 HDDs would correspond to 10 heated days when te average external temperature is $11.9°C$, and 121.5 HDDs to 20 heated days. Of course 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 B

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

	Tenants: Indoor temp. ($°C$)		Owners: Indoor temp. ($°C$)	
Ln(Heating & hot water costs per m^2)	-0.94***	(0.33)	-1.17***	(0.17)
Dwelling m^2	-0.002	(0.00)	-0.004***	(0.00)
Heating Fuel: (Oil as base category)				
Gas	0.20***	(0.05)	-0.20***	(0.05)
Electricity	-0.25**	(0.11)	0.09	(0.08)
Wood	-0.26**	(0.12)	-0.71***	(0.11)
Heat pump	-0.13	(0.09)	-0.42***	(0.08)
District heating	0.17**	(0.08)	-0.12	(0.09)
Other	-0.02	(0.17)	-0.75***	(0.15)
Household size	-0.05***	(0.02)	-0.06***	(0.02)
Income: (<3,000 CHF as base category)				
3,000-4,499 CHF	0.32***	(0.11)	0.23	(0.17)
4,500-5,999 CHF	0.31***	(0.11)	0.35**	(0.16)
6,000-8,999 CHF	0.40***	(0.12)	0.39**	(0.15)
9,000-12,000 CHF	0.40***	(0.11)	0.46***	(0.16)
>12,000 CHF	0.45***	(0.13)	0.42***	(0.16)
Education	-0.11***	(0.02)	-0.10***	(0.02)
Individual heating costs (0/1)	-0.40***	(0.07)	-0.11**	(0.05)
Minergie (0/1)	-0.15	(0.11)	-0.17***	(0.06)
Constant	24.38***	(0.90)	25.27***	(0.52)
County FE	YES		YES	
Year FE	YES		YES	
N	5,591		5,465	

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 15.1 for tenants and 26.6 for owners.

Appendix C

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

Rebound effect: 9.4% (0.14/1.49 = 0.094)

Appendix D

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 D: 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.

References

Aydin, E., Kok, N., and Brounen, D. (2017). Energy efficiency and household behavior: the rebound effect in the residential sector. *The RAND Journal of Economics*, 48(3):749–782.

Berkhout, P. H., Muskens, J. C., and Velthuijsen, J. W. (2000). Defining the rebound effect. *Energy policy*, 28(6-7):425–432.

Brännlund, R., Ghalwash, T., and Nordström, J. (2007). Increased energy efficiency and the rebound effect: Effects on consumption and emissions. *Energy economics*, 29(1):1–17.

Cellura, M., Di Gangi, A., Longo, S., and Orioli, A. (2013). An italian input–output model for the assessment of energy and environmental benefits arising from retrofit actions of buildings. *Energy and Buildings*, 62:97–106.

Chitnis, M., Fouquet, R., and Sorrell, S. (2020). Rebound effects for household energy services in the UK. *The Energy Journal*, 41(4).

Chitnis, M. and Sorrell, S. (2015). Living up to expectations: Estimating direct and indirect rebound effects for UK households. *Energy Economics*, 52:S100–S116.

CIBSE, T. (2006). Degree-days: theory and application. *London: The Chartered Institution of Building Services Engineers*, 16.

Dettli, R., Gsponer, G., and Kaufmann, Y. (2003). Erklärung der kantonalen Unterschiede von Energiekennzahlen bei Neubauten. *Energiewirtschaftliche Grundlagen, BFE, Bern.*

Dubin, J. A., Miedema, A. K., and Chandran, R. V. (1986). Price effects of energy-efficient technologies: a study of residential demand for heating and cooling. *The RAND Journal of Economics*, pages 310–325.

Dyson, M. E., Borgeson, S. D., Tabone, M. D., and Callaway, D. S. (2014). Using smart meter data to estimate demand response potential, with application to solar energy integration. *Energy Policy*, 73:607–619.

Fell, D. and King, G. (2012). Domestic energy use study: to understand why comparable households use different amounts of energy. *Department for Energy and Climate Change Report*.

Fowlie, M., Greenstone, M., and Wolfram, C. (2018). Do energy efficiency investments deliver? Evidence from the weatherization assistance program. *The Quarterly Journal of Economics*, 133(3):1597–1644.

Gram-Hanssen, K., Christensen, T. H., and Petersen, P. E. (2012). Air-to-air heat pumps in real-life use: Are potential savings achieved or are they transformed into increased comfort? *Energy and Buildings*, 53:64–73.

Haas, R. and Biermayr, P. (2000). The rebound effect for space heating empirical evidence from austria. *Energy policy*, 28(6-7):403–410.

Hediger, C., Farsi, M., and Weber, S. (2018). Turn it up and open the window: On the rebound effects in residential heating. *Ecological economics*, 149:21–39.

Hunt, L. C., Ryan, D. L., et al. (2014). Catching on the rebound: Why price elasticities are generally inappropriate measures of rebound effects. Technical report, Surrey Energy Economics Centre (SEEC), School of Economics, University of Surrey.

Infras, TEP, and Prognos (2019). Analyse des schweizerischen Energieverbrauchs 2000 - 2018 nach Verwendungszwecken. Technical report, Swiss Federal Office of Energy.

Kratena, K. and Wüger, M. (2010). The full impact of energy efficiency on households' energy demand. Technical report, WIFO Working Papers.

Lang, G. and Lanz, B. (2021). Climate policy without a price signal: Evidence on the implicit carbon price of energy efficiency in buildings. *Journal of Environmental Economics and Management*, page 102560.

Madlener, R. and Hauertmann, M. (2011). Rebound effects in German residential heating: do ownership and income matter?

Milne, G. and Boardman, B. (2000). Making cold homes warmer: the effect of energy efficiency improvements in low-income homes. *Energy policy*, 28(6-7):411–424.

Nadel, S. (2012). The Rebound Effect: Large or Small? Aceee white paper, American Council for an Energy-Efficient Economy.

Nadel, S. (2016). The potential for additional energy efficiency savings including how the rebound effect could affect this potential. *Current Sustainable/Renewable Energy Reports*, 3(1-2):35–41.

Nosperger, S., Osso, D., and Raynaud, M. (2017). A proposal to go beyond the rebound effect: how to evaluate the financial value of comfort after retrofitting? Technical report, Conference Paper.

Orea, L., Llorca, M., and Filippini, M. (2015). A new approach to measuring the rebound effect associated to energy efficiency improvements: An application to the US residential energy demand. *Energy economics*, 49:599–609.

Oreszczyn, T., Hong, S. H., Ridley, I., Wilkinson, P., Group, W. F. S., et al. (2006). Determinants of winter indoor temperatures in low income households in England. *Energy and Buildings*, 38(3):245–252.

Palmer, J., Terry, N., and Pope, P. (2012). How much energy could be saved by making small changes to everyday household behaviours. *A report for Department of Energy and Climate Change*.

Reimers, H., Jacksohn, A., Appenfeller, D., Lasarov, W., Hüttel, A., Rehdanz, K., Balderjahn, I., and Hoffmann, S. (2021). Indirect rebound effects on the consumer level: A state-of-the-art literature review. *Cleaner and Responsible Consumption*, page 100032.

Schmitz, H. and Madlener, R. (2020). Direct and indirect energy rebound effects in german households: A linearized almost ideal demand system approach. *The Energy Journal*, 41(5).

Schwarz, P. M. and Taylor, T. N. (1995). Cold hands, warm hearth? Climate, net takeback, and household comfort. *The Energy Journal*, 16(1).

Sorrell, S. and Dimitropoulos, J. (2008). The rebound effect: Microeconomic definitions, limitations and extensions. *Ecological Economics*, 65(3):636–649.

Sorrell, S., Dimitropoulos, J., and Sommerville, M. (2009). Empirical estimates of the direct rebound effect: A review. *Energy policy*, 37(4):1356–1371.

Streicher, K. N., Padey, P., Parra, D., Bürer, M. C., and Patel, M. K. (2018). Assessment of the current thermal performance level of the Swiss residential building stock: Statistical analysis of energy performance certificates. *Energy and Buildings*, 178:360–378.

SwissEnergy (2019). Stratégie du programme SuisseEnergie 2021 à 2030. Technical report, Swiss Federal Office of Energy.

Thomas, B. A. and Azevedo, I. L. (2013). Estimating direct and indirect rebound effects for US households with input–output analysis. Part 2: Simulation. *Ecological Economics*, 86:188–198.

Tilov, I., Farsi, M., and Volland, B. (2019). Interactions in Swiss households' energy demand: A holistic approach. *Energy Policy*, 128:136–149.

Volland, B. (2016). Efficiency in Domestic Space Heating: An Estimation of the Direct Rebound Effect for Domestic Heating in the US. Technical report, IRENE Working Paper.

Weber, S., Burger, P., Farsi, M., Martinez-Cruz, A. L., Puntiroli, M., Schubert, I., Volland, B., et al. (2017). Swiss Household Energy Demand Survey (SHEDS): Objectives, design, and implementation. Technical report, IRENE Institute of Economic Research.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.