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How effective is carbon taxation on residential heating demand? A household-level analysis

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Abstract

This paper investigates the impact of the Swiss CO_2 levy on households' heating demand. Using a difference-in-differences approach combined with inverse probability of treatment weighting, we test whether the 2016 and 2018 carbon tax rate increases had a short-run impact on Swiss households' heating and hot water expenditures—i.e. a proxy for heating consumption. Micro-level data from the Swiss Household Energy Demand Survey are used to estimate the models. Our regression analysis shows that heating consumption decreases with time for all households, but it does not detect any clear short-run impact of the CO_2 levy on fossil fuel users in comparison to non-fossil fuel users. We nevertheless find that many factors significantly affect heating consumption, such as setting the thermostat at a lower temperature. Even though further research is needed regarding possible long-run impacts, our findings challenge the relevance of this policy instrument under its current form to lower households' CO_2 emissions. Considering that its rate is regularly increased based on short-run emission targets, households may have too little time to adapt. The tax design might thus need to be revised to take into account the slow reaction time.

Keywords: Carbon tax, energy consumption, fossil fuel, policy evaluation, inverse probability of treatment weighting, difference-in-differences.

JEL classification: C21, C23, H23, Q41, Q58.

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1 Introduction

Given science's current state of knowledge concerning the role played by anthropogenic greenhouse gas (GHG) emissions in climate change (Stern, 2007), there is now a clear need for ambitious policy action. As part of its strategy to curb climate change, Switzerland introduced a tax on carbon dioxide (CO_2) emissions on January 1, 2008. Carbon taxes are policy instruments intended to correct negative externalities (Pigou, 1920; Baumol, 1972): they give pollution a cost, hence incentivizing emitters to take action to become more environmentally friendly.

The Swiss carbon tax, known under the name of "CO_2 levy", is designed as a steering tax: of its proceeds, about two-thirds are redistributed to households and firms, while the remaining third is used to finance a building renovation program and a technology fund. Tax collection is performed by the Federal Custom Administration when imported fuels cross the Swiss borders or when they leave a tax-exempted warehouse to be sold. The tax rate is expressed in CHF per ton of CO_2 (tCO_2)[1]. The tax level is adapted if CO_2 emission reduction targets set by law are missed[2]. Hence, while it was CHF 12/tCO_2 in 2008, the rate was then raised almost every second year as targets were missed, reaching CHF 96 in 2018, with a legal potential maximum of CHF 120 under the current version of the law[3]. It only applies to fossil fuels used to produce heat and electricity, as motor fuels such as gasoline are already imposed through the petroleum tax.

Although some firms can be exempted from paying the tax—they can participate in the emissions trading scheme or commit to reduce their emissions instead—, households have no alternative but to pay the tax on all their fossil non-motor fuel purchases, i.e. mainly extra-light oil and natural gas used for heating and hot water[4]. To reduce their tax burden, households need to consume less fossil fuels, which can be realized through behavioral changes (set thermostat lower, air less often, etc.), renovations (of windows, heating system, etc.), or—more radically—installation of renewable heating

[1] At the time of writing CHF 1 $\approx$ USD 1.10.

[2] The current version of the Federal Act on the Reduction of CO_2 Emissions (CO_2 Act) is available at https://www.fedlex.admin.ch/eli/cc/2012/855/en [accessed April 22, 2021]. The CO_2 levy is presented in Chapter 5 of the law. The intermediate targets are specified in article 94 of the Ordinance for the Reduction of CO_2 Emissions (CO_2 Ordinance) available at https://www.fedlex.admin.ch/eli/cc/2012/856/en [accessed April 22, 2021].

[3] The tax will indeed be raised to CHF 120 in 2022 since the target defined for 2020 (67% of the 1990 emissions) was missed. A revision of the CO_2 Act, in which the maximum tax rate would have been raised to CHF 210, has been rejected on June 13, 2021 by 51.6% of the Swiss voters.

[4] In 2016, heating and hot water account for about 38% of final energy consumption in Switzerland, making it the largest source of end use energy demand. For a complete description and analysis of heating in Switzerland, see Narula et al. (2019).

systems such as heat pumps or solar panels. The CO_2 levy is precisely intended to lead to such adaptation strategies from households so that their tax burden is minimized: the higher the tax, the stronger the incentives for becoming more energy-sufficient and energy-efficient.

However, the extent and the speed of reactions to a carbon tax are open to debate. The effectiveness of the tax relies on the assumption that individuals are *homines oeconomici*, who correctly interpret the price signal of a Pigouvian tax and react by lowering their fossil fuel demand accordingly. Such a situation can however not be taken for granted. Different factors may erode the impact of the carbon tax on households' reaction: imperceptibility of the price signal; lack of knowledge and incorrect understanding of the CO_2 levy; bounded rationality. The literature in behavioral economics argues that individuals do not always behave rationally from an economic point of view (Congdon et al., 2009). Moreover, the price-elasticity of demand for fossil fuels is generally estimated as being rather low (see e.g. Baranzini and Weber, 2013; Labandeira et al., 2017). Hence, the expectation that the CO_2 levy pushes people to reduce fossil fuel consumption is far from obvious and deserves empirical investigations.

This paper evaluates the effectiveness of the Swiss CO_2 levy, focusing on the residential sector. It investigates whether households who rely on fossil fuels to heat their homes do adapt their energy demand—relative to households who rely on non-fossil fuels—following an increase of the levy. More precisely, it analyzes the impacts of the tax rate increases that took place in 2016 (+40%) and 2018 (+14%) and tests the hypothesis that the tax increases led households who use oil or gas as main heating fuel to lower their heating consumption in comparison to other households. Household-level data collected in five waves (2016-2020) of the Swiss Household Energy Demand Survey (SHEDS) are used.

The advantage of using revealed household-level data is twofold. First, in the context of energy demand, tax elasticities usually appear different (larger) from price elasticities. Studies relying on (ex-ante) simulations may therefore use a wrong (price) elasticity to infer about the impact of taxes. Second, observations at the market level result from the combined reaction of various types of actors, not only households but also firms, and it seems likely that the two groups react differently. Investigating households' reaction is only possible with household-level data and is less frequent in the literature than analyses of firm's reaction, probably because few databases provide measurements at this disaggregate level. Considering that households are responsible for the consumption of more than 50% of the petroleum products and natural gas used in the heating sector in Switzerland (SFOE, 2021), a separate analysis for this group of agents seems justified.

Our empirical strategy relies on a difference-in-differences (DID) approach: heating fuel consumption of the treatment group (households with fossil fuel heating systems, i.e. using heating oil or natural gas) is compared to that of the control group (households with non-fossil fuel heating systems, i.e. heat pumps, electricity, solar panels, wood or district heating) throughout the survey period, which includes the 2016 and 2018 CO_2 levy rate rises, so that average treatment effects on the treated (ATT) can be estimated[5]. To correct for imbalances in covariates between the two groups, inverse probability of treatment weighting (IPTW) are used: each treated household receives a weight of 1 while each control household receives a weight that reflects how similar it is to treated ones (see Austin, 2011). This strategy constitutes an improvement over the standard DID approach since it makes the two groups comparable regarding observable characteristics that could affect the outcome of interest.

With our estimation strategy, we intend to look at the short-run behavioral impact of carbon taxation, that is, the adoption of energy-saving behaviors regarding the consumption of fossil heating fuels. The general conclusion of our econometric analysis is that the CO_2 levy has no clearly discernible short-run effect on Swiss households' energy consumption of fossil heating fuels. This finding does not imply that the CO_2 levy is a bad instrument nor does it exclude possible reactions over the longer run[6], but it does put certain aspects of the design of the Swiss CO_2 levy into question. In particular, the pace at which the tax rate increases (almost every second year) may be too hasty to leave households a chance to adjust if the main channel to decrease fuel consumption is not via a decrease in the amount of heating services consumed but indeed by heating systems renovations and/or changes. The announcement effect might not suffice: whether the tax rate will increase or not depends on countrywide CO_2 emissions reduction, not only on individual decisions to abate, so that future costs remain uncertain when the decision to renovate or not must be taken. The lack of salience from the tax can be pointed as a further probable cause for households non-reaction, as tax increases are hardly perceptible because of substantial market price volatility. Limited decision capacity regarding heating consumption and energy-efficient renovations might also play a role, as well as households' limited understanding of the tax mechanism.

[5]The treatment group represents approximately 60% of homes in Switzerland (Source: Swiss Federal Statistical Office, *Survey on the energy sources of residential buildings*, 2017).

[6]By definition, switching from a fossil fuel heating system to a renewable heating system is a long-run reaction, and such changes are not considered in our sample.

The article is structured as follows. Section 2 provides background knowledge by reviewing relevant literature and contextualizing the Swiss CO_2 levy. Section 3 presents the analytical framework and the econometric model used to test the research hypothesis. Section 4 describes the data and explains how weights are assigned to each household in order to achieve covariate balance between fossil fuel users and non-fossil fuel users. Section 5 presents and discusses the results of our empirical estimations. Section 6 provides policy implications and concludes.

2 Background

As coined by Andersen (2010), research undertaken on carbon taxation moved from *ex-ante* simulation in the 1990s (e.g. Nordhaus, 1993) to *ex-post* analyses using actual data (e.g. Lin and Li, 2011). However, empirical studies relying on micro-econometric methods are still scarce. Martin et al. (2014) assess the impact of the British carbon tax on manufacturing firms and identify a negative effect on energy intensity and electricity use. In their review of British Columbia's (BC) CO_2 tax, Murray and Rivers (2015) quote a few studies relying on difference-in-differences approaches to estimate the impact of the tax on GHG emissions and fossil fuel consumption, and they all report negative impacts as could be expected from a theoretical point of view. Andersson (2019) uses a synthetic control method to analyze the impact of carbon taxation on CO_2 emissions from the transport sector in Sweden between 1990 and 2005. He finds an average yearly drop of 6% in emissions attributable to the carbon tax over the period. Bernard and Kichian (2019) estimate the short- and long-run impacts of BC's carbon tax on diesel demand using time-series models. They find a combined reduction of 1.24 liter in monthly per capita diesel consumption, which corresponds to a reduction of 1.3% of the related emissions. Xiang and Lawley (2019) investigate the impact of BC's carbon tax on residential natural gas consumption. They compare results from a fixed-effect regression model and a synthetic-control model with state/province-level panel data and find that the consumption of natural gas decreased on average by 6.9 to 10.1% per year over the period considered. None of these papers however considers the effects of carbon taxes on households at a microeconomic level.

Indeed, the literature on the impact of carbon taxes on households in terms of GHG emission reduction is very limited. Most studies on households tend to focus on distributional aspects (see Beck et al., 2015; Brännlund and Nordström, 2004; Callan et al., 2009; Chapa and Ortega, 2017; Renner, 2018; Tiezzi, 2005; Williams et al., 2014), leaving effectiveness aside. Labandeira and Labeaga (1999) provide one of the few attempts to evaluate the potential effect of a CO_2 tax on households. They combine an input-output analysis and a simulation with micro-level data to look at the distributional and behavioral effects of an hypothetical carbon tax in 1994 in Spain. They find a small reduction of energy-related carbon dioxide emissions by households, but this result must be considered cautiously since it relies on a simulation rather than on observation of an actual carbon tax. Lawley and Thivierge (2018) analyze the impact of BC's carbon tax on gasoline demand using household-level data. Their results show that a carbon tax of 5 cents per liter reduces gasoline consumption by 5 to 8%. This finding indicates that carbon taxation is effective in inducing individuals to lower their consumption of fossil fuels in the transportation sector. Brülhart et al. (2020) simulate the potential impact of an airline ticket tax in Switzerland with different scenarios. They estimate that a tax ranging from CHF 30 to CHF 120 could reduce CO_2 emissions from the airline sector by 5% to 11% thanks to a lowering of the number of passengers and kilometers traveled. Nevertheless, whether Lawley and Thivierge (2018) and Brülhart et al.'s (2020) conclusions extend to thermal fuels remains uncertain.

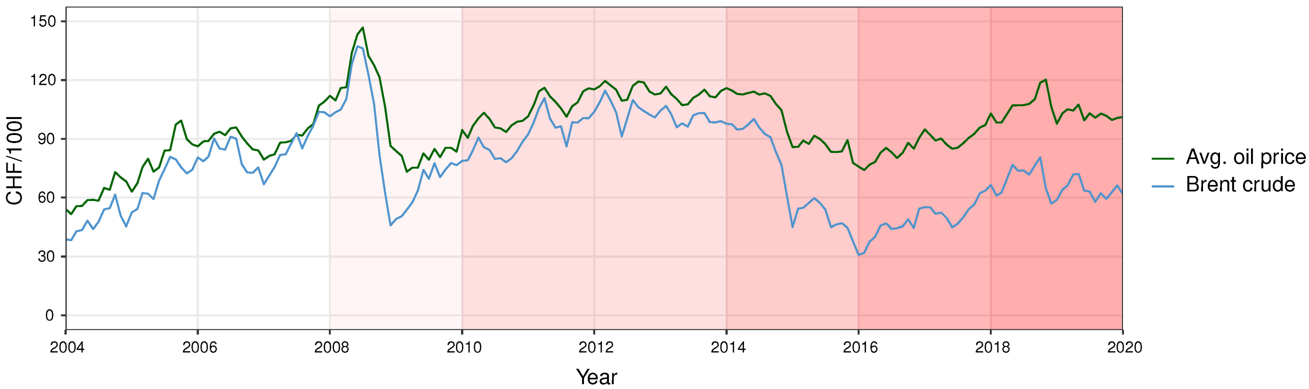
Tiezzi (2005) briefly discusses effectiveness considerations in her appraisal of the welfare effects of the Italian carbon tax. She computes price-elasticities of demand for domestic (i.e. mainly heating) and transport fuels and finds them to be respectively -1.057 and -1.282 at the sample mean, which suggests that taxing CO_2 may play a significant role in Italy's environmental policy to lower GHG emissions. However, these elasticities only provide *ex-ante* information on potential effects and might not hold in other socio-economic, geographical and institutional contexts than Italy in the 1980s-90s. Indeed, Labandeira et al. (2017) conduct a meta-analysis on the price elasticities of energy demand and find that these elasticities are rather low, especially in the short run (less than 1 year in their definition). They report that average short-run elasticities from the literature for different fuels range from -0.149 to -0.201, whereas long-run elasticities range from -0.372 to -0.572. Focusing on heating oil, average short-run and long-run elasticities take the values -0.188 and -0.535, respectively[7]. Little reaction to carbon taxes' can therefore be expected, especially in the short run. This might be due to the fact that substantial changes in energy consumption for heating require costly adaptation strategies such as renovations, which are only possible in the long run. In the short run, only behavioral adaptation strategies can be expected, such as heating less, airing less often and when heaters are off, starting to heat later in the season, or heating only rooms when they are occupied (see Hediger et al., 2018).

[7] Estimations can vary quite substantially depending on the statistical method and the nature of the data used.

Weber and Gill (2016) estimate price elasticities of heating consumption in Germany using household-level longitudinal data and investigate the puzzling empirical finding reported in the literature that, counter-intuitively, the elasticity of homeowners is often lower than that of tenants in absolute value. They find that the type of building and the level of initial (i.e. in the first period of the panel) heating consumption actually explain the aforementioned result: tenants usually have a higher heating consumption per m^2 of floor surface, which, the authors explain, is connected to a higher elasticity because of their greater potential to reduce consumption. Tenants also live on average in larger buildings with lower outside surface to indoor volume ratios, so that heating less or airing less often have a lower impact on indoor temperatures than in smaller building. It is thus easier for tenants than for owners to lower their heating consumption while keeping their level of comfort constant. It should nevertheless be noted that their (short-run) price elasticity estimates are relatively low, ranging from -0.251 to -0.429, which is similar to those reported by Labandeira et al. (2017).

Although estimated price elasticities of energy demand are generally low, the literature on tax salience (see Fochmann et al., 2010; Chetty et al., 2009) shows that taxes have larger behavioral impacts than equivalent price changes, in contradiction to what is expected under full economic rationality. Andersson (2019) estimates tax-elasticities to be about three times larger than price-elasticities in the case of gasoline in Sweden. Both Rivers and Schaufele (2015) and Bernard and Kichian (2018) find that British Columbia's carbon tax had a larger impact on gasoline demand than an equivalent increase in price. Li et al. (2014) in the USA and Baranzini and Weber (2013) in Switzerland get similar results for gasoline taxes, which suggests taxes on fossil motor fuels are likely to display salience and therefore command larger responses than market price variations of similar magnitudes. Whether this is also the case in the residential sector remains uncertain. Nevertheless, these findings suggest that carbon taxes might have stronger impacts than market price changes not bearing the label "tax".

Beside their effects on prices, taxes can thus have an impact through their mere existence, as consumers seem to dislike the idea of paying them. Such a phenomenon is particularly relevant in the case of the Swiss CO_2 levy, because market price fluctuations are so important that they completely mask the tax changes, as illustrated in Figure 1. Since its introduction in 2008, the level of the tax has been raised four times in a decade, reaching in 2018 a level eight times higher than ten years earlier. Yet, the price of oil decreased sharply at the end of 2014 and remained at a lower level thereafter. As a consequence, tax increases left heating oil's market price more or less unchanged, thereby possibly leaving consumers without reaction. Nevertheless, if the carbon tax is sufficiently salient and consumers view it differently from market price variability, an effect can be expected even in absence of a visible price increase because of tax aversion. Figure 1 shows that average heating oil prices in Switzerland follow those on international markets, but it also shows how the spread between national and international prices widens as the carbon tax rate increases. The effect of the CO_2 levy is not directly visible through jumps in prices, but it appears to affect market prices in the longer run. Its actual salience for households is therefore ambiguous.



Sources: Swiss Federal Statistical Office, Swiss National Bank, U.S. Energy Information Administration
Note: The intensity of the red shaded background indicates the level of the Swiss CO_2 levy. Per tCO_2, the rate was CHF 12 in 2008, CHF 36 in 2010, CHF 60 in 2014, CHF 84 in 2016 and CHF 96 in 2018.

Figure 1: Evolution of the average heating oil price in Switzerland and Europe Brent crude

Existing research on the Swiss CO_2 levy however does not address this type of concern. It rather focuses on effectiveness by either using simulations (Ecoplan et al., 2015; Ecoplan, 2017) to establish the aggregate counterfactual situation that would prevail in absence of carbon tax, or by surveying firms (TEP Energy, 2016). While Ecoplan et al. (2015) find a negative effect of the tax on CO_2 emissions and a positive one on energy substitution away from oil, their results are by nature hypothetical and might therefore differ from those of an observational study. The main advantage of such analyses based on simulations is their ability to provide an anticipated expectation for effects of the tax before it is actually implemented (or increased). In fact, this methodology appears as the only possibility to conduct such an ex-ante exercise. However, after the tax is actually implemented, revealed behavior can be observed and should be investigated using ex-post analyses. Hence, we argue there is room for further research projects on the topic, especially empirical ones, as a gap remains in the literature on carbon taxation using empirical methods to establish causal effects.

3 Analytical framework

We use a difference-in-differences (DID) approach to compare the fuel consumption trajectories followed by fossil fuel users (treatment group) and non-users (control group) over a five-year time period. Our treatment is the exposure to the CO_2 levy and its 2016 and 2018 increases, which is expected to have a psychological impact on fossil fuel users through tax aversion—a hypothesis in line with the literature presented in Section 2. We thus intend to estimate the effect of subsequent behavioral changes such as shutting off heating at night, airing less often and not heating with windows open, heating only occupied rooms, or starting to heat later in the season.

DID allows to estimate causal effects (Lechner, 2011) under the classical Rubin causal model (see Imbens and Rubin, 2015). The key idea of DID methodology is to establish a counterfactual (unobserved) outcome for the treatment group using the actual (observed) outcome of a control group that is similar enough so that similar outcomes would be expected for both groups in absence of any treatment—the so-called *common trends assumption*. The validity of any finding in a DID model therefore relies on the comparability between the treatment and control groups, as the average treatment effect on the treated (ATT) is defined as the difference between the actual and the counterfactual outcomes for the treated.

Randomized control trial (RCT) is the gold standard in this regard: by randomly sampling observation units from the same population, it ensures that treated and non-treated units do not systematically differ. However, outside the laboratory, it is often impossible to achieve such a high degree of similarity. The CO_2 levy constitutes a so-called *natural* experiment, in the sense that observations units are differently affected by the introduction and increases of the tax, but the allocation of treatment (paying the tax) is not exogenously controlled as in an RCT. We thus need to ensure *ex-post* that treatment and control units are indeed comparable.

To do so, we use inverse probability of treatment weighting (IPTW) as covariate-balancing method (see Austin and Stuart, 2015). The idea is to assign larger weights w_i to units most likely to be in the group (treatment or control) they do not actually belong (Austin, 2011), which helps to estimate the average treatment effect (ATE) on the whole population. When one is interested in estimating the ATT instead, these weights are set equal to 1 for the treated units and to $e_i/(1 - e_i)$ for the non-treated, where e_i is unit i's probability of being treated, that is, a propensity score (PS). It is defined as $e_i = Pr(T_i = 1|X_i)$ where T_i is a dummy indicating the treatment ($T_i = 1$) or control ($T_i = 0$) status of i and X_i is a set of covariates used to estimate e_i (Austin and Stuart, 2015). IPTW relies on the covariate balancing properties of propensity scores (Rosenbaum and Rubin, 1983; Li et al., 2016): conditional on the PS, covariates included in X_i should be balanced between treatment and control units. Said otherwise, all units with the same PS should have the same distribution of X_i (Austin, 2011). Confounding caused by observables can thus be mitigated. Because our dataset is composed of repeated cross-sections, we estimate PSs for each time period separately. We thus ensure that treatment and control groups are comparable at each time period[8].

The estimation of e_i is subject to a couple of important decisions. First, one needs to consider carefully the variables to include, as this will determine for which observables balance should be achieved. Brookhart et al. (2006) recommend to include in the estimation procedure not only covariates that are related to the treatment variable, but also those which are related to the outcome variable without necessarily being linked to the treatment. As underlined by Caliendo and Kopeinig (2008), omitting important variables might result in a biased estimation of the treatment effect. The inclusion of squared terms and interactions should also be considered (see Imbens and Rubin, 2015). A thorough consideration of existing theory and a careful examination of available information are therefore advisable to select relevant variables.

The second choice is how to estimate e_i. While the traditional approach is to use a logistic regression model, alternative methods have been proposed. For instance, Lee et al. (2010) suggest to use classification and regression trees, and Imai and Ratkovic (2014) propose a generalized method of moments that includes a covariate balancing condition, which they call the covariate balancing propensity score (CBPS). Deciding which estimation method to use is thus far from obvious; it is therefore advisable to run different ones until proper covariate balance is achieved. In this paper, we use CBPS because the weights w_i obtained with this technique perform best in terms of covariate balance.

A DID regression is then estimated using weighted least squares (see e.g. Romano and Wolf, 2017), where the dependent variable y_{it} is household's i heating fuel consumption during year t. We take the

[8] Stuart et al. (2014) propose an IPTW method for repeated cross-sectional data with two periods and binary treatment, where the sample is split in four groups, that is, one per period-treatment combination. The probability of belonging to each of these groups is estimated for each individual in the sample using multinomial logistic regression. This method is however not suitable in our case due to the high number of period-treatment combinations (i.e. 5 periods $\times$ 2 groups = 10), which strongly increases the risk that weights take extreme values in practice.

natural logarithm of y_{it} and specify the model as follows:

$$\ln y_{it} = \gamma \cdot T_i + \sum_{t=2017}^{2020} \Big(\delta_t \cdot \big(T_i \times \mathbb{1}_{\{year=t\}} \big) \Big) + x'_{it} \cdot \beta + \tau_t + \varepsilon_{it} \tag{1}$$

where T_i is individual treatment status, $\mathbb{1}_{\{\cdot\}}$ is an indicator function taking the value 1 when the condition in braces is true, x_{it} is a vector of independent variables that contains a set of region fixed effects[9] to account for time-invariant (i.e. geographical, institutional and cultural) specificities, τ_t are year fixed effects, and ε_{it} is an error term. δ_t are coefficients showing the impact on the dependent variable of being in the treatment group in year t, that is, the treatment effect for each year.

The CO_2 levy has been raised in January 2016 and January 2018. If such increases do have the intended impact, one should expect relative decreases in heating fuel consumption for fossil fuel users compared to others shortly afterwards. Because of data-related reasons (see Section 4), our dependent variable measures heating fuel consumption with a one-year lag. The short-run effectiveness of the CO_2 levy should therefore be observed in 2017 and 2019 and in our estimations it is captured by coefficients δ_{2017} and δ_{2019}.

4 Data

4.1 Dataset

Data used in this study come from the Swiss Household Energy Demand Survey (SHEDS)[10], which covers a wide range of aspects related to households' energy demand, preferences, behaviors, as well as psychological and socioeconomic characteristics. Between 2016 and 2020, approximately 5,000 households representative of the Swiss population with respect to gender, age, tenancy status and region were surveyed every year between April and June. A substantial share of the respondents answered several waves of the survey, so that the dataset is a combination of longitudinal and repeated cross-sectional data.

For our purpose, we use yearly heating and warm water expenses (HWWE) stated by the respondents in combination with information about fuel prices to construct the dependent variable. To account

[9] In this analysis, regions correspond to Swiss cantons.

[10] See Weber et al. (2017) for details on SHEDS.

for the impact of market price fluctuations on HWWE, we deflate them by price indices for each fuel type. By doing so, HWWE are expressed in market prices of a single reference year—in our case 2015—so that remaining variations reflect changes in quantities. The variable obtained thus mirrors heating fuel consumption.

HWWE are obtained directly from the survey respondents, who are requested to state the amount indicated on their most recent heating bill. The expenses measured in year t therefore mostly relate to energy consumed during year $t-1$. Indeed, to heat their home during the winter, households must have purchased fuel in advance, hence during the preceding year[11]. This is especially true in the case of heating systems running on oil (and sometimes on natural gas), whereby a tank must be filled, but less so for new renewable technologies such as heat pumps or district heating, whereby the user obtains energy directly from the network. Hence, we should only expect to detect an impact—if any—one year after each of the two CO_2 tax increases that took place during our observation period.

Because actual energy consumption is usually unknown to respondents, HWWE are the most closely-related information that can be collected through a survey. When asked about their HWWE, respondents can state whether they use their last bill to answer or if they only provide an estimation. They can moreover indicate whether the amount they pay is based on actual heat consumption or another factor such as the size of their home. That gives us an opportunity to check the consistency of our results when restricting our sample to households with the most accurate answers (based on bills) or who have a direct control on their heating bills (based on their own fuel consumption). It should be noted that the top and bottom 1% of HWWE per m^2 of surface observed in the sample have been dropped to remove probable aberrant responses[12,13].

The dataset also contains data on the type of fuel used for space heating and warm water. This information is used to construct our treatment variable by splitting the sample between fossil fuel users (i.e. the treatment group) and non-fossil fuel users (i.e. the control group)[14]. Oil and gas users

[11] The one-year lag is also valid for rented dwellings. In such cases, the owner purchases fuel in advance and establishes a final invoice for the tenants only at the end of the heating period.

[12] We use HWWE per m^2 rather than HWWE itself in the trimming procedure because large HWWE are plausible for large accommodations. The excluded values are those for which the relation between heating expenses and accommodation size is unrealistic.

[13] Trimming has been performed independently for the treatment and control groups in each time period. Trimming at 2.5% and 5% thresholds has also been performed, without significant differences in the results (available on request).

[14] Only space heating is considered to allocate households between control and treatment groups. Warm water is not considered because it only represents a minor share of total HWWE[15] and warm water expenses generally cannot be disentangled from space heating expenses. Therefore, even if a household in the treatment group uses a non-fossil fuel for warm water, most of its HWWE come from heating and should thus be affected by the CO_2 levy. Conversely, households

constitute the treatment group, while all others (i.e. households using electricity, wood, heat pumps, solar panels or district heating) make up the control group. Respondents with an unspecified type of fuel have been removed from our sample because this information is necessary to allocate them to the treatment and control groups. Households connected to district heating have been kept because, although we do not know which energy source is used to produce heat, fossil fuels are only used in a small minorities of heating plants (about 7% in Switzerland, see Hangartner and Ködel, 2021). We therefore assume they use heat produced from energy sources exempted from the CO_2 levy.

Table 1 presents the distribution of heating fuels for our sample and for the Swiss population. As can be seen, the share of fossil fuel users in the sample is relatively stable between 2016 and 2020. It is however slightly larger than the share of heating oil and gas users observed at the country-level. Overall, the share of non-fossil fuel users is comparable between our sample and Switzerland, although the distribution of specific fuels is not totally equivalent between the two, with deviations especially for wood, heat pumps, and district heating. These differences may be explained by the over-representation of urban households in our sample[16].

Our dataset also includes socioeconomic characteristics, geographic indications, environmental and energy-related information, as well as characteristics of the dwelling and the heating system. Table A1 (in appendix) presents all variables we use in the estimation of IPTW weights and later in the regres-

Fuel type	Switzerland	Sample				
	2017	2016	2017	2018	2019	2020
Proportions (%)						
Oil	39.4	42.6	42.5	41.9	42.0	40.4
Gas	20.7	25.9	23.8	24.2	25.1	26.4
Electricity	6.9	6.7	6.2	5.7	5.6	4.6
Wood	10.1	5.3	5.6	6.0	5.1	5.2
Heat pump	17.9	12.3	15.2	14.6	14.8	16.2
Solar	0.3	0.0	0.0	0.0	0.0	0.0
District heating	4.2	7.3	6.8	7.6	7.3	7.2
Other	0.6					
Observations		2054	3305	2468	2004	1813

Note: Data for Switzerland come from Swiss Federal Statistical Office's *Survey on the energy sources of residential buildings*, 2017. Because we need to know whether households use fossil heating fuels or not, other—hence unspecified—types of fuel have been removed from our sample.

Table 1: Distribution of heating fuels

using fossil fuel for warm water only will be included in the control group even though they are in fact affected by the CO_2 tax, but only on a minor share of their expenses.

[16] 37% of households in our sample live in a municipality of at least 20,000 inhabitants and 22% in a municipality of at least 50,000 inhabitants, against 30% and 17% for Switzerland in 2019, respectively (Source: Swiss Federal Statistical Office, *Statistique des villes suisses*, 2021).

sion analyses. They cover all factors identified in the literature as influencing energy consumed for residential heating.

Our sample consists in a combination of longitudinal and repeated cross-sectional observations because not all respondents answered all survey waves. We however treat it as repeated cross-sections, as accounting for its partially longitudinal structure from an econometric perspective would cost a prohibitively large share of available observations. We nevertheless keep only households who have been living in their accommodation since 2015 and who did not change heating fuel during the 2016–2020 period, so that such changes do not affect the validity of reported HWWE relative to the characteristics of the accommodation and are not correlated to the treatment variable—i.e. using fossil fuel for heating. We are thus able to limit the impacts of some of the drawbacks of not having a full panel to carry out our analysis.

We also emphasize that dropping households who changed heating fuel (and thus heating systems) is consistent with our objective of identifying short-run impacts of the CO_2 levy. One possible (desired) response to the tax increases is to switch from a fossil fuel heating system to a renewable heating system, thereby totally escaping the tax payment. Such changes are however likely to occur only in the relatively long run, as they involve major decisions and investments. In that sense, our estimates will voluntarily provide a lower bound of the CO_2 levy impacts. Our goal is to estimate the impact of behavioral changes that can be adopted in the short run, that is, changing some habits—e.g. heating at night or with windows open—in order to limit heating waste.

4.2 Descriptive statistics

Table 2 presents some descriptive statistics for the treatment and control groups, with all years pooled. Student's t-statistics for the difference in means between the two groups are provided in the last column. Most differences can be related to the fact that the control group includes more house-owners whereas the treatment group contains more tenants living in apartments. Being house-owner is correlated with a higher income and a stronger propensity to live outside urban areas, as owning real estate usually requires important financial resources and enough land availability. From a decision-making and practical perspective, it is also easier to choose a (non-fossil) heating fuel when owning one's accommodation, and when the latter is a (single-family) house. Such differences highlight the importance of the weighting strategy, which is expected to give larger weights to non-house owners in the control groups to achieve a satisfactory covariate balance and improve comparability between fossil fuel users and non-fossil fuel users.

Variable	Treatment		Control		t-statistic
	Mean	S.D.	Mean	S.D.	
HWWE	1406.33	980.14	1229.13	953.84	9.35
Age	51.43	14.88	49.15	14.50	7.93
Tertiary education	0.44	0.50	0.46	0.50	−1.77
Income	7905.54	2920.42	8188.18	2945.44	−4.89
Household size	2.29	1.36	2.52	2.01	−6.45
At least 1 child	0.33	0.47	0.39	0.49	−6.58
Environmental adaptation	3.57	0.95	3.60	0.93	−1.69
Energy literacy	3.65	1.17	3.66	1.22	−0.46
Owner	0.41	0.49	0.54	0.50	−13.59
House	0.36	0.48	0.50	0.50	−14.38
Owner × House	0.27	0.44	0.41	0.49	−15.09
Surface (m^2)	119.06	67.22	135.54	75.40	−11.50
Construction year	1990.10	149.02	1989.76	108.56	0.14
Minergie	0.09	0.29	0.28	0.45	−23.00
Living room temperature	20.78	1.04	20.80	1.08	−1.21
City	0.54	0.50	0.38	0.49	16.21
Agglomeration	0.29	0.45	0.31	0.46	−2.34
Countryside	0.17	0.38	0.31	0.46	−15.74
Observations	7786		3858		

Note: t-statistics for the difference in means between the treatment and control groups.

Table 2: Descriptive statistics

4.3 Estimation of weights

To make treatment and control groups balanced, weights w_i are constructed using PSs e_i estimated with the aforementioned CBPS method. CBPS is implemented using the eponymous package in R (Imai and Ratkovic, 2014). A binary regression is estimated with the treatment status, i.e. a dummy taking the value 1 for households whose heating system uses fossil fuel (oil or gas) and 0 otherwise, as the dependent variable and all variables presented in Table A1 as independent variables. The latter have been selected because of their expected influence on both the probability of treatment and the outcome variable. They cover all relevant characteristics of households and their accommodations that are available in our dataset. Weights are constructed as described in Austin (2011): $w_i = T_i + (1 - T_i) \cdot e_i/(1 - e_i)$.

Table 3 provides some balance metrics for the unweighted and weighted samples. It reports standardized differences in means, variance ratios (for continuous variables only) (see Austin, 2009), and Kolmogorov-Smirnov (KS) statistics (see Austin and Stuart, 2015), both before and after adjustment through weighting for the treatment and control groups with all years pooled. The closer to 0 the difference in means and the KS-statistics and the closer to 1 the variance ratios, the better, as it indicates a more similar distribution of covariates between the treatment and control groups (Austin and Stuart, 2015; Kainz et al., 2017). All covariates become much more similar in distribution after adjustment, which implies that the comparability of the treatment and control groups improves substantially thanks to the weighting strategy. The estimated ATTs are therefore expected to be more accurate when weights are accounted for in the DID regressions.

Variable	Standardized mean diff.		Variance ratio		KS-statistic	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Age	0.153	<0.001	1.052	0.981	0.079	0.017
Tertiary education	−0.017	<0.001			0.017	<0.001
Income	−0.087	<0.001	1.004	0.984	0.041	0.011
Household size	−0.170	<0.001	0.459	0.773	0.060	0.005
At least 1 child	−0.062	<0.001			0.062	<0.001
Environmental adaptation	−0.033	<0.001	1.038	0.975	0.012	0.008
Energy literacy	−0.009	<0.001	0.932	0.963	0.017	0.008
Owner	−0.133	<0.001			0.133	<0.001
House	−0.140	<0.001			0.140	<0.001
Owner × House	−0.142	<0.001			0.142	<0.001
Surface	−0.245	<0.001	0.795	1.063	0.127	0.021
Construction year	0.002	<0.001	1.884	1.051	0.234	0.125
Minergie	−0.182	<0.001			0.182	<0.001
Living room temperature	−0.024	<0.001	0.918	0.852	0.033	0.031
City	0.156	<0.001			0.156	<0.001
Agglomeration	−0.021	<0.001			0.021	<0.001
Countryside	−0.135	<0.001			0.135	<0.001

Note: Variance ratios are only provided for continuous variables.

Table 3: Covariate balance statistics

5 Results

5.1 Regression analysis

Results from a series of regressions of the natural logarithm of deflated HWWE on treatment-year combination dummies, plus the set of aforementioned exogenous covariates and regional fixed effects, are presented in Table 4[17][18]. We compare results from two adjustment methods: covariate adjustment

[17] Coefficients for regional fixed effects are not displayed in Table 4 for the sake of space and because their values do not follow any clear pattern.

[18] We do not include energy price (in CHF/kWh) as an independent variable for two reasons. First, energy prices provided by the Swiss Federal Statistical Office vary based on consumption profiles and quantities bought, so that a choice should be made to a price for each fuel, implying some imprecision, as we do not know which price households actually pay. Second, no data is available regarding district heating, discarding many observations from the control group if the price variable is included. We however provide results when energy price is included in Table A2, where it can be seen that the variable is hardly significant in two specifications only. We therefore choose not to include this variable

only (i.e. standard DID with control variables), or both covariate adjustment and IPTW[19] with three different subsamples: (i) entire sample, (ii) respondents who used their bill to answer (i.e. no estimated HWWE), and (iii) respondents whose HWWE are based on their actual heat consumption. The restricted subsamples should allow to get more precise results, as estimated HWWE are noisy by definition and people whose HWWE are not based on their actual heat consumption have fewer incentives to react to the CO_2 levy because of the public good issue. Nevertheless, any restriction leads to a smaller sample, which in turn leads to increased risks of imprecision in the estimation procedure and a possible lack of external validity due to a more specific sample composition[20].

Results in Table 4 show that using fossil heating fuels is related to higher deflated HWWE than using non-fossil sources of energy by 12.2 to 17.2%, presumably because heating systems using fossil fuels are on average older and therefore less efficient in terms of calorific power per CHF spent than renewable heating systems. However, energy consumed for heating does not clearly diverge between the two groups over time. Although the coefficient for the interaction between the treatment indicator and the 2019 year dummy is significant at the 5% level in some specifications, the coefficient for the subsequent year is significant in only one specification. These results suggest that there might have been a temporary decrease in energy consumption among fossil fuel users following the 2018 tax rate increase. This effect, however, did not last, so that no definite conclusion can be drawn regarding the short-run effectiveness of the CO_2 levy on Swiss households' energy demand. The absence of significant coefficients in other specifications also cast some doubts regarding the short-run effects detected in our statistical analysis. Although a false negative cannot be completely dismissed, different factors could explain our finding, such as the lack of control over one's own energy consumption for heating or a potentially inelastic demand for heating and warm water—which would be consistent with the literature on the price elasticity of energy demand (see Labandeira et al., 2017). It should be noted that, in most specifications, the coefficients for years 2018–2020 are negative and significant—with a larger value for 2020—suggesting that overall heating consumption diminishes over time, as deflated HWWE decrease. This trend is however not different between the treatment and control groups[21].

in our main results table. Energy price data are available at `https://www.bfs.admin.ch/bfs/en/home/statistics/catalogues-databases/tables.assetdetail.18324899.html` [accessed on August 17, 2021].

[19] Elze et al. (2017) call the latter the *doubly robust* IPTW method.

[20] Combining both restrictions leads to the loss of about 75% of the initial sample. We therefore refrain from combining the two restrictions.

[21] We also tried to distinguish between heating oil and natural gas users, but results (available on request) are inconclusive and therefore not reported.

	(1)	(2)	(3)	(4)	(5)	(6)
Fossil fuel	0.172***	0.142***	0.144***	0.172***	0.130**	0.122**
	(0.034)	(0.049)	(0.043)	(0.036)	(0.051)	(0.048)
Fossil fuel × 2017	0.032	0.003	0.017	0.051	0.061	0.042
	(0.044)	(0.061)	(0.055)	(0.050)	(0.068)	(0.063)
Fossil fuel × 2018	−0.030	−0.051	−0.045	−0.034	−0.040	−0.018
	(0.048)	(0.066)	(0.059)	(0.054)	(0.073)	(0.069)
Fossil fuel × 2019	−0.125**	−0.130*	−0.053	−0.149**	−0.139**	−0.042
	(0.052)	(0.068)	(0.066)	(0.059)	(0.071)	(0.078)
Fossil fuel × 2020	−0.034	−0.067	0.059	−0.101	−0.181**	0.007
	(0.053)	(0.074)	(0.068)	(0.064)	(0.089)	(0.080)
Year: 2017	−0.101**	−0.061	−0.022	−0.084	−0.107	−0.021
	(0.048)	(0.065)	(0.059)	(0.056)	(0.077)	(0.070)
Year: 2018	−0.234***	−0.134**	−0.138**	−0.194***	−0.133*	−0.142*
	(0.050)	(0.068)	(0.062)	(0.059)	(0.080)	(0.074)
Year: 2019	−0.248***	−0.079	−0.240**	−0.318***	−0.118	−0.316***
	(0.077)	(0.100)	(0.099)	(0.089)	(0.119)	(0.113)
Year: 2020	−0.334***	−0.193***	−0.317***	−0.288***	−0.094	−0.283***
	(0.045)	(0.066)	(0.056)	(0.055)	(0.078)	(0.067)
Age	0.114***	0.101***	0.112***	0.115***	0.101***	0.117***
	(0.006)	(0.008)	(0.009)	(0.008)	(0.013)	(0.013)
Tertiary education	0.042***	0.059***	0.037*	0.026	0.056**	0.025
	(0.015)	(0.019)	(0.020)	(0.020)	(0.026)	(0.024)
ln(income)	0.183***	0.162***	0.148***	0.186***	0.175***	0.164***
	(0.020)	(0.025)	(0.028)	(0.026)	(0.035)	(0.034)
Household size	0.003	0.004	0.007	−0.001	−0.011	0.022
	(0.008)	(0.009)	(0.018)	(0.012)	(0.028)	(0.018)
At least 1 child	0.118***	0.081***	0.114***	0.111***	0.103**	0.081**
	(0.021)	(0.025)	(0.038)	(0.029)	(0.052)	(0.040)
Environmental adaptation	−0.027***	−0.007	−0.012	−0.023**	−0.002	0.003
	(0.008)	(0.010)	(0.011)	(0.011)	(0.016)	(0.014)
Energy literacy	0.065***	0.049***	0.056***	0.083***	0.057***	0.081***
	(0.010)	(0.013)	(0.016)	(0.012)	(0.016)	(0.021)
Owner	0.247***	0.242***	0.299***	0.340***	0.319***	0.411***
	(0.055)	(0.075)	(0.080)	(0.066)	(0.091)	(0.098)
Owner × Energy literacy	−0.059***	−0.073***	−0.062***	−0.092***	−0.099***	−0.090***
	(0.013)	(0.018)	(0.019)	(0.016)	(0.022)	(0.023)
House	0.059*	0.041	0.210***	0.067*	0.088	0.253***
	(0.033)	(0.042)	(0.043)	(0.038)	(0.055)	(0.050)
Owner × House	0.112***	0.152***	0.017	0.110**	0.126**	−0.033
	(0.038)	(0.048)	(0.050)	(0.045)	(0.063)	(0.058)
Surface	0.021***	0.019***	0.018***	0.023***	0.021***	0.017***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Construction year	−0.001**	−0.002**	−0.002***	−0.002**	−0.002**	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Minergie	−0.190***	−0.263***	−0.172***	−0.188***	−0.254***	−0.161***
	(0.021)	(0.027)	(0.026)	(0.023)	(0.029)	(0.029)
Living room temperature	0.043***	0.039***	0.044***	0.043***	0.045***	0.048***
	(0.007)	(0.009)	(0.010)	(0.010)	(0.014)	(0.013)
City	0.044**	0.004	0.028	0.053**	0.031	0.050*
	(0.018)	(0.022)	(0.024)	(0.023)	(0.031)	(0.030)
Countryside	0.073***	0.053*	0.080***	0.082***	0.073**	0.099***
	(0.022)	(0.028)	(0.026)	(0.025)	(0.034)	(0.029)
HDD	0.010	0.035	−0.002	−0.031	0.016	−0.029
	(0.029)	(0.037)	(0.039)	(0.034)	(0.048)	(0.043)
Constant	3.142***	3.014***	3.932***	4.263***	3.329**	4.356***
	(0.886)	(1.105)	(1.172)	(1.047)	(1.481)	(1.360)
IPTW	No	No	No	Yes	Yes	Yes
Estimated HWWE excl.	No	Yes	No	No	Yes	No
Actual consumption only	No	No	Yes	No	No	Yes
N	11644	6034	6274	11644	6034	6274
Adj. R^2	0.186	0.173	0.208	0.179	0.165	0.208

Notes: ***p-value < 0.01; **p-value < 0.05; *p-value < 0.1. Region fixed effects are included in the estimation but not displayed. Age, surface and construction year have been divided by 10, and HDD by 100.

Table 4: Regression results

Most other coefficients are significant and have the expected signs, which shows that meaningful relationships are detected by our model where they exist. Concerning socioeconomic variables, age is linked to a higher heating consumption, a finding consistent with Brounen et al. (2012), who relate this result to the fact that the elderly spend more time at home than younger people. While results are not always significant regarding tertiary education when weights are introduced, income is positively connected to higher HWWE, with an estimated elasticity comprised between 14.8% and 18.6%. Presence of children in the household is also positively linked to higher HWWE.

Interestingly, energy literacy has diverging effects for owners and tenants: while it is linked to lower HWWE for owners, the coefficient is positive for tenants. Our hypothesis is that owners who are better informed about energy are able to lower their heating consumption, as they have means to effectively manage their consumption. On the other hand, tenants with high HWWE might learn more about energy-related issues but still remain unable to lower their HWWE by lack of decision-making power over their energy consumption for heating. It should also be noted that the owner dummy has a positive and significant coefficient, which means that owners have—on average and *ceteris paribus*—a higher heating consumption than tenants. Although this result seems counter-intuitive, an explanation might be that owners are on average wealthier than tenants. Like income, wealth lowers the relative marginal burden of HWWE on households' budgets.

Regarding the characteristics of the dwelling, we find that living in a house has a significantly positive effect when the sample is restricted to households whose HWWE are based on their actual heating consumption. On the other hand, when all types of households are considered, only house-owners seem to have larger HWWE. These results are certainly caused by the fact that more than 60% of households whose HWWE are based on their actual heating consumption are owners, so that the interaction between ownership status and living in a house loses significance when applying this restriction to the sample.

Unsurprisingly, households living in accommodations with larger surfaces have higher deflated HWWE, while those who live in more recent buildings or in Minergie[22] buildings have a lower heating consumption. Households living in accommodations whose average room temperature is higher also have higher HWWE. Living in the countryside is linked to higher heating consumption, poten-

[22]Minergie is the most widespread construction label for new or renovated buildings in Switzerland. It certifies that buildings attain a certain level of housing comfort, but also of energy-efficiency. It is supported by the federal and cantonal governments. More information on `https://www.minergie.ch` [accessed on April 22, 2021].

tially because of less energy-efficient homes and heating systems, but also because of lower external temperatures than in more densely populated areas.

Overall, even though a number of factors are found to exert an impact on Swiss households' heating demand, the 2016 and 2018 carbon tax increases do not seem to have provoked any clearly detectable short-run change in fossil fuel users' behaviors regarding the way they heat their home. This finding questions the adequacy of the current design of the CO_2 levy concerning households: expecting short-run reactions or increasing the tax rate further if nothing happens might not give them enough time to adapt or to invest in long-run energy-saving measures like renovations.

6 Conclusion and policy implications

Our results suggest that households do not quickly adapt their behaviors to the progressive increase of the CO_2 levy. Of course, it should be emphasized that only short-run effects are considered here; it is probable that taxing CO_2 also exerts longer-run effects, especially if the rate reaches higher levels. In particular, it can be expected to lead to more renovations in the future, as well as transitions to renewable energy sources for heating—two of the main goals of carbon taxation. Although deflated HWWE might not be the best proxy for heating demand, these results provide some evidence that stronger action is needed to enhance the effectiveness of the Swiss carbon taxation system on households' thermal fossil fuel consumption. As previously mentioned, fossil fuels' market prices are subject to large exogenous variability, which renders the impacts of the carbon tax hardly visible. Hence, the current carbon tax seems to lack salience in the short run as households do not quickly react to either its mere presence (tax aversion) or its effect on prices.

Another issue worth mentioning is that most respondents seem to not properly understand the functioning of the Swiss CO_2 levy. Burger et al. (2018) indeed underline the fact that a substantial proportion of the population misunderstands this instrument: a third of fossil fuel users believe they pay no tax at all, half of non-fossil fuel users incorrectly think they pay the carbon tax, and only 14% of all respondents more or less correctly guess how much they are receiving through the tax redistribution scheme, an information they can easily find on their health insurance bills[23]. This limited knowledge suggests that Swiss households are not fully aware of how much the carbon tax actually affects them,

[23] In Switzerland, residents have to directly pay their health insurance bills. The amounts redistributed as proceeds from the CO_2 levy are explicitly mentioned as deductions on these bills.

which makes them unlikely to take (correct) action in response to the tax. As shown by Labandeira et al. (2017), the price-elasticity of demand for heating oil is generally low, especially in the short run, so that most short-run carbon tax effects are to be expected from the psychological impact of taxation, which seems only likely if households are correctly informed.

In addition, some households might lack the capacity of taking action to decrease the tax burden because their heating bills are not based on their actual consumption but on another factor such as the size of their home, which is the standard case for tenants and apartment-dwellers. A "split incentive issue" may then arise (see e.g. Gillingham et al., 2012), i.e. a situation where households have little incentive to lower their heating demand because of the minor impact it would have on their own HWWE. Moreover, tenants and apartment-dwellers have less decision power over renovations, which means that even if they wanted to, they would not be able to improve the energy efficiency of their homes. Therefore, a significant share of Swiss households cannot be expected to substantially react to the CO_2 levy, even in the longer run, as they have little incentives and/or capacity to do so.

From a policy perspective, these findings have important implications. Although the CO_2 levy is based on sound economic reasoning and its general principle is not to be debated anymore, some specific aspects of its design could be improved. First, the CO_2 levy seems imperfectly designed to nudge (most) households, as it only targets (the minority of) those who can directly act on their heating demand. Putting more emphasis on non-pricing measures targeting owners such as renovation subsidies and stricter regulations on energy efficiency and the use of fossil fuels could help, as would the development of district heating projects in densely populated areas (see Narula et al., 2019). Second, people are on average not well informed about how they are affected, which means it is unlikely to steer behavior in the intended direction, hence contributing to the insignificant effect estimated in the regression analysis. Improved communication from the authorities would be needed in that regard—it would also help to distinguish exogenous fuel price fluctuations on the market from the tax, which could strengthen its psychological impact. Finally, as the CO_2 levy is one of the main tools the Swiss government has set up to fight climate change, its apparent lack of (short-run) effectiveness challenges its relevance: complementary and alternative measures might be more effective concerning households and needed to reach sufficient CO_2 emission abatement (see Ó Broin et al., 2015). The short-run dimension of the issue must be emphasized, as the tax rate is increased if CO_2 emission reduction thresholds are not met, and from 2008 to 2018 the achievement of these thresholds was checked biennially, showing that short-run efficiency is a criteria guiding this policy instrument.

Raising the tax incrementally every second year may in fact prove detrimental to its effectiveness. As widely discussed in the psychological literature (see e.g. Kurz et al., 2015), a number of environmentally relevant behavior patterns are frequent, stable, and persistent. In this context, small tax increases might be largely ignored by consumers and could be insufficient to trigger a reaction in the short run. Simultaneously, consumers could be displaced to a new psychological reference-point after each small tax increment, thereby yielding only modest reactions even when the tax has become relatively large. On the contrary, implementing larger step-changes would probably lead to quicker and more substantial behavioral adaptations[24]. A counter-argument against large tax increases is of course that social acceptability is more complicated to achieve in such cases (World Bank, 2019). Policy makers in charge of carbon taxation clearly face a difficult trade-off between efficiency and social acceptability.

Further ex-post empirical work should look at longer-run trends in fossil heating fuel consumption to see how investment decisions evolve over time. The question of the socially optimal tax rate as well as the optimal tax rate increases should also be investigated in order to better inform policy makers on the path that should be followed to efficiently lower CO_2 emissions caused by households, while ensuring social acceptability and people compliance. Research on households' preferences toward heating could also provide more information on how to design efficient nudges that could be implemented in complement to carbon taxation.

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[24]Regarding long-run investments such as heating system replacement and renovation, the current system might work as far as people are informed of the CO_2 emissions abatement trajectory set by the authorities. Yet, without any clear announcement effect, the nudge provoked by incremental tax increases might not be sufficient to stimulate investment. In particular, as it is not possible to know in advance whether emissions targets will be reached or not, and thus whether the CO_2 levy rate will increase or not, individuals have lower incentives to invest, because the profitability of such investment is uncertain beforehand.

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Appendix

Variable	Scale	Description
Socioeconomics		
Age	Integer	Age of the respondent.
Tertiary education	Binary	The respondent has a tertiary level of education.
Income	Continuous	Monthly income of the household.
Household size	Integer	Number of people in the household.
At least 1 child	Binary	At least one child is present in the household.
Environment and energy		
Environmental adaptation	1–5	The respondent agrees that he/she is ready to take steps to adopt environmentally friendly behaviors even if it causes daily inconveniences (totally disagree–totally agree).
Energy literacy	0–5	Level of energy literacy of the respondent measured as the number of correct answers to the following true/false questions: • The biggest share of energy consumed in a Swiss household is for heating purposes. (True) • CO_2 emissions play a crucial role in global warming. (True) • Simply lowering the heating temperature in an average household by 1°C can help to cut down the heating demand by 6%. (True) • Coal is a renewable energy resource. (False) • Hydroelectric power plants account for 10% of total Swiss electricity production. (False)
Accommodation		
Ownership	Binary	The household owns its accommodation.
Type of accommodation	Categorical	The type of accommodation in which the household lives (house or flat).
Year of construction	Integer	Year of completion of the accommodation's construction.
Minergie	Binary	The accommodation complies with Minergie or better energy-efficiency standards.
Living room temperature	Continuous	Average temperature in the living room during the day (in °C).
Residential environment	Categorical	The type of area in which the household lives (city, agglomeration, countryside).

Table A1: List of variables

	(1)	(2)	(3)	(4)	(5)	(6)
log(energy price)	0.070*	0.066	0.086*	−0.024	−0.066	0.018
	(0.038)	(0.054)	(0.046)	(0.059)	(0.086)	(0.064)
Fossil fuel	0.242***	0.203***	0.212***	0.220***	0.196*	0.175***
	(0.043)	(0.065)	(0.051)	(0.060)	(0.102)	(0.067)
Fossil fuel × 2017	0.038	−0.005	0.020	0.070	0.006	0.022
	(0.049)	(0.073)	(0.059)	(0.067)	(0.107)	(0.073)
Fossil fuel × 2018	−0.013	0.013	−0.034	−0.042	−0.007	−0.042
	(0.053)	(0.079)	(0.063)	(0.074)	(0.125)	(0.085)
Fossil fuel × 2019	−0.123**	−0.072	−0.047	−0.185**	−0.141	−0.064
	(0.058)	(0.082)	(0.070)	(0.079)	(0.114)	(0.090)
Fossil fuel × 2020	0.007	0.016	0.087	−0.088	−0.174	−0.006
	(0.060)	(0.092)	(0.073)	(0.102)	(0.149)	(0.100)
Year: 2017	−0.103*	−0.059	−0.019	−0.141*	−0.096	−0.033
	(0.053)	(0.076)	(0.063)	(0.077)	(0.127)	(0.086)
Year: 2018	−0.251***	−0.208**	−0.148**	−0.221***	−0.207	−0.153
	(0.056)	(0.081)	(0.066)	(0.082)	(0.141)	(0.094)
Year: 2019	−0.271***	−0.131	−0.275***	−0.240**	−0.052	−0.277**
	(0.082)	(0.111)	(0.103)	(0.110)	(0.157)	(0.121)
Year: 2020	−0.388***	−0.282***	−0.361***	−0.301***	−0.091	−0.282***
	(0.052)	(0.085)	(0.061)	(0.089)	(0.131)	(0.085)
Age	0.112***	0.100***	0.108***	0.104***	0.107***	0.117***
	(0.006)	(0.008)	(0.009)	(0.014)	(0.020)	(0.017)
Tertiary education	0.040**	0.057***	0.032	0.016	0.072**	0.039
	(0.016)	(0.020)	(0.020)	(0.029)	(0.036)	(0.027)
ln(income)	0.178***	0.156***	0.143***	0.174***	0.156***	0.171***
	(0.021)	(0.027)	(0.029)	(0.036)	(0.050)	(0.040)
Household size	0.003	0.006	0.007	0.002	−0.022	0.017
	(0.008)	(0.009)	(0.019)	(0.015)	(0.042)	(0.019)
At least 1 child	0.125***	0.079***	0.115***	0.125***	0.106	0.083*
	(0.022)	(0.026)	(0.039)	(0.037)	(0.080)	(0.046)
Environmental adaptation	−0.029***	−0.012	−0.013	−0.026**	−0.013	−0.010
	(0.008)	(0.010)	(0.011)	(0.013)	(0.018)	(0.014)
Energy literacy	0.064***	0.050***	0.059***	0.096***	0.064***	0.095***
	(0.010)	(0.013)	(0.017)	(0.017)	(0.024)	(0.026)
Owner	0.255***	0.243***	0.316***	0.419***	0.328***	0.463***
	(0.058)	(0.079)	(0.084)	(0.087)	(0.126)	(0.121)
Owner × Energy literacy	−0.059***	−0.071***	−0.065***	−0.106***	−0.094***	−0.105***
	(0.014)	(0.019)	(0.020)	(0.020)	(0.030)	(0.028)
House	0.080**	0.066	0.240***	0.099**	0.116*	0.326***
	(0.034)	(0.044)	(0.045)	(0.048)	(0.067)	(0.056)
Owner × House	0.094**	0.122**	−0.005	0.092	0.098	−0.077
	(0.039)	(0.051)	(0.052)	(0.057)	(0.077)	(0.065)
Surface	0.021***	0.018***	0.017***	0.022***	0.019***	0.016***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Construction year	−0.001**	−0.002**	−0.003***	−0.003**	−0.003*	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Minergie	−0.179***	−0.244***	−0.170***	−0.156***	−0.236***	−0.140***
	(0.022)	(0.029)	(0.027)	(0.028)	(0.037)	(0.033)
Living room temperature	0.043***	0.040***	0.045***	0.049***	0.049**	0.057***
	(0.008)	(0.010)	(0.010)	(0.014)	(0.022)	(0.017)
City	0.030	−0.012	0.018	0.029	0.006	0.045
	(0.019)	(0.023)	(0.025)	(0.030)	(0.043)	(0.035)
Countryside	0.080***	0.050*	0.084***	0.089***	0.075*	0.109***
	(0.022)	(0.029)	(0.026)	(0.030)	(0.042)	(0.032)
HDD	0.007	0.042	−0.008	−0.008	0.046	−0.012
	(0.030)	(0.038)	(0.039)	(0.041)	(0.062)	(0.048)
Constant	3.094***	2.651**	3.924***	3.861***	2.883	3.817**
	(0.912)	(1.138)	(1.200)	(1.301)	(1.996)	(1.537)
IPTW	No	No	No	Yes	Yes	Yes
Estimated HWWE excl.	No	Yes	No	No	Yes	No
Actual consumption only	No	No	Yes	No	No	Yes
N	10805	5546	5894	10805	5546	5894
Adj. R^2	0.188	0.175	0.211	0.183	0.172	0.22

Notes: ***p-value < 0.01; **p-value < 0.05; *p-value < 0.1. Region fixed effects are included in the estimation but not displayed. Age, surface and construction year have been divided by 10, and HDD by 100.

Table A2: Regression results including energy price