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The impact of CO_2 taxation on Swiss households' heating demand*

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Abstract

This paper investigates the impacts 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 carbon tax rate increase had a short-term impact on Swiss households' heating consumption and propensity to renovate. Micro-level data from the 2016 and 2017 waves of the Swiss Household Energy Demand Survey (SHEDS) are used to estimate the models. In both cases, no statistically significant effect can be detected across a variety of specifications. Even though further research is needed to investigate possible long-run impacts, our findings question the relevance of this policy instrument under its current form to lower households' greenhouse gas emissions. Additional measures might be implemented to improve its efficiency.

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 and the potentially dreadful consequences they might cause (Stern 2007), it seems now clear that there is a need for policy action, as illustrated by the 2015 Paris Agreement and the engagements taken by several states to mitigate their GHG emissions. As part of its strategy to limit its impact on climate change, Switzerland introduced a tax on carbon dioxide on 1st January 2008. Carbon taxes are policy instruments based on the idea of Pigouvian taxation to correct negative externalities (Baumol 1972; Pigou 1920); they give pollution a cost, hence incentivising emitters to take action to become more environmentally friendly. Taxing GHG emissions is a cost-efficient way to tackle the issue of human activities' impact on the environment. By introducing such a tax, the Swiss government hoped to lower GHG emissions relative to 1990 levels, as stated in the Federal Act on the Reduction of CO_2 Emissions.

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 programme and a technology fund. Tax collection is performed by the Federal Custom Administration (FCA) when imported fuels crosse the Swiss borders or when it leaves a tax-exempted warehouse to be sold. The tax rate is expressed in terms of CHF per ton of CO_2 equivalent (tCO_2eq), with the greenhouse effect of GHG other than carbon dioxide being converted based on a standardised table. The tax level is adapted if reduction targets set in the law are not met; hence, while it was at CHF 12/tCO_2eq when the levy was introduced in 2008, it was then raised several times as targets were missed, reaching CHF 36 in 2010, CHF 60 in 2014, CHF 84 in 2016 and CHF 96 in 2018, with a legal potential maximum of CHF 120 under the current version of the law.[1]

Although some firms can benefit from legal provisions that allow them to be exempted from paying the tax and therefore request a full refund if they meet some strict conditions, households cannot avoid paying it on all their fossil non-motor fuel purchase, i.e., mainly extra-light oil and natural gas used for heating. Their only way to escape the tax is by not using fossil fuels for heating, for instance by using a heat pump, electricity, wood pellets or solar panels. They can also reduce the tax burden by consuming less fossil fuels through two main different means: renovations

[1]The Federal Act on the Reduction of CO_2 Emissions is planned to be revised in 2020, with a potential increase in the maximum tax rate.

(of windows, heating system, roof, façade, etc.) and behavioural changes (heating less, using smart thermostats, ventilating less, etc.). The CO_2 levy can therefore be expected to lead to such adaptation strategies from households so that they minimise their carbon tax burden. The higher the tax, the stronger the incentives for renovating and adopting more energy-efficient behaviours.

However, there are reasons to put these claims in question. They rely on the assumption that individuals are all *homines oeconomici* who perfectly understand the price signal produced by a Pigouvian tax and react to it by lowering their fossil fuel demand accordingly, thus maximising their welfare. Such a situation cannot be taken for granted. Different factors may erode the impact of the carbon tax on households: low price-elasticity of demand for fossil fuels; non-utility maximising individuals; imperceptibility of the price signal by economic agents; lack of knowledge and incorrect perceptions of the CO_2 levy. The literature in behavioural economics argues that individuals tend to not always behave rationally from an economic point of view (Congdon, Kling, and Mullainathan 2009); hence, the expectation that the Swiss carbon tax pushes people to reduce their fossil fuel consumption is far from obvious and deserves empirical investigations.

This paper focuses on the question of the effectiveness of the Swiss CO_2 levy. It investigates whether households adapt their energy demand for heating from fossil sources and improve the energy efficiency of their homes following an increase of the levy. More precisely, it analyses at the impacts of the 2016 40% tax rate increase and test the hypotheses that the tax increase both led to lower fossil heating fuel consumption and a higher propensity to renovate for those households who use oil or gas as main heating fuel in comparison to the others. Household-level data collected in two waves of the Swiss Household Energy Demand Survey (SHEDS) are used. This survey is conducted yearly on a rolling panel of approx. 5,000 households.

The general analytical framework is a difference-in-differences (DID) estimation: outcomes of the treated group (fossil fuel users) is compared to those of the control group (non-fossil fuel users) before and after the 2016 carbon tax rate rise, so that the average treatment effect on the treated (ATT) can be obtained. Because of imbalances in covariates between the two groups, inverse probability of treatment weights for the estimation of an ATT are used: treated households receive 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 makes the two groups comparable regarding observable characteristics that could affect the outcome of interest, which is an improvement over the standard DID estimation.

The general conclusion of the econometric analysis is that the CO_2 levy had no visible effect on Swiss households' energy consumption of fossil heating fuels or propensity to renovate in the short term. The lack of salience from the tax can be pointed as a probable cause, as it is hardly perceptible by households through its impact on market prices. Limited decision capacity regarding heating consumption and energy-efficient renovations might also play a role, as well as households' probable lack of knowledge on the tax's mechanisms.

The article is structured as follows. Section 2 provides background knowledge by briefly reviewing relevant literature and by contextualising the Swiss CO_2 levy. Section 3 presents the analytical framework and the econometric models used to test the two research hypotheses. Section 4 describes the data and explains the estimation of the weights. Section 5 summarises the results and discusses them. Section 6 concludes.

2 Informational background

As coined by Andersen (2010), research undertaken on the topic of carbon taxation moved from *ex-ante* modelling that was prevalent in the 1990s (see for instance Nordhaus 1993) to *ex-post* analyses that use actual data (e.g. Lin and X. Li 2011). However, truly empirical studies are still scarce. Martin et al. (2014) assessed the impact of the British carbon tax on manufacturing at the level of enterprises and found it had a negative effect on energy intensity and electricity use. In their review of British Columbia's CO_2 tax, Murray and Rivers (2015) quote a few studies that use difference-in-differences approaches to estimate the impact of the tax on GHG emissions and fossil fuel consumption, which all report the negative impacts that could be expected from a theoretical point of view. None of those papers considers the effects of carbon taxes on households at a microeconomic level, though.

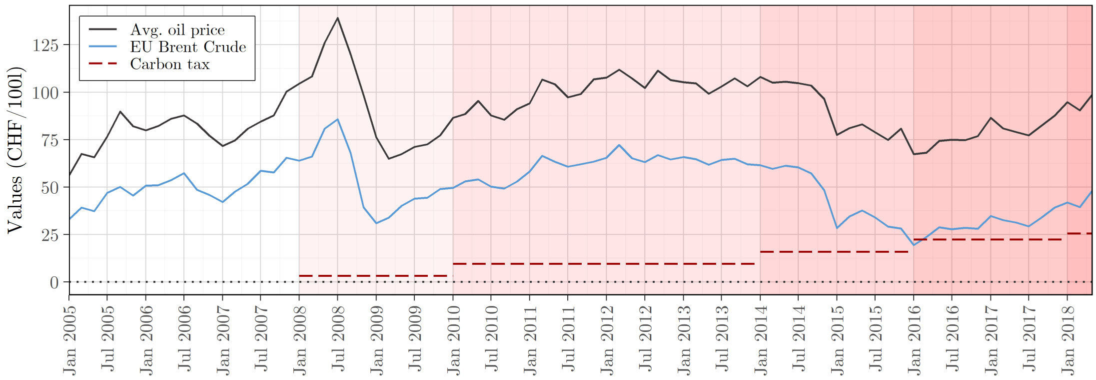
Indeed, literature on the effect of carbon taxes on households in terms of GHG emission reduction is very limited. Most studies focusing on households rather consider distributional aspects (see Beck et al. 2015; Brännlund and Nordström 2004; Callan et al. 2009; Chapa and Ortega 2017; Renner 2018; Tiezzi 2005; Williams et al. 2014), leaving effectiveness aside. Labandeira and Labeaga (1999) provide one of the rare attempts to evaluate the potential impact 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 behavioural effects of an exogenously set hypothetical carbon tax in 1994 in Spain. They find a small diminution of energy-related carbon dioxide emissions by households, but this result is limited in that it does not come from an evaluation of the actual impact of a real carbon tax.

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 found 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 its 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 between 1985 and 1996. Moreover, tax-elasticities of demand for fossil fuels might even be larger than that: Andersson (2017) estimated them to be about three times larger than price-elasticities in the case of gasoline in Sweden, because of consumers' tax aversion.

Andersson's findings are in line with most of the literature on tax salience (see Fochmann et al. 2010), that is, that taxes tend to have larger behavioural impacts than equivalent price changes. For instance, Chetty et al. (2009) find in an experiment that posting tax-inclusive prices in shops reduces demand in comparison to when only tax-free prices are displayed. This suggests that being aware of paying taxes matters when deciding on a purchase. 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 the gasoline tax, which suggests taxes on fossil fuels are likely to display salience.

This finding has some interesting implications, especially in times when fossil fuel prices fluctuate strongly, as has been the case since the 1970s: it means that beside their effects on prices, taxes can have an impact through their mere existence, as consumers seem to dislike the idea of paying them. This is particularly relevant in the case of the Swiss CO_2 levy: since its introduction in 2008, it was raised several times to reach in 2018 a level that is eight times higher than ten years before, but the price of oil, the main fossil fuel consumed by Swiss households, sharply decreased at the end of 2014 to stay at a lower level, as can be seen on Figure 1. In this context, the impact of the tax on heating oil's market price may well go unnoticed, which would make consumer unlikely to react to it. Nevertheless, if the Swiss carbon tax is salient, an effect can be expected even in the absence of a visible price increase, because of tax aversion.

Figure 1: Evolution of the average heating oil price in Switzerland, Europe Brent Crude and the Swiss carbon tax rate



Sources: FSO, FOEN, SNB, U.S. EIA

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 2017; Ecoplan, EPFL, and FHNW 2015) to model counterfactuals of what would have happened if there had been no carbon tax in Switzerland, or by surveying firms (TEP Energy 2016). If Ecoplan et al. (2015) find the tax had a negative effect on CO_2 emissions and a positive one on energy substitution away from oil, there results are by nature hypothetical and therefore might differ from those of an observational study. Hence, there is plenty of room for other research projects on the topic, especially empirical ones, as there seems to be a gap in the literature on carbon taxation using empirical methods to establish causal effects.

3 Analytical framework

This paper uses a DID approach to figure out whether the 2016 increase in the Swiss CO_2 levy rate had any short-term impact on 1) households' fossil heating fuel consumption, and 2) fossil fuel users' propensity to make energy-saving renovations. DID allows to estimate causal effects (Lechner 2011) under the classical Rubin causal model (see Imbens and Rubin 2015). The idea behind DID is to model the potential outcome for the treatment group if it had not been treated by using the actual outcome of a control group that is similar enough to the treatment group so that outcomes for both would have been the same if they had been assigned the same treatment status. This is called the *common trends assumption*, i.e., without intervention both groups would have followed the same evolution. The validity of any finding in a DID model therefore relies on the comparability between the treatment and control groups, as the ATT is defined as the difference between the actual outcome for the treated and their (unobserved) counterfactual outcome.

Randomised control trials (RCTs) are the gold standard in this regard: by randomly sampling units of observation from the same population, it ensures that treated and non-treated units do not systematically differ. However, outside the lab, it is often impossible to achieve such a high degree of similarity; with the CO_2 levy, we are in the situation of a natural experiment, which means the allocation of treatment (paying the carbon tax) cannot be exogenously controlled to imitate an RCT. We thus need to ensure *ex-post* that treatment and control units are comparable.

To do so, inverse probability of treatment weighting (IPTW) is used. The idea behind this method is to give a larger weight to units that are the most likely to be in the treatment group in which they are not (Austin 2011), which helps to estimate the average treatment effect on the whole population (ATE). When one is interested in estimating the ATT instead, these weights are equal to 1 for the treated units and to $\frac{e_i}{1-e_i}$ for the non-treated, where e_i is unit i's probability of being treated, that is, a propensity score (PS) (Austin and Elizabeth A. Stuart 2015). It is defined as $e_i = Pr(Treat_i = 1|X_i)$ where X_i is the set of covariates used to estimate e_i. IPTW relies on the covariate balancing properties of propensity scores (F. Li, Morgan, and Zaslavsky 2016; Rosenbaum and Rubin 1983): conditional on the PS, covariates included in X_i should be balanced between treatment and control units. Said differently, all units with the same PS should have the same distribution of X_i (Austin 2011). Confounding caused by observables can thus be mitigated.

With longitudinal data, weights need to be estimated for each time period if covariates vary across time (see Kupzyk and Beal 2017). However, it might happen that instead of panel data, only repeated cross-sections are available. In this situation, Stuart et al. (2014) propose another IPTW method for cases with two periods ($Post_t \in \{0, 1\}$) and binary treatment ($Treat_i \in \{0, 1\}$), i.e., the most basic DID situation. They split the sample into four groups: group 1 contains units for which $Treat_i = 1$ & $Post_t = 0$; group 2 contains units for which $Treat_i = 1$ & $Post_t = 1$; group 3 contains units for which $Treat_i = 0$ & $Post_t = 0$; and group 4 contains units for which $Treat_i = 0$ & $Post_t = 1$. They propose to estimate four PS $e_k(X_i)$ for each unit, i.e. one per group k, with $k \in \{1, 2, 3, 4\}$. They then construct weights for each unit i: $w_i = e_1(X_i)/e_g(X_i)$ where $e_1(X_i)$ is the probability for unit i of being in group 1 given X_i and $e_g(X_i)$ is the probability for the same unit of being in its actual group g. This strategy balances covariate distribution between groups according to the reference group of treated units in the pre-treatment period.

Units in groups 2-4 that are the most likely to be in group 1 thus receive greater weights than those which are not. Both types of weights are used in our analysis, since the first hypothesis is tested using a combination of longitudinal and repeated cross-sectional data, while the second hypothesis relies on a test using panel data only.

Estimating the PS to compute the weights can be challenging because of two main issues. The first concerns the variables to include, and therefore 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 an increasing bias. 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 issue is how to estimate the PS. If the traditional approach is to use logistic regression, some researchers (e.g., Lee et al. (2010)) suggest to use classification and regression trees (CARTs), for instance. Imai and Ratkovic (2014) propose another method based on generalised method of moments (GMM) framework that includes a covariate balancing condition, which they call the covariate balancing propensity score (CBPS). Deciding on which estimation method to use is thus far from obvious; it is therefore advisable to test different ones until proper covariate balance is achieved. In this paper, it has been decided to use both (multinomial) logistic regression and CBPS to construct the weights. As shown in section 4, weights obtained through CBPS achieve a high level of balance among covariates, which fulfils the goal of the IPTW method.

With the help of these weights, two different DID models are set up: a first one to test the hypothesis that the 2016 carbon tax increase led to lower fossil heating fuel demand, and a second one to test the hypothesis that the tax rise increased the propensity to renovate of fossil fuel users. The first model takes a log-linear form, with the dependent variable $\ln y_{it}$ being the natural logarithm of yearly heating expenditures, transformed to a quantity using an energy price index (more on this in the next section) . It can be formalised as follows :

$$\ln y_{it} = \beta_0 + Treat_i\beta_1 + Post_t\beta_2 + (Treat_i * Post_t)\beta_3 + G_{it}\beta_4 + \varepsilon_{it} \qquad (1)$$

where G_{it} is a set of covariates and ε_{it} is a stochastic error term. The ATT is given by β_3.

The second model has a similar form, but slightly differs in that the dependent variable r_{it} is binary, as it indicates whether a household renovated its heating system, windows, façade and/or roof during the year. It therefore takes the form of a logit model, which affects the common trends assumption of DID. Indeed, as shown by Puhani (2012), in non-linear DID models this assumption shall be replaced by the common trends of the non-linear transformation assumption (on this, see also Blundell and Dias 2009; Lechner 2011). The specification of the model is therefore the following:

$$Pr(r_{it}) = \Lambda\big(\gamma_0 + Treat_i\gamma_1 + Post_t\gamma_2 + (Treat_i * Post_t)\gamma_3 + H_{it}\gamma_4 + \upsilon_{it}\big) \quad (2)$$

where $Pr(r_{it})$ is the probability that $r_{it} = 1$, H_{it} is a set of covariates, υ_{it} a stochastic error term and $\Lambda(\cdot)$ is the logistic function, i.e., $\Lambda(\cdot) = \frac{\exp(\cdot)}{1+\exp(\cdot)}$. The ATT is then given by:

$$ATT = \Lambda\big(\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3 + \bar{H}\gamma_4\big) - \Lambda\big(\gamma_0 + \gamma_1 + \gamma_2 + \bar{H}\gamma_4\big) \quad (3)$$

and not simply γ_3 due to the non-linear transformation (Puhani 2012).

4 Data

4.1 Dataset

Data used in this study come from the Swiss Household Energy Demand Survey (SHEDS). SHEDS is a multidisciplinary survey managed by the Swiss Competence Center for Research in Energy, Society and Transition (SCCER-CREST)[2] that covers a wide range of aspects related to Swiss households' energy demand, preferences, behaviour, as well as psychological and socio-economic characteristics. Since 2016, approximately 5,000 households are surveyed every year, of which a share responded several times. The database is therefore a combination between a panel and repeated cross-sections. It should also be noted that some questions are usually added, updated or dropped between survey waves, and some are also only asked once to respondents so that they spend less time answering the questionnaire on the follow-

[2] https://www.sccer-crest.ch/

ing year, if they decide to do so. Hence, depending on the variable considered, some restrictions on the size and composition of the dataset need to be imposed.

Two subsets of the SHEDS database are used, both drawn from the 2016 and 2017 waves of the survey. The first one, which is used to test for the impact of the change in CO_2 tax rate on fossil heating fuel demand, consists in a combination of longitudinal and repeated cross-sectional observations in order to keep as many observations as possible. When asked about their heating expenditures, respondents could state whether they used their last heating bill to answer or if they only provided an estimation; as estimations are unlikely to be precise enough to detect real changes in heating consumption, respondents who did not use their bill to answer are dropped from the sample, which has a strong impact on its size. In this context, using only observations for which longitudinal information is available would further restrict the sample size to a point where results would be too imprecise, hence the need to include also observations for which only cross-sectional information is available. The top and bottom 1% of the sample have moreover been dropped to remove outliers that are likely aberrant responses.

To test the hypothesis that the 2016 tax rate increase had a positive impact on the propensity of fossil fuel users to renovate, longitudinal data need to be used as precise information on renovations was only collected in the 2017 survey wave, while information necessary to construct other covariates was collected in both waves. Only households who did not move to a new home between the two waves are included so that information on renovations can be used. Despite missing data, a sample with a reasonable number of observations can be drawn from the SHEDS database to carry out a statistical analysis.

SHEDS contains various characteristics about Swiss households. The most important in our case are the two dependent variables, i.e., yearly heating expenditures and whether any renovation took place and when. Heating expenditures *per se* do not tell much about changes in volumes when compared across years because of changes in energy prices. 2016 values are therefore divided by a price index that takes 2015 as basis year so that expenditures in the post-treatment period are expressed in prices of the pre-treatment period. The influence of changes in energy prices on the values of expenditures can thus be attenuated, so that only variations caused by changes in volumes remain. Data on the evolution of fuel prices is obtained from the consumer price index of the Swiss Federal Statistical Office. Another point to consider is that each survey wave was launched in April-May of 2016 and 2017; it is hence assumed that when asked about their last annual heating expenditures, respondents provided information from the previous year (hence

2015 and 2016, respectively), as most people pay their heating bills in Summer in Switzerland.

Precise information on renovations was collected in the 2017 wave: people were asked if and when a renovation last took place for four items: windows, heating system, façade and roof. It is hence possible to construct a binary variable for each household-year observation that tells if a renovation had been undertaken in the preceding year (i.e., 2015 and 2016, before and after the carbon tax rate change). Information on why the renovation took place is also available, making it possible to know if a household consciously considered the CO_2 levy while taking its decision.

Other relevant data include socio-economic characteristics (income, education, age of respondent, household size), valuation of the environment,[3] geographical indications (type of living area, part of Switzerland), as well as information on the accommodation (type of building, floor surface, building year, conformity to Minergie standards[4]). Most of these variables will be used as controls in the regression analyses.

4.2 Weights estimation

IPT weights are constructed using PS estimated by both logistic regression and the CBPS method. For the first hypothesis, the multinomial extension of the logistic regression needs to be used as four different PS are estimated (one per group). For the second one, standard logistic regression and CBPS are used to estimate pre-treatment and post-treatment weights. CBPS is implemented using the eponymous package on R.[5]

The dependent variable for the estimations is the treatment indicator, i.e., a dummy taking the value 1 for households whose heating system uses fossil fuels (oil or gas). Independent variables are the ones over which balance is to be achieved. For the first hypothesis, these variables are: being home-owner, living in a house, living in the countryside, living in Romandie, building year of the home, floor surface, conformity to Minergie standards, renovation of the heating system after 2010, valuation of the environment, having a tertiary level of education, natural logarithm

[3]This variable is constructed from two questions about how much the respondent valued the protection of the environment and preventing pollution on a 1-to-5 scale, where 5 corresponds to the maximum valuation. The variable is the average of these two indicators.

[4]`www.minergie.ch`

[5]`https://cran.r-project.org/web/packages/CBPS/index.html`

of monthly income, size of the household and average room temperature. These variables have been chosen because of their likely influence on both the probability of treatment and the outcome variable. They cover most relevant characteristics of households and their accommodations.

For the second hypothesis, most variable are kept, except that the renovation of the heating system and the average room temperature are dropped because of endogeneity with the outcome variable (propensity to renovate), and a dummy indicating if the respondent consider being risk-taker in financial terms is added, as it might influence their probability of undertaking renovations due to potentially high costs.

For the first hypothesis, the weights described in Stuart et al. (2014) are used (see previous section). For the second hypothesis, weights are constructed to estimate the ATT, as described in Austin (2011): $w_i = Treat_i + \frac{(1-Treat_i)e_i}{1-e_i}$. Information on the balance in covariates achieved with these weights is provided in the next subsection.

4.3 Descriptive statistics

Table 1 presents a statistical summary of the characteristics of the four groups used to test the first hypothesis; the second sample is very similar to it, except in terms of number of observations (568 households over the two time periods). It can be noted that group sizes tend to vary, with half the observations in group 2; however, when only respondents whose heating expenses are based on their actual consumption are considered, groups are more balanced.

The main differences between the treatment and control groups come from the fact that the control groups tends to contain more house-owners than the treatment groups, which contains more tenants living in apartments. The treatment groups therefore tend to live in smaller, older and less energy-efficient homes, and have lower incomes. The weighting strategy is therefore expected to give more importance to non-house owners in the control groups to achieve a satisfactory covariate balance.

One noticeable thing is that heating and hot water expenditures seem not to have changed a lot between the pre- and post-treatment periods when expressed in 2015 prices. This suggests it is likely that the 2016 carbon tax increase had no noticeable impact on heating demand by fossil fuel users in comparison to non-fossil fuel users. Results presented in the next section seem to confirm this observation.

Table 1: Descriptive statistics

Statistic	Group 1	Group 2	Group 3	Group 4
Heating and hot water	1,531.64	1,509.09	1,375.05	1,414.02
expenses (2015 prices)	(863.27)	(916.41)	(1,041.52)	(996.81)
Heating bill based on actual consumption	0.49	0.50	0.75	0.78
Average room temperature	20.82	20.84	20.93	20.74
	(1.03)	(1.03)	(1.08)	(1.06)
Owner	0.47	0.41	0.69	0.62
House	0.31	0.33	0.51	0.56
Surface (m^2)	123.02	116.00	149.01	140.92
	(72.59)	(65.02)	(68.40)	(68.71)
Building year	1,972.00	1,967.34	1,986.17	1,979.36
	(28.78)	(34.85)	(37.04)	(47.61)
Minergie	0.10	0.08	0.41	0.32
Recent renovation of the heating system	0.22	0.26	0.13	0.23
Age of respondent	55.76	53.14	53.05	50.92
	(14.40)	(14.69)	(13.65)	(13.67)
Income	7,861.04	7,699.36	8,715.00	8,415.12
	(2,706.07)	(2,878.42)	(2,903.33)	(2,847.19)
Tertiary education	0.41	0.43	0.46	0.47
Household size	2.10	2.15	2.34	2.41
	(1.09)	(1.12)	(1.13)	(1.18)
Valuation of the	4.30	4.20	4.34	4.22
environment	(0.71)	(0.73)	(0.61)	(0.71)
Believe oil price will increase	0.71	0.77	0.75	0.78
City	0.54	0.55	0.30	0.33
Agglomeration	0.28	0.29	0.40	0.32
Countryside	0.18	0.16	0.30	0.34
Romandie	0.25	0.23	0.25	0.23
Alps	0.22	0.21	0.21	0.24
East	0.27	0.31	0.30	0.29
West	0.25	0.25	0.24	0.24
Observations	376	1,012	100	377
% Total	20.16	54.26	5.36	20.21

Note: Standard deviation in parenthesis for non-binary variables. Group 1 contains treated units in the pre-treatment period; group 2 contains treated units in the post-treatment period; group 3 contains control units in the pre-treatment period; group 4 contains control units in the post-treatment period.

Table 2 provides some balance measures for the sample when CBPS weights are used for both the sample used to test hypothesis 1 and the sample used to test hypothesis 2. It reports the maximum absolute values of standardised differences in means as well as Kolmogorov-Smirnov statistics for continuous variables, and only maximum absolute differences in proportions for binary variables, both before and after adjustment across all groups. For the first sample, all four groups are compared among themselves, while for the second sample only the treatment and control groups are compared before and after the application of the treatment, as the same households are considered in both periods, which is not the case in the first sample. The smaller are these measures, the better, as it means the distribution of covariates between the treatment and control groups is similar in both the pre- and post-treatment periods. As can be seen, the balance in covariates achieved by using these weights is quite good, especially for the second sample, which means the comparability of the treatment and control groups should be improved by the use of IPTW. The results of the regression analysis are therefore expected to be more robust when weights are included than when they are not.

Table 2: Covariate balance across treatment groups

	Sample 1				Sample 2			
	Mean diff.		KS		Mean diff.		KS	
	Unadj.	Adj.	Unadj.	Adj.	Unadj.	Adj.	Unadj.	Adj.
Owner	0.598	0.073			0.277	0.000		
House	0.522	0.057			0.384	0.000		
House*Owner	0.425	0.062			0.316	0.000		
Countryside	0.392	0.093			0.395	0.000		
Romandie	0.046	0.081			0.136	0.000		
Building year	0.508	0.049	0.401	0.193				
Built before 2000					0.652	0.000		
Surface (m^2)	0.483	0.067	0.291	0.138	0.069	0.000	0.091	0.088
Minergie	0.664	0.027			0.969	0.000		
Heat. sys. renov.	0.393	0.034						
Avg. temp.	0.179	0.034	0.099	0.078				
University	0.120	0.037			0.094	0.000		
Income (log)	0.332	0.013	0.162	0.065	0.151	0.000	0.091	0.053
HH size	0.258	0.069	0.147	0.082	0.104	0.000	0.066	0.027
Envir. val.	0.230	0.061	0.076	0.040	0.146	0.000	0.045	0.052
Risk-taker					0.093	0.000		

Note: Only maximum values across all groups are reported for both (standardised) mean differences and Kolmogorov-Smirnov statistics.

5 Results

5.1 Regressions

Results for the first hypothesis are displayed in Table 3. The first two columns display the results from regressions without weights, while the four others include either multinomial logit weights (columns 3 and 5) or CBPS weights (columns 4 and 6). Out of robustness concerns, two models have been tested solely with observations from respondents whose heating expenditures depend only on their actual consumption, and not on some other parameters such as the size of their home (columns 5 and 6). These two models are therefore supposed to be the most robust of the six, as data they use should be more reliable. As a better balance in covariates is achieved by using CBPS weights, the sixth model is preferred over the others.

In all specifications, the coefficient of the interaction between the treatment and the period dummies is not significant, indicating that the 2016 carbon tax increase seems to have exerted a negligible impact on the heating demand of fossil fuel users. Some covariates have a significant effect on the outcome variable across all models:

living in a house, living in Romandie, building year of the dwelling, floor surface and income. It is not surprising to find that living in a house or having a large floor surface are linked to high expenditures for heating. Similarly, it can be expected that the more recent the building, the more energy-efficient it is; hence the negative impact of the building year variable. The effect found for income means that richer households tend to demand more heating than poorer ones, everything else being constant, which is again not a surprise, as richer households have the financial means to afford heating more their homes than poorer ones. It is interesting to note that inhabitants of the French-speaking part of Switzerland demand on average more heating than the others; it is however hard to find a convincing explanation for this phenomenon outside the 'cultural difference' one. Further research could be done on that element. In general, it can be concluded that the tax rate increase had no significant short term impact on fossil heating fuel consumers, even in the most robust model. Most other coefficients are nevertheless significant and with the expected signs, which shows that meaningful relationships can be detected by our model where they exist.

Results from regressions used to test the second hypothesis are presented in Table 4. The panel contains 568 households, of which 181 are in the control group and 387 in the treatment group. Again, models with and without weights have been run to allow for a better check of the consistency of the results. Columns 1 to 3 display models without IPT weights: the first and second ones are standard logit models, while the third includes random effects. In these models, no statistically significant effect can be found for the coefficient of the interaction term between the treatment allocation and treatment period dummies. This could be due to imbalances in the covariates; hence, IPTW models are run (columns 4 and 5), but the results do no differ much, except that the coefficients of some covariates that were previously significant are not any more. Only the dummy indicating if the construction year of the building is before 2000 remains significant, but the coefficient of interest stays statistically not different from 0. This means the CO_2 tax increase had no visible impact on the probability that fossil fuel users renovate when compared to non-fossil fuel users. This result corroborates the previous one, that the 2016 carbon tax increase had no short term effects on Swiss households in terms of heating demand and propensity to renovate.

As robustness checks, three other specifications have been run. Columns 6 to 8 of Table 4 present models that use only information from house-owners. House-owners are the households who have the leeway regarding decisions over the renovation of their homes; hence, short-term effects of the carbon tax increase might be easier to detect in this subsample because they can decide to renovate more freely and

Table 3: Results - Weighted DID models

	Dependent variable:					
	Real heating & hot water expenditures (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.01	0.02	−0.07	−0.12	0.02	−0.02
	(0.08)	(0.08)	(0.14)	(0.13)	(0.12)	(0.12)
Fossil fuel	0.20**	0.25***	0.23	0.18	0.14	0.11
	(0.08)	(0.08)	(0.15)	(0.14)	(0.14)	(0.14)
Post*	−0.08	−0.06	0.03	0.08	0.02	0.06
Fossil fuel	(0.09)	(0.09)	(0.14)	(0.14)	(0.13)	(0.13)
Owner		0.11***	0.04	0.08*	0.001	−0.02
		(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
House		0.15***	0.27***	0.24***	0.50***	0.55***
		(0.05)	(0.04)	(0.04)	(0.06)	(0.06)
Countryside		0.002	−0.01	−0.04	0.03	0.03
		(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Romandie		0.17***	0.15***	0.14***	0.20***	0.21***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Building year		−0.001*	−0.001*	−0.001**	−0.002***	−0.002***
		(0.001)	(0.001)	(0.0005)	(0.0005)	(0.0005)
Surface (m^2)		0.002***	0.001***	0.001***	0.001**	0.001***
		(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Minergie		−0.18***	−0.12**	−0.12**	0.04	0.03
		(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Renovation of		−0.003	−0.02	0.01	−0.03	−0.05
heat. sys.		(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Envir. val.		0.04*	0.07***	0.04**	0.03	0.03
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
University		−0.03	0.01	0.01	0.02	0.002
		(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Income (log)		0.14***	0.15***	0.10**	0.15**	0.14**
		(0.05)	(0.05)	(0.04)	(0.06)	(0.06)
HH size		0.04**	0.02	0.04***	−0.005	−0.01
		(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Avg. temp.		0.02	0.01	0.02	0.02	0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	6.97***	6.67***	6.49***	7.50***	8.01***	8.86***
	(0.07)	(1.12)	(1.16)	(1.04)	(1.19)	(1.08)
Observations	1,865	1,865	1,865	1,865	1,057	1,057
IPTW	No	No	MNL	CBPS	MNL	CBPS
Actual cons.	No	No	No	No	Yes	Yes
Adjusted R^2	0.01	0.12	0.11	0.11	0.12	0.12

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 4: Results - IPTW logit DID models

	Dependent variable:							
	Renovation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.19	0.19	0.19	−0.28	−0.31	0.56	0.76	0.82
	(0.38)	(0.40)	(0.41)	(0.58)	(0.61)	(0.55)	(0.65)	(0.66)
Fossil fuel	0.69**	0.68*	0.70*	0.45	0.42	0.98*	1.13**	1.20**
	(0.33)	(0.36)	(0.37)	(0.45)	(0.48)	(0.52)	(0.55)	(0.56)
Post*Fossil fuel	−0.13	−0.14	−0.13	0.33	0.36	−0.37	−0.61	−0.67
	(0.43)	(0.44)	(0.47)	(0.61)	(0.65)	(0.63)	(0.71)	(0.71)
Owner		0.09	0.10	0.23	0.22			
		(0.24)	(0.27)	(0.34)	(0.35)			
House		0.49**	0.52*	0.33	0.41			
		(0.25)	(0.27)	(0.32)	(0.31)			
Countryside		−0.20	−0.21	0.07	−0.07	−0.34	−0.22	−0.23
		(0.25)	(0.25)	(0.30)	(0.29)	(0.35)	(0.34)	(0.34)
Romandie		0.42*	0.44*	0.18	0.17	0.42	0.34	0.32
		(0.22)	(0.23)	(0.28)	(0.28)	(0.37)	(0.31)	(0.32)
Built before 2000		0.99***	1.02***	0.83**	0.80**	0.75	0.57	0.59
		(0.32)	(0.32)	(0.34)	(0.36)	(0.46)	(0.39)	(0.39)
Surface (m^2)		0.0001	−0.0000	−0.001	−0.002	0.0007	0.0000	−0.0001
		(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Minergie		0.42	0.44	0.21	0.20	0.44	0.38	0.45
		(0.31)	(0.32)	(0.33)	(0.34)	(0.48)	(0.47)	(0.47)
University		0.09	0.09	0.01	0.02	−0.36	−0.37	−0.42
		(0.20)	(0.21)	(0.24)	(0.24)	(0.33)	(0.30)	(0.30)
Income (log)		−0.36	−0.37	−0.10	−0.30	0.10	0.28	0.28
		(0.29)	(0.30)	(0.34)	(0.37)	(0.51)	(0.42)	(0.42)
HH size		0.03	0.03	−0.09	−0.05	0.09	0.06	0.06
		(0.09)	(0.09)	(0.11)	(0.11)	(0.14)	(0.13)	(0.13)
Envir. val.		−0.05	−0.05	−0.13	−0.11	0.13	0.11	0.09
		(0.11)	(0.14)	(0.13)	(0.13)	(0.24)	(0.17)	(0.17)
Risk-taker		0.57**	0.58**	0.20	0.28	0.86*	0.41	0.53
		(0.27)	(0.28)	(0.31)	(0.31)	(0.45)	(0.43)	(0.42)
Constant	−2.58***	−0.61	−0.78	−1.70	0.12	−5.64	−6.43*	−6.48*
	(0.30)	(2.55)	(2.74)	(3.21)	(3.55)	(4.71)	(3.74)	(3.78)
Observations	1,136	1,136	1,136	1,136	1,136	566	566	566
IPTW	No	No	No	MNL	CBPS	No	MNL	CBPS
Random effects	No	No	Yes	No	No	Yes	No	No
Nagelkerke pseudo-R^2	0.008	0.035	NA	0.022	0.024	NA	0.033	0.038

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

therefore more rapidly. However, no such effect is found, either when a random effect model is used or IPT weights are included. We are therefore unable to reject the hypothesis that the 2016 carbon tax increase had no short-term impact on renovation decisions among Swiss households.

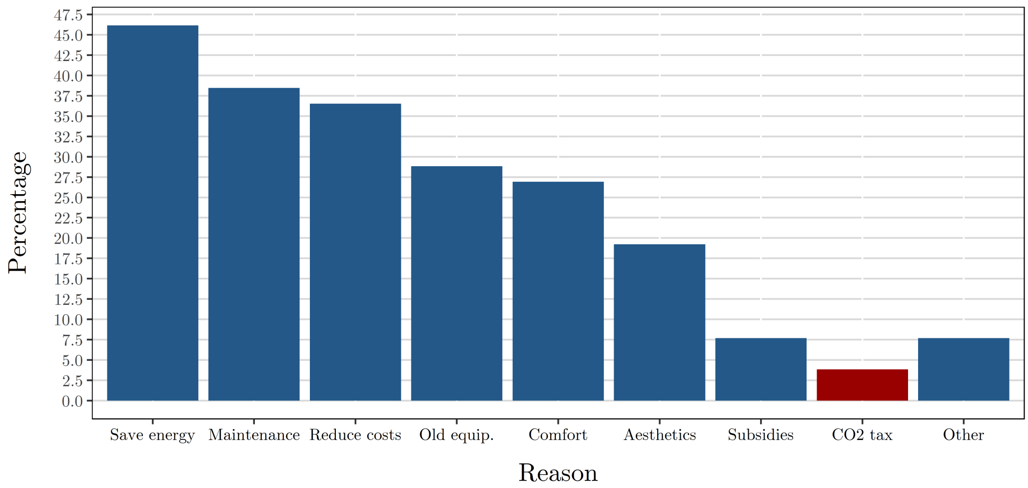
5.2 Discussion and policy implications

Our results suggest that Swiss households cannot be expected to quickly react to the progressive increase of the CO_2 levy. Although heating expenditures corrected for changes in fuel prices might not be the best proxy for heating demand, these results provide some evidence that more action is needed to enhance the effectiveness of the Swiss carbon taxation system regarding households. Decisions to renovate seem not to be a direct consequence of the existence of the carbon tax: only few SHEDS participants mention it as a reason for renovating. Figure 2 shows the reasons provided by respondents who renovated in either 2015 or 2016 [6] As can be seen, the CO_2 levy was mentioned only 3.85% of the time as a reason for renovations, the lowest of all offered choices. Most of the time, saving energy, reducing energy costs and replacing an outdated equipment were indicated. As previously said, the impact of the tax on fossil fuels' market prices is hardly visible given the large exogenous variations affecting them. Hence, the Swiss carbon tax seems to lack salience as households do not react to either its mere presence (tax aversion) or its effect on prices, although the latter channel could be effective if the tax had a more visible impact on fossil fuel prices, if we consider the reasons provided by respondents.

Of course, it should be remembered that only short-term effects are considered here; it is probable that taxing CO_2 will have some longer-term effects, especially if the rate applied reaches higher levels. Another point is that most respondents seem not to properly know how the Swiss CO_2 levy works. In the 2018 SHEDS report, Burger et al. (2018) underline the fact that most respondents tend to lack understanding of 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 guessed how much they were receiving through the tax redistribution scheme, an information they can easily find on their health insurance bills. It should furthermore be noted that a short description of the CO_2 levy was provided before the question was asked. This apparent lack of knowledge coupled with small share of respondents who mentioned the tax as reason

[6] It should be noted that there are data on reasons to renovate for only 52 observations of the panel because only owners were asked to provide a reason, and not all of them answered.

Figure 2: Reasons for renovating



that pushed them to renovate suggests Swiss households are unlikely to take action to decrease the amount of carbon tax they pay because they are not fully aware of how much it effectively costs them.

In addition, some households might lack the capacity of taking action to pay less tax because they do not pay their heating bill on the basis of actual consumption but on another factor such as the size of their home, which is often the case of tenants and apartment-dwellers. In this context, a 'split incentive issue' arises (see e.g., Gillingham, Harding, and Rapson 2012). Households in these situations have indeed little incentive to lower their heating demand, as it would have only a minor impact on their heating bills if their neighbours do not do the same. Moreover, tenants and apartment-dwellers have less decision power over renovations, which means that even if they wanted, they could not improve the energy-efficiency of their homes because they would not have the capacity to do so. Therefore, a significant share of Swiss households cannot be expected to substantially react to the CO_2 levy, as they have little reason and/or capacity to do so.

From a policy perspective, these findings have important implications. First, the CO_2 levy seems imperfectly designed to nudge households, as it only targets those who can directly act on their heating demand. Second, people are on average not well informed about how they are affected, which means it is unlikely to steer their behaviour in the intended direction, hence the lack of effect found in the regression analysis. Finally, as it is one of the main tools the Swiss government has set up to fight climate change, its apparent lack of effectiveness questions its relevance: complementary or alternative measures might be more effective, especially in the short term. It should be noted that the short-term aspect of the issue is important to consider, as the tax rate is increased if GHG emission reduction thresholds are not met, and up to 2018 the achievement of these thresholds was checked biennially. This means short term efficiency is a criteria used to manage this policy instrument; hence, in the absence of short-term effects on households, it becomes possible that the tax be raised above its optimal middle-to-long-term level if households need time to react.

6 Conclusion

Although more and more countries implement carbon taxation schemes to lower GHG emissions, little empirical studies of their effectiveness exist, in particular in the residential sector. To contribute to the literature on the topic, this paper analyses the effectiveness of the Swiss CO_2 levy to push households who use fossil heating fuels to lower their heating consumption and to increase their propensity to undertake energy-efficiency-enhancing renovations. Household-level data gathered as part of the SHEDS project is used to construct two datasets to test the two aforementioned hypotheses.

Using IPTW within a DID framework comparing the year before and the year after the 2016 carbon tax rate increase, it is found that fossil fuel users seem not to have followed different patterns in terms of heating consumption and propensity to renovate than non-fossil fuel users in the short term. It can therefore be concluded that the Swiss CO_2 levy is likely to lack incentive power to reach its goal of lowering GHG emissions from households. These findings question the adequacy of the design of this policy instrument regarding households, especially given its central position in the strategy of the Swiss federal government to fight anthropogenic climate change.

Further work should look at longer-term trends in fossil heating fuel consumption, and should also look at the replacement rate of polluting heating technology by cleaner ones. The question of the optimal tax rate should also be investigated in order to better inform policy makers on the path to follow to efficiently lower GHG emissions caused by households. Finally, qualitative information on households' preferences regarding heating could also provide more information on how to more efficiently nudge them so that they consume less fossil fuels.

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