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Climate policy without a price signal: Evidence on the implicit carbon price of energy efficiency in buildings*

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Abstract

Based on data for a portfolio of 548 multi-unit buildings observed over 16 years, we quantify the impacts of more than 400 energy efficiency interventions among 240 treated buildings. We exploit variation in the timing of investments to provide evidence that treated and control buildings follow the same trend in the absence of energy efficiency investments, and use staggered difference-in-differences regressions to document building-level energy savings, CO_2 abatement, and heating expenditure reductions. We find considerable heterogeneity in the price of carbon implicitly associated with alternative interventions, with estimates for frequently subsidized measures well above available benefit estimates for avoided emissions.

Keywords: Regulation; implicit carbon price; energy efficiency investments; energy savings; staggered design; climate policy.

JEL Codes: H21; H23; Q41; Q49; Q58; R31.

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1 Introduction

Market-based approaches to regulate externalities associated with CO_2 emissions generate a carbon price that signals which investments are worth pursuing. In practice, however, countries often pursue alternative policies that target specific investments to reduce fossil fuel use. One prominent example is the widespread promotion of energy efficiency investments in buildings through highly subsidized weatherization programs.[1] This approach to regulation implies that the price of carbon is implicitly defined by investment decisions (Gillingham and Stock, 2018). In turn, policy-makers are left with the difficult task of selecting interventions that are worth pursuing, in the sense that the associated implicit price of carbon (i.e., the cost of reducing CO_2 emissions by one tonne) is below estimates of avoided damages (Muller and Mendelsohn, 2009; Greenstone et al., 2013).

The purpose of this paper is to provide empirical evidence on the implicit carbon price of alternative energy efficiency investments in buildings, and illustrate the extent of heterogeneity across frequently targeted interventions. We employ data for a portfolio of 548 buildings managed by a single Swiss company, observed from 2001 to 2016, representing 12,820 units rented on the market (94% residential).[2] During the observation period, 240 buildings benefited from energy efficiency investments, and our data allow us to derive forensic evidence for the implicit carbon price across the following interventions: insulation of exterior walls, roof or attic, replacement of windows, installation of smart thermostats that optimize heating operations using real-time information (e.g., weather forecasts), replacement of the boiler, including fuel switching from heating oil to natural gas.[3]

The primitive to estimate the implicit price of carbon is energy savings, which determines both

1 In developed countries, around 40 percent of energy use is associated with buildings (Fernandez, 2007), and the IEA (2017) estimates worldwide energy efficiency investment at USD 231 billion in 2016, with 133 billion in the buildings sector alone. Concrete policies promoting efficiency in buildings include the "Weatherization Assistance Program" in the U.S. and the "KfW Energy Efficiency Program" for energy efficient construction and refurbishment in Germany.

2 Energy consumption patterns is known to differ across commercial and residential uses, see for example Costa and Kahn (2011) and Kahn et al. (2014). Our sample does not include purely commercial buildings, and we come back to the presence of a small share of commercial leases below.

3 We also consider three interventions that do not directly target energy efficiency, but were included in a number of investment bundles, namely the installation of individual space heating meters, hot water meters, and solar thermal collectors.

reductions of carbon emissions and financial savings associated with lower energy use.[4] One empirical challenge to identify energy savings is non-random assignment of energy efficiency investments, and in turn the estimation of a counterfactual baseline energy use (Fowlie et al., 2018; Burlig et al., 2017). In the setting we consider, building-level expenses in relation to heating fuel consumption are fully passed forward to tenants, so that property owners do not benefit directly from reduced heating costs (see Levinson and Niemann, 2004; Gillingham et al., 2012). Put differently, tenants who directly benefit from improved energy efficiency cannot influence investment decisions. This prevents direct self-selection extensively discussed in the evaluation of renovation programs targeting owner-occupied properties (Metcalf and Hassett, 1999; Allcott and Greenstone, 2017). Instead, investment decisions likely reflect expectations about indirect benefits, including property maintenance costs and market value (see Brounen and Kok, 2011; Eichholtz et al., 2013; Walls et al., 2017).

In an attempt to mitigate selection bias associated with investment decisions, we exploit the fact that 308 buildings experienced no energy-related investments. These buildings constitute a candidate control group to estimate counterfactual energy use among treated buildings in the absence of investments. Importantly, the timing of energy efficiency investments across buildings implies that treated buildings gradually enter the post-treatment period, which allows us to compare pre-treatment trends for treated and control buildings over fourteen years of data. In a nutshell, our data shows that, before energy efficiency investments, treated buildings use on average more energy per square meter relative to control. Moreover, the difference is approximately constant with time, which suggests that the evolution of energy use in control buildings provides relevant information to inform a counterfactual for treated buildings.[5]

Based on this, we implement a staggered difference-in-differences estimation strategy (Autor, 2003; Stevenson and Wolfers, 2006), and we start by quantifying energy savings associated with individual energy efficiency interventions, controlling for year and buildings fixed effects, local weather shocks and fuel prices, as well as complementarity effects across interventions (Mulder

[4] In all the buildings we consider, tenants share a single central heating appliance that operates on either heating oil or natural gas. As described below, we use standard conversion factors to quantify CO_2 emissions associated with each fuel.

[5] Note that average energy use in both treated and control buildings trends downward during the observation period. One implication is that energy use declines with time even without energy efficiency investments, which makes the use of a control group particularly important to identify the causal effect of interventions.

et al., 2003). Providing evidence on heterogeneous energy savings associated with alternative energy efficiency investments is the first contribution of our work, and it is important because policies (e.g., subsidies for wall insulation or windows replacement) typically target interventions based on expected energy savings. Because of non-random treatment assignment, however, our estimates represent an average treatment effect on the treated (ATET), which potentially differs from the average treatment effect (ATE) and from the average treatment effect on the non-treated (ATENT). And because treated buildings use on average more energy relative to control, we test for treatment effect heterogeneity as a function of pre-treatment energy use. This allows us to provide evidence about energy savings for an average building in the portfolio (ATE) and for control buildings (ATENT).

We then exploit financial information on energy efficiency investments to quantify the implicit price of carbon associated with alternative interventions.[6] This delivers the main contribution of our work, and we proceed in two steps. First, we employ difference-in-differences regressions to estimate how CHF 1 invested in energy efficiency affects building-level CO_2 emissions. Second, we similarly quantify how each investment affects building-level annual heating expenditures. Together with standard engineering estimates on the lifetime of building elements and a discount rate (0% or 6%), we carry out inference on the implicit price of carbon. Intuitively, we construct a statistical counterpart to the often-cited "McKinsey curve" (McKinsey & Company, 2009), ranking energy efficiency interventions from the least to the most expensive.[7]

Overall, our empirical results demonstrate substantial heterogeneity in energy savings across alternative investments. For example, widely subsidized investments such as exterior wall insulation and the replacement of windows are associated with energy savings of 18 and five percent, respectively. For these two interventions, point estimates for the implicit price of carbon are around CHF 1,000 per tonne of CO_2. This is an order of magnitude above the CO_2 tax prevailing Switzerland (CHF 84/tCO_2 in 2016 SFOEN, 2018), and well in excess of estimated benefits of avoided emissions discussed in Greenstone et al. (2013, around USD 40/tCO_2, about the same

[6] Note that financial data refer to a common 2015 baseline, with an exchange rate of about CHF 1 = USD 1.

[7] We emphasize, however, that our estimates do not capture broader welfare impacts associated with energy efficiency investments, such as improved comfort for tenants and transaction costs for property owners (e.g., administrative costs). Evidence derived in the context of owner-occupied properties suggests that non-monetary costs are important (Fowlie et al., 2015; Allcott and Greenstone, 2017).

in CHF). By contrast, roof insulation and the installation of smart thermostats decreases energy use by around 10 percent on average, but the implicit carbon price is significantly lower. For roof insulation estimates are around 200 CHF/tCO_2, whereas most specifications indicate *negative* estimates for smart thermostats, suggesting that these investments are optimal even in the absence of externalities. We also find, however, that energy savings for smart thermostats tend to increase with pre-treatment energy use, so that the implicit price of carbon estimated for treated buildings is likely a lower bound for the corresponding population of non-renovated buildings.

Our work contributes to a growing literature quantifying the economic cost of reducing CO_2 emissions. A survey by Gillingham and Stock (2018) reports a range starting at -190 USD/tCO_2 for behavioral energy interventions (such as social comparison feedback; see Allcott and Mullainathan, 2010) and going up to 2900 USD/tCO_2 for transportation-related policies limiting emissions intensity (Holland et al., 2009). Gillingham and Stock (2018) discuss an estimate of 350 USD/tCO_2 for investments in buildings' energy efficiency, which is derived from Fowlie et al. (2018) in the context of the Weatherization Assistance Program offered to a sample of low-income homeowners in the U.S. state of Michigan. More specifically, results by Fowlie et al. (2018) refer to various bundles of interventions (including combinations of furnace replacement, roof and wall insulation, and infiltration reduction), and a weighted average of our preferred estimates is slightly above 380 CHF/tCO_2 (95% confidence interval: 247.28-518.27). Relative to Fowlie et al. (2018), we show that heterogeneity within the realm of buildings' energy efficiency interventions generates a range of implicit carbon prices corresponding to the much broader set if interventions considered in Gillingham and Stock (2018).

Our work is also related to a wider literature on imperfect information in the context of energy efficiency investments, one of the major components of the energy efficiency gap (Allcott and Greenstone, 2012; Gillingham and Palmer, 2014; Gerarden et al., 2017). For example, Joskow and Marron (1992) emphasize the use of realized energy savings (rather than *ex-ante* engineering projections) to evaluate energy efficiency programs, and mounting empirical evidence suggests that realized savings associated with energy efficiency in buildings generally fail to meet *ex-ante* projections (e.g., Grimes et al., 2016; Zivin and Novan, 2016; Liang et al., 2017; Burlig et al., 2017; Allcott and Greenstone, 2017; Fowlie et al., 2018).[8] One potential source of discrepancy between projected and realized savings is increased consumption of energy services (a rebound effect, see Gillingham et al., 2016).[9]

Relative to these studies, our data does not allow us to identify potential differences between projected and realized energy savings, or a rebound effect. Moreover, the context of our study is novel. First, whereas the bulk of the literature focuses on (semi-)detached properties, our results refer to apartment buildings. While these represent only 20 percent of dwellings in the U.S., among European countries the share amounts to 42 percent. Second, our data afford a rare investigation of energy efficiency investment behavior outside of specific policy programs (Metcalf and Hassett, 1999, is another exception). Despite these differences, our estimate of energy savings across interventions (around 12 percent on average) closely aligns with the above studies. Our paper instead documents heterogeneity across interventions often targeted by policies, and provides a first step in understanding implications for the associated implicit carbon price.

The paper proceeds as follows. Section 2 describes our data, identification strategy, and econometric approach. Section 3 presents our results. Section 4 briefly discusses our results and concludes.

2 Empirical strategy

This section first provides an overview of our data, including the nature and timing of energy efficiency investments. We then report evidence on trends in energy use among treated and control buildings, which provides the basis for our identification strategy. Finally, we lay out our econometric approach to estimate energy savings, CO_2 emissions abatement, and reductions in heating expenditures, and the associated implicit price of carbon.

[8] See also Aroonruengsawat et al. (2012), Jacobsen and Kotchen (2013), Levinson (2016) and Kotchen (2017) for evidence on energy savings associated with buildings construction standards, and Davis et al. (2014) on a government program targeting refrigerator and air conditioner efficiency.

[9] Empirical evidence reported in Aydin et al. (2017) suggests that energy rebound is between 25 and 40 percent, whereas Davis (2008) and Fowlie et al. (2018) instead report insignificant estimates. Instead, engineering projections may be overoptimistic and/or installation works may fail to meet expectations (see also Giraudet et al., 2018).

2.1 Context and data overview

Our work is primarily based on accounting data tracking a portfolio of multi-unit buildings over time. The portfolio is managed by a single private company active in the market for pension funds and real estate investments. All 548 buildings in the portfolio are located in the western part of Switzerland (see Appendix A).

The main outcome of interest is annual building-level heating energy use, measured in kilowatt hours (kWh) of either heating oil or natural gas, where years run from July to July so as to cover the entire heating season (November to March). CO_2 emissions are calculated with standard conversion factors: 264 gCO_2/kWh for heating oil and 202 gCO_2/kWh for natural gas (IPCC, 1996). We also observe building-level heating bills charged to tenants (in 2015 CHF), which comprise operation costs for the central heating system (e.g., including subscription fee to the services operating smart thermostats),[10] as well as a number of building-level characteristics such as total surface area, construction year, and the number of rented units. Moreover, while all the buildings in the portfolio are located in a relatively confined area and subject to similar climatic conditions, we use heating degree day data derived from the closest weather station (MeteoSwiss, 2019) to capture local demand shocks.[11]

For each building, we have information on the type and timing of energy efficiency investments. There are nine (possibly combined) interventions: (i) *wall insulation* is thermal insulation of a building's exterior wall or envelope; (ii) *roof insulation* denotes thermal insulation of a building's roof or attic; (iii) *windows replacement* refers to the replacement of the building's exterior windows, with improved thermal insulation; (iv) *smart thermostats* is the installation of a system that uses real-time information to optimize operations of the central heating appliance;[12]

[10] In the setting we consider, financial incentives associated with energy use are only indirect. First, all the tenants make monthly down payments for their use of heating energy until the actual use of heating oil or natural gas is billed in July each year. This implies a delay between energy use and energy bills. Second, a majority of tenants do not have an individual meter, and pay building-level energy costs in proportion to the volume of their property (see Kandul et al., 2019, for a discussion). Note that the installation of individual meters is included in the set of treatments we consider.

[11] Heating degree days measure the difference between the local average outdoor temperature on a given day and $20°C$ (the recommended indoor temperature by convention), cumulated over a particular heating season (defined as days with average temperature below $12°C$).

[12] More specifically, the system takes into account a variety of parameters such as the building's physical characteristics, geographical position, local weather situation and forecast to optimize the temperature of the heating system, including peak heat load control.

Table 1: Staggered investments across interventions and years

	'02	'03	'04	'05	'06	'07	'08	'09	'10	'11	'12	'13	'14	'15	Total
Wall insulation	1	1	1	1	5	2	3	6	2	7	2	0	5	2	38
Roof insulation	0	0	0	1	5	1	1	5	5	10	3	0	5	2	38
Windows replacement	1	2	2	0	5	2	2	7	17	11	11	0	8	3	71
Smart thermostats	0	0	0	0	0	0	0	0	0	0	0	2	15	22	39
Boiler replacement	4	3	5	2	4	6	5	7	5	10	17	18	11	22	119
Boiler replacement (oil-gas)	0	0	0	0	3	3	0	1	5	1	2	10	13	26	64
Space heat meters	1	0	0	0	1	0	0	3	0	1	0	2	0	3	11
Hot water meters	3	0	0	0	1	0	1	3	2	1	0	2	0	1	14
Solar installation	0	0	0	0	0	0	0	0	0	0	1	3	1	3	8
Total	10	6	8	4	24	14	12	32	36	41	36	37	58	84	402

Notes: This table reports the number and types of interventions over time for all 548 buildings in our data (240 treated), corresponding to the beginning of the intervention.

(v) *boiler replacement* stands for the replacement of the primary appliance supplying heat to the building, without switching fuel; (vi) *boiler replacement (oil-gas)* denotes the replacement of the primary appliance supplying heat to the building, including switching from heating oil to natural gas; (vii) *space heat meters* refers to the installation of unit-level meters for space heating consumption; and (viii) *hot water meters* is the same for hot water consumption; and (ix) *solar installation* is the installation of solar thermal collectors that contribute to the building's hot water supply.

The staggered timing of investments across buildings is illustrated in Table 1. Importantly, some of the interventions we consider may take several months to complete, even years for some of the larger investments. In our empirical analysis, we distinguish between years before treatment, during treatment, and after treatment, so as to control for any work-related impacts on energy use during the intervention period. In line with this, the timing in Table 1 refers to the beginning of the intervention.

In total, our data includes 402 interventions targeting 240 buildings, with 88 buildings receiving more than one intervention. As can be expected, the number of energy efficiency investments increases with time, with some interventions such as smart thermostats and solar thermal collectors starting later in time (2013 and 2012, respectively). The remaining 308 buildings have not undergone any energy-related intervention during the period we consider, and we refer to these buildings as our control group.[13]

For each intervention we also observe financial information on total investment cost (2015 prices), with two exceptions. First, individual meters and solar thermal collectors are not strictly speaking energy efficiency improvements, and we do not observe the associated investment cost. While we do observe the timing of installation for these interventions and can estimate energy savings, a lack of financial data implies that we cannot estimate the implicit price of carbon associated with these interventions. Second, investment cost data is missing for one instance of wall insulation, five installations of smart thermostats, and 13 boiler replacements (with fuel switching). In the estimation of the implicit price of carbon, we control for interventions with missing financial data with a set of separate treatment dummies capturing the timing of interventions.

2.2 Identification: Pre-treatment trends in energy use

The objective of this section is to motivate our strategy to identify causal evidence on energy savings and the implicit price of carbon associated with alternative investments in energy efficiency. Intuitively, we use observed outcomes for control buildings to inform a counterfactual post-treatment trajectory for energy use in treated buildings. This difference-in-differences strategy requires an assumption that, without energy efficiency investments, energy use among treated and control buildings follow the same trend.

We start by briefly discussing summary statistics for our sample, reported in Table 2, together with a comparison of treated and control buildings (using pre-treatment values where relevant).[14] Overall, treated buildings use more energy per square meter, are slightly older, contain smaller apartments, and command lower rents relative to control. These differences, which presumably reflect expected profitability associated with energy efficiency investments, are not necessarily a threat to identification. Instead, we need credible evidence that control buildings provide a plausible counterfactual for treated buildings in the absence of investments.

The parallel trend assumption underlying our identification strategy is documented in Figure

[13] Note that we can only identify the impact of interventions for which we have at least one observation before the treatment and one observation after the treatment. This leads us to treat buildings with interventions in 2001 or 2016 as part of the control group.

[14] Buildings included in the portfolio are not meant to be representative of the underlying population of buildings. In particular, as compared to 2016 data from SFSO (2019a), they tend to be slightly more recent and contain significantly more units (see notes in Table 2).

Table 2: Summary statistics for buildings

	All buildings				Treated buildings	Control buildings	Diff.	(t-stat.)
	Mean	St. Dev.	Min	Max	Pre-treat. mean	Mean		
Annual energy use (kWh/m^2)	171.64	48.53	19.74	422.19	190.82	156.70	34.12***	(8.70)
Total surface area (m^2)	1736.90	1260.16	228.00	12130.00	1825.72	1667.68	158.03	(1.46)
Construction year[a]	1972.58	25.50	1870.00	2016.00	1968.87	1975.48	-6.61**	(-3.03)
Number of units[b]	23.36	16.43	3.00	167.00	24.73	22.30	2.43	(1.72)
Avg. unit size[c]	3.22	0.65	1.18	5.50	3.13	3.28	-0.15**	(-2.68)
Monthly rent[d] (CHF/m^2)	16.26	3.10	6.61	45.28	15.57	16.81	-1.24***	(-4.74)
Heating degree days[e]	2863.04	265.92	0.00	4371.00	2883.82	2845.65	38.17	(1.64)
Commercial units (%)	0.06	0.11	0.00	0.93	0.06	0.05	0.01	(1.19)

Notes: 548 buildings are observed, with 240 in the treatment group and 308 in the control group. For treated buildings we report pre-treatment averages. [a]Average construction year of buildings in Switzerland: 1963.3 (SFSO, 2019a). [b]Total number of residential and/or commercial leases; average for Switzerland: 4.9 (SFSO, 2019a). [c]Average number of rooms per unit; average for Switzerland: 3.3 (SFSO, 2019a). [d]Average monthly rent for Switzerland: 13.7 CHF/m^2 (SFSO, 2019a). 2015 prices; exchange rate approx. CHF 1 = USD 1. [e]Heating degree days measure the difference between the local average outdoor temperature in a given day and $20°C$, cumulated over a given heating season (see footnote 11). *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

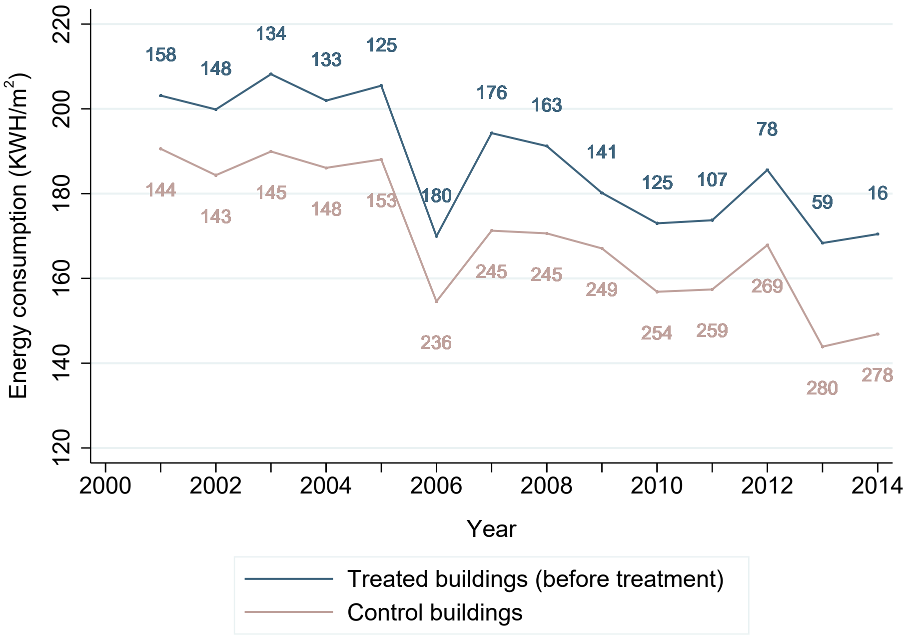
1. Specifically, we report average building-level annual energy use (in kWh/m^2) over time for treated and control buildings. Given the staggered nature of investments (see Table 1), treated buildings that enter the during-treatment period drop out of the pre-treatment trend, so that the number of buildings in the treatment group declines with time (after 2014 the number of pre-treatment observations falls to zero, and is therefore not reported). In addition, some buildings enter or exit the portfolio during the observation period (unbalanced panel), so that the number of observations in the control group also varies.[15]

Two main observations emerge. First, pre-treatment differences in average energy use between treated and control buildings remain stable with time. One remarkable feature of the data is that evidence of a parallel trend can be documented even though treated buildings enter the during-treatment period. Below we use this feature of the data to provide more formal regression-based evidence that, in the absence of investments, the pre-treatment changes in the difference between treated and control buildings is not statistically significantly different from zero.

The second observation is that pre-treatment energy use for both groups of buildings trends downward. While explaining this trend is beyond the scope of our analysis, a number of comments are in order. First, our data covers a relatively long period of time, and climate change

[15] See Appendix B for the corresponding figure derived for a subsample of 285 buildings that remain in the portfolio over the entire horizon. We come back to potential sample selection issues in the robustness section by providing empirical results for the balanced dataset.

Figure 1: Trend in pre-treatment energy use for treated and control buildings



Notes: This figure reports pre-treatment average energy use (in kWh/m^2) for treated and control buildings over time, together with the number of buildings used to calculate group-specific averages (i.e., the number of observations per group per year). In the treatment group, the number of pre-treatment observations decreases with time as buildings enter the during-treatment period. The number of control buildings also varies with time, reflecting entry in and exit from the portfolio of buildings. From 2015 onwards, all buildings in the treatment group have entered the during-treatment period.

can be observed in the form of milder temperatures experienced during the heating season.[16] Second, the market price of heating oil and natural gas has increased by 43.6 and 30.3 percent respectively (SFSO, 2019b), and our analysis controls for potential fuel price effects (aside from year fixed effects). Finally, a CO_2 tax on heating oil and natural gas has been levied since 2008, starting at CHF 12/tCO_2 and gradually reaching CHF84/tCO_2 in 2016 (SFOEN, 2018).

For our purpose, evidence of a downward trend implies that buildings' energy use is expected to decline even in the absence of energy efficiency investments. It follows that this trend is important for identifying energy savings and the implicit price of carbon associated with energy efficiency investments.

[16] From 2001 to 2016, long-term average temperature series from MeteoSwiss (2019) suggest that annual outdoor temperatures increased from 5.46°C to 6.07°C, and from 1.37°C to 1.87°C in the winter.

2.3 Econometric estimation

Based on evidence that treated and control buildings follow the same trend in the absence of energy efficiency investments, we now lay out a simple staggered difference-in-differences strategy to quantify the impact of energy efficiency interventions on energy use, CO_2 emissions, and heating expenditures, and in turn provide evidence on the associated implicit price of carbon.

Formally, we denote energy use for building i and year t as e_{it} (in kWh/m^2), and write our baseline regression model as:

$$\ln(e_{it}) = \beta T_{it} + \mu D_{it} + \gamma W_{it} + \alpha_i + \alpha_t + \epsilon_{it}\,, \tag{1}$$

where T_{it} is a post-treatment indicator equal to one if the works associated with investment in building i is completed in t, D_{it} is a during-treatment indicator equal to one if an intervention in building i has started but is not completed in t, W_{it} is a vector of control variables that includes the log of building-level heating degree days and log of fuel prices (either heating oil or natural gas), α_i and α_t are fixed effects for buildings and years respectively, and ϵ_{it} is an error term. The coefficient β measures the change in energy use after an intervention is completed, averaged over all post-treatment periods, relative to an estimated counterfactual outcome.

While Equation (1) is the main workhorse of the existing literature, it averages the impact of heterogeneous energy efficiency investments both across interventions and over time. For our purpose, we use it in the context of an event-study regression (e.g., Autor, 2003), and estimate treatment effects for each pre-treatment and post-treatment years (the coefficient for the last pre-treatment period is normalized to zero). This provides a formal test of pre-treatment parallel trends, and also allows us to relate our results to existing empirical evidence cited above documenting energy savings for renovation bundles.[17]

In order to capture heterogeneous energy savings across different interventions, indexed by k, we augment the baseline specification as follows:

$$\ln(e_{it}) = \alpha_i + \alpha_t + \sum_k (\beta_k T_{kit} + \mu_k D_{kit}) + \gamma W_{it} + \epsilon_{it}\,, \tag{2}$$

[17] We also consider results for an even-study regression where the dependent variable is in levels, corresponding to Figure 1. This does not allow us to discriminate across functional forms.

where the coefficients β_k measure energy savings associated with each intervention. We further consider two extensions. First, we include interaction terms capturing all observed combinations of interventions T_{kit}. These terms control for potential complementarity effects across retrofits applied to the same building, so that β_k quantifies the impact of each individual intervention. Second, we investigate possible treatment effect heterogeneity as a function of pre-treatment energy use. To do so, we interact post-treatment dummies T_{kit} with pre-treatment average energy use, and normalize the interaction term with respect to either the sample average or the average of the control group. In these specifications, the main effects β_k capture energy savings for buildings with pre-treatment energy use corresponding to the sample-average (ATE) and to the average of non-renovated buildings (ATENT), respectively.

Next, we derive evidence about the implicit price of carbon for each intervention. For this purpose, we employ a set of continuous post-treatment variables I_{kit} that are zero in pre-treatment and during-treatment years, and equal to investment cost (CHF per m^2) associated with intervention k and building i in each post-treatment year. Alternatively, these variables can be viewed as an interaction between the set of post-treatment dummies T_{kit} and investment costs per m^2.[18] Based on this, regression for CO_2 emissions (in kg CO_2/m^2) can be written as:

$$co2_{it} = \alpha_i + \alpha_t + \sum_k (\theta_k I_{kit} + \mu_k D_{kit}) + \gamma W_{it} + \epsilon_{it}\,, \tag{3}$$

where θ_k can be interpreted as the average change in CO_2 emissions in relation to a CHF 1 investment in intervention k. Similarly, the regression for annual heating costs (in CHF/m^2) is given by:

$$cost_{it} = \alpha_i + \alpha_t + \sum_k (\lambda_k I_{kit} + \mu_k D_{kit}) + \gamma W_{it} + \epsilon_{it}\,, \tag{4}$$

where λ_k captures the average change in annual heating cost associated with CHF 1 invested in intervention k. We note that regressions in levels facilitate the estimation of the implicit price of carbon, and we come back to implications for the parallel trend assumption and the associated event-study regressions below.

We then straightforwardly combine estimates resulting from equations (3) and (4), together

[18] As mentioned previously, we control for interventions with missing financial data by including a set of post-treatment dummies T_{kit}.

with standard assumptions about the lifetime of each building element and discount rates, to carry out statistical inference on the implicit price of carbon associated with intervention k (in CHF/t CO_2). See Appendix C for the details.

We close this section by listing robustness checks on equations (2-4) and the resulting implicit price of carbon. Specifically, we derive results for three alternative subsamples. First, we exclude buildings that use natural gas and focus on those that use heating oil as their pre-treatment heating fuel. Note that, among this sample, some buildings initially use heating oil but switch to natural gas following replacement of the central heating appliance. Second, we estimate the implicit price of carbon for the subsample of buildings that contain residential leases only. This allows us to document whether the presence of a small share of commercial leases affects our results. Lastly, we consider the set of buildings that are present in the portfolio over the entire period of observation (i.e., balanced sample). This provides evidence about a potential sample selection effect.

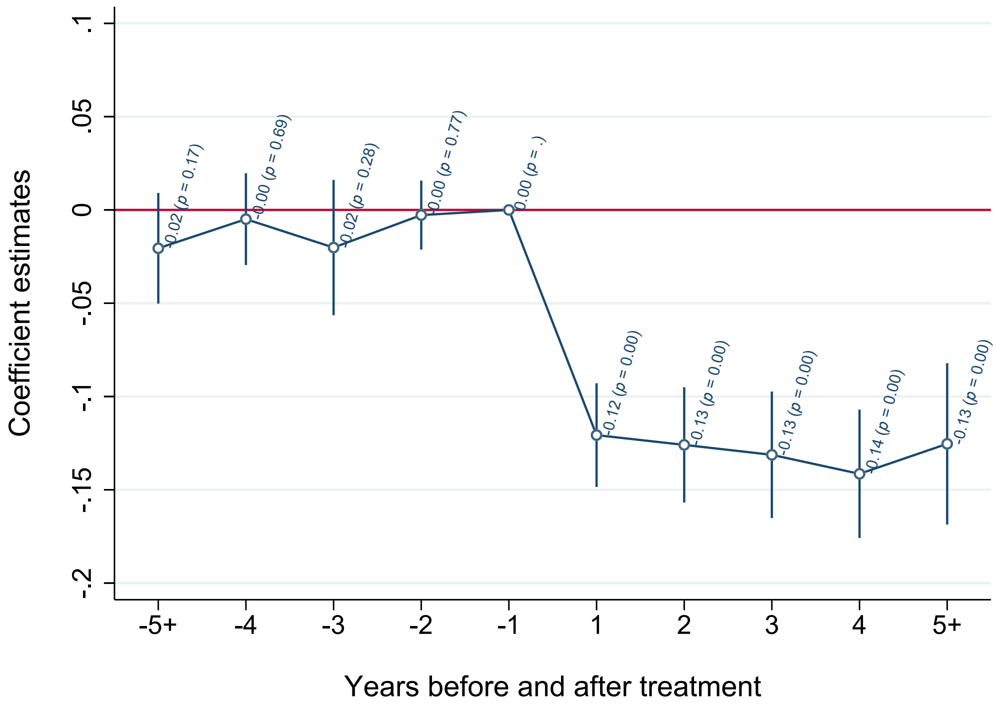
3 Estimation results

This section reports empirical results. First, we quantify the impact of energy efficiency investments on buildings' energy use, and document heterogeneity in energy savings across interventions. Second, we estimate the implied change in CO_2 emission reductions and energy expenditures, and derive the implicit price of carbon associated with alternative energy efficiency investments. Finally, we report results for three subsamples of buildings.

3.1 Energy efficiency investments and energy use

We start with an event-study regression for the log of annual building-level energy use on a set of pooled pre- and post-treatment dummies, control variables, building and year fixed effects, as well as during-treatment dummies (equation 1). Regression coefficients associated with energy efficiency interventions are reported graphically in Figure 2, together with cluster-robust 95% confidence intervals (see Appendix D for the corresponding regression table). These coefficients measure the change in energy use relative to control for a given pre- or post-treatment year, where the coefficient for the last pre-treatment period is normalized to zero.

Figure 2: Panel fixed effects event study results for pooled energy efficiency investments



Notes: The graph displays point estimates, 95% confidence intervals and p-values from an event-study regression of the log of buildings' annual energy use per m^2 on pre- and post-treatment dummies for pooled energy efficiency interventions, control variables, building and year fixed effects, and during-treatment dummies. The last pre-treatment period ($t = -1$) is defined as the reference category. Inference is derived from standard errors clustered at the building-level (N=548). See Appendix D for the corresponding results table.

For all years leading up to an intervention, coefficient estimates are not statistically significantly different from zero. This provides further support for the parallel trend assumption discussed previously. By contrast, all post-treatment coefficients are negative and statistically significantly different from zero. This indicates that, following an energy efficiency investment, energy use sharply declines relative to control, with energy savings of around 12 percent on average and stable with time. The scale of energy savings is broadly in line with other studies (for example, Liang et al., 2017 report savings of 8 percent for residential buildings and 12 percent for commercial buildings, and Fowlie et al., 2018 reports energy savings of 10 to 20 percent on average).

Table 3 documents how energy savings vary across interventions (equation 2). In columns (1) and (2) we report OLS regression estimates without and with control variables, respectively.

Table 3: Alternative energy efficiency investments and heterogeneous energy savings

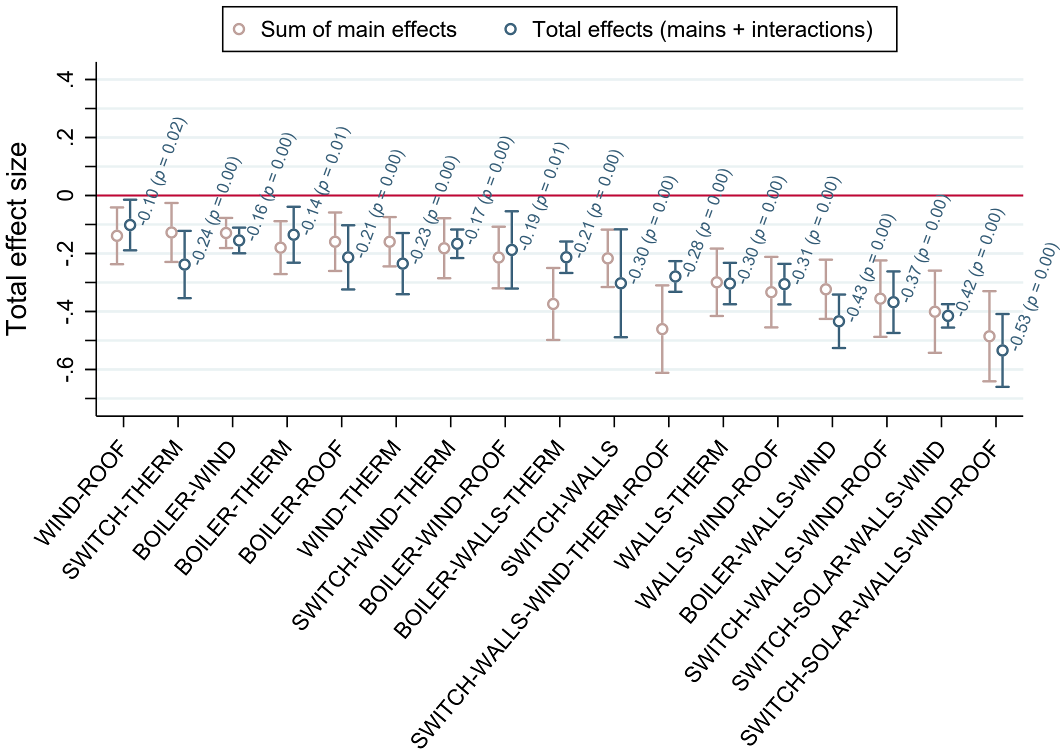
	Individual treatments	Time-varying controls	Treatment interactions	Energy use interaction evaluated at sample average	Energy use interaction evaluated at control group average
	(1)	(2)	(3)	(4)	(5)
Wall insulation	-0.21***	-0.21***	-0.19***	-0.18***	-0.17***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Roof insulation	-0.08**	-0.08**	-0.08*	-0.08	-0.07
	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)
Windows replacement	-0.06***	-0.06***	-0.05***	-0.06***	-0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Smart thermostats	-0.10***	-0.09***	-0.11**	-0.10***	-0.06
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)
Boiler replacement	-0.08***	-0.07***	-0.07***	-0.06**	-0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Boiler replacement (oil-gas)	-0.04	-0.02	-0.02	0.001	0.02
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Space heat meters	0.08	0.08	0.03	0.09	0.06
	(0.06)	(0.06)	(0.07)	(0.08)	(0.06)
Hot water meters	-0.06	-0.05	-0.04	-0.11	-0.07
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)
Solar installation	-0.16***	-0.16***	-0.13**	-0.20**	-0.22*
	(0.06)	(0.06)	(0.05)	(0.09)	(0.12)
Control variables	no	yes	yes	yes	yes
Treatment interactions	no	no	yes	yes	yes
x pre-treatment energy use					
Sample average	no	no	no	yes	no
Control group average	no	no	no	no	yes
Observations	7,047	7,047	7,047	7,047	7,047
Buildings (clusters)	548	548	548	548	548
Adj. R-squared	0.20	0.21	0.21	0.21	0.21

Notes: The dependent variable is the log of buildings' annual energy use in kWh/m^2, see equation (2). Column (1) reports OLS estimates for post-intervention dummies (T_{kit}), controlling for during-treatment dummies, building fixed effects, and year fixed effects. Column (2) adds control variables (log-heating degree days and log-fuel prices). Column (3) adds the full set of treatment interactions (i.e., all observed combinations of interventions). Column (4) adds an interaction between each treatment variable and standardized pre-treatment energy use evaluated at the sample average, while column (5) reports the same but instead normalizes interaction terms at the average of the control group. Standard errors are clustered at the building-level and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

In column (3) we add interaction terms capturing complementarities across interventions. In columns (4) and (5), we add a set of interaction terms between each treatment dummy and *pre*-treatment average energy use standardized at the sample average and at the average of control buildings, respectively. In all regressions, we control for building and year fixed effects and include during-treatment dummies. Cluster-robust standard errors are reported in parentheses.

Results show that estimates are broadly consistent across columns (1) to (3), and confirm large heterogeneity in energy savings across interventions. Exterior wall insulation delivers the largest energy savings (around 20% reduction in energy use on average), followed by solar ther-

Figure 3: Total energy savings for observed combinations of interventions



Notes: This figure provides point estimates, 95% confidence intervals and p-values (obtained via the delta method) for selected combinations of energy efficiency investments, derived from regression results reported in Table 3, column 3. WALLS is *wall insulation*, ROOF is *roof insulation*, WIND is *windows replacement*, THERM is *smart thermostats*, HEAT is *boiler replacement*, SWITCH is *boiler replacement (oil-gas)* and SOLAR is *solar installation*.

mal collectors and smart thermostats. Energy savings implied by roof insulation and windows / boiler replacement (without fuel switching) are below ten percent. We find little evidence that switching from oil to gas or installing individual meters have an impact on energy use.

The extent of complementarities between interventions is illustrated in Figure 3, which uses estimates in Table 3, column 3, to compute *total* effect size for a subset of observed combinations of interventions.[19] Results suggest that adding all relevant interaction terms does not affect estimated energy savings significantly as compared to a sum of main effects only. This is in line with the observation that energy savings associated with individual interventions are not significantly affected by the inclusion of interaction terms for multiple interventions (column 2

[19] For example, energy savings associated with a total effect size of -0.53 is $\exp(-0.53) - 1$, or a decline in energy use of about 41 percent.

vs. 3). In other words, complementarities between interventions appear to be modest.

Lastly, estimates reported in columns (4) and (5) suggest that pre-treatment energy use has a statistically significant (negative) effect on energy savings in the case of smart thermostats and boiler replacement (without fuel switching). This implies that energy savings evaluated for control buildings (ATENT) are significantly smaller as compared to results for the treatment group (ATET). For other interventions, we find little evidence that pre-treatment use affects energy savings, which suggests that ATET and ATENT do not differ significantly.

3.2 CO_2 emissions, heating expenditures, and the implicit carbon price

We now turn to evidence on CO_2 emissions abatement and heating expenditures in relation to financial data on energy efficiency investments, and later derive implications for the implicit price of carbon. In Table 4, columns (1) and (2) provide regression results for equations (3) and (4), respectively.[20] More specifically, column (1) regresses CO_2 emissions (in kg CO_2/m^2) on investment costs for all treatments considered (I_{kit}, in CHF/m^2), and column (2) regresses annual heating expenditures (in CHF/m^2) on the same. In both regressions we control for building and year fixed effects, during-treatment dummies, control variables, interaction terms for multiple interventions, and include post-intervention dummies for interventions with missing financial data. Standard errors clustered at the building level are reported in parentheses.

Results in column (1) indicate that all energy efficiency investments considered imply a statistically significant reduction in CO_2 emissions. However, the scale of emission reductions differs widely across interventions. For example, investing in exterior wall insulation leads to a reduction of emissions by 0.01 kg CO_2/CHF, whereas investing in smart thermostats instead decreases CO_2 emissions by 5.37 kg/CHF invested. Importantly, the ranking across interventions implied by these results sharply differs from the corresponding ranking for energy savings (see, e.g., Table 3, column 3).

Column (2) further shows that most energy efficiency investments have a statistically significant impact on heating expenditures. The reduction in heating-related expenditures is largest for the installation of smart thermostats, with a reduction of CHF 1.99/CHF invested, even though

[20] In Appendix D, Table D1, we report results for a set of event-study regressions, suggesting that pre-treatment trends for CO_2 emissions and energy expenditures among treatment and control buildings are parallel. Table D1 also reports results for a specification using log-transformed outcome variables, which yield similar conclusions.

Table 4: CO_2 emissions, heating costs, and estimates for the implicit carbon price

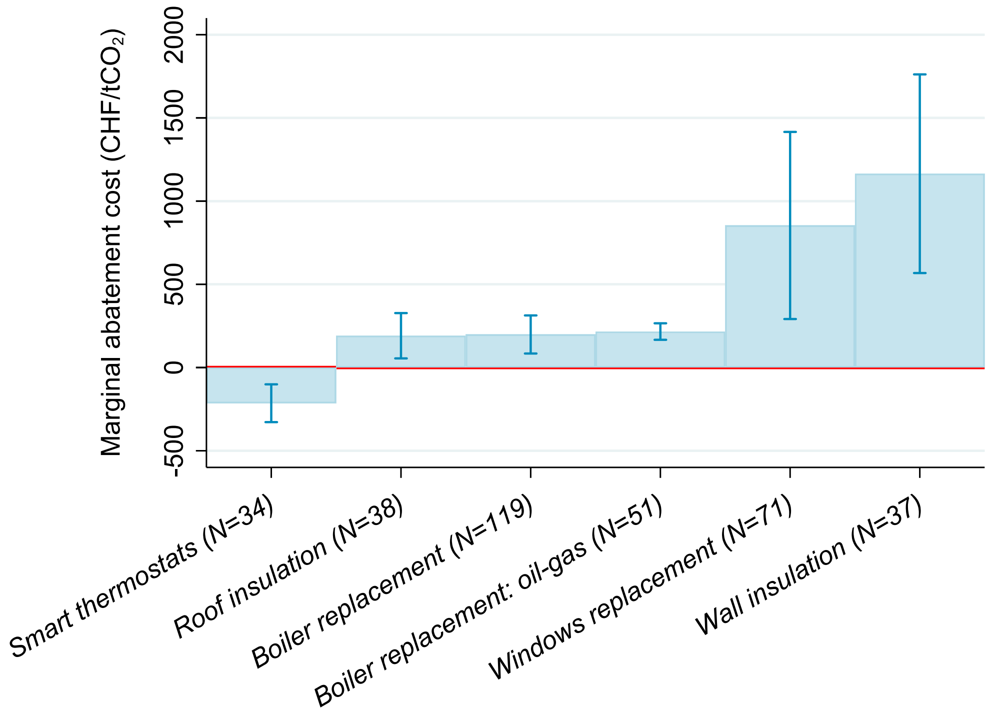
	Regression results		Estimates for the implicit price of carbon (CHF/tCO_2)			
	CO_2 emissions (kg/m^2)	Heating cost (CHF/m^2)	Average use lifetime		Heavy use lifetime	
			$\delta = 0\%$	$\delta = 6\%$	$\delta = 0\%$	$\delta = 6\%$
	(1)	(2)	(3)	(4)	(5)	(6)
Wall insulation	-0.01***	-0.003***	939.50***	1,161.96***	1,113.75***	1,328.45***
	-0.003	(0.0006)	(287.65)	(303.42)	(331.35)	(346.80)
Roof insulation	-0.07***	-0.03***	-53.35	190.48***	59.15	270.67***
	(0.02)	(0.01)	(75.30)	(69.14)	(89.33)	(93.52)
Windows replacement	-0.02***	-0.01*	655.24**	850.10***	1,281.77***	1,435.77***
	(0.01)	(0.003)	(312.22)	(284.87)	(490.33)	(473.02)
Smart thermostats	-5.37***	-1.99***	-358.76***	-227.92***	-352.56***	-254.57***
	(1.31)	(0.64)	(91.44)	(59.08)	(91.27)	(67.05)
Boiler replacement	-0.08***	-0.02***	38.30	198.60***	136.72	275.78***
	(0.02)	(0.01)	(75.10)	(58.30)	(88.78)	(77.21)
Boiler replacement (oil-gas)	-0.13***	0.01	263.54***	216.50***	326.25***	285.45***
	(0.01)	(0.01)	(51.19)	(25.39)	(53.78)	(32.35)
Observations	7,047	7,047				
Buildings (clusters)	548	548				
Adj. R-squared	0.45	0.66				

Notes: Column (1) is a regression of annual CO_2 emissions (in kg CO_2/m^2) on post-treatment investment cost variables (I_{kit}, in CHF/m^2). Column (2) is a regression of annual heating costs (in CHF/m^2) on post-treatment investment cost variables (I_{kit}, in CHF/m^2). Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1. Both regressions control for building and year fixed effects, during-treatment dummies, control variables, interaction terms between treatments, and post-treatment dummies for interventions with missing financial data. Standard errors are clustered at the building-level and reported in parentheses. Based on columns (1) and (2), columns (3) to (6) report estimates for the implicit price of carbon, with standard errors obtained via the delta method reported in parentheses. Assumptions about lifetime assumptions for each investment are provided in Appendix C, Table C1. Columns (3) and (5) provide undiscounted results ($\delta = 0\%$), and columns (4) and (6) use a discount rate of six percent ($\delta = 6\%$). *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

annual operational expenses (subscription costs) partly offset financial savings associated with lower energy use. By contrast, investments in windows replacement is marginally significant, and boiler replacement with fuel switching is found to have a positive impact on heating expenses, which reflects the slightly higher cost of natural gas relative to heating oil (although the point estimate is not statistically significantly different from zero).

Next, we exploit results from columns (1) and (2) to derive estimates for the implicit price of carbon associated with each intervention. Results are reported in columns (3) and (4) for average lifetime assumptions and in columns (5) and (6) for heavy-use lifetimes (see Appendix C, Table C1, for the details), with odd columns reporting undiscounted results and even columns using a six percent discount rate. For each estimate of the implicit carbon price, we use the delta method to obtain robust standard errors and report these in parentheses. In Figure 4, we further illustrate the ranking across interventions based on estimates reported in column (4). This can

Figure 4: Ranking for the implicit price of carbon across interventions



Notes: The graph displays point estimates and 95% confidence intervals for estimates of the implicit price of carbon. See Table 4, column (4), for the corresponding results. Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1.

be interpreted as a version of the marginal abatement cost curve by McKinsey & Company (2009) based on realized energy savings instead of engineering projections.

Estimates suggest that the implicit price of carbon for wall insulation and windows replacement are particularly high in comparison to other interventions. This holds across the range of assumptions considered in Table 4. Moreover, although 95% confidence bounds are quite wide, these are quite distinct from estimates associated with roof insulation, boiler replacement (with and without fuel switching), and smart thermostats.

By contrast, we estimate that the implicit price of carbon associated with smart thermostats is negative across all specifications considered. The implicit carbon price for roof insulation is also negative (not statistically different from zero) for a lifetime of 80 years and a discount rate of zero, but stands at around CHF 200/tCO_2 for a 6 percent discount rate. Similarly, the implicit price of carbon associated with boiler replacement is somewhere between zero and CHF 300/tCO_2.

Table 5: Energy savings and implicit carbon prices for buildings using heating oil

	Energy use (kWh/m^2)	CO_2 emissions (kg/m^2)	Heating cost (CHF/m^2)	Implicit price of CO_2
	(1)	(2)	(3)	(4)
Wall insulation	-0.19***	-0.01***	-0.003***	1,208.41***
	(0.05)	(0.003)	(0.0007)	(332.30)
Roof insulation	-0.08	-0.10***	-0.04***	116.77*
	(0.07)	(0.02)	(0.01)	(62.26)
Windows replacement	-0.04**	-0.02***	-0.005**	1,008.54**
	(0.02)	(0.01)	(0.002)	(415.70)
Smart thermostats	-0.15***	-3.33**	-1.83***	-336.75
	(0.03)	(1.47)	(0.60)	(207.49)
Boiler replacement	-0.05***	-0.08***	-0.01*	260.18***
	(0.02)	(0.02)	(0.01)	(89.90)
Boiler replacement (oil-gas)	0.01	-0.11***	0.01	261.46***
	(0.03)	(0.01)	(0.01)	(43.09)
Observations	5,012	5,012	5,012	
Buildings (clusters)	334	334	334	
Adj. R-squared	0.46	0.53	0.75	

Notes: This table focuses on the subsample of buildings that use heating oil. Column (1) reports OLS estimates for a regression of log-annual energy use in kWh/m^2 on post-intervention dummies (T_{kit}). Column (2) is a regression of annual CO_2 emissions in kg CO_2/m^2 on investment cost (in CHF/m^2). Column (3) is a regression of annual heating costs (in CHF/m^2) on investment cost (in CHF/m^2). Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1. All regressions control for building and year fixed effects, during-treatment dummies, control variables, treatment interactions, and post-treatment dummies for interventions with missing financial data. Standard errors are clustered at the building-level and reported in parentheses. Based on columns (2) and (3), column (4) reports estimates for the implicit price of carbon assuming average building element lifetimes and a $\delta = 6\%$ discount rate. Cluster-robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

In sum, there is large heterogeneity in the implicit price of carbon, and the ranking of interventions does not correlate with estimates for energy savings reported previously. A weighted average across interventions based on the frequency of renovations suggest an implicit carbon price associated with energy efficiency in buildings of 382.77 CHF/tCO_2 (95% confidence interval: 247.28-518.27). This estimate is relatively close to a value of 350 USD/tCO_2 discussed in Gillingham and Stock (2018) in reference to energy efficiency in buildings, although both the setting (Fowlie et al., 2018) and some of the underlying assumptions are quite different.

3.3 Further evidence on energy savings and the implicit carbon price

This section provides further evidence on heterogeneous energy savings and implications for the implicit carbon price for three alternative subsamples: (i) buildings that use heating oil (Table 5); (ii) buildings with residential leases only (Table 6); and (iii) buildings that remain in the portfolio

Table 6: Energy savings and implicit carbon prices for purely residential buildings

	Energy use (kWh/m^2)	CO_2 emissions (kg/m^2)	Heating cost (CHF/m^2)	Implicit price of CO_2
	(1)	(2)	(3)	(4)
Wall insulation	-0.20***	-0.01***	-0.002***	1,774.08***
	(0.08)	(0.002)	(0.0008)	(592.51)
Roof insulation	-0.09	-0.09***	-0.03***	134.33*
	(0.06)	(0.03)	(0.01)	(71.25)
Windows replacement	-0.05**	-0.02***	-0.01*	763.46**
	(0.02)	(0.01)	(0.005)	(303.58)
Smart thermostats	-0.08	-2.52*	-0.65	-147.75
	(0.06)	(1.50)	(0.68)	(164.67)
Boiler replacement	-0.06***	-0.08***	-0.02***	232.53***
	(0.02)	(0.02)	(0.01)	(68.13)
Boiler replacement (oil-gas)	-0.01	-0.11***	0.01	249.37***
	(0.03)	(0.01)	(0.01)	(42.60)
Observations	4,209	4,209	4,209	
Buildings (clusters)	322	322	322	
Adj. R-squared	0.24	0.49	0.69	

Notes: This table focuses on the subsample of buildings with residential leases only. Column (1) reports OLS estimates for a regression of log-annual energy use in kWh/m^2 on post-intervention dummies (T_{kit}). Column (2) is a regression of annual CO_2 emissions in kg CO_2/m^2 on investment cost (in CHF/m^2). Column (3) is a regression of annual heating costs (in CHF/m^2) on investment cost (in CHF/m^2). Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1. All regressions control for building and year fixed effects, during-treatment dummies, control variables, treatment interactions, and post-treatment dummies for interventions with missing financial data. Standard errors are clustered at the building-level and reported in parentheses. Based on columns (2) and (3), column (4) reports estimates for the implicit price of carbon assuming average building element lifetimes and a $\delta = 6\%$ discount rate. Cluster-robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

over the entire observation period (Table 7). In each table, column (1) reports regression results for energy savings (equation 2), column (2) focuses on CO_2 emissions in relation to investment cost (equation 3), and column (3) provides evidence on heating expenditures (equation 4). In all regressions, we include control variables, building and year fixed effects, during-treatment dummies, interaction terms controlling for multiple interventions, and post-treatment dummies for interventions with missing financial data. Next, column (4) uses estimates from columns (2) and (3) to estimate the implicit price of carbon based on an assumption of average lifetime for building elements and a six percent discount rate. Cluster-robust standard errors are reported in parentheses throughout. Appendix E provides summary statistics for each subsample.

We start with the sample of 334 buildings that use heating oil, including 168 treated buildings, with some of them switching to natural gas during the period of interest. Results reported in Table 5 for energy savings, CO_2 abatement and changes in energy expenditures align closely with

Table 7: Energy savings and implicit carbon prices for the balanced subsample

	Energy use (kWh/m^2)	CO_2 emissions (kg/m^2)	Heating cost (CHF/m^2)	Implicit price of CO_2
	(1)	(2)	(3)	(4)
Wall insulation	-0.21***	-0.01***	-0.003***	1,158.48***
	(0.06)	(0.003)	(0.0007)	(324.97)
Roof insulation	-0.08	-0.10***	-0.03***	121.11*
	(0.07)	(0.02)	(0.01)	(63.01)
Windows replacement	-0.03*	-0.02**	-0.004**	1,088.40**
	(0.02)	(0.01)	(0.002)	(472.93)
Smart thermostats	-0.14***	-12.39**	1.83	101.14
	(0.03)	(5.32)	(1.43)	(107.37)
Boiler replacement	-0.05***	-0.07***	-0.01	299.17***
	(0.02)	(0.02)	(0.01)	(98.26)
Boiler replacement (oil-gas)	-0.003	-0.10***	0.003	265.52***
	(0.03)	(0.01)	(0.01)	(48.31)
Observations	4,560	4,560	4,560	
Buildings (clusters)	285	285	285	
Adj. R-squared	0.49	0.56	0.77	

Notes: This table focuses on the subsample of buildings that are observed from 2001 to 2016 (balanced panel). Column (1) reports OLS estimates for a regression of log-annual energy use in kWh/m^2 on post-intervention dummies (T_{kit}). Column (2) is a regression of annual CO_2 emissions in kg CO_2/m^2 on investment cost (in CHF/m^2). Column (3) is a regression of annual heating costs (in CHF/m^2) on investment cost (in CHF/m^2). Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1. All regressions control for building and year fixed effects, during-treatment dummies, control variables, treatment interactions, and post-treatment dummies for interventions with missing financial data. Standard errors are clustered at the building-level and reported in parentheses. Based on columns (2) and (3), column (4) reports estimates for the implicit price of carbon assuming average building element lifetimes and a $\delta = 6\%$ discount rate. Cluster-robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

corresponding estimates for the full sample (Table 3, column 3). In turn, point estimates and the ranking for implicit carbon prices are also very similar. One noteworthy difference is the negative estimate for smart thermostats, which is not statistically significantly different from zero.

Table 6 reports results for the sample of 322 purely residential buildings, including 131 treated buildings. Overall, point estimates tend to be less precisely estimated, implying again that the negative estimate associated with smart thermostats is not statistically significantly different from zero. Nevertheless, the ranking for the implicit price of carbon remains. This suggests that the small share of commercial leases in the buildings we consider (around 6 percent on average) do not affect overall results significantly.

Lastly, results for the balance subsample, reported in Table 7, refer to 285 buildings (151 treated) observed over 16 years. Results for energy savings are overall very similar, although as expected standard errors are slightly larger. Moreover, the ranking of implicit carbon prices is similar, with the exception of boiler replacement measures. One important difference, however, is a positive impact of smart thermostats on heating cost (statistically indistinguishable from zero), presumably on account of the subscription fees. In turn, the point estimate for the implicit price of carbon associated with smart thermostat is positive, although not statistically significantly different from zero.

4 Discussion and conclusion

In this paper, we have used data for a portfolio of multi-unit buildings to provide novel evidence on heterogeneous impacts of energy efficiency as a carbon abatement strategy. Our data includes a rich array of alternative interventions, allowing us to document heterogeneity in energy savings and to carry out statistical inference on the implicit price of carbon associated with alternative energy efficiency interventions. Given a non-random treatment assignment, our identification strategy relies on the staggered nature of investments to motivate the use of buildings with no intervention as a control group.

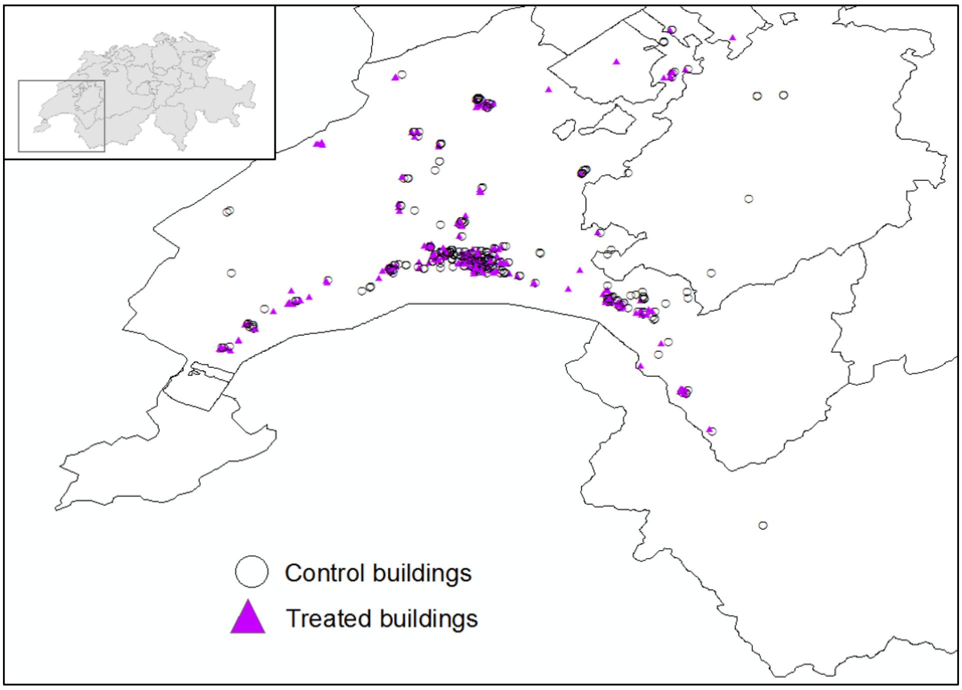
Our results confirm that frequently subsidized measures such as wall insulation and windows replacement achieve significant energy savings, with respectively 19 and five percent on average. We also find, however, that these interventions are an expensive strategy to abate CO_2. By contrast, installing smart thermostats is relatively cheap, with some of our specifications even suggesting a negative implicit carbon price. We emphasize that negative estimates are found to be sensitive to the use of alternative subsamples, and that energy savings for this particular intervention may be lower for buildings in the control group. In sum, smart thermostats are consistently found to be the cheapest option for carbon abatement, but the implicit carbon price associated with this specific intervention is likely to be higher among non-renovated buildings.

The implicit price of carbon provides a simple metric to compare alternative investment strategies. Our results can be interpreted as an illustration of the difficulty for policy-makers to select specific abatement measures instead of relying on a transparent carbon price. First, we find that the range of implicit carbon prices in the narrow domain of energy efficiency in buildings is large. This confirms the importance of empirical work on the cost of CO_2 abatement in order to evaluate policy decisions. Second, our results for smart thermostats suggest that new technologies can achieve significant energy savings at a relatively low cost. A natural tendency for policy-makers to favor established abatement strategies (e.g., for which we have *ex-post* data) will fail to incentivize these emerging abatement opportunities.

While our results show consistency with other settings, we close by emphasizing that evidence on the implicit price of carbon is by construction context-dependent (Gillingham and Stock, 2018). Given a lack of global carbon pricing policy in the near future, further work on the impact of specific abatement investment seems warranted. For example, our analysis abstracts from important welfare impacts such as improved comfort for tenants (e.g., less variability in indoor temperature levels) or lower maintenance costs for property owners. Energy efficiency investments also have distributional implications, notably through changes in rents. These considerations all have implications for investment decisions and for the design of public policies, and are left for future research.

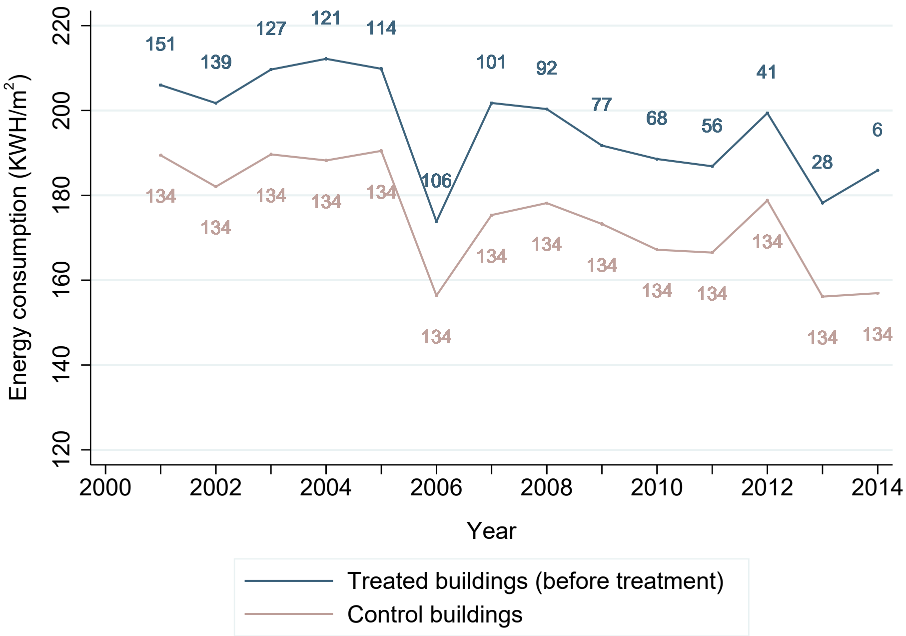
Appendix A Location of buildings

Figure A1: Geographical distribution of buildings across treatment and control groups



Appendix B Pre-treatment trends in the balanced sample

Figure B1: Trend in pre-treatment energy use for treated and control buildings (balanced sample)



Notes: This figure reports pre-treatment average energy use (in kWh/m^2) for treated and control buildings over time, together with the number of buildings used to calculate group-specific averages (i.e., the number of observations per group per year). In the treatment group, the number of pre-treatment observations decreases with time as buildings enter the during-treatment period. From 2015 onwards, all buildings in the treatment group have entered the during-treatment period.

Appendix C Estimation of the implicit price of carbon

This appendix provides the details for the estimation of the implicit price of carbon associated with alternative interventions. First, we compute total CO_2 abatement associated with a unit investment in each energy efficiency intervention, denoted by $\overline{CO2}_k$. This is mainly based on our estimate for annual CO_2 abatement (in kg / CHF invested), θ_k, scaled to obtain tonnes of CO_2. In addition, we make an assumption about the lifetime of each building element (denoted ω_k, in years), which is derived from engineering sources and reported in Table C1. The total change in tCO_2 per CHF invested is then given by: $\overline{CO2}_k = -\omega_k \cdot \theta_k / 1000$. The inverse of this quantity gives the financial cost associated with a 1 tCO_2 reduction of emissions.

Table C1: Assumptions about the lifetime of building elements

Treatment	Lifetime (in years) under		Based on
	Average use	Heavy use	
Exterior walls	80	70	SIA (2004) and CRB (2012)
Roof or attic	40	30	SIA (2004)
Windows	50	30	SIA (2004)
Smart thermostats	15	10	CRB (2012)
Boiler appliance	40	30	SIA (2004)

Second, the interventions we consider also reduce expenditures on heating fuels, and we compute total financial savings associated with a unit investment in each energy efficiency intervention, denoted $\overline{cost_k}$. Given our notation, we have that investing CHF 1 in retrofit k saves, each year, λ_k on average in terms of heating expenditures. Using an assumption about the discount rate δ, we can write total financial savings over the lifetime of the building element as: $\overline{cost_k} = -\sum_{t=0}^{\omega_k}(1+\delta)^{-t} \cdot \lambda_k$. Note that this also involves an assumption that fuel prices remain consistent with the values observed over the estimation period.

Finally, we combine the two measures and write the implicit price of carbon as: $P_k = \frac{1}{\overline{CO2}_k}\left(1 - \overline{cost_k}\right)$. Intuitively, reducing CO_2 emissions by one tonne requires an investment of CHF $\frac{1}{\overline{CO2}_k}$, and this investment in turn saves a total of $\frac{1}{\overline{CO2}_k} \cdot \overline{cost_k}$ in terms of fuel expenditures. Given estimated standard errors for θ_k and λ_k, we use the delta method to carry out statistical inference on P_k.

Appendix D Results for panel fixed effects event-study regressions

Table D1: Event study regression results for pooled energy efficiency investments

	Energy use		CO_2 emissions		Heating cost	
	ln(kWh/m^2)	kWh/m^2	ln(kg/m^2)	kg/m^2	ln(CHF/m^2)	CHF/m^2
	(1)	(2)	(3)	(4)	(5)	(6)
5+ years before (t_{-5}):	-0.02	-3.06	-0.01	-0.34	-0.02	-0.67***
	(0.02)	(2.36)	(0.02)	(0.60)	(0.01)	(0.21)
4 years before (t_{-4}):	-0.01	-0.89	-0.01	-0.20	-0.01	-0.35
	(0.01)	(2.43)	(0.01)	(0.58)	(0.01)	(0.23)
3 years before (t_{-3}):	-0.02	-2.74	-0.02	-0.63	-0.01	-0.28
	(0.02)	(2.27)	(0.02)	(0.56)	(0.01)	(0.20)
2 years before (t_{-2}):	-0.003	-1.00	-0.001	-0.16	0.002	-0.06
	(0.01)	(1.79)	(0.01)	(0.46)	(0.01)	(0.16)
1 year after (t_{+1}):	-0.12***	-19.86***	-0.18***	-6.78***	-0.07***	-1.05***
	(0.01)	(2.34)	(0.02)	(0.65)	(0.02)	(0.24)
2 years after (t_{+2}):	-0.13***	-20.92***	-0.17***	-6.66***	-0.09***	-1.41***
	(0.02)	(2.57)	(0.02)	(0.69)	(0.02)	(0.28)
3 years after (t_{+3}):	-0.13***	-21.01***	-0.17***	-6.61***	-0.10***	-1.36***
	(0.02)	(2.84)	(0.02)	(0.75)	(0.02)	(0.31)
4 years after (t_{+4}):	-0.14***	-22.78***	-0.18***	-6.83***	-0.11***	-1.66***
	(0.02)	(2.78)	(0.02)	(0.73)	(0.02)	(0.29)
5+ years after (t_{+5}):	-0.13***	-19.56***	-0.16***	-6.31***	-0.07***	-0.97***
	(0.02)	(3.47)	(0.02)	(0.85)	(0.02)	(0.35)
Observations	7,047	7,047	7,047	7,047	7,047	7,047
Buildings (clusters)	548	548	548	548	548	548
Adj. R-squared	0.18	0.31	0.24	0.37	0.71	0.64

Notes: OLS coefficients reported. Column (1) reports a regression of the log of buildings' annual energy use in kWh/m^2 on a pooled intervention dummy (=1 if any energy efficiency investment is applied), where each pre-treatment and post-treatment year represents a separate category (t_{+1}, t_{+2}, etc.). The last pre-treatment period t_{-1} is the reference category, with the associated coefficient normalized to zero. In column (2), the dependent variable is annual energy use in levels. Corresponding results are reported in column (3) and (4) for CO_2 emissions in kg CO_2/m^2 (logs and levels, respectively), while column (5) and (6) report results for annual heating expenditures in CHF/m^2 (logs and levels, respectively). Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1. All regressions include control variables, year and buildings fixed effects, and during-treatment dummies. Standard errors are clustered at the building-level and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

Appendix E Robustness: Summary statistics for subsamples

Table E1: Building characteristics across subgroups

	Heating oil buildings			Purely residential buildings			Balanced panel		
	All	Treated	Control	All	Treated	Control	All	Treated	Control
Annual energy use (kWh/m^2)	185.18	198.48	171.71	174.43	195.54	159.96	188.00	201.45	172.85
Total surface area (m^2)	1588.23	1725.98	1448.81	1353.42	1403.06	1319.37	1561.5	1721.75	1380.92
Construction year[a]	1962.22	1963.57	1960.87	1972.89	1967.14	1976.84	1960.49	1961.96	1958.84
Number of units[b]	22.27	24.12	20.4	18.48	19.88	17.52	21.98	24.38	19.27
Avg. unit size[c]	3.11	3.09	3.13	3.25	3.09	3.36	3.09	3.08	3.10
Monthly rent[d] (CHF/m^2)	15.29	14.82	15.76	15.97	15.20	16.52	15.17	14.70	15.70
Heating degree days[e]	2882.21	2888.41	2875.48	2883.47	2892.75	2876.61	2881.09	2884.93	2876.76
Commercial units (%)	0.05	0.05	0.04	0.00	0.00	0.00	0.04	0.04	0.04
Observations	334	168	166	322	131	191	285	151	134

Notes: This table reports summary statistics for subsamples used in the robustness section. For treated buildings pre-treatment averages are reported. [a]Average construction year of buildings in Switzerland: 1963.3 (SFSO, 2019a). [b]Total number of residential and/or commercial leases; average for Switzerland: 4.9 (SFSO, 2019a). [c]Average number of rooms per unit; average for Switzerland: 3.3 (SFSO, 2019a). [d]Average monthly rent for Switzerland: 13.7 CHF/m^2 (SFSO, 2019a). Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1. [e]Heating degree days measure the difference between the local average outdoor temperature in a given day and 20°C, cumulated over a given heating season (see footnote 11).

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