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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 239 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. Our results show that a ranking of interventions based on realized energy savings yields substantially different priorities as compared to a ranking of implicit carbon prices, with estimates of frequently subsidized measures (such as wall insulation and windows replacement) well in excess of available benefit estimates for avoided emissions.

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, regulation often targets 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,

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[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.

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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 (see e.g. 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 draw a comparison to energy savings 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, 239 buildings benefited from energy efficiency investments, and our data allow us to derive forensic evidence for the implicit carbon price associated with the following interventions: insulation of exterior walls, roof or attic, replacement of windows, installation of smart heating control that optimizes heating operations using real-time information (e.g., weather forecasts), and replacement of the boiler, including fuel switching from heating oil to natural gas.

The primitive to estimate the implicit price of carbon is energy savings, which determines both reductions of carbon emissions and financial savings associated with lower energy use.[3] 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; Qiu and Patwardhan, 2018). In the setting we consider, investment decisions by portfolio managers are not random but are instead based on dilapidation, and energy efficiency interventions reflect expectations about increased market value and rents (see Brounen and Kok, 2011; Eichholtz et al., 2013; Walls et al., 2017) rather than financial savings associated with lower energy use. In fact, building-level expenses in relation to heating fuel consumption are fully passed on to tenants in the building, 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 make heating decisions and directly benefit from improved energy efficiency cannot influence decisions to renovate their dwelling. This mitigates self-selection into treatment extensively discussed in the evaluation of renovation programs targeting owner-occupied properties (Metcalf and Hassett, 1999; Allcott and Greenstone, 2017).

In order to estimate counterfactual energy use among treated buildings in the absence of investments, we exploit the fact that 309 buildings experienced no energy-efficiency investments over the estimation period. These never-treated buildings constitute a candidate control group. Importantly, the timing of energy efficiency investments across buildings implies that treated buildings gradually enter the post-treatment period ("timing groups"), which allows us to compare pre-treatment trends for treated and control buildings over fourteen years of data.[4] In a nutshell, our data show that, before energy efficiency investments, treated buildings use on average more energy per square meter relative to control, although the difference is approximately constant with time. This suggests that the evolution of energy use in control buildings provides relevant information to document the causal impact of energy efficiency investments on energy use, even in the presence of non-random treatment assignment.[5]

Based on evidence that treated and control buildings follow the same trend before treatment, we implement a staggered difference-in-differences estimation strategy (Autor, 2003; Stevenson and Wolfers, 2006; Fuest et al., 2018). We start by quantifying energy savings associated with individual energy efficiency interventions, controlling for year and building fixed effects, local weather shocks and fuel prices, as well as complementarity effects across interventions (Mulder et al., 2003).[6] This provides evidence about energy savings associated with alternative energy efficiency investments, which is important because policies (e.g., subsidies for wall insulation or windows replacement) typically target interventions based on expected energy savings. Non-random treatment assignment implies, however, that 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).

Next, we exploit financial information on energy efficiency investments to quantify the implicit price of carbon associated with alternative interventions.[7] This delivers the main contribution of our work, and we proceed in two steps. First, we employ difference-in-differences regressions to estimate how USD 1 invested in energy efficiency affects building-level CO_2 emissions. Second, we similarly quantify how investments affect 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.

[2] Energy consumption patterns are 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 below we come back to the presence of a small share of commercial units.

[3] In all the buildings we consider, tenants share a single central heating appliance that operates on either heating oil or natural gas, and we use standard conversion factors to compute CO_2 emissions. Also, the interventions we consider are not expected to affect electricity use, mainly because there are no cooling appliances.

[4] Throughout the text, we refer to never-treated buildings as our control group. However, our identification strategy implies that not-yet-treated buildings also contribute to the estimation of a counterfactual for treated buildings, which effectively means that treatment and control groups are changing over time. As a robustness check, we exclude never-treated buildings from the analysis and solely rely on the timing of interventions to identify the impact of interventions.

[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 energy efficiency interventions.

[6] A growing literature suggests that two-way fixed effects estimation can be biased if treatment effects vary over time, as staggered adoption implies that observations in the middle of the panel (mid-adopters) receive more weight (see Borusyak and Jaravel, 2017; Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020). Together with a number of robustness checks to document this issue, we provide evidence that, in our context, treatment effects are stable with time. We also follow Burlig et al. (2020) and check that our results are not overly sensitive to outliers and model specification (see also Souza, 2019). We come back to this below.

[7] Note that investment data is in Swiss francs. We adjust prices to a common 2015 baseline and, for comparability with the literature, we use a corresponding exchange rate of approx. CHF 1 = USD 1 to report our results in USD throughout.

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.[8]

Overall, our empirical results demonstrate that a ranking of interventions based on implicit carbon prices differs substantially from a ranking using realized energy savings, and this has policy implications. For example, widely subsidized investments such as exterior wall insulation and the replacement of windows are associated with energy savings of around 15 and four percent, respectively. For these two interventions, point estimates for the implicit price of carbon are around USD 1000 per tonne of CO_2. This is an order of magnitude above the CO_2 tax prevailing in Switzerland (USD 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). By contrast, roof insulation and the installation of smart heating control decrease energy use by eleven and seven percent on average, respectively, but the implicit carbon price is significantly lower. For roof insulation, estimates are around 200 USD/tCO_2, whereas most specifications indicate *negative* estimates for smart heating control, suggesting that these investments are optimal even in the absence of externalities. We also find, however, that energy savings for smart heating control 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-treated buildings. Finally, we find only modest evidence of complementarity among energy savings measures.

1.1. Relation to the literature

Our work contributes to a 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 our paper builds on a number of studies documenting heterogeneity of energy savings associated with energy efficiency interventions in buildings. One common finding is that realized savings generally fail to meet *ex-ante* projections (e.g., Grimes et al., 2016; Maher, 2016; Zivin and Novan, 2016; Allcott and Greenstone, 2017; Liang et al., 2017; Fowlie et al., 2018).[9] One potential source of discrepancy between projected and realized savings is increased consumption of energy services (a rebound effect, see Gillingham et al., 2016). 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. Engineering projections may also be overoptimistic and/or installation works may fail to meet expectations (see Giraudet et al., 2018; Christensen et al., 2021).

As mentioned above, one key challenge in this literature is selection into treatment, and a number of recent studies emphasize the use of machine learning approaches to estimate counterfactual energy use in the absence of energy efficiency investments (Qiu and Patwardhan, 2018, provides an overview). For example, Burlig et al. (2020) use hourly data on electricity consumption among a set of schools together with an estimation procedure based on the least absolute shrinkage and selection operator (LASSO) to show that fixed effect estimation can be sensitive to outliers as well as to the selection of fixed effects. Similarly, Souza (2019) and Christensen et al. (2021) use data from the Weatherization Assistance Program (WAP) to test various machine learning algorithms and document heterogeneity in the gap between projected and realized savings. In our context, we test for the sensitivity of our results to the approaches suggested by Burlig et al. (2020), although we emphasize that our yearly data smooths a lot of the variability and therefore limits the scope for rich predictive models to outperform alternative fixed effect specifications.

While our work is methodologically related to the above papers, our data do not allow us to identify potential differences between projected and realized energy savings. Instead, our results more directly contribute 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 WAP 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). Our results fall in the same ballpark, as a weighted average of our preferred estimates is slightly above 380 USD/tCO_2 (95% confidence interval: 247.28–518.27). In addition, we show that heterogeneity within the realm of buildings' energy efficiency interventions generates a range of implicit carbon prices that corresponds to the much broader set of interventions considered in Gillingham and Stock (2018).

One important feature of the WAP is that it focuses on low income households in the US and offers relatively cheap bundles of energy efficiency interventions. The context of our study provides a complementary perspective. First, whereas the bulk of the literature focuses on (semi-)detached properties, our results refer to multi-unit apartment buildings.[10] Second, in our setting property owners do not financially benefit from energy savings, which mitigates the issue of self-selection into treatment and underpins the parallel trend assumption. Third, our data also afford a rare investigation of energy efficiency investment behavior outside of specific

[8] 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).

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

[10] While these represent around 20 percent of dwellings in the U.S., among European countries the share amounts to 42 percent.

policy programs (Metcalf and Hassett, 1999, is another exception). Despite these differences, our estimates of energy savings across interventions (around eleven percent on average) closely align with the above studies. In addition, we make use of our detailed financial data to provide novel evidence comparing the ranking of alternative energy efficiency interventions in terms of energy savings and implicit carbon prices.

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. Second, we report evidence on trends in energy use among treated and control buildings, which provides the basis for our identification strategy. Third, 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. Lastly, we discuss a number of tests to help assess the robustness and validity of our estimates.

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, Fig. A.1).

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 USD), which comprise operation costs for the central heating system (e.g., including subscription fees to the services operating smart heating control),[11] 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.[12]

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 heating control* is the installation of a system that uses real-time information to optimize operations of the central heating appliance;[13] (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 include 402 interventions targeting 239 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 heating control and solar thermal collectors starting later in time (2013 and 2012, respectively).[14] The remaining 309 buildings have not undergone any energy-related intervention during the period we consider, and we refer to these buildings as our control group.

For each intervention we also obtain 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 are missing for one instance of wall insulation, five installations of smart heating control, and 13

[11] 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., 2020, for a discussion). Note that the installation of individual meters is included in the set of treatments we consider.

[12] 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)

[13] 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 heating supply, including peak heat load control.

[14] 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. Moreover, given the small number of observations for solar thermal collectors, we do not report these interventions further (although we control for these throughout).

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 heating control	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 (239 treated), corresponding to the beginning of the intervention.

Table 2
Summary statistics for intervention-specific investment costs.

	Investment cost in USD/unit		Investment cost in USD/m^2	
	Mean	St. Dev.	Mean	St. Dev.
Wall insulation	13,470.78	10,612.40	203.65	169.00
Roof insulation	5926.77	4150.26	87.51	58.00
Windows replacement	6116.70	3772.04	91.47	58.54
Smart heating control	49.90	26.31	0.69	0.37
Boiler replacement	2657.24	1316.23	36.10	19.94
Boiler replacement (oil–gas)	5296.79	2490.97	79.36	37.59

Notes: 219 treated buildings with intervention-specific investment costs are observed (out of 239 treated buildings overall). 2015 prices; exchange rate approx. USD 1 = USD 1.

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.

Table 2 reports summary statistics for investment costs across interventions. Because we consider multi-units properties, we scale total cost by either the number of units in each building or total surface area (in m^2), which facilitate comparisons with other contexts. The resulting figures show that wall insulation is the most expensive intervention, whereas roof insulation, windows replacement and boiler replacement (with oil to gas switching) imply comparable investment costs on average. The installation of smart heating control is significantly less costly.

While working with a specific Swiss context makes comparisons with other settings subject to caution, we now discuss how the magnitude of investment costs relates to alternative data sources. For example, in the context of the WAP extensively discussed in the literature, Fowlie et al. (2018) report average investment costs of about USD 5000 per unit, and Christensen et al. (2021) show average spending per unit of USD 350 for wall insulation, USD 950 for roof insulation and USD 640 for windows. These figures are substantially lower than what we report in Table 2. We emphasize, however, that the WAP targets low-income households in the U.S., which can explain the very moderate cost of intervention bundles studied in these papers. By contrast, investment costs in our dataset are more comparable to evidence reported for "deep" energy retrofits among standard residential properties. Specifically, a comprehensive report summarizing cost data across different U.S. case studies (Cluett and Amann, 2014, adjusted for 2015 prices) suggests investment costs of USD 115–360/m^2 for wall insulation (USD 11,000–20,000 per unit), USD 200–350/m^2 for roof insulation (USD 20,000 per unit), and USD 430–715/m^2 for windows replacement (cost per unit not available). These figures are significantly higher than those reported in the context of the WAP, and we believe that they are more comparable to the context we consider. Despite these differences, by definition estimates for the implicit price of carbon derived in Fowlie et al. (2018) remain a relevant point of reference.

2.2. Identification: Pre-treatment trends in energy use

The objective of this section is to motivate our strategy to identify energy savings and the implicit price of carbon associated with alternative investments in energy efficiency. Intuitively, we mainly rely on 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 3, together with a comparison of treated and control buildings (using pre-treatment values where relevant).[15] Overall, treated buildings tend to be older and command lower

[15] 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 3).

Table 3
Summary statistics for buildings.

	All buildings				Treated buildings	Control buildings	Diff.	(t-stat.)
	Mean	St. Dev.	Min	Max	Pre-treat. mean	Mean		
Construction year[a]	1972.35	25.44	1870.00	2016.00	1968.76	1975.16	−6.40**	(−2.93)
Monthly rent[b] (USD/m^2)	16.14	3.21	0.00	45.28	15.50	16.65	−1.14***	(−4.19)
Vacancy rate (%)	0.06	0.04	0.00	0.63	0.06	0.06	−0.001	(−0.17)
Annual energy use (kWh/m^2)	171.64	48.53	19.74	422.19	190.77	156.85	33.92***	(8.64)
Heating degree days[c]	2865.04	232.92	2477.00	4371.00	2895.65	2841.36	54.29**	(2.72)
Annual heating cost (USD/m^2)	13.33	4.10	2.32	36.44	13.42	13.26	0.15	(0.43)
Oil heating indicator	0.61	0.49	0.00	1.00	0.70	0.54	0.17***	(3.99)
Total surface area (m^2)	1736.93	1260.20	228.00	12,130.00	1818.75	1673.64	145.11	(1.34)
Number of units[d]	23.36	16.43	3.00	167.00	24.66	22.36	2.29	(1.62)
Avg. unit size[e]	3.22	0.65	1.18	5.50	3.13	3.28	−0.15**	(−2.64)
Commercial units (%)	0.06	0.11	0.00	0.93	0.06	0.05	0.01	(1.19)

Notes: 548 buildings are observed, with 239 in the treatment group and 309 in the control group. For treated buildings we report pre-treatment averages. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

[a]Average construction year of buildings in Switzerland: 1963.3 (SFSO, 2019a).

[b]Average monthly rent for Switzerland: 13.7 USD/m^2 (SFSO, 2019a).

[c]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 2.1).

[d]Total number of residential and/or commercial leases; average for Switzerland: 4.9 (SFSO, 2019a).

[e]Average number of rooms per unit; average for Switzerland: 3.3 (SFSO, 2019a). 2015 prices; exchange rate approx. USD 1 = USD 1.

rents as compared to control buildings, although the rate of vacant units is similar in both groups. We also observe that energy use per square meter is higher among treated buildings, which can at least be partly accounted for by a larger number of heating degree days relative to control. More interestingly, annual heating costs are not significantly higher among treated buildings, confirming that financial savings for tenants is not a major criteria in how buildings are selected into treatment. We note that treated buildings are also more likely to use heating oil, which tends to be cheaper than natural gas and therefore accounts for lower heating costs despite higher energy use.[16]

Overall, while we do observe some differences between treated and control buildings, evidence suggests that selection into treatment reflects expected profitability associated with energy efficiency investments rather than expected financial savings associated with lower energy use. Moreover, we emphasize that these differences are not necessarily a threat to identification of energy savings and the implicit price of carbon. Instead, we need credible evidence that the evolution of buildings without interventions provides a plausible counterfactual for treated buildings in the absence of investments.

To motivate the use of buildings without interventions as a control group, Fig. 1 documents the parallel trend assumption underlying our identification strategy. 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). This implies that the number of buildings in the control group varies with time, and that some of the buildings entering the portfolio end up getting treated during the renovation period, so that the number of pre-treatment observations for treated buildings can also increase.[17]

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 can be observed in the form of milder temperatures experienced during the heating season.[18] Second, the market price of heating oil and natural gas has increased by 43.6 and 30.3 percent respectively (SFSO, 2019b). A CO_2 tax on heating oil and natural gas has been levied since 2008, starting at USD 12/tCO_2 and gradually reaching USD84/tCO_2 in 2016 (SFOEN, 2018). In our analysis we control for potential fuel price effects (aside from year fixed effects).

[16] We emphasize that electricity does not enter heating energy use in the buildings we consider, as cooling appliances are not available. We note that this is in line with the Swiss context, as 2015 data shows that air conditioning amounts to 0.13% of residential energy end uses in Switzerland (see Prognos, 2018), compared to 8% in the U.S. (see EIA, 2019, for example).

[17] See Appendix B, Fig. B.1, for the corresponding figure derived for a subsample of 285 buildings that remain in the portfolio over the entire horizon (balanced panel). We come back to potential sample selection issues in the robustness section by providing empirical results for the balanced dataset.

[18] 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.

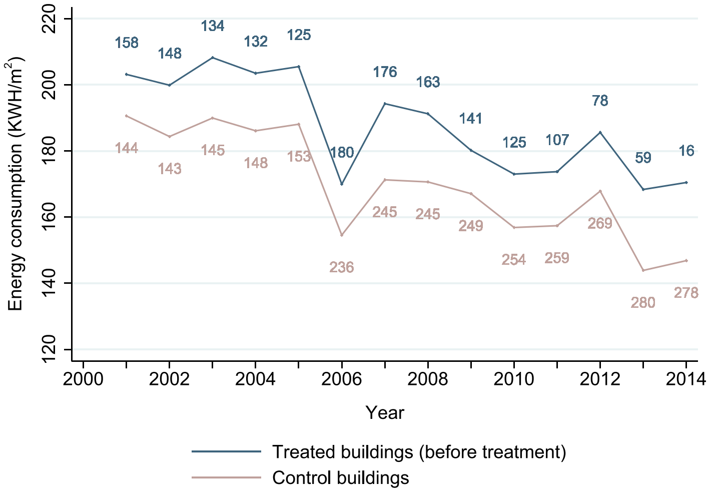


Fig. 1. Trends in pre-treatment energy use for treated and control buildings.
Notes: This figure reports pre-treatment average energy use (in kWh/m^2) for treated and control buildings over time, together with the number of buildings used to calculate group-specific averages (i.e., the number of observations 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.

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.

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 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:

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

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 Eq. (1) is the main workhorse of the existing literature, it averages the impact of different 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 year (the coefficient for the last pre-treatment period is normalized to zero). This provides a formal test of pre-treatment parallel trends, evidence for the temporal stability of the treatment effect estimates, and also allows us to relate our results to existing empirical evidence cited above documenting energy savings for renovation bundles.

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

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

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 individual impact of each 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 standardize 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-treated buildings (ATENT), respectively.

Table 4
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 heating control	15	10	CRB (2012)
Boiler appliance	40	30	SIA (2004)

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 (USD 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 square meter.[19] 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 USD 1 investment in intervention k. Similarly, the regression for annual heating costs (in USD/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 USD 1 invested in intervention k.

We then straightforwardly combine estimates resulting from Eqs. (3) and (4), together 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 USD/t CO_2). Specifically, we first 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/USD 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 4. The total change in tCO_2 per USD 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.

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 USD 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 USD $\frac{1}{\overline{CO2}_k}$, 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.

We close this section by noting two dimensions that are important for the interpretation of our estimates for the implicit price of carbon. On the one hand, the social cost of carbon is expected to increase with time (e.g., Golosov et al., 2014), which implies that the set of socially profitable investments will expand. On the other hand, climate change has and will imply milder winters, so that heating energy consumption is expected to decline further even in the absence of investments. One implication is that the set of interventions we consider may deliver less energy savings in the future. We note, however, that our estimates do take this downward trend into account over the estimation period.

2.4. Robustness and validity tests

We now discuss how we document robustness and validity of our results for Eqs. (2)–(4). One first concern is that, in the setting we consider, difference-in-differences estimates combine information from the control group (never-treated buildings) and from treated buildings by exploiting the variation in treatment timing (i.e. earlier and later renovated buildings, or timing groups). In turn, Goodman-Bacon (2021) shows that, if the treatment effect increases with time, estimates from a difference-in-differences strategy will be biased towards mid-adopters. Moreover, the bias is expected to increase in the absence of a control group.

To address this issue, we derive results for three alternative subsamples. First, we exclude control buildings from the estimation and consider only the 239 buildings that are treated sometime between 2001 and 2016. This implies that identification solely relies on the staggered nature of investments in order to estimate a counterfactual trajectory for the outcomes considered. Second, we consider the set of buildings that are present in the portfolio over the entire period of observation (i.e., balanced sample). This

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

provides evidence regarding a potential sample selection effect, but also changes the weight given to mid-adopters in the estimation. Third, we derive results for buildings with investments in energy efficiency occurring in 2011 or later (i.e., late adopters). These results provide evidence about the consistency of treatment effects over time, and again change the weight given to different timing groups, documenting a potential bias in our results.

Next, we implement the estimation strategy of Burlig et al. (2020) to address concerns that fixed effect estimation may be sensitive to outliers and model specification (see also Souza, 2019). First, we estimate Eqs. (2)–(4) on a sample that excludes observations below the 1st or above the 99th percentile of energy use (see Burlig et al., 2020). This allows us to assess how energy savings and implicit carbon prices are affected by the presence of outliers. Second, we employ LASSO, a type of regularized regression, to generate building-specific models of energy consumption. The LASSO algorithm makes use of cross-validation in order to parameterize the degree of model saturation and select the best predictors. In our context, the set of candidate variables includes all control variables as well as observed energy use for all (other) control buildings in the dataset. We train the building-specific models exclusively on pre-treatment data and use the estimated models to predict (out-of-sample) post-treatment energy consumption. Finally, we embed counterfactual energy use in a panel fixed effects estimation to identify causal effects. In particular, we run regressions for the difference between observed and predicted energy use for each building on the variables listed in Eq. (2) as well as a post-treatment dummy (equal to one during the out-of-sample prediction period). We then repeat the procedure for Eqs. (3) and (4), which provides us with alternative estimates for energy savings and implicit carbon prices that are based on flexible machine learning predictions of building-level treatment effects.

The three final robustness checks focus on alternative subsamples. First, we investigate the issue of tenant turnover, and in particular the possibility that energy efficiency interventions affect the composition of tenants in the buildings. To do so, we estimate an event-study regression where the outcome is the share of new leases every year, and also estimate Eqs. (2) to (4) for the subset of buildings with tenant turnover rates below the median during and after treatment. This captures the possibility that the tenants who remain in the building after an interventions have different preferences, which may imply differences in behavior and energy savings. Second, the buildings we consider include around 6 percent of commercial leases on average, and evidence suggests that energy use can differ between commercial and residential users (Costa and Kahn, 2011; Kahn et al., 2014). We therefore estimate energy savings and the implicit price of carbon for the set of 322 purely residential buildings. Lastly, we estimate energy savings and implicit carbon prices for the subset of interventions with below-median investment costs (in USD/m^2). This documents the possibility that the scale of our results is affected by the financial cost of investments.

3. Estimation results

This section reports our empirical results. First, we quantify the impact of energy efficiency investments on buildings' energy use, and document energy savings associated with alternative interventions. Second, we estimate the implied change in CO_2 emission reductions and energy expenditures, and derive a ranking of implicit carbon prices for alternative energy efficiency investments. Finally, we discuss the magnitude of potential biases affecting our main results and present evidence derived for different subsamples of buildings.

3.1. *Energy efficiency investments and energy use*

We start with an event-study regression for 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 (Eq. (1)). Regression coefficients associated with energy efficiency interventions are reported graphically in Fig. 2, together with cluster-robust 95% confidence intervals (see Appendix C, Table C.1, for the corresponding regression results). 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.

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 representing on average around 20 kWh/m^2 each year, or around 10.5 percent of pre-treatment average among treated buildings (190.77 kWh/m^2, see Table 3). Importantly, the results show that the treatment effects are stable with time, which is consistent with results reported in Maher (2016), and is a first piece of evidence suggesting that the bias associated with our fixed effect estimation strategy is likely to be small (e.g., Goodman-Bacon, 2021). Quantitatively, 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, report energy savings of 10 to 20 percent on average).

Table 5 quantifies intervention-specific energy savings (Eq. (2)). In columns (1) and (2) we report OLS regression estimates without and with control variables, 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.[20]

[20] In Fig. C.1 of Appendix C we report event-study results for individual interventions. While statistical power declines due to the smaller number of observations, results are overall qualitatively comparable to those for the pooled renovations. In particular, we find little evidence against differential trends among treated and control buildings, and energy savings estimates remain stable in post-treatment periods.

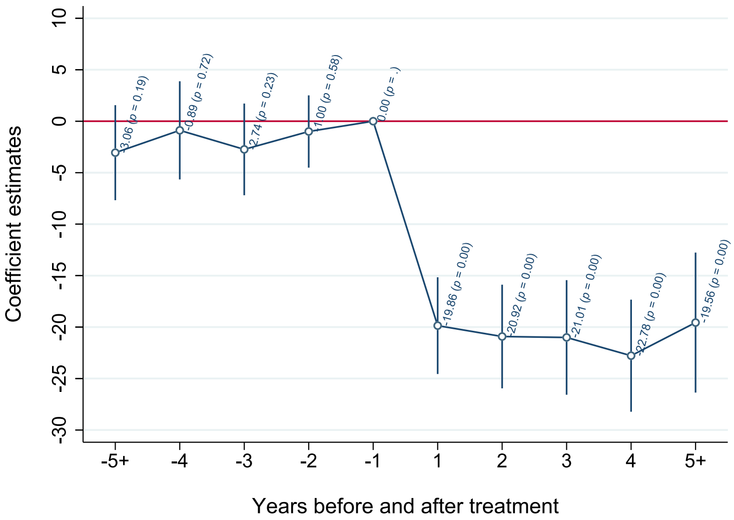


Fig. 2. Panel fixed effects event study results for pooled energy efficiency investments.
Notes: The graph displays point estimates, 95% confidence intervals and p-values from an event-study regression of buildings' annual energy use (kWh/m^2) on pre- and post-treatment dummies for pooled energy efficiency 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 based on standard errors clustered at the building-level. See Appendix C for the corresponding results table.

Table 5
Alternative energy efficiency investments and energy savings.

	Individual treatments	Time-varying controls	Treatment interactions	Energy use interaction evaluated at	
				Sample average	Control group average
	(1)	(2)	(3)	(4)	(5)
Wall insulation	−31.96***	−31.96***	−29.35***	−24.83***	−21.85***
	(6.78)	(6.78)	(7.86)	(6.58)	(6.76)
Roof insulation	−11.98**	−12.04**	−13.73	−10.09	−8.86
	(5.85)	(5.84)	(8.73)	(9.62)	(10.91)
Windows replacement	−9.47***	−9.50***	−8.10***	−7.73***	−7.13**
	(2.71)	(2.70)	(2.79)	(2.73)	(3.15)
Smart heating control	−17.79***	−17.52***	−20.85***	−19.95***	−15.47***
	(3.70)	(3.68)	(4.45)	(3.11)	(3.01)
Boiler replacement	−13.96***	−13.79***	−13.65***	−9.34***	−5.30**
	(2.93)	(2.93)	(3.28)	(2.39)	(2.59)
Boiler replacement (oil–gas)	−3.92	−3.16	−3.81	2.40	6.26
	(4.11)	(4.04)	(4.77)	(4.11)	(4.38)
Space heat meters	10.44	10.40	3.30	11.97	8.35
	(8.50)	(8.48)	(9.43)	(10.14)	(8.31)
Hot water meters	−4.43	−4.32	−2.89	−12.20	−6.70
	(8.21)	(8.22)	(8.50)	(9.36)	(7.54)
Control variables	No	Yes	Yes	Yes	Yes
Treatment interactions × pre-treatment energy use	No	No	Yes	Yes	Yes
Sample average	No	No	No	Yes	No
Control group average	No	No	No	No	Yes
Observations	7046	7046	7046	7046	7046
Buildings (clusters)	548	548	548	548	548
Adj. R-squared	0.35	0.35	0.35	0.37	0.37

Notes: The dependent variable is buildings' annual energy use in kWh/m^2, see Eq. (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.

Results show that estimates are broadly consistent across columns (1) to (3), and confirm large differences in energy savings across interventions. Exterior wall insulation delivers the largest energy savings (around 15 percent reduction in pre-treatment energy use on average), followed by smart heating control (around 11 percent), whereas roof insulation and boiler replacement

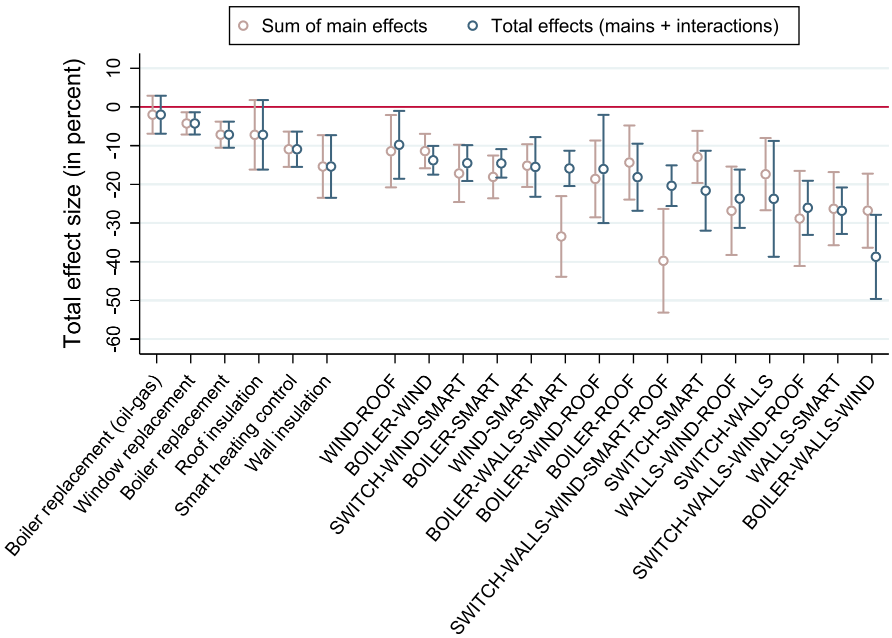


Fig. 3. Total energy savings for observed combinations of interventions.
Notes: This figure provides point estimates, 95% confidence intervals and p-values (obtained via the delta method) for selected combinations of energy efficiency investments, derived from regression results reported in Table 5, column (3). WALLS is *wall insulation*, ROOF is *roof insulation*, WIND is *windows replacement*, SMART is *smart heating control*, HEAT is *boiler replacement*, and SWITCH is *boiler replacement (oil–gas)*.

(without fuel switching) save around seven percent on average. Energy savings implied by windows replacement are around four 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 Fig. 3, which uses estimates in Table 5, column (3), to compute *total* effect size (in percent) for a subset of observed combinations of interventions. 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 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 tend to have a negative impact on energy savings. One implication is that energy savings evaluated for control buildings (ATENT) are slightly smaller as compared to results for the treatment group (ATET). However, we note that differences across subgroups are not statistically significant as 95% confidence intervals largely overlap.[21]

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 6, columns (1) and (2) provide regression results for Eqs. (3) and (4), respectively.[22] More specifically, column (1) regresses CO_2 emissions (in kg CO_2/m^2) on investment costs for all treatments considered (I_{kit}, in USD/m^2), and column (2) regresses annual heating expenditures (in USD/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/USD, whereas smart heating control instead decreases CO_2 emissions

[21] In fact, these results may be an artifact of our specification in levels, and using a log-transformed outcome variable confirm that ATET and ATENT do not differ significantly when treatment effects are measured as percentages.

[22] In Appendix C, Table C.1, 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 6
CO_2 emissions, heating costs, and estimates for the implicit carbon price.

	Regression results		Estimates for the implicit price of carbon (USD/tCO_2)			
	CO_2 emissions	Heating cost	Average use lifetime		Heavy use lifetime	
	(kg/m^2)	(USD/m^2)	$\delta = 0\%$	$\delta = 6\%$	$\delta = 0\%$	$\delta = 6\%$
	(1)	(2)	(3)	(4)	(5)	(6)
Wall insulation	−0.01***	−0.003***	941.59***	1164.61***	1116.25***	1331.48***
	(0.003)	(0.0006)	(288.61)	(304.51)	(332.47)	(348.06)
Roof insulation	−0.07***	−0.03***	−53.60	191.06***	59.26	271.50***
	(0.02)	(0.01)	(75.51)	(69.49)	(89.64)	(94.01)
Windows replacement	−0.02***	−0.01*	657.92**	853.68***	1287.12***	1441.82***
	(0.01)	(0.003)	(314.09)	(286.82)	(493.52)	(476.29)
Smart heating control	−5.68***	−1.99***	−337.66***	−214.50***	−331.80***	−239.56***
	(1.28)	(0.64)	(89.61)	(57.95)	(89.51)	(65.82)
Boiler replacement	−0.08***	−0.02***	38.30	198.68***	136.77	275.89***
	(0.02)	(0.01)	(75.14)	(58.36)	(88.85)	(77.29)
Boiler replacement (oil–gas)	−0.13***	0.01	263.23***	216.23***	325.86***	285.09***
	(0.01)	(0.01)	(51.11)	(25.34)	(53.69)	(32.28)
Observations	7046	7046				
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 USD/m^2). Column (2) is a regression of annual heating costs (in USD/m^2) on post-treatment investment cost variables (I_{kit}, in USD/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 Table 4. 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.

by 5.68 kg/USD invested. Importantly, the ranking across interventions implied by these results differs significantly from the one associated with energy savings (Table 5, column 3).

Column (2) further shows that most energy efficiency investments have a statistically significant impact on heating expenditures. The reduction is largest for the installation of smart heating control (USD 1.99/USD invested) even though annual operational expenses (subscription costs) partly offset financial savings associated with lower energy use. By contrast, investment 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 Table 4 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 Fig. 4, we further illustrate the ranking across interventions and show sensitivity to alternative assumptions about the discount rate and expected lifetime of elements. This can 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 lifetime and discounting assumptions considered, although estimates for windows replacement tend to be more sensitive. Moreover, although 95% confidence bounds are quite wide, these estimates differ sharply from those associated with roof insulation, boiler replacement (with and without fuel switching), or smart heating control. By contrast, we estimate that the implicit price of carbon associated with smart heating control 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 USD 200/tCO_2 for a more reasonable discount rate of six percent. Similarly, the implicit price of carbon associated with boiler replacement is around USD 200/tCO_2.

In sum, the implicit price of carbon varies significantly across interventions, and the implied ranking does not align with estimates for energy savings reported previously. A weighted average across interventions based on the frequency of renovations suggests an implicit carbon price associated with energy efficiency in buildings of 382.77 USD/tCO_2 (95% confidence interval: 247.28–518.27). As mentioned previously, this estimate is relatively close to a value of 350 USD/tCO_2 discussed in Gillingham and Stock (2018) in reference to the WAP.

3.3. Sensitivity of implicit carbon price estimates across alternative subsamples

In Table 7 we provide further evidence about the implicit carbon price for the following subsamples: (i) treated buildings only (column 1); (ii) buildings that remain in the portfolio over the entire observation period (column 2); (iii) buildings renovated in 2011 or later (column 3); (iv) dropping outliers for energy use (column 4); (v) flexible LASSO estimation (column 5); (vi) buildings

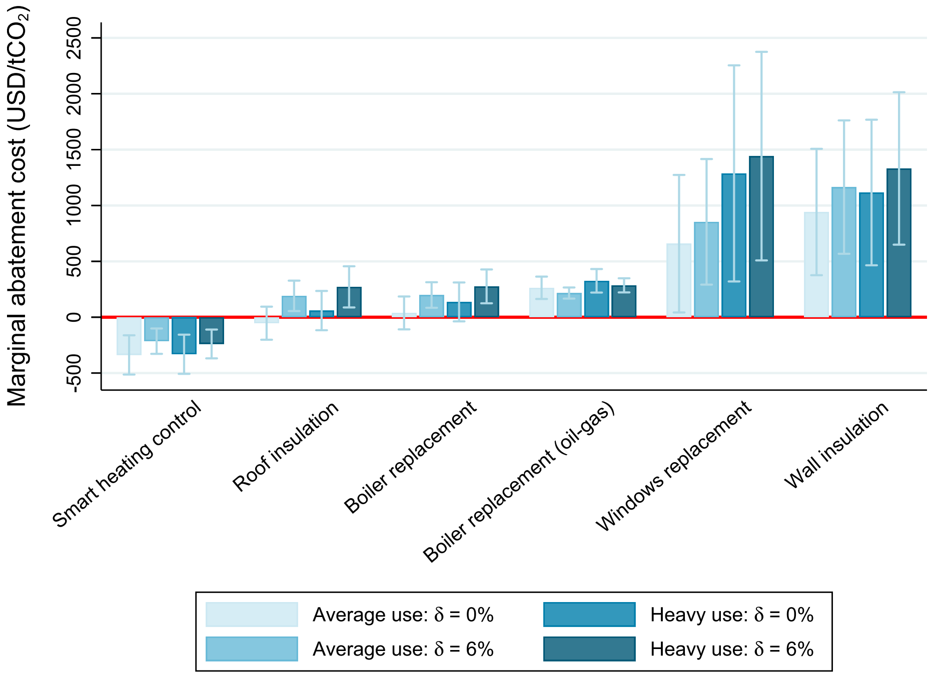


Fig. 4. Ranking for the implicit price of carbon across interventions.
Notes: The graph displays point estimates and 95% confidence intervals for estimates of the implicit price of carbon. See Table 6, columns (3–6), for the corresponding results. Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1.

with high tenant turnover (column 6); (vii) buildings with residential leases only (column 7); and (viii) interventions with low investment costs (column 8). In Appendix D, Table D.1, we provide summary statistics for each subsample (see also Table 3) and regression results supporting estimates in Table 7 are reported in Appendix E, Tables E.1 to Table E.8.

In column (1), Table 7, we start by excluding control buildings from the analysis and focus on 239 treated buildings that benefit from investments at some point between 2001 and 2016. This implies that estimates in Table E.1 only exploit differences in the timing of the investments (staggered adoption) to inform the trajectory of the counterfactual outcome. The results in Appendix E show that energy savings estimates align closely with those derived in the presence of a control group of buildings that did not benefit from any energy efficiency intervention (see Table 5, column (3). Similarly, CO_2 abatement, changes in energy expenditures, and in turn point estimates for implicit carbon prices are also very similar to our baseline results.

Results derived for the balanced subsample of 285 buildings (151 treated) observed over 16 years also imply energy savings estimates that are very similar to our main results, although as expected standard errors are slightly larger (see Table E.2). Moreover, as shown in Table 7 column (2), the ranking of implicit carbon prices is similar, with the exception of boiler replacement measures. One notable difference is a positive impact of smart heating control on heating cost (statistically indistinguishable from zero), presumably on account of the subscription fees mentioned earlier. In turn, the point estimate for the implicit price of carbon associated with smart heating control is positive, although not statistically significantly different from zero.

Turning to late adopters, we consider 141 buildings with interventions taking place in 2011 or later. Results reported in Table E.3 suggest larger energy savings for exterior wall insulation as compared to our baseline results (Table 5, column 3), although implicit carbon prices are virtually identical (Table 7, column 3). A similar pattern emerges for boiler replacements (with oil to gas switching), which suggests that the scale of renovation (incl. its financial cost) has expanded with time without affecting our metric of interest. For other interventions, estimates are comparable to our baseline results, although standard errors increase for roof insulation and windows replacement.

Taken together, the analysis presented so far can be interpreted as evidence that our staggered difference in differences research design is robust to a number of caveats discussed in the literature. On the one hand, results that omit untreated buildings suggest that our control group can be used to generate a plausible counterfactual for renovated buildings in the absence of investments (despite the observed differences between the treatment and control buildings discussed in Table 3).[23] On the other hand, results using a balanced panel and late adopters suggest that changing the weights given to different timing groups does not significantly affect our estimates. This is also in line with Fig. 2, which shows that the impact of the interventions we consider is approximately

[23] The decomposition technique of Goodman-Bacon (2021) applied to our baseline specification (see Eq. (1)) confirms that the majority of our difference-in-differences estimate is based on comparisons of treated buildings with the control group (64% weight), whereas comparisons with treated buildings in other timing groups are less important.

Table 7
Estimates for the implicit price of carbon across alternative subsamples.

	Treated buildings (1)	Balanced subsample (2)	Late adopters (3)	Outliers trimmed (4)	LASSO estimation (5)	Low tenant turnover (6)	Residential buildings (7)	Lower-cost interventions (8)
Wall insulation	794.36***	1158.48***	1106.65***	1260.54***	1038.71***	1296.82***	1780.11***	1167.57***
	(281.27)	(324.97)	(347.81)	(246.18)	(253.38)	(416.38)	(595.25)	(361.71)
Roof insulation	155.26**	121.11*	580.48	171.21***	140.98**	288.65**	134.87*	167.83*
	(75.93)	(63.01)	(394.02)	(61.50)	(58.48)	(119.67)	(71.75)	(99.34)
Windows replacement	795.62***	1088.40**	663.77	911.85***	618.22**	1116.19***	768.78**	291.09**
	(281.65)	(472.93)	(456.08)	(312.11)	(279.77)	(412.32)	(307.31)	(137.33)
Smart heating control	−286.06***	101.14	−165.21**	−196.95***	−249.41***	−57.58	−104.42	−89.48
	(67.95)	(107.37)	(72.45)	(50.04)	(60.66)	(105.87)	(123.66)	(121.96)
Boiler replacement	175.36***	299.17***	203.51***	226.56***	161.25***	154.56*	232.89***	90.00
	(54.78)	(98.26)	(73.66)	(57.72)	(62.09)	(79.40)	(68.32)	(111.97)
Boiler replacement (oil–gas)	218.18***	265.52***	223.06***	214.28***	262.29***	218.36***	248.75***	202.09***
	(27.72)	(48.31)	(29.68)	(24.46)	(31.28)	(20.23)	(42.42)	(39.09)
Observations	3416	4560	5584	6906	6577	5364	4208	6465
Buildings (clusters)	239	285	450	544	481	429	322	548

Notes: This table reports estimates of the implicit price of carbon across interventions assuming average building element lifetimes and a $\delta = 6\%$ discount rate. Column (1) is based on buildings that are treated between 2001 and 2016 and excludes never-treated buildings in the control group; Column (2) uses only buildings that are observed from 2001 to 2016 (balanced panel); Column (3) focuses on the subsample of buildings that have their first renovation in 2011 or later (late adopters); Column (4) excludes observations below the 1st or above the 99th percentile of energy consumption; Column (5) is based on the results from a set of a regressions using LASSO-based prediction errors; Column (6) focuses on the set of buildings with below-median tenant turnover during and after renovation; Column (7) uses data for buildings with residential leases only; and Column (8) focuses on the subsample of interventions that are associated with below-median investment costs (in USD/m^2). Regression results supporting these estimates are reported in Appendix E. All prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1. Cluster-robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

constant in post-treatment periods (see also Fig. C.1 in Appendix C). In sum, in the setting we consider, a potential bias resulting from variation in treatment timing is likely to be small.

Next, we consider two additional potential caveats of our fixed effect estimator discussed in the literature, namely sensitivity of the results to the presence of outliers and possible functional form specification bias. We apply two approaches suggested in Burlig et al. (2020). First, trimming outliers in energy use below the 1st and above the 99th percentile does not significantly affect our results, as estimates for energy savings (Table E.4) and implicit carbon prices reported in Table 7, column 4, are very similar to our baseline results. Second, a LASSO-based estimation strategy produces somewhat more pronounced differences, although point estimates are also comparable and the ranking across interventions remains the same (Tables E.5 and 7, column 5). This suggests that our fixed effect estimation is not overly sensitive to the issues discussed in Burlig et al. (2020).

Another threat to identification is the possibility that energy efficiency interventions affect tenant turnover and, in turn, that treated buildings attract tenants with specific preferences. To document this issue, we first use an event-study regression where the outcome is the share of new leases every year. The results, reported in Appendix C, Fig. C.2, suggest that tenant turnover increases, although the difference relative to control buildings is mostly statistically insignificant and small (less than two percentage points, whereas the share of new leases every year is approx. 15% on average in the control group). We further consider results for the set of buildings with below-median tenant turnover. Energy savings estimates for buildings with low turnover (Table E.6) are similar to our baseline results, except for roof insulation, where savings are smaller, and boiler replacement (oil–gas) which shows negative and statistically significant energy savings. Moreover, while our point estimate for the implicit carbon price associated with windows replacement in buildings with below-median tenant turnover is slightly higher (Table 7, column 6), the ranking of our interventions remains largely unaffected. This supports the view that our results are not driven by changes in the composition of tenants.

Next, we investigate whether the presence of around 6 percent of commercial leases on average affects our results, and consider the sample of 322 purely residential buildings (including 131 treated buildings). Results for energy savings are reported in Table E.7, and implicit carbon prices are in Table 7, column 7. Overall, point estimates tend to be less precisely estimated, implying that the negative estimate associated with smart heating control is not statistically significantly different from zero. Nevertheless, the ranking for the implicit price of carbon remains. This suggests that the presence of buildings with a small share of commercial units does not overly affect our results.

Our last robustness check derives results for the set of treated buildings with investment costs below the median. Results in Table E.8 suggest again that energy savings associated with windows replacements are lower, and in turn that the associated implicit price of carbon is also lower (see Table 7, column 8). To a lesser extent, the same is true for boiler replacements, which shows lower implicit carbon price (not statistically significantly different from zero) relative to our baseline estimates. This suggests some heterogeneity in how investments perform, although overall our ranking of measures and differences between energy savings and implicit carbon prices remain.

4. Discussion and conclusion

In this paper, we have used data for a portfolio of multi-unit buildings to provide novel evidence on energy efficiency investments in buildings as a carbon abatement strategy. Our data includes a rich array of alternative interventions, allowing us to estimate energy savings for a range of frequently subsidized interventions, and to carry out statistical inference on the implicit price of carbon associated with these investments. Given 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 15 and four percent on average. We also find, however, that these interventions are an expensive strategy to abate CO_2. By contrast, installing smart heating control 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. Put differently, smart heating control is consistently found to be the cheapest option for carbon abatement, but the implicit carbon price associated with this specific intervention may also be higher than what our main specification suggests.

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 investment signal that could be afforded by a 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 beyond ex-post estimates of energy savings. Second, our results for smart heating control 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. Third, among the buildings we consider, cooling appliances are not present. In recent years, however, higher temperatures in summer have led to an increase in the demand for cooling. This may induce an increase of electricity use, and interventions that improve thermal insulation may have additional benefits in mitigating higher electricity use. This is in sharp contrast with the declining trend in heating energy use that has and will occur due to milder winter temperatures.

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 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 likely affect investment decisions and the design of public policies, and represent important areas for future investigation.

Appendix A. Location of buildings

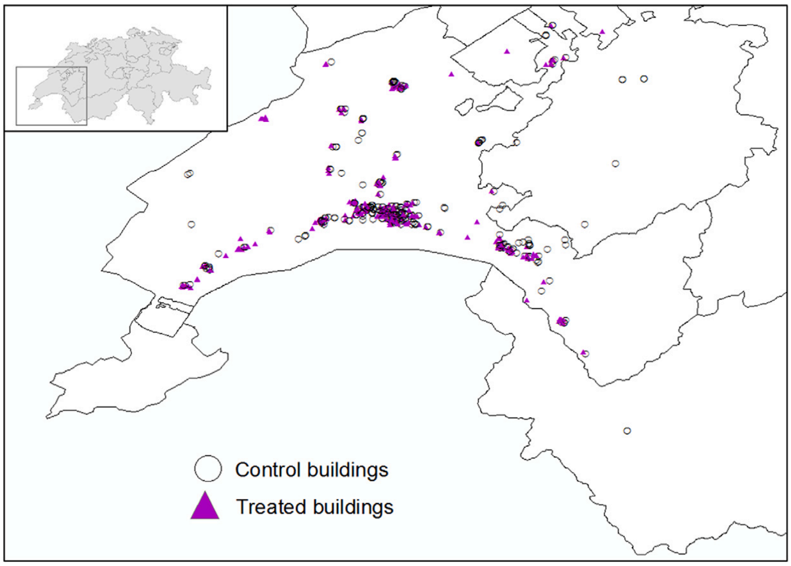


Fig. A.1. Geographical distribution of buildings across treatment and control groups.

Appendix B. Pre-treatment trends in the balanced sample

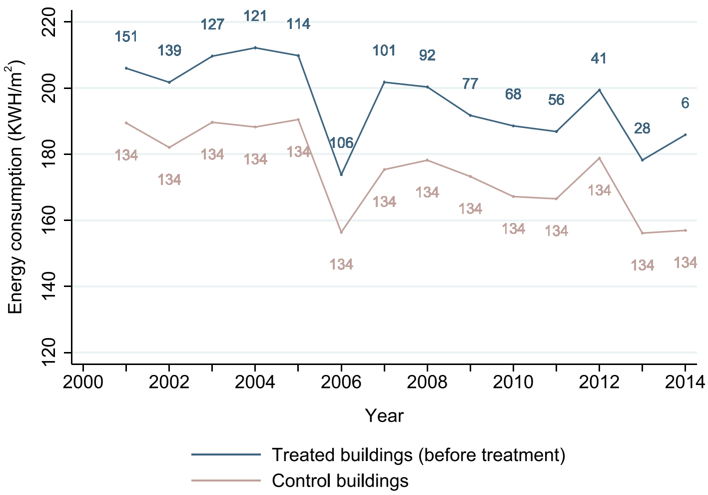
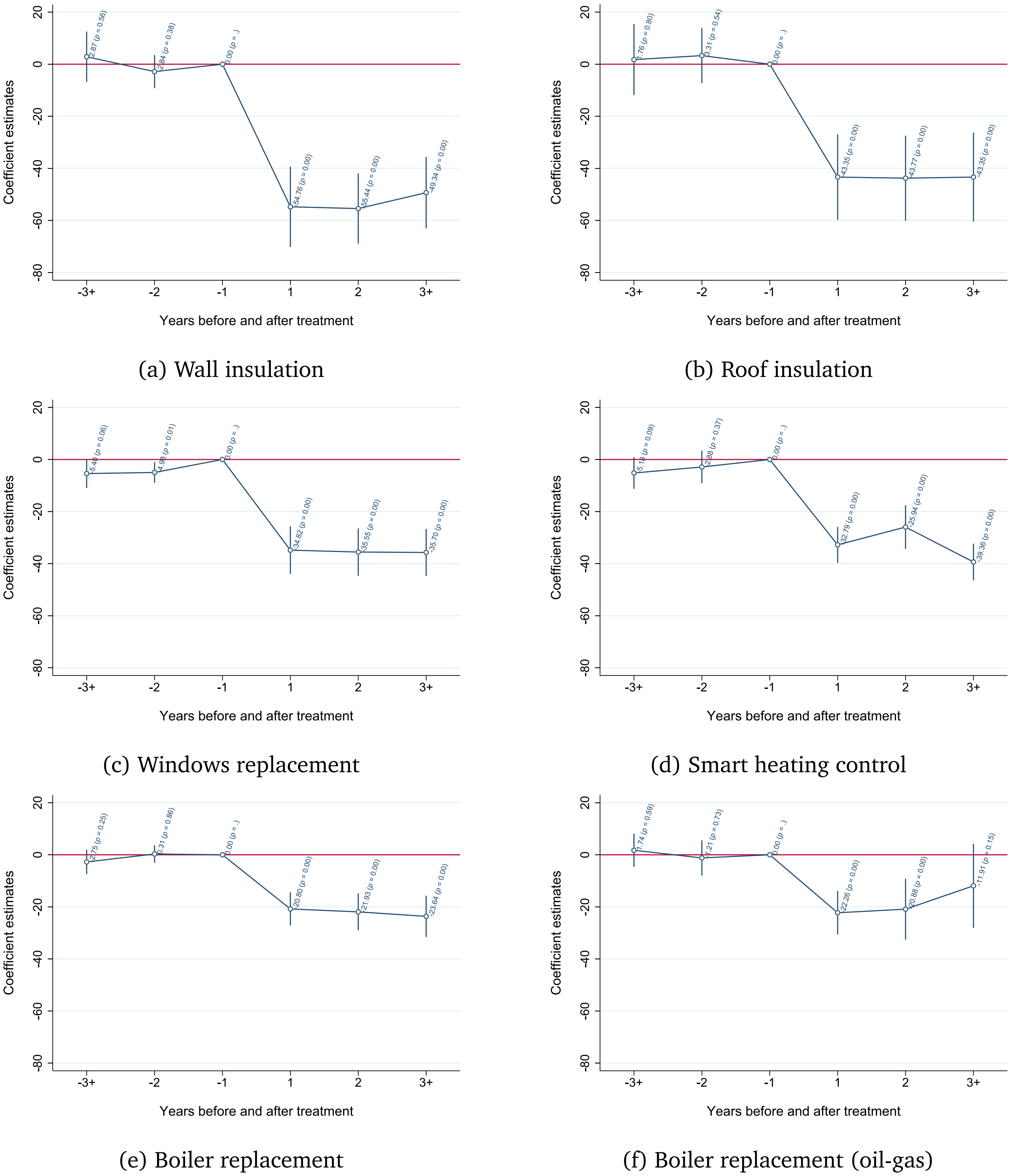


Fig. B.1. Trends in pre-treatment energy use for treated and control buildings (balanced sample).
Notes: This figure reports pre-treatment average energy use (in kWh/m^2) for treated and control buildings over time, together with the number of buildings used to calculate group-specific averages (i.e., 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. Results for panel fixed effects event-study regressions



(a) Wall insulation (b) Roof insulation

(c) Windows replacement (d) Smart heating control

(e) Boiler replacement (f) Boiler replacement (oil-gas)

Fig. C.1. Event study results for individual interventions.
Notes: The graph displays point estimates, 95% confidence intervals and p-values from an event-study regression of buildings' annual energy use (kWh/m^2) on pre- and post-treatment dummies for individual 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. Post-treatment periods after t_{+3} grouped to one single category.

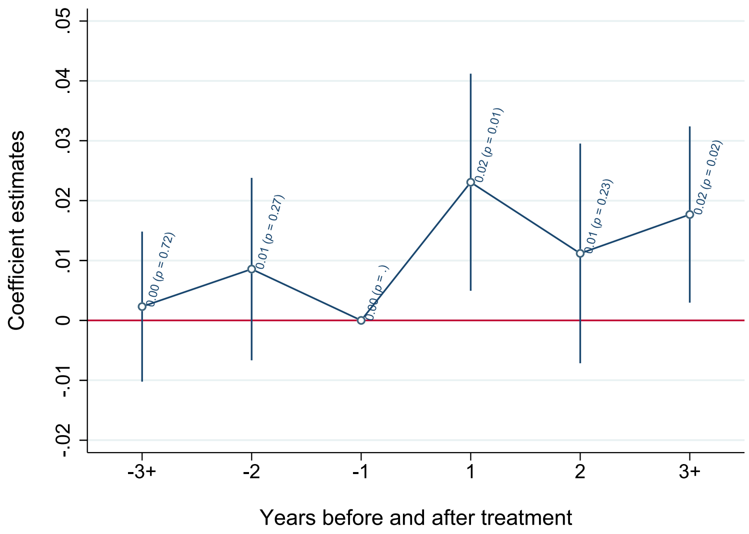


Fig. C.2. Panel fixed effects event study results for tenant turnover.
Notes: The graph displays point estimates, 95% confidence intervals and p-values from an event-study regression of the share of new leases per year and post-treatment dummies for pooled energy efficiency interventions, control variables, building and year fixed effects, and during-treatment dummies. The last pre-treatment period ($t = -1$) is defined as the reference category. Inference is based on standard errors clustered at the building-level.

Table C.1
Event study regression results for pooled energy efficiency investments.

	kWh/m^2 (1)	kg/m^2 (2)	USD/m^2 (3)
5+ years before (t_{-5}):	−3.06	−0.34	−0.67***
	(2.36)	(0.60)	(0.21)
4 years before (t_{-4}):	−0.89	−0.20	−0.35
	(2.43)	(0.58)	(0.23)
3 years before (t_{-3}):	−2.74	−0.63	−0.28
	(2.27)	(0.56)	(0.20)
2 years before (t_{-2}):	−1.00	−0.16	−0.06
	(1.79)	(0.46)	(0.16)
1 year after (t_{+1}):	−19.86***	−6.78***	−1.05***
	(2.40)	(0.65)	(0.24)
2 years after (t_{+2}):	−20.92***	−6.66***	−1.41***
	(2.57)	(0.69)	(0.28)
3 years after (t_{+3}):	−21.01***	−6.61***	−1.36***
	(2.84)	(0.75)	(0.31)
4 years after (t_{+4}):	−22.78***	−6.83***	−1.66***
	(2.78)	(0.73)	(0.29)
5+ years after (t_{+5}):	−19.56***	−6.31***	−0.97***
	(3.47)	(0.85)	(0.35)
Observations	7046	7046	7046
Buildings (clusters)	548	548	548
Adj. R-squared	0.30	0.37	0.64

Notes: OLS coefficients reported. Column (1) reports a regression 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. Corresponding results are reported in column (2) for CO_2 emissions in kg CO_2/m^2, while column (3) reports results for annual heating expenditures in USD/m^2. Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1. All regressions include control variables, year and building 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 D. Robustness: Summary statistics for subsamples

Table D.1
Building characteristics across subsamples.

	Balanced panel			Late adopters			Excluding outliers		
	All	Treated	Control	All	Treated	Control	All	Treated	Control
Construction year[a]	1960.49	1961.96	1958.84	1973.30	1969.28	1975.16	1972.28	1968.76	1975.07
Monthly rent[b] (USD/m^2)	15.17	14.70	15.70	16.41	15.89	16.65	16.10	15.40	16.65
Vacancy rate (%)	0.06	0.06	0.06	0.05	0.05	0.06	0.06	0.06	0.06
Annual energy use (kWh/m^2)	188.00	201.45	172.85	165.79	185.39	156.85	169.68	186.69	156.35
Heating degree days[c]	2881.09	2884.93	2876.76	2856.80	2890.64	2841.36	2843.59	2848.97	2839.42
Annual heating cost (USD/m^2)	12.38	12.02	12.78	13.68	14.60	13.26	13.24	13.31	13.19
Oil heating indicator	1.00	1.00	1.00	0.56	0.60	0.54	0.61	0.69	0.54
Total surface area (m^2)	1561.50	1721.75	1380.92	1713.76	1801.69	1673.64	1738.32	1821.95	1673.64
Number of units[d]	21.98	24.38	19.27	22.95	24.24	22.36	23.39	24.72	22.36
Avg. unit size[e]	3.09	3.08	3.10	3.23	3.11	3.28	3.22	3.13	3.28
Commercial units (%)	0.04	0.04	0.04	0.05	0.06	0.05	0.06	0.06	0.05
Observations	285	151	134	450	141	309	548	239	309
	Low tenant turnover			Inexpensive renovations			Purely residential buildings		
	All	Treated	Control	All	Treated	Control	All	Treated	Control
Construction year[a]	1973.52	1969.19	1975.16	1972.39	1968.76	1975.28	1972.49	1967.14	1976.25
Monthly rent[b] (USD/m^2)	16.41	15.77	16.65	16.14	15.50	16.64	15.97	15.20	16.52
Vacancy rate (%)	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.06
Annual energy use (kWh/m^2)	166.48	192.13	156.85	171.93	190.77	157.17	174.43	195.54	159.96
Heating degree days[c]	2867.64	2937.65	2841.36	2865.91	2895.65	2842.61	2882.91	2893.92	2875.36
Annual heating cost (USD/m^2)	13.41	13.81	13.26	13.33	13.42	13.26	13.22	13.32	13.15
Oil heating indicator	0.57	0.65	0.54	0.62	0.70	0.55	0.66	0.76	0.58
Total surface area (m^2)	1669.95	1660.12	1673.64	1737.44	1818.75	1673.71	1353.42	1403.06	1319.37
Number of units[d]	22.71	23.62	22.36	23.36	24.66	22.34	18.48	19.88	17.52
Avg. unit size[e]	3.22	3.05	3.28	3.22	3.13	3.28	3.25	3.09	3.36
Commercial units (%)	0.05	0.04	0.05	0.06	0.06	0.05	0.00	0.00	0.00
Observations	425	116	309	544	239	305	322	131	191

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]Average monthly rent for Switzerland: 13.7 USD/m^2 (SFSO, 2019a).
[c]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 2.1).
[d]Total number of residential and/or commercial leases; average for Switzerland: 4.9 (SFSO, 2019a).
[e]Average number of rooms per unit; average for Switzerland: 3.3 (SFSO, 2019a). 2015 prices; exchange rate approx. CHF 1 = USD 1.

Appendix E. Robustness: Regression results

This appendix provides regression results supporting estimates in Table 7. We consider the following dimensions: (i) treated buildings only (Table E.1); (ii) buildings that remain in the portfolio over the entire observation period (Table E.2); (iii) buildings renovated in 2011 or later (Table E.3); (iv) dropping outliers for energy use (Table E.4); (v) flexible LASSO estimation (Table E.5); (vi) buildings with low tenant turnover (Table E.6); (vii) buildings with residential leases only (Table E.7); and (viii) interventions with low investment costs (Table E.8).

In each table, column (1) reports regression results for energy savings (Eq. (2)), column (2) focuses on CO_2 emissions in relation to investment cost (Eq. (3)), and column (3) provides evidence on heating expenditures (Eq. (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 results in 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.

Table E.1
Energy savings and implicit carbon prices for the subsample of treated buildings.

	Energy use (kWh/m^2) (1)	CO_2 emissions (kg/m^2) (2)	Heating cost (USD/m^2) (3)	Implicit price of CO_2 (4)
Wall insulation	−29.37***	−0.01***	−0.004***	794.36***
	(8.78)	(0.01)	(0.001)	(281.27)
Roof insulation	−15.42*	−0.08***	−0.03***	155.26**
	(8.95)	(0.02)	(0.01)	(75.93)
Windows replacement	−9.95***	−0.02***	−0.01**	795.62***
	(3.15)	(0.01)	(0.003)	(281.65)
Smart heating control	−21.02***	−4.86***	−2.25***	−286.06***
	(4.44)	(1.33)	(0.65)	(67.95)
Boiler replacement	−14.99***	−0.08***	−0.03***	175.36***
	(3.43)	(0.02)	(0.01)	(54.78)
Boiler replacement (oil–gas)	−4.08	−0.13***	0.01	218.18***
	(4.52)	(0.01)	(0.01)	(27.72)
Observations	3416	3416	3416	
Buildings (clusters)	239	239	239	
Adj. R-squared	0.45	0.56	0.70	

Notes: This table focuses on the subsample of buildings that are treated between 2001 and 2016 and excludes never-treated buildings in the control group. Column (1) reports OLS estimates for a regression of 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 USD/m^2). Column (3) is a regression of annual heating costs (in USD/m^2) on investment cost (in USD/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.

Table E.2
Energy savings and implicit carbon prices for the balanced subsample.

	Energy use (kWh/m^2) (1)	CO_2 emissions (kg/m^2) (2)	Heating cost (USD/m^2) (3)	Implicit price of CO_2 (4)
Wall insulation	−34.96***	−0.01***	−0.003***	1158.48***
	(10.42)	(0.003)	(0.0007)	(324.97)
Roof insulation	−14.68	−0.10***	−0.03***	121.11*
	(11.98)	(0.02)	(0.01)	(63.01)
Windows replacement	−5.38*	−0.02**	−0.004**	1088.40**
	(3.07)	(0.01)	(0.002)	(472.93)
Smart heating control	−19.79***	−12.39**	1.83	101.14
	(6.18)	(5.32)	(1.43)	(107.37)
Boiler replacement	−10.06***	−0.07***	−0.01	299.17***
	(3.82)	(0.02)	(0.01)	(98.26)
Boiler replacement (oil–gas)	0.51	−0.10***	0.003	265.52***
	(5.63)	(0.01)	(0.01)	(48.31)
Observations	4560	4560	4560	
Buildings (clusters)	285	285	285	
Adj. R-squared	0.48	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 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 USD/m^2). Column (3) is a regression of annual heating costs (in USD/m^2) on investment cost (in USD/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.

Table E.3
Energy savings and implicit carbon prices for late adopters.

	Energy use (kWh/m^2) (1)	CO_2 emissions (kg/m^2) (2)	Heating cost (USD/m^2) (3)	Implicit price of CO_2 (4)
Wall insulation	−54.65***	−0.01***	−0.003***	1106.65***
	(16.21)	(0.003)	(0.0009)	(347.81)
Roof insulation	−7.79	−0.03	−0.02**	580.48
	(6.17)	(0.02)	(0.01)	(394.02)
Windows replacement	−5.20	−0.03*	−0.01	663.77
	(5.08)	(0.02)	(0.01)	(456.08)
Smart heating control	−21.13***	−6.41***	−1.74*	−165.21**
	(4.61)	(1.73)	(0.98)	(72.45)
Boiler replacement	−15.12***	−0.08***	−0.02***	203.51***
	(4.49)	(0.02)	(0.01)	(73.66)
Boiler replacement (oil–gas)	−12.81***	−0.13***	0.01*	223.06***
	(4.70)	(0.01)	(0.01)	(29.68)
Observations	5584	5584	5584	
Buildings (clusters)	450	450	450	
Adj. R-squared	0.30	0.41	0.65	

Notes: This table focuses on the subsample of buildings that have their first renovation in 2011 or later (late adopters). Column (1) reports OLS estimates for a regression of 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 USD/m^2). Column (3) is a regression of annual heating costs (in USD/m^2) on investment cost (in USD/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.

Table E.4
Energy savings and implicit carbon prices with outliers trimmed.

	Energy use (kWh/m^2) (1)	CO_2 emissions (kg/m^2) (2)	Heating cost (USD/m^2) (3)	Implicit price of CO_2 (4)
Wall insulation	−26.26***	−0.01***	−0.003***	1260.54***
	(7.00)	−0.002	(0.0006)	(246.18)
Roof insulation	−13.03	−0.08***	−0.03***	171.21***
	(8.82)	(0.02)	(0.01)	(61.50)
Windows replacement	−7.93***	−0.02***	−0.01**	911.85***
	(2.61)	(0.01)	(0.003)	(312.11)
Smart heating control	−24.39***	−6.89***	−2.20***	−196.95***
	(4.23)	(1.31)	(0.63)	(50.04)
Boiler replacement	−12.59***	−0.08***	−0.02***	226.56***
	(2.49)	(0.01)	(0.01)	(57.72)
Boiler replacement (oil–gas)	−2.48	−0.13***	0.01	214.28***
	(4.63)	(0.01)	(0.01)	(24.46)
Observations	6906	6906	6906	
Buildings (clusters)	544	544	544	
Adj. R-squared	0.44	0.53	0.69	

Notes: This table focuses on the subsample excluding observations below the 1st or above the 99th percentile of energy consumption. Column (1) reports OLS estimates for a regression of 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 USD/m^2). Column (3) is a regression of annual heating costs (in USD/m^2) on investment cost (in USD/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.

Table E.5
Energy savings and implicit carbon prices with LASSO estimation.

	Energy use (kWh/m^2) (1)	CO_2 emissions (kg/m^2) (2)	Heating cost (USD/m^2) (3)	Implicit price of CO_2 (4)
Wall insulation	−27.82***	−0.01***	−0.003***	1038.71***
	(8.21)	(0.003)	(0.001)	(253.38)
Roof insulation	−15.12**	−0.08***	−0.04***	140.98**
	(6.70)	(0.02)	(0.01)	(58.48)
Windows replacement	−13.44***	−0.03**	−0.01***	618.22**
	(5.02)	(0.01)	(0.003)	(279.77)
Smart heating control	−16.68***	−5.20***	−2.11***	−249.41***
	(4.18)	(1.05)	(0.67)	(60.66)
Boiler replacement	−14.85***	−0.08***	−0.03***	161.25***
	(3.72)	(0.02)	(0.01)	(62.09)
Boiler replacement (oil–gas)	−4.09	−0.12***	0.02***	262.29***
	(5.62)	(0.01)	(0.01)	(31.28)
Observations	6577	6577	6577	
Buildings (clusters)	481	481	481	
Adj. R-squared	0.26	0.37	0.20	

Notes: Column (1) reports OLS estimates for a regression of LASSO-based prediction errors (i.e., the building-by-year-specific difference between observed and predicted energy use) in kWh/m^2 on post-intervention dummies (T_{kit}). Column (2) is a regression of LASSO-based prediction errors in annual CO_2 emissions in kg CO_2/m^2 on investment cost (in USD/m^2). Column (3) is a regression of LASSO-based prediction errors in annual heating costs (in USD/m^2) on investment cost (in USD/m^2). Prices refer to a 2015 baseline; exchange rate approx. CHF 1 = USD 1. All regressions control for a post-training dummy (equal to one during the out-of-sample prediction period, or post-treatment), 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.

Table E.6
Energy savings and implicit carbon prices for interventions with low tenant turnover.

	Energy use (kWh/m^2) (1)	CO_2 emissions (kg/m^2) (2)	Heating cost (CHF/m^2) (3)	Implicit price of CO_2 (4)
Wall insulation	−24.14*	−0.01***	−0.002***	1296.82***
	(12.45)	(0.003)	(0.0008)	(416.38)
Roof insulation	−3.10	−0.06***	−0.02***	288.65**
	(9.69)	(0.02)	(0.01)	(119.67)
Windows replacement	−9.88***	−0.02***	−0.002	1116.19***
	(3.15)	(0.01)	(0.003)	(412.32)
Smart heating control	−13.22**	−5.11**	−0.56	−57.58
	(6.39)	(2.08)	(0.94)	(105.87)
Boiler replacement	−14.29***	−0.10***	−0.03**	154.56*
	(4.74)	(0.03)	(0.01)	(79.40)
Boiler replacement (oil–gas)	−13.54***	−0.15***	0.02**	218.36***
	(4.83)	(0.02)	(0.01)	(20.23)
Observations	5364	5364	5364	
Buildings (clusters)	429	429	429	
Adj. R-squared	0.31	0.38	0.65	

Notes: This table focuses on the subsample of buildings that have below-median tenant turnover after renovation. Column (1) reports OLS estimates for a regression of 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.

Table E.7
Energy savings and implicit carbon prices for purely residential buildings.

	Energy use (kWh/m^2) (1)	CO_2 emissions (kg/m^2) (2)	Heating cost (USD/m^2) (3)	Implicit price of CO_2 (4)
Wall insulation	−26.26**	−0.01***	−0.002***	1780.11***
	(12.35)	(0.002)	(0.0008)	(595.25)
Roof insulation	−15.17	−0.09***	−0.03***	134.87*
	(12.01)	(0.03)	(0.01)	(71.75)
Windows replacement	−9.05**	−0.02***	−0.01*	768.78**
	(3.63)	(0.01)	(0.005)	(307.31)
Smart heating control	−19.84***	−3.38***	−0.61	−104.42
	(5.72)	(1.19)	(0.69)	(123.66)
Boiler replacement	−10.79***	−0.08***	−0.02***	232.89***
	(3.32)	(0.02)	(0.01)	(68.32)
Boiler replacement (oil–gas)	−3.35	−0.11***	0.01	248.75***
	(5.48)	(0.01)	(0.01)	(42.42)
Observations	4208	4208	4208	
Buildings (clusters)	322	322	322	
Adj. R-squared	0.37	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 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 USD/m^2). Column (3) is a regression of annual heating costs (in USD/m^2) on investment cost (in USD/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.

Table E.8
Energy savings and implicit carbon prices for lower-cost interventions.

	Energy use (kWh/m^2) (1)	CO_2 emissions (kg/m^2) (2)	Heating cost (USD/m^2) (3)	Implicit price of CO_2 (4)
Wall insulation	−33.09***	−0.01***	−0.003***	1167.57***
	(11.42)	(0.003)	(0.0007)	(361.71)
Roof insulation	−12.36	−0.08**	−0.03***	167.83*
	(9.37)	(0.04)	(0.01)	(99.34)
Windows replacement	−4.95	−0.05***	−0.02***	291.09**
	(3.50)	(0.02)	(0.01)	(137.33)
Smart heating control	−22.65***	−10.38***	−1.54	−89.48
	(5.64)	(2.17)	(2.15)	(121.96)
Boiler replacement	−8.32**	−0.09*	−0.04***	90.00
	(4.01)	(0.05)	(0.02)	(111.97)
Boiler replacement (oil–gas)	−2.45	−0.20***	0.04***	202.09***
	(7.08)	(0.02)	(0.01)	(39.09)
Observations	6465	6465	6465	
Buildings (clusters)	548	548	548	
Adj. R-squared	0.26	0.35	0.67	

Notes: This table focuses on the subsample of interventions that are associated with below-median investment costs (in USD/m^2). Column (1) reports OLS estimates for a regression of 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 USD/m^2). Column (3) is a regression of annual heating costs (in USD/m^2) on investment cost (in USD/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.

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