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Residential Heat Energy Savings During a Crisis: How much Do Retail Prices Matter?*

Sophie M. Behr†‡ Till Köveker†‡ Merve Kücük§¶

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Abstract

The 2022 energy crisis led to sharp energy price surges and prompted public appeals and government programs to reduce energy consumption. This paper isolates energy savings driven by retail price increases from non-price driven savings attributable to other crisis-related factors such as public appeals. Using German residential energy billing data and a DiD-PSM approach, we identify average price-driven savings. We employ machine learning to estimate building-level price-driven and non-price-driven savings, and analyze their variation with socio-economic characteristics using census data. Our findings reveal that energy savings were driven by non-price factors instead of price increases, and homogeneous across socio-economic characteristics.

JEL-Classification: Q41, Q48

Keywords: Energy crisis, Energy policy, Causal inference, Double machine learning

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1 Introduction

The 2022 Russian invasion of Ukraine caused an energy crisis that strongly affected European countries with high dependence on Russian natural gas imports. The interruption of the Russian gas supply led to rising gas prices, which had knock-on effects on other energy prices. Discussions about potential gas shortages in the winter of 2022/23 alongside the fear of resulting power cuts, industrial production disruptions, and job losses led to the formulation of saving targets by the European Union (EU) and several individual countries (European Council 2022). Germany, Europe's largest economy and biggest importer of Russian gas until the crisis (U.S. Energy Information Administration 2022), announced an ambitious gas saving target of 20% (Bundesministerium für Wirtschaft und Klimaschutz 2022b).

Energy consumers in Germany were urged to save energy through numerous public calls by the government and various interest groups. For example, the German minister for economic affairs, Robert Habeck, made a public appeal to *"Join the effort! By saving energy, we can reduce Germany's dependence on Russian imports and help protect the climate"* (Bundesministerium für Wirtschaft und Klimaschutz 2022a; own translation). These appeals were backed with a portfolio of government programs, which included informing households about untapped energy saving potentials and their energy prices (The Press and Information Office of the Federal Government 2022), mandatory optimization of buildings' heating system operation (Federal Ministry of Economic Affairs and Climate Action 2022b), binding limits on heating of public buildings (ibid.), and support measures to shield households from the financial burden of exploding energy prices (Federal Ministry of Economic Affairs and Climate Action 2022a). A challenge for the design of these emergency measures was the uncertainty about how strong energy consumption would respond to higher prices and how much savings could be achieved through other non-price interventions.

This paper explores the extent to which energy savings during the European energy crisis were driven by higher retail prices or by other factors, such as public appeals. A growing literature studies energy demand in the crisis with mixed evidence on the role of prices (Ruhnau et al. 2023; Jamissen et al. 2024; Dertwinkel-Kalt et al. 2024; Bruguet 2025; Ahlvik et al. 2026; Singhal et al. 2026; Amberg et al. 2025). Several studies acknowledge the role of other crisis-related confounding factors, including the public discourse surrounding the energy crisis, appeals to save energy, and behavioral interventions (Ahlvik et al. 2026; Dertwinkel-Kalt et al. 2024; Roth and Schmidt 2023; Jamissen et al. 2024). Drawing on building-level billing data on residential heat energy consumption and prices, we estimate how residential heat energy demand responds to retail price changes. By comparing buildings facing price changes with a control group of buildings with constant prices, we can comprehensively account for other crisis-related confounding factors. Furthermore, we quantify heat energy savings that cannot be attributed to building-level retail price changes, thereby characterizing the impact of other factors such as public discourse and appeals to save energy.

In the first part of our analysis, we estimate the retail-price-driven (henceforth price-driven) heat energy savings using a difference-in-differences framework with propensity score matching (DiD-PSM). Buildings that experienced an increase in energy prices in 2022 constitute the treatment group and buildings with constant prices the control group. The type of tariff (mostly one- or two-year contracts), the timing of contract renewal, and suppliers' wholesale market procurement strategy determined whether and to what extent households' prices increased. Since households could not plausibly have anticipated the Russian invasion of Ukraine and the ensuing energy crisis, and accordingly choose their suppliers and contract structures, sorting into or out of treatment is very unlikely. Nevertheless, we match on building and socio-economic characteristics, as well as temperature to rule out any remaining differences in the treatment and control group. Using the same framework we estimate short-run heat energy price elasticities during the crisis. Having a control group, which is exposed to the same non-price-factors as treated buildings, ensures that the estimated elasticities are not inflated by the contemporaneous appeals and programs to save energy. We find that heat energy savings in buildings with retail price increases were, on average, very close to and not significantly different from savings in a matched control group of buildings with constant prices, resulting in a price elasticity of residential heat energy demand which is not statistically different from zero. Our results imply that residential heat energy consumption did not react to experienced price increases in the short-run.

Second, we employ double machine learning (DML) to flexibly analyze socio-economic heterogeneities in price-driven energy savings. To this end, we complement the building-level energy dataset with socio-economic characteristics from the German microcensus. Using the DML procedure, we then estimate building-level treatment effects and use non-parametric kernel regressions to explore how they vary with socio-economic variables. We find that price-driven savings hardly varied with socio-economic factors, indicating a homogeneous response to experienced price increases.

In the third part of our analysis, we again use machine learning techniques to estimate residential heat energy savings driven by crisis-related factors other than building-level retail price changes. For simplicity, we refer to these non-retail-price-driven savings as non-price-driven energy savings, while recognizing that they may be driven by a multitude of factors including the broader discourse on rising energy costs and energy price levels. We first train a least absolute shrinkage and selection operator (Lasso) regression model to predict energy consumption on pre-crisis data. Then, we use the model's predictions to obtain building-level counterfactual energy consumption for 2022 had the energy crisis not occurred. The difference between observed and counterfactual energy consumption yields estimates of non-price-driven savings for buildings with constant prices during the crisis. We find that non-price-induced savings on average amounted to 11.7% of a building's energy consumption in 2021 and about two thirds of total heat energy savings during the crisis in our sample. This implies that residential heat energy savings during the crisis were, besides weather effects, driven by non-price factors such as public appeals, savings programs, and the general public discourse about the crisis. Finally, we again employ non-parametric kernel regressions to investigate how the building-level estimates of non-price-driven energy savings vary with socio-economic characteristics. Similar to price-driven savings, non-price-driven savings do not vary significantly with most socio-economic characteristics, except for social benefits that cover heating costs. In particular, non-price-driven savings decrease slightly with the share of social benefit recipients. One possible reason is, that although households did not significantly react to experienced price-changes, they may have reacted to the overall discourse about rising heating costs, which would be reflected in the non-price-driven savings in our empirical framework.

This paper relates to several strands of the literature on households' energy consumption during the European energy crisis, on the role of prices and non-price factors to achieve energy savings and on heterogeneity in the residential heat energy demand response to the crisis. First, we speak to the literature on the effectiveness of energy prices to drive savings during crises.[1] There is a general consensus that heat energy savings in the European energy crisis went beyond what can be explained by mild temperatures (see e.g., Roth and Schmidt 2023). However, the role of prices remains ambiguous. Some studies find a significant price response of energy demand among households and small consumers (Ahlvik et al. 2026; Ruhnau et al. 2023; Bruguet 2025).[2] In particular for Germany, where the transparency of residential heat energy prices is low, several studies, however, find much lower or even insignificant price effects. For example, Jamissen et al. (2024) only estimate a very small price-response of gas consumption after controlling for public attention to the crisis. Further evidence, based on self-reported survey data, also suggests that increased prices had little impact on savings (Dertwinkel-Kalt et al. 2024), and Singhal et al. (2026) find that thermostat settings are largely uncorrelated with expected energy costs. Together, these findings point to substantial uncertainty about the role of prices in driving savings during the crisis. We contribute to this literature by identifying short-term price-driven heat energy savings using billing data on consumption and prices while comprehensively controlling for contemporaneous non-price-driven savings. We document that buildings with price increases, on average, did not save significantly more heat energy than buildings with constant prices. Furthermore, isolating price-driven savings from non-price-driven savings enables us to estimate a price elasticity of heat energy demand during the crisis which is not inflated by contemporaneous non-price-driven energy savings.

Second, we speak to a growing body of research on the effectiveness of public appeals to conserve energy during crises. Evidence on the effectiveness of such appeals during the 2022/23

1. Several existing studies investigate price elasticities of residential heat energy demand during times-as-usual (see e.g., Rubin and Auffhammer 2024; Trotta et al. 2022; Schulte and Heindl 2017; Ó Broin et al. 2015; Hanemann et al. 2013). Labandeira et al. (2017) provides an overview of of short and long term elasticities for different energy carriers.

2. On a related note, Amberg et al. (2025) also find that households significantly reacted to a financial reward program for residential gas savings during the energy crisis.

crisis is mixed. While Bruguet (2025) finds that government messaging in France to reduce electricity demand was only moderately effective, Jamissen et al. (2024) estimate a significant effect of public attention to the crisis on gas savings in Germany. Moreover, studies primarily focused on the impact of high energy prices also acknowledge that non-price factors played an important role in driving heat energy savings (Ahlvik et al. 2026; Ruhnau et al. 2023; Jamissen et al. 2024; Dertwinkel-Kalt et al. 2024; Bruguet 2025). Overall, much of the literature points to sizable effects of public appeals and salience during crises, including evidence from the 2008 California electricity crisis (Reiss and White 2008) and the 2015 Cape Town water crisis (Brick et al. 2023). Further studies on the effects of moral suasion (Ito et al. 2018) and social comparisons (Allcott and Kessler 2019) on residential energy consumption additionally underscore the relevance of non-price factors. We add to this literature by proposing a machine learning based approach to estimate non-price-driven savings, and by documenting that, in our sample, about two thirds of residential heat energy savings were driven by non-price factors.

Finally, we relate to the literature of heterogeneous household responses to residential heat and electricity price changes (Ahlvik et al. 2026; Schmitz and Madlener 2020; Rubin and Auffhammer 2024). These studies analyze effect heterogeneity using subgroup analyses or interaction effects, which imply restrictive functional form assumptions. We contribute to this literature by applying DML, which enables us to relax these restrictions and non-parametrically estimate non-linear relationships between socio-economic characteristics and price-responses.[3] We thus complement this literature by applying recent causal machine learning methods allowing us to flexibly explore heterogeneous responses to changes in heat energy prices.

The remainder of this paper is organized as follows: Section 2 provides background information by discussing the historical gas trade relationship between Germany and Russia as well as how the Russian invasion of Ukraine in February 2022 altered this relationship. This section also offers an overview of residential energy consumption and energy billing in Germany. Section 3 presents the data and descriptive statistics. Section 4 discusses our empirical strategy and explains the three methods used to estimate price-driven and non-price-driven energy savings. In section 5, we present and discuss the results, before concluding in Section 6.

2 Background

2.1 The Energy Crisis and its Implications for Germany

In 2021, before the Russian invasion of Ukraine, Russia was the main fossil fuel supplier to the EU with market shares of 26% of petroleum oil and 44% of natural gas imports (Wettengel 2024). However, not all European countries were equally dependent on fossil fuel imports from Russia. One of the most exposed countries was Germany. In 2021, it imported 98% of its oil

3. To our knowledge, the only existing study applying DML to study residential heat energy consumption is Amberg et al. (2025). In contrast to our paper, they study household responses to a reward program, whereas we investigate responses to changes of actual heat energy prices.

and 95% of its natural gas (Wettengel 2024); out of which 34% and 55% originated from Russia, respectively (Bachmann et al. 2022).[4] However, this situation substantially changed with the Russian invasion of Ukraine in February 2022.

Already in the months preceding the invasion, Russia began restricting its gas supply to Germany. After the start of the war, Germany announced plans to reduce its dependence on Russian gas by 2024. With EU embargos on Russian coal and oil, Germany also drastically reduced imports of these two energy carriers from Russia (Wettengel 2024). Russia preempted Germany's plans of reducing its dependence on imports of Russian gas by gradually cutting the flow of gas to Germany until a complete halt in late summer 2022, briefly before the explosions of the Nord Stream pipelines (ibid.).

Following the invasion of Ukraine and the reduction of gas supply from Russia, gas wholesale prices in Germany temporarily increased to more than ten times the pre-war levels observed in 2021.[5] The rising wholesale prices were ultimately also reflected in higher end-user prices. At their peak early in September 2022, households faced a gas price of around 22 cents per kilowatt-hour (kWh) when concluding new contracts compared to approximately 6 cents/kWh before the crisis (VERIVOX 2025). These high prices and the supply interruption in late summer 2022 led to intense public discussions and worries about the possibility of gas shortages during the winter of 2022/23.

In response to this situation, the German government called upon all economic actors to save energy wherever and whenever possible, while simultaneously trying to secure other sources for natural gas imports (Bundesministerium für Wirtschaft und Klimaschutz 2022a; Bundesministerium für Wirtschaft und Klimaschutz 2022c). The resulting efforts to save energy proved successful, as the German economy reduced overall gas consumption by approximately 20% between July 2022 and March 2023 compared to previous years, with industrial gas consumption dropping by 26% and household consumption decreasing by 17% (Moll et al. 2023).

2.2 Residential Energy Consumption and Billing in Germany

In Germany, heat energy is billed annually with consumers paying monthly or quarterly installments. The installments are calculated based on households' historical consumption. The objective of the monthly installments is to spread the cost of energy evenly throughout the year, and can be adjusted at any point during the billing cycle. At the end of the yearly billing cycle, the actual energy consumption is reconciled against the estimated energy consumption on which the advance payments are based. Additional payments or reimbursements are made to account for differences between advance payments and actual costs of consumed heat. Due

4. Germany had a 50-year long natural gas trade relationship with Russia that was founded on an agreement made in 1958 under which West Germany was providing pipes for the Druzhba pipeline ("Friendship Pipeline") in return for Russian natural gas. This pipeline, operational in 1964, was the world's longest oil pipeline linking Russia with much of eastern Europe (Sullivan 2022).

5. During much of 2021, wholesale gas prices were below 20 EUR/MWh (Engie 2022) and temporarily increased to more than 300 EUR/MWh at the height of the crisis in August 2022 (Bundesnetzagentur 2023).

to the annual billing cycle, prices are not very salient and most households might not be aware of their exact heat energy price (Dertwinkel-Kalt et al. 2024). However, irregular price changes during a running contract as in the crisis are more visible to residential consumers because energy suppliers are legally obliged to inform them in writing with an advance notice of at least four weeks (Bundesnetzagentur 2024; § 41 EnWG Energielieferverträge mit Letztverbrauchern Energiewirtschaftsgesetz). This advance notice must clearly outline the nature of and reason for the change, allowing consumers ample time to assess its impact and, if necessary, to renegotiate their contract or to switch providers.[6] In practice, however, switching providers proved difficult during the crisis. For gas, switching rates fell from 12.9% in 2021 to 8.9% in 2022 representing a drop of roughly a third as surging prices left few cheaper alternatives on the market (Bundesnetzagentur and Bundeskartellamt 2023). District heating consumers face an entirely different situation as switching providers is simply not possible. German district heating is typically operated by vertically integrated monopolies controlling production, grid, and supply, leaving consumers with no alternative within their network (Bürger et al. 2019).

The strong increase of residential energy prices in Germany posed substantial burdens on households (Kröger et al. 2023; Behr et al. 2026). At the end of 2022, the German government introduced one-off relief payments to alleviate these burdens to some extent. The support measure consisted of covering the monthly installments of residential gas and district heating customers for December 2022. Support measures for households using other heat energy carriers, such as oil and wood pellets, were designed differently. These relief payments did not alter households' marginal prices due to their lump-sum nature.

3 Data

3.1 Data Sources

Data on Heat Energy Consumption and Expenditure: Our final dataset comprises residential annual heat energy billing data of more than 50,000 German multi-family buildings[7] from 2017 until 2022[8] by *ista*, one of the largest service providers for heat energy billing in Germany. The dataset contains information on building-level energy consumption, energy ex-

6. In some buildings, residents have a direct contract with the energy provider. In other buildings, especially in multi-apartment buildings, the landlord or building management company signs a central energy contract with the energy provider for the entire building. In the latter buildings, information about price changes may reach energy-consuming residents less quickly because the energy provider must first inform the landlord or management company, their contractual partner, of price changes. Although landlords or building management companies are not legally obligated to immediately inform energy-consuming residents of price changes, they have strong incentives to do so quickly to avoid having to advance the price difference and potential conflicts and to enable tenants to adapt their heating behavior.

7. In 2022, approximately 62% of the German population lived in apartments and 12% lived in semi-detached housing, making the total share of the population living in multi-family houses 74% (Statista 2023).

8. In 2023, the German government introduced further interventions including a price cap on heat energy to further shield households from the high heat energy prices. As this price-cap strongly altered households' perception of marginal prices (Dertwinkel-Kalt et al. 2024) and, thus, households' reaction to energy prices, we limit our analysis to the years up to 2022.

penditures, the billing periods, the energy carrier, total living space, number of apartments, hot water consumption, and the buildings' zip-code.[9] Based on the heat energy consumption and expenditures, we calculate kWh prices for each year and building.[10]

As the buildings in our sample all have central heat energy contracts, all apartment units face the same price per kWh. This allows us to interpret the calculated kWh price as the marginal price faced by each household in the same building, rather than an average price of different contracts.

During the energy crisis, the German government adopted a relief package to reduce the energy price burden on households and firms. This package included the so-called *December relief payments* which were announced in November 2022 for gas and district heating users. These payments meant that the state paid for the December heat energy costs of residents, i.e. one twelfth of the yearly payments. Thus, we can easily account for the December relief payments in our price calculation for buildings using gas and district heating. We limit our analysis to these two energy carriers because we cannot determine the exact amount of support for other carriers.

The amount of the payments were independent of actual energy consumption to remain energy saving incentive-compatible. There were also relief payments for other energy carriers, such as heating oil or wood pellets. Unlike gas and district heating relief payments, these were not automatically paid out to households. Households heating with heating oil or wood pellets had to actively apply for these relief payments. As we do not know which households received relief payments, we are unable to calculate the prices they faced. Therefore, we solely focus on gas and district heating, excluding buildings using other heat energy carriers from the sample.[11] Since our main empirical strategy relies on comparing buildings with price increases to buildings with constant prices, we drop buildings from our sample where prices decreased in 2022. Furthermore, we also limit the sample to observations where the annual billing cycle corresponds to the calendar year, i.e. running from January 1^{st} to December 31^{st}.The crisis itself may have motivated some homeowners to switch to a different heat energy carrier, e.g. from gas to district heating. To ensure that our results are not driven by such carrier switches, we drop buildings that experienced a switch in energy carrier at any point between 2017 and 2022. To reduce sensitivity to extreme values and potential measurement error, we exclude the

9. Zip-codes in this paper refer to German postal codes ("Postleitzahlen").

10. The observed heat energy expenditures are based on two-part tariffs. They thus include a base fee and a consumption-dependent component, which is the marginal price per kWh multiplied by the consumed heat energy. To calculate marginal prices per kWh, we first need to subtract the base fee from the observed expenditure. We estimate building-type-specific base fees by by running univariate OLS regressions of total expenditures on heat energy consumption by energy carrier and quartile of energy consumption. The intercept of these regressions is the average base fee by building-type. To obtain building-level base fees, we first compute the share of the base fee in the total expenditure by building-type, and multiply this share with each building's total expenditure, to obtain building-specific base fee estimates. For each building, we then subtract the base fee from the observed total expenditure to obtain the variable consumption-dependent expenditure component, and, finally divide it by heat energy consumption to obtain marginal heat energy prices per kWh.

11. Gas and district heating together cover 63% of German buildings (Destatis 2018).

top and bottom 2.5% of the distributions of apartment size, heat energy consumption, yearly change of heat energy consumption, and prices.

Data on Climate Factors: To control for local temperature effects, we employ the publicly available zip-code level climate factors by the German Weather Service ("Deutscher Wetterdienst").[12] These climate factors are calculated for 12-month periods as quotients of the mean annual degree days, which are calculated with reference to the time series of the Potsdam reference station, and the current annual degree days for the respective zip-code. In all parts of the analysis, we control for weather by including the climate factor up to the third polynomial as an explanatory variable.

Data on Working from Home: To account for potential changes in work and leisure time patterns due to the Covid-19 pandemic, we control for working from home. We rely on zip-code level data on working from home collected and made available by *infas360*.[13] Specifically, we observe the average number of days per week spent working from home on a scale from zero to five workdays for the period before, during, and after the pandemic at the zip-code level. To adjust for reporting differences before, during, and after the pandemic,[14] we normalize the observed zip-code work-from-home rates by the national work-from-home rate from the federal statistical office of Germany, *Destatis*.[15]

Data on Socio-Economic Characteristics: We merge data of the German microcensus[16] to the energy billing dataset to investigate how effects vary with socio-economic characteristics. The microcensus is the largest annual household survey in Germany and contains rich information at both the individual and on household level. In the microcensus as well as in the energy billing dataset, households and buildings are anonymized. However, both datasets include detailed regional information, allowing us to merge the microcensus data at a granular regional-level. In the microcensus, a household's location is indicated by its municipal identification number (AGS), not by its zip-code as in the main energy billing dataset. In a first step, we thus calculate AGS-level averages of the socio-economic variables of interest, namely age, income, unemployment, years of schooling, and share of people receiving social benefits covering heating costs. In the second step, we merge the AGS-level dataset to the energy billing data using zip-code-to-AGS correspondence tables.[17]

12. Data on climate factors can be downloaded from the website of the German Weather Service: https://www.dwd.de/DE/leistungen/klimafaktoren/klimafaktoren.html.

13. Data on Working from Home can be downloaded here https://datenkatalog.infas360.de/dataset/cdp?.

14. For the post-pandemic period, we observe the employer-reported planned number of working-from-home days rather than the realized number.

15. Data on national trends can be downloaded here https://www.destatis.de/DE/Presse/Pressemitteilungen/Zahl-der-Woche/2023/PD23_28_p002.html.

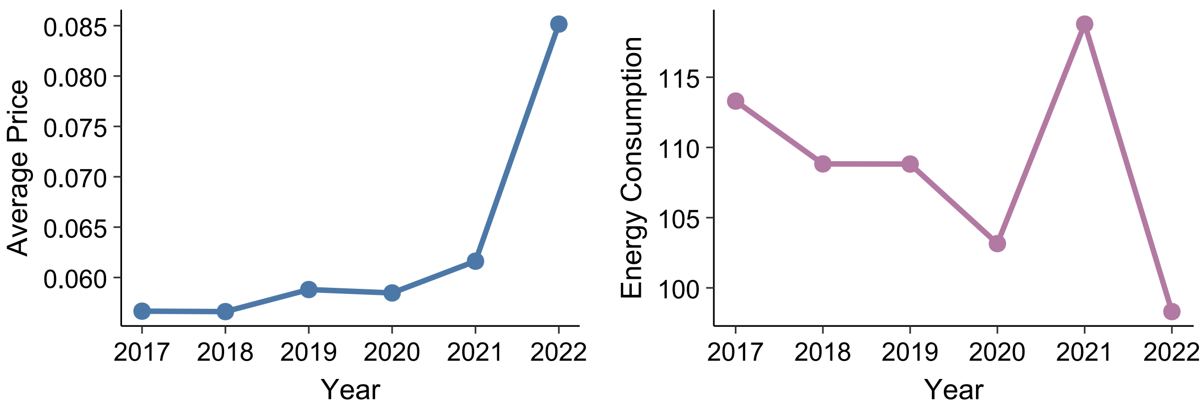
16. For detailed metadata of this dataset see Research Data Center (RDC) (2021, 2020).

17. If several AGS-codes map into one zip-code, then we compute the zip-code level value as a weighted average of the corresponding AGS-level values. The weights of each AGS-code correspond to the number of individuals surveyed in this AGS-code in the microcensus. In some cases several AGS-codes map into one zip-code, and some of these AGS-codes also map into other zip-codes. When computing the zip-code level mean, the weight of the latter AGS-codes is then divided by the number of zip-codes that they map into. In case an AGS-code maps into several zip-codes, we thus assume that its population is equally spread across all corresponding zip-codes.

Since distributional effects of policies can be overlooked when using zip-code means of socio-economic outcomes (Reguant et al. 2025), we exploit the fact that dwelling characteristics are related to socio-economic characteristics to obtain more granular variation of socio-economic characteristics. We use the most recent pre-crisis microcensus wave from 2018, which contains the supplementary survey on dwelling conditions. We train a Lasso-model on the microcensus dataset to estimate how dwelling characteristics contained in both the microcensus and the energy billing dataset relate to socioeconomic characteristics. Using the energy billing data, we then predict how a building's deviation from regional average dwelling characteristics are related to deviations in socio-economic characteristics. We then add these predicted deviations in socio-economic characteristics to the regional averages to obtain more granular building-level variation in socio-economic characteristics. A more detailed explanation of this approach is provided in Appendix A.1.

Election data: To examine the heterogeneity of energy savings by political orientation, we use data from the last federal election before the crisis, held in 2021.[18] In the election in 2021, seven parties were elected for parliament. We define political support as the aggregate vote share of parties represented in either governing coalition during the period under study.[19] As the election data are available at the AGS-level, we merge them using the same zip-code-to-AGS correspondence procedure applied to the microcensus data.

Figure 1: Heat energy price and consumption between 2017-2022.



(a) Heat energy price in Euro per kWh between 2017-2022.

(b) Heat energy consumption in kWh per square meter between 2017-2022. Note that this is not temperature-adjusted.

3.2 Descriptive Statistics

Figure 1 presents heat energy prices and heat energy consumption from 2017 to 2022 for the entire dataset. The strong crisis-related energy price hike is visible in Panel (a) and the decline

18. The data are available here: Die Bundeswahlleiterin (2022).

19. These include CDU/CSU, SPD, Bündnis 90/Die Grünen, and FDP.

in energy consumption per square meter during the crisis is given in Panel (b).

Table 1 presents the descriptive statistics for the control and treatment group for the pre-treatment period as well as the year 2022, the year of the crisis. The top panel of the table shows means and standard deviations for building-level characteristics, the climate factor, and working from home. The middle and lower panels show means and standard deviations for the socio-economic characteristics from the microcensus and election outcomes. For the treatment group, prices rose strongly between 2021 and 2022, on average by 42.4%. The weather-unadjusted heat energy consumption in the same year fell by by 17.1% in the treatment group and by 17.3% in the control group. 2,982 buildings did not experience a change in their kWh price, meaning that the control group corresponds to approximately 5% of our sample in 2022.

Table 1: Overview of descriptive statistics for ista metering data, the German weather service, infas360, federal election data, and the German micro census.

	Control group		**Treatment group**	
	Panel A: Main variables			
	2017-2021	2022	2017-2021	2022
Price (Cent/kWh)	5.41 (1.27)	5.65 (1.20)	5.83 (1.49)	8.68 (2.77)
Price change (%)	1.84 (9.53)	-0.00 (0.57)	2.54 (9.64)	42.40 (38.07)
Heat consumption (kWh)	109.35 (34.46)	96.96 (31.18)	111.92 (35.63)	98.99 (32.40)
Heat consumption change (%)	2.48 (15.38)	-17.34 (11.88)	2.36 (15.13)	-17.08 (12.45)
Size apartment (sqm)	76.70 (23.49)	76.72 (23.44)	78.37 (24.18)	78.45 (24.18)
Number apartments	11.95 (11.57)	11.91 (11.50)	10.07 (10.47)	10.00 (10.40)
Share of gas (%)	0.92 (0.27)	0.93 (0.26)	0.87 (0.33)	0.88 (0.33)
Climate factor	1.15 (0.10)	1.21 (0.09)	1.15 (0.10)	1.21 (0.09)
Working from home (%)	14.37 (10.12)	23.40 (8.03)	13.73 (9.90)	22.69 (7.94)
Observations	14,119	2,982	260,357	55,254
	Panel B: Socio-economic variables			
	2018		2018	
Year of birth	1973.24 (4.78)		1972.89 (4.49)	
Social benefits (%)	0.02 (0.03)		0.02 (0.03)	
Net income (€)	1465.67 (225.00)		1489.07 (232.48)	
Years schooling	12.49 (0.76)		12.54 (0.81)	
Unemployment (%)	0.03 (0.03)		0.03 (0.03)	
Observations	2,982		55,250	
	Panel C: Political variables			
	2021		2021	
Support governing parties (%)	0.78 (0.06)		0.79 (0.06)	
Observations	2,982		55,258	

Notes: The table reports the means and standard deviations (in parentheses) of the main variables used in the analysis for the unmatched sample. The micro census variables show the predicted means and standard deviations estimated with the Lasso-model described in Section 3 and Appendix A.1.

4 Methodology and Empirical Strategy

During the 2022 energy crisis, price hikes coincided with several non-price factors that may have led to energy savings, such as public appeals, various government programs and regulations aimed at reducing energy consumption. The simultaneous occurrence of price hikes and non-price factors poses an empirical identification challenge to isolate price-driven from non-price-driven savings. In Appendix A.2, we illustrate this identification challenge using a simple theoretical model that features a household's decision on how much energy to consume depending on prices and public appeals to save energy. The model shows that, when energy prices and public appeals are correlated, non-price-driven savings can lead to an omitted variable bias in the estimation of price-driven savings and vice versa. During the energy crisis, there was a clear temporal correlation of price hikes and the rise of non-price factors for energy savings, such as public appeals. Hence, we design our empirical strategy to carefully isolate savings driven by retail price changes faced by residents, i.e price-driven savings, from savings that cannot be attributed to such changes, i.e. non-price-driven savings.

4.1 Estimation of Price-Driven Savings & Energy Price Elasticities

4.1.1 Average Effects

Method 1: Difference-in-Differences with Propensity Score Matching To estimate price-driven energy savings, we apply a DiD-PSM approach, where the dependent variable is residential energy consumption per square meter. We consider a building as treated if its energy price increased between 2021 and 2022. The control group consists of buildings for which prices stayed constant throughout this period.

As discussed in Section 3, our price variable contains some noise as we need to subtract estimated base fees from observed expenditures in order to compute marginal per kWh heat energy prices. To account for the noise in the price variable, we consider buildings to be untreated if their price change in 2022 was below 1%.[20]

To increase the comparability of the treatment and the control group as well as to improve the plausibility of the parallel trends assumption, we apply 1:1 nearest neighbor propensity score matching with replacement.[21] We estimate the propensity score in a logistic regression by regressing the treatment group indicator on a set of matching variables, namely the number of apartments in the building, the average apartment size, a building's baseline heat energy price, its baseline heat energy consumption per square meter, the climate factor up to its third

20. In Section 5.1 we conduct robustness checks by varying this threshold and find that it does not significantly affect our results.

21. In Section 5.1.1, we show that our results are robust to using 5:1 matching instead of 1:1 matching.

polynomial,[22] the work-from-home rate, and several baseline socio-economic variables,[23] and on year and energy carrier fixed effects. As suggested by Peter C. Austin (2011a), we match on the logit of the propensity score and use a caliper width of 0.2 standard deviations, which is considered to be optimal by Peter C. Austin (2011b). Furthermore, we enforce exact matching by year and energy carrier to avoid that an observation is matched to another observation from a different year or to a different type of energy carrier. Finally, we ensure common support by discarding observations that fall outside of the support of the treatment group's propensity score distribution.

Using the matched sample, we then estimate average price-driven savings in the treatment group with a DiD model. Having a setup with common treatment timing and only one post-treatment period, we can estimate average price-driven savings using a simple "binarized" DiD estimator (Callaway et al. 2024):

$$ln(e_{it}) = \lambda_i + \mu_t + \delta D_{it} + \epsilon_{it} \tag{1}$$

D_{it} is a binary treatment indicator taking the value of one in 2022 for buildings that were exposed to a price increase during the energy crisis and zero otherwise. The associated parameter $\hat{\delta}$ is an estimate of the average effect on energy consumption of being exposed to a price increase during the crisis.

In the estimation, each observation is weighted by its matching weight $w_{i,t}$. $ln(e_{it})$ is the logarithm of residential energy consumption per square meter in building i during year t. γ_i and μ_t capture building and time fixed effects, ϵ_{it} is the error term. Our coefficient of interest is δ which indicates the ATT or the average price-driven energy savings in 2022 of buildings that were exposed to a price increase during the energy crisis.

To allow for potential non-linearities in the energy demand function we estimate price-driven savings by treatment intensity. Thus, we categorize buildings that experienced a retail price increase in 2022 into three treatment groups: those with price increases of <25%, between 25% - 50%, and >50%. The control group remains the same, i.e. group of buildings with constant prices in 2022. We repeat the above matching procedure by separately matching each one of the three treatment groups to the control group. For all three of the matched samples, we apply the DiD-PSM procedure described above to estimate the average price-driven savings for each price-increase level. Additionally, we estimate energy carrier specific effects by analogously repeating the described matching procedure and the DiD-PSM estimation using the sample of gas-heated buildings only and using the sample of district-heated buildings only.

22. We include higher order polynomials of the climate factor because the relationship between energy consumption and temperature is non-linear. Several papers argue that higher order polynomials should also be included in the propensity score equation when there is evidence of a non-linear relationship between the explanatory variable and the outcome (Brookhart et al. 2006; Caliendo and Kopeinig 2008).

23. These include the average net income per person, years of schooling, age, the unemployment rate, and the share of the population receiving social benefits covering heating costs.

Identification, Validity of the Control Group and Matching Diagnostics The key identifying assumption of our DiD-PSM estimation is that the trend in average energy consumption would have been the same between the treatment group and the matched control group in a hypothetical crisis-scenario in which the treatment group is not exposed to price hikes.[24] In other words, the parallel trends assumption implies that non-price-driven savings are on average equal between the two matched groups during the crisis year 2022.

While the assumption is untestable, we provide evidence in support of parallel trends with the event study in Figure 2. The figure shows the year-specific treatment coefficients that we obtain by estimating the following event-study specification on the matched sample:

$$ln(e_{it}) = \lambda_i + \mu_t + \sum_{\tau=2018}^{2022} \gamma_\tau D_{i\tau} + \delta D_{it} + \epsilon_{it} \tag{2}$$

The event study in Figure 2 clearly shows that, on average, the trends in energy consumption between the matched treatment and the control group were not significantly different before the energy crisis.

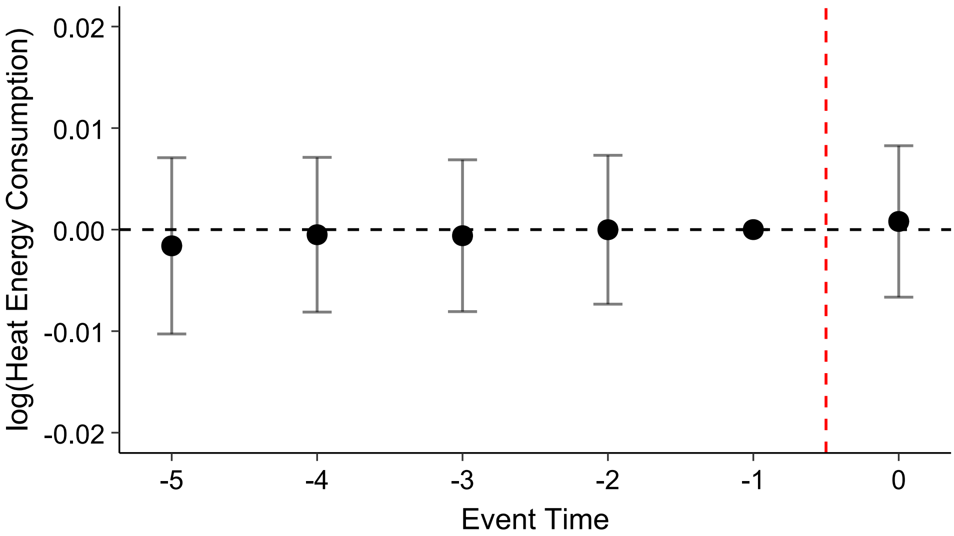
It is very unlikely that there may have been any form of active sorting into or, in our case, rather out of treatment at the building level. The variation in prices is due to households' different tariff types (mostly one- or two-year contracts), the timing of their contract renewal, and the contract position of their suppliers.[25] Landlords or building managers will not have strategically opted for shorter or longer contract periods to avoid having to renew the contracts in the middle of the crisis, as the crisis was not foreseeable when concluding the contracts. However, prices could also increase if the contract period did not end in the middle of the crisis; either because the energy provider went bankrupt or because they had to increase prices due to increased energy provision costs.[26] Whether the energy provider went bankrupt or faced increased energy provision costs that they had to pass-on to consumers largely depended on their wholesale energy-provision contracts. It is unlikely that, when concluding the energy contracts, landlords or building managers may have taken into consideration whether an energy provider buys its energy through short-term or long-term wholesale energy-provision contracts. Thus, we do not expect any building-level unobservables to be correlated with treatment assignment, because there was no active sorting into or out of treatment. Marx et al. (2024) show that

24. Besides parallel trends identification in a DiD also requires the no anticipation assumption and the stable unit treatment value assumption (SUTVA). In our setting, no anticipation most likely holds, as households could hardly anticipate the energy crisis in 2021. For SUTVA to hold, we need to assume that building i's energy consumption does not depend on the treatment status of building $j \neq i$. In other words, there should be no spillovers from the treatment status of one building on the energy consumption of other buildings. If our units of analysis were apartments, one may be concerned about spillover effects as it is well known that heating of one apartment has effects on the temperature in adjacent apartments. However, our analysis is at the building-level, which is why such concerns do not apply in our setting and we are confident that SUTVA holds.

25. Energy suppliers who purchased their energy through long-term contracts were less likely to default or to increase their prices than energy suppliers that had to buy their energy on the spot market in 2022.

26. In the case of district heating, energy provision contracts even contain price adjustment clauses such that consumer prices increase if energy provision costs increase.

Figure 2: Event study supporting parallel trends



The figure shows the event study coefficients from estimating Equation 2 on the matched sample. The x-axis displays the time to treatment in years, where 0 corresponds to the energy crisis in 2022. The displayed event study coefficients indicate the estimated year-specific treatment effects and placebo treatment effects. Vertical bars indicate 95% percent confidence intervals that are calculated

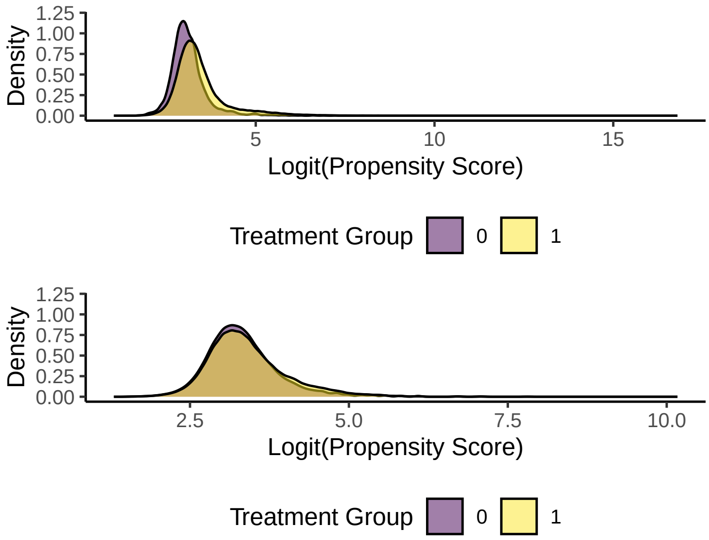
parallel trends is threatened when treatment reflects dynamic choices through selection on past outcomes, learning, or Roy-style selection. None of these channels operates here, as treatment was determined supplier-side by contract terms fixed before the crisis, leaving households and landlords no margin to condition treatment status on past or anticipated consumption.

Nevertheless, treatment assignment may not have been entirely random. If energy providers in some areas relied more on long-term wholesale contracts than in others, then we may have an uneven distribution of treated and control buildings across Germany. This does not threaten the validity of the parallel trends assumption, as long as areas with higher and lower shares of treated buildings do not have different energy consumption trends. The event study results in Figure 2 indicate that such diverging energy consumption trends are most likely not present. To be on the safe side, we nevertheless additionally perform a robustness check where we do exact matching by "Raumordnungsregion" (hereon referred to as "spatial-planning region" or "region"), which is a geographic area defined for spatial planning purposes in Germany and lies between NUTS-2 and NUTS-3 regions.[27] This addresses the potential issue of diverging energy consumption trends between spatial-planning regions with higher and lower shares of treated buildings and additionally controls for any differences in region-level unobservables between treated and controls. Even though any active sorting into or out of treatment seems unlikely, we choose to apply a DiD-PSM approach in order to balance out any observable differences

27. There are a total of 96 spatial-planning regions in Germany.

between treatment and control group.

Figure 3: Distributions of the Logit of the Propensity Score by Treatment Group



The figure shows the distribution of the logit of the propensity score by treatment group before (top panel) and after (bottom panel) matching.

Figure 3 displays the distributions of the logit of the propensity score of treated and control buildings before and after matching. After matching, the two distributions in the lower panel are very similar, suggesting that the matching was successful in further improving the comparability of the treatment and the control group. This is confirmed by Figure A.1, which shows that the matching procedure reduces the standardized mean difference between the treatment and the control group below 0.1, which is the conventional threshold for good covariate balance (Peter C Austin 2009), for all variables except for the baseline energy price. In the latter case, the post-matching difference is nevertheless very close to the 0.1 threshold. Before matching, the variance ratios of all variables is already between the conventional thresholds of 0.5 and 2 (Zhang et al. 2019). Still, the matching further improves variance ratios of almost all variables.

As the pool of potential control buildings is relatively small, we implement matching with replacement to improve the quality of the matches. Following Abadie and Spiess (2022); Colmer et al. (2024), we use two-way clustered standard errors. The first cluster is on the building level to account for serial correlation. The second cluster is on the matched-pair-year level to account for dependence among observations linked through the matching procedure.

Calculation of Elasticities Besides estimating the price-driven savings during the energy crisis, we calculate the corresponding energy price elasticities using the arc formula (Feehan 2018):

$$\eta = \frac{\frac{e_{2022} - e_{2021}}{\frac{e_{2022}+e_{2021}}{2}}}{\frac{p_{2022} - p_{2021}}{\frac{p_{2022}+p_{2021}}{2}}} \tag{3}$$

To estimate the price-elasticity of energy demand during the crisis in 2022, we slightly adjust our main estimation Equation 1. Instead of using the logarithm of energy consumption per square meter as the dependent variable, we now use a building's energy consumption per square meter normalized by the building's average energy consumption in 2021 and 2022:

$$\frac{e_{it}}{\frac{e_{i,2021}+e_{i,2022}}{2}} = \lambda_i + \mu_t + \delta D_{it} + \epsilon_{it} \tag{4}$$

In Equation 4, δ stands for the average price-driven energy savings of the treatment group as a percentage of the average energy consumption in 2021 and 2022 which corresponds to the denominator of Equation 3. We obtain $\hat{\eta}$, the estimate of the price elasticity of energy demand, by dividing $\hat{\delta}$ by the average price increase of the treatment group in 2022, normalized by the treatment group's average price in 2021 and 2022.[28]

4.1.2 Heterogeneous effects

Method 2: Double Machine Learning We use DML proposed by Chernozhukov et al. (2018) which allows us to explore heterogeneities of price-driven savings in a more flexible way than it is possible with our previous DiD-PSM approach. In particular, the DML framework allows us to model non-parametric effect heterogeneity so that we can obtain a detailed picture of how non-price savings vary with socio-economic variables.

In our application of DML, we closely follow the implementation described in Knaus (2022). As DML models have mainly been developed for cross-sectional data, we only use the year 2022 for our analysis. Our dependent variable is Δe_i, the change in energy consumption per square meter compared to 2021 in kWh. The treatment variable D_i is a binary variable taking the value of one if a building's energy price increased during the crisis and zero if the price remained constant. We use a rich set of control variables including the change in the climate factor up to the third polynomial, the one-year lag of the climate factor, a building's baseline energy price, its baseline energy consumption per square meter, the change in the work-from-home rate, several building characteristics (number of apartments per building, average apartment size, energy carrier) and a set of socio-economic variables (average income per person, share population receiving social benefit covering heating costs, unemployment rate, average years of schooling, and age).

First, we flexibly predict building-specific treatment probabilities, $\hat{\phi}(X_i)$, using a Lasso-

28. As we estimate $\hat{\delta}$ using a regression with matching weights, we also use these matching weights to calculate the treatment group's weighted average price increase and weighted average price in 2021 and 2022. All averages that we refer to above are, thus, weighted averages.

model and five-fold cross-fitting. Then we predict the building-specific treatment-specific outcome (i.e. the change in energy consumption), $\hat{\pi}(d, X_i)$, again using a Lasso-model and five-fold cross-fitting. In a third step, we plug the predicted $\hat{\phi}(X_i)$ and $\hat{\pi}(d, X_i)$ into the following formula for the doubly robust score of the potential outcome:

$$\hat{\Gamma}_i(d, X_i) = \hat{\pi}(d, X_i) + \frac{J(d)(\Delta e_i - \hat{\pi}(d, X_i))}{\hat{\phi}(X_i)} \tag{5}$$

$d \in \{0, 1\}$ takes the value of 0 to indicate the untreated state and 1 to indicate the treated state and the variable $J(d) = \mathbf{1}(D_i = d)$ indicates whether a building i's actual treatment status corresponds to d. For each building i, we thus obtain two doubly robust potential outcome scores: one potential outcome score under treatment $\hat{\Gamma}_i(1, X_i)$ and one potential outcome without treatment $\hat{\Gamma}_i(0, X_i)$. We then take the difference of the two doubly robust potential outcome scores to obtain a pseudo-outcome for each building:[29]

$$\hat{\Delta}_i = \hat{\Gamma}_i(1, X_i) - \hat{\Gamma}_i(0, X_i) \tag{6}$$

The pseudo-outcome $\hat{\Delta}_i$ cannot directly be interpreted as a building-specific treatment effect. However, it is an unbiased signal of the building-specific treatment effect (Semenova and Chernozhukov 2021), as the Neyman orthogonality of the doubly robust score ensures insensitivity to bias in the estimations of $\phi(X_i)$ and $\pi(d, X_i)$. Thus, we can use it to explore effect heterogeneities by running non-parametric kernel regressions of $\hat{\Delta}_i$ on various socio-economic variables.

Identification DML identification relies on an unconfoundedness or conditional independence assumption (Knaus 2022). This differs from the identifying assumption in our previous DiD-PSM approach, which relies on parallel trends. Conditional independence is more difficult to defend than parallel trends. As discussed in Section 4.1.1, it is very unlikely that buildings could have actively sorted into or out of treatment. Therefore, we are confident that there are no relevant unobserved building-level differences between the treatment and the control group. The DML flexibly controls for a rich set of covariates and thereby further reduces the likelihood of any remaining omitted variable bias. Finally, the confidence interval of the ATT estimated using DiD-PSM is very similar to the confidence interval of the ATT estimated using DML (see Section 5.1.2), which is a further indicator in support of the validity of the DML estimation.

Finally, the ATT obtained using the DML procedure is of a similar magnitude to the ATT that we find using DiD-PSM. The two ATTs are not statistically from another, which further

29. The pseudo-outcome in Equation 6 is the pseudo-outcome for the ATE, however, it is not a doubly-robust score for the ATT (Knaus 2022). When estimating the ATT, we again follow Knaus (2022) and use the slightly adjusted doubly-robust score:

$$\hat{\Delta}_i^{ATT} = \frac{J(d=1)(\Delta e_i - \hat{\pi}(d=0, X_i))}{\hat{\phi}(d=1)} + \frac{J(d=0)\hat{\phi}(d=1, X_i)(\Delta e_i - \hat{\pi}(d=0, X_i))}{\hat{\phi}(d=1)\hat{\phi}(d=0, X_i)}$$

increases our confidence in the validity of the DML results.

4.2 Estimation of Non-Price-Driven Savings

Method 3: Lasso Prediction of Counterfactual Energy Consumption Our estimations of price-driven savings during the energy crisis rely on using a control group of buildings that were not exposed to price hikes to construct a counterfactual.

We train a Lasso-model with ten-fold cross-validation on the years before the energy crisis. The dependent variable is a building's energy consumption per square meter e_{it} and the explanatory variables are a building's baseline energy consumption per square meter, the number of apartments, the average apartment size, the local work-from-home rate, climate factors up to the third polynomial, and several socio-economic characteristics (average income per person, share population receiving social benefit covering heating costs, unemployment rate, average years of schooling, and age). The Lasso-model achieves an out-of-sample R^2 of 0.76 showing that it can produce good predictions of energy consumption in the test sample. Using this Lasso model we predict a building's energy consumption per square meter in 2022, $\hat{e}_{i,2022}$, for a counterfactual scenario where the energy price crisis had not happened. $\widehat{\Delta e}_{i,2022}$ is the difference between the counterfactual energy consumption, $\hat{e}_{i,2022}$, and the observed energy consumption, $e_{i,2022}$. $\widehat{\Delta e}_{i,2022}$ has different interpretations for buildings with constant prices in the crisis and for buildings where prices increased. For buildings with constant prices, we denote this difference as $\widehat{\Delta e}^{0}_{i,2022}$. This object is an estimate for building-level non-price-driven savings (see discussion of identification below). For buildings where prices increased, the difference $\widehat{\Delta e}^{1}_{i,2022}$ needs to be interpreted as the sum of non-price-driven savings and price-driven savings; consequently, it is not of much interest, since the two cannot be disentangled.

By taking the average of $\widehat{\Delta e}^{0}_{i,2022}$, we obtain an estimate of average non-price-driven savings for buildings with constant prices. Similar to the final step of the DML procedure, we can now also regress $\widehat{\Delta e}^{0}_{i,2022}$ on socio-economic variables using non-parametric kernel regressions to explore heterogeneities in non-price savings during the energy crisis.

Identification Identification of the non-price-driven savings relies on the argument that short-term changes in energy consumption can only come from a limited set of factors. Besides the crisis-related non-price factors - like public appeals and saving programs - these factors are retrofits, changes in the annual temperature, reactions to price-changes, and changes in work-from-home patterns.[30]

Thermal retrofits require significant planning and execution time (Singhal et al. 2026), such that retrofits leading to energy savings in 2022 were largely predetermined before the crisis. They will, therefore, also affect buildings with constant prices and, thus, our estimate of non-

30. Changes in work-from-home patterns are particularly relevant when comparing 2022 – when Covid-restrictions were largely waived – with the year 2021 which still had several Covid-lockdowns and stay-at-home regulations.

price-driven savings. However, the bias from the effect of existing retrofits is at most 0.5%[31] i.e., more than one order of magnitude smaller than our estimate of non-price-driven savings. The small effect of thermal retrofits is mostly due to Germany's low annual retrofit rate.

Other factors, such as socio-economic changes or changes in living habits, are stickier and will therefore only have a negligible effect on year-on-year changes in energy consumption. As we focus on buildings that had a constant price from 2021 to 2022, changes in energy consumption in 2022 can only come from changes in temperature, changed work-from-home rates, or the multiple non-price-factors related to the energy crisis, such as appeals to save and energy savings programs (besides the small effects of retrofits). Since our machine learning model flexibly accounts for climate factors and for the work-from-home rate, the difference between the predicted counterfactual energy consumption and the observed actual energy consumption should correspond to the crisis-related non-price-driven energy savings.

5 Results and Discussion

5.1 Price-driven Savings and Heat Energy Price Elasticities

5.1.1 Average Price-Driven Savings

In our sample, we observe total heat energy savings of 17% on average[32], which is consistent with households' reduction of gas consumption (Moll et al. 2023), and similar in magnitude to aggregate energy savings in Germany during the crisis.[33] We first estimate price-driven savings to understand how much of these large overall savings can be attributed to the price hikes.

Table 2 presents the results of the price-driven savings estimation with Equation 1. We find that energy savings in buildings where heat energy prices increased were, on average, not significantly different than in control buildings where prices stayed constant (see Table 2 Column (a)). The 95%-confidence interval of estimated price-driven consumption response is narrow (-0.6% – 0.9%) showing that households adjusted their heat energy consumption by less than 1% in response to the strong realized price changes in the short-run. To corroborate our results, we perform a number of robustness checks that we present at the end of this section.

The surprising result that heat energy savings are not significantly higher in buildings where prices rose during the crisis than in the control group of buildings with constant prices implies that the large overall heat energy savings were driven by non-price factors (for a detailed discussion and estimation results of non-price-driven savings, see Section 5.2) and the relatively

31. The annual thermal retrofit rate in Germany is below 1% in 2022 (Bundesverband energieeffiziente Gebäudehülle e.V. 2025) and "standard" retrofits deliver about 50% of energy savings on average (Ballarini et al. 2014).

32. One concern might be whether observed reductions in heat energy consumption were offset by increased use of alternative heating sources. Survey evidence from six European countries (Denmark, Germany, the Netherlands, Norway, Poland, and Switzerland) collected in early 2023 suggests this substitution was limited. In fact, Germany had the lowest rate of households acquiring additional heating appliances among all countries surveyed at only 14.8%, while the dominant response was to lower indoor temperatures, use blankets, and wear extra clothing (Jaeger-Erben et al. 2025).

33. In 2022, Germany reduced its natural gas consumption by 15.7% (AG Energiebilanzen e. V. 2023).

Table 2: DiD-PSM: Full sample and by treatment intensity.

Dependent Variable:	log(Heat Energy Consumption)			
	(a)	(b)	(c)	(d)
Model:	Main DiD	%Δp<=25%	25%<%Δp<=50%	%Δp>50%
Variables				
Treated	0.0014	0.0030	−0.0073*	−0.0046
	(0.0037)	(0.0037)	(0.0038)	(0.0037)
Fixed-effects				
Building	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	332,076	139,077	109,754	113,107
R^2	0.910	0.911	0.913	0.910

Two-way clustered standard errors (building and matched-pair-year) in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

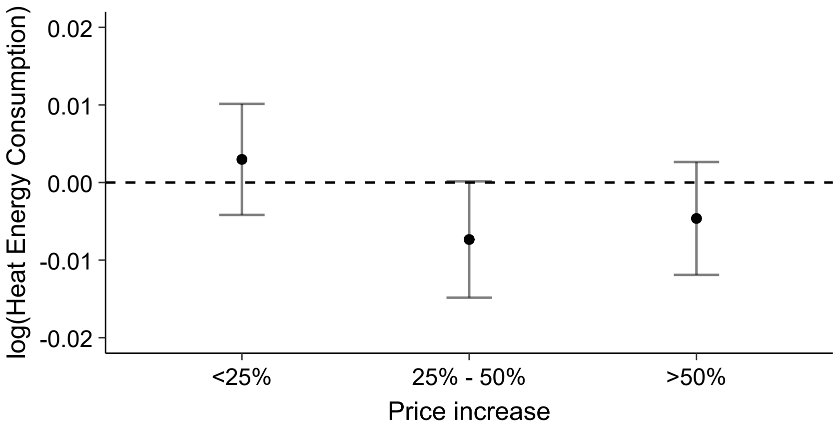
warm temperatures in 2022. Besides weather effects, households thus saved because of non-price factors such as public appeals, savings programs, and the general discourse about high energy prices – not however in response to actual building-level price changes. This result is in line with other studies studying household responses to the crisis in Germany. Dertwinkel-Kalt et al. (2024) find that households' gas savings where not significantly impacted by individual economic incentives and Singhal et al. (2026) find that households' expectations of cost increases are uncorrelated to their actual thermostat settings during the crisis. This is relevant for energy policy in times of crisis as it implies that sufficient short-term savings to avoid energy scarcity are unlikely to be achieved through high energy prices alone, particularly in countries with high information frictions in the residential energy market, such as Germany (see Section 2).

The insignificant price-driven savings translate to an insignificant short-term arc-elasticity of demand (95%-confidence interval: -0.017, 0.029). While this result is in line with results from other studies using survey data (Dertwinkel-Kalt et al. 2024; Singhal et al. 2026), studies using aggregate data report significant price-elasticities during the crisis in Germany (Ruhnau et al. 2023; Jamissen et al. 2024). Ruhnau et al. (2023) report gas savings of small consumers (households and small commercial consumers) consistent with a price elasticity of -0.16. However, they caution that this price elasticity may be inflated by public campaigns and ethical motivations to save energy. Jamissen et al. (2024) also use aggregate data, but control for public awareness of the crisis using Google Trends data thereby controlling for effects of the crisis discourse and public appeals. They find a much lower price elasticity of gas demand of small consumers of -0.04 (95%-confidence interval: -0.068, -0.005). Although they estimate a significant price elasticity, their confidence interval intersects with ours. Moreover, their estimation strategy only partially accounts for non-price factors. Controlling for additional factors, such as regulatory changes to residential heating systems the operation, would likely have brought their estimate even closer to ours.[34]

To understand if the low price responsiveness prevails across all levels of price increases, we estimate price-driven savings for three subgroups: buildings with a price increase of <25%, 25%–50%, and >50%. The event study plots of the DiD-PSM by subgroup indicate that parallel trends also hold for different levels of price-increase (see Appendix Figure A.5). Columns (b) - (d) of Table 2 and Figure 4 present the DiD-PSM results for the three subgroups. Price-driven savings are not significant at the 5%-level in any of the subgroups and point estimates always imply savings smaller than 1%. However, point estimates become negative at price-increases above 25%, which may indicate a potential weak reaction to high price hikes. This evidence is only suggestive, though, as 95%-confidence intervals of all three subgroups overlap and include the zero.

An analysis by energy carrier confirms the previous findings. Price-driven savings and heat energy price elasticities are not significantly different from zero in both the subsample of buildings heated with gas or in the group of buildings using district heating (see Table A.1 and Figures A.2 & A.3b).

Figure 4: Price-driven savings by treatment group



The figure shows estimates of price-driven energy savings during the crisis by treatment group. The coefficients indicate the estimated treatment effects on log energy consumption of being exposed to a price increase during the crisis. Vertical bars indicate 95% percent confidence intervals that are calculated using standard errors clustered at the building-level.

34. The low short-run price elasticity we estimate is consistent with evidence from other residential energy markets also under non-crisis conditions. For example, Deryugina et al. (2020) exploit a natural experiment in the Illinois residential electricity market under non-crisis conditions and find short-run price elasticities of electricity demand to be close to zero yet growing substantially over longer time horizons.

Robustness checks

We perform a battery of robustness checks to confirm the validity of our results. First, we vary the control group threshold (see columns (a) and (b) of Table A.2 in Appendix A.5). In our analysis we consider a price change below 1% as observing no price change. In our robustness checks we use alternative thresholds of 0.5% and 1.5%. We find that increasing the threshold of the control group to a price change of 1.5% as well as decreasing the threshold to 0.5% does not significantly alter our results. In both cases, price-driven savings remain insignificant and smaller than 1% in absolute value.

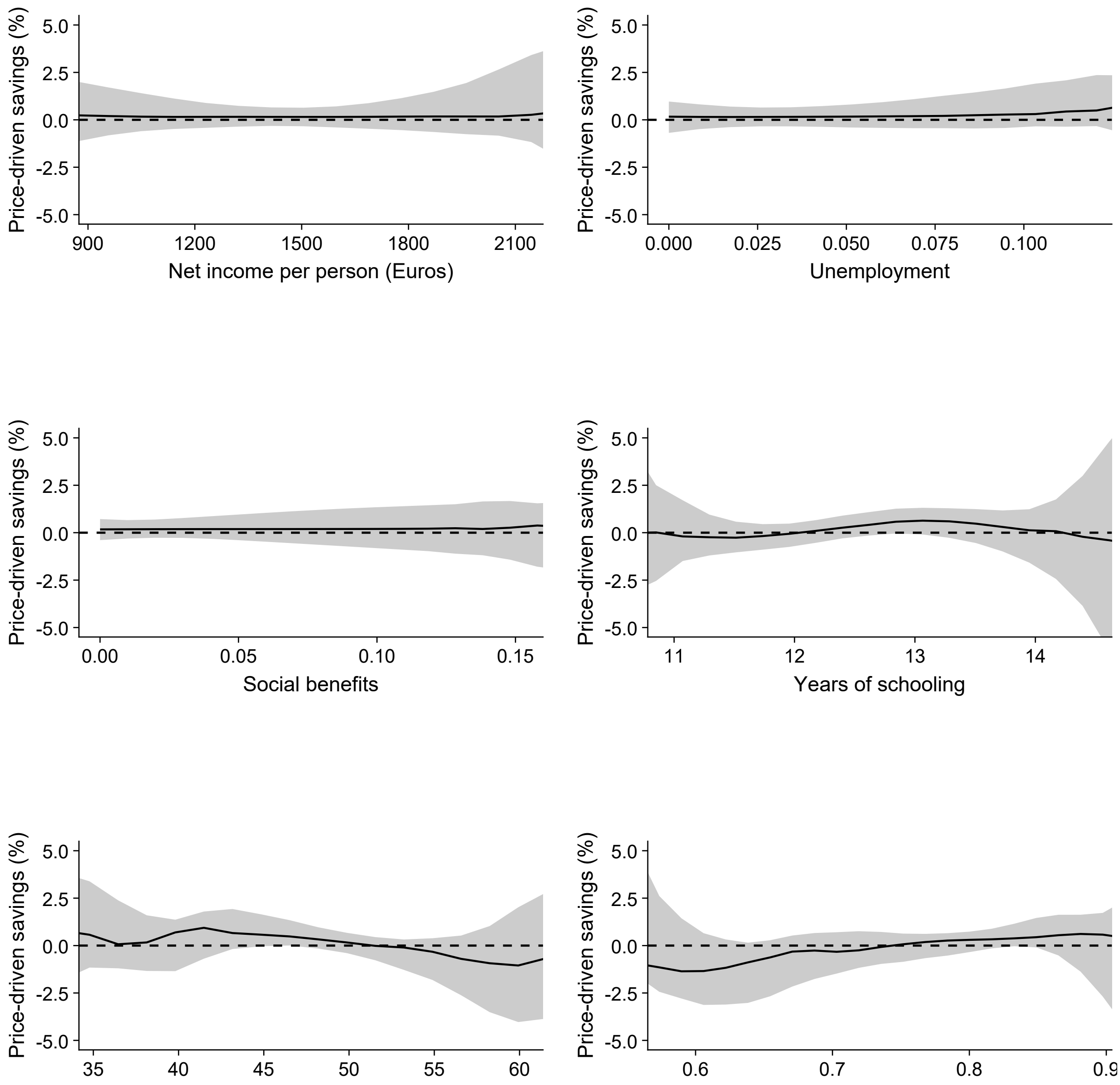
In a second robustness check, we enforce exact matches at the level of spatial-planning regions. This robustness check serves two purposes: First, it avoids that buildings from former East-Germany are matched to buildings from former West-Germany. Due to historical differences, households in East- and West-German households may, on average, have different attitudes toward Russia, the War in Ukraine, and in general different levels of trust in the media and government (Braun and Trüdinger 2023). Therefore, they may have different non-price motives to save energy. Second, as discussed in the methodology section, some spatial-planning regions may have higher shares of treated buildings than others due to potentially different wholesale contract positions of the regional energy providers. Thus, by matching on spatial-planning regions, we also avoid that any region-level unobservables may bias our results. Column (c) of Table A.2 shows that the price-driven savings with matching at the level of spatial-planning region are, as in the first two robustness checks, not significantly different from our main specification. This, again, corroborates the result that households hardly reacted to actual price increases.

Third, we run our estimations on a balanced sample of buildings that are observed throughout all years of our analysis. This robustness check addresses concerns that results may be driven by compositional changes in the unbalanced panel of our main estimation. We again obtain a treatment effect that is insignificant and very close to zero (see column (d) of Table A.2.

In the last robustness check, we perform 5:1 matching instead of 1:1 nearest neighbor matching. The results are shown in Column (e) of Table A.2 and are again very similar to the price-driven savings from the main specification.

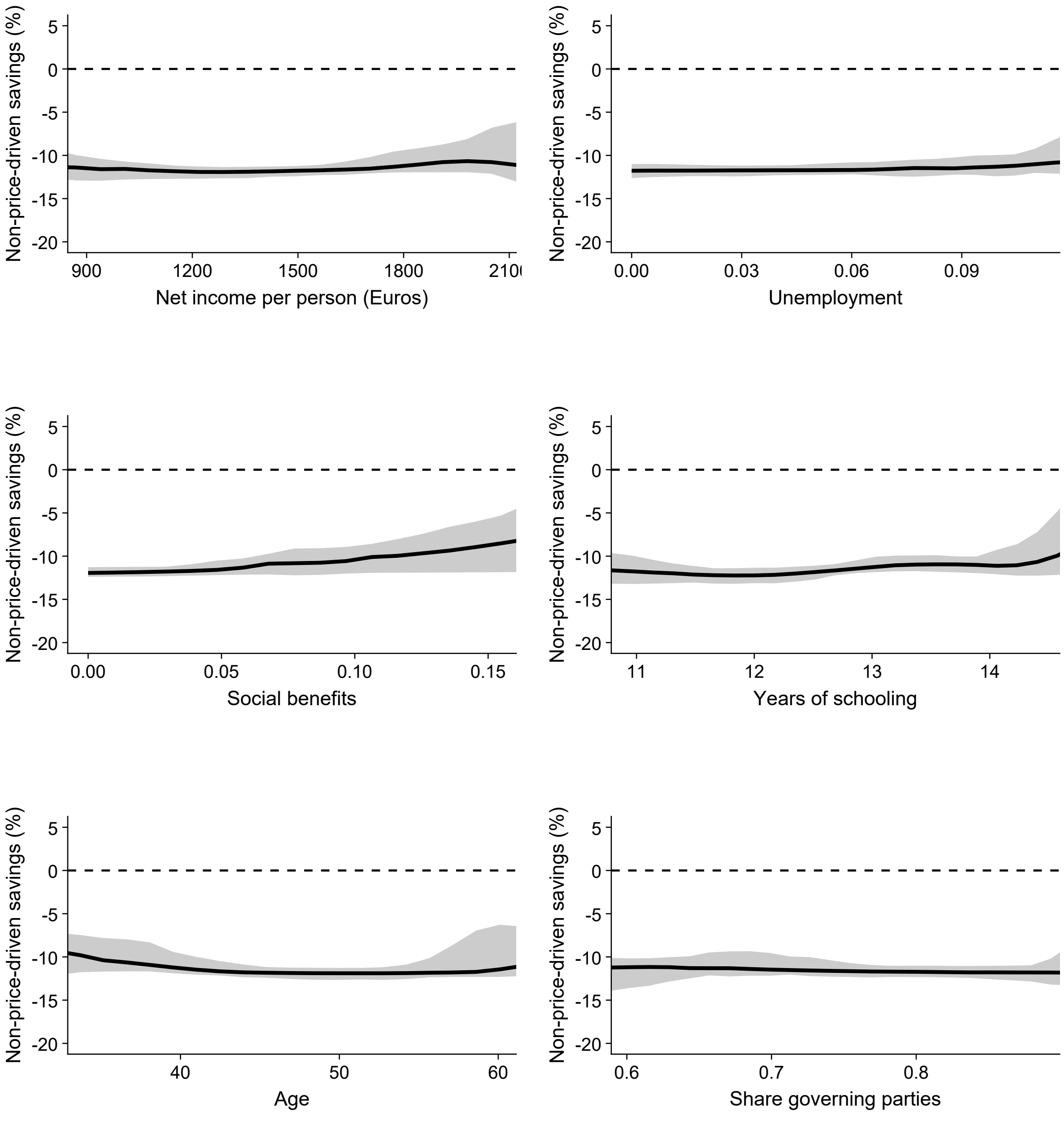
Finally, Figure A.5 in Appendix A.5 shows the event-study plots for all five robustness specifications. We do not observe significant pre-treatment coefficients in any robustness specification, which is a further strong indication of the plausibility of the parallel trends assumption. Overall, our findings on price-driven savings appear to be robust against a number of potential concerns regarding the definition of our control group, region-specific effects, as well as further alternative methodological choices.

Figure 5: Heterogeneity of price-driven savings



The figure shows how price-driven savings vary with different socio-economic characteristics. The black line is an estimated non-parametric local polynomial regression function obtained by regressing DML-pseudo outcomes $\hat{\Delta}_i$ on socio-economic characteristics. The shaded areas indicate 95% confidence intervals based on heteroskedasticity-robust standard errors. As $\hat{\Delta}_i$ is based on a doubly robust score $\hat{\Gamma}_i$ and cross-fitting, we can we can ignore the first step estimation procedure and treat the pseudo outcomes $\hat{\Delta}_i$ as known when calculating the standard errors (Ahrens et al. 2026; Knaus 2022).

Figure 6: Heterogeneity of non-price-driven savings



The figure shows how non-price-driven savings vary with different socio-economic characteristics. The black line is an estimated non-parametric local polynomial regression function that we obtain by regressing estimated non-price-driven savings on socio-economic characteristics. The shaded areas indicate 95% confidence intervals based on 100 bootstrap iterations.

5.1.2 Socio-Economic Heterogeneities of Price-Driven Savings

Next, we explore how price-driven energy savings vary with socio-economic characteristics using the DML procedure described in Section 4.1.2. We first flexibly estimate building-level pseudo outcomes $\hat{\Delta}_i$ using DML. These building-level pseudo outcomes are unbiased estimates of building-level price-driven savings. In a second step, we investigate effect heterogeneities by regressing the pseudo outcomes on socio-economic characteristics using non-parametric local polynomial regressions.

As discussed in Section 4.1.2, correct identification of the pseudo-outcomes relies on a conditional independence assumption. This assumption is more restrictive and less easily testable than the identifying assumptions of the previous DiD-PSM approach. The 95%-cofidence interval of the ATT estimated using the DML procedure ranges from -0.3% – 0.6% and is, thus, very close to the ATT estimated using DiD-PSM (95%-confidence interval: -0.6% – 0.9%). The high similarity of the treatment effect estimates obtained using DML and DiD-PSM indicates that the DML-procedure correctly identifies price-driven savings.

Figure 5 shows the estimated relationships between price-driven savings and a set of socio-economic variables: net income per person, the unemployment rate, the share of social benefit recipients, years of schooling, age, and the share of votes for governing parties in the last election. None of the socio-economic variables exhibits a significant correlation with price-driven savings. This result underscores that households did not significantly show significant short-term reactions to actual increases in heat energy prices, neither on average, nor in any socio-economic subgroup we observe.

5.2 Non-price-driven savings

5.2.1 Average non-price-driven savings

Across buildings with constant prices in the crisis, the average non-price-driven savings are 11.7 % (95%-confidence interval: 11.1 % – 12.2 %[35]) of a building's energy consumption in the previous year. In our sample, total heat energy savings amounted to approximately 17% during the crisis. Thus, non-price-driven savings accounted for about two thirds of the observed reduction in heat energy consumption. As price-driven savings are insignificant and close to zero, the remaining savings can be attributed to the comparatively warm temperatures in 2022. This underscores the important role that factors beyond retail price transmission played for short-term savings during the energy crisis.

The estimation of non-price-driven energy savings produces results which are in line with the price-driven savings estimated using DiD-PSM. We repeat the estimation of counterfactual energy consumption in 2022 for the group of treated buildings using the same Lasso model. This allows us to also compute the difference between counterfactual and observed energy consumption in 2022 for treated buildings. For treated buildings this difference is an estimate of the

35. All confidence intervals for non-price-driven energy savings are based on 100 bootstrap iterations.

sum of non-price-driven and price-driven energy savings in contrast to the control group where it is a direct estimate of non-price-driven savings (see Section 4.2). We find that, for treated buildings, the average difference between counterfactual and observed energy consumption in 2022 is 11.6% of pre-crisis energy consumption. This figure is very close to, and not significantly different, from the estimated 11.7 % of non-price-driven energy savings of the control group, implying that price hikes did not lead to higher energy savings among treated buildings.

5.2.2 Socio-Economic Heterogeneities of Non-Price-Driven Savings

To explore heterogeneities, we regress estimated non-price-driven savings on different socio-economic variables, again using non-parametric local polynomial regressions. Figure 6 shows heterogeneities of non-price-driven energy savings along several socio-economic characteristics. Similar to price-driven savings, non-price-driven savings do not significantly vary with most socio-economic characteristics. The only exception is social benefits covering heating costs where non-price-driven savings slightly decrease with the share of social benefit recipients. Even though households did not significantly react to actual price-changes, they may have reacted to the overall discourse on rising heat energy costs, which would be reflected in non-price-driven savings. Households receiving social benefits covering heat energy costs may have reacted less to this overall discourse and therefore displayed lower non-price-driven savings.

6 Conclusion

In this paper, we examine the effects of the energy crisis in 2022 alongside the contemporaneous appeals and energy saving programs on energy consumption in Germany. We apply three different methods - DiD-PSM and two machine learning based approaches - to estimate price-driven energy savings, energy price elasticities, and non-price-driven energy savings during the crisis. We also analyze how both types of energy savings vary with various socio-economic characteristics. Our analysis is based on a unique dataset of residential building-level heat energy prices and consumption that we combine with administrative data on socio-economic characteristics from the German microcensus, and further data on weather conditions and electoral outcomes.

Our analysis surprisingly reveals that households in buildings exposed to retail heat energy price increases did not save significantly more heat energy in 2022 than households in a matched control group of buildings where prices stayed constant during the crisis. Instead, we find that non-price factors such as public appeals to save, heat energy saving programs, or the general discourse about rising heating costs account for about two thirds of the large overall residential heat energy savings. The comparatively warm temperatures during 2022 account for about one third of the observed heat energy savings in our sample. The very small and insignificant response to experienced retail price hikes also implies that the short-run price elasticity of residential heat energy demand is insignificant and close to zero.

The important role of non-price factors points to promising avenues for future research.

Quantifying to what extent non-price savings were driven by public appeals, moral considerations, or other factors such as the discourse about heating costs is important for future energy policy. Understanding how much of the observed short-term savings were driven by changes in heating behavior or by fast low-level retrofits would offer further relevant insights into the persistence of savings and households' adjustment capacity.

Our analysis carries several methodological and policy implications. Methodologically, we propose and implement an approach for estimating price-driven energy savings and energy price elasticities that prevents the overestimation of the price-driven consumption response by comprehensively controlling for contemporaneous non-price-driven energy savings using an adequate control group. Moreover, we use double machine learning to analyze heterogeneities in non-price-driven savings and apply another machine learning based approach to estimate non-price-driven savings. On the policy side, our findings offer valuable insights into emergency interventions and the design of public policies to achieve short-term energy savings to avoid energy shortages during energy crises.

Crucially, our results suggest that simply allowing energy prices to escalate in times of energy shortages is insufficient for achieving the necessary short-run energy demand reductions in the residential sector. This is particularly the case for countries like Germany, where the residential heat energy sector is marked by strong information frictions. During the 2022 energy crisis, public appeals and energy saving programs played a much larger role than retail price increases in achieving short-term heat energy savings in Germany's residential sector.

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A Appendix

A.1 Prediction of variation in socio-economic characteristics

In a first step, we use the microcensus and its supplementary survey on dwelling conditions from 2018 to train a Lasso-model to predict how dwelling characteristics are related to socio-economic characteristics. The dependent variables are the socio-economic characteristics used for the heterogeneity analysis (income, employment status, social benefit recipient status and age). The explanatory variables are dwelling characteristics (number of apartments and apartment size) and AGS-fixed effects. The Lasso-model is trained with five-fold cross-validation.

Second, we demean the building characteristics in the energy billing dataset at the zip-code level. We then multiply these demeaned building characteristics with the corresponding Lasso-coefficients to obtain predictions of how socio-economic characteristics of a building's residents deviate from the zip-code level average.

Finally, for each socio-demographic variable, we add a building's predicted deviation from the zip-code level average to its actual zip-code level average of that variable that we computed based on the microcensus data.

A.2 Theoretical Framework

We first present a simple theoretical model of energy consumption that describes a household's utility maximization problem, which consists of allocating its budget between consuming energy and consuming a composite consumption good. The central feature of the model is that it allows for a specific disutility from energy consumption, reflecting the non-price-driven motivations to save energy during the crisis.

In this model, a household derives utility from consuming energy e and a composite consumption good x. The household's utility from consuming energy also depends on non-monetary motivations to save energy. These non-monetary motivations can be influenced by public campaigns or government appeals for saving energy. Following Perino (2015), we model this using a utility function $u(e, x, m)$, where m is a parameter representing the effect of campaigns or appeals to save energy. A change in m changes the marginal rate of substitution between e and x. The price of energy is p and the composite consumption good is the numeraire. The household has income w that it can spend on e and x. For ease of exposition, we again follow Perino (2015) and use a constant elasticity of substitution (CES) utility function:

$$u(e, x, m) = \left[\frac{1}{1+m}e^r + \frac{m}{1+m}x^r\right]^{1/r} \tag{7}$$

An increase in m reduces the weight in the utility function on e and increases the weight on x. Thus, an increase in m represents a campaign or appeal with the message to reduce energy consumption. Maximizing $u(e, x, m)$ subject to the budget constraint $pe + x = w$ yields the optimal energy consumption:

$$e^* = \frac{p^{-\sigma} w}{m^\sigma + p^{1-\sigma}} \tag{8}$$

Taking the differential of e^* gives:

$$de^* = \underbrace{-\frac{\sigma m(mp)^{\sigma-1} + 1}{(m^\sigma + p^{1-\sigma})^2}}_{\frac{\partial e^*}{\partial p}} \, dp \underbrace{-(m^\sigma p^{1-\sigma)})^2 \sigma m^{\sigma-1}}_{\frac{\partial e^*}{\partial m}} \, dm \tag{9}$$

First note that both partial derivatives are negative because $\sigma, m, p \geq 0$ and $\sigma, m \geq 0$.

$$\frac{\partial e^*}{\partial p} = -\frac{\sigma m(mp)^{\sigma-1} + 1}{(m^\sigma + p^{1-\sigma})^2} \leq 0 \tag{10}$$

$$\frac{\partial e^*}{\partial m} = -(m^\sigma p^{1-\sigma)})^2 \sigma m^{\sigma-1} \leq 0 \tag{11}$$

Intuitively, this means that the optimal consumption of energy e^* decreases with rising price p as well as with stronger public campaigns m. Dividing both sides of the differential of e^* in Equation 9 by dp gives us the total derivative of energy consumption with respect to the price of energy:

$$\frac{de^*}{dp} = \underbrace{-\frac{\sigma m(mp)^{\sigma-1} + 1}{(m^\sigma + p^{1-\sigma})^2}}_{\frac{\partial e^*}{\partial p}} \underbrace{-(m^\sigma p^{1-\sigma)})^2 \sigma m^{\sigma-1}}_{\frac{\partial e^*}{\partial m}} \frac{dm}{dp} \tag{12}$$

We easily see that the total derivative $\frac{de^*}{dp}$ only corresponds to the partial derivative $\frac{\partial e^*}{\partial p}$ if m is unrelated to p, i.e. if $\frac{dm}{dp} = 0$. However, $\frac{dm}{dp}$ was larger than zero during the 2022 energy price crisis when the price hikes were met with calls from several public actors to reduce energy consumption (i.e. an increase in m). Therefore, during the crisis, the total derivative of $\frac{de^*}{dp}$ corresponded to the combined partial effects of $\frac{\partial e^*}{\partial p}$ and $\frac{\partial e^*}{\partial m}$ (times $\frac{dm}{dp}$).

Consequently, regressing e^* on p without explicitly modeling m would yield an estimate of the effect of p on e^*, which is biased by the effect of m on e^*. Therefore, to be able to properly isolate the effect of prices on energy consumption, we explicitly model non-monetary motivations in our empirical strategy.

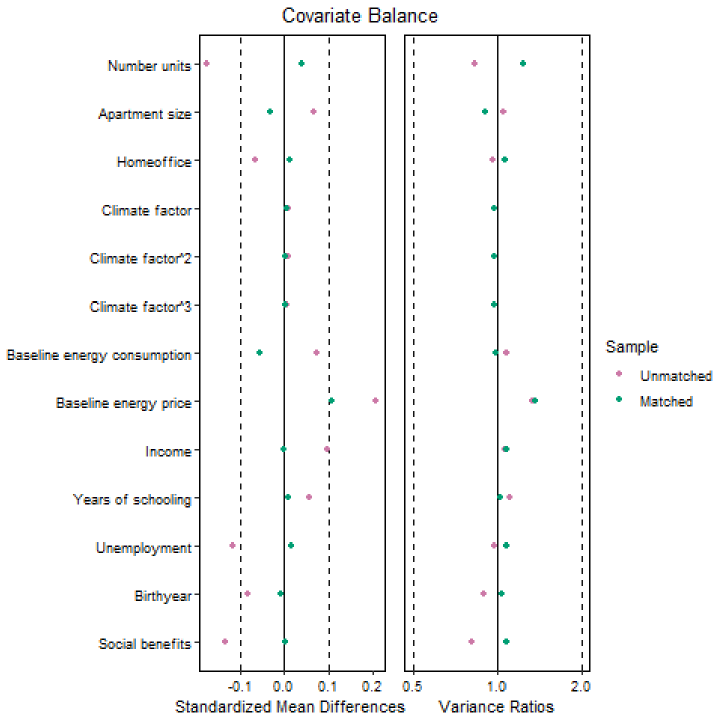
Similarly, Equation 13 shows that the total derivative $\frac{de^*}{dm}$ only corresponds to the partial derivative $\frac{\partial e^*}{\partial m}$ if $\frac{dp}{dm} = 0$. As mentioned, this was not the case during the crisis. Hence, when estimating the effect of public appeals on energy consumption, or - more generally - estimating non-price-driven savings, one needs to carefully control for the contemporaneous effect of price hikes. To ensure that our estimated non-price-driven savings are not biased by the price hikes, we only use buildings where prices stayed constant during the crisis for the estimation of non-price-driven energy savings (see Section 4.2).

$$\frac{de^*}{dm} = \underbrace{-\frac{\sigma m(mp)^{\sigma-1}+1}{(m^\sigma + p^{1-\sigma})^2}}_{\frac{\partial e^*}{\partial p}} \frac{dp}{dm} \underbrace{-(m^\sigma p^{1-\sigma)})^2 \sigma m^{\sigma-1}}_{\frac{\partial e^*}{\partial m}} \tag{13}$$

The model's results provide several empirical predictions. First, it trivially predicts that rising energy prices should lead to reduced energy consumption. Second, it projects that households reduce their energy consumption in 2022 compared to 2021, even if their prices stayed constant and that these savings vary with the strength of the non-monetary savings motives. Finally, it shows that in order to isolate the partial effect of energy prices on energy consumption, one must adequately control for non-monetary savings and vice versa.

A.3 Further Matching Diagnostics

Figure A.1: Loveplot of the covariate balance



The figure shows standardized mean differences and variance ratios between the treatment and the control group before and after matching.

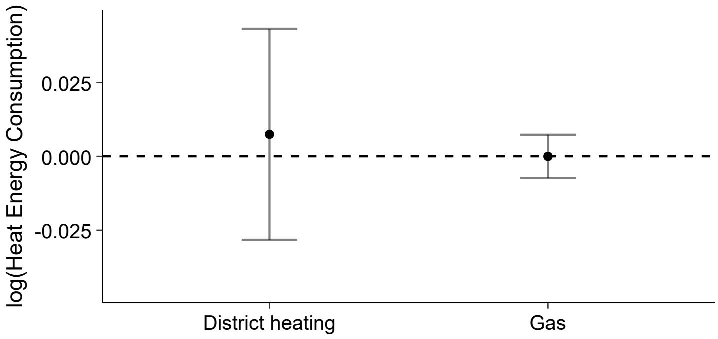
A.4 Results by Treatment Group and by Energy Carrier

Table A.1: DiD-PSM by type of carrier.

Dependent Variable:	log(Heat Energy Consumption)	
Model:	Gas	District Heat
Treated	-1.86×10^{-5}	0.0075
	(0.005)	(0.0182)
Fixed-effects		
id	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	291,460	40,616
R^2	0.903	0.935

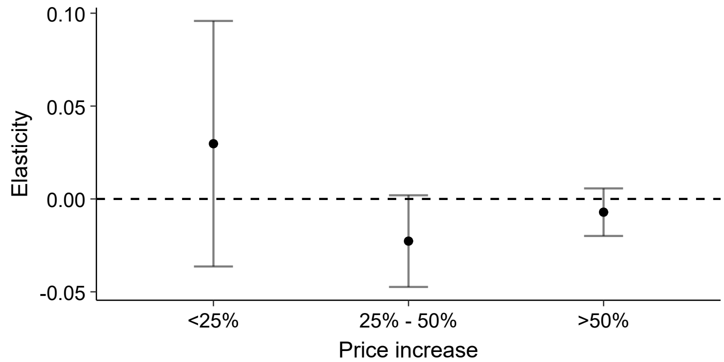
Two-way clustered standard errors (building and matched-pair-year) in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure A.2: Price-driven savings by carrier

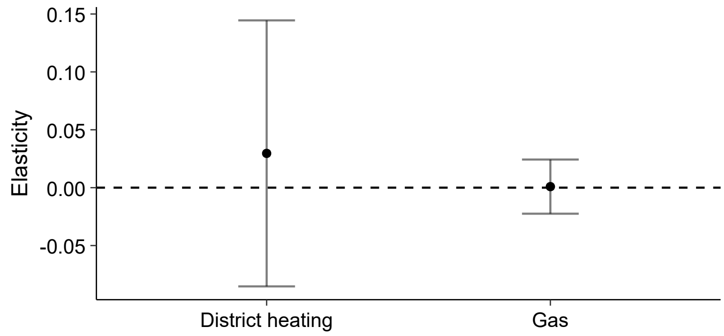


The figure shows estimates of price-driven energy savings during the crisis by energy carrier. The coefficients indicate the estimated treatment effects on log energy consumption of being exposed to a price increase during the crisis. Vertical bars indicate 95% percent confidence intervals that are calculated using two-way clustered standard errors at the building and matched-pair-year level.

Figure A.3: Elasticity by treatment group and carrier.



(a) Elasticity by treatment group.

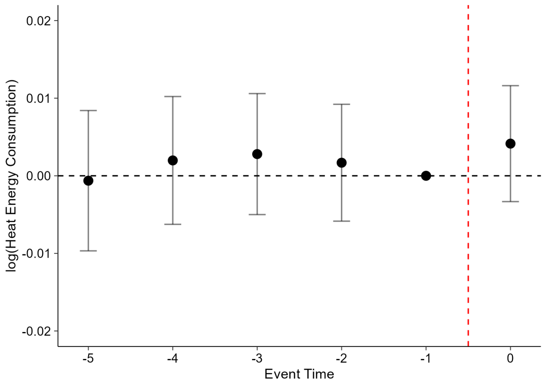


(b) Elasticity by energy carrier.

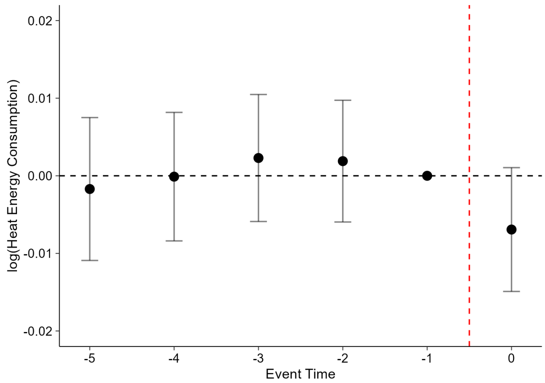
The figure shows estimates of the short-term energy price elasticity during the crisis by treatment group (Panel (a)) and by energy carrier (Panel (b)). Vertical bars indicate 95% percent confidence intervals that are calculated using two-way clustered standard errors at the building and matched-pair-year level.

Figure A.4: Event studies by treatment group.

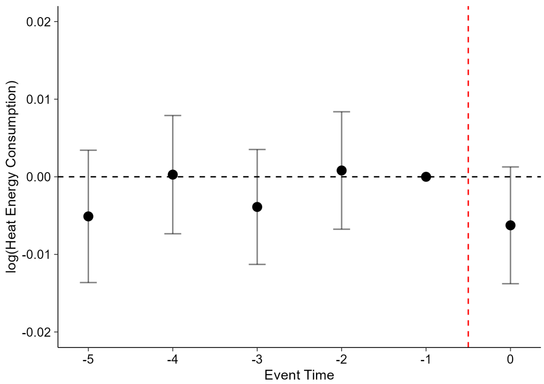
(a) Event study for buildings with price increases of <25%



(b) Event study for buildings with price increases of 25% - 50%



(c) Event study for buildings with price increases of >50%

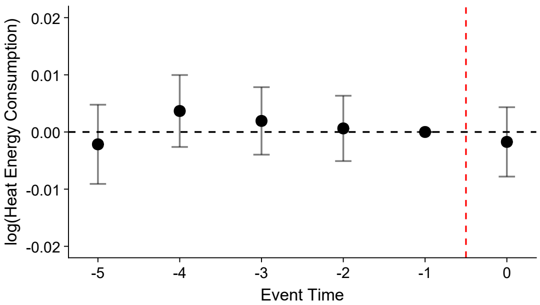


The figure shows the event study coefficients from estimating equation 2 on the matched sample of control buildings and treated buildings with price increases of <25% (Panel (a)), with price increases of 25% - 50% (Panel (b)) and with price increases of >50% (Panel (c)). The x-axis displays the time to treatment in years, where 0 corresponds to the energy crisis in 2022. The displayed event study coefficients indicate the estimated year-specific treatment effects and placebo treatment effects. Vertical bars indicate 95% percent confidence intervals that are calculated using standard errors clustered at the building-level.

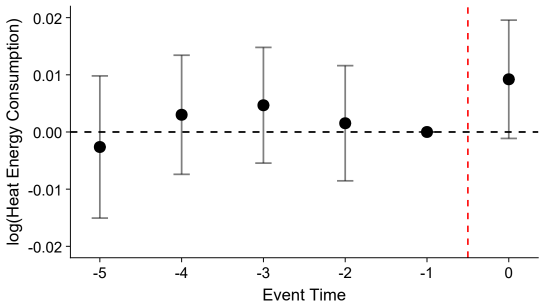
A.5 Robustness

Figure A.5: Robustness: Event study plots of different DiD-PSM specifications

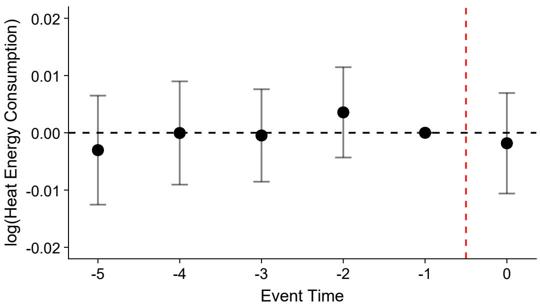
(a) Larger control group cutoff (1.5%)



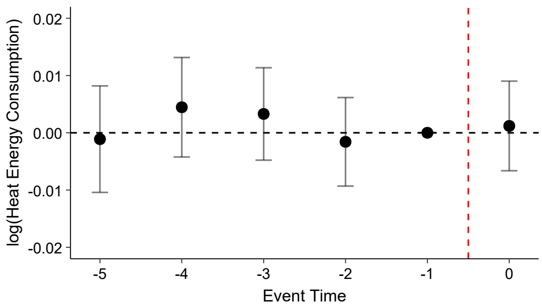
(b) Smaller control group cutoff (0.5%)



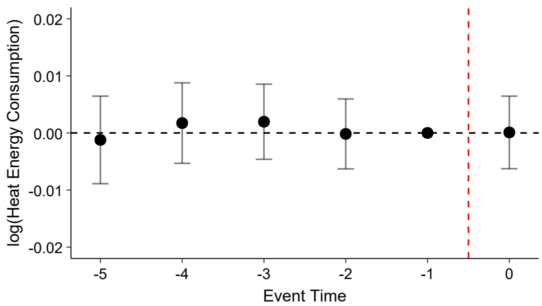
(c) Exact matching on the regional level



(d) Balanced sample



(e) Five to one matching



The figure shows event studies for various DiD-PSM robustness checks. Panel (a) shows the event study with exact matching by spatial-planning regions. Panel (b) shows the event study with a balanced panel. Panel (c) shows using 5:1 matching. The x-axis displays the time to treatment in years, where 0 corresponds to the energy crisis in 2022. The displayed event study coefficients indicate the estimated year-specific treatment effects and placebo treatment effects. Vertical bars indicate 95% percent confidence intervals that are calculated using two-way clustered standard errors at the building and matched-pair-year level.

Table A.2: Robustness check: different DiD-PSM specifications.

Dependent Variable:	log(Heat Energy Consumption)				
	(a)	(b)	(c)	(d)	(e)
Model:	Control threshold: 1.5%	Control threshold: 0.5%	Regional matching	Balanced sample	5:1 Matching
Variables					
Treated	-0.0026	0.0079	-0.0017	0.0002	-0.0004
	(0.0030)	(0.0049)	(0.0041)	(0.0037)	(0.0032)
Fixed-effects					
id	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	335,774	326,578	292,663	257,946	332,343
R^2	0.910	0.910	0.910	0.912	0.910

Two-way clustered standard errors (building and matched-pair-year) in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*