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Who Pays for Higher Energy Costs? Distributional Effects in the Housing Market

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ABSTRACT

WHO PAYS FOR HIGHER ENERGY COSTS? DISTRIBUTIONAL EFFECTS IN THE HOUSING MARKET

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We examine how rising energy costs affect rental housing markets and inequality. Using listing data for the 30 largest German cities from 2015–2024, we find that higher energy prices are passed through to net rents in high-rent segments, where inefficient properties see significant rent reductions, but not in lower-priced segments. This asymmetry reflects tighter markets and lower demand elasticity in the affordable segment. Consequently, low-income households face much larger increases in total housing costs. Our results show how segmented housing markets can amplify inequality when energy prices rise, highlighting important distributional implications for climate policy.

Keywords: Housing Markets, Energy Prices, Climate Change, Inequality
JEL classification: R31, Q41, Q54, D31

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1 Introduction

In many cities, the cost of housing has been rising steadily for decades. While higher rents are a well-recognised driver of affordability pressures, a less widely noted trend is the rapid increase in household energy costs. Over the past 30 years, energy prices in many countries have grown at roughly four times the pace of net rents (Table 1). For households, this means that energy now accounts for a much larger share of total living expenses – around 5% of income in most advanced economies, with one in five households spending over 10% (International Energy Agency, 2024). At the same time, residential energy use is a major source of greenhouse gas emissions, responsible for about 34% of global CO_2 output (UNEP, 2024). Policymakers have proposed higher energy prices as a way to drive efficiency and cut emissions. Yet such measures, combined with long-run price trends, raise a critical question: when energy becomes more expensive, who ultimately bears the cost? This paper examines that question and shows that higher energy prices are partly passed through to rents – tending to benefit higher-income households while placing a heavier burden on lower-income ones, thereby deepening existing inequalities.

A key driver of this unequal burden is that rising energy prices affect low- and high-priced housing differently. When energy prices rise, the cost of occupying an energy-inefficient home increases relative to a more efficient one, making such units less attractive to tenants. This shift in demand puts downward pressure on the rents landlords can charge for inefficient homes. How much rents adjust depends on two factors: the sensitivity of tenant demand to total housing costs and the tightness of the market segment.

Housing markets are highly segmented: even within the same city, higher- and lower-income households typically search in different rent brackets (Piazzesi et al., 2020). Using online listings data for German cities, we find that this segmentation is key to understanding rent adjustments. When energy prices rise, demand – as measured by online search activity – responds far more strongly in higher-priced segments, where landlords typically face fewer potential tenants. This stronger demand response leads to larger rent reductions for inefficient units in these segments. In contrast, in lower-priced segments – where competition among tenants is more intense – the pass-through from energy prices to rents is close to zero. Consequently, low-income households experience an increase in total housing costs that is nearly three times greater than that faced by higher-income households.

We use listing-level data on residential rental properties in the 30 largest German cities from 2015 to 2024, provided by Value AG,[1] which consolidates listings from over 100 online and offline platforms. The dataset covers more than 1 million rental listings and includes detailed property characteristics such as size, age, location, heating type, and annual

[1]We thank Sebastian Hein from Value AG for giving us access to the data.

Table 1: Percentage change in energy costs and net rent from 1995 to 2024

Country	Δ Net rent	Δ Energy costs	Energy expenditure ratio
United Kingdom	120	330	4
Germany	50	212	5.4
France	56	206	4.5
Switzerland	42	152	2.1
United States	166	136	2.8

Notes: Energy costs and net rent are based on the decomposition of consumer price index (CPI) data sourced from national indices provided by the OECD, except for the United States, where data are drawn from the Consumer Price Index for All Urban Consumers (CPI-U) published by the U.S. Bureau of Labor Statistics (BLS). Net rent reflects actual rents paid for housing; in the U.S., this corresponds to the rent of primary residences. Residential energy costs include electricity, gas, and other fuels. The energy expenditure ratio for UK, Germany, France, and US measures the residential energy costs for heating and electricity over average household income in 2021 provided by International Energy Agency (2023). The energy expenditure ratio for Switzerland is the residential energy costs plus transport fuel over average household income in 2020 provided by Bundesamt für Statistik (2023).

energy need per square meter (kWh/m^{2}a) from the legally required energy performance certificate. We focus on apartments, the dominant housing type in German cities, and exploit substantial variation in energy efficiency even among similar-rent dwellings to identify the effects of energy cost shocks across the value distribution.

Germany's rental market is large – 58% of the population rents, with higher shares in cities – and contracts are typically open-ended and standardized. Energy costs are borne by tenants and can be substantial, especially for the many energy-inefficient dwellings. Rent increases for sitting tenants are tightly regulated, so adjustments to higher energy costs occur mainly in new contracts, which our listings capture.

Our empirical approach regresses net rents on heating bill including detailed property characteristics as well as city-time and ZIP Code fixed effects to control for temporal shocks and local market conditions. This specification isolates how rising heating costs differentially affect rents across the energy efficiency distribution.

Our baseline hedonic regressions reveal a strong and statistically significant pass-through of energy costs to rents. However, this effect varies markedly across the rent value distribution. We find that the pass-through is mainly driven by the upper end of the market, with apartments in the top quintile experiencing a €0.39 reduction in net rents for each €1 increase in the heating bill. The effect weakens steadily as rents decrease, becoming statistically insignificant in the bottom quintile of the rent-value distribution. These results hold across alternative model specifications and data subsamples. We find similar heterogeneity in the owner-occupied market: high-end buyers capitalize future energy costs into prices far more than low-end buyers.

Motivated by the segmentation of housing markets – and the fact that budget constraints prevent many households from searching in higher-priced segments – we test whether the sensitivity of housing demand to energy prices varies across the rent distribution. Using data from Immoscout24, Germany's largest real estate platform, we proxy renter demand by the number of applications a listing receives and estimate a Poisson pseudo-maximum likelihood regression of contact activity on total housing costs (net rent plus heating costs). In the top rent quintile, higher total housing costs significantly reduce applications for energy-inefficient apartments, while in the bottom quintile the effect is only about one-third as large. This pattern suggests that in high-rent segments, where markets are thinner, landlords face steep declines in applications, creating an incentive to reduce rents and partially offset higher heating costs. By contrast, in lower-priced segments, low demand elasticity and intense competition among budget-constrained renters leave landlords with little incentive to reduce rents.

We find that total housing costs rise three times more for low-income households than for high-income households. Using the sharp increase in energy prices after the Russian invasion of Ukraine as an event study, we estimate that income inequality between the top and bottom 10% of the distribution grew by 1.6% within a year, with the absence of rent pass-through in the bottom segment accounting for about 40% of this increase. These results underscore the role of energy prices and housing market structure in amplifying the distributional consequences of energy cost shocks. This poses a clear policy challenge: in affordable segments, tenants face both higher costs and little incentive for landlords to improve efficiency, calling for targeted measures – such as retrofit subsidies, concessional financing, or regulatory mandates – to prevent rising energy prices from worsening inequality and slowing emissions reduction.

Related literature. This paper contributes to the literature on housing unaffordability and its role in shaping income inequality (Albouy et al., 2016; Dustmann et al., 2021). Existing work shows that accounting for rent and mortgage costs reveals substantially greater post-housing-cost inequality. We extend this literature by showing that energy price changes – an understudied driver of housing expenses – can further exacerbate inequality in a segmented rental market, thereby linking two strands of research: housing costs and energy price–inequality dynamics (Doremus et al., 2022; Fetzer et al., 2024; Schulte and Heindl, 2017).

We also contribute to the literature on the energy efficiency gap, which has often focused on average Environmental, Social, and Governance (ESG) or "green" premiums in housing and asset markets (Busse et al., 2013; Gerarden et al., 2017; Grigolon et al., 2018; Myers, 2019). To our knowledge, we are the first to document that these capitalization effects vary systematically across market segments: the premium fluctuates with energy prices but is concentrated entirely in the upper rental segment, with no comparable shift in the lower segment. This result aligns with the split-incentive problem in rental housing (Davis, 2012; Gillingham et al., 2012), where landlords in the affordable segment face little market pressure to improve efficiency because tenants bear the full burden of energy costs

– underscoring the need for targeted regulatory or subsidy-based retrofitting policies.[2]

Finally, we add to the broader literature on market structure and the incidence of taxes and costs. Prior studies have examined how regulation and policy interventions affect tenant outcomes (Bakker and Datta, 2025), how demand shocks interact with supply constraints (Carozzi et al., 2024), and how market power shapes the pass-through of housing taxes (Watson and Ziv, 2024). Our results show that differences in demand elasticity and pricing power across the rent distribution critically shape the transmission of demand-side cost shocks, such as energy price increases, to housing costs. This highlights the role of market microstructure and segmentation in determining who ultimately bears the burden of economic shocks (Han and Strange, 2015; Piazzesi et al., 2020).

The remainder of the paper is structured as follows. Section 2 outlines the institutional setting and describes the data sources. Section 3 presents our estimates of the pass-through of energy costs to rents. Section 4 analyzes the sensitivity of housing demand to changes in energy costs. Section 5 provides a series of robustness checks supporting our main results. Section 6 investigates the distributional consequences of the sharp rise in energy prices following the Russian invasion of Ukraine. Section 7 concludes.

2 Institutional Setting & Data

2.1 Institutional Setting

Germany has one of the highest renter shares in Europe: 58% of households rent, rising to 84% in Berlin and 80% in Hamburg (Statistische Bundesamt, 2024). Even at the top of the income distribution, many households rent, though the share declines with income – from 80% among those earning under €1,500 per month to 37% among those earning over €4,000.[3] Given this prevalence, especially in cities, our main analysis focuses on how rising energy costs are passed through to rents. We also show that our core results hold in the owner-occupied market, where energy costs are capitalized into housing prices.

The rental market is highly regulated. Over 90% of contracts are standardized and open-ended, with rent increases governed by federal law. For existing contracts, the Kappungsgrenze limits net rent increases to 20% over three years.[4] In designated tight markets, the Mietpreisbremse caps initial rents in new contracts at 10% above the local average (Mietspiegel).[5] Graduated (Staffelmiete) and CPI-linked (Indexmiete) contracts

[2] In the German context, Singhal et al. (2025) find only small differences in energy efficiency levels across tenure types.

[3] Dustmann et al. (2021) show that the top-quintile renter share is much higher in Germany than in the U.S. (17%) or UK (14%).

[4] See §558 BGB.

[5] See §556d BGB.

also exist but together account for less than 10% of agreements.[6]

German rental contracts distinguish between net rent (*Kaltmiete*) – paid to the landlord – and total housing costs (*Warmmiete*), which add operating expenses such as heating and utilities. Online listings usually report both, allowing prospective tenants to infer heating costs even without consulting the energy efficiency rating. All rent regulations apply only to the net rent.

Utility charges, including heating, are generally based on actual energy use. In buildings with central or district heating, payments are often made via the landlord, but at least 50% of heating costs must be consumption-based, with the rest allocated by floor area. This ensures tenants retain incentives to conserve energy. Fixed-rate heating arrangements are generally prohibited, except in specific settings such as student housing, retirement homes, hotels, and furnished short-term rentals – all excluded from our analysis.Heating expenses in Germany are usually paid in equal monthly installments – either directly to the energy supplier (*Abschlagszahlungen*) or, for tenants, as part of the rent (*Betriebskostenvorauszahlung*). At the end of each 12-month period, the supplier or landlord reconciles these advances with actual consumption, issuing a refund or an additional bill.

Our analysis measures the pass-through of energy costs to rents using an apartment's annual energy need for heating and hot water, as reported in its Energy Performance Certificate (EPC). EPCs have been mandatory since 2008 and must be presented to prospective buyers; since May 2014, they are also required in online property listings.[7] EPCs report energy need in kilowatt-hours per square meter per year (kWh/m^{2}a) and assign an efficiency rating from A+ (most efficient) to H (least efficient).[8]

Germany, unlike many other EU countries, allows two legally recognized types of Energy Performance Certificates (EPCs) for existing residential buildings. The demand certificate (*Bedarfsausweis*) estimates annual final energy use under standardized conditions,[9] dividing the result by floor area to yield energy need in kWh/m^{2}a. The consumption certificate (*Verbrauchsausweis*) instead uses metered energy use from the previous three heating years, adjusted for annual weather conditions. Both report efficiency in kWh/m^{2}a for comparability. Owners may choose the type of EPC, except when a demand certificate is mandatory (e.g., for pre-1977 buildings with fewer than five units or for new builds). Our baseline analysis controls for the EPC type.

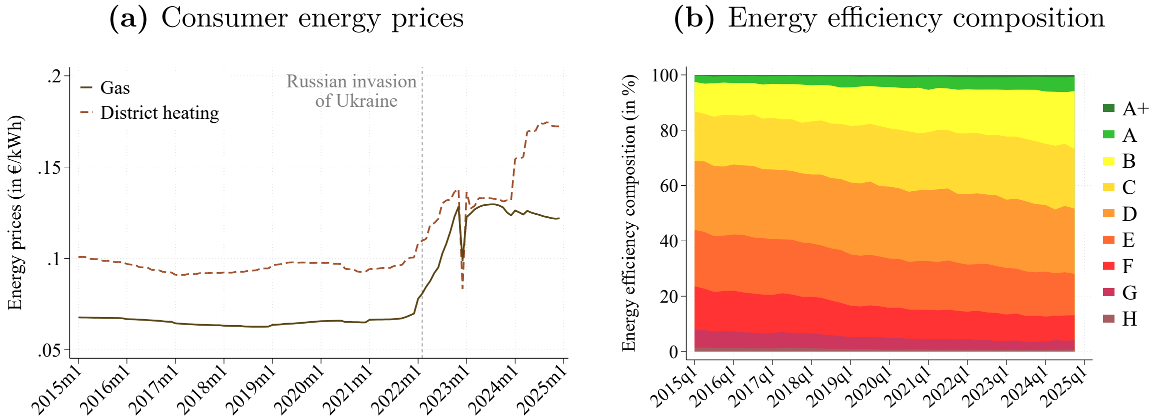
[6]See `https://www.iwkoeln.de/presse/iw-nachrichten/ralph-henger-christian-oberst-nur-22-prozent-haben-eine-indexmiete-abgeschlossen.html` (in German).

[7]Roughly half of listings omit EPCs despite this requirement; robustness checks using a missing-dummy hedonic regression show that non-compliance does not bias our results.

[8]See `https://www.gesetze-im-internet.de/geg/anlage_10.html` for the official thresholds used to classify ratings.

[9]Defined by DIN V 18599, which models heat losses through the building envelope, ventilation, domestic hot water, and system efficiencies based on a reference climate and a 20°C indoor setpoint.

Figure 1: Energy prices and energy efficiency composition, Germany (2015–2024)



Notes: Panel (a) displays the monthly consumer prices for natural gas (solid line) and district heating (dashed line) in €/kWh from 2015 to 2024. These prices are derived from the German Consumer Price Index for natural gas including operating costs (CC13-05421) and for district heating and similar services (CC13-04550), as published by the Federal Statistical Office (Destatis). To express the series in €/kWh, we use a baseline natural gas price of €0.0675/kWh as of mid-2015 (from Destatis), and a district heating price of €0.17/kWh as of May 2024 (from the German Consumer Advice Center). Panel (b) shows the composition of energy efficiency of the apartments in the sample for each year-quarter. Energy efficiency is based on the energy efficiency in kWh/m²a; displayed according to the official energy efficiency labels from A+ (most efficient) to H (least efficient).

Germany also offers substantial variation in energy costs, particularly after the Russian invasion of Ukraine in February 2022.[10] As shown in Figure 1, consumer gas and district heating prices were stable at around €0.07/kWh and €0.10/kWh, respectively, until early 2022, when both nearly doubled. We exploit this sharp and persistent increase to estimate the pass-through of heating costs to rents.

2.2 Data

We use two complementary real estate datasets. The first is advertisement-level data from the Value AG VALUE Market Database.[11] Value AG applies a web-scraping algorithm to collect listings from over 100 online and offline platforms, covering the vast majority of the German market. Our sample includes the 30 largest German cities[12] from January 2015 to December 2024. The second dataset is RWI-GEO-RED (v11),[13] based on rental listings from ImmoScout24 – the largest online rental platform in Germany – covering the same cities from January 2015 to July 2024. Listings contain detailed information on rent,

[10] Section 6 details government interventions in the consumer energy market following the invasion.

[11] We thank Sebastian Hein for providing the data. More information: `https://www.value-marktdaten.de/en/portfolio/market-database/`.

[12] Berlin, Hamburg, München, Köln, Frankfurt am Main, Düsseldorf, Stuttgart, Leipzig, Dortmund, Bremen, Essen, Dresden, Nürnberg, Hannover, Duisburg, Wuppertal, Bochum, Bielefeld, Bonn, Mannheim, Karlsruhe, Münster, Augsburg, Wiesbaden, Mönchengladbach, Gelsenkirchen, Aachen, Braunschweig, Kiel, Chemnitz.

[13] `https://www.rwi-essen.de/forschung-beratung/weitere/forschungsdatenzentrum-ruhr/datenangebot/rwi-geo-red-real-estate-data`.

Table 2: Summary statistics, Germany (2015-2024)

	Mean	Std. Dev.	Min	Median	Max	N
Listing						
Net rent (€)	644.57	360.98	150.00	539.92	3450.00	988,390
Living area (m^2)	66.13	21.04	30.00	63.00	150.00	988,390
Energy efficiency (kWh/m^{2}a)	118.05	46.42	21.60	113.00	281.00	988,390
Heating bill (€/month)	55.21	29.42	3.84	48.81	464.93	988,390
Time-on-market (days)	43.38	60.19	0.00	18.00	365.00	988,390
Applications	46.36	150.75	0.00	4.00	5548.00	875,885
Energy costs (€/kWh)						
Gas price	0.08	0.03	0.06	0.07	0.13	120
District heating price	0.11	0.02	0.08	0.10	0.17	120

Notes: The table presents summary statistics for the key variables used in our analysis. The variables net rent, living area, energy efficiency, heating bill, and time-on-market are based on the Value AG dataset for 30 largest German cities from 2015 to 2024. The number of rental applications comes from the RWI-GEO-RED dataset for 30 largest German cities from 2015 to 2024. Energy cost variables are constructed using the German Consumer Price Index (CPI) for natural gas, including operating costs (CC13-05421), and for district heating and similar services (CC13-04550), as reported by the Federal Statistical Office (Destatis). To convert the CPI indices into €/kWh, we anchor the series using a baseline gas price of €0.0675/kWh (mid-2015, Destatis) and a district heating price of €0.17/kWh (May 2024, German Consumer Advice Center).

size, energy characteristics, and other features, typically presented in text and tables.[14] Importantly, the dataset also records user activity, including the number of applications per listing, which we use as a proxy for rental demand.

Both datasets provide detailed listing-level information. To ensure comparability, we apply a uniform cleaning procedure. We drop listings lacking data on energy efficiency[15] or construction year, as well as those online for more than one year. The sample is restricted to units with gas or district heating – together covering about 90% of German apartments[16] – and excludes properties under monument protection, which differ structurally and often receive subsidies. To limit extreme values, we trim the bottom and top 1% of the energy efficiency distribution, exclude very small (<30 m^2) and very large (>150 m^2) units, and remove simultaneously the bottom and top 1% of rent and rent-per-square-meter within each city-year. In RWI-GEO-RED, we also drop the top 5% of listings by number of rental applications within each city-year.

2.3 Measurements

In this subsection, we describe the construction of the main variables in detail.

Net rent. Our main variable of interest is the net rent – what a tenant pays the landlord excluding heating and other utilities. As our data come from online listings, we observe

[14] Figure A1 in the appendix shows that ImmoScout24 closely resembles the Value AG sample in key observable characteristics.

[15] Figure A2 shows that listings with and without energy efficiency information do not differ systematically in observable characteristics.

[16] Figure A3 shows that gas accounts for over 50% of listings between 2015 and 2024, followed by district heating at about 40%.

the asking rent for vacant units. In Germany, rent negotiations are relatively rare,[17] making asking rents a reliable proxy for contract rents. Each listing reports both the initial asking rent when posted and the final asking rent before removal. We use the initial asking rent; because mid-listing price changes are uncommon, this choice does not affect our results.

Heating bill. The heating bill for apartment i in year-month t (when the listing was posted) is computed as:

$$\text{Heating bill}_{i,t} = \text{Energy efficiency}_i \times \text{Living area}_i \times \text{Energy price}_{i,t}. \tag{1}$$

Energy efficiency measures the annual energy needed for heating and hot water, expressed in kWh/m²a and reported on the Energy Performance Certificate (EPC). Higher values indicate lower efficiency and greater exposure to energy price changes. EPCs are based either on a demand approach (engineering estimates from building characteristics) or a consumption approach (metered use over the past three heating years, weather-adjusted). In both cases, the metric is normalized by living area. In our sample, average energy need is 118 kWh/m²a (range: 22–281). Multiplying energy efficiency by living area yields total annual energy need (kWh/a). The datasets also report heating systems, including fuel source and type. Between 2015 and 2024, about 50% of listings use gas and 40% district heating, with the remainder using oil, electricity, or alternative systems (e.g., heat pumps, solar). We focus on gas and district heating, which together account for ~90% of listings.

Energy prices for gas and district heating come from consumer price indices (CPI) published by Destatis[18], anchored to known €/kWh levels – €0.0675/kWh for gas in mid-2015 (Destatis) and €0.17/kWh for district heating in May 2024 (German Consumer Advice Center). Average prices over the sample are €0.08/kWh (SD = €0.03) for gas and €0.11/kWh (SD = €0.02) for district heating. Prices are highly correlated ($\rho = 0.91$) and vary throughout the period, with the largest spike following the Russian invasion of Ukraine. Robustness checks using weekly ZIP-code–level gas prices from Verivox yield similar results.

We impute the heating bill for each listing using its energy need, size, and the corresponding monthly energy price. This approach provides a consistent, comparable measure of heating costs, avoiding issues in landlord-reported non-rent housing expenses, which often mix heating with unrelated charges (e.g., water, cleaning, taxes). Nonetheless, reported non-rent costs track our imputed heating bill closely (slope = 1.05; Figure A4), with the intercept (€120) reflecting non-heating charges – about 67% of total non-rent

[17] The average rental listing receives 46 applications (Table 2), indicating strong landlord bargaining power and limited scope for negotiation.

[18] Gas: CC13-05421; district heating: CC13-04550.

expenses. This share matches German Tenants' Association estimates of roughly 60%.[19]

Rental applications. As a measure of housing demand, we use the number of rental applications submitted by interested tenants on ImmoScout24, Germany's largest real estate platform. This variable is available exclusively in the RWI-GEO-RED database.

The number of applications per listing provides a direct and active measure of housing demand. To apply, prospective tenants must send a message to the landlord and complete a form, which may voluntarily include personal information such as income and occupation. This process requires effort and engagement, thereby distinguishing genuine interest from passive browsing behavior.

Property characteristics. Both datasets report detailed property characteristics, including ZIP Code, construction year, maintenance condition, floor space, kitchen type, and amenities such as a balcony, terrace, or garden. Additional variables include floor number, number of rooms, parking spaces, monument protection status, and whether the listing is posted by a commercial provider. Because construction year is strongly correlated with energy efficiency – our key explanatory variable – we exclude listings missing this information to reduce potential confounding from building age. Summary statistics for all characteristics are provided in Table A3 in the appendix.

Market segments. For the empirical analysis, we split the sample into rent-level quintiles within each city-year.[20] If high-rent apartments were uniformly energy-efficient, we would lack the variation needed to estimate heterogeneous effects. However, Figure 2 shows that although efficiency is more common in the top quintile, substantial overlap in energy need exists across all segments. Table A4 in the appendix reports additional summary statistics by rent-level quintile.

3 The pass-through of energy costs to rents

3.1 Empirical framework

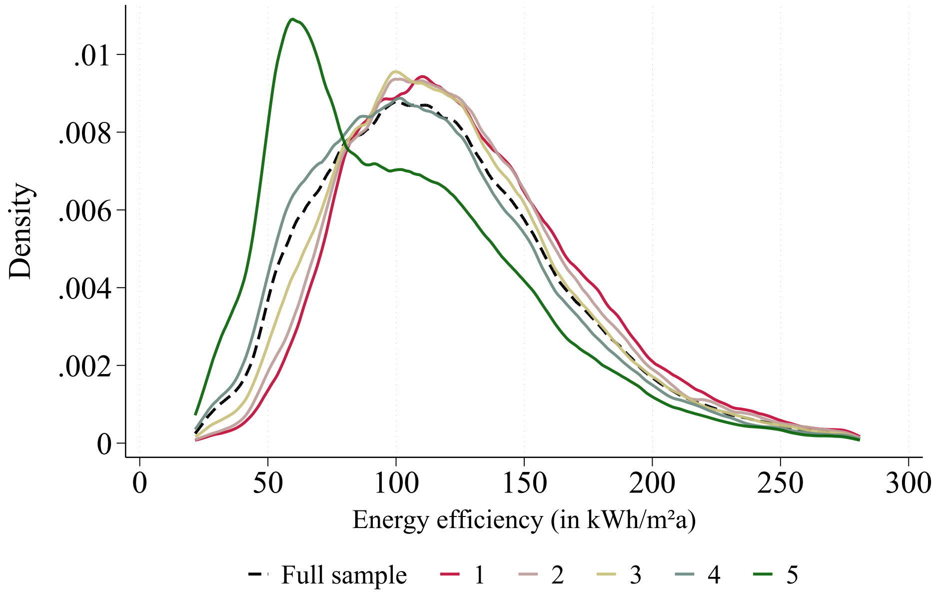
To investigate the pass-through of energy costs to net rents, we estimate the following hedonic regression:

$$\text{Net rent}_{i,t} = \rho \text{Heating bill}_{i,t} + \Gamma X_i + \lambda_{zip} + \mu_{c,t} + \phi_{h,t} + \varepsilon_{i,t}, \tag{2}$$

[19] `https://mieterbund.de/app/uploads/2025/01/20241220-3.pdf`

[20] Robustness checks show that our results are insensitive to the number of segments or the segmentation method.

Figure 2: Apartment's energy efficiency across rent level quintiles



Notes: The figure shows the distribution of energy efficiency (in kWh/m²a) across rent-level quintiles using a kernel density estimation. Rent-level quintiles are defined based on the net rent within each city and year. The figure is derived from the Value AG dataset from 2015 to 2024. The black dashed line represents the average energy efficiency distribution for the full sample. The solid lines display the distributions for each rent-level quintile, where quintile 1 denotes the bottom segment and quintile 5 the top.

where Net rent$_{i,t}$ is the monthly rent in euros net of heating costs and other utilities expenses for listing i in year-month t. Heating bill$_{i,t}$ refers to the total monthly heating cost in euros, calculated according to equation (1) as the product of the energy need of apartment i (in kWh/month) and the corresponding gas or district heating price (in €/kWh) in year-month t, matched according to the apartment's heating fuel type. A higher energy need indicates a less energy-efficient apartment.

To make apartments comparable and isolate the impact of heating costs on net rents, we control for an extensive set of property characteristics – size, size^2, building year, maintenance status, furnishing classification, floor number, number of rooms, kitchen, balcony, garden, parking space, and commercial supplier – summarized by X_i.[21] Since construction year is strongly correlated with energy efficiency (Figure A5 in the appendix), we include fixed effects for building-year categories to absorb the effect of construction year type on net rent – independent of its correlation with energy efficiency – e.g., the premium of living in a historical building built before the war compared to a post-war construction.[22] To capture time-varying effects of key property attributes, we additionally interact size, size^2, building-year categories, maintenance status, and furnishing classification with year fixed effects.

[21] Table A1 in the appendix provides the full list of property characteristics control variables.

[22] The categories are: 1900-1949, 1950-1979, 1980-1999, and 2000-2024. Results are robust to alternative specifications for construction year controls, as shown in Panels (b) and (c) of Table A9 in the robustness section.

Moreover, we control for location-specific factors by including ZIPCode fixed effects, λ_{zip}. To account for both national and city-specific time trends, we include city-by-year-month fixed effects, $\mu_{c,t}$. Moreover, we include heating-system-by-year-month fixed effects, $\phi_{h,t}$, to absorb time-varying differences in the valuation of gas and district heating systems over time. In our baseline analysis, we restrict the sample to apartments with gas and district heating systems, which represent around 90% of all apartments in Germany. We cluster the standard errors at the ZIP Code level to account for heteroskedasticity and spatial correlation.[23]

The coefficient of interest, ρ, captures the pass-through of heating costs to net rents. To identify ρ, we exploit the cross-sectional variation in apartments' energy needs.[24] A value of $\rho = -1$ indicates full pass-through, meaning that any change in the heating bill is entirely offset by an equivalent adjustment in net rent. A value of $\rho \in (-1, 0)$ indicates partial pass-through, where only a portion of the increase in heating costs is reflected in the rent. Conceptually, ρ measures the sensitivity of net rents to heating costs and is therefore equivalent to the rent or price premium that an energy-efficient property commands over a less efficient one – the so-called *green premium* (e.g., Galvin, 2023).

Moreover, ρ can be interpreted as the share of rising heating costs borne by landlords. If $\rho = -1$, landlords absorb the full increase, keeping tenants' total housing costs (net rent plus heating bill) unchanged. If $\rho = 0$, tenants bear the full burden through higher heating costs.[25]

In the following, we estimate regression (2) using the Value AG dataset from 2015 to 2024 to assess the average pass-through of heating costs to net rents. We then divide the sample based on net rent levels to examine heterogeneity in the pass-through across market segments.

3.2 Results

Average pass-through. Table 3 presents the estimated coefficient of interest, ρ, which captures the average pass-through of heating costs to net rents. Across all specifications, the coefficient is negative and statistically significant, indicating that higher heating costs are associated with lower net rents. In terms of magnitude, the average pass-through is substantial: in the most saturated regression specification (column 3), a €1 increase in

[23] Our results are robust for clustering at the city-level. However, due to the small number of clusters, i.e. 30 cities, we cluster at the ZIP-Code level.

[24] Because the heating bill equals time-invariant energy need multiplied by the year-month–specific energy price, it varies only at the year-month level. In our baseline regression, year-month fixed effects absorb this time variation, so identification of ρ relies on cross-sectional differences in heating bills. As shown in Table A9, results are robust to using weekly energy prices and exploiting time variation in the energy prices in addition to the cross-sectional variation in the energy efficiency of apartments for identification.

[25] Note that estimates are based on new rental listings and do not capture adjustments to existing rents.

Table 3: Average pass-through of energy costs to rents

				Russian invasion	
	(1) Full sample	(2) Full sample	(3) Full sample	(4) Pre	(5) Post
Heating bill	-1.5783***	-0.4808***	-0.4834***	-0.4995***	-0.4643***
	(0.0452)	(0.0272)	(0.0268)	(0.0314)	(0.0329)
Property characteristics		✓	✓	✓	✓
ZIP-Code FE	✓	✓		✓	✓
City × Year-month FE	✓	✓		✓	✓
Heating type × Year-month FE		✓	✓	✓	✓
ZIP-Code × Year-month FE			✓		
N	988,387	988,387	980,080	767,033	221,350
Adj. R^2	0.83	0.87	0.89	0.88	0.86
N cluster	989	989	984	986	985
Avg. net rent (€/month)	645	645	643	620	731
Avg. energy efficiency (kWh/m²a)	118	118	118	120	111
Avg. heating bill (€/month)	55	55	55	50	74

Notes: The table reports the average pass-through of heating bill to net rents from regression (2). Column (1) includes only ZIP-code and city-by-year-month fixed effects. Column (2) adds a comprehensive set of property characteristics as detailed in Table A1 in the appendix as well as heating type-by-year-months fixed effects. Column (3) restricts identification to within-ZIP-code variation by including ZIP-code-by-year-month fixed effects. Columns (4) and (5) present estimates for two distinct time periods: before the Russian invasion of Ukraine (January 2015 to January 2022) and after the invasion (February 2022 to December 2024), respectively. The last two rows report the average monthly net rent (in €), the average energy efficiency (in kWh/m²a), and the average monthly heating bill (in €) for the sample used in each specification. The analysis is based on rental online listings provided by Value AG, covering the 30 largest German cities from 2015 to 2024. The sample is restricted to apartments with gas and district heating type. Standard errors are clustered at the ZIP-Code level with ***p<0.01, **p<0.05, *p<0.1.

heating costs is associated with a €0.48 decrease in net rent.[26]

These results imply that a more energy-efficient apartment with an energy efficiency of 30 kWh/m²a would command a rent premium of approximately €48 per month compared to an otherwise similar apartment with an energy efficiency of 130 kWh/m²a.

Columns (4) and (5) test whether the results are driven solely by the sharp energy price increase following Russia's invasion of Ukraine in February 2022 (Figure 1). We split the sample into pre-invasion (January 2015–January 2022) and post-invasion (February 2022–December 2024) periods. The pass-through remains statistically significant and sizable in both. In fact, the pre-invasion estimate is slightly larger (–0.50), indicating that the results are not solely attributable to the invasion-related price shock.

Heterogeneous pass-through. Motivated by the fact that housing demand varies across market segments, we next test for heterogeneity in the pass-through of heating costs to net rents. To do so, we divide the sample into quintiles based on net rent within each city and year.[27] We then estimate regression (2) separately for each segment.

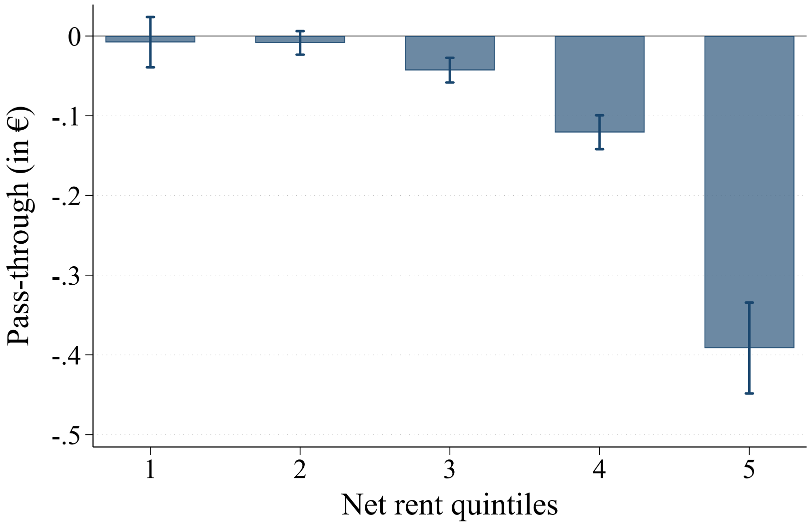
Figure 3 shows the estimated coefficients ρ from regression (2) by net rent quintile, along with 95% confidence intervals.[28] The figure reveals a monotonic increase in the

[26] The pass-through estimate exceeding 1 in absolute value, as shown in column (1), is largely driven by the strong correlation between energy need and construction year. When controlling for construction year and additional property characteristics in column (2), the estimated pass-through declines to –0.48.

[27] Our results are robust to alternative sample splits as shown in the robustness section.

[28] See Table A5 in the Appendix for tabular results.

Figure 3: Heterogeneous pass-through of energy costs to rents



Notes: The figure displays the estimated coefficients ρ and their respective 95% confidence intervals from regression (2) with net rent as dependent variable on heating bill, estimated separately for each rent-level quintile. Rent-level quintiles are defined by dividing the sample into five groups based on net rent within city and year. The analysis is based on rental listings provided by Value AG, covering the 30 largest German cities from 2015 to 2024. The sample is restricted to apartments with gas and district heating systems. The regression includes ZIP-Code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A1 in the appendix for a detailed list). Standard errors are clustered at the ZIP-Code level. The corresponding results in tabular form are reported in Table A5.

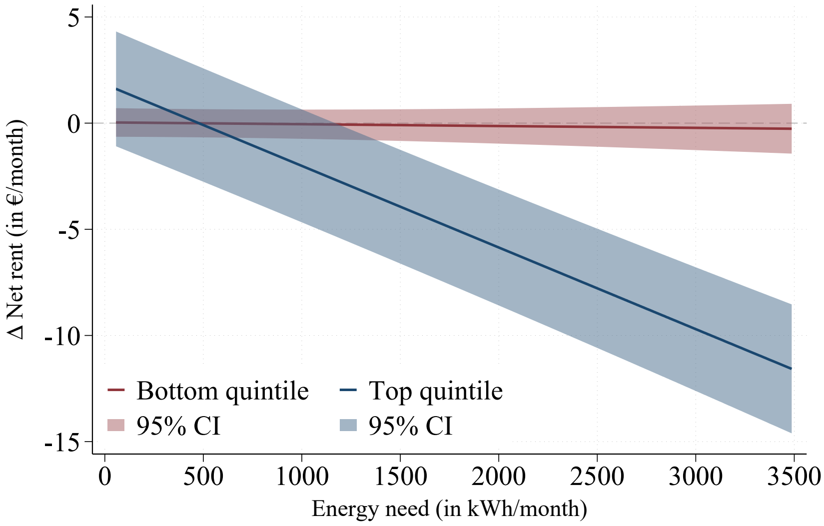
pass-through across rent quintiles. While the estimate for the lowest quintile is small and statistically insignificant, the pass-through in the top quintile is statistically significant and sizable at –0.39.

The heterogeneous pass-through implies that renters in the bottom segment bear the full burden of rising energy prices, whereas households in the upper market segment bear only about 60% of the increase in heating costs. The remaining share is absorbed by landlords through adjustments in the net rent. Moreover, the results suggest that a green premium is absent in lower rent segments but positive and economically meaningful in higher segments of the market.

Decomposing the pass-through. While ρ measures the impact of heating costs on the relative valuation of properties along their energy efficiency, it does not show us how the rent level changes with heating prices. To decompose ρ into the level effect on rents for energy-efficient and -inefficient properties, we estimate the following modified version of the baseline regression specification (2):

$$\text{Net rent}_{i,t} = \rho \underbrace{\text{Energy need}_i \times \text{Energy prices}_{i,t}}_{\text{Heating bill}_{i,t}} + \beta \text{Energy prices}_{i,t}$$
$$+ \Gamma X_i + \lambda_{zip} + \mu_{c,q} + \phi_{h,q} + \varepsilon_{i,t}. \tag{3}$$

Figure 4: Change in net rent to a €0.01/kWh increase in energy prices



Notes: The figure shows the change in monthly net rent (in €) following a €0.01/kWh increase in energy prices, plotted against different levels of apartment energy need. Results are displayed separately for apartments in the bottom rent-level quintile (red line) and the top quintile (blue line), along with their 95% confidence intervals. The net rent response is computed as $0.01 \times (\beta + \rho \times \text{Energy need}_i)$, using estimates from regression (3), which is run separately for each rent-level quintile. The analysis is based on rental listings from Value AG, covering the 30 largest German cities from 2015 to 2024. Table A6 in the appendix shows the results for all rent quintiles in tabular form.

where $\mu_{c,q}$ and $\phi_{h,q}$ are city-by-year-quarter and heating type-by-year-quarter fixed effects, Energy need_i denotes the energy needed to heat the apartment i (in kWh/month), and $\text{Energy prices}_{i,t}$ is the energy price for heating type i in year-month t.

The key difference compared to regression (2) is that we include only year-quarter fixed effects, so that the variation in energy prices – varying at the monthly level – is not absorbed by the fixed effects. Moreover, specification (3) allows us to identify how net rents change in response to energy price increases for apartments with different levels of energy need.

Specifically, the effect of a change in energy prices on net rents is given by $(\beta + \rho \times \text{Energy need}_i) \times \Delta\text{Energy prices}_t$, where $\Delta\text{Energy prices}_t$ is the change in energy prices. This expression captures both the direct level effect through β and the differential effect depending on the apartment's energy need through ρ.

Figure 4 displays the change in net rent for apartments in the bottom and top rent-level quintiles in response to a €0.01/kWh increase in energy prices – roughly one-third of the standard deviation in energy prices between 2015 and 2024. In the bottom rent-level quintile, where there is no significant pass-through of rising energy prices to net rents, the net rent remains unchanged – even for energy-inefficient apartments facing a larger increase in heating bills. In contrast, in the top rent segment, net rents for energy-inefficient apartments decrease significantly as energy prices rise.

Overall, our results highlight that focusing solely on the average pass-through masks substantial heterogeneity across market segments. On average, landlords of energy-inefficient apartments absorb almost half of the burden of rising energy costs, but this pattern is largely concentrated in high-value rental segments. In contrast, renters in the low-value segment bear the full burden, as net rents in this segment do not adjust in response to higher energy costs.

3.3 External validity

To assess whether our findings extend beyond the rental market, we replicate our analysis in the owner-occupied (sales) market. If market segmentation is indeed driving the heterogeneous pass-through of energy costs–as our rental market results suggest-then we should observe similar patterns in the sales market. For this purpose, we use sales listings from Value AG over the same period as in the rental analysis. To ensure comparability, we apply the same data cleaning procedures used for the rental listings and estimate the same regression model specified in equation (2). The only adjustment is that we replace the dependent variable, the net rent, with the sales price.

Since the pass-through of rising energy costs to sales prices reflects the present value of all future heating expenditures, we translate our estimates into an annualized pass-through using a standard present-value framework. Following existing literature, we assume that households form expectations about future energy costs based on current prices – implying a random walk process for energy prices (Anderson et al., 2013; Grigolon et al., 2018; Myers, 2019). Under this assumption, we can infer the implied annualized pass-through of a permanent increase in energy costs to sales prices by multiplying the estimted pass-through with the discount rate.[29] However, our main finding regarding the heterogeneity of the pass-through is independent of the assumption used to annualize the effect.

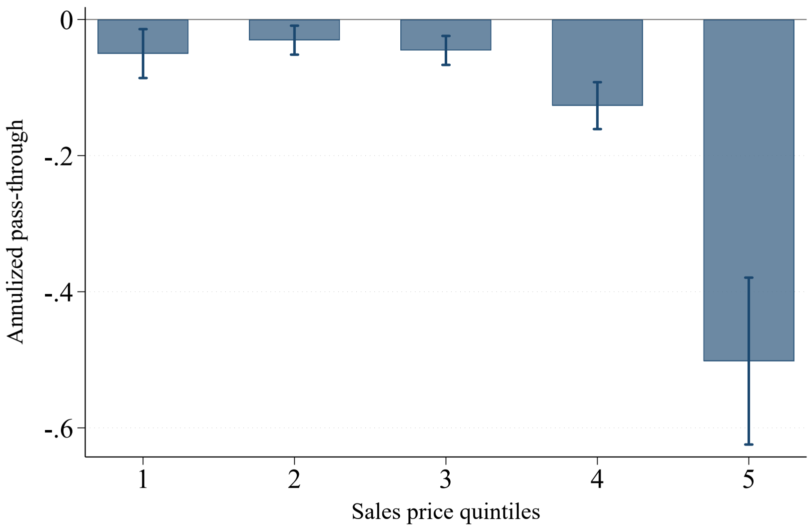
Figure 5 displays the annualized pass-through of energy costs to sales prices. Consistent with our previous findings, the sales market also exhibits a segmented response: apartments in the bottom segment show only a modest adjustment to changes in energy costs, whereas those in the top segment exhibit a strong pass-through. The pass-through in the sales market is also comparable in magnitude to that observed in the rental market. This suggests that our main result – the unequal capitalization of energy costs across market segments – extends beyond the rental market and applies more broadly to the sales market as well. This further supports that our findings are not driven by rental market regulations, as the sales market in Germany remains largely unregulated.

4 Sensitivity of housing demand to energy costs

In the previous section, we documented substantial heterogeneity in the pass-through of heating costs to rents – and, consequently, in the distribution of the financial burden

[29] See Appendix A.1 for a detailed derivation of the annualization procedure.

Figure 5: Heterogeneous pass-through of energy costs to sales price



Notes: The figure displays the rescaled estimated coefficients ρ and their respective 95% confidence intervals from regression (2) with sales price in euros as dependent variable, estimated separately for each sales price quintile. Sales price quintiles are defined by dividing the sample into five groups based on sales price within city and year. The analysis is based on sales listings provided by Value AG, covering the 30 largest German cities from 2015 to 2024. The sample is restricted to apartments with gas and district heating systems. The regression includes ZIP-Code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A1 in the appendix for a detailed list). Standard errors are clustered at the ZIP-Code level. The annualized pass-through is derived by multiplying the estimated ρ with the discount rate. We use the average 10y mortgage rate over the sample period from 2015 to 2024 as discount rate, which is 2.17%. The corresponding results in tabular form are reported in Table A7.

of rising heating costs between tenants and landlords. But why do landlords bear any portion of this burden? Higher heating costs increase the overall cost of housing. Because units with higher energy need are disproportionately affected by rising costs – relative to otherwise similar, energy-efficient units – demand for inefficient housing may decline, exerting downward pressure on their rents. Consequently, the extent to which heating costs are passed through to rents depends on the elasticity of housing demand with respect to total housing costs.

4.1 Total housing costs and rising energy prices

To assess the impact of heterogeneous pass-through of heating costs to net rents on total housing costs, we compute the change in total housing costs following a change in heating costs as:[30]

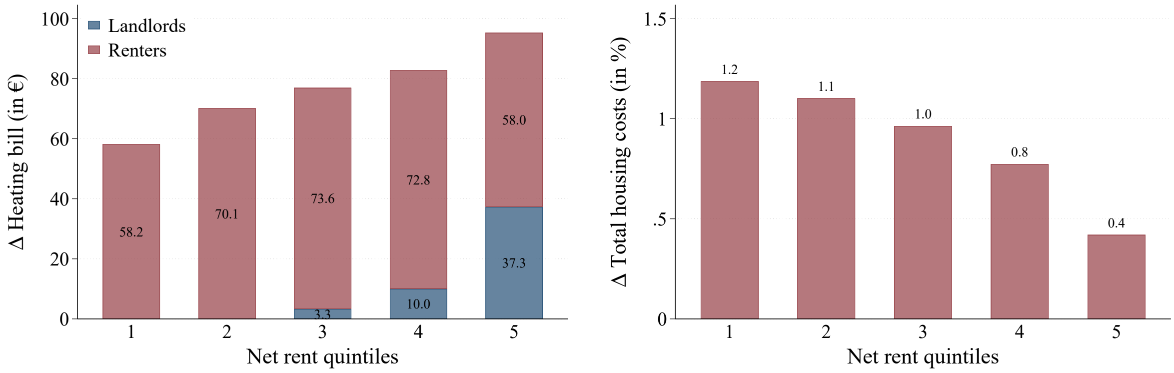
$$\text{Total housing costs}_{i,t+1} = \text{Total housing costs}_{i,t} + (1+\rho) \times \Delta\text{Heating bill}_{i,t+1} \qquad (4)$$

where the first term on the right-hand side is the annual total housing costs before the heating costs increase. The second term reflects the increase in the heating bill, adjusted

[30]See Section A.2 in the appendix for the derivation of equation (4).

Figure 6: Change in heating bill and total housing costs after €0.01/kWh increase in energy prices

(a) Change in heating bill **(b)** Change in total housing costs



Notes: Panel (a) illustrates the change in the annual heating bill (in €) following a €0.01/kWh increase in energy prices. The blue segment of each bar represents the portion of the increase borne by landlords, calculated using the estimated pass-through coefficient $|\rho|$ from equation (2) – i.e., the share of the heating bill passed on to net rent – for each net rent quintile as shown in Figure 3 multiplied by the change in heating bill. The red segment indicates the share borne by renters, calculated as $(1+\rho)$ multiplied by the change in the heating bill. Panel (b) presents the percentage change in total housing costs resulting from a €0.01/kWh increase in energy prices. The change in total housing costs is computed using equation (4).

for the degree of cost pass-through to the net rent (captured by $1+\rho$).[31] This formulation allows us to quantify how much of the increase in heating costs is ultimately borne by tenants, and how this burden varies across different market segments.

Panel (a) of Figure 6 illustrates the change in the annual heating bill following a €0.01/kWh increase in energy prices. Apartments in the bottom rent segment are significantly smaller – averaging 45 m^2 compared to 93 m^2 in the top segment – but only slightly less energy-efficient, with an average energy need of 128 kWh/m^2a versus 102 kWh/m^2a. As a result, the annual heating bill increases with the rent segment, from €58.2 in the bottom segment to €97.3 in the top segment. However, due to the partial pass-through of energy costs to net rents, renters in the top segment bear only about 60% of the increase, as shown by the red bars, while the remaining 40% is absorbed by landlords (blue bars). In contrast, the absence of any rent adjustment in the bottom segment means tenants in this group bear the full burden of rising heating costs.

Panel (b) of Figure 6 illustrates how the rising heating bill increases total housing costs for renters. Following a €0.01/kWh increase in energy prices, total housing costs for an average apartment in the bottom rent segment rise by 1.2%. In contrast, because energy costs represent a smaller share of total housing expenses in the top segment – and because a portion of the higher heating bill is absorbed by landlords – the increase in total housing costs for renters in the top segment is just 0.4%.

[31] We abstract from changes in net rents that are unrelated to the increase in energy prices in order to isolate the impact of the heating bill on total housing costs. This is consistent with our baseline specification (2), in which overall changes in net rents are absorbed by the year-month fixed effects.

4.2 Housing demand elasticities

Empirical framework. To estimate housing demand elasticities, we use data on the number of rental applications per listing from the RWI-GEO-RED dataset, which is based on ImmoScout24, Germany's largest online real estate platform. The dataset includes search activity variables to measure demand for each listing. A rental application is recorded each time a potential tenant expresses interest by sending a direct message to the landlord through the platform. This process involves completing a form with personal information – such as income and occupation – and writing a message, making it a relatively effortful action. Therefore, the number of applications provides an active and reliable measure of housing demand, reflecting genuine interest rather than passive browsing behavior.

We estimate the housing demand elasticity with respect to total housing costs using a Poisson pseudo-maximum likelihood regression (Gourieroux et al., 1984; Hausman et al., 1984; Santos Silva and Tenreyro, 2006).[32] We use a Poisson regression for mainly two reasons: first, the dependent variable is count data and as such always a positive integer, and second, many listings have zero applications and as such the logarithm is undefined.[33] Dropping all listings with zero applications introduces a selection bias and also rescaling the variable by a constant is inappropriate as it introduces an bias (Winkelmann, 2008). Santos Silva and Tenreyro (2011) show that the Poisson pseudo-maximum likelihood estimator is well behaved, even when the proportion of zeros in the sample is very large.

We estimate the following conditional mean using a Poisson pseudo-maximum likelihood estimator:

$$\mathbb{E}\Big[\text{Applications}_{i,t} \mid \mathbb{X}\Big] = \exp\Big[\epsilon \log(\text{Total housing costs}_{i,t}) \\ + \tau \log(\text{TOM}_i) + \Gamma X_i + \lambda_{zip} + \mu_{c,t} + \phi_{h,t}\Big], \tag{5}$$

where the dependent variable is the number of applications by interested renters of listing i in year-month t. $\mathbb{X}$ summarizes all independent variables. $\log(\text{Total housing costs}_{i,t})$ is the natural logarithm of the total housing costs, defined as the sum of the net rent plus the heating bill of apartment i in year-month t. As the number of applications depends on the listings availability online, we include the logarithm of the time-on-market, $\log(\text{TOM}_i)$ as a control variable for the length of the ad's availability.[34]

To make apartments comparable, we control for a comprehensive set of property characteristics, summarized by X_i.[35] Similar to our previous regression (2), we include ZIP-

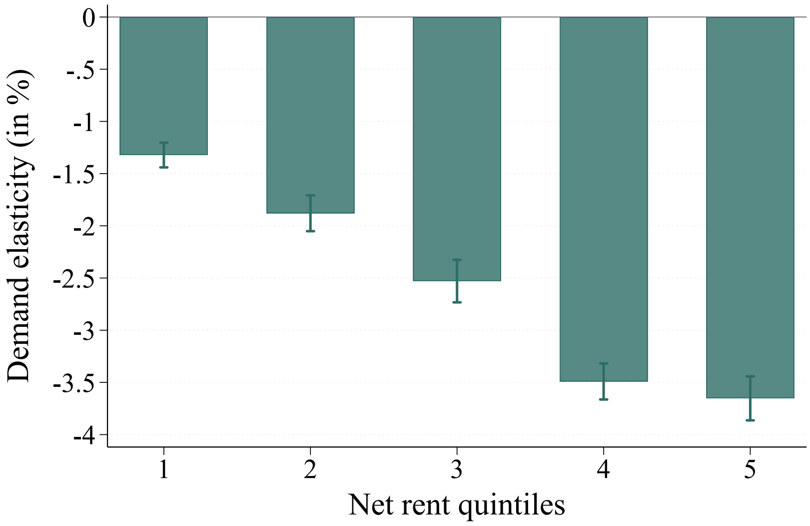
[32] Our results remain robust when estimated using OLS, as shown in the robustness section.

[33] See Winkelmann (2008) for an overview econometric analysis of count data.

[34] Time-on-market is defined such that one day online is coded as 1, such that the logarithm is always defined.

[35] Table A2 in the appendix provides a complete list of controls.

Figure 7: Heterogeneous demand elasticities across rent quintiles



Notes: The figure displays the housing demand elasticity with respect to the total housing costs. The bars show the estimated ϵ from regression (5) of number of applications on the total housing costs; estimated separately for each rent-level quintile along with their respective 95% confidence intervals. Rent-level quintiles are defined by dividing the sample into five groups based on net rent within city and year. The analysis is based on rental listings from the RWI-GEO-RED dataset, covering the 30 largest German cities from January 2015 to July 2024. The sample is restricted to apartments with gas or district heating systems. The regression includes the logarithm of the time-on-market in days, ZIP code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A2 in the appendix for details). Standard errors are clustered at the ZIP code level. The corresponding tabular results are provided in Table A8.

Code fixed effects, λ_{zip}, city-by-year-month fixed effects, $\mu_{c,t}$, as well as heating type-by-year-month fixed effects, $\phi_{h,t}$. Similar to our previous analysis, we restrict our analysis to apartments with gas and district heating system. We cluster the standard errors at the ZIP-Code level to account for heteroskedasticity and spatial correlation.

The coefficient ϵ gives an estimate of the elasticity of housing demand to a change in total housing costs. The total housing costs are defined as the sum of the net rent and the energy bill. As renters do not care which fraction they pay to landlords and the utility provider, housing demand depends on the total housing costs. When energy costs rise, the energy bill of inefficient apartments increase more compared to efficient ones and as such conditional on not adjusting the net rent, total housing costs increase more for energy-inefficient apartments compared to efficient counterparts. The coefficient ϵ provides an estimate how much demand, measured by the number of applications for a individual listings, changes when total housing costs increase. Accordingly, a 1% increase of total housing costs reduces demand by ϵ%. To examine how demand elasticity varies across rent-level segments, we estimate regression (5) separately for each rent-level quintile.

Results. Figure 7 presents the estimated demand elasticities across rent-level quintiles.[36] Consistent with our findings on the heterogeneous pass-through across rent seg-

[36]Table A8 in the appendix reports the estimates for the full sample as well as by rent-level quintile in tabular form.

ments, housing demand is more than twice as sensitive to changes in total housing costs in the upper segment. Specifically, a 1% increase in total housing costs reduces the number of applications by 1.32% in the bottom quintile, compared to a 3.65% decline in the top quintile.

These findings are consistent with our earlier results on the heterogeneity of the pass-through of energy costs to rents. In the top segment, landlords with low energy-efficient apartments face a significant and sizable decline in demand and are therefore more likely to reduce net rents in response to rising heating costs. In contrast, landlords in the bottom segment experience only a small change in demand for energy-inefficient units and, as a result, have little incentive to adjust net rents. This rationalizes the absence of rent adjustments in response to heating cost increases in the lower market segment.

4.3 Interpreting heterogeneous elasticities across the rent distribution

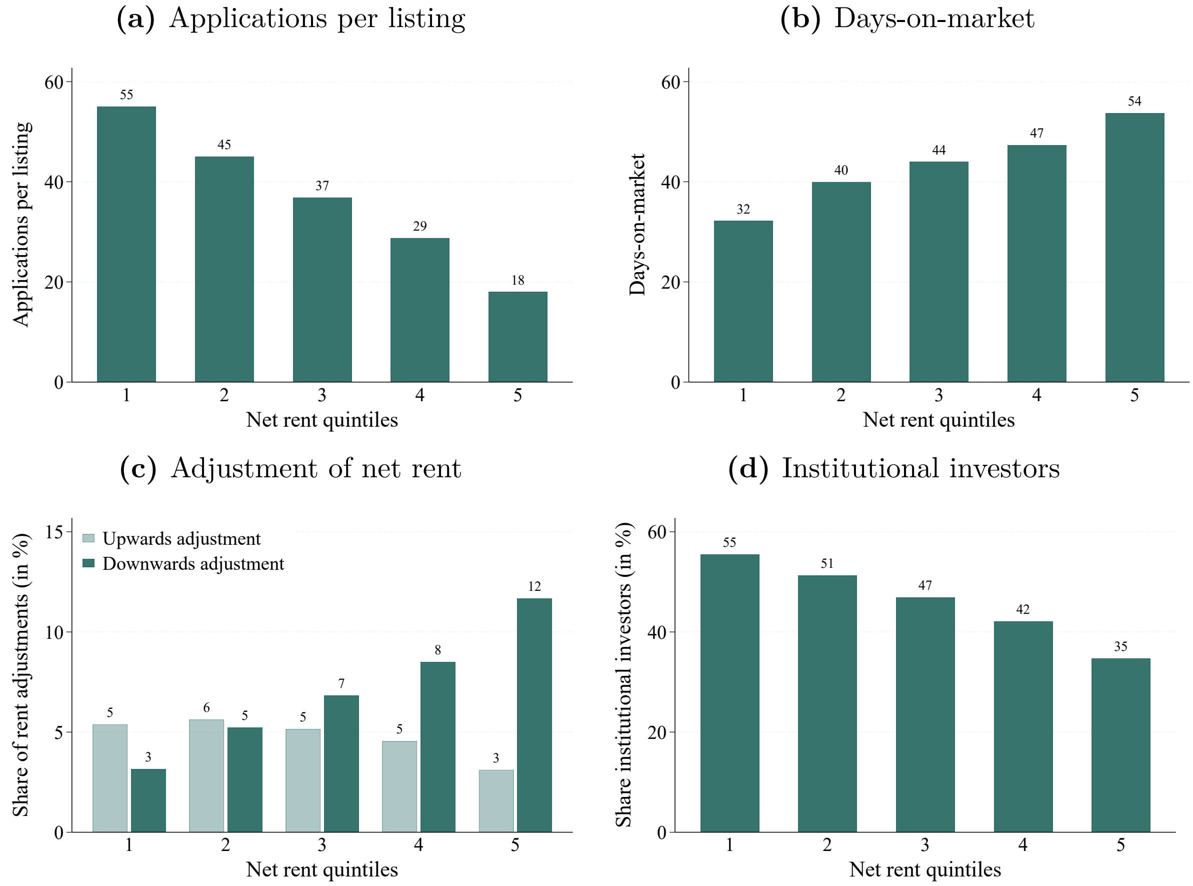
In Section 4.2, we showed that the elasticity of housing demand with respect to total housing costs varies systematically across the rent distribution. In this section, we provide two complementary explanations for this pattern: differences in rental market tightness and differences in attentiveness to energy prices.

Market tightness. The first explanation relates to differences in market tightness across the rent distribution. Panel (a) of Figure 8 plots the average number of rental applications per listing for each rent segment. Landlords in the bottom rent quintile receive an average of 55 applications per listing, compared to only 18 in the top quintile. This suggests that the rental market in the bottom segment is substantially thicker than in the upper segment.

Consistent with the notion of varying rental market thickness across the rent distribution, we find that properties in the lower-rent segment tend to exhibit shorter times on the market and are less likely to experience rent renegotiation or adjustment. These results are shown in panel (b) and panel (c) of Figure 8. On average, properties in the highest rent segment of the market remain on the market for 22 days longer than those in the lowest rent segment. Additionally, listings for higher-rent properties experience a reduction in the asking rent in 12% of cases, whereas this occurs in only 3% of listings in the lower-rent segment. In contrast, rental listing in the lower segment have a higher likelihood of rents increases: in 5% of cases the rent increase in the lowest segment compared to only 3% in the highest segment.

Although the lower tightness of the rental market in the top segment may limit landlords' pricing power, this effect could be counteracted by market concentration among institutional landlords – and the associated market power. We approximate landlord con-

Figure 8: Market structure and liquidity across rent quintiles, Germany (2015–2024)



Notes: Panel (a) shows the average number of rental applications by potential renters per listing across net rent quintiles. Panel (b) shows the average time-on-market – measured as the number of days between the listing going online and offline – across rent quintiles. Panel (c) presents the share of listings with rent changes during their time online. The light green bars indicate the share of listings where the rent increased (i.e., last listed rent > first listed rent), while the dark green bars indicate the share with a rent decrease (i.e., last listed rent < first listed rent). Panel (d) shows the share of rental listings by institutional investors across rent quintiles. Rent quintiles are defined within each city and year based on net rent. Panel (a) and (d) is based on rental listings from the ImmoScout24 platform covering the 30 largest German cities from 2015 to July 2024. Panels (b) and (c) use listings from the Value AG dataset covering the same cities from 2015 to December 2024.

centration by calculating the share of rental listings from institutional investors. While we do not observe the exact number of properties listed by each institutional investor, these landlords typically hold portfolios that are orders of magnitude larger than those of individual "mom-and-pop" landlords. As panel (d) of Figure 8 shows, institutional investors have a substantially stronger presence in the lower rent segments of the market. This reinforces the mechanism whereby landlords' pricing power is greater in the bottom segment – driven both by a much thicker rental market and by the higher concentration of institutional investors.

Attentiveness to energy costs A second potential explanation for the heterogeneous response across the rent distribution is differential attentiveness to energy cost changes. If higher-income households were simply more attentive, this could explain the variation in demand elasticity. However, this channel is unlikely to be the main driver. Energy costs are generally salient for all tenants: heating costs are displayed in online listings, tenants see the full cost structure when signing a contract, and they are regularly confronted with energy bills.[37]

We also test whether payment arrangements for heating bills affect pass-through patterns. In apartments with central heating, tenants typically pay their heating costs indirectly via the landlord as part of monthly service charges. In apartments with individual floor heating, tenants pay the bill directly to the utility provider, which could plausibly heighten attentiveness to energy costs. If attentiveness were the driver of our results, we would expect different pass-through patterns across these groups. In practice, we find that the magnitude and significance of the pass-through are similar in both cases (Figure A7). While estimates vary slightly – likely due to smaller sample sizes – the main pattern persists.

Another constraint is the limited ability of low-income households to reduce energy use when prices rise. Many already consume near the minimum required to meet basic needs, leaving little scope for further cuts. Higher-income households have more flexibility, allowing them to adjust energy use rather than reduce other essentials. Low-income households, by contrast, are more likely to cut back on food or discretionary goods.[38] This helps explain why housing demand in lower segments is both less elastic and more constrained.

Survey evidence also suggests attentiveness is high and mostly constant across the income distribution. Using the 2021 wave of the German Heating and Housing Panel (Frondel et al., 2023), we find that 85% of low-income respondents agree that current energy costs are high, compared to 74% among high-income households. Expectations of future price increases are uniformly high at about 90%. We further test for systematic differences in climate change awareness using proxies for political preferences and attitudes toward CO_2 pricing. Support for the Green Party rises modestly from 22% in the bottom income group to 27% in the top (panel b, Figure A8). Support for CO_2 pricing is lower among low-income respondents (42% vs. 52%), largely due to affordability concerns – 62% in the bottom group see it as a heavy burden, compared to 27% in the top (panel c). Yet nearly half of low-income respondents still support CO_2 pricing, and majorities across all groups agree it increases inequality. This indicates that climate awareness – and by extension attentiveness to energy costs – is present across the income spectrum and rent segments.

Pass-through, demand elasticity, and market tightness. Standard matching models of the housing market predict that rent pass-through from higher heating costs depends in particular on two factors: (i) the probability of a match between landlord and tenant

[37] For apartments with central heating, tenants pay the heating bill via the landlord, with at least 50% based on actual consumption, preserving salience.

[38] See Schulte and Heindl (2017) for evidence in German housing markets.

– primarily determined by market tightness – and (ii) the elasticity of housing demand with respect to total housing costs.[39] When energy prices rise, total housing costs increase proportionally to the heating-cost change. In segments with high demand elasticity, even a small cost increase sharply reduces applications, prompting landlords to lower rents to cushion the impact – producing a more negative pass-through. In low-elasticity segments, the same cost increase barely affects demand, enabling landlords to pass on most or all of the increase. In tighter markets, landlords also face a higher probability of quickly finding a suitable tenant even after an increase in energy prices, further reducing their incentive to lower rents.

Our results are consistent with this framework. In the bottom rent quintile, markets are very tight and elasticity is low; despite higher heating costs, demand remains strong, and landlords have little incentive to reduce rents – yielding no detectable pass-through. At the top of the market, where tightness is lower and elasticity higher, landlords face a steeper drop in applications, motivating rent reductions that partially offset the increase in heating costs. This joint pattern across rent segments reconciles the observed differences in pass-through with the measured variation in demand elasticity.

5 Robustness

To ensure the robustness of our findings on the pass-through of heating costs to net rents, this section presents a series of sensitivity checks and explores alternative mechanisms.

5.1 Regression misspecification

While our baseline specification includes a comprehensive set of apartment characteristics, detailed location fixed effects, and time controls, it is important to test whether the estimated pass-through remains consistent under alternative specifications.

Control variables Our variable of interest, the heating bill, may be correlated with other variables that are either omitted or insufficiently controlled for in our baseline regression specification (2). As a result, our estimate of the coefficient ρ could be biased due to omitted variable bias. One potential concern is that the heating bill is strongly correlated with the building's construction year, as newer buildings tend to be more energy efficient. However, the relationship between construction year and energy efficiency is likely non-linear and may not be fully captured by our baseline model, which includes construction year category fixed effects. To address this concern, we re-estimate the baseline regression using alternative specifications for construction year. In specification (b)

[39] See Bakker and Datta, 2025 for an example of a full-fledged housing matching model used to estimate pass-through to housing costs. A third factor could be attentiveness, but we find no significant differences in attentiveness proxies across rent segments.

of Table A9 in the appendix, we replace the fixed effects with a continuous measure of construction year and its squared term to allow for non-linearities in the relationship between building year and rent. In specification (c), we exclude all apartments built after 2015 while retaining the baseline controls for construction year, to ensure our results are not driven solely by very new buildings. Across both alternative specifications, the estimated pass-through remains negative and statistically significant, albeit slightly smaller in magnitude when newer buildings are excluded. These results confirm that our findings are robust to alternative ways of controlling for construction year.

Outliers In the baseline analysis, our dependent variable is monthly net rent measured in euros. To ensure that outliers or skewness in the rent distribution are not driving our results, we re-estimate the baseline regression using the log of net rent as the dependent variable.[40] In this log-linear specification, coefficients can be interpreted as percentage changes. To facilitate comparison with our baseline results expressed in level terms, we multiply the log coefficients by the average net rent. This rescaling allows us to recover a level-based interpretation of the energy cost pass-through that is consistent with our main approach.

The results from the log specification remain qualitatively robust, with a somewhat smaller average pass-through compared to the baseline, as shown in Panel (d) of Table A9. Consistent with our baseline findings, we observe no significant pass-through for the lower rent segment and a statistically significant pass-through for the higher segment, albeit slightly smaller in magnitude.

Alternative dataset Due to differences in data coverage, we use separate datasets for the estimation of pass-through to rents and for the demand elasticity analysis. To ensure that our baseline results are not driven by dataset choice, we re-estimate regression (2) using the ImmoScout24 dataset, which is also employed in the elasticity estimation. The results are presented in panel (f) of Table A9. Although this dataset contains fewer observations, the main findings remain both qualitatively and quantitatively consistent. We continue to observe a sizable average pass-through of energy costs to rents, comparable in magnitude to our baseline estimates. As before, there is no evidence of pass-through in the lower rent segment, whereas the upper segment exhibits a statistically significant effect.

Sample split In our baseline analysis, we split the sample into quintiles based on net rent. To verify that our results are not dependent on this specific segmentation, we apply alternative approaches to divide the sample into market segments.

[40] Although the relationship between net rent, heating bill, and total housing costs is additive, this log transformation serves as a robustness check to ensure that skewness in the rent distribution does not bias our results.

First, we use net rent per square meter within each city and year to define quintiles. Panel (f) of Table A9 shows that our results are robust to this alternative definition. However, the estimated pass-through declines when using net rent per square meter. This can be explained by the fact that rent per square meter does not account for the possibility of downsizing if the overall net rent becomes unaffordable.

Second, we apply a machine learning approach using k-means clustering to partition listings into five groups. K-means clustering assigns each observation to the nearest cluster center and recalculates the centers iteratively to minimize within-group variance. A key advantage of this method is that it can incorporate multiple variables – in our case, both net rent and apartment size – so that the resulting segments reflect broader differences in housing characteristics rather than price alone. We compute the k-means for five groups based on the standardized log(Net rent) and the standardized log(Living area). The correlation between the baseline segmentation (quintiles based on net rent) and the k-means segmentation is 0.87. Panel (g) of Table A9 shows that our findings are robust to this multidimensional segmentation. The estimated pass-through for the bottom quintile under k-means clustering is similar to that obtained using net rent per square meter, while the pass-through for the top segment is closer to the baseline estimate based on net rent.

Finally, we vary the number of groups to test whether our results depend on the chosen number of segments. Figure A6 in the appendix shows that the results are robust when using tertiles (panel (a)) or deciles (panel (b)).

5.2 Alternative energy efficiency measurements

As a robustness check, we restrict the sample to listings that report an energy demand certificate (*Bedarfsausweis*) only. In contrast to the energy consumption certificate (*Verbrauchsausweis*), which is based on historical energy use and can be influenced by tenant behavior, the energy demand certificate provides a standardized, expert-based assessment of a building's energy performance under uniform conditions. By focusing on this subset, we ensure that our measure of energy need reflects the structural efficiency of the dwelling rather than individual consumption patterns. As shown in panel (h) of Table A9, the estimated pass-through remains qualitatively similar and significant, confirming that our results are not driven by differences in EPC type. Focusing on listings with the demand certificate increase the magnitude of the pass-through suggesting that market participants place greater value on the more objective and standardized information provided by the demand certificate.

Although listings with energy efficiency information do not systematically differ in observable characteristics from those without, as shown in Figure A2 in the appendix, we perform a robustness check using a missing-dummy approach to address potential concerns about selection bias stemming from missing energy efficiency data. Specifically, we include a dummy variable indicating whether the information on the energy efficiency is missing and set the energy need to zero for these listings. This allows us to retain the full sample while controlling for systematic differences between listings with and without reported EPCs. Panel (i) of Table A9 shows that the estimated pass-through of energy costs to rents is comparable in magnitude and statistical significance. This suggests that our findings are not driven by selective reporting of energy efficiency information in online listings.

5.3 Regulation

The German rental housing market is highly regulated.[41] More than 90% of rental contracts are standardized and open-ended. The rent dynamics of these contracts are governed by federal law. First, rent increases for existing contracts are subject to legal limits. After signing a rental agreement, the net rent may only increase by a maximum of 20% over a three-year period.[42] As our analysis focuses on new rental contracts, our results are not directly affected by the regulation of existing rental contracts.

Second, since 2015, new rental contracts have been subject to regulation in cities with tight housing markets. In municipalities where rents are rising significantly faster than the national average, local governments can impose caps on new rents, limiting them to no more than 10% above the local average, as defined in the official rent index (*Mietspiegel*).[43] These caps vary by property characteristics such as size, age, and location. If these caps are more binding at the lower end of the market, this could partially explain the weaker pass-through of energy cost shocks for low-rent apartments. However, our findings remain robust when excluding the influence of rent regulation. Table A10 in the appendix lists cities that implemented the rent cap and the year of adoption. While nearly all large cities adopted the cap – except for Chemnitz – four cities (Braunschweig, Hannover, Dresden, Leipzig) introduced it only recently, in 2021 and 2022. As a robustness check, we re-estimate the pass-through using data from these five cities prior to the cap's implementation (2015–2020). The results, shown in panel (j) of Table A9, confirm that our findings hold even in the absence of rent cap regulations.

Following the Russian invasion of Ukraine, energy prices rose sharply, as shown in Panel (a) of Figure 1. In response, the German government introduced a gas price brake, which came into effect in March 2023.[44] To ensure that our results are not solely driven by the sharp increase in energy prices following the invasion or by subsequent government

[41] Our results on the heterogeneous pass-through also hold in the sales market, as shown in Figure 5. Since the sales market is largely unregulated in Germany, this provides further evidence that our findings are not driven by rental market regulations.

[42] This is known as the *Kappungsgrenze* in German. See §558 BGB.

[43] This regulation is commonly referred to as the *Mietpreisbremse* in German. See §556d BGB.

[44] See Section 6 for details on the gas price brake.

interventions in the energy market, we re-estimate our main specification using data from the pre-invasion period, January 2015 to January 2022. Panel (k) of Table A9 shows that the key findings remain qualitatively unchanged. This provides reassurance that our results are not simply a reflection of the energy crisis or policy responses triggered by the Russian invasion of Ukraine.

5.4 Regional and weekly energy prices

We test the sensitivity of our results to regional variation in energy prices using weekly ZIP-code–level gas price data from Verivox, one of Germany's largest price comparison platforms.[45] The dataset contains, on average, 25 weekly new gas contract offers per ZIP code from 2015–2024. This allows us to incorporate finer temporal (weekly) and spatial (ZIP-code) variation, but the analysis is limited to gas-heated apartments, as no comparable district-heating data exist.

As shown in Figure A9 (panel a), average gas prices in the Verivox and Destatis series track closely until Q3 2021. Thereafter – and especially after the Russian invasion – Verivox prices spike to nearly €0.40/kWh versus €0.12/kWh in Destatis. From 2023, Destatis prices exceed Verivox's, with both converging by end-2024. Panel (b) shows substantial regional price variation across ZIP codes, which briefly narrows after the invasion before returning to pre-invasion levels by 2024. We re-estimate regression (2) using the imputed weekly heating bill from Verivox prices. Results (Figure A10, panel a) remain robust, though the top-quintile pass-through is slightly smaller – mainly reflecting the sharper post-invasion price spike in Verivox data (panel b). Restricting to the pre-invasion period (Jan 2015–Jan 2022) yields estimates nearly identical to our baseline.

5.5 Demand elasticity estimation

We assess the robustness of our demand elasticity estimates through three checks. First, we re-estimate elasticities using OLS instead of Poisson pseudo–maximum likelihood. Although PPML is preferred given the many zeros in applications data, we test OLS by transforming the dependent variable to $\ln(1 + y)$, where y is applications. Results (Table A11, panel b) are qualitatively similar but smaller in magnitude, likely due to the transformation. Second, we restrict the sample to listings with at least one application to focus on the intensive margin. Estimates (panel c) are only slightly smaller than the baseline across rent quintiles. Third, we replace applications with clicks as a broader demand measure. While applications signal stronger intent, clicks capture preliminary interest. Results (panel d) remain consistent, though the top-quintile elasticity is similar to that of the second quintile – possibly reflecting browsing of high-priced listings out of

[45] We thank Verivox, and Jan Suppes, for providing access to the dataset.

curiosity rather than intent to apply.

6 The Russian Invasion of Ukraine and inequality

The Russian invasion of Ukraine in February 2022 triggered a sharp surge in German energy costs. Wholesale gas prices jumped by 180% within two weeks of the invasion.[46] Many households were initially shielded from the full increase by contractual price guarantees lasting 6 to 12 months.[47] In March 2023, the government introduced the *Gaspreisbremse* (gas price brake), capping prices for 80% of historical consumption at €0.12/kWh for gas and €0.095/kWh for district heating until April 2024.[48]

Despite these measures, average consumer energy prices in the year after the invasion were roughly 60% higher – about €0.03/kWh more – than in the year before (Figure 1). Using our estimated rent pass-throughs, we assess how this unevenly increased total housing costs across rent segments and, in turn, affected post-housing income inequality. Since low-income households are concentrated in the bottom segment of the rental market, the incomplete rent adjustment there means they must fully absorb the higher heating costs. In the top segment, where part of the energy-cost rise is offset by rent reductions, tenants bear only part of the increase, shifting some of the burden to landlords.

To link rent segments to household income, we use the 2022 German Microcensus, which reports net rents and rent burdens for five monthly net income groups: <€1,500, €1,500–€2,000, €2,000–€3,000, €3,000–€4,000, and >€4,000. Average net rents in the Value AG quintiles closely match those in the Microcensus, allowing a mapping from rent quintiles to income groups.[49] We impute average household net income for each quintile by dividing Value AG net rents by the corresponding rent burdens from the Microcensus.[50] Estimated monthly incomes range from €1,260 in the bottom quintile to €8,279 in the top (Table A12, col. 6). Holding incomes fixed and adjusting only total housing costs according to equation (4) – adding the increase in the heating bill borne by renters – gives the change in post-housing income for each segment. This isolates the direct distributional

[46] Before the invasion, about one-third of Germany's total energy consumption came from Russia, including roughly 50% of natural gas imports and one-third of oil imports. Households account for 31% of total gas use, mainly for heating, with another 7% used to produce district heating (Bachmann et al., 2024). This overlap helps explain the strong correlation between gas and district heating prices.

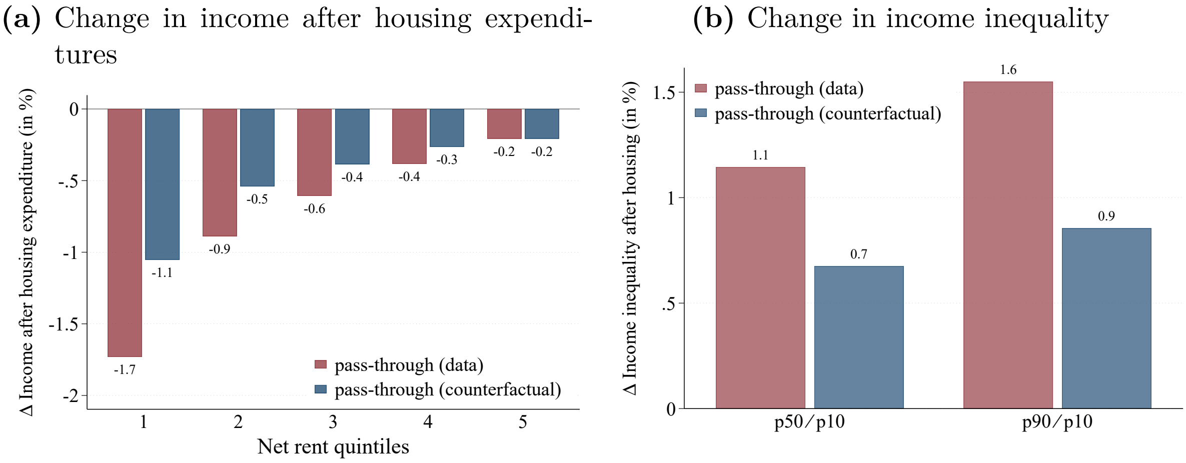
[47] See Garnadt et al. (2023) for an overview of Germany's energy supply contract structures.

[48] The official name of the law is *Erdgas-Wärme-Preisbremsengesetz* (EWPBG). Without this cap, prices would have peaked at €0.16/kWh in March 2023 (Garnadt et al., 2023).

[49] E.g., the bottom quintile in Value AG (€389) matches the first two Microcensus groups (€392 combined). The second quintile aligns with €2,000–€3,000, the third with €3,000–€4,000, and the fourth with >€4,000. The top quintile has no direct match. See Table A12 for details.

[50] Rent burden is defined as net rent divided by net household income. As the Microcensus reports net rent plus utilities (excluding heating), we back out income and then recalculate the burden using net rent only. For the unmatched top quintile, we apply the burden of the highest Microcensus group, likely understating actual income.

Figure 9: The Russian Invasion of Ukraine and impact on income inequality



Notes: Panel (a) displays the change in household net income after housing expenditures with the estimated pass-through as shown in Figure 3 across rent quintiles (red bars) and the change in household net income after housing expenditures with the same pass-through across rent quintiles as in the top quintile (blue bars) one year after the Russian invasion of Ukraine, shown separately for each net rent quintile. Net rent quintiles are defined within each city and year based on net rent. The change in the energy prices by €0.03/kWh is calculated as the increase in average energy costs one year before and after the beginning of the Russian invasion of Ukraine in February 2022. Panel (b) shows the percentage change in income inequality with the estimated pass-through as presented in Figure 3 for the bottom 10% of income distribution vs. the median household net income and for the bottom 10% vs. top 10% of the household net income distribution (red bars). The blue bars show the change in income inequality assuming the same pass-through as for the top rent quintile across all segments.

effect of the invasion-induced energy price shock.

Panel (a) of Figure 9 shows the change in income after housing expenditures one year after the Russian invasion. Red bars reflect the actual change, using equation (4) and our estimated pass-through for each rent quintile. Blue bars show a counterfactual in which all quintiles have the top-quintile pass-through, isolating the effect of heterogeneous pass-through on income inequality.

High-income households are less affected by rising energy costs because heating expenses make up a smaller share of their budgets and because part of the cost increase is offset by rent reductions. As a result, income after housing costs fell by –1.7% in the bottom quintile but only –0.2% in the top, a gap of 1.5 percentage points. Under uniform pass-through at the top-quintile rate, the drop for the bottom quintile would shrink by almost 0.6 percentage point (to –1.1%).

These differences increase post-housing income inequality. Comparing the bottom to the top quintile (roughly the bottom and top 10% of the income distribution), the income gap widened by 1.6% after the energy-cost rise; with uniform pass-through, the increase would have been 0.9% – 0.7 percentage point smaller (Panel b). A similar pattern emerges for the median (third quintile) versus the bottom: inequality increased by 1.1% in reality, but only 0.7% under uniform pass-through.

7 Conclusion

Using listing-level data for 30 large German cities from 2015 to 2024, we find that rising energy prices widen the rent gap between more and less energy-efficient apartments, but almost entirely in the upper market segments. In these segments, greater demand elasticity leads landlords to absorb part of the heating cost increase through lower rents. By contrast, in the affordable segment, rents do not adjust, leaving tenants to bear the full burden. This asymmetric pass-through not only amplifies existing inequalities but also weakens landlords' incentives to invest in energy efficiency where such upgrades are most needed. Our results point to a clear policy challenge: in affordable market segments, tenants face both higher total housing costs and minimal protection from future energy price increases, while landlords have little market incentive to improve energy efficiency. Addressing this requires targeted measures – such as retrofit subsidies, low-interest financing, or regulatory mandates – focused on the lower end of the market, where energy-inefficient stock is concentrated. Without such interventions, rising energy prices risk deepening affordability pressures, worsening inequality, and slowing progress toward emissions reduction goals in the housing sector.

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Appendix

A Mathematical derivations

A.1 Annualized pass-through of energy costs to sales prices

To annualize the pass-through of the energy costs to sales prices, we use the present-value equation given by:

$$\beta_{1,t} = \sum_{j=1}^{\infty} \frac{\beta^A_{1,t+j}}{(1+r)^j}, \tag{i}$$

where $\beta_{1,t}$ is the estimated pass-through of regression (2) on sales prices and $\beta^A_{1,t+j}$ is the annual pass-through.

Assuming that households expect that energy costs follow a random walk, i.e. $\beta^A_{1,t+j} = \rho^A \; \forall j$, we can rearrange equation (i) to:

$$\beta_1 = \beta^A_1 \sum_{j=1}^{\infty} \left(\frac{1}{1+r}\right)^j \tag{ii}$$

As the discount rate $r > 0$, the geometric series converges to $\frac{1}{r}$, yielding our final expression to annualize the pass-through:

$$\beta^A_1 = \beta_1 \times r \tag{iii}$$

A.2 Derivation of Equation (4)

Equation (4) gives the change in total rents after a change in energy costs account for the pass-through to net rents.

$$\text{Total housing costs}_{i,t+1} = \text{Total housing costs}_{i,t} + (1+\rho) \times \Delta\text{Heating bill}_{i,t+1}, \tag{4}$$

To derive equation (4), we start with the definition of the total housing costs, which is given by:

$$\text{Total housing costs}_{i,t} = \text{Net rent}_{i,t} + \underbrace{\text{Energy efficiency}_i \times m^2_i \times \text{Energy price}_{i,t}}_{\text{Heating bill}_{i,t}} \tag{i}$$

The total housing costs after an increase in energy prices is given by iteration equation (i) on period forward.

Using regression (2), we can derive the change in the net rent after an change in the energy costs. Taking the partial derivative of equation (2) w.r.t. energy costs yields:

$$\frac{\partial \text{Net rent}_{i,t}}{\partial \text{Heating bill}_{i,t}} = \rho \tag{ii}$$

Hence, the net rent after a change in energy prices (denoted by ΔHeating bill$_{i,t+1}$) is given by:

$$\text{Net rent}_{i,t+1} = \text{Net rent}_{i,t} + \rho \times \Delta\text{Heating bill}_{i,t+1} \tag{iii}$$

Note that, as we include year-month fixed effects in our baseline specification (2), we abstract from changes in net rents that are unrelated to the heating costs. This allows us to isolate the impact of the heating bill on total housing costs. Consequently, equation (iii) does not include a term for the overall change in net rent.

Substituting equation (iii) into equation (i) for $t + 1$ yields:

$$\text{Total rent}_{i,t+1} = \text{Net rent}_{i,t} + \rho \times \Delta\text{Heating bill}_{i,t+1} + \text{Heating bill}_{i,t+1} \tag{iv}$$

Using the definition of the total rent, given by equation (i), to substitute Net rent$_{i,t}$ yields equation (4).

B Data

Table A1: List of property characteristics controls (X_i): Pass-through estimation

Variable	**Description**
Living area × Year	Living area in square meters interacted with year fixed effects.
Living area^2 × Year	Square of living area in square meters interacted with year fixed effects.
Construction year categories × Year	Categorical variable for year of construction interacted with year fixed effects. Construction year categories are defined as: 1900-1949, 1950-1979, 1980-1999, and 2000-2024.
Condition classification × Year	Categorical variable for property condition interacted with year fixed effects. Categories are defined as: good, standard, bad, new, planned.
Furnishing classification × Year	Categorical variable for level of furnishing interacted with year fixed effects. Categories are defined as: simple-standard, good, upscale-high-quality.
Number of rooms	Categorical variable for number of rooms of the apartment.
Floor number	Categorical variable for floor on which the apartment is located.
Fitted kitchen	Dummy for presence of a fitted kitchen.
Parking space	Dummy for availability of at least one parking space.
Garden	Dummy for presence of a garden.
Balcony	Dummy for balcony presence.
Heating system categories	Category of type of heating system. Categories are defined as: Floor heating (unit-based heating), central heating (building-based heating), room heating (individual heaters per room), not specified (no information on heating system).
Energy need includes hot water	Dummy if energy consumption includes hot water.
Energy certificate type	Dummy for demand-based certificate.
Commercial provider	Dummy if the listing is from a commercial provider.

Notes: The table shows the list of property characteristics control variables contained in the matrix X_i using the Value AG dataset.

Table A2: List of property characteristics controls (X_i): Demand elasticity estimation

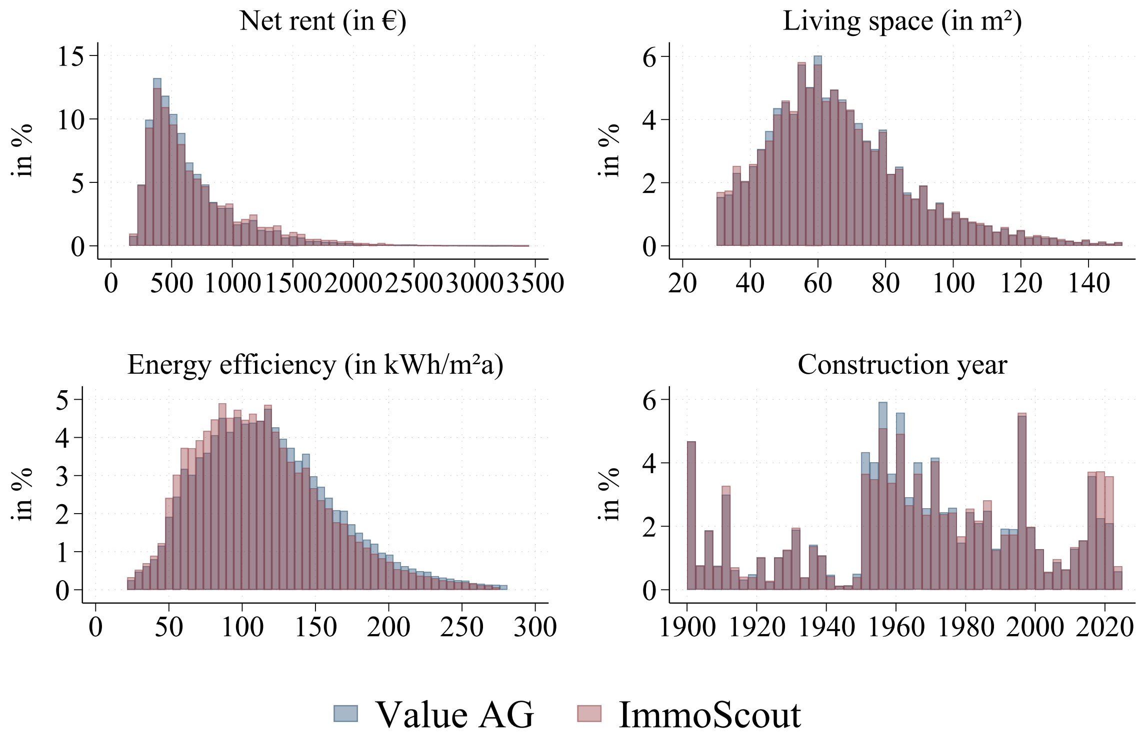
Variable	**Description**
Living area	Living area in square meters interacted with year fixed effects.
Living area^2	Square of living area in square meters interacted with year fixed effects.
Construction year categories	Categorical variable for year of construction interacted with year fixed effects. Construction year categories are defined as: 1900-1949, 1950-1979, 1980-1999, and 2000-2024.
Condition classification	Categorical variable for property condition interacted with year fixed effects. Categories are defined as: good, standard, bad, new, planned.
Furnishing classification	Categorical variable for level of furnishing interacted with year fixed effects. Categories are defined as: simple-standard, good, upscale-high-quality.
Number of rooms	Categorical variable for number of rooms of the apartment.
Floor number	Categorical variable for floor on which the apartment is located.
Fitted kitchen	Dummy for presence of a fitted kitchen.
Parking space	Dummy for availability of at least one parking space.
Garden	Dummy for presence of a garden.
Balcony	Dummy for balcony presence.
Energy certificate type	Dummy for demand-based certificate.
Commercial provider	Dummy if the listing is from a commercial provider.

Notes: The table shows the list of property characteristics control variables contained in the matrix X_i using the RWI-GEO-RED (ImmoScout24) dataset.

C Additional Results

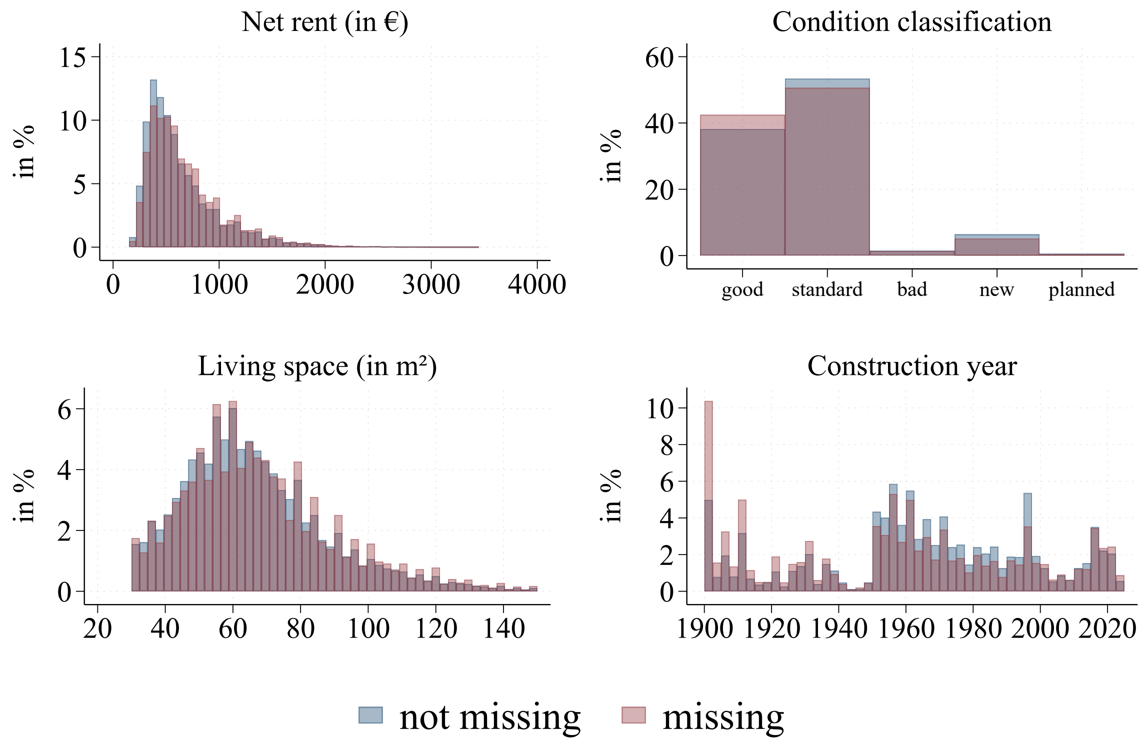
C.1 Figures

Figure A1: Comparison of Value AG and ImmoScout24 dataset



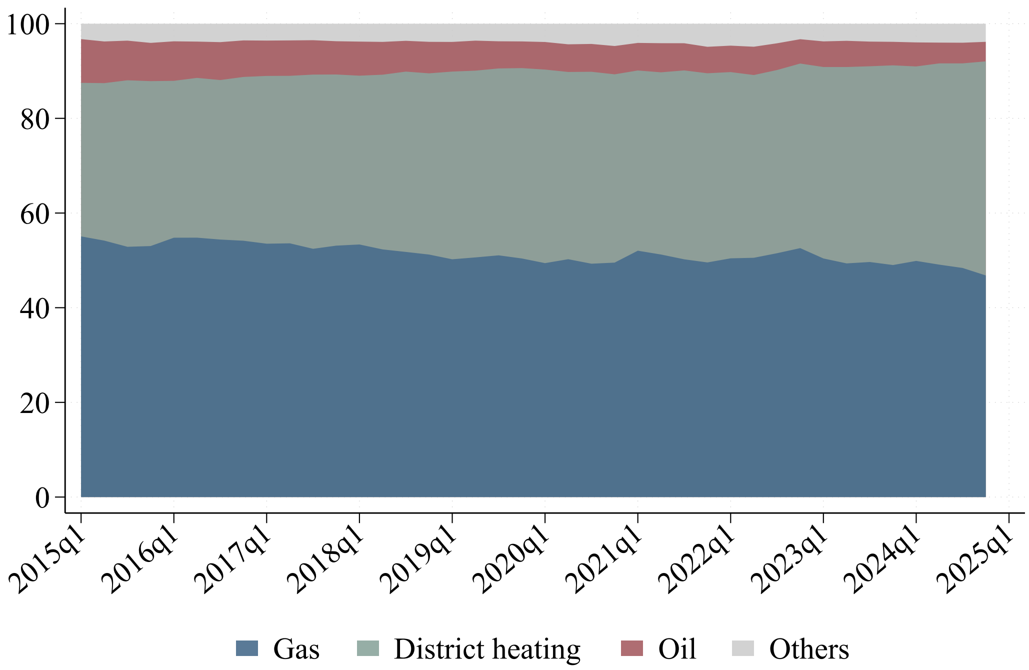
Notes: The figure displays the distribution of net rent (in €), living space (in m²), energy efficiency (in kWh/m²a), and construction year for listings in the ValueAG dataset (blue bars) and the ImmoScout24 dataset (red bars). The ValueAG sample includes all listings from 2015 to 2024, while the ImmoScout24 sample covers listings from 2015 to July 2024.

Figure A2: Comparison sample with and without information on energy efficiency



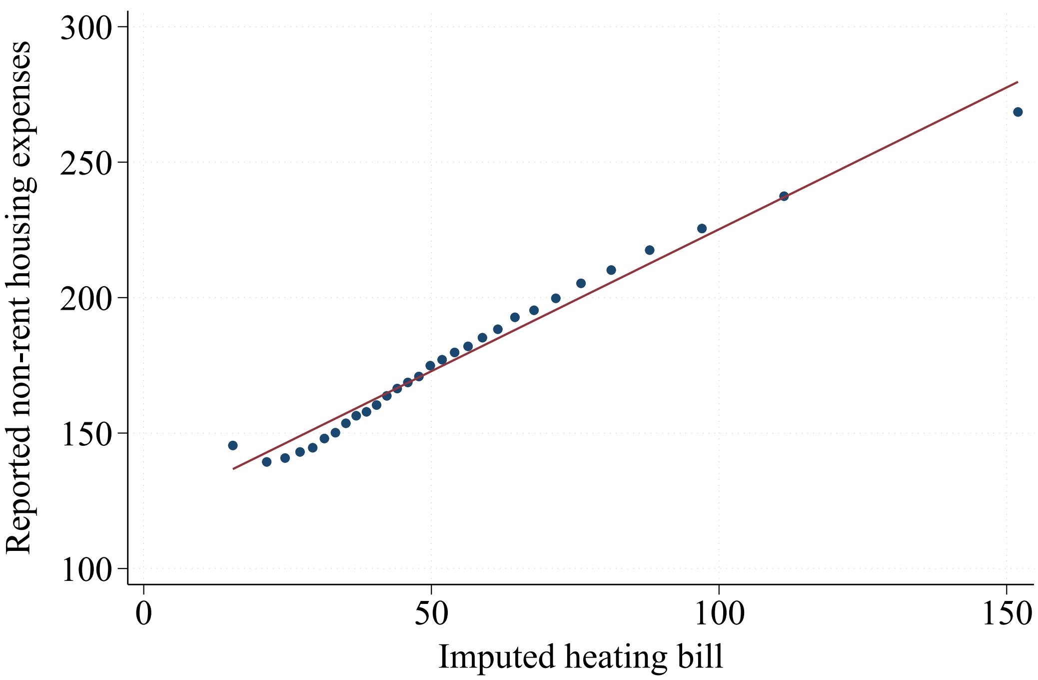
Notes: The figure displays the distribution of net rent (in €), living space (in m²), construction year, and maintenance status for listings with information on the energy efficiency (blue bars) and without information on the energy efficiency (red bars). The sample is based on the Value AG dataset and includes all listings from 2015 to 2024.

Figure A3: Heating type over time, Germany (2015-2024)



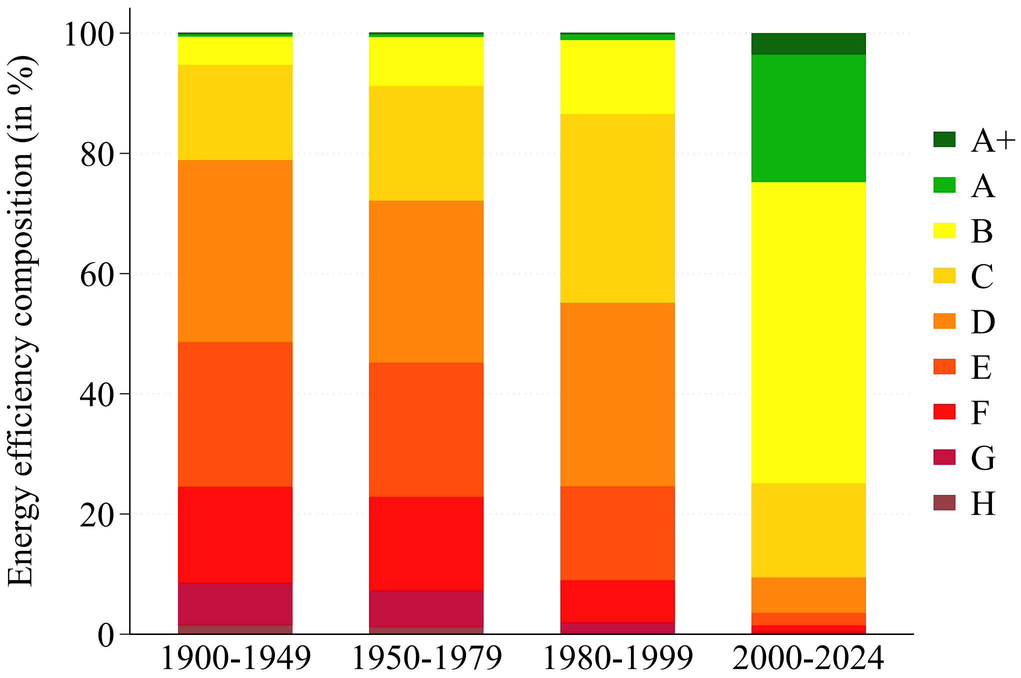
Notes: The figures shows the composition of heating types over time. The category "Others" is composed of combined heat and power heating, pellet heating, solar panel, electricity and heat pump. The sample is based on the Value AG dataset and includes all listings from 2015 to 2024 which report the heating fuel source.

Figure A4: Comparison of reported non-rent housing expenses and imputed heating bill



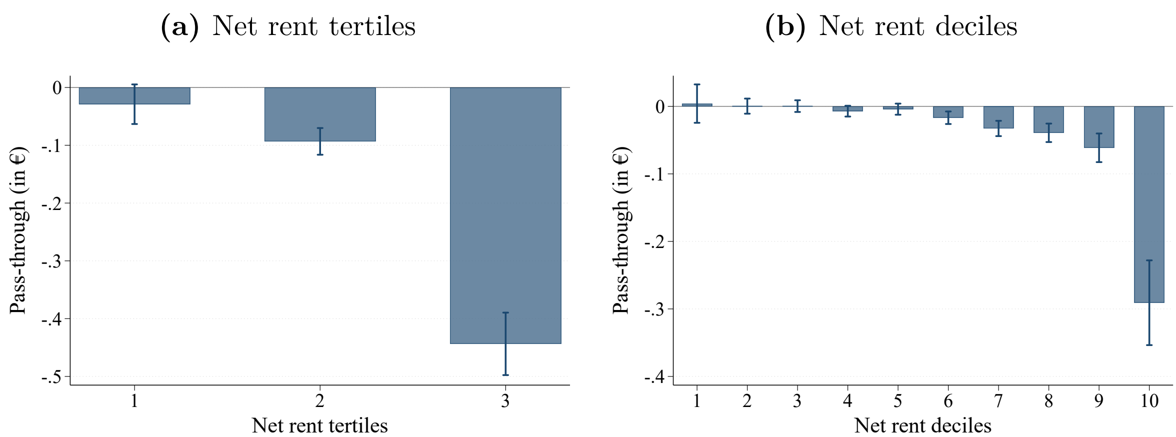
Notes: The figure displays a binscatter plot comparing the imputed heating bill – calculated according to equation (1) – with the reported non-rent housing expenses for each listing. The sample is drawn from the Value AG dataset and includes all listings from 2015 to 2024.

Figure A5: Energy efficiency by construction year categories, Germany (2015-2024)



Notes: The figure shows the composition of energy efficiency labels as reported on the energy performance certificate across the construction year categories in percent. The sample is drawn from the Value AG dataset and includes all listings from 2015 to 2024.

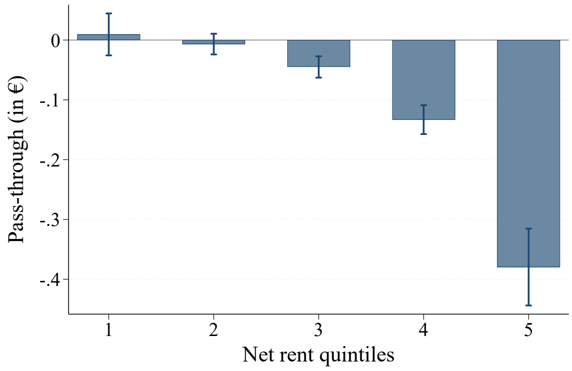
Figure A6: Alternative sample split: Pass-through of heating bill to net rent across



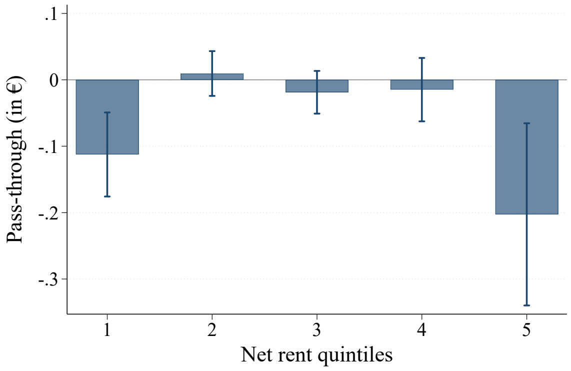
Notes: Panel (a) shows the estimated coefficients ρ and their respective 95% confidence intervals from regression (2) with the net rent as dependent variable on heating bill, estimated separately for each rent-level tertile. Panel (b) shows estimated coefficients ρ and their respective 95% confidence intervals, estimated separately for each rent-level deciles. Rent-level tertile and deciles are defined by dividing the sample into three and ten groups based on net rent within city and year, respectively. The analysis is based on rental listings provided by Value AG, covering the 30 largest German cities from 2015 to 2024. The sample is restricted to apartments with gas and district heating systems. The regression includes ZIP-Code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A1 in the appendix for a detailed list). Standard errors are clustered at the ZIP-Code level.

Figure A7: Pass-through of heating bill to net rent for different heating systems

(a) Central heating system



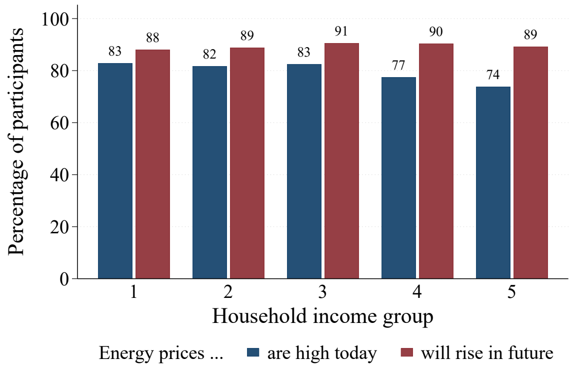
(b) Floor heating system



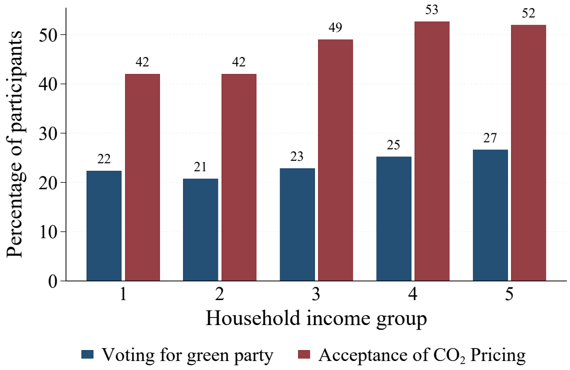
Notes: Panel (a) displays the estimated coefficients ρ and their respective 95% confidence intervals from regression (2) with the net rent as dependent variable on heating bill, estimated separately for each rent-level quintile for apartments with central heating system. Panel (b) shows the pass-through across rent-level quintiles using only apartments with floor heating system. Rent-level quintiles are defined by dividing the sample into five groups based on net rent within city and year. The analysis is based on rental listings provided by Value AG, covering the 30 largest German cities from 2015 to 2024. The sample is restricted to apartments with gas and district heating systems. The regression includes ZIP-Code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A1 in the appendix for a detailed list). Standard errors are clustered at the ZIP-Code level.

Figure A8: Attentiveness and awareness to energy prices and climate change

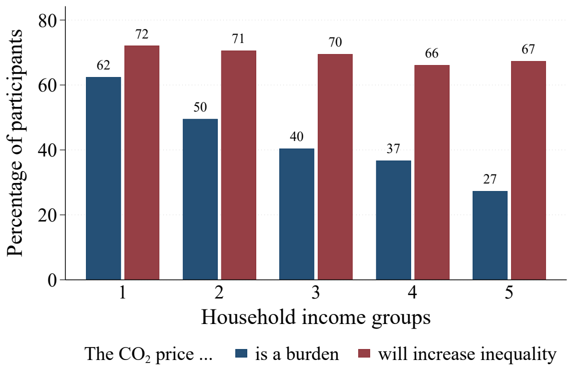
(a) Attentiveness to energy prices



(b) Awareness to climate change



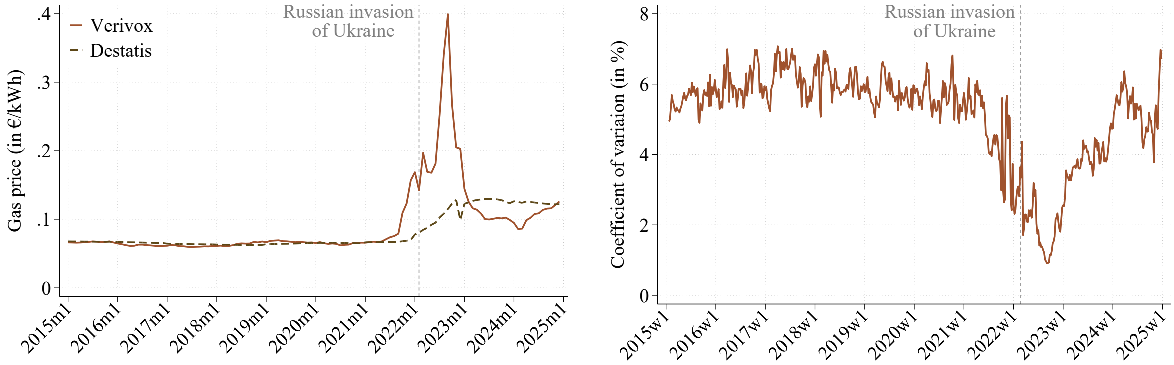
(c) Consequences of CO_2 price



Notes: Panel (a) shows the percentage of participants that state *agree* or *strongly agree* to the statement "Energy costs in Germany are high." relative to all participants answering the question (blue bar) and participants that *agree* or *strongly agree* to the statement "Heating energy costs for private households will rise in the future" (red bar) across income groups. Panel (b) shows the share of participants voting for the green party (Bündnis 90/ Die Grünen) (blue bar) and the percentage of participants that state *agree* or *strongly agree* to the statement "I think the introduction of the CO2 price is good overall" across income groups (red bar). Panel (c) shows the percentage of participants that state *agree* or *strongly agree* to the statement "The CO2 price is a heavy financial burden for me" (blue bar) and the percentage of participants that state *agree* or *strongly agree* to the statement "The CO2 price increases inequality in Germany" (red bar) across income groups. Income groups are defined as follows: less than €1,700; €1,700 to under €2,700; €2,700 to under €3,700; €3,700 to under €4,700; and above €4,700, respectively. The analysis is based on the first wave (2021) of the German Heating and Housing Panel survey (Frondel et al., 2023).

Figure A9: Regional weekly gas prices

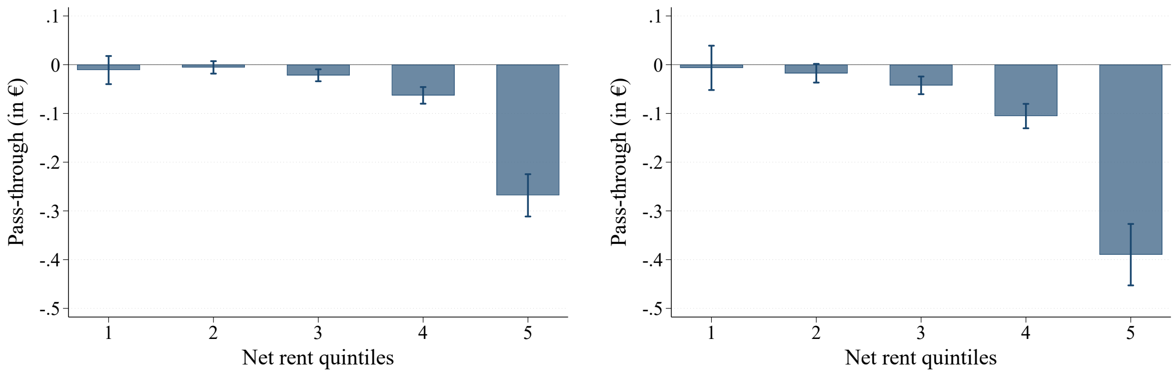
(a) Destatis vs. Verivox **(b)** Regional variation



Notes: Panel (a) shows the monthly gas prices in €/kWh from the Federal Statistical Office (Destatis) (dashed line) alongside the average monthly gas prices in €/kWh from the Verivox dataset (solid line). Panel (b) displays the coefficient of variation – defined as the standard deviation divided by the mean gas price – for gas prices at the ZIP-code level, calculated for each year-week using the Verivox dataset and expressed in percent.

Figure A10: Pass-through to rents using regional energy prices

(a) Full sample, 2015–2024 **(b)** Pre Russian invasion, 2015- January 2022



Notes: Panel (a) displays the estimated coefficients ρ and their corresponding 95% confidence intervals from regression (2), where the dependent variable is the net rent. The regression is estimated separately for each rent-level quintile using weekly ZIP-code-level gas prices from Verivox. Panel (b) presents the estimated pass-through across rent-level quintiles using only the pre-invasion period from 2015 to January 2022. Rent-level quintiles are defined by dividing the sample into five groups based on net rent within each city and year. The analysis is based on rental listings provided by Value AG, covering the 30 largest German cities from 2015 to 2024. The sample is restricted to apartments with gas and district heating systems. The regression includes ZIP-Code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A1 in the appendix for a detailed list). Standard errors are clustered at the ZIP-Code level.

C.2 Tables

Table A3: Property characteristics statistics

	Mean	Std. Dev.	Min	Median	Max	N
Net rent (€)	644.57	360.98	150.00	539.92	3450.00	988,390
Living area (m^2)	66.13	21.04	30.00	63.00	150.00	988,390
Energy efficiency (kWh/m^2a)	118.05	46.42	21.60	113.00	281.00	988,390
Heating bill (€/month)	55.21	29.42	3.84	48.81	464.93	988,390
Construction year	1965.62	32.72	1900.00	1965.00	2025.00	988,390
Number rooms	2.49	0.84	1.00	2.00	9.00	988,133
Floor	2.15	2.04	-1.00	2.00	49.00	944,689
Kitchen $\in \{0, 1\}$	0.37	0.48	0.00	0.00	1.00	988,390
Guest toilet $\in \{0, 1\}$	0.13	0.34	0.00	0.00	1.00	988,390
Bathroom w/ window $\in \{0, 1\}$	0.31	0.46	0.00	0.00	1.00	988,390
Parking space $\in \{0, 1\}$	0.31	0.46	0.00	0.00	1.00	988,390
Garden $\in \{0, 1\}$	0.19	0.39	0.00	0.00	1.00	988,390
Balcony $\in \{0, 1\}$	0.73	0.45	0.00	1.00	1.00	988,390
Energy demand certificate $\in \{0, 1\}$	0.38	0.48	0.00	0.00	1.00	988,390
Commercial provider $\in \{0, 1\}$	0.88	0.33	0.00	1.00	1.00	988,390

Notes: The table reports summary statistics of the property characteristics. The data are drawn from the ValueAG dataset covering the period from 2015 to 2024.

Table A4: Summary statistics across rent-level quintiles

		Net rent quintiles				
	Full sample	1	2	3	4	5
Net rent (€)	644.57	365.72	478.76	580.72	724.14	1080.30
	(360.98)	(116.02)	(156.53)	(199.66)	(268.80)	(445.25)
Net rent per sqm (€)	9.62	8.30	8.78	9.32	10.13	11.62
	(3.76)	(3.00)	(3.24)	(3.44)	(3.79)	(4.27)
Living area (m^2)	66.13	45.48	56.07	63.64	72.58	93.36
	(21.04)	(9.74)	(10.41)	(11.29)	(13.27)	(19.84)
Energy efficiency (kWh/m^2a)	118.05	127.95	125.05	120.89	114.07	102.06
	(46.42)	(44.93)	(44.50)	(44.58)	(45.84)	(47.57)
Heating bill (€/month)	55.21	42.03	50.60	55.48	59.44	68.75
	(29.42)	(19.79)	(23.47)	(26.07)	(29.45)	(38.12)
Construction year	1965.62	1961.87	1960.95	1963.22	1966.88	1975.29
	(32.72)	(25.75)	(27.95)	(30.66)	(34.65)	(40.52)
Number rooms	2.49	1.75	2.22	2.49	2.75	3.23
	(0.84)	(0.62)	(0.62)	(0.65)	(0.68)	(0.78)
Floor	2.15	2.25	2.14	2.10	2.09	2.16
	(2.04)	(2.28)	(2.03)	(1.95)	(1.93)	(1.98)
Kitchen $\in \{0, 1\}$	0.37	0.25	0.30	0.36	0.42	0.52
	(0.48)	(0.43)	(0.46)	(0.48)	(0.49)	(0.50)
Guest toilet $\in \{0, 1\}$	0.13	0.01	0.03	0.06	0.15	0.41
	(0.34)	(0.10)	(0.16)	(0.24)	(0.36)	(0.49)
Bathroom w/ window $\in \{0, 1\}$	0.31	0.27	0.32	0.32	0.32	0.31
	(0.46)	(0.44)	(0.47)	(0.47)	(0.47)	(0.46)
Parking space $\in \{0, 1\}$	0.31	0.18	0.22	0.28	0.36	0.53
	(0.46)	(0.38)	(0.41)	(0.45)	(0.48)	(0.50)
Garden $\in \{0, 1\}$	0.19	0.14	0.16	0.18	0.21	0.27
	(0.39)	(0.34)	(0.36)	(0.38)	(0.41)	(0.44)
Balcony $\in \{0, 1\}$	0.73	0.55	0.67	0.75	0.80	0.86
	(0.45)	(0.50)	(0.47)	(0.43)	(0.40)	(0.35)
Energy demand certificate $\in \{0, 1\}$	0.38	0.30	0.34	0.35	0.39	0.50
	(0.48)	(0.46)	(0.47)	(0.48)	(0.49)	(0.50)
Commercial provider $\in \{0, 1\}$	0.88	0.90	0.89	0.88	0.86	0.85
	(0.33)	(0.30)	(0.31)	(0.33)	(0.34)	(0.36)

Notes: The table reports the mean values with standard deviations in parentheses. The first column presents statistics for the full sample, followed by columns for each rent-level quintile. Rent-level quintiles are defined based on the net rent within each city and year. The data are drawn from the ValueAG dataset covering the period from 2015 to 2024.

Table A5: Heterogeneous pass-through of energy costs to rents

		Net rent quintiles				
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	1	2	3	4	5
Heating bill	-0.48***	-0.01	-0.01	-0.04***	-0.12***	-0.39***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)
Property characteristics	✓	✓	✓	✓	✓	✓
City × Year-month FE	✓	✓	✓	✓	✓	✓
ZIP-Code FE	✓	✓	✓	✓	✓	✓
Heating type × Year-month FE	✓	✓	✓	✓	✓	✓
N	988,387	199,715	198,270	197,061	197,214	196,107
Adj. R^2	0.87	0.89	0.96	0.97	0.96	0.90
N cluster	989	977	980	983	986	983
Avg. net rent (€/month)	645	366	479	581	724	1,080
Avg. energy efficiency (kWh/m²a)	118	128	125	121	114	102
Avg. heating bill (€/month)	55	42	51	55	59	69

Notes: The table shows the result of regression (2), estimated separately for each rent-level quintile. Rent-level quintiles are defined by dividing the sample into five groups based on net rent within city and year. The analysis is based on rental listings provided by Value AG, covering the 30 largest German cities from 2015 to 2024. The sample is restricted to apartments with gas and district heating systems. The regression includes ZIP-Code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A1 in the appendix for a detailed list). Standard errors are clustered at the ZIP-Code level with ***p<0.01, **p<0.05, *p<0.1.

Table A6: Decomposing the pass-through

		Net rent quintiles				
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	1	2	3	4	5
Energy costs × Energy need	-0.48***	-0.01	-0.01	-0.04***	-0.12***	-0.38***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)
Energy costs	193.53***	3.68	22.84	13.24	74.40	183.25
	(60.60)	(34.51)	(28.36)	(32.24)	(47.09)	(138.28)
Property characteristics	✓	✓	✓	✓	✓	✓
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
ZIP-Code FE	✓	✓	✓	✓	✓	✓
Heating type × Year-quarter FE	✓	✓	✓	✓	✓	✓
N	988,387	199,716	198,270	197,062	197,215	196,109
Adj. R^2	0.87	0.89	0.96	0.97	0.96	0.90
N cluster	989	977	980	983	986	983
Avg. net rent (€/month)	645	366	479	581	724	1,080
Avg. energy efficiency (kWh/m²a)	118	128	125	121	114	102
Avg. heating bill (€/month)	55	42	51	55	59	69

Notes: The table shows the result of regression (3) with net rent as dependent variable, estimated separately for each rent-level quintile. Rent-level quintiles are defined by dividing the sample into five groups based on net rent within city and year. The analysis is based on rental listings provided by Value AG, covering the 30 largest German cities from 2015 to 2024. The sample is restricted to apartments with gas and district heating systems. The regression includes ZIP-Code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A1 in the appendix for a detailed list). Standard errors are clustered at the ZIP-Code level with ***p<0.01, **p<0.05, *p<0.1.

Table A7: Heterogeneous pass-through of energy costs to sales prices

	(1)	(2)	(3)	(4)	(5)	(6)
		Sales price quintiles				
	Full sample	1	2	3	4	5
Heating bill	-29.55***	-2.31***	-1.40***	-2.09***	-5.83***	-23.13***
	(1.91)	(0.84)	(0.50)	(0.50)	(0.81)	(2.88)
Property characteristics	✓	✓	✓	✓	✓	✓
City × Year-month FE	✓	✓	✓	✓	✓	✓
ZIP-Code FE	✓	✓	✓	✓	✓	✓
Heating type × Year-month FE	✓	✓	✓	✓	✓	✓
N	263,318	53,660	52,482	52,435	52,215	51,988
Adj. R^2	0.85	0.91	0.97	0.97	0.96	0.86
N cluster	986	967	971	973	971	926
Avg. sales price (€)	321,690	149,943	217,918	281,521	373,263	593,631
Avg. energy efficiency (kWh/m²a)	118	131	125	120	112	100
Avg. heating bill (€/year)	755.62	560.49	680.50	758.22	838.56	945.91
Annualized pass-through	-0.64	-0.05	-0.03	-0.05	-0.13	-0.50

Notes: The table shows the result of regression (2) on sales price as dependent variable, estimated separately for each sales price quintile. Sales price quintiles are defined by dividing the sample into five groups based on sales price within city and year. The analysis is based on sales listings provided by Value AG, covering the 30 largest German cities from 2015 to 2024. The sample is restricted to apartments with gas and district heating systems. The regression includes ZIP-Code fixed effects, city-by-year-month fixed effects, and a comprehensive set of control variables (see Table A1 in the appendix for a detailed list). The annualized pass-through is derived by multiplying the estimated coefficient with the discount rate. We use the average 10y mortgage rate over the sample period from 2015 to 2024 as discount rate, which is 2.17%. Standard errors are clustered at the ZIP-Code level with ***p<0.01, **p<0.05, *p<0.1.

Table A8: Heterogeneous housing demand elasticities across rent quintiles

	(1)	(2)	(3)	(4)	(5)	(6)
		Net rent quintiles				
	Full sample	1	2	3	4	5
log(Total housing costs)	-2.14***	-1.32***	-1.88***	-2.53***	-3.49***	-3.65***
	(0.04)	(0.06)	(0.09)	(0.10)	(0.09)	(0.11)
Property characteristics	✓	✓	✓	✓	✓	✓
City × Year-month FE	✓	✓	✓	✓	✓	✓
ZIP-Code FE	✓	✓	✓	✓	✓	✓
Heating type × Year-month FE	✓	✓	✓	✓	✓	✓
N	841,679	162,221	168,648	168,580	170,336	169,432
Pseudo R^2	0.77	0.83	0.82	0.81	0.78	0.72
N cluster	1296	1032	1040	1046	1058	1049
Avg. number of applications	37	55	45	37	29	18
Avg. net rent (€/month)	704	386	510	631	792	1,191
Avg. energy efficiency (kWh/m²a)	112	122	119	115	108	97
Avg. heating bill (€/month)	57	43	51	57	61	71

Notes: The table show the estimated housing demand elasticity from regression (5) with the number of rental applications per listing as dependent variable across rent-level quintiles. Rent-level quintiles are defined by dividing the sample into five groups based on net rent within city and year. The analysis is based on rental listings from the online platform ImmoScout24, covering the 30 largest German cities from 2015 to July 2024. The sample is restricted to apartments with gas or district heating systems. Estimates are based on a Poisson maximum likelihood estimator. The regression includes the logarithm of the time-on-market in days, ZIP code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A2 in the appendix for details). Standard errors are clustered at the ZIP code level, with ***p<0.01, **p<0.05, *p<0.1.

Table A9: Robustness checks for the pass-through of energy costs to rents

		Net rent quintiles				
	Full sample	1	2	3	4	5
(a) Baseline						
Heating bill	-0.48***	-0.01	-0.01	-0.04***	-0.12***	-0.39***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)
Regression misspecification						
(b) Construction year + Construction year²						
Heating bill	-0.57***	-0.01	-0.01	-0.05***	-0.13***	-0.40***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)
(c) Construction year<2015						
Heating bill	-0.35***	-0.03*	-0.01	-0.03***	-0.08***	-0.18***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)
(d) Dependent variable: log(Net rent)						
Heating bill	-0.22***	-0.01	-0.01	-0.04***	-0.10***	-0.22***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
(e) Alternative dataset: ImmoScout24						
Heating bill	-0.50***	0.02	-0.01	-0.04***	-0.10***	-0.44***
	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)	(0.06)
(f) Sample split: Net rent per square meter						
Heating bill	-0.48***	-0.06***	-0.08***	-0.14***	-0.18***	-0.24***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
(g) Sample split: k-means clustering						
Heating bill	-0.48***	-0.06*	-0.10***	-0.20***	-0.26***	-0.35***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Alternative energy efficiency measurements						
(h) Energy demand certificate						
Heating bill	-0.70***	0.01	-0.02	-0.05***	-0.15***	-0.60***
	(0.04)	(0.03)	(0.01)	(0.01)	(0.02)	(0.04)
(i) Missing dummy energy efficiency						
Heating bill	-0.47***	-0.01	-0.03***	-0.05***	-0.09***	-0.25***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Regulation						
(j) Cities without rent cap						
Heating bill	-0.51***	-0.04	-0.05***	-0.02	-0.10***	-0.47***
	(0.06)	(0.03)	(0.02)	(0.02)	(0.03)	(0.06)
(k) Pre Russian Invasion of Ukraine						
Heating bill	-0.50***	-0.01	-0.03***	-0.06***	-0.13***	-0.39***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.04)

Notes: The table presents a series of robustness checks to assess the stability of our main results. Panel (a) shows the baseline segmented results visualized in Figure 3. Panel (b) modifies the control for construction year by including it as a continuous variable along with its square. Panel (c) excludes all apartments constructed after 2010. Panel (d) shows the effect on the natural logarithm of the net rent; all else as in the baseline specification. The coefficients are rescaled using the average net rent times the estimated coefficient. Panel (e) uses the ImmoScout24 data for the same specification as in the baseline. Panel (f) shows the result using the baseline specification using market segments based on net rent per square meter quintiles. Panel (g) shows the results using the baseline specification with market segments based on k-means clustering with Euclidean distance measure for standardized log(net rent) and log(size). Panel (h) restricts the sample to listings with an energy demand certificate (*Bedarfsausweis*) only. Panel (i) includes all listings, introducing a missing-value indicator for the energy efficiency. Panel (j) shows the result for only five cities (Hannover, Chemnitz, Leipzig, Dresden, Braunschweig) before they implemented the rent cap starting in 2021. Panel (k) shows the results using the sample before the Russian Invasion of Ukraine in February 2022. Standard errors are clustered at the ZIP code level with ***p<0.01, **p<0.05, *p<0.1.

Table A10: Implementation of rent cap for largest 30 cities

City	Rent cap introduced	First effective date
Berlin	Yes	01.06.2015
Hamburg	Yes	01.07.2015
Bielefeld	Yes	01.07.2015
Bochum	Yes	01.07.2015
Bonn	Yes	01.07.2015
Dortmund	Yes	01.07.2015
Duisburg	Yes	01.07.2015
Düsseldorf	Yes	01.07.2015
Essen	Yes	01.07.2015
Gelsenkirchen	Yes	01.07.2015
Köln	Yes	01.07.2015
Mönchengladbach	Yes	01.07.2015
Münster	Yes	01.07.2015
Aachen	Yes	01.07.2015
Wuppertal	Yes	01.07.2015
Augsburg	Yes	01.08.2015
München	Yes	01.08.2015
Nürnberg	Yes	01.08.2015
Karlsruhe	Yes	01.11.2015
Mannheim	Yes	01.11.2015
Stuttgart	Yes	01.11.2015
Frankfurt am Main	Yes	27.11.2015
Wiesbaden	Yes	27.11.2015
Bremen	Yes	01.12.2015
Kiel	Yes	01.12.2015
Braunschweig	Yes	01.01.2021
Hannover	Yes	01.01.2021
Dresden	Yes	13.07.2022
Leipzig	Yes	13.07.2022
Chemnitz	No	–

Notes: The table shows for the 30 largest German cities in the sample whether they introduced a rent cap, column (2), and in column (3) the first effective date.

Table A11: Robustness checks for the housing demand elasticity

	Full sample	Net rent quintiles 1	2	3	4	5
(a) Baseline						
log(Total housing costs)	-2.14***	-1.32***	-1.88***	-2.53***	-3.49***	-3.65***
	(0.04)	(0.06)	(0.09)	(0.10)	(0.09)	(0.11)
(b) OLS						
log(Total housing costs)	-2.03***	-1.38***	-2.03***	-2.14***	-2.23***	-2.26***
	(0.05)	(0.06)	(0.07)	(0.08)	(0.08)	(0.08)
(c) Intensive margin						
log(Total housing costs)	-2.08***	-1.31***	-1.82***	-2.47***	-3.44***	-3.48***
	(0.04)	(0.06)	(0.09)	(0.10)	(0.09)	(0.11)
(d) Number of clicks on listing						
log(Total housing costs)	-1.59***	-1.35***	-1.56***	-1.66***	-1.73***	-1.56***
	(0.02)	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)

Notes: The table presents a series of robustness checks to assess the stability of housing demand elasticity estimation. Panel (a) shows the baseline segmented results visualized in Figure 7. Panel (b) shows the housing demand elasticity estimation using OLS for the full sample and across net rent quintiles. Panel (c) shows the housing demand elasticity with restricting the sample to listing with at least one application. Panel (d) shows the housing demand elasticity using the number of clicks on the online listing as dependent variable. Rent-level quintiles are defined by dividing the sample into five groups based on net rent within city and year. The analysis is based on rental listings from the online platform ImmoScout24, covering the 30 largest German cities from 2015 to July 2024. The sample is restricted to apartments with gas or district heating systems. The regression includes the logarithm of the time-on-market in days, ZIP code fixed effects, city-by-year-month fixed effects, heating type-by-year-month fixed effects, and a comprehensive set of control variables (see Table A2 in the appendix for details). Standard errors are clustered at the ZIP code level with ***p<0.01, **p<0.05, *p<0.1.

Table A12: Microcensus vs. Value AG: Imputed income

Microcensus			Value AG		Imputed
Income groups	Rent burden	Net rent	Rent quintiles	Net rent	Income
< 2,000 €	30.9	392	1	389	1260
2,000 - 3,000 €	20.3	491	2	511	2518
3,000 - 4,000 €	17	585	3	621	3653
> 4,000 €	13.9	777	4	773	5563
	13.9		5	1151	8279

Notes: Column (1) to (3) the income groups with their respective rent burden (in %) and net rent from the Microcensus 2022. Rent burden is defined as the net rent over household net income. Column (4) and (5) show the net rent for each rent quintiles in 2022 from the Value AG sample. Column (6) shows the imputed income by dividing the net rent from Value AG by the rent burden. As the largest income group in the microcensus does not match the net rent in the top quintile, we assume the same rent burden as in the largest group of the microcensus. Income refers to the net monthly household income.

References

Frondel, Manuel, Andreas Gerster, Kerstin Kaestner, Michael Pahle, Anne Schwarz, Puja Singhal, and Stephan Sommer (2023). *Wärme- und Wohnen-Panel - Welle 1.* `https://doi.org/10.7807/ghhp:experiment:v1`.