Monetary Policy, Property Prices and Rents: Evidence from Local Housing Markets*

Martin Groiss[1] and Nicolas Syrichas[2]

[1]University of Duisburg-Essen
[2]Freie Universität Berlin, Berlin School of Economics

February 16, 2025

Abstract

Does monetary policy affect house prices and rents differently, and if so, how? To answer this question, we assemble a new monthly regional dataset from 35 million real estate listings over the period 2007-2023. We exploit high-frequency monetary policy surprises for causal identification. Focusing on Germany, where half of households rent, we find that expansionary monetary policy significantly boosts house prices. Forward guidance and quantitative easing have more pronounced and persistent effects than conventional rate cuts. Rents also rise, albeit more modestly and less persistently. Price increases are driven by strong growth in housing demand and a declining number of houses for sale, tightening the owner-occupied market more than the rental market. Linking these findings to survey microdata, we show that renters are becoming homeowners at a higher rate and homeowners reduce home-to-home moves. This implies that accommodative monetary policy can widen price-to-rent ratios, fueling housing affordability pressures, and potentially exacerbating the wealth gap between owners and renters.

Keywords: housing markets, monetary policy, rents, property prices, forward guidance, quantitative easing, household mobility
JEL codes: E52, R21, R31

*We are grateful to Christiane Baumeister, Natalia Danzer, Britta Gehrke, Michael Lamla, Helmut Lütkepohl, Errikos Melissinos, Dieter Nautz, Ahmet Ali Taskin, Giorgio Topa, and participants of seminars at Goethe University Frankfurt, Freie Universität Berlin, the Bonn-Frankfurt-Mannheim PhD Workshop 2024, EEA/ESEM 2024, and the Residential Housing Markets Vienna 2024 conference for their valuable comments. All remaining errors are our own. Correspondence: University of Duisburg-Essen, Universitätsstraße 2, 45141 Essen, Germany
E-Mail: martin.groiss@uni-due.de, nicolas.syrichas@fu-berlin.de

1 Introduction

Housing choice is among the most important decisions that households make. It not only determines where individuals live but also affects consumption, savings, and mobility, playing a critical role in shaping long-term wealth accumulation. Central to this decision are financing conditions and interest rates, which dictate the affordability of a mortgage for potential homeowners. Monetary policy instruments—such as policy rates, Forward Guidance (FG), and Quantitative Easing (QE)—directly influence these financing conditions, thereby affecting home purchase prices. Yet, aside from their well-documented impact on house prices, monetary policy decisions can also have significant effects on rents—a market segment that matters for a large share of households but has been often overlooked. Understanding these dynamics is not only academically relevant, but also crucial for policymakers, given that housing costs fundamentally shape housing affordability, residential segregation, and overall welfare (Fogli and Guerrieri, 2019; Guerrieri, Hartley, and Hurst, 2013; Favilukis, Mabille, and Van Nieuwerburgh, 2023).

This paper bridges this gap by providing new empirical evidence on the dynamic causal effects of monetary policy on both residential property prices and rents.[1] We also contribute by analysing the related effects on rental demand and supply, and by distinguishing the effects between different monetary policy instruments. We use a unique monthly dataset from Immobilienscout24, Germany's largest online platform, covering owner-occupied and rental units from January 2007 to June 2023. The dataset includes detailed, geo-referenced price data and property characteristics that allow us to construct inflation- and quality-adjusted indices at the district level. With more than 35 million observations (with half of the listings referring to rental units) spanning nearly all of Germany's 401 districts, our data provide an ideal setting for disentangling the transmission of monetary policy shocks across housing segments. Using this dataset also allows us to tackle two major challenges observed in the literature. First, it is crucial to use monthly data due to the frequency of monetary policy meetings. Second, the granularity at district-level is important, since the housing market is strongly segmented.

Another well known problem is that the prevailing interest rates are endogenous to the business cycle conditions. To overcome this issue, we identify monetary policy shocks using high-frequency changes in financial market variables following closely the methodology of Altavilla, Brugnolini, Gürkaynak, Motto, and Ragusa (2019). After controlling for the information effect embedded in monetary announcements, these approach yields exogenous variation in policy rate, FG, and QE measures. In our baseline specification, we instrument

[1] To be precise, throughout the paper, we use "property prices" and "house prices" interchangeably to refer to owner-occupied dwellings.

the Euro Area Shadow Rate (Krippner, 2013) with a linear combination of all three surprise series—a "general" expansionary shock. In a second step, we use the three instruments separately to distinguish between conventional and unconventional effects. We incorporate these shocks as instruments in a two-stage panel local projection framework (Jordà, Schularick, and Taylor, 2015) to derive our results.

We find that a "general" expansionary monetary policy shock precipitates a significantly stronger increase in house prices than rents. Specifically, a one standard deviation reduction in the Euro Area Shadow Rate—equivalent to 24 basis points—yields a house price increase of more than 2.5% after three years. The reaction of house prices gradually increases over the first 18 months and then stabilises. In contrast, the response in the rental market is more immediate, but also much smaller. The impact on rents materialises within the first few months, reaching a peak increase of around 1%. Our findings are robust to more direct measure of financing conditions. When we replace the Shadow Rate with Germany's average 10-year mortgage rate—reflecting the long-term borrowing costs most relevant for homebuyers—we observe a similar pattern: house prices increase significantly, peaking at about 3% after 18 months and then stabilizing, while the impact on rents remains modest and transient.

We further differentiate the impact of various monetary policy tools. We find that short-term rate cuts have a temporary effect on house prices, while FG and QE have more substantial and lasting effects. For example, after two years, house prices rise by more than 2.4% in response to QE, by about 1.2% in response to an FG shock, but only by 1% and statistically insignificantly after policy rate cuts. Rents increase by about 1.2% following QE interventions. At the same time, the responses of rents to policy rate cuts are small or even slightly negative. These results emphasize the importance of considering the specific type of monetary policy tool when analyzing housing market effects.

Next, we exploit the richness of our dataset to assess how the transmission of monetary policy varies across regions. Previous work has documented pervasive heterogeneity in the transmission of monetary policy to housing markets across US counties (Aastveit and Anundsen, 2022; Fischer, Huber, Pfarrhofer, and Staufer-Steinnocher, 2021). While we find temporary stronger monetary policy effects on house prices in urban regions, where housing supply is usually less elastic, there are no significant differences to rural regions after three years. Although Germany exhibits substantial cross-sectional variation in house prices and rents, we find little evidence that standard supply and demand factors such as land availability or demographic shifts deliver heterogeneous responses to common monetary policy shocks. However, rent controls and related interventions appear to dampen the positive effects of expansionary monetary policy on rents, in addition to overall regulatory dampening effects.

To elucidate the underlying mechanisms driving the differential responses of house prices and rents, we utilise our listings data to construct measures of housing market tightness, specifically the number of listings and contact attempts per listing-day. These measures capture shifts in supply and demand conditions in response to monetary policy shocks. A cut in the Shadow Rate induces a significant increase in the demand for properties for sale almost immediately, while rental demand rises more gradually. Concurrently, the number of listings for sale decline markedly, whereas the reduction in rental listings is relatively modest. This suggests that the more pronounced increase in house prices relative to rents cannot only be attributed to the stronger increase in housing demand, but also to a sharper contraction in the supply of units for sale following expansionary policy shocks.

Finally, we use the well-established Socio-Economic Panel, survey microdata from Germany, to understand why listings fall and buyer demand increases after an expansionary monetary shock. Tracking households over a three-year horizon, we find that monetary loosening prompts a significant fraction of existing homeowners to postpone or cancel moves. The effects are particularly pronounced when monetary policy affects future mortgage conditions. Meanwhile, on the rental side, rent-to-rent transitions increase after monetary policy expansions, so that the turnover of rental listings is less affected after policy shocks.

Our results carry important implications for policy-making, especially in central European countries with a large fraction of renters such as Germany, Austria, Switzerland and Denmark. Central banks should account for the significant and enduring impact of expansionary monetary policies, especially unconventional tools, on house prices. These policies may inadvertently exacerbate housing affordability challenges for first-time buyers and low-income households and widen wealth disparities between homeowners and renters. To address these concerns, policymakers might consider complementary measures aimed at facilitating housing supply and turnover in regions experiencing heightened price pressures. Additionally, implementing stricter regulations on buy-to-let investments in a period of loosening monetary policy and providing incentives for the development of affordable housing can help to mitigate the inflationary effects on property prices and rents.

1.1 Related Literature

A large body of literature investigates how monetary policy affects house prices, but often neglects the rental segment, e.g. Kuttner (2014), Williams et al. (2015), and Jordà et al. (2015), for a summary of early contributions, and Gorea, Kryvtsov, and Kudlyak (2022), Hülsewig and Rottmann (2021), Aastveit and Anundsen (2022), and Corsetti, Duarte, and Mann (2022), for more recent studies using high-frequency identification approaches. Gorea et al. (2022), for example, combine micro-level listing data and high-frequency monetary policy shocks to document a pronounced, immediate rise in US house prices after conventional rate cuts, yet omit rental responses altogether. Koeniger, Lennartz, and Ramelet (2022), Dias and Duarte (2019), and Lazarowicz and Richard (2023) are the first studies measuring rental outcomes, but rely on small scale annual survey data or monthly country-level indicators. Given that monetary policy decisions are made every few weeks and regional housing markets are strongly segmented, neither is ideal. In contrast, we use a detailed dataset of property listings, covering both for-sale and rental properties, which allows us to measure the impact of monetary policy on both market segments at a more granular level and monthly frequency.

Our paper also relates to work on how unconventional monetary policy tools influence real estate. Gorea et al. (2022) find that FG and QE lead to faster house price growth in the US than conventional rate cuts. Hülsewig and Rottmann (2021) show that house prices rise when the ECB embarks on accommodative unconventional measures in the Euro Area. In the German context, Boddin, te Kaat, Ma, and Rebucci (2024) and Berg, Haselmann, Kick, and Schreiber (2023) highlight how QE-induced portfolio rebalancing among wealthier investors fueled urban house price booms. Building on these findings, we track both house prices and rents and document their systematic responses to FG and QE shocks across Germany's administrative regions, providing a comprehensive view of monetary policy transmission in segmented housing markets.

Our paper contributes to a third strand that examines the heterogeneous effects of monetary policy across geographically segmented housing markets (e.g., Corsetti et al., 2022; Aastveit and Anundsen, 2022; Koeniger et al., 2022; Flor and Klarl, 2023). In contrast to these studies, we find that standard supply and demand factors such as land availability, demographic shifts or construction activity explain only a small part of the regional heterogeneity in house price growth when associated with monetary policy.

Our paper builds on recent research highlighting the critical role of monetary policy-induced mortgage financing in shaping household mobility and tenure decisions. In the US, Fonseca and Liu (2024) shows that rising mortgage rates create substantial "lock-in" effects. These effects sharply reduce house mobility and tighten the supply of housing, pushing up prices. Ringo (2024) shows that higher interest rates further disadvantage low-income and first-time buyers. We find similar mechanisms in Germany.

Roadmap The remainder of the paper is structured as follows. Section 2 outlines key institutional features of the German housing market. Section 3 describes our dataset and the construction of quality-adjusted regional price and rent indices. Section 4 explains the identification strategy based on high-frequency monetary policy surprises, and Section 5 details the econometric framework. Section 6 presents our main findings, distinguishes between policy instruments, and examines regional heterogeneity. Section 7 offers insights into the underlying mechanisms, including wealth effects and tenure transitions. Finally, Section 8 concludes and discusses policy implications.

2 Institutional Background

Germany is one of Europe's largest countries in terms of both area and population. Its administrative structure consists of 16 federal states subdivided into 401 districts, known as *Kreise* (singular: *Kreis*), equal to NUTS-3 regions. Of these, 294 are rural districts (*Landkreise*) and 107 are urban districts (*Stadtkreise*). By the end of 2022, 21 districts had populations exceeding 500,000, and 316 had populations over 100,000. At the lower end of the distribution, the least populous districts are Pirmasens, Suhl, and Zweibrücken, with populations of 40,682, 37,009, and 34,534, respectively.

Germany's housing market offers a distinctive environment for examining how various monetary policy instruments affect property prices and rents. Two features are particularly salient. First, Germany's comparatively low homeownership rate has fostered a robust rental sector. Second, recent regulatory changes and stable mortgage financing structures shape the local transmission of both conventional and unconventional monetary policies.

Dominant Rental Market: Germany's housing market is characterised by a homeownership rate of approximately 50% and is significantly lower than the EU average of 69% (Eurostat, 2018) and the rates observed in the UK and the US. In Germany, renting is culturally accepted and institutionally supported through strong tenant protections and a wide supply of rental units (Kaas, Kocharkov, Preugschat, and Siassi, 2021; Huber and Schmidt, 2022). Similar trends are observed in Austria, Switzerland, and Denmark. Consequently, shifts in financing conditions are likely to affect both rental and owner-occupied housing segments, highlighting the unique dual sensitivity of Germany's housing market to monetary policy. See Appendix A.1 for a more detailed description about homeonwership rates across censuses and regions in Germany.

Composition of the Housing Stock: Private individuals and commonhold owners account for the lion's share of Germany's residential units (see Table A.2). Other ownership forms such as cooperatives, municipal housing companies, and federal or state entities comprise smaller shares. This ownership structure implies that private landlords, who tend to be more sensitive to financing conditions, mediate much of the housing market's response to monetary policy. Publicly owned units, both in our sample and nationwide, represent a relatively small fraction of the rental housing stock.

Rental Market Regulation: Since the early 2000s, regulation in the German rental market has been relatively stable and at a comparatively low level (Kholodilin, 2016). However, in 2015, the introduction of the Mietpreisbremse ("Rental Break") brought significant changes. This legislation limits the rent that landlords can charge, capping the net cold rent at no more than 10% above the locally comparable rent, as defined by the regional rent index. Tenants paying rents above this threshold are entitled to a reduction. Exceptions to this law include properties rented for the first time after October 1, 2014, and those that have undergone significant modernization, valued at approximately one-third of the cost of a comparable new building (Richter, 2023).[2] See Mense, Michelsen, and Kholodilin (2023) for a more comprehensive description of the rent regulation in Germany.

3 Data

We primarily use real estate listings from ImmobilienScout24, Germany's largest online platform for residential sales and rentals. Subsections 3.1–3.5 describe the construction of this dataset, detail the data-cleaning steps, and provide descriptive evidence on prices and rents across German districts. Subsection 3.6 then documents all additional data sources employed in our econometric analysis.

3.1 Real Estate Listings

We construct a panel dataset of regional house prices and rents using version 10 of the scientific RWI-GEO-RED dataset.[3] This dataset comprises real estate listings from ImmobilienScout24, Germany's largest platform for real estate advertisements. The unit of observation is a residential property listing, categorised into four types: houses for sale, apartments for sale, houses for rent, and apartments for rent, with monthly data from January 2007 to June 2023.

For each listing, we have information on the asking price or rent (both "warm" and "cold"),[4] the month and year the listing was created and removed, the number of days the advertisement was online, the number of times it appeared in search results, and the number of contacts (email requests) and visits (mouse clicks) it elicited. Unfortunately, we do not know

[2] In August 2020, Berlin's state government implemented a more stringent rent cap, known as the "Mietendeckel," which froze rents for five years at June 2019 levels and imposed limits based on the age and amenities of housing. However, the law was later ruled unconstitutional by Germany's Federal Constitutional Court and abolished on April 15, 2021.

[3] The dataset is compiled and provided by the Research Data Centre (*Forschungsdatenzentrum* or FDZ Ruhr) at the Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI Essen) (Klick and Schaffner, 2019).

[4] In Germany, "cold rent" refers to the base rent, while "warm rent" includes heating costs and sometimes other utilities.

whether a property was sold or withdrawn from the market. However, we do observe when the same unit was re-posted multiple times and whether its sales price (rent) or some of its characteristics have changed between postings. Each listing includes user-provided information on property characteristics such as the number of rooms, property type, year built, living area, and other amenities. In total, there are 76 distinct attributes available for users to provide information. For additional background on the ImmobilienScout24 platform and its user attributes, see B.1 and B.2, respectively. Table B.5 provides a complete list of variables we received.

ImmobilienScout24 does not directly provide the addresses of the listed properties but includes their geo-locations. Using the 2015 geographical shapefiles provided by the Federal Agency for Cartography and Geodesy, RWI Essen transforms these geo-coded locations into broader administrative areas, such as postal codes, municipalities, districts (Kreise), or local labour market regions (Kosfeld and Werner, 2012).[5] Throughout this paper, we use district-level (Kreis) administrative boundaries and refer to them as regions.[6]

The primary advantage of employing the ImmobilienScout24 dataset lies in its comprehensive coverage across time and space. It provides detailed property characteristics that define the *quality* of the property, along with highly granular *location* data covering all of Germany on a *monthly* basis. In contrast, other transaction-based spatial datasets in Germany used in other studies, such as Bulwiengesa or GREIX, are available at lower frequencies and with coarser geographical dimensions, rendering them less suitable for our empirical analysis (Kindermann, Le Blanc, Piazzesi, and Schneider, 2021; Amaral, Dohmen, Schularick, and Zdrzalek, 2023).[7]

3.2 Data Preparation

In processing the data, we exclude observations where identical listings reappear as new entries within six months of the previous listing, to avoid counting repetitions as new entries. Next, we exclude properties with missing information on price, location, living area, number

[5]Several districts changed names or were merged into different districts over the 2007–2023 period. The vast majority of geo-coded coordinates in the 2015 shapefiles and their respective administrative matches are consistent with current boundaries, except for the region of Osterode am Harz, which was merged into Göttingen on October 31, 2016. Table B.4 lists all administrative adjustments during 2007–2023.

[6]We choose to analyse variation at the Kreis level rather than using a smaller aggregation unit to avoid losing a significant number of observations. Unlike in the United States, the sales market in Germany is less liquid, and focusing on narrower geographical areas at a monthly frequency would limit our analysis to densely populated areas, thereby restricting the geographical dimension of this study. However, our results are similar to estimates at the municipality level.

[7]Kindermann et al. (2021) utilise annual-frequency, non-quality-adjusted data from Bulwiengesa across all regions. Conversely, Amaral et al. (2023) compile a quarterly, quality-adjusted transaction-based dataset, but it is limited to only a handful of cities.

of rooms, or those identified as social housing[8] or castles. We apply restrictions based on property size, excluding houses (apartments) smaller than 35 m^2 (20 m^2) and those with more than 15 rooms (8 rooms). Finally, we limit the sample to dwellings with sale prices between €150/m^2 and €20,000/m^2, and rent prices between €2.50/m^2 and €45/m^2. Additionally, we remove ultra-popular listings by trimming entries at the 99th percentile based on the number of clicks they received.[9]

We assign the listings data to regions and organise it by the listing date by month and year. Our cleaned dataset contains 17,807,089 units for sale across 397 regions and 18,182,468 units for rent across 364 regions in Germany, covering the period from January 2007 to June 2023. A detailed account of the data cleaning methodology, including the number of observations excluded at each stage, is provided in Appendix B.3.

Tables B.6-B.9 present descriptive statistics of how listing duration, average (log) real prices, contacts, and property characteristics have evolved over time. Prices and rents both move upward, while contacts per listing also increase over time. At the same time, the number of available listings drops both for the rental and sales market.

The house prices and rents in our dataset are presented in nominal terms. To make these values comparable over time and as regional consumer price indexes are not publicly available, we deflate property prices and rents by the state-level consumer prices index.

In some regions, there are months with an insufficient number of listings recorded. To minimise noise, we exclude any region-month pairs with fewer than 10 observations and any regions with more than 10% missing data. For regions where the missing data are below this threshold, we impute the missing entries after the hedonic regression using simple linear interpolation. Varying the cutoff point to 5 or 20 observations does not affect our results (see Figure F.9 in the Appendix).

3.3 Data Limitations

Our dataset is unique in terms of scope and depth, not only in Germany but across Europe, and offers significant advantages over other publicly available datasets. However, it inevitably has some limitations. First, listing prices may systematically differ from transaction prices, especially at remote locations. Therefore, we compare our listings data with transaction sales data aggregated at the city level in Appendix B.7.[10] Notably, both trends

[8] Social housing consists roughly 0.01% of the apartments for sale and 2.25% for the apartments for rent in our sample.

[9] Trimming is done separately for apartments and houses, and for sales and rentals.

[10] Transaction data for rents at the regional level are unavailable. Nonetheless, selection bias for rents is arguably less of a concern. Using French data, Chapelle and Eyméoud (2022) demonstrates that bargaining is less

and levels align well overall, although some discrepancies emerge, particularly in smaller regions. Since our analysis focuses on growth rates, any potential level bias is less of a concern. To further alleviate any remaining doubts, we show in Figure F.10 that the corresponding Impulse Response Function (IRF) arising from transaction-based sales indices versus our listings data indices (for the same cities) deliver very similar estimates.

A second concern is the representativeness of Immobilienscout24's market share. Although it is Germany's leading real estate platform, our sample lacks demographic information on property buyers and renters over time. Thus, we cannot provide direct evidence that listings of Immobilienscout24 are representative of the overall pool of house purchasers or rentals. However, marketplaces such as Similarweb provide web analytics on user demographics and market shares. A recent snapshot from Similarweb indicates that Immobilienscout24 attracts approximately 41 million visitors each month, while the following four online search competitors collectively attract 24 million visitors. Importantly, Immobilienscout24 usage is not concentrated among younger searchers as one might have expected, since around 40% of its users are aged 45 years or older, closely resemble those of other competing online platforms like Immowelt.[11] These statistics suggest that online postings well represent the overall market sales and rentals.

3.4 Regional Hedonic Indices

In this subsection, we use our cleaned dataset to construct regional house price and rent indices in Germany that account for quality variation. An ideal house price index measures the price variation of a representative property over time. The dominant econometric strategy is the repeat-sales method, which tracks prices of the same property sold multiple times. However, this method is impractical at the regional level, especially in illiquid markets like Germany. Therefore, we employ the commonly used "time-dummy" approach that lies within the spectrum of hedonic regressions (Hill and Rambaldi, 2022). This method offers three main practical advantages compared to other hedonic methods: it is easy to implement, utilises the entire dataset—requiring less data per period—and provides standard errors for the estimated price indices.

Let $p_{i,t}^{l,\tau}$ denote the inflation-adjusted property price or (cold) rent i listed in month-year t in location l for tenure $\tau \in [s, r]$ (sale or rent). Then, for each location l and for each tenure τ we separately estimate:

$$ln(p_{i,t}^{l,\tau}) = \alpha^{l,\tau} + \gamma_t^{l,\tau} + \beta^{l,\tau} X_{i,t}^{l,\tau} + \varepsilon_{i,t}^{l,\tau} \tag{1}$$

of an issue and posted prices closely approximate actual rents.

[11]See Appendix B.2 for a more detail breakdown of users characteristics

where $\alpha^{l,\tau}$ is the constant and $X_{i,t}$ is a vector of housing characteristics of that property. The control variables including a second degree polynomial of the size of the property in squared metres (to capture any non-linear effects), a set of categorical variables for the number of rooms, two separate dummy variables for the presence of a guest toilet and cellar, age of the property in five-year categorical intervals, 22 categories indicating the property class (e.g. semi-detached or terraced house, apartment, penthouse apartment etc), dummy variables about the property condition (e.g. first occupancy, renovated, well kept etc) and a full set of post-code dummies. For the sales market, we include an indicator variable for properties sold with tenants in place.[12] For the rental market, we include additional user costs ("Nebenkosten") as an explanatory variable. Appendix B.6 provides detailed information on all variables used in the hedonic regression and their treatment.

In each region, the estimated regression exhibits strong explanatory power. For house sales, the R^2 ranges from 0.58 to 0.92, with an average of 0.76. For rents, the R^2 values are similar. When we exclude the time fixed effects γ_t, the R^2 decreases to a range of 0.49 to 0.83, with a mean of 0.67. This indicates that our rich set of control variables, other than time-fixed effects, explains a significant portion of the variation in sales and rent prices.

The variable to construct the indices γ_t denotes the time (month-year) fixed effects that we estimate separately for each location l and tenure τ. Notice that the reference period (i.e. γ_t=2007:01) dummy is omitted from the regression and is normalised to 0 for each location l and tenure τ. In this context, the (exponent) estimates of $\gamma_t^{l,s}$ and $\gamma_m^{l,r}$ can be interpreted as the location-specific listed sales price and rent indices with respect to January 2007. To illustrate this consider a house with characteristics $\bar{X}$ posted in January 2012 in location l_1. Then the price ratio with respect to a house with the same characteristics $\bar{X}$ and location l_1 that is listed for sale in January 2007 is given as:

$$\frac{\bar{p}^{l_1,s}_{2012:01}}{\bar{p}^{l_1,s}_{2007:01}} = \frac{exp(\hat{\alpha}^{l_1,s} + \hat{\gamma}^{l_1,s}_{2012:01} + \hat{\beta}^{l_1,s}\bar{X}^{l_1,s})}{exp(\hat{\alpha}^{l_1,s} + \hat{\gamma}^{l_1,s}_{2007:01} + \hat{\beta}^{l_1,s}\bar{X}^{l_1,s})} = \frac{exp(\hat{\gamma}^{l_1,s}_{2012:01})}{exp(\hat{\gamma}^{l_1,s}_{2007:01})} = exp(\hat{\gamma}^{l_1,s}_{2012:01})$$

and thus $exp(\hat{\gamma}^{l_1,s}_{2012M1})$ can be interpreted as price sale index.

Our analysis will include the examination of whether property prices and rents listed in different locations react differently to monetary policy surprises. Notably, our rental indices measure the flow of newly listed rents rather than the stock of existing rents in the market. By focusing exclusively on new listings, we eliminate the need to impute costs associated with

[12] In Germany, selling a rented property does not terminate the lease; the new owner assumes it. However, the buyer may later terminate the tenancy for personal use. Under Section 577 of the German Civil Code (BGB), tenants have a right of first refusal if the property was converted into a condominium and sold for the first time, unless sold to a family member.

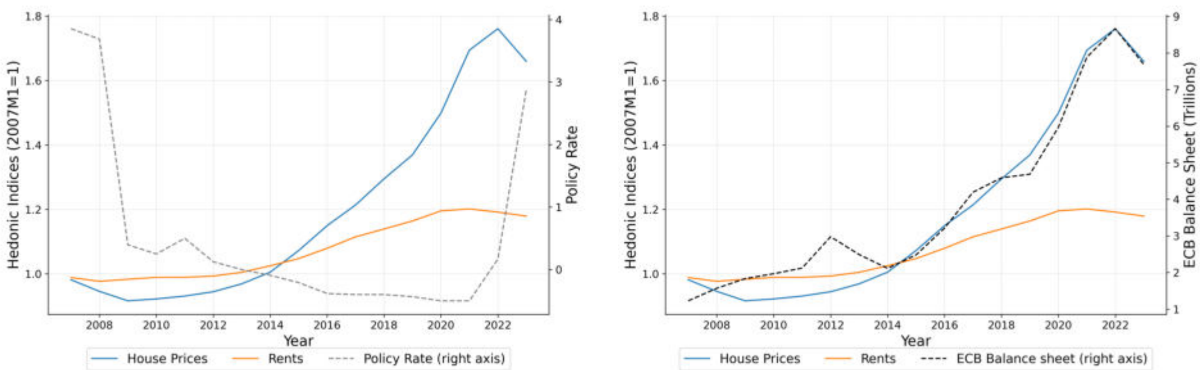
existing rents, as is typically applied in traditional rental price indices. While this approach excludes renegotiated or renewed rents, it allows for a concentrated analysis of changes in the flow of new rental agreements.

Recent literature has identified seasonal patterns in housing markets, particularly at the local level (Ngai and Tenreyro, 2014; Kajuth and Schmidt, 2011). To ensure that our analysis is not compromised by seasonal fluctuations, we adjust our hedonic indices for calendar patterns using the US Census Bureau's X-13ARIMA-SEATS software.

3.5 Monetary Expansion and evolution of House Prices and Rents

Before proceeding with our econometric analysis, we present descriptive evidence on the evolution of house prices and rents in Germany during expansionary monetary policy solely based on our listings data.

Figure 1: Monetary Policy Rate, House Price and Rent Developments



Note: This figure plots the ECB's monetary policy rate (left graph) and the ECB's balance sheet volume (right graph) against indices capturing the house prices and rents in Germany over the period from January 2007 to June 2023. Aggregate indices (left axis) are calculated as the unweighted average of the hedonic regional house price and rent indices. To ease visualization, we smooth the house prices and rents series using a 12-month moving average. The reference period is January 2007.

Aggregate Developments Figure 1 shows the evolution of hedonic house prices and rents in Germany from 2007:01 to 2023:06. Following the GFC, German house prices rose by about 70% in real terms between 2010 and 2022, before declining amid recent monetary policy shifts. This development is noteworthy, given Germany's historically stable housing market.[13] Figure 1 also illustrates a strong correlation between the European Central Bank's (ECB) mone-

[13]Unlike other advanced economies, Germany saw limited increases in house prices and rents before the GFC. From 1994 to 2006, US home prices rose by 115%, whereas German nominal house prices declined by 4%. For a more detailed account of house price developments in Germany, see Kindermann et al. (2021).

tary expansion and the path of house prices and rents from 2007 to 2023. Over this period, Germany experienced an unprecedented increase in house prices, alongside a more moderate rise in rents, that coincided with expansionary monetary policy, in particular, balance sheet expansion (see the right-hand panel of Figure 1).

Interestingly, the price-to-rent ratio increased substantially until the monetary policy reversal in 2022. This pattern is consistent with a large body of empirical research demonstrating that housing booms often feature a rising price-to-rent ratio and a growing segmentation between owner-occupied and rental markets (Amaral et al., 2023; Favilukis et al., 2023; Dong, Liu, Wang, and Zha, 2022).

Regional House Prices and Rents Figure 2 depicts the regional cumulative growth in house prices and rents from 2007 to 2023. It shows the huge variation across districts, which is an important reason for the regional analysis. Berlin and its surrounding areas, as well as regions in Bavaria and southern Germany, exhibit the largest increases in both prices and rents. In contrast, central regions experienced more modest price appreciation, and several German regions show no significant rent growth at all. By comparison, in Berlin and Bavaria, rents have increased by 50% or more. Figure C.5 in the Appendix provides additional details on the evolution of prices and rents across different geographical segments, illustrating that both urban and rural areas—and both western and eastern parts of the country—have seen relatively uniform growth in house prices and rents. On the other hand, at smaller market units house price and rent growth is vastly heterogeneous.

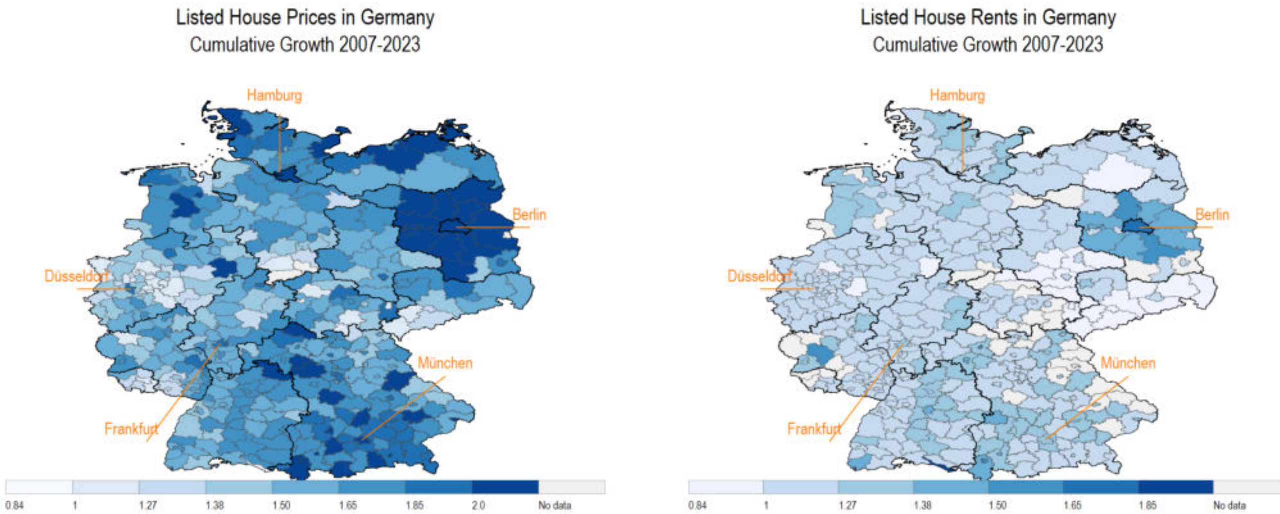
3.6 Other Data

In addition to the real estate listings, our empirical strategy relies on several other data sources to construct a battery of control variables and auxiliary measures. A summary on selected variables are provided below for more detailed description see Appendix D.

Macroeconomic and Financial Variables In our baseline model, we use as cyclical controls the German consumer price index and district-level unemployment rates from the *Federal Statistical Office* (*Destatis*) and the *Bundesagentur für Arbeit*, respectively. The short-term and long-term interest rates (OIS and government bond yields) are obtained from Refinitiv and the *ECB's Statistical Data Warehouse*. The ECB's balance-sheet data come from its consolidated financial statements. All variables are at monthly frequency.

Regional Demographics and Employment We gather district-level population counts, and demographic structures such as the share of young cohorts from *Destatis* and the *Federal Employment Agency* (Bundesagentur für Arbeit). We also use the *SIAB* (Stichprobe Integrierter Arbeitsmarktbiographien) dataset from the *Institute for Employment Research* (IAB) to con-

Figure 2: Cumulative House Price and Rent Growth across Germany



Notes: These maps illustrate the spatial variation in the cumulative growth of house prices (left) and rents (right) across Germany's regions for the period from January 2007 to June 2023. Darker blue tones indicate higher growth factors. The indices are adjusted for quality and inflation as described in Section 3. To produce the plots, we use version 4.0 shapefiles from the UC Davis Data Lab.

struct average wage measures by district. All these variables are available at annual frequency.

Housing Supply Constraints Land availability constraints are measured using geospatial data on water and protected areas for each district in 2006 provided by the *Leibniz Institute of Ecological Urban and Regional Development (IOER)*. We combine these with state-level housing completion statistics from *Destatis* at a monthly frequency.

Regulations and Rent Controls We track the implementation of the *Mietpreisbremse* (rental brake) and other local rent-control measures using administrative decrees published on regional government websites and aggregated by legal reference portals (e.g., `https://www.refrago.de/`).

Survey Microdata for Household Mobility For analyzing household transitions between renting and owning, we rely on household panel data from the German Socio-Economic Panel (*SOEP*). These data contain detailed information on household demographics, income, and housing status and are analysed at quarterly frequency by splitting the interviewed households by quarter.

4 Monetary Policy Identification

The analysis of monetary policy is potentially subject to an endogeneity bias arising from reversed causality and omitted variables. Hence, a reliable identification strategy is crucial for an empirical analysis with causal interpretation. Our setting of regional house prices has the advantage to be less prone to these concerns, because it is highly unlikely that the ECB considers house price developments at the district level when making Eurozone-wide monetary policy decisions. However, monetary policy decisions may reflect national housing market conditions.

To address potential endogeneity adequately, we employ exogenous monetary policy surprises derived from a high-frequency identification (HFI) approach, aligning with prior studies in the Euro Area, the US and beyond. In particular, we utilise the Euro Area Monetary Policy Event-Study Database by Altavilla et al. (2019) to capture monetary policy surprises on Governing Council meeting days since the introduction of the euro. Exploiting the whole term structure of risk free interest rates to describe monetary policy, we derive three relevant and orthogonal shock series categorised as "Target Rate," "FG," and "QE" shocks, in line with Altavilla et al. (2019). This approach not only generates exogenous monetary policy shocks but also allows us to disentangle the effects of conventional and unconventional monetary policies. We extend the approach by correcting for potential information effects embedded within the shocks (Jarociński and Karadi, 2020). Details for the construction of the shocks can be found in the Appendix E.

For the construction of monthly measures of monetary policy shocks, we aggregate high-frequency surprises by simple summation within each month. If there is no Governing Council monetary policy meeting in a given month, the size of the monetary policy shock for that month is set to zero. Figure 3 plots the monthly time series of policy shocks. The surprises are normalised so that a Target Rate shock has unit effect on the 1-month OIS rate, the FG shock has a unit effect on the 2-year OIS rate and the QE shock has a unit effect on the 10-year OIS rate. A positive value of a monetary policy shock is interpreted as a contractionary monetary policy shock during that month. It is therefore possible that shocks can have a positive values even in months with interest rate cuts or QE, because a stronger central bank reaction was expected by the market participants. The impact of the surprises on various financial assets are in line with expectations and can be found in Table E.11 in the Appendix. Note that we observe non-zero QE shocks before the GFC, since balance sheet operations have also been conducted before 2008 and conventional monetary policy had effects on long-term rates. Setting the QE shocks to zero before 2008 does not change our results.

Figure 3: Euro Area Monetary Policy Surprise Series (2007-2023)

Notes: This figure plots the monthly monetary policy surprise series from January 2007 up to June 2023. Shocks are constructed using a high-frequency identification. The "Target Rate" (blue line), FG (black line), and "QE" (green line) shocks are identified as as the first three principal components respectively using changes in OIS rates in a narrow window around ECB monetary decision announcements. The surprises are normalised so that a Target shock has unit effect on the 1-month OIS rate, the FG has a unit effect on the 2-year OIS rate and the QE shock has a unit effect on the 10-year OIS rate.

5 Econometric Strategy

To estimate the dynamic causal effects of monetary policy changes on residential house prices and rents, we implement a local projection framework with instrumental variables (IV-LP) introduced by Jordà et al. (2015). In the first stage, we regress the changes in monetary policy tools on the exogenous monetary policy surprises and a set of control variables, isolating the exogenous variation in monetary policy. In the second stage, we utilise the fitted values from the first stage to estimate the impulse responses of house prices and rents across various horizons, thereby ensuring causal interpretation.

We chose to employ local projection methods over a dynamic factor model employed in related papers (e.g. Del Negro and Otrok, 2007; Fischer et al., 2021; Corsetti et al., 2022) for three reasons. First, our panel setting controls for any time-invariant heterogeneity at the local level and allows the inclusion of several regional and national control variables in a single equation. Second, LP establish the analysis of dynamic non-linearities and heterogeneities in an intuitive and direct way, as we will show in Section 6.4. Moreover, LP IRF tend to be more robust to miss-specifications (at long horizons) (Olea, Plagborg-Møller, Qian, and Wolf, 2024). On the other hand, LP are quite demanding as it involves a distinct IV regression for each impulse horizon. For this reason, we limit the impulse horizon to 36 months.

5.1 Instrumental Variable Panel Local Projection

Let $y_{l,t}$ denote the house price or rent index for region (Kreis) l in period (month) t. To estimate the impulse response functions of house prices and rents to a monetary policy surprise up to H months ahead, we employ the following panel regression:

$$ln(y_{l,t+h}) - ln(y_{l,t-1}) = c_l^h + \sum_{k=1}^{K} \alpha_k^h \Delta ln(y_{l,t-k}) + \beta^h \widehat{policy_t^p} + \phi^h(L) X_{l,t}^h + u_{l,t+h}^h, \quad h = 0, 1, ..., H \tag{2}$$

where the dependent variable, $\ln(y_{l,t+h}) - \ln(y_{l,t-1})$, represents the cumulative relative change in the house price or rent index over h months.[14] The right-hand side of equation 2 includes K lags of the dependent variable to account for autocorrelation inherent in housing indices. The term c_l^h represents region-specific fixed effects at horizon h, capturing time-invariant unobserved heterogeneity across locations and regional characteristics that may influence aggregate demand.[15] The error term is denoted by $u_{l,t+h}^h$ and is potentially serially and cross-sectionally correlated. We also include a vector of control variables $X_{l,t}^h$, containing lagged variables of cyclical indicators at the local level, with $\phi^h(L)$ being a lag polynomial of order L.

[14] We use the growth rate between period $t+h$ and the period immediately preceding the shock $(t-1)$ as the dependent variable. This approach allows us to isolate the effect, akin to a Difference-in-Difference methodology and limits potential estimation bias due to persistence in y_t (Jordà and Taylor, 2024).

[15] The bias identified by Nickell (1981), which arises from the inclusion of lagged dependent variables as controls in the presence of fixed effects in dynamic models with small samples, should not be a concern with our time series of 198 months, as the bias asymptotically approaches zero. In Figure F.14 in the Appendix we plot the estimated IRF without including fixed effects, and the results remain virtually unchanged. Likewise, because of the length of the time series, our LP estimates should not suffer from the small sample bias reported by Herbst and Johannsen (2024).

Because the policy indicators $\widehat{policy_t^p}$ are invariant across regions, including time fixed effects is not possible as it would absorb all variation in this explanatory variable. This might raise concerns that other concurrent shocks (not orthogonal to monetary policy) might be influencing house prices or rents. In Appendix F, we address this issue by incorporating a series of regional and national aggregate controls into our analysis. Our main findings remain robust to these additions.

Our parameter of interest, β^h, measures the impact of an exogenous change in a monetary policy tool on house prices or rents at horizon h. A key challenge to our econometric strategy is that the true monetary policy shock is unobserved and must be inferred. Any of the monetary policy surprise series derived in Section 4, or a linear combination thereof, can serve as an indirect measure of the true monetary shock. However, since these series are designed as partial measures (in a 3h window) of the intended shock, they are susceptible to measurement error (Stock and Watson, 2018; Nakamura and Steinsson, 2018). To address this concern, we do not treat the series as direct measures of the true monetary shock but rather use them as external instruments, following the approach suggested by Ramey (2016) and Stock and Watson (2018).

For any set of variables Z_t^p to be valid instruments for the monetary policy indicator $policy_t^p$, the following three conditions must be satisfied:

$$(i) \quad \mathbb{E}(\epsilon_t^p Z_t^p) = \alpha \neq 0 \quad (relevance); \tag{3}$$

$$(ii) \quad \mathbb{E}(\epsilon_t^o Z_t^p) = 0 \quad (contemporaneous\ exogeneity); \tag{4}$$

$$(iii) \quad \mathbb{E}(\epsilon_{t+j} Z_t^p) = 0 \quad for \quad j \neq 0 \quad (lead-lag\ exogeneity) \tag{5}$$

where ϵ_t^p is the true (unobserved) policy shock p, approximated by the contemporaneous change in the monetary policy tool p after controlling for covariates in X. ϵ_t^o represents all other shocks at time t and ϵ_{t+j} captures all future and past shocks.

Condition, (i), is the relevance requirement, stipulating that the instruments Z_t^p are contemporaneously correlated with the shock series. Conditions (ii) and (iii) are the exogeneity conditions, indicating that Z_t^p should be uncorrelated with any other shocks ϵ_t^o and with all future and past shocks. For more details of the three conditions, see Stock and Watson (2018).

5.2 Econometric Specification

Instrumental Variables As the short-term interest rate was constrained by the zero lower bound for a substantial part of our sample period and the ECB used several tools in parallel, we employ the Shadow Rate estimated by Krippner (2013) to represent the overall stance of monetary policy. In our baseline specification, we instrument the Shadow Rate with a linear combination of the three monetary policy surprise series. This IV approach allows us to isolate the exogenous component of monetary policy changes relevant for our analysis.

In a second step we employ the three monetary policy surprise series as separate instruments to distinguish between the effects of conventional and unconventional monetary policies. We measure conventional policy through changes in the 1-month Overnight Index Swap (OIS) rate, instrumented by Target Rate shocks that capture short-term fluctuations.[16] FG is proxied by monthly changes in 2-year OIS rates—which reflect the ECB's forecast horizon—and is instrumented by FG surprises. For QE, we use the QE shock series as instruments for changes in the ECB's balance sheet. Due to the weak correlation between these variables and to adjust for the pre-QE period when QE shocks are still non-negative, we incorporate QE announcement dummies as additional instruments, following Dedola, Georgiadis, Gräb, and Mehl (2021). As we show in Section 6.3, this distinction of monetary policy tools is important as house prices and rents respond significantly differently.

Lag and Control Variable Selection In our baseline model specification, we choose $K = 6$ to effectively account for the autoregressive dynamics of house prices/rents over the preceding two quarters. For the control variables X_t^l, we follow the methodology outlined by Stock and Watson (2018) and incorporate the lagged high-frequency monetary policy surprises. Moreover, we add cyclical controls such as the German inflation rate (calculated as the year-on-year change in the Harmonized Consumer Price Index) and the Kreis-specific unemployment rate, both lagged. These controls are included to improve the relationship between the policy tools and their instrumental variables, and to address any remaining concerns regarding the exogeneity of our instruments. In our preferred specification, we include three lags of the monetary policy surprise series and six lags of the other control variables. Note that our findings are robust to variations in these lag choices (see Appendix Figure F.13).

Standard Errors To ensure robust inference, we estimate the first stage regression and the LP with standard errors consistent to spatial correlation, heteroskedasticity and serial correlation. These so-called Conley standard errors accounts for the spatial dependence between adjacent housing markets by considering the distance in a linearly decreasing manner up to 100km (Conley, 1999, 2008).[17] A spatial correlation cutoff of 100 km, in line with Aastveit and Anundsen (2022), is applied to reflect the limited influence of distant regions outside the same commuting zone on regional house prices. Details on the Conley standard errors can

[16] We use the 1-month OIS rate instead of the ECB's policy rate as the latter was at the zero lower bound for most of our sample period and the relevant policy rate switched from the Main Refinancing Operations rate to the Deposit Facility Rate.

[17] We use geographic data from the Bundesamt für Kartographie und Geodäsie to calculate distances between Kreis centroids, based on their latitudes and longitudes, as in Colella, Lalive, Sakalli, and Thoenig (2019).

be found in Appendix G.

Smoothing While local projections impose few restrictions on the dynamics of $y_{l,t}$, they can yield highly volatile estimates, particularly with our hedonic listings estimates, which exhibits significant monthly noise. To enhance interpretability, we smooth the outcome variable using a backward-looking moving average (current and previous two months) of the indices, following Coibion, Gorodnichenko, Kueng, and Silvia (2017) and Cloyne, Ferreira, and Surico (2020). Excluding this step in our estimation procedure does not affect our conclusions albeit the responses are more jagged (see Figure F.16).

5.3 Diagnostic Tests

While we are not the first to use the shocks identified by Altavilla et al. (2019) as monetary policy instruments, we perform a series of diagnostic tests to ensure the validity of our econometric strategy.

Relevance To establish instrument relevance, we first assess the strength of the monetary policy surprises as instruments for the endogenous policy variables. Table G.12 reports the Kleibergen-Paap robust F-statistics (Kleibergen and Paap, 2006) obtained from the first-stage regressions, using the same control variables as in our baseline second-stage regression. We present the results separately for each instrument at 12, 24 and 36 month horizons. For completeness, we perform the F-tests separately for the housing and rent samples, obtaining similar results in both cases. The findings indicate that both the linear combination of the three surprise series and each individual series serve as reasonably strong instruments for changes in the Shadow Rate, the 1-month OIS rate, the 2-year OIS rate, and the balance sheet. All F-statistics exceed the threshold of 10 recommended by Stock, Wright, and Yogo (2002) across all horizons.[18]

Lead and Lag Exogeneity The identification strategy could also be compromised by a potential violation of the assumption of lead and lag exogeneity. To address this concern, we follow the methodology proposed by Stock and Watson (2018) to test whether house prices or rents predict any of the monetary policy surprises. To do so, we regress the monetary policy shocks on the lags of the hedonic house price and rent indices. The results indicate that the lags of these dependent variables have no significant explanatory power over the monetary policy shocks (see Table G.13), thereby supporting the assumption of lag exogeneity. Regarding lead exogeneity, it is satisfied by the definition of shocks as unexpected surprises, provided that

[18] While the Kleibergen-Paap F-test is widely used, a potential concern is that it primarily addresses issues of under-identification rather than weak instruments (Andrews, Stock, and Sun, 2019). Therefore, we also employ the robust F-test proposed by Olea and Pflueger (2013) without control variables, which yields confirming results.

future values are not included as instruments (Stock and Watson, 2018).

Contemporaneous Exogeneity It is important to emphasise that by construction with a principal component analysis, the policy shocks are uncorrelated with each other (i.e orthogonality of the factors). In addition, the narrow windows around the policy announcement results in serially uncorrelated shocks. Moreover, Altavilla et al. (2019) checked and excluded other simultaneous shocks, such as financial market responses, within the narrow time frames to guarantee exogeneity of the shock series.

6 Monetary Policy Effects on House Prices and Rents

This section examines the effects of monetary policy shocks on house prices and rents. Subsection 6.1 analyses the impact of changes in the overall monetary policy stance, measured by Shadow Rate. In subsection 6.2, we examine the transmission through long-term mortgage rates. Then, subsection 6.3 distinguishes between conventional and unconventional monetary policies, highlighting their differential effects in magnitude and timing. Finally, subsection 6.4 investigates how the effects of monetary policy shocks vary across regions.

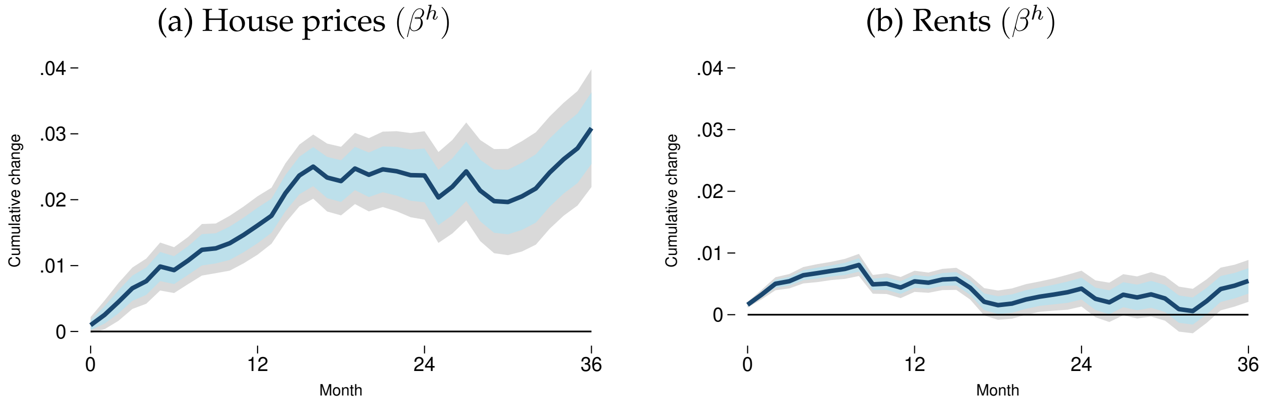
6.1 Baseline Results

In our baseline specification, we examine the cumulative change in our hedonic house price and rent indices over the first 36 months following a one standard deviation reduction (-0.24 percentage points) in the ECB's Shadow Rate (Krippner, 2013). Panels (a) and (b) of Figure 4 present the IV estimates of β^h from equation 2. The solid lines represent the point estimates, while the shaded areas denote the 68% and 90% confidence intervals, using Conley (1999, 2008) standard errors.

The average responses across German regions for house prices and rents are positive and statistically significant. The values build up gradually, reaching 1.5% for house prices and 1% for rents within the first year. House prices increase by 2.5% 18 months after the shock and remain at this level before increasing slightly more towards end of the estimation horizon. Rents, on the other hand, never rise beyond 1%. While rents show a more immediate reaction after the shock, this effect fades over time, and the estimates are not always statistically significant in the second half of the forecast horizon. Therefore, the impact of expansionary monetary policy on rents is significantly smaller than that on house prices, driving them apart.

In order to evaluate the relevance of monetary policy for the housing markets, we also run a variance decomposition exercise. In particular, we follow Gabriel, Klein, and Pessoa (2023)

Figure 4: House price and rent responses to Shadow Rate cut (IV-LP)



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.24 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2007 to June 2023. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using Conley (1999, 2008) standard errors, as explained in Section 5.2.

and adjust the R^2 estimator of Gorodnichenko and Lee (2020) for an IV panel LP framework with controls. The fraction of the forecast error variance of $ln(y_{l,t+h})$ explained by $policy_t^p$ on the horizon h is estimated as R^2 of the following regression:

$$\hat{f}_{l,t+h} = \alpha_0 \widehat{policy^p_{t+h}} + \alpha_1 \widehat{policy^p_{t+h-1}} + ... + \alpha_h \widehat{policy^p_t} + \epsilon_{i,t+h} \tag{6}$$

where $\hat{f}_{i,t+h}$ is the forecast error from regression 2 and $\widehat{policy^p_t}$ are the fitted values from regressing $policy_t^p$, on the same set of explanatory variables as in equation 2. Note that consistency with the IV panel LP framework requires the predicted values of the Shadow Rate on the three monetary policy shocks from the first stage regression as the measure of $policy_t^p$.

Table 1 summarises the variance decomposition, highlighting the contribution of shifts in Shadow Rate to common fluctuations in both property prices and rents across regions. For house prices, the immediate influence is modest, about 0.4% of the forecast error variance at three months, but it rises steadily over time, reaching 5.6% by the three-year mark. In the case of rents, monetary policy shocks initially play a negligible role, yet their impact grows sharply by 18 months, accounting for roughly 7.5% before settling at slightly below 5% after three years. These patterns suggest that while the short-run impact of monetary policy is muted, it becomes a significant driver of property market dynamics over the medium- to long-term.

Table 1: Importance of Monetary Policy Shocks on Property Prices and Rents

Horizon (months)	**3**	**6**	**12**	**18**	**24**	**30**	**36**
House Prices	0.4	1.2	1.7	2.1	2.7	3.7	5.6
Rents	0.0	0.6	4.0	7.5	7.0	5.2	4.9

Notes: Forecast error variance decomposition of house prices and rents based on local projections (2).

Comparing the results, our estimates align with previous evidence on monetary policy shocks on house prices in the US and other countries surveyed by Williams et al. (2015). The size of our estimates are broadly consistent, but similar to recent research at the higher end of the spectrum (e.g., Aastveit and Anundsen, 2022; Koeniger et al., 2022). In the rental market, the positive and persistent effects we identify resemble those reported by Koeniger et al. (2022) in Germany using survey data, but diverge from the negative effects documented by Dias and Duarte (2019, 2022) and Lazarowicz and Richard (2023) for the US and UK, respectively. The differences imply that the transmission of monetary policy to the rental sector may be institution-specific, with Germany representing a distinct case relative to Anglo-Saxon markets.

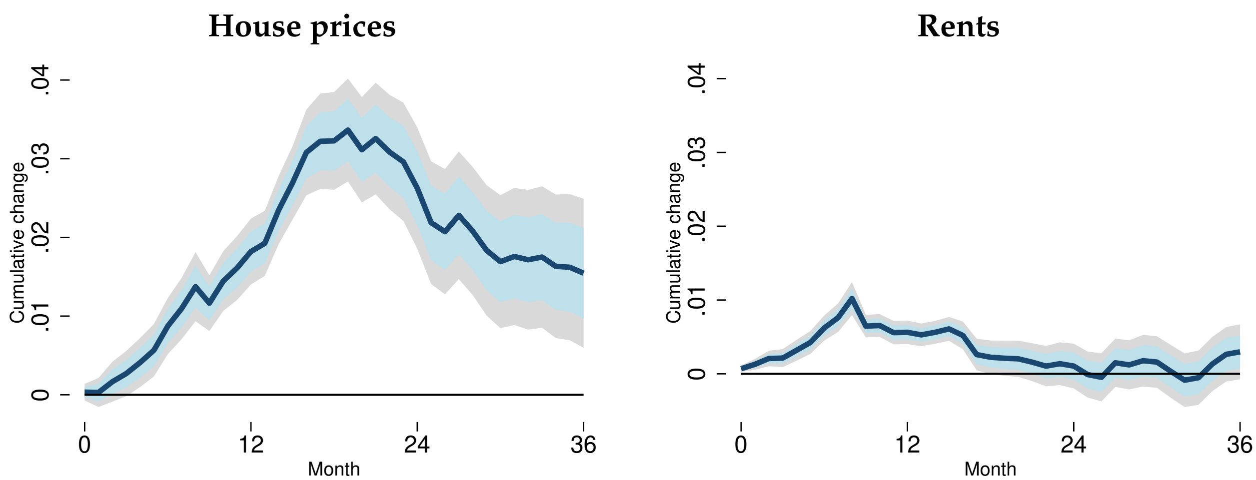
We undertake a comprehensive set of robustness checks, detailed in Appendix F, to verify the consistency of our baseline findings. Specifically, we re-estimate our models (i) excluding the COVID-19 period, (ii) using municipality-level instead of Kreis-level data, (iii) varying the minimum number of listings for the index construction, (iv) comparing our results to IRFs on transaction data, (v) jointly including all three policy measures, (vi) adding further financial and macroeconomic controls, (vii) altering the lag structure, (viii) dropping fixed effects to address potential Nickell (1981) bias, and (ix) expanding the spatial clustering radius from 100km to 200km. Across all these specifications, the positive effects of expansionary monetary policy shocks on both house prices and rents remain unchanged, reinforcing our main conclusion that expansionary shifts in monetary conditions significantly increase property prices and to a certain extent rents.

6.2 Monetary Policy Transmission through Mortgage Rates

For anyone looking to buy a home, especially first-time buyers, long-term mortgage rates are more relevant than the short-term nominal interest rate set by central banks. In Germany, fixed-rate mortgages of five years and more dominate the market and since 2015, especially loans with 10-year fixed rates have become common (see Figure H.18). Variable-rate mortgages, widespread in other parts of Europe, are very rare in Germany.[19] To understand how changes in mortgage rates driven by monetary policy affect the housing market, we re-estimate the IRFs but replacing the Euro Area Shadow Rate with Germany's average long-term mortgage interest rate. Thereby, we focus on the borrowing costs that matter most to home-buyers.[20]

Figure 5 reports the effects of a one standard deviation (0.11 percentage points) decline in the 10-year mortgage rate. House prices and rents climb quickly and significantly. Eighteen months after the shock, house prices are up by around 3%. The effect gradually declines but remains at about 2% after three years. Rents, by contrast, peak at just 1% after six months, and by the 36-month mark, the effect has disappeared entirely.

Figure 5: House price and rent responses to 10-year mortgage rate cut (IV-LP)



Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price and rent indices to a 1 SD (0.11 pp) reduction in the 10-year and longer mortgage interest rates in Germany (instrumented with all shocks). Impulse responses are at the monthly frequency using data from January 2007 to June 2023. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using Conley (1999, 2008) standard errors.

These results mirror the effects of a Shadow Rate cut and highlight how crucial financing costs are for understanding Germany's housing market. In Section 7, we show that these results can be rationalised by the fact that expansionary monetary policy shocks prompt a significant share of renters to become homeowners, and, over this horizon, reduce the incidence of renting relative to owning.

[19] Unlike in the US, refinancing is costly in Germany, and options for releasing home equity are limited.

[20] We choose the average mortgage rate for 10 years and beyond as it is the rate with the longest maturity available at the ECB data portal and allows to compare our results to the findings from the US of Gorea et al. (2022).

6.3 Conventional vs Unconventional Monetary Policy Effects

Shadow Rates serve as a useful indicator of the overall monetary policy stance, especially when the effective lower bound is binding. However, since the GFC, monetary policy has become multidimensional both in Europe and globally which likely induces asymmetric effects on house prices and rents. To investigate these distinctions, we separately analyse the responses to 1 standard deviation expansionary changes in the short-term nominal interest rate (1-month OIS rate, -0.16 pp), the 2-year OIS rate (-0.2 pp), and the ECB's balance sheet (+ €117 billion). In summary, while conventional rate cuts produce short-lived gains in house prices and limited rent responses, unconventional tools—particularly QE—induce more persistent price growth and modest but enduring rent increases. These findings underscore the importance of distinguishing between policy instruments when assessing monetary transmission to the housing market.

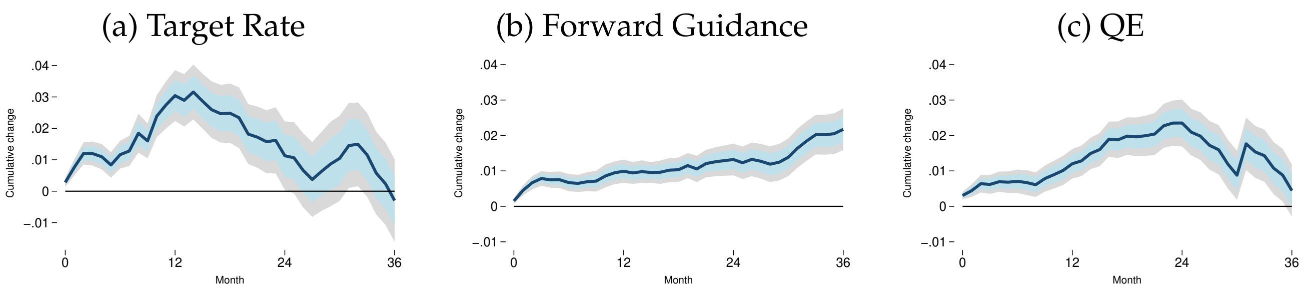
House Prices (Panel A of Figure 6): A cut in short-term rates generates an immediate and statistically significant increase in house prices, peaking at roughly 3% after 14 months. After two years, however, this effect diminishes and becomes statistically insignificant, indicating that conventional policy rate cuts yield only temporary house price gains. In contrast, unconventional tools have a more pronounced and sustained impact. A reduction in the 2-year OIS rate—our proxy for FG—raises house prices by about 1% after one year and maintains statistically significant effects through the three-year horizon, eventually reaching a 2% peak. QE, captured by an expansion of the ECB's balance sheet, leads to a hump-shaped response, with house prices climbing steadily and peaking above 2.5% after two years before gradually tapering off. Notably, QE and FG effects remain statistically significant over the entire period we consider. In terms of magnitude, QE and short-term rate cuts tend to generate larger effects than FG in the first two years.

Rents (Panel B of Figure 6): Rents react more modestly. Following a cut in the policy rate, rents rise modestly for about a year but then lose significance after two years, echoing previous findings that the effect of rate cuts on rents can be limited and sometimes negative over longer horizons (Corsetti et al., 2022; Dias and Duarte, 2019). Unlike the US and UK contexts, however, we do not observe a pronounced negative rent response. Instead, both FG and QE drive modest but persistent increases in rents. In the case of FG, the rent response hovers between 0% and 0.5%, whereas QE induces a more pronounced and lasting uplift, reaching about 1% after two years and staying at that level thereafter.

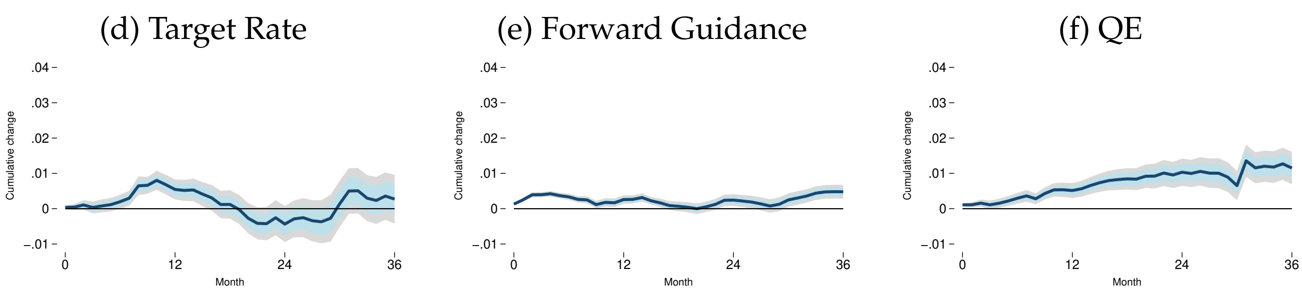
The stronger and more persistent effect of QE on both prices and rents suggests that as QE elevates asset values and makes homeownership increasingly costly, part of these rising housing costs are eventually passed on to tenants. This mechanism may dominate any opposing

Figure 6: House price and rent responses - Policy decomposition

Panel A: Prices



Panel B: Rents



Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price indices to a 1 SD (0.16 pp) reduction in the 1-month OIS rate, a 1 SD (0.2 pp) reduction in the 2-year OIS rate, and a 1 SD (117 billion €) expansion of the ECB's balance sheet. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06. Confidence intervals are based on Conley (1999, 2008) HAC and spatially robust standard errors.

effects, such as potential reductions in rental demand due to improved mortgage affordability. As house prices surge, it becomes harder for renters to transition into homeownership, thereby allowing landlords to maintain or increase rents over the medium term.

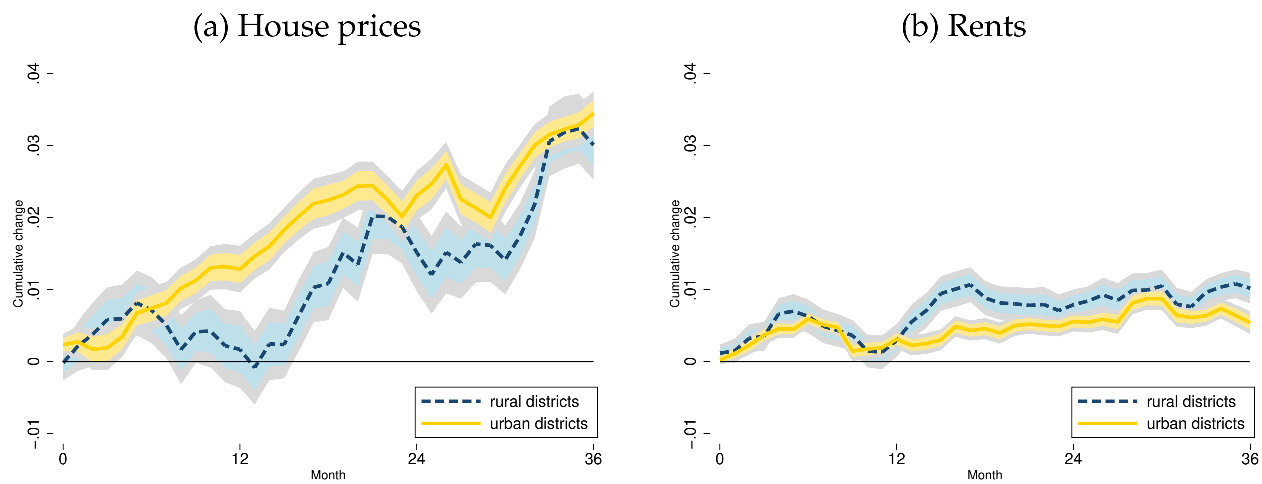
6.4 Heterogeneity Across Regions

While previous IRFs capture the average impact of monetary policy on local housing markets, they may conceal regional variations. Using our detailed dataset, we examine whether specific regional characteristics drive these effects. Overall, we find little evidence that monetary policy increases regional disparities in house prices or rents. Instead, policy impacts are generally uniform across regions, regardless of supply constraints, demographics, or wage structures.

Urban-rural differences

Following the literature on spatial economics, a natural starting point is the split between urban and rural regions.[21] Our goal is to understand whether the increase in house prices and rents is driven mostly by urban regions as someone would suspect from Figure 2. Figure 7 compares the IRFs of an expansionary monetary policy shock to housing prices in rural and urban regions. Splitting the sample reveals notable differences in how monetary policy affects local housing markets. Both regions see prices rise after an expansionary shock, but the timing and magnitude vary. Urban areas react more sharply and immediately, reflecting tighter supply conditions and potentially more elastic demand. Rural districts eventually catch up in terms of price growth, but their response is more gradual, suggesting that housing supply and demand fundamentals differ from urban settings. Interestingly, rents react more quickly and strongly in rural regions, highlighting structural differences across housing tenure.

Figure 7: House price and rent responses - urban versus rural districts



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.24 percentage points) reduction in the Shadow Rate, distinguishing between urban and rural regions. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using cluster robust standard errors.

Housing supply elasticities

We next investigate whether supply-side constraints shape the regional response of housing markets to monetary policy. Building on the premise that tighter land-use regulation and limited land availability amplify price reactions to policy shocks, we incorporate interaction terms between monetary shocks and proxies for local supply constraint factors into our

[21] Urban regions (Kreis) are denoted as those with Stadtkreis status, rural regions are those denoted as Landkreis according to Destatis classification (see also Section 2).

framework. This allows us to assess whether regions with more inelastic supply conditions exhibit stronger price adjustments, as documented by Aastveit and Anundsen (2022) for the United States. Our baseline econometric framework is extended as follows:

$$ln(y_{l,t+h}) - ln(y_{l,t-1}) = c_l^h + c_t^h + \sum_{k=1}^{K} \alpha_k^h \Delta ln(y_{l,t-k}) + \beta_S^h Supply_{l,t-1} \times \widehat{policy_t^p} + \\ + \phi^h(L) X_{l,t}^h + u_{l,t+h}^h, \quad h = 0, 1, ..., H \quad (7)$$

where the coefficient β_S^h of the new interaction term $Supply_{l,t-1} \times \widehat{policy_t^p}$ captures the differential impact of monetary policy depending on the regional housing supply elasticity after h months. This interaction effect is instrumented by the interaction of our high-frequency policy shocks and the proxy of the supply-side constraint explained below. Note that a higher value of $Supply_{l,t-1}$ indicates tighter supply constraints. Crucially, this specification allows us to include month-year fixed-effects denoted by c_t^h that control for other potential macroeconomic shocks that might contaminate our findings. We also include lags of time-varying supply factors to the control variables $X_{l,t}^h$. We estimate equation 7 separately for each housing supply proxy for the period January 2007 to December 2019. This excludes the COVID-19 pandemic to reduce sensitivity to outliers and address data availability issues after 2020. In Table 2 we present the estimated coefficients β_S^h at three different horizons. All coefficients are expressed in percentage terms.

Unfortunately, housing supply elasticity estimates in the spirit of Saiz (2010) do not exist for Germany. To address this issue, we make use of several alternative indicators that could be thought as proxy of housing supply elasticities. First, we consider a measure land availability to construct new buildings provided by the IOER, the Leibniz Institute of Ecological Urban and Regional Development. This variable measures for each region the share of unavailable land for residential housing due to water, mining, wetland, settlements or traffic. However, as noted by Bednarek, Kaat, Ma, and Rebucci (2021), Germany's more homogeneous topography suggests that physical land constraints are unlikely to deliver US results. As alternative measures we consider the share of newly constructed houses or the number of (lagged) housing listings, representing the extensive margin of supply, and the (lagged) average floorspace per listing, representing the intensive margin. As these variables describe the ease of supply, we will look at their inverse effects to compare it to land constraints. While these variables are not as exogenous as land constraints, they vary considerably across months and regions. As suggested by Borusyak, Hull, and Jaravel (2022), the exogeneity of the shock variable is sufficient for maintaining the causal interpretation of the policy effects in the IV setting.[22] Fi-

[22]The interaction effects can be interpreted as a shift-share instrument, where we link an exogenous aggregated shock to local and potentially endogenous exposure shares.

nally, we use the rental regulation introduced after 2015 as a proxy of regulatory stringency at Kreis-level. The idea is that the districts implemented the law at different points in time after 2015, and some others did not, which provides variation of regulatory constraints independent to monetary policy shocks.

Land unavailability Panel A of Table 2 shows that the availability of land to construct new buildings does not significantly influence the transmission of monetary policy across German regions, likely due to limited regional variation.

New dwellings In contrast, Panel B indicates that a lower share of new properties leads to a slower and weaker change of prices and rents after an expansionary monetary policy shock. Therefore, some of the regional variation of house prices across Germany can be assigned to the interplay between monetary policy and construction activity. In contrast to the findings in the US, tighter construction conditions do not lead to faster monetary policy transmission. As new dwellings are less strictly regulated, a higher share of them leads to faster price dynamics.

Listings and floorspace These effects are not found for the overall number of listings when existing dwellings are included. Panel C indicates that regions with many few housing listings experience a similar increase in house prices following expansionary monetary policy shocks compared to others. Along the intensive margin, monetary policy has stronger effects when the average size of properties decline. However, this effect seems to be only temporary.

Rental break Panel D shows that the rental break, introduced in several municipalities since 2015, serves as a proxy for regulatory stringency, significantly mitigating the effects of monetary policy on rents, while not affecting house price dynamics. This regulation limits the pass-through of monetary easing into the rental market, which would have otherwise fueled substantial rent increases. This also highlights the necessity of analyzing both markets separately.

Demand-side factors

Beside housing supply factors, also demand factors could amplify the monetary policy transmission and lead to heterogeneous effects across regions due to region-specific excess demand. To this end, in Appendix J we investigate the role of demographics, labour market tightness and wage differences by replacing the supply factors in equation 7 with a selection of demand factors. Overall, we find a weaker role of demand factors that rarely leads to significant effects as shown in Table J.14.

Table 2: Impact of Housing Supply Constraints on the Transmission of Monetary Policy

		House Price			Rent		
		h = 12	h = 24	h = 36	h = 12	h = 24	h = 36
Panel A: Unavailable Land							
β_S^h	Δ Shadow Rate * unavailable land	0.0090	0.0137	0.0014	-0.0011	-0.0038	-0.0097**
		(0.0110)	(0.0148)	(0.0141)	(0.0036)	(0.0041)	(0.0056)
Panel B: Share of New Dwellings (inverse)							
β_S^h	Δ Shadow Rate * Share of new Dwellings (-)	-0.0600**	-0.0246	-0.0912**	-0.0494**	-0.0559**	-0.0401*
		(0.0305)	(0.0326)	(0.0423)	(0.0205)	(0.0265)	(0.0312)
Panel C: Standardised Listings and Floorspace (inverse)							
β_S^h	Δ Shadow Rate * Std(Listings, t-1, -)	-0.0099	-0.0306	-0.0608	0.0105	-0.0325*	-0.0161
		(0.0824)	(0.0933)	(0.0872)	(0.0229)	(0.0303)	(0.0401)
β_S^h	Δ Shadow Rate * Std(Floorspace, t-1, -)	0.369*	1.005***	0.148	0.0573	-0.200**	-0.102
		(0.284)	(0.376)	(0.399)	(0.0959)	(0.0908)	(0.112)
Panel D: Rental Break							
β_S^h	Δ Shadow Rate * $\mathbb{1}$(Rental Break)	0.159	-0.293	-0.158	-0.528***	-0.246*	-0.323*
		(0.281)	(0.394)	(0.575)	(0.164)	(0.205)	(0.283)

Notes: The coefficients are reported in percent changes of house prices/rents. Conley standard errors (Conley, 1999, 2008) are in parentheses. The Shadow Rate represents a one standard deviation (-0.24 pp) expansionary change. Unavailable land is measured by the share of land covered by water, wetlands, mines, traffic, or settlement infrastructure in 2006 (percent). The share of new buildings is measured by newly built dwellings among all listings. Lagged listings and floorspace are standardised (coefficients represent a 1 SD increase). * $p < 0.32$, ** $p < 0.10$, *** $p < 0.01$.

7 Investigating the Mechanisms

So far, we have established that expansionary monetary policy raises house prices more strongly and persistently than rents. To understand why, this section delves into the underlying mechanisms that could explain these disparities. We examine indicators of housing market tightness such as number of listings and contact attempts and then link these to underlying household behavior and tenure choices.

7.1 Responses of Housing Demand and Supply

To explore how expansionary monetary policy affects housing demand and supply, we analyse monthly indicators such as the contacts per listing-day and the number of listings per region. In order to adjust our housing demand proxy for quality differences, we employ the same methodology described in Section 3.4 for deriving hedonic prices, but for contacting attempts per listing-day. Specifically, for each location and tenure type, we separately regress the number of contacts per listing-day on various housing characteristics that determine quality, while controlling for month-year fixed effects.[23] To ensure data quality, our

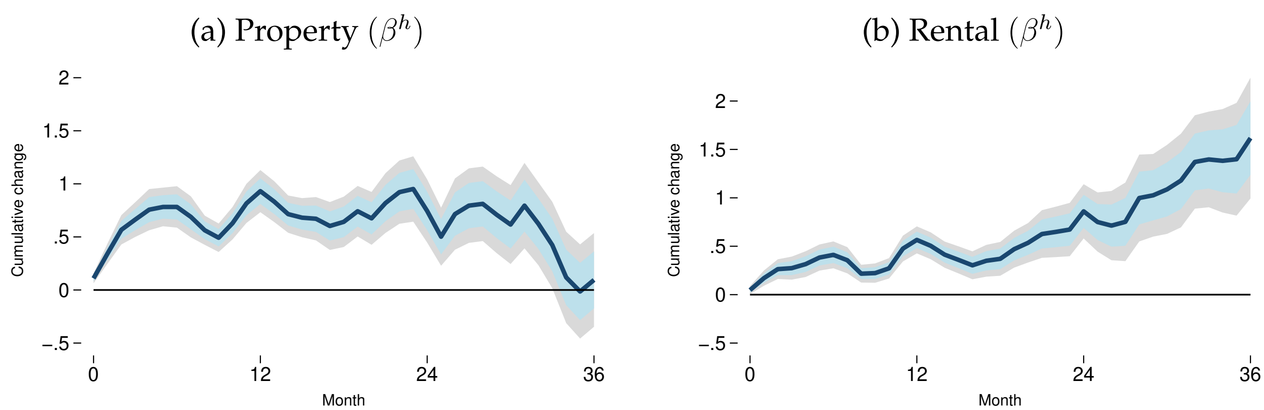
[23]Unlike house prices and rents, we do not take the natural logarithm of contacts per listing-day to avoid complications associated with zero or near-zero values. Consequently, the hedonic regressions are performed in

sample is restricted to January 2009 through December 2019, thereby avoiding the erratic behavior observed during the COVID-19 period and accounting for the poor quality of contact data prior to 2009. For the our supply proxy, the number of listings, hedonic regressions are not performed, as the average number of listings for a given month-year is only defined at the regional level. As we do not have data issues with the number of listings, we consider the whole sample period, but the results are similar for the period 2009-2019. We linearly interpolate missing values where appropriate and adjust for seasonality using the US Census Bureau's X-13ARIMA-SEATS package.

Responses of Contacts per Listing Day

Figure 8 illustrates the IV-LP responses of contacts per day to a one standard deviation reduction in the Shadow Rate.[24] The figure reveals that demand for properties, as measured by contacts per listing-day, increases markedly for both the sales and rental markets. Specifically, the surge in demand is approximately twice as large in the sales market compared to the rental market during the initial two-year period, but this effect reverses over a three-year horizon. Given the baseline average contacts per day of 0.27 for properties and 1.54 for rental properties, these effects are not only statistically significant but also economically important, particularly for the sales market.

Figure 8: Demand responses - Contacts per listing day



Notes: The figure displays the responses (β^h) of the average contacts per listing day for property (left) and rental (right) objects to a 1 SD (0.24 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2009 to December 2018. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using Conley (1999, 2008) standard errors.

In the sales market, the heightened demand can be attributed to two primary channels. The

levels.

[24] To mitigate the influence of volatility in less densely populated regions, we exclude the top and bottom 1% of changes in quality-adjusted average contacts/day for each period.

first is direct and straightforward: as shown by Table E.11 and discussed in Section 6.2, long-term interest rates decline significantly, making house financing more accessible. Additionally, a second, indirect channel may be at play. Expansionary monetary policy in the Euro Area is causing higher labor earnings in Germany, especially for individuals at the lower end of the income distribution as shown by Groiss (2023). These combined effects likely explain the substantial increase in demand for house purchases observed in our data.

Given the high proportion of renters in Germany, it is also plausible that a significant fraction of renters opt to become homeowners under increasing labor earnings and favorable financing conditions. To quantify the relevance of this mechanism, we leverage micro-level survey data from the German Socioeconomic Panel (SOEP). SOEP is a well known longitudinal dataset and can be thought as the German equivalent of the PSID in the US. Following the approach by Koeniger et al. (2022), we analise the cumulative effect of expansionary monetary policy shocks on the probability of a tenure change over three years. Details regarding the dataset and regression design are provided in Appendix I.

Table 3 presents the significant positive effect of expansionary monetary policy on the likelihood of becoming a property owner and a negative effect on reverting to tenancy. Specifically, a 0.25 percentage point reduction in monetary policy shocks increases the probability of transitioning from renting to property ownership by 1.5% over three years and decreases the probability of becoming a renter by 1.7%. Conversely, these effects are slightly offset by a reduction in the propensity of existing homeowners to move to a new property. Table 4 illustrates that following a 0.25 pp expansionary monetary policy shock, the probability of existing homeowners moving to a new property declines by 1.8% over the same period. While quantifying the aggregate housing demand implications of these channels is challenging without a formal model, the empirical evidence suggests an overall increase in housing demand.

Turning our attention to the rental market, the weaker demand responses compared to the property market are in line with the negative and weakly significant effects regarding renting in Table 3. The increasing demand appears to be mostly driven by a rise in rent-to-rent transitions. Table 4 indicates that expansionary monetary policy shocks lead to an 11% increase in tenants moving to new tenancies within a three-year period. Rising incomes associated with such policy shocks likely facilitate this decision. In a model of housing mobility developed by Ngai and Sheedy (2024), rising incomes encourage households to search for and transition to higher-quality housing.[25]

[25] While the model specifically addresses ownership-to-ownership transitions, the implications are likely applicable to the rental market as well.

Table 3: Housing tenure transition

	renter to owner				owner to renter			
	All	PR	FG	QE	All	PR	FG	QE
Cum. 3y effect (0.25pp cut)	1.489**	-3.476***	3.686***	1.279***	-1.725*	-0.608*	-0.944*	-0.174
	(0.815)	(0.497)	(0.556)	(0.197)	(1.084)	(0.447)	(0.772)	(0.180)
Lagged macro controls	✓	✓	✓	✓	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Household fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	265,963	265,963	265,963	265,963	265,963	265,963	265,963	265,963

Notes: The dependent variable is 1 if a household changed tenure status in the respective direction and 0 if it does not. Standard errors are clustered by quarter of the interview to capture cross-household effects by the aggregate monetary policy shocks. Macro controls include 4 lags of unemployment rate and inflation. Household controls include age, age squared, employment status, years of education, migration background, and gender of household reference person, household size, log household income and Bundesland. The coefficient represents the cumulative effect over three years of a -25 bp shock and is obtained by summing over current and 11 lags of respective monetary policy shock, PR = policy rate, FG = Forward Guidance, QE = Quantitative Easing. * p<0.32, ** p<0.10, *** p<0.01.

Table 4: Housing transition

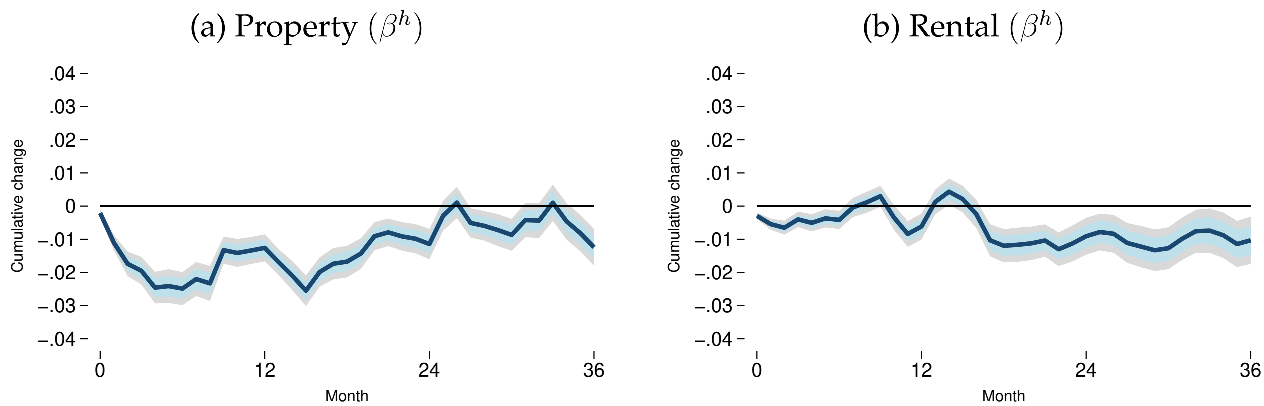
	owner to owner				renter to renter			
	all	PR	FG	QE	all	PR	FG	QE
Cum. 3y effect (0.25pp cut)	-1.835*	5.557***	-5.711***	-1.681***	11.922**	4.249**	5.473*	2.200*
	(1.318)	(0.497)	(0.462)	(0.297)	(4.594)	(2.485)	(4.027)	(01.163)
Lagged macro controls	✓	✓	✓	✓	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Household fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Quarter fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	265,963	265,963	265,963	265,963	265,963	265,963	265,963	265,963

Notes: The dependent variable is 1 if a household moved and remained in the same tenure and 0 if it does not. Standard errors are clustered by quarter of the interview to capture cross-household effects by the aggregate monetary policy shocks. Macro controls include 4 lags of unemployment rate and inflation. Household controls include age, age squared, employment status, years of education, migration background, and gender of household reference person, household size, log household income and Bundesland. The coefficient represents the cumulative effect over three years of a -25 bp shock and is obtained by summing over current and 11 lags of respective monetary policy shock, PR = policy rate, FG = Forward Guidance, QE = Quantitative Easing. * p<0.32, ** p<0.10, *** p<0.01.

Responses of the Number of Listings

Figure 9 presents the cumulative change in the number of listings following a one standard deviation reduction in the Shadow Rate. For the sales market, the number of listings on Immobilienscout24 initially declines by up to 3%, but this effect converges back to zero after two years. Our findings echo the results of earlier studies using US data (Gorea et al., 2022; Fonseca and Liu, 2024). Gorea et al. (2022) observe small but significantly negative effects on listings following expansionary monetary policy shocks, particularly those related to QE. In contrast, the decline in new listings for rental properties is more moderate and stabilises at around a 1% reduction after 18 months. Overall, we can conclude that these negative supply-side effects in the sales market, coupled with rising demand, contribute to increasing house prices and the observed divergence between listed house prices and rents in Germany.

Figure 9: Supply responses - Listings



Notes: The figure displays the responses (β^h) of the number of listings for property (left) and rental (right) objects to a 1 SD (0.24 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2007 to June 2023. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using Conley (1999, 2008) standard errors.

At first glance, the findings on the number of listings may appear puzzling since aggregate statistics show that housing completion rates over this period has increased markedly as financing got cheaper. However, newly built properties account only for a small fraction of the new listings in the data. One plausible explanation for the observed decline in listings is that rational sellers optimise the timing of property listings to capitalise on higher future demand and sale prices. As most of the the sales transactions are driven by listings and less so by transaction speed (Ngai and Sheedy, 2020), home movers are the key to understand the drop in listings. As Table 4 shows, house moves drop significantly after expansionary monetary policy shocks and thus less houses are listed for sale in the website. The negative effects are driven by FG and QE that drive future long-term rates highlighting that home movers postpone their decisions for sale in the future. One explanation is the mortgage lock-in as suggested by Fonseca and Liu (2024).[26] A decrease in interest rates allows the borrower to lock-in the mortgage rate for a specified time period at the prevailing market interest rate.

[26] A key difference between Germany and the US regarding mortgage contracts lies in prepayment penalties (known as Vorfälligkeitsentschädigung). In Germany, most mortgages cannot be refinanced at will without incurring a substantial penalty if the borrower repays early. While longer-term fixed interest rates can protect households against upward rate shifts, these prepayment penalties become a strong disincentive to sell or refinance early when interest rates fall. From a household's perspective, the potential gain from moving to a cheaper mortgage is partially offset by having to compensate the lender for lost interest income via the prepayment fee.

As a result the probability of moving for property owners, who wish to retain favorable financing conditions, declines. Relocating would necessitate negotiating new, potentially more expensive mortgage contracts, thereby diminishing the incentive to move.

A similar logic applies to the rental market, where listings also decline following expansionary monetary policy shocks, but only slightly. Although tenants become more mobile and are willing to upgrade their rental units, landlords facing rent control regulations (such as the Mietpreisbremse) have fewer incentives to immediately re-list their properties at only marginally higher regulated rents. Instead, they delay re-listing, hoping for more favorable market conditions or the opportunity to modernise properties to exempt them from rent caps. As a result, despite stronger demand conditions, rental supply contracts in the short run, reinforcing the differential price and rent dynamics observed in response to expansionary monetary policy.

7.2 An Alternative Channel: The Buy-to-Let Market

An alternative yet complementary channel contributing to heightened demand for house sales, especially among higher-income groups, is the buy-to-let market. The German tax system provides incentives that makes property investments more attractive to wealthier households. For instance, interest paid on mortgage debt for rental properties is tax-deductible. Moreover, landlords are eligible for depreciation allowances on rental properties further reducing the tax burden. These provisions effectively lower the after-tax cost of owning and maintaining a rental unit, thus encouraging households to expand their buy-to-let portfolios against traditional fixed-income assets like bonds.

There is growing evidence supporting this mechanism. Boddin et al. (2024) show, using the German Panel on Household Finances (PHF)[27] that affluent and church-affiliated households in Germany rebalanced their portfolios towards buy-to-let investments during periods of QE. Similarly, Berg et al. (2023) find that QE prompted real estate managers and hedge funds to increase their holdings of residential housing. While these studies focus specifically on QE, it is reasonable to assume that the same logic extends to other tools such as FG and interest rate adjustments. In the entire 2009–2019 period, expansionary monetary policy and moderate borrowing rates coexisted with a tax environment supportive of rental property ownership.

[27] The PHF is a panel survey conducted by the German Bundesbank that examines household finance and wealth in Germany. It encompasses details about the balance sheet, pensions, income, work life, and other demographic characteristics of private households residing in Germany.

8 Conclusions

In this paper, we establish how changes in monetary policy tools affect regional property prices and rents within a large European economy characterised by a liquid rental sector and historically stable house prices. Exploiting an online dataset of 35 million real estate listings for both houses and apartments over a 16 year horizon, we demonstrate that expansionary monetary policy measures both conventional rate cuts and unconventional interventions such as FG and QE generate significant but differentiated effects on property prices and rents.

We summarise our findings into three key results. First, expansionary monetary policy systematically raise house prices and rents, but persistence and magnitude of the impact vary by instrument. While short-term interest rate cuts induce only transitory effects, FG and, in particular, QE produce more sustained and pronounced house price growth over the medium term. Second, although rents also respond positively to policy easing, these effects are smaller and less persistent than for house prices. Third, we find limited evidence that monetary policy exacerbates regional dispersion significantly in either house prices or rents. Instead, policies appear to propagate relatively uniformly across regions, regardless of differences in supply constraints, local demographics, or wage structures. While local construction activity and rent regulations influence the amplitude of transmission to some extent, these channels could not explain much of the increase in house prices and rents over this period.

Our analysis shed some light on the way expansionary monetary policy propagates into house prices and rents, through a reduction in mortgage financing costs and changes in housing tenure. One the one hand, more favourable financing conditions increase the demand for (better) housing. On the other hand, the reduced incentives for existing homeowners to move or to sell and become renters dampens the turnover of properties and constrains the supply of new listings, further reinforcing price pressure. Meanwhile, on the rental side, demand for rent rises especially as higher incomes encourage rent-to-rent upgrades and overall listing dynamics are less constrained. Our micro-level evidence thus highlights that the number and type of tenure transitions are instrumental in shaping how monetary policy shocks transmit through the housing market. A rich quantitative model to quantify the magnitude and general equilibrium effects could be beneficial but is left for future research.

From a policy perspective, these findings carry important implications for housing affordability and financial stability. Central banks need to recognise that unconventional measures, while beneficial in stimulating aggregate demand, have consequences for housing markets that might be stronger than intended. Not only do they significantly raise house prices, but they may also have sizable, more persistent effects on rental markets, which predominantly consist of young and borrowing-constrained households, increasing the gap between property-owners and renters.

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Online Appendix

A Institutional Setting Germany

This section provides key facts about homeownership rates and the ownership of the housing stock in Germany. Due to the absence of reliable data or a centralised registry of residential buildings, the analysis relies on information derived from the census surveys conducted in 2011 and 2022.

A.1 Homeonwership Rates in Germany

Table A.1 illustrates the homeownership landscape in Germany based on the 2011 and 2022 Censuses. By 2022, the total number of dwellings had grown to approximately 43.11 million, marking an increase of 2.56 million units since 2011. Owner-occupied residences saw a modest rise from 17,292,029 (42.60%) in 2011 to 17,824,355 (41.36%) in 2022. In contrast, rental properties expanded significantly from 21,199,913 units (52.35%) to 23,059,310 units (53.46%). The predominant growth in rental units is likely attributable to population increases driven by substantial immigration following the Syrian civil war and the Russo-Ukrainian conflict.

Table A.1: Housing Status in 2011 and 2022

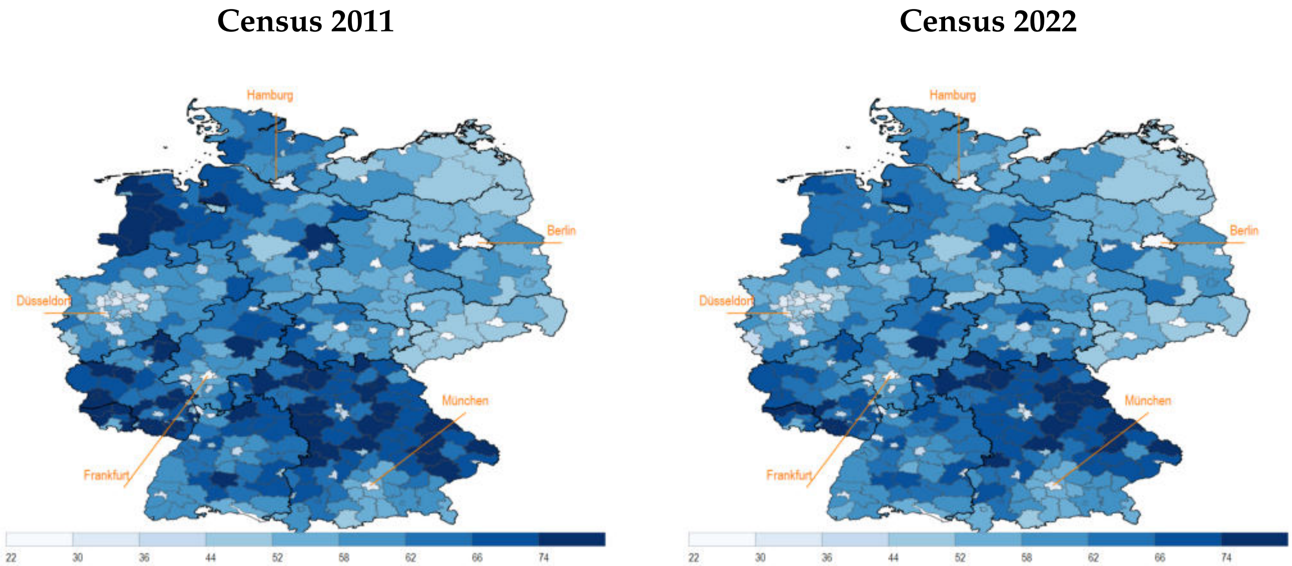
Row		2011		2022		Δ	
		Number	**%**	**Number**	**%**	**Number**	**%**
1	**Owner-occupied**	17,292,029	42.60	17,824,355	41.36	532,326	3.08
2	**Rented out**	21,199,913	52.35	23,059,310	53.46	1,859,397	8.77
3	**Holiday dwelling**	224,529	0.55	297,939	0.69	73,410	32.69
4	**Vacant**	1,828,846	4.51	1,924,985	4.47	96,139	5.26
	Total	40,545,317	100.00	43,106,589	100.00	2,561,272	6.32

Figure A.1 presents the regional variation in homeownership rates across Germany. Our analysis relies on data from the 2011 Census,[28] where we exclude holiday/leisure and vacant dwellings from the total count. The homeownership rate is then calculated by taking the ratio of owner-occupied dwellings to the adjusted total number of dwellings.[29]

[28] The data source can be accessed at Zensus 2011.

[29] As noted in subsection B.4, regional boundaries have changed since 2011. To ensure consistency throughout the paper, we mapped the 2011 census boundaries to the 2021 boundaries, as detailed in Table B.4. For districts

Figure A.1: Homeonwership in Germany according to Census 2011 and 2022



Note: The figure visualises the spatial variation in homeownership rates across Germany's Kreis (regions) using Census 2011 and 2022 data. The number in brackets indicates the number of regions in each category. Darker red tones indicate higher homeownership rates.

A.2 Composition of Regional Housing Stock

In this subsection, we draw on publicly available data from the 2011 and 2022 Census to illuminate the composition and ownership structure of the German housing stock. According to the 2022 Census, there were approximately 19.4 million residential buildings and 43.1 million dwellings recorded. Compared to the 2011 Census, this represents an increase of roughly one million additional buildings and 2.5 million additional dwellings.

As shown in Table A.2, private individuals and commonhold owners[30] own the vast majority of residential dwellings while other forms of ownership, including cooperatives, municipal companies, and federal or state bodies, account for relatively smaller shares. This distribution highlights the predominance of private ownership in the German housing landscape.

that have merged since 2011, we calculated the homeownership rate by taking the unweighted average across the merged regions.

[30]Commonhold ownership refers to shared ownership structures in multi-unit buildings, such as condominiums or apartment blocks, where owners share responsibility for common areas while owning their units outright.

Table A.2: Dwellings ownership distribution in 2011 and 2022.

Row	Ownership Category	2011		2022		Δ	
		Number	%	Number	%	Number	%
1	Commonhold owners	8,956,419	22.1	9,277,939	21.5	321,520	3.59
2	Private individual(s)	23,728,698	58.5	24,926,768	57.8	1,198,070	5.05
3	Housing co-operative	2,086,453	5.1	2,175,781	5.0	89,328	4.28
4	Municipal housing company	2,294,246	5.7	2,679,282	6.2	385,036	16.79
5	Private sector housing company	2,183,196	5.4	2,728,586	6.3	545,390	24.96
6	Other private sector company	681,420	1.7	768,228	1.8	86,808	12.74
7	Federation or State	298,337	0.7	185,490	0.4	-112,847	-37.84
8	Non-profit organisation	316,539	0.8	364,511	0.8	47,972	15.15
	Total	40,545,308	100	43,106,589	100	2,561,281	6.32

Data Source: Census 2011 and Census 2022 conducted in Germany: The data are freely accesible at https:/ergebnisse.zensus2022.de/datenbank/online/variables

B Immobilienscout24 Data

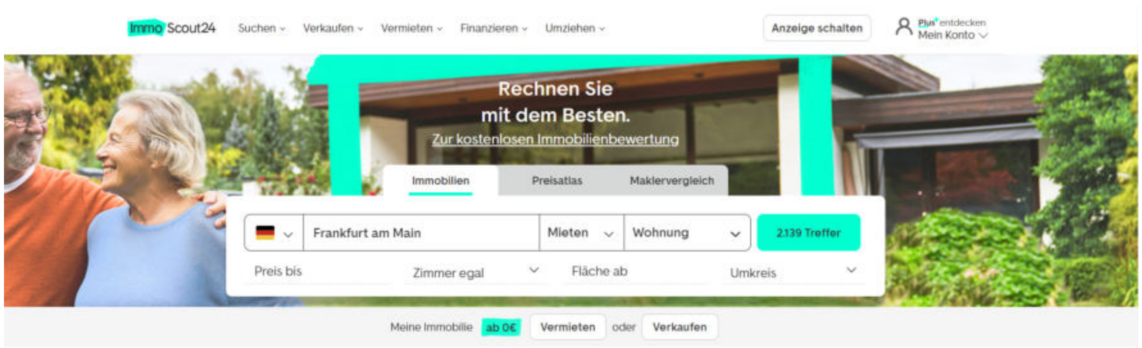
In this section of the Appendix, we provide comprehensive details about our housing listings dataset. Appendix B.1 offers an overview of the Immobilienscout24 online platform, while Appendix B.2 delves into the inferred user attributes of Immobilienscout24 visitors. The data cleaning procedures are thoroughly discussed in Appendix B.3, and location adjustments are detailed in Appendix B.4. Appendix B.6 provides an in-depth discussion of the variables used in the hedonic regression analysis. Finally, Appendix B.7 compares the levels and time trends of aggregate Immobilienscout24 listings with alternative transaction-based datasets.

B.1 Background

Immobilienscout24 stands as the leading online platform for real estate listings in Germany, serving a wide range of users including real estate providers, property owners, tenants, and buyers. The platform operates across three countries—Germany, Austria, and Spain—and together with its mobile app, it draws in roughly 41 million visitors each month.

The platform is accessible online at https://www.immobilienscout24.de. When users land on the German-language website, they encounter an interface similar to the one shown in Figure B.2. The site guides users to select their country, input the location of their search (whether by city, address, or postal code), choose the transaction type (buy or rent), and specify the type of property (house, apartment, or other options).

Figure B.2: Immobilienscout24 web portal



Moreover, the platform provides a variety of filtering tools, enabling users to narrow down their search by specifying property features beyond just location. Users can define their budget by setting minimum and maximum price limits, and they also have the option to indicate the number of rooms they are looking for.

B.2 User Demographic Characteristics

To better understand the demographic profile of ImmobilienScout24 users, we rely on data from a traffic snapshot provided by Similarweb.[31] According to Similarweb, 96% of ImmobilienScout24.de's users are based in Germany, with approximately 62.56% identifying as male. The age distribution is as follows: 16.81% are aged 18–24, 25.31% are 25–34, 18.08% are 35–44, 17.91% are 45–54, 12.27% are 55–64, and 9.62% are 65 and older. This analysis is publicly accessible at the following link: https://www.similarweb.com/website/immobilienscout24.de/#demographics. Unfortunately, the free version of Similarweb does not provide direct evidence on regional market variations or historical market share trends.

B.3 Cleaning Details

In this section we present the details of our cleaning approach that results in our final dataset. Table B.3 provides the summary of the procedure outlined in detail in the text below.

Repeated entries The raw dataset has numerous repeated entries stemming from two reasons. The first reason is that it merges snapshots of data taken on various dates. The first set of data was retrieved in November 2015, and since then, updates have occurred roughly every 6 months. As a result, active listings during the initial retrieval reappear as duplicates in

[31]Similarweb Ltd. is a global company specializing in software development and data aggregation, with a focus on web analytics, traffic, and performance analysis.

Table B.3: Data Cleaning Procedure Summary

	Sales		Rents	
	Houses	Apartments	Houses	Apartments
Raw Data	16,348,047	9,901,472	1,414,458	24,290,761
Duplicates				
(-) Repeated entries	11,326,849	7,148,366	1,070,648	17,634,142
Filtering				
(-) missing prices/rents	11,294,826	7,133,422	1,069,399	17,631,100
(-) missing post-codes	-	-	-	-
(-) living area $< 20\ m^2$	-	7,112,422	-	17,523,530
(-) living area $< 35\ m^2$	11,251,695	-	1,064,523	-
(-) properties without rooms	11,180,575	7,099,643	1,063,662	17,518,833
(-) castles	11,178,213	-	1,063,399	-
(-) sale price per m^2 >€20000	11,175,157	7,097,478	-	-
(-) sale price per m^2 <€150	11,092,320	7,076,158	-	-
(-) rental price per m^2 >€45	-	-	1,063,304	17,513,846
(-) rental price per m^2 <€2.5	-	-	1,057,479	17,482,766
(-) more than 8 rooms	-	7,064,816	-	17,479,623
(-) more than 15 rooms	10,919,720	-	1,056,531	-
(-) clicks above 99th percentile	10,812,329	6,994,760	1,046,074	17,136,394
Censoring				
(-) districts with < 10 in m/y				
Final Dataset	17,807,089		18,182,468	

subsequent retrievals. The second reason relates to the fact that certain properties are advertised multiple times within a six month time-frame. To address this issue we only retain the most recent instances of properties, effectively keeping the last occurrence or "spell" of each property in the dataset.[32] After applying this filter, our dataset contains 11,326,849 houses for sale, 7,148,366 apartments for sale, 17,634,142 apartments for rent and 1,070,648 houses for rent. The fact that around 50% of the listings are for rentals reflect the low home-ownership rates in Germany documented in Section 2.

Filtering We drop for the sample properties with missing sale and rent price, post-code or size of the property that has been characterised by RWI as implausible value. Then, we exclude ultra-luxurious properties with a sale price of more than €6,000,000 or a (cold) rental price that exceeds €6,000 per month. We also exclude under-market value properties that might indicate an attempt of the seller to manipulate the Immobilienscout24 algorithm in her favour. We erase all dwellings with asked sale price less than €10,000 or rental price less than

[32] If a property was advertised two or more times in spells longer than 6 months apart or if its characteristics have been substantially revised, i.e., refurbished or modernised, it is treated as a separate entry.

€130. Finally, we censor the price of the property per m^2 for each class (apartment for rent, apartment for sale, house for rent, house for sale). Houses and apartments for sale are censored between €150 and €20,000 per m^2 and rental units between €2.5 and €45 per m^2. The living area is restricted between 25 and 400 square metres for apartments and between 45 and 800 square metres for houses. On top, we omit flats with more than 8 rooms and houses with more than 15 rooms. To ensure that our results are not driven from any remaining outliers (or scams) we trimmed properties at the top 1% in terms of contacts by property type separately for the sale and rental marker.

Censoring Immobilinescout24 is the dominant real estate platform in Germany with wide geographical coverage. Nonetheless some areas are sparsely populated with less active sales and/or rental markets. In order to have a continuous time series with sufficient number of observations for each month and location we drop all districts with less than 10 listings per month for each tenure (= sale or rent). Our clean dataset contains 17,807,089 (18,182,468) units for sale (rent) across 397 (364) districts in Germany.[33] Lastly, we deflate the nominal values using the state specific CPI at the monthly frequency.[34]

B.4 Regional Mapping

The RWI Essen classify the regions according to the Amtlicher Gemeindeschlüssel (AGS).[35] Changes to the AGS occurred over time due to administrative reforms or boundary adjustments, reflecting updates in the municipal structure. In this section we, summarise the changes occurred over the 2007-2021 horizon.

[33]In 2011, several districts underwent mergers or name changes, and we consistently utilise the most recent names throughout the paper. For instance, in 2011 the districts of *Nordvorpommern* and *Südvorpommern* were renamed to *Vorpommern-Rügen* and *Vorpommern-Greifswald*, respectively. In addition, the district *Soltau-Fallingbostel* changed its name to Heidekreis and the newly established *Ludwigslust-Parchim* district is now part of the *Schwerin* district. The table B.4 in the Appendix shows the mapping from 2011 into the new administrative districts.

[34]We normalise the Consumer Price Index to 100 across all states in 2007:01. The data are publicly available and obtained through the Federal Statistical Office database.

[35]The Amtlicher Gemeindeschlüssel (AGS) is an 8-digit code used to uniquely identify German municipalities. It reflects the federal state, district, and specific municipality, and is essential for administrative and statistical purposes.

Table B.4: District mapping - Old Identifiers to New Identifiers

Kreis old name	Old Identifier	Kreis new name	New Identifier
Stendal (until 30.06.2007)	15363	Stendal	15090
Aue-Schwarzenberg (until 31.07.2008)	14191	Erzgebirgskreis	14521
Leipziger Land (until 31.07.2008)	14379	Leipzig	14729
Meißen (until 31.07.2008)	14280	Meißen	14627
Zwickau (until 31.07.2008)	14167	Zwickau	14524
Aachen (until 20.10.2009)	05313	Städteregion Aachen	05334
Aachen (until 20.10.2009)	05354	Städteregion Aachen	05334
Bad Doberan (until 03.09.2011)	13051	Landkreis Rostock	13072
Demmin (until 03.09.2011)	13052	Mecklenburgische Seenplatte	13071
Greifswald (until 03.09.2011)	13001	Vorpommern-Greifswald	13075
Güstrow (until 03.09.2011)	13053	Landkreis Rostock	13072
Ludwigslust (until 03.09.2011)	13054	Ludwigslust-Parchim	13076
Mecklenburg-Strelitz (until 03.09.2011)	13055	Mecklenburgische Seenplatte	13071
Müritz (until 03.09.2011)	13056	Mecklenburgische Seenplatte	13071
Neubrandenburg (until 03.09.2011)	13002	Mecklenburgische Seenplatte	13071
Nordvorpommern (until 03.09.2011)	13057	Vorpommern-Rügen	13073
Nordwestmecklenburg (until 03.09.2011)	13058	Nordwestmecklenburg	13074
Ostvorpommern (until 03.09.2011)	13059	Vorpommern-Greifswald	13075
Parchim (until 03.09.2011)	13060	Ludwigslust-Parchim	13076
Rügen (until 03.09.2011)	13061	Vorpommern-Rügen	13073
Stralsund (until 03.09.2011)	13005	Vorpommern-Rügen	13073
Uecker-Randow (until 03.09.2011)	13062	Vorpommern-Greifswald	13075
Wismar (until 03.09.2011)	13006	Nordwestmecklenburg	13074
Osterode am Harz (until 31.10.2016)	03156	Göttingen	03159
Göttingen (before 2016)	03152	Göttingen	03159

B.5 ImmobilienScout Variables

Table B.5: ImmobilienScout24 list of housing characteristics

Category	Variables	
Identifier	Unique object ID	
Time period	1. Beginning of ad (year)	
	2. Beginning of ad (month)	
	3. End of ad (year)	
	4. End of ad (month)	
Object features	5. Elevator in object	22. Number of rooms
	6. Facilities of object	23. Number of floors
	7. Number of bathrooms	24. Construction phase
	8. Balcony at object	25. Assisted living for elderly
	9. Protected historic building	26. Granny flat in object
	10. Kitchenette in object	27. Public housing
	11. Floor in which object is located	28. Type of real estate
	12. Usable as holiday home	29. Rented when sold
	13. Available from	30. Rental income per month in euros
	14. Guest toilet in object	31. Number of ancillary rooms
	15. (Shared) garden available	32. Accessible, no steps
	16. Pets allowed	33. Number of bedrooms
	17. House type	34. Living area
	18. Flat type	35. Plot area
	19. Cellar in object	36. Usable floor space
	20. Common charge for community	37. Garage/parking space available
	21. association (in euros/month)	
Energy structure information	38. Year that object was built	43. Heating costs
	39. Type of energy performance certificates	44.Type of heating
	40. Energy efficiency rating	45. Year of last modernisation of object
	41. Energy consumption per year/sq.m.	46. Condition of object
	42.Warm water consumption included	
	in energy consumption	
Price information	47. Brokerage at contract conclusion	51. Inclusive rent in euros
	48.Heating costs covered by inclusive rent	52. Utilities in euros
	49. Purchasing price in euros	53. Price of parking space in euros
	50. Security deposit	
Regional information	54.German state	57. Municipality Identifier (AGS, 2015)
	55. $1km^2$ raster cell following INSPIRE	58. Postcode of address
	56. Local labour market	59. District identifier (AGS, 2015)
	(Kosfeld and Werner, 2012)	
Meta-information of ad	60. Number of clicks on customer profile	65. Number of hits of ad
	61. Number of clicks on contact button	66. Days of availability of ad
	62. Number of clicks on customer URL	67. Date of data retrieval
	63. Number of clicks on share button	68. Spell counter within object identifier
	64. Number of hits of ad	

B.5.1 Variation of Key Variables 2007-2023

Table B.6: Mean- Sales (2007-2023)

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023*
Duration			59.19	56.99	53.18	52.30	44.15	42.48	45.45	48.05	44.55	48.98	36.51				
Ln Real Price	12.07	12.06	11.97	12.02	11.98	12.02	12.05	12.06	12.14	12.13	12.15	12.24	12.31	12.40	12.49	12.55	12.52
Contacts			1.80	2.55	2.66	2.75	2.87	4.20	4.47	4.90	5.21	6.20	2.46				
Con/lis Day			0.06	0.11	0.14	0.15	0.18	0.32	0.40	0.41	0.42	0.48	1.16				
Real Price (m^2)	1,719	1,665	1,585	1,619	1,593	1,658	1,747	1,837	1,933	1,934	1,967	2,160	2,300	2,539	2,803	2,815	2,667
Rooms	4.56	4.66	4.51	4.61	4.69	4.69	4.68	4.60	4.63	4.62	4.68	4.66	4.69	4.62	4.59	4.68	4.69
Listings (sum)	1,292	1,355	1,337	1,277	1,272	1,282	1,297	1,298	1,174	930	908	804	784	736	587	864	529

Notes: **Duration** denotes the average number of days a listing remains on the platform before its removal. **Ln Real Price** is the average of all inflation-adjusted property prices (in natural logarithm). **Contacts** represents the average number of contact requests (e.g., emails) that sellers receive for a given listing. **Con/lis Day** (contacts per listing-day) is the average contact attempts per day. **Real Price (m^2)** is the inflation-adjusted price per square meter. **Rooms** indicates the mean number of rooms listed per property. **Listings** captures the annual number of valid listings after cleaning in thousands, as detailed in Section B.3. The period 2023* includes data up to June 2023.

Table B.7: Median - Sales (2007-2023)

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023*
Duration			30.00	29.00	26.00	25.00	20.00	17.00	21.00	23.00	22.00	27.00	20.00				
Ln Real Rent	12.10	12.09	12.05	12.08	12.03	12.06	12.09	12.12	12.21	12.00	12.24	12.31	12.37	12.45	12.55	12.60	12.57
Contacts			0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	0.00				
Con/lis Day			0.00	0.00	0.00	0.00	0.00	0.03	0.02	0.00	0.02	0.04	0.14				
Real Price (m^2)	1,586	1,514	1,433	1,455	1,410	1434	1,494	1,551	1,619	1,650	1,665	1,833	1,942	2,158	2,387	2,463	2,366
Rooms	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
Listings (sum)	1,292	1,355	1,337	1,277	1,272	1,282	1,297	1,298	1,174	930	908	804	784	736	587	864	529

Notes: **Duration** denotes the median number of days a listing remains on the platform before its removal. **Ln Real Price** is the median of all inflation-adjusted property prices (in natural logarithm). **Contacts** represents the median number of contact requests (e.g., emails) that sellers receive for a given listing. **Con/lis Day** (contacts per listing-day) is the median of the ratio of *Contacts* to the daily availability of the listing on the platform. **Real Price (m^2)** is the median of the inflation-adjusted sale price per square meter. **Rooms** indicates the median number of rooms listed per property. **Listings** captures the annual number of valid listings after cleaning in thousands. The period 2023* includes data up to June 2023.

Table B.8: Mean - Rents (2007-2023)

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023*
Duration			36.86	33.71	31.81	30.92	28.17	27.01	26.70	23.28	26.21	28.38	24.95				
Ln Real Rent	6.05	6.03	6.07	6.06	6.07	6.07	6.12	6.12	6.11	6.13	6.16	6.19	6.20	6.23	6.25	6.24	6.23
Contacts			6.13	6.47	7.73	8.24	9.02	11.56	15.68	20.31	27.08	29.96	11.99				
Con/lis Day			0.54	0.65	0.99	1.11	1.38	1.77	2.75	4.17	5.20	5.39	7.56				
Real Rent (m^2)	6.28	6.23	6.45	6.45	6.46	6.49	6.69	6.79	6.87	7.05	7.43	7.73	7.94	8.35	8.64	8.30	8.24
Rooms	2,86	2,83	2.82	2.82	2.83	2.83	2.85	2.84	2.78	2.73	2.75	2.75	2.73	2.71	2.65	2.71	2.71
Listings (sum)	1,341	1,251	1,335	1,446	1,369	1,400	1,403	1,381	1,072	920	801	744	836	910	867	776	392

Notes: **Duration** denotes the average number of days a listing remains on the platform before its removal. **Ln Real Rent** is the average of all inflation-adjusted property rents (in natural logarithm). **Contacts** represents the average number of contact requests (e.g., emails) that sellers receive for a given listing. **Con/lis Day** (contacts per listing-day) is the average contact attempts per day. **Real Rent (m^2)** is the inflation-adjusted rent per square meter. **Rooms** indicates the mean number of rooms listed per property. **Listings** captures the annual number of valid listings after cleaning in thousands, as detailed in Section B.3. The period 2023* includes data up to June 2023.

Table B.9: Median - Rents (2007-2023)

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023*
Duration			19.00	17.00	15.00	15.00	14.00	13.00	13.00	11.00	13.00	15.00	13.00				
Ln Real Rent	5.98	5.95	6.00	6.01	6.01	6.01	6.07	6.07	6.04	6.00	6.09	6.14	6.15	6.21	6.24	6.24	6.22
Contacts			2.00	2.00	2.00	2.00	2.00	4.00	5.00	8.00	11.00	14.00	1.00				
Con/lis Day			0.07	0.08	0.09	0.09	0.11	0.21	0.32	1.00	0.75	0.85	1.38				
Real Rent (m^2)	5.72	5.66	5.84	5.85	5.89	5.91	6.11	6.16	6.17	6.00	6.59	6.87	7.00	7.41	7.76	7.48	7.30
Rooms	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Listings (sum)	1,341	1,251	1,335	1,446	1,369	1,400	1,403	1,381	1,072	920	801	744	836	910	867	776	392

Notes: **Duration** denotes the median number of days a listing remains on the platform before its removal. **Ln Real Rent** is the median of all inflation-adjusted property rents (in natural logarithm). **Contacts** represents the median number of contact requests (e.g., emails) that sellers receive for a given listing. **Con/lis Day** (contacts per listing-day) is the median of the ratio of *Contacts* to the daily availability of the listing on the platform. **Real Rent (m^2)** is the median of the inflation-adjusted rent per square meter. **Rooms** indicates the median number of rooms listed per property. **Listings** captures the annual number of valid listings after cleaning in thousands, as detailed in Section B.3. The period 2023* includes data up to June 2023.

B.6 Hedonic Regression - Details

In this section, we provide a detailed explanation of the hedonic regression framework used to construct regional sales and rent indices for representative housing units, as introduced in Section 3.4. The primary objective of our analysis is to eliminate variations in property prices and rents attributable to observable quality characteristics. This approach allows us to derive sales and rent indices that are independent of individual property attributes

Our dataset comprises listings in which sellers provide information through a structured questionnaire. The questionnaire mandates the inclusion of specific fields: the property address, the listed price or rent, and the living space (*Wohnfläche*). Additionally, sellers may voluntarily disclose further attributes of the property, often supplemented by photographs. These supplementary attributes include a range of categorical variables, such as the presence of amenities like guest toilets or cellars. Table B.5 provides the complete list of all offered amenities in our sample.

In our hedonic regression, we aim to include as many amenities as possible. However, the voluntary nature of many questionnaire items and users' reluctance to respond to certain questions result in a significant number of missing entries. To address this challenge, we follow Klick and Schaffner (2021) by incorporating "missing dummy" variables for each categorical attribute with incomplete entries. Specifically, when landlords omit responses to binary questions (e.g., whether the property includes a guest toilet or a cellar), we interpret the missing entries as indicating the absence of these features. This inference is based on the assumption that landlords are more likely to leave such fields blank when the answer is straightforwardly negative, thereby implicitly conveying the non-existence of the queried attribute.

We add in the hedonic regression the following variables:

- **Property Size:** We use the variable *wohnflaeche* that denotes the living space in terms of m^2. This variable is mandatory and observed in all instances.
- **Number of Rooms:** We retained properties with 1 to 15 rooms and apartments with 1 to 8 rooms. In Germany, room counts exclude kitchens, bathrooms, and corridors. Some "zimmeranzahl" entries include half rooms—rooms between 6 and 10 square metres as per the outdated but still-used DIN 283 norm—resulting in non-integer values. We rounded these up to the nearest integer and created 14 dummy variables for properties with more than one room. (excluding properties with 1 room)
- **Age of the Property:** Approximately 20% of properties lack a reported or valid construction year; we treat these as missing and create an indicator variable. A small frac-

tion lists the construction year as before 1000, which we also consider missing. For the remaining properties, we calculate age by subtracting the construction year from the listing year and create dummy variables in 5-year intervals. Properties listed before construction are assigned to a separate dummy category.

- **Type of Property:** We categorise properties into 22 distinct types, treating missing values as separate category. The categories are: (1) Not specified house, (2) Single-family house (detached), (3) Semi-detached house, (4) Terraced house, (5) Terraced house (middle unit), (6) Terraced house (end unit), (7) Bungalow, (8) Farmhouse, (9) Mansion, (10) Block of flats, (11) Other property for living, (12) Special property, (13) Attic flat, (14) Flat, (15) Raised ground floor flat, (16) Maisonette, (17) Penthouse, (18) Souterrain, (19) Flat with terrace, (20) Other flat, (21) Not specified apartment, and (22) Two-family house.

- **Cellar:** A dummy variable that takes the value of 1 indicating that the seller has answered yes in the questionnaire, otherwise is 0.

- **Guest toilet:** A dummy variable that takes the value of 1 indicating that the seller has answered yes in the questionnaire, otherwise is 0.

- **Postal Codes:** We exclude all properties with missing postal codes and include a full set of dummy variables for each postal code area.

- **Property Condition:** We categorised properties based on their condition into 11 distinct categories: (1) Not specified, (2) First occupancy, (3) First occupancy after reconstruction, (4) Like new, (5) Reconstructed, (6) Modernized, (7) Completely renovated, (8) Well kept, (9) Needs renovation, (10). We included these condition categories as dummy variables in our analysis.

- **Rented When Sold:** Only applicable for the sales regression. In Germany, it is common for properties to be sold with tenants in place, transferring the rental contract to the new owner. We assign a dummy variable to properties sold under these conditions.

- **Additional User Costs:** Only applicable for the rents regression. We included "Nebenkosten" as an additional explanatory variable. This variable represents all supplementary expenses payable to landlords beyond the base rent. For cases where additional costs were not reported, we assigned a value of zero.

Not all variable characteristics are available or relevant in certain districts. For example, smaller rural regions predominantly feature single-family houses, limiting the variety of property types available for sale or rent. However, this does not pose a threat for our hedonic regression design.

B.7 Comparison with Transaction Prices at Different Market Segments

A limitation of our dataset is the lack of transaction prices and information about whether a listing resulted in an actual sale or rent. This gap raises concerns that a fraction of listed prices could significantly differ from the final transaction prices, potentially introducing bias into our results. To understand the extent and sign of this bias, we compare our dataset with a transaction-based dataset from an alternative source.

German Real Estate Index (GREIX) A recent study by Amaral et al. (2023) compiles and disseminates quarterly transaction-level real estate data for 18 cities in West Germany. The raw micro-data are collected from historical notarial archives and are then processed and aggregated at the city level across market segments (apartment, single-family houses and multi-family houses). For more information about the data and access visit this link GREIX project.

We use the transaction-based aggregate data from the project to directly compare it with our listings data. Specifically, we retrieve the average nominal price per square metre from inflation-unadjusted data, separately for apartments and single-family houses. We chose inflation-unadjusted data to avoid any bias arising from our different measures used to deflate the series. Additionally, we exclude multi-family houses from our analysis due to the challenges in reconciling this market segment with the multi-family units in our dataset.

Next, we use our raw Immobilienscout24 listings data and apply the same cleaning procedure as Amaral et al. (2023). The goal is to make the two datasets comparable and limit any discrepancy that might arise due to the fact that our cleaning process is more elaborated and restrictive. The process is the following:

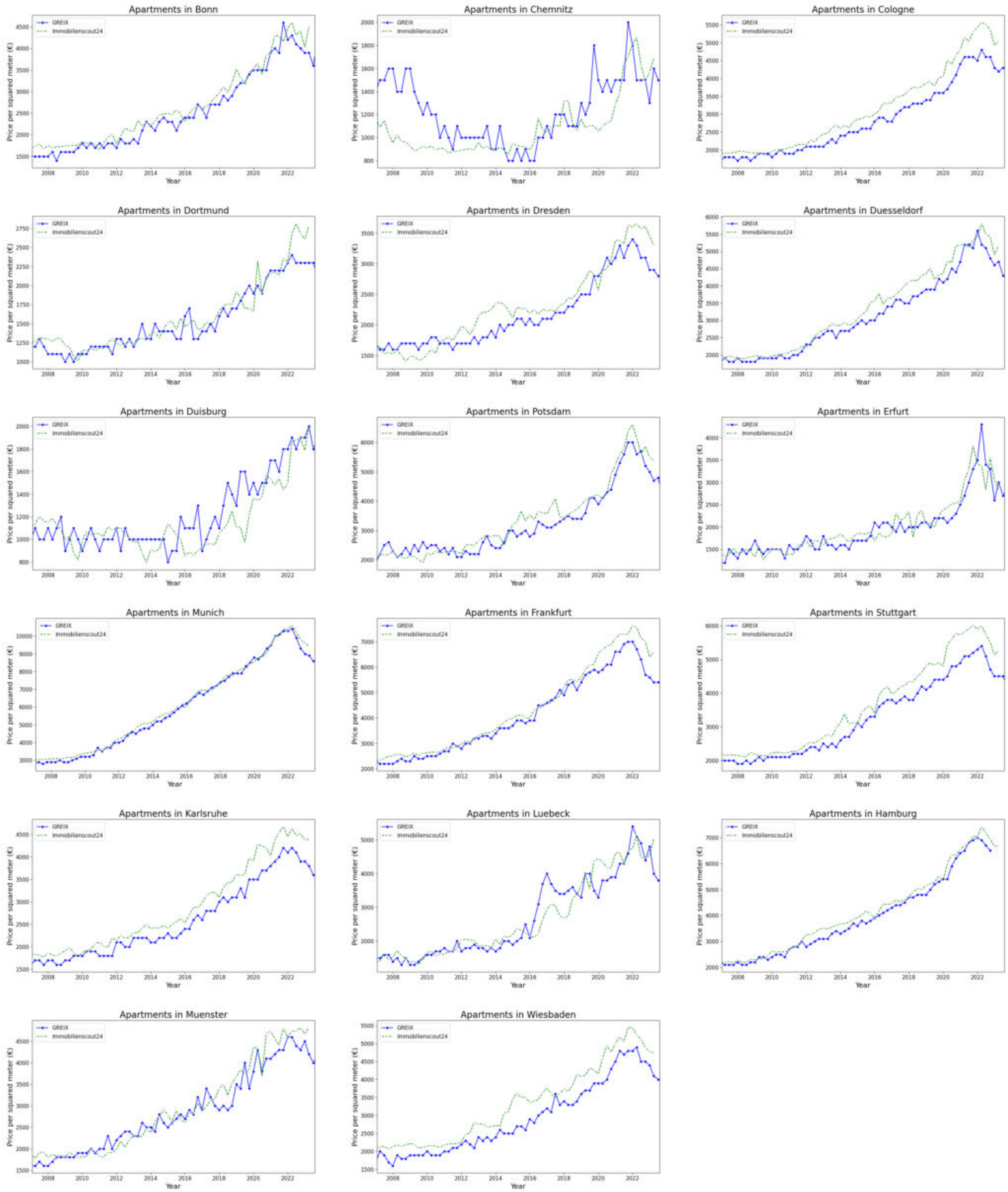
Apartments We use only the raw file "WK_SUF" that contains all apartments for sale in Immobilienscout24. Following closely the documentation of Amaral et al. (2023), we first remove the listings that contain missing prices or living area for each year. Properties already listed on the market but with construction date three years or longer in the future are excluded. Additionally, we apply windsorization to the data by removing outliers. Specifically those outside the 99th and 1st percentiles for purchase price, and living area. We also remove duplicate entries using apartment IDs, keeping only the last listed record with identical price and features within a close time frame. Lastly, any repeated entries for the same property within a short period that show price discrepancies are also removed.

Single family houses The procedure for single family houses is more involved. We use the raw file "HK_SUF" that contains all listed houses for sale. We use the variable "kategorie_Haus"" (house type) to identify the housing segment. We keep all the house types with entries a) Single-family house (detached), b) Single-family house, and c) Semi-detached house. We also include the missing entries in in the single family houses "kategorie_Haus" as the vast majority of the missing entries (9%) should belong in this category.[36] As in apartments, we remove the listings that contain missing prices or living area. Properties already listed on the market but with construction date three years or longer in the future are excluded. We remove entries with missing prices, living area or plot area. Additionally, we apply windsorization to the data by removing outliers specifically those outside the 99th and 1st percentiles for purchase price, and living area for each year. We also remove duplicate entries using apartment IDs, keeping only the last listed record with identical price and features within a close time frame. Lastly, any repeated entries for the same property within a short period that show price discrepancies are also removed.

Figures B.3 and B.4 plot the evolution of the apartments' price per squared metre computed from the listings data vis-a-vis the transaction data for all cities where data are available. While there are some deviations, the trends and patterns are broadly similar. Figure F.10 replicates the IRF of monetary policy shocks on apartment prices from Section 6 at the quarterly frequency and shows that the responses of transaction prices to a Shadow Rate reduction are not significantly different to the responses of listing prices.

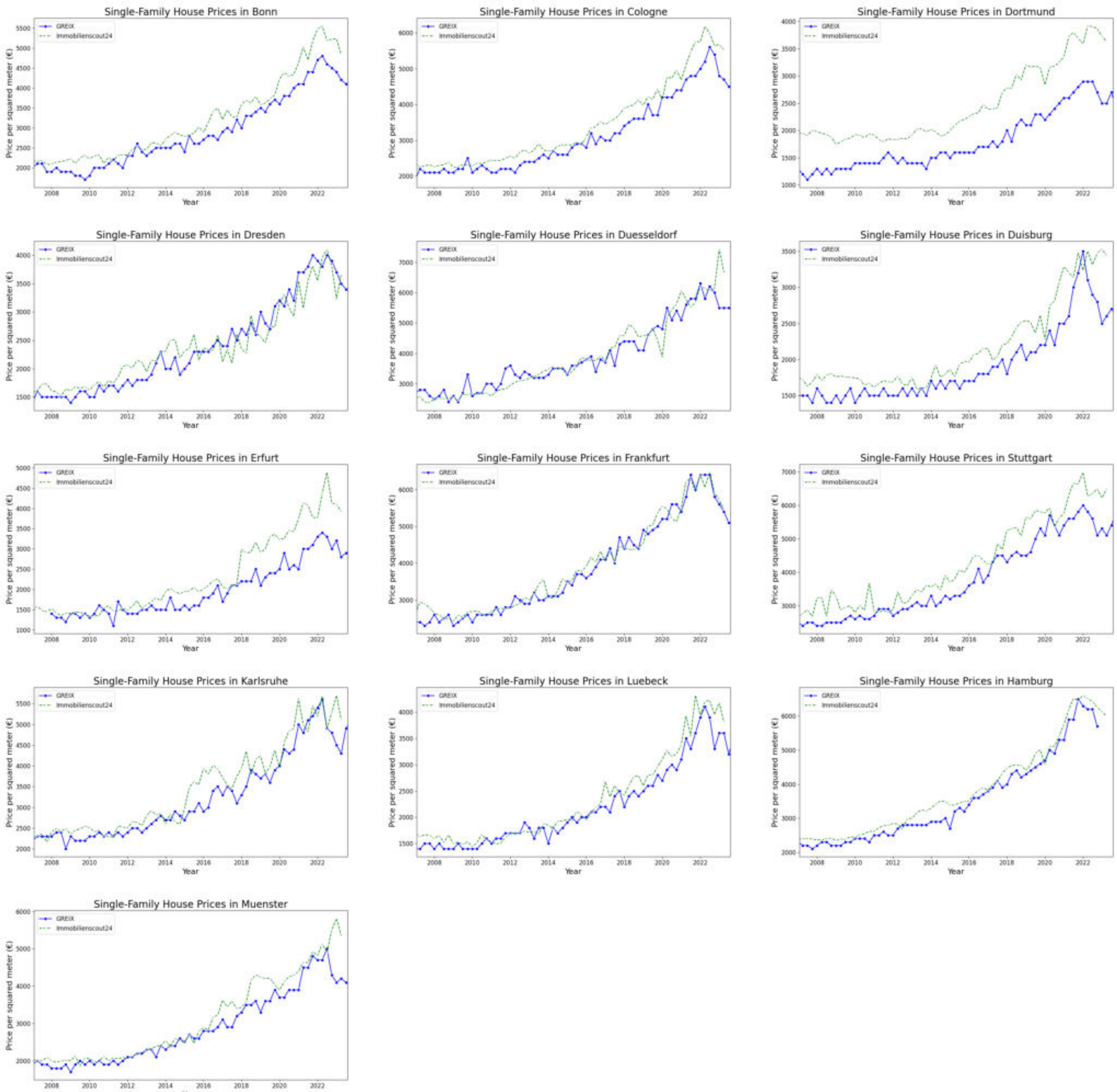
[36] We also replicate our analysis excluding missing entries and the final results appear almost identical

Figure B.3: Apartment Sales Price - Transactions vs Listings



Notes: Each panel plots the evolution of average listing prices from ImmobilienScout24 (green line) against transaction-based GREIX data (blue line) for apartments in the indicated city. All series are nominal (unadjusted for inflation). See Appendix B.7 for details on data sources, cleaning, and comparability.

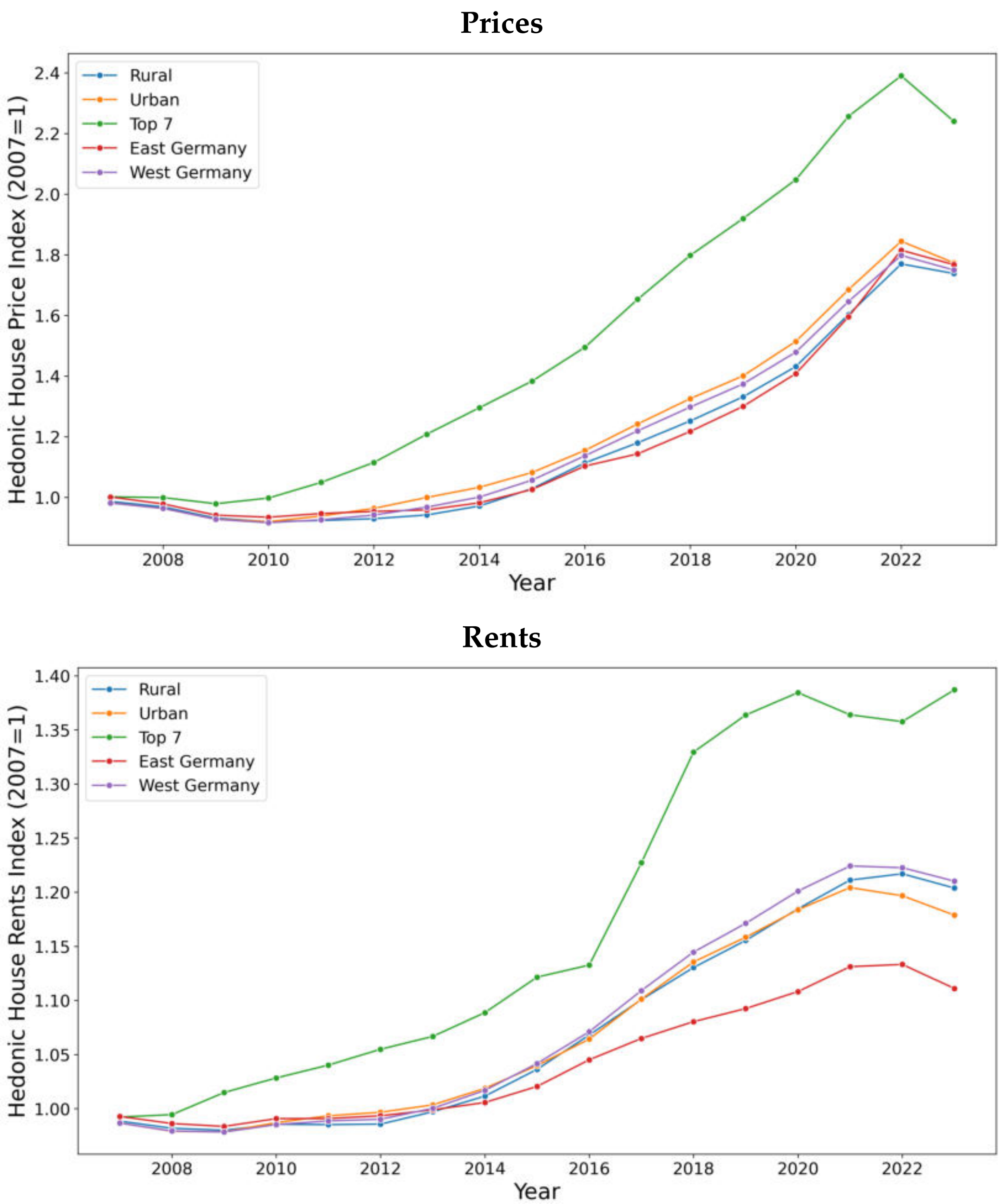
Figure B.4: Single Family house Sales Price - Transactions vs Listings



Notes: Each panel plots the evolution of average listing prices from ImmobilienScout24 (green line) against transaction-based GREIX data (blue line) for single-family houses in the indicated city. All series are nominal (unadjusted for inflation). See Appendix B.7 for details on data sources, cleaning, and comparability.

C Evolution of Hedonic House Prices and Rents Indices

Figure C.5: House Price and Rent Growth Across Geographical Segments



Notes: The charts depict the cumulative growth rates of prices (top) and rents (bottom) across various geographical areas for the period 2007–2023. All the time series have been smoothed using a 12-month moving average to facilitate comparisons. The “Top 7” refers to the districts of Berlin, Frankfurt am Main, Munich, Stuttgart, Dusseldorf, Hamburg, and Cologne, which are major metropolitan hubs in Germany. “Urban areas” include all districts classified as city states, while “rural areas” encompass all Landkreise (rural districts). Additionally, the analysis acknowledges the historical division between East and West Germany, prior to reunification.

D Data sources

In this section of the appendix, we provide details on additional data that we use in the empirical exercise. Table D.10 summarises the variables and the sources that are discussed in this section. Data on the house prices and rents are separately discussed in Appendix B.

Table D.10: Variable description

Variable	Aggregation	Description	Source
House price index	Kreis	Time-fixed effects of Kreis-specific hedonic regressions based on real listing prices from Immobilienscout24, seasonal adjusted	RWI-GEO-RED
Rent index	Kreis	Time-fixed effects of Kreis-specific hedonic regressions based on real rents, seasonal adjusted	RWI-GEO-RED
GREIX	Kreis	German Real Estate index based on transaction data of 18 German cities, quarterly	greix.de
Contacts/day	Kreis	Time-fixed effects of Kreis-specific hedonic regressions based on the number of clicks on contact button adjusted by ad availability, seasonal adjusted (2009-2019)	RWI-GEO-RED
Listings	Kreis	Number of posted real estate ads per month and Kreis, seasonal adjusted	RWI-GEO-RED
Urban	Kreis	Indicator if region is urban, rural or intermediate according to NUTS classification	Eurostat
Home ownership	Kreis	Share of households owning the housing they are living in (owner vs tenants)	Destatis
Land unavailability	Kreis	Share of Kreis unavailable for residential housing due to water, mining, wetland, settlements or traffic (in 2006)	IOER
Rental Break	Kreis	Indicator if Mietpreisbremse is in place in at least one municipality	Refrago.de
New construction	Kreis	Share of listings advertising housing that is less than one year old	RWI-GEO-RED
Floorspace	Kreis	Average usable floor space advertised	RWI-GEO-RED
Unemployment rate	Kreis	Unemployed workers as share of population, seasonal adjusted	Bundesagentur für Arbeit
Cumulative population growth	Kreis	Population growth between 2007 and 2023, quarterly data monthly interpolated	Destatis
Young population	Kreis	Share of people between 25 and 30 years old	Destatis
Wage	Kreis	Average real gross wage, (2007-2019)	SIAB

East Germany	Kreis	Indicator if region is in East Germany (area of the former German Democratic Republic + Berlin)	
CPI	Country	German Consumer Price Index, base month = 2007:01	Destatis
Policy Rate	Country	ECB Main Refinancing Rate (flexible and fixed)	ECB Data Warehouse
OIS rates	Country	Overnight Index Swap rates, maturities 1 month to 10 ten years	Refinitiv
Balance Sheet	Country	ECB Balance sheet volume	ECB Data Warehouse
Shadow Rate	Country	Euro Area Shadow Rate as constructed by Krippner (2013)	ljkmfa.com
10 year mortgage rate	Country	10-year mortgage interest rate, Germany	ECB Data Warehouse
S&P 500	Country	S&P 500 stock market index, 3 month growth rate	ECB Data Warehouse
Commodity price	Country	ECB Commodity Price Index, 3 month growth rate	ECB Data Warehouse
DAX	Country	DAX, German stock market index, 3 month growth rate	Bundesbank
Yield curve	Country	Difference between the 10-year and 2-year German bond yields, 3 month change	Bundesbank
Population growth	Country	Registered population, 3 month growth rate	Destatis
Change tenure	Household	Indicator variable, change in housing tenure (renter-to-owner or owner-to-renter) in the last year	SOEP
Change housing	Household	Indicator variable, change in housing without tenure change (renter-to-renter or owner-to-owner) in the last year	SOEP
Age	Household	Age of the household representative	SOEP
Employment status	Household	Employment status of the household's reference person	SOEP
Education	Household	Years of education of the household's reference person	SOEP
Migration	Household	Indicator variable of migration background of the household's reference person	SOEP
Gender	Household	Indicator variable of the gender of the household's reference person	SOEP
HH size	Household	Number of people living in the household	SOEP
Income	Household	Overall household income	SOEP
Bundesland	Household	Federal state in which the household is located	SOEP

Note: If not specified, variables have monthly frequency and span the period January 2007 to June 2023. SOEP variables are available at a quarterly frequency until 2022:Q4.

E Monetary Policy Shock Series - Details

Throughout this paper we follow the approach by Altavilla et al. (2019) to derive high frequency monetary policy shock series based on the Euro Area Monetary Policy Event-Study Database. The series are constructed by measuring the reaction of several financial variables at different maturities around a tight window of 2.5 hours capturing the ECB's press release and the press conference after a monetary policy decision. The reasonable identification assumption is that new information arriving within the narrow window does not influence the monetary policy decision and thus allows for an exogenous interpretation of the shocks. Although our housing data only covers the period 2007-2023, we use information of all Governing Council meetings since the introduction of the euro to derive the exogenous shocks.[37]

The monetary policy surprises are derived from the Principal Components Analysis (PCA) of the intraday movements in Overnight Index Swap (OIS) rates with maturities ranging from one month to ten years.[38] The PCA identifies three relevant factors to describe the ECB's monetary policy. These factors do not have a direct interpretation, however, as it is shown by Swanson (2021) that by applying an orthogonal rotation this allows for an interpretable distinction without changing the information. With these rotations is possible to interpret these three orthogonal factors as "Target Rate" shock, "Forward Guidance" shock and "QE" shock. Thereby, we not only create exogenous monetary policy shocks but also disentangle the effects of conventional and unconventional monetary policies. The surprises are normalised so that a Target Rate shock has unit effect on the 1-month OIS rate, the FG shock has a unit effect on the 2-year OIS rate and the QE shock has a unit effect on the 10-year OIS rate. The loadings of the shocks on different maturities are depicted in Figures E.6a-E.6c. Notice that the series account for the possibility of information effects included in the shocks (Jarociński and Karadi, 2020). Specifically, the the "poor man's sign restriction" is applied to nullify the effects in all policy meetings in which the information effect dominates the monetary policy effect.[39]

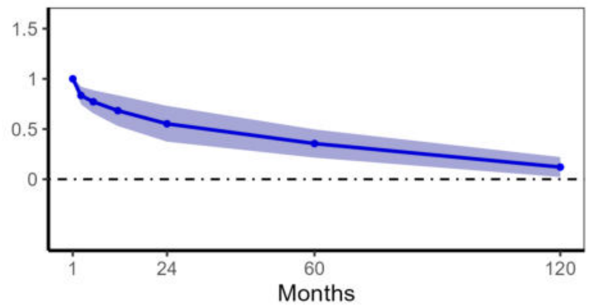
Table E.11 presents the impact of aggregated monetary policy surprises, as measured by Al-

[37]Following Altavilla et al. (2019) we drop the observations of 9-2001, 10-2008, 11-2008 and 4-2009 due to the financial market turbulence and uncertainty after the terrorist attack of 9/11 and the Lehman bankruptcy that might blur actual monetary policy effects. For similar reasons, we also remove the observations 11-2011 (first Governing Council of Mario Draghi), 3-2020 (start of the Covid pandemic) and 3-2022 (Russian attack on Ukraine).

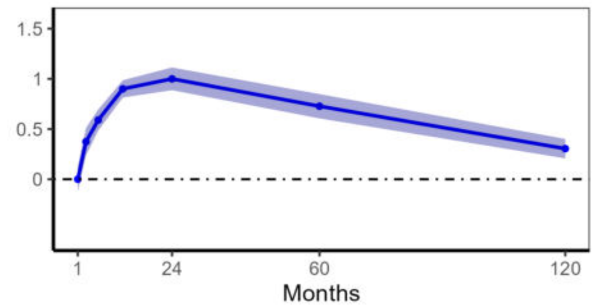
[38]For maturities beyond one year prior to August 2011, intraday OIS data were unavailable, so German government bond yields data were used instead.

[39]We decided against using the shock series provided by Jarociński and Karadi (2020) since they use the 3-month EONIA swap changes as shocks. As we want to compare the different policy tools and focus on a period where policy rates were little moving, it is not surprising that this shock series is not a strong instrument to the Shadow Rates by Krippner (2013) or balance sheet changes.

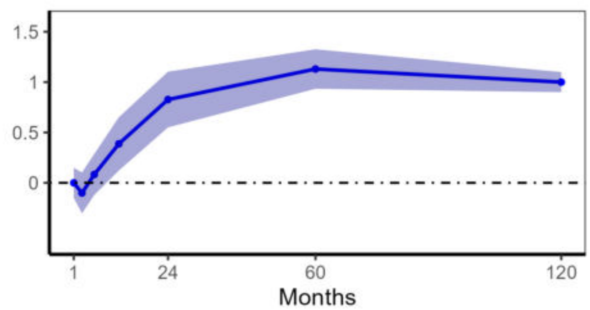
Figure E.6: Factor loadings - Monetary policy shocks



(a) Factor loadings - Target Rate



(b) Factor loadings - FG



(c) Factor loadings - QE

Note: The plots represent the factor loadings of the first three factors of the PCA over different maturities (1 month to 10 years), rotated and scaled to the one-month OIS rate (Target Rate), two-year OIS rate (FG) and ten-year OIS rate (QE). The shaded areas represent 95% confidence intervals. Source: own calculations based on the EA-MPD

tavilla et al. (2019), on monthly financial assets during the announcement month. The event-study regressions are specified as

$$y_t = \alpha + \beta \text{policy}_t + \varepsilon_t,$$

where t indexes monetary policy announcements, y_t represents the financial asset of interest, and policy_t denotes the measure of the monetary policy surprise. The sample period spans from January 2007 to June 2023. Variations in the number of observations across different columns are due to data availability in the earlier part of the sample period.

Table E.11: High frequency shocks - Financial market responses

	(1) OIS 1M	(2) OIS 6M	(3) OIS 2Y	(4) OIS 5Y	(5) OIS 10Y	(6) DE 2Y	(7) DE 10Y	(8) STOXX50	(9) EUR-USD
Target Rate	0.990***	0.917***	0.682***	0.461***	0.157**	0.703***	0.183**	-0.148***	0.0393**
	(19.34)	(11.31)	(6.24)	(5.09)	(2.09)	(6.41)	(2.20)	(-5.82)	(2.54)
Forward	0.0153	0.585***	0.930***	0.642***	0.219**	1.003***	0.234***	-0.0367**	0.0260**
	(0.45)	(10.93)	(12.89)	(6.16)	(2.52)	(13.87)	(4.26)	(-2.18)	(2.54)
QE	0.00179	0.191**	0.879***	1.191***	1.048***	0.984***	1.131***	-0.0621***	0.116***
	(0.04)	(2.56)	(8.73)	(13.88)	(14.68)	(9.75)	(14.77)	(-2.65)	(8.16)
Constant	0.108	0.0244	-0.209	-0.155	-0.0684	-0.132	0.0262	-0.130**	-0.0630*
	(0.99)	(0.14)	(-0.89)	(-0.72)	(-0.38)	(-0.57)	(0.15)	(-2.39)	(-1.90)
R2	0.711	0.630	0.672	0.715	0.693	0.706	0.633	0.244	0.367
N	158	158	158	104	105	158	158	158	158

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

F IRF - Robustness Exercises

This section presents several robustness exercises to verify the validity of the baseline results in Section 6.

Excluding COVID-19 period Figure F.7 reports the responses of house prices and rents to expansionary monetary policy shocks for a sample ending before the COVID-19 pandemic (2007:01–2019:12). While the pandemic period was associated with high uncertainty and unusual policy measures that could blur the identification of monetary shocks, our results remain similar in magnitude. The rent response is somewhat larger and more persistent, but does not exceed 1%.

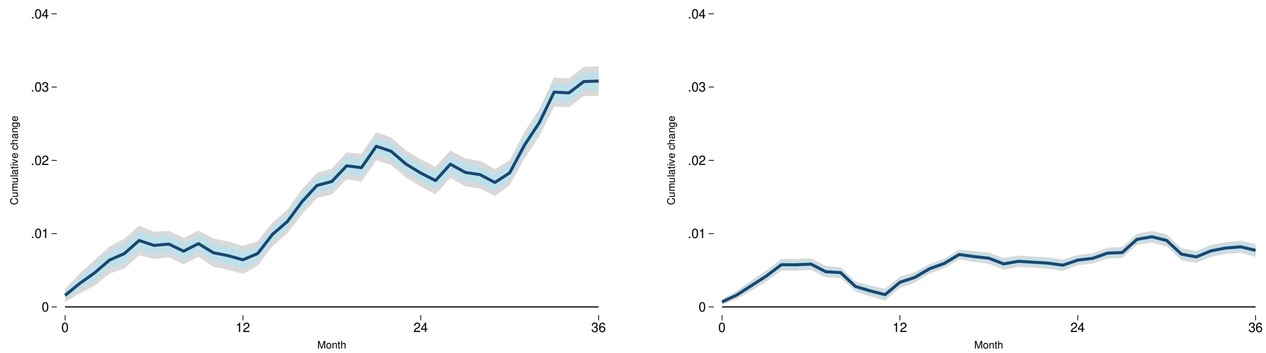
Finer Geographical Aggregation: Municipality Next, we assess whether the baseline estimates depend on the regional level of aggregation. Figure F.8 shows the impulse responses (IRFs) when using municipality-level data instead of county-level data. We chose the district level for our main specification to accommodate both the segmentation of regional housing markets and the availability of sufficient listings in less populous regions (which is more difficult at the municipality level). As the municipality-level IRFs are close to the baseline, the choice of aggregation does not appear to affect the results.

Minimum Listings Threshold To check whether sparsely populated regions with few listings bias the results, we vary the threshold for the minimum number of monthly listings per district from 10 to 5 or 20. Figure F.9 indicates that although this modifies the number of districts in the sample, the IRFs remain unchanged.

Comparison with Transaction Data We also consider whether our listing-based data yield

Figure F.7: House price and rent responses - Pre-Covid pandemic

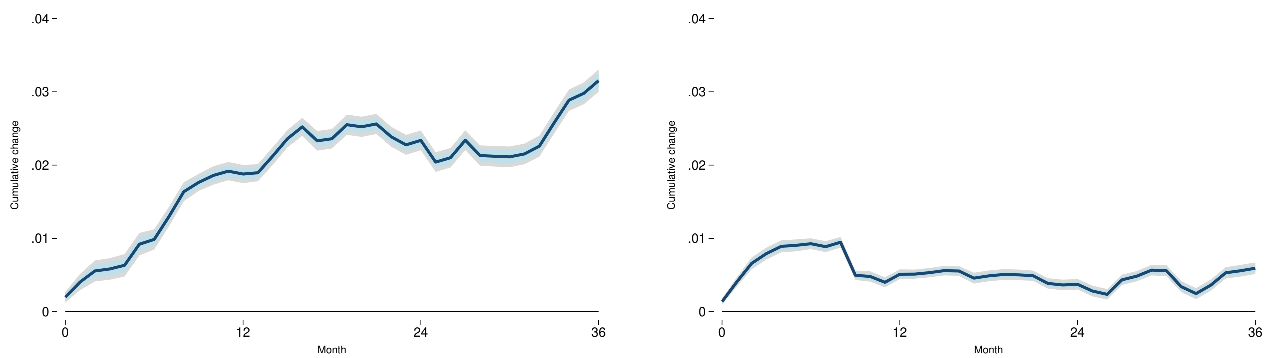
(a) House prices (β^h) (b) Rents (β^h)



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.24 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2007 to December 2019. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using cluster robust standard errors.

Figure F.8: House price and rent responses - Municipality level

(a) House prices (β^h) (b) Rents (β^h)



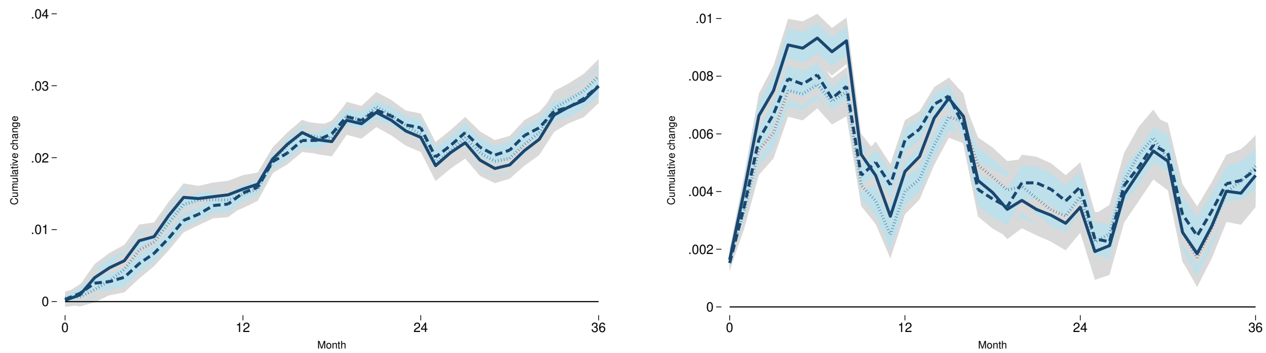
Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.24 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2007 to June 2023. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using cluster robust standard errors.

systematically different estimates from transaction-based data captured by the GREIX indices (Amaral et al., 2023), which are available for only 18 cities at a quarterly frequency. After harmonizing our sample accordingly, we find in Figure F.10 that the estimated responses remain positive and lie within the baseline confidence bands.

Adding Policy Tools as controls In Figure F.11, we explore whether including all three monetary policy instruments and their associated high-frequency instruments simultaneously changes the results. If anything, the differences become more pronounced: (i) QE exhibits

Figure F.9: House price and rent responses - observation threshold

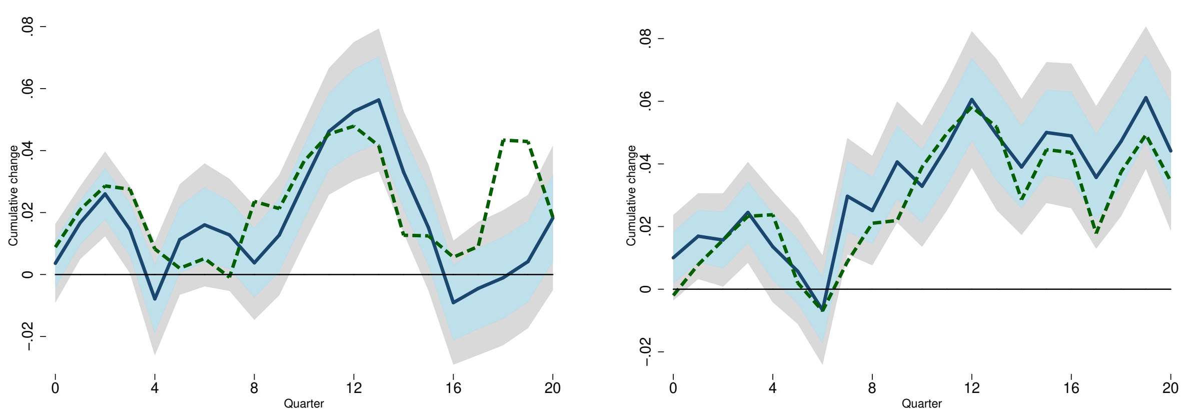
(a) House prices (β^h) (b) Rents (β^h)



Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price and rent indices to a 1 SD (0.24 pp) reduction in the Shadow Rate. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06. The graph depicts cluster robust standard errors. Kreis (district) included in sample if: minimum 5 observations per Kreis-month = solid line, min. 10 observations per Kreis-month (baseline) = dashed line, min. 20 observations per Kreis-month = dotted line.

Figure F.10: Shadow Rate responses - Transactions vs Listings

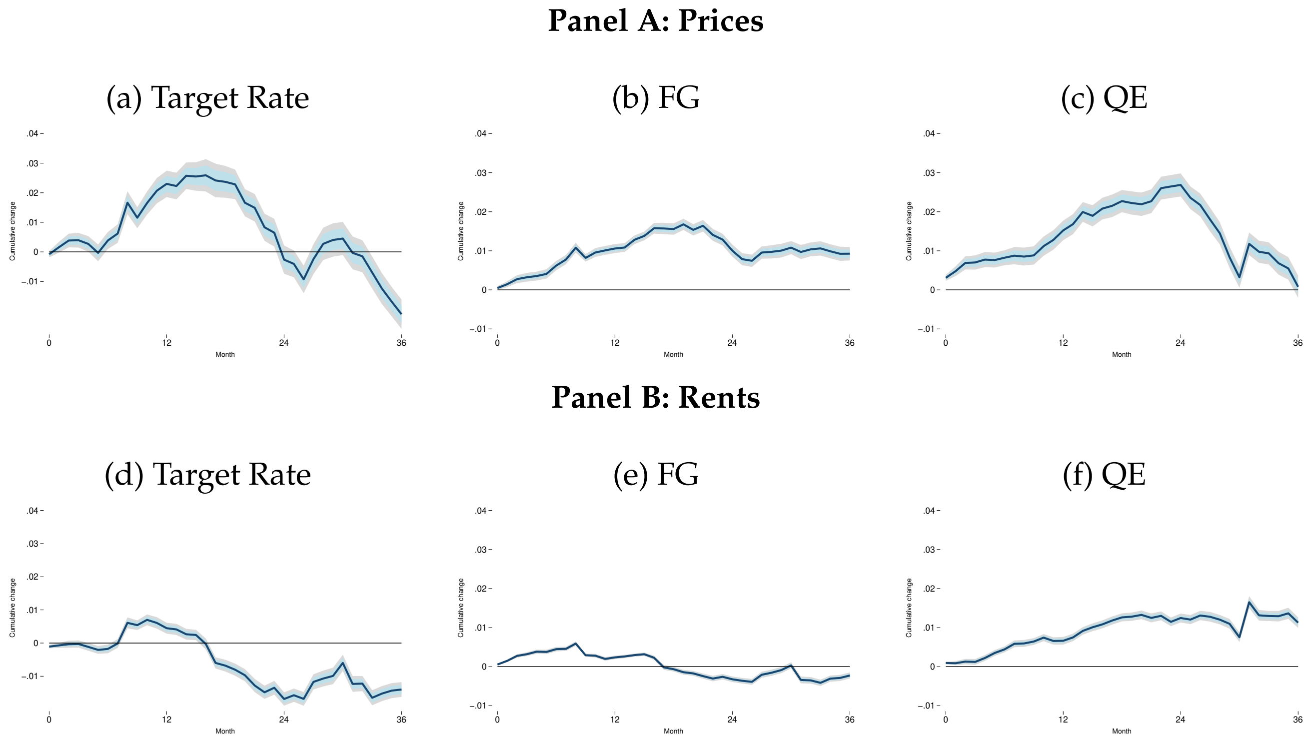
Apartments **Single Family Houses**



Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price indices based on transaction (green) and listing data (blue) to a 1 SD (0.45 pp) reduction in the Shadow Rate. Impulse responses are at the quarterly frequency using data from 2007-Q1 to 2022-Q4. Confidence intervals are based robust standard errors.

the strongest impact on house prices, (ii) short-term rate changes have a weaker but still significant effect, and (iii) FG is somewhat in between. For rents, QE again has the strongest impact, while short-term interest rate changes generate a small negative response and FG remains close to zero. We do not rely on this fully specified model as our preferred specification, however, because the decomposition of policy tools is less clear when all exogenous

Figure F.11: House price and rent responses - Direct policy comparison



Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price indices to a 1 SD (0.16 pp) reduction in the 1-month OIS rate, a 1 SD (0.2 pp) reduction in the 2-year OIS rate, and a 1 SD (117 billion €) expansion of the ECB's balance sheet - all included in the same regression. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06. Confidence intervals are based on cluster robust standard errors.

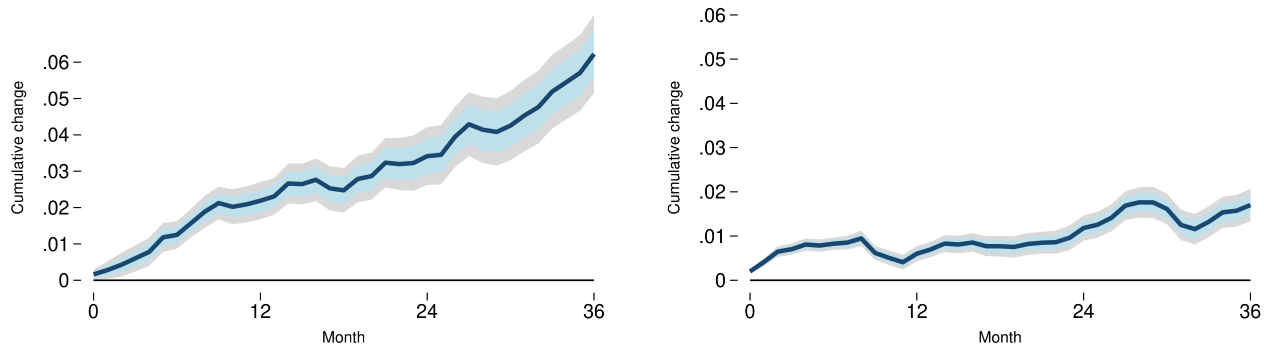
instruments overlap, especially during the pre-QE period.

Controlling for Additional Confounding factors Although high-frequency monetary policy shocks are currently the state-of-the-art approach for identifying exogenous variation in monetary policy, there are remaining concerns regarding confounding factors. Following Gorea et al. (2022) and Bauer and Swanson (2023), we therefore add several potential controls: the 3-month growth rates of the S&P 500, the DAXX, the ECB's commodity price index, and state population[40], as well as the 3-month change in the German yield curve. These are included alongside our regional unemployment rate and German CPI inflation. As seen in Figure F.12, controlling for these additional variables slightly increases the estimated effects on house prices and rents, but does not alter them qualitatively. The most noticeable difference is that the rent response becomes more persistent—bringing the estimates for the Shadow Rate closer to the effects of unconventional monetary policies.

[40] State-level population data are reported quarterly so we linearly interpolate them to a monthly frequency.

Figure F.12: House price and rent responses - additional controls

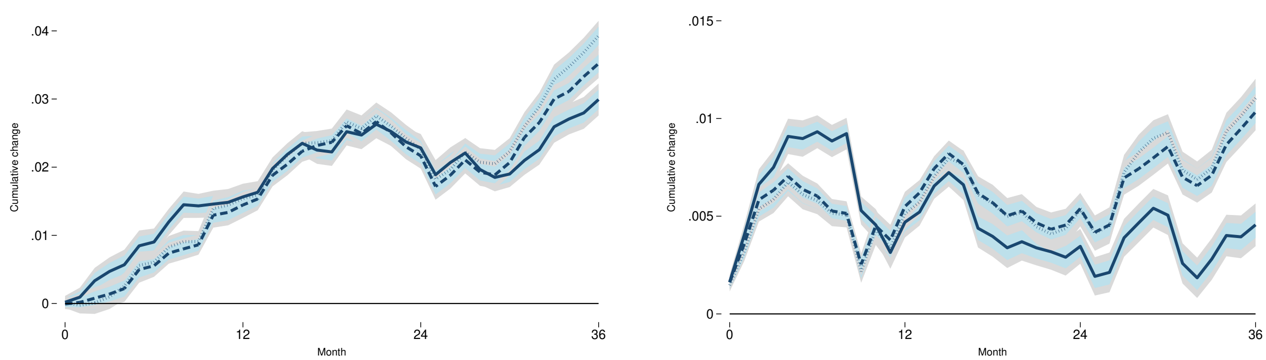
(a) House prices (β^h) (b) Rents (β^h)



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.24 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2007 to June 2023 and controlled for additional (financial) control variables. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using Conley (1999, 2008) standard errors.

Figure F.13: House price and rent responses - lag variation

House prices **Rents**



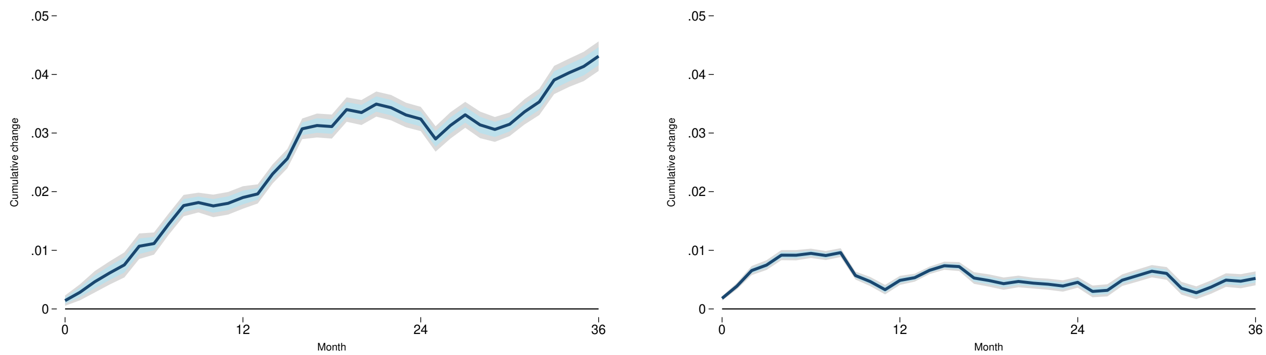
Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price and rent indices to a 1 SD (0.24 pp) reduction in the Shadow Rate. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06. Cluster robust standard errors. 3 lags of house price/rent growth = solid line, 6 lags = dashed line, 12 lags = dotted line

Lag Structure Lastly, our results are also robust to changes in the lag structure. Using 3 or 12 lags instead of 6 does not lead to meaningful changes in the IRFs. Figure F.13 illustrates that these alternative lag lengths produce very similar impulse responses.

Without fixed effects The inclusion of fixed effects and lagged dependent variables introduces a bias in the estimates when the time dimension of the panel data set is short Nickell (1981). With 198 months of observations, this bias should be negligible as it tends to zero as the number of months increases. Nevertheless, we show the IRFs when we remove the

Figure F.14: House price and rent responses - without Fixed Effects

(a) House prices (β^h) (b) Rents (β^h)



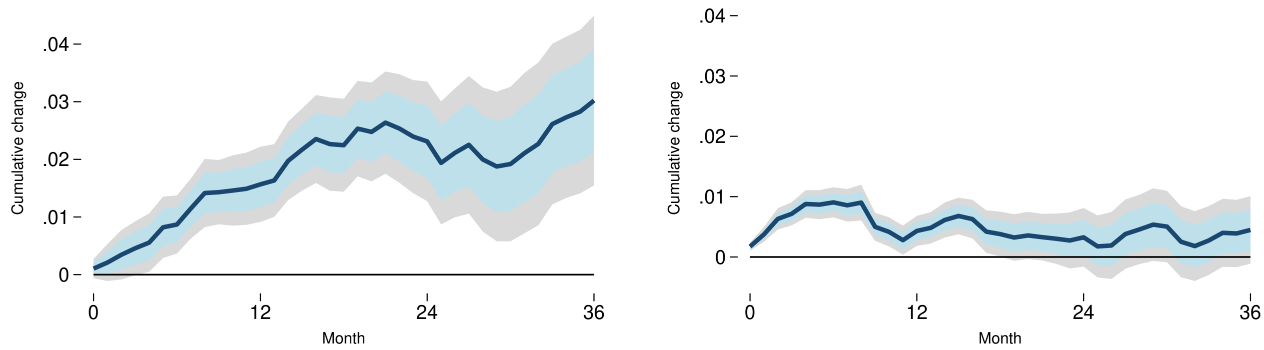
Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.24 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2007 to June 2023, without district fixed effects. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using cluster robust standard errors.

district fixed effects to avoid the Nickell bias (but allow for potential omitted variable bias) in Figure F.14. The results are very similar to our baseline, only slightly larger for the house price responses.

Larger commuting zone Finally, we check the sensitivity of our results to the assumptions made for the derivation of the Conley standard errors. Figure F.15 shows the confidence bands when we consider all districts up to 200km away from the center of each district to allow for larger commuting zones and hence, more conservative inference. Although the confidence bands become wider, our conclusions are still the same and based on statistically significant estimates.

Figure F.15: House price and rent responses - larger SE cluster

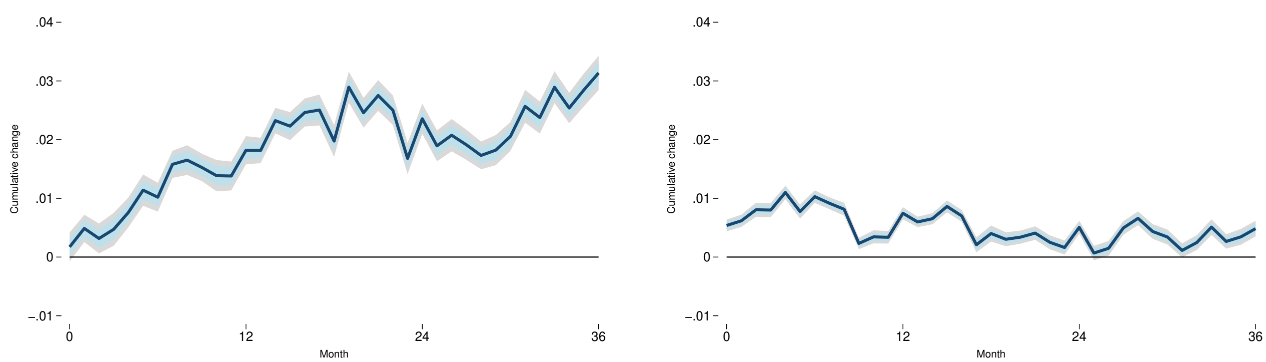
(a) House prices (β^h) (b) Rents (β^h)



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.24 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2007 to June 2023, without district fixed effects. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using Conley (1999, 2008) standard errors, with a distance cutoff of 200km.

Figure F.16: House price and rent responses - without smoothing

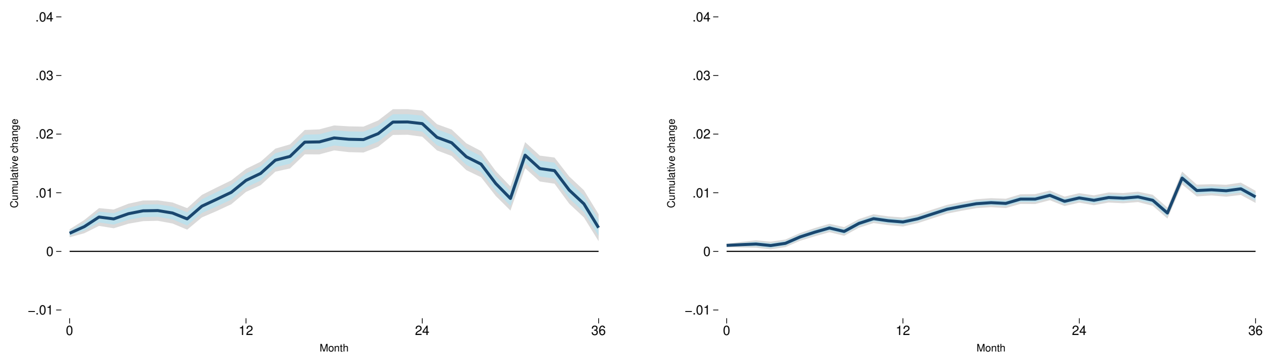
(a) House prices (β^h) (b) Rents (β^h)



Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price and rent indices to a 1 SD (0.24 pp) reduction in the Shadow Rate. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06. The graph depicts cluster robust standard errors.

Figure F.17: House price and rent responses - QE shock after 2009

(a) House prices (β^h) (b) Rents (β^h)



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (117 billion €) expansion of the ECB's balance sheet. The QE shocks are set to zero before 2009:05. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using cluster robust standard errors.

G Conely Standard Errors Details

Conley Standard Errors are a method used to account for spatial or serial correlation in econometric models, particularly in situations where traditional assumptions about error independence across observations are violated. This technique is especially relevant for datasets with a geographical or time-based structure, where disturbances may exhibit spatial or temporal dependence. Descriptive statistics show that regional house prices and rents are correlated across time and regions. Hence, close districts and months in the previous quarter might also influence the error structure, so that we estimate a so-called Spatial Error Model (SEM) by applying Conley (1999, 2008) Standard Errors.

Conley's approach has several relevant features ideal for analysing spatial data, like the application of a distance decay function. Thereby, it assumes that correlations between errors decay with distance. Observations closer to each other (spatially or temporally) are expected to be more strongly correlated than those farther apart. Conley standard errors also include a cutoff distance, so that correlations only up to a certain maximum distance or time lag are considered. Beyond this window, correlations are assumed negligible. Finally, Conley standard errors also incorporate robustness to heteroskedasticity, i.e., they adjust for cases where error variance is not constant across observations.

Analytically, suppose $u_i u_j$ represents the error term for observation i, and errors u_i, u_j are correlated if i and j are close in space or time. The covariance matrix of the errors, Σ, is estimated using:

$$\Sigma_{ij} = K\left(\frac{d(i,j)}{\lambda}\right) \cdot \hat{u}_i \hat{u}_j \tag{8}$$

with $d(i,j)$ being the distance between observations i and j (spatial or temporal). λ is the bandwidth parameter determining the range of influence and K is the kernel function specifying the decay of correlation with distance. The covariance matrix is then used to compute corrected standard errors.

Table G.12: First Stage F-Statistic - House prices and Rents

	12 months	24 months	36 months
Shadow Rates	150.3	131.8	124.9
Policy Rate	100.4	104.8	106.0
2y OIS Rate	497.1	972.1	962.0
Balance Sheet	89.3	89.7	95.2

Note: This table shows the Kleinbergen-Paap rk F-Statistics for different policy tool - instrument combinations across different horizons for the house price regressions: 1m OIS Rate - Target Rate shocks, 2y OIS Rate - FG shocks, Balance Sheet - QE shocks and QE announcement dummies, Shadow Rates - Target Rate, FG and QE shocks

	12 months	24 months	36 months
Shadow Rates	141.1	123.7	117.8
Policy Rate	95.8	99.1	99.9
2y OIS Rate	469.1	923.4	914.1
Balance Sheet	87.2	87.3	91.8

Note: This table shows the Kleinbergen-Paap rk F-Statistics for different policy tool - instrument combinations across different horizons for the rent regressions: 1m OIS rate - Target Rate shocks, 2y OIS Rate - FG shocks, Balance Sheet - QE shocks and QE announcement dummies, Shadow Rates - Target Rate, FG and QE shocks

Table G.13: Lead-lag exogeneity test

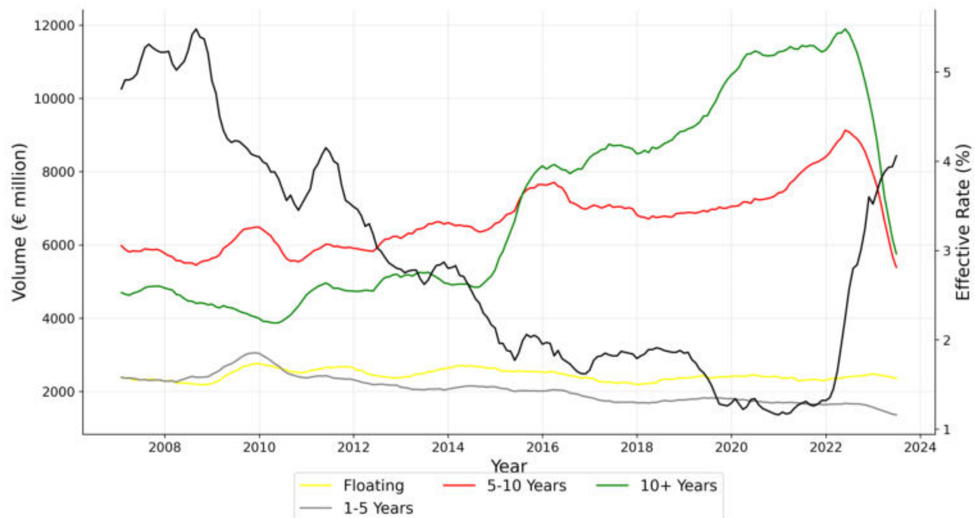
	(1)	(2)	(3)	(4)	(5)	(6)
	Target	Forward	QE	Target	Forward	QE
House price index (t-1)	0.189	-1.072	-1.577			
	(0.18)	(-0.96)	(-1.43)			
House price index (t-2)	-0.576	1.894	0.980			
	(-0.98)	(0.98)	(1.17)			
House price index (t-3)	0.941	-0.504	-0.167			
	(0.79)	(-0.46)	(-0.17)			
House price index (t-4)	-1.102	-1.841	-0.489			
	(-0.82)	(-0.93)	(-0.60)			
House price index (t-5)	-0.0480	2.996	1.190			
	(-0.07)	(1.11)	(1.13)			
House price index (t-6)	0.275	-0.731	0.0989			
	(0.32)	(-0.55)	(0.10)			
Rent index (t-1)				-0.371	-2.958	-4.794
				(-0.21)	(-0.75)	(-1.56)
Rent index (t-2)				-0.610	1.591	1.655
				(-0.43)	(0.35)	(0.60)
Rent index (t-3)				-0.748	2.988	2.135
				(-0.27)	(0.80)	(0.87)
Rent index (t-4)				-0.0983	-0.0542	0.189
				(-0.03)	(-0.02)	(0.09)
Rent index (t-5)				2.523	-2.641	-5.479*
				(0.85)	(-0.62)	(-1.69)
Rent index (t-6)				-1.680	3.186	6.210*
				(-0.56)	(1.02)	(1.87)
Constant	0.331	-0.847	0.0210	0.970	-2.177	0.153
	(0.67)	(-1.52)	(0.03)	(0.77)	(-1.54)	(0.11)
N	76169	76169	76169	69761	69761	69761

This table reports the regression estimates of the policy shock series (Target Rate, FG and QE) on the lags of house price and rent indices to evaluate the lag exogeneity assumption.
t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

H Mortgage Loans Composition-Germany

Unlike homeownership rates, the composition of mortgage loans in Germany closely mirrors that of the United States.[41] As depicted in Figure H.18, the majority of mortgages in Germany are fixed-rate, typically for a period of five years or more, with only a small fraction issued as floating-rate loans. Notably, the volume of mortgage loans with a fixed rate of 10 years or more has increased significantly since 2015. Conversely, variable-rate mortgage loans remain relatively uncommon and have seen a decline in volume over time. Interestingly, the volume of mortgage loans with a 10-year fixed rate surpassed those with a five-year fixed rate until 2022, when both saw a sharp decline.

Figure H.18: Residential Mortgage Volumes Across Loan Types



Notes: The figure shows the composition of residential mortgages to households across Germany from January 2007 to June 2023, compared with the effective mortgage rate (black line). The yellow line represents the volume of variable-rate loans, the grey line indicates loans with a fixed rate of 1 to 5 years, the red line shows loans with a fixed rate for 5 to 10 years, and the green line represents loans with a fixed rate for 10 years or more. The series are adjusted using a 12-month moving average. The effective mortgage rate in Germany across all banks is plotted on the secondary axis. All data are sourced from the Bundesbank website.

[41] In France, Germany, and the Netherlands, mortgages are predominantly fixed-rate, while in other Euro Area countries, mortgages are mixed. For a cross-country comparison, see Albertazzi, Fringuellotti, and Ongena (2024).

I SOEP Data

In order to identify the reasons for the increased demand and reduced supply in housing following expansionary monetary policy shocks, we use the microdata of the German Socioeconomic Panel (SOEP). This panel dataset provides household (and individual) level data from 1984 to 2022 (version 39) on various topics, including tenure, moving decisions, wealth, income and other household characteristics (Goebel, Grabka, Liebig, Kroh, Richter, Schröder, and Schupp, 2019). While the survey has an annual frequency, we know the quarter of the interviews, which allows us to assign the respective monetary policy changes at a quarterly frequency and avoid annual aggregation. We follow the approach by Koeniger et al. (2022), who use the SOEP (version 35) to analyse the transition between renting and owning due to monetary policy changes, among other issues, and provide a broad set of robustness checks for the validity of these data and analyses.

Regression Analysis

In our analysis we use data from 2005:Q1 to 2022:Q4 and start the analysis of tenure changes in 2007 to match the sample period of the RWI-GEO-RED data. Our sample comprises 265,963 interviews with (more than double than Koeniger et al. (2022)). The unit of observation is a household interviewed in a quarter of a given year. On overage a household is interviewed 5 times (over 5 or more years). Due to the annual survey frequency and the changing amount of interviews across quarters, we can neither run a quarterly household panel local projection nor an quarterly aggregate local projection. To still get the effect of expansionary monetary policy changes over a three year horizon, we use the regression framework suggested by Koeniger et al. (2022) and analyse the response of various dependent variables to the monetary policy shocks over the current and last 11 quarters:

$$Change_{iqy} = c + \beta z_{qy} + \gamma X_{iqy} + D_q + D_y + D_i + \epsilon_{iqy} \tag{9}$$

where $Change_{iqy}$ is a dummy variable that describes a change in the housing situation of household i in quarter q of year y. In particular, we look at the transition from owning to renting, renting to owning, one property to another property, and one rental object to another rental object, respectively. X_{iqy} contains various household and macro controls, including age, squared age, employment status, years of education, migration background, and gender of the household reference person, household size, the household income and a Bundesland dummy. In addition, we include four lags of the unemployment rate and the HICP inflation similar to our local projection framework. D_q is a quarter dummy to account for seasonal differences and D_y is a year dummy to capture aggregate business developments like the pandemic. In contrast to Koeniger et al. (2022), we also include household fixed effects D_i

to reduce a remaining selection and omitted variable bias. We cluster the standard errors by the quarter of interview due to the periodical interview design and potential spillovers of aggregate monetary policy shocks across households.

The coefficient of interest is β which describes the effects of expansionary monetary policy shocks captured in the vector z_{qy}. The vector contains the high-frequency monetary policy shocks derived in Section 4 aggregated at quarterly frequency. To account for the different timing of the monetary policy meetings, we apply an weighted average that weights earlier decisions stronger.[42] We include the current and eleven lags of the quarterly Target Rate, FG and QE shocks simultaneously to analyse the effects over a three year horizon. The cumulative 3-year effect scaled to a 0.25 pp cut of all policies and each policy separately is presented in Tables 3 and 4. Our results in Table 3 are in line with the findings of Koeniger et al. (2022). We also find that expansionary monetary policy changes lead to increase in the transition from renters to owner and reduce the transition from owner to renters. In contrast to their findings, our effects are (weakly) statistically significant, potentially due to the larger sample and more controls which increase the efficiency of our estimation.

J Monetary Policy transmission - Additional Results

For the analysis of the heterogeneity in the monetary policy transmission due to demand-side factors, the baseline econometric framework is extended as follows:

$$ln(y_{l,t+h}) - ln(y_{l,t-1}) = c_l^h + c_t^h + \sum_{k=1}^{K} \alpha_k^h \Delta ln(y_{l,t-k}) + \beta_D^h Demand_{l,t-1} \times \widehat{policy_t^p} + \\ + \phi^h(L) X_{l,t}^h + u_{l,t+h}^h, \quad h = 0, 1, ..., H \quad (10)$$

where the coefficient β_D^h of the new interaction term $Demand_{l,t-1} \times \widehat{policy_t^p}$ captures the differential impact of monetary policy depending on the demand proxy after h months.

An increase in the **population growth** could lead to excess demand in housing and thereby, a shortage which intensifies the monetary policy effects. As shown by Table J.14, we only find small and weakly significant effects after two years, which points to at most transitory intensification of monetary policy effects. Also a higher **share of young people** in a Kreis could increase the demand for housing when they move out from their parents' home as suggested

[42] First, we sum over all shocks from a specific type during the last 92 days (e.g. on September 15 I consider all shocks since June 15, the duration of a quarter) to obtain an aggregate for each day. Then, we use these values to calculate the average for each specific quarter (e.g. Q3-2020). Thereby, earlier shocks are weighted higher, since they affect a quarter longer than those shocks realised at the end.

by Bednarek et al. (2021). Again, the increase in housing demand affects the policy transmission at most for two years. Similarly, the increase in **net migration** into a Kreis, and thereby the increase in housing demand, leads to a stronger monetary policy effect only temporarily. While the **unemployment rate** is an important factor to describe the development of house prices and rents, it does not seem to matter for the transmission heterogeneity of monetary policy, as the effects are generally small and statistically not significant (except for rents after two years).

We also consider the role of income in the transmission of monetary policy on house prices and rents. We use the **average gross wages** of each Kreis from the Stichprobe integrierter Arbeitsmarktbiographien (SIAB), a 2% random sample of the German working population, by the Institute for Employment Research (IAB) (Graf, Grießemer, Köhler, Lehnert, Moczall, Oertel, Schmucker, Schneider, Seth, Thomsen, and vom Berge, 2023). In regions with lower wages, more households are constraint in their ability and willingness to pay higher prices for house and rents. Therefore, we expect a weaker transmission of monetary policy on house prices and rents in poorer districts. Using the middle (3rd) wage quintile as baseline, we find that the monetary policy transmission on house prices gets stronger and faster in the richer regions. Similarly, we find temporarily stronger rent increases two years after a policy shock. In line with our findings on the demand channel, we find slightly weaker, monetary policy effects on house prices and rents in **East Germany**, where we observe lower population growth, lowest average wages and higher unemployment rates.

Table J.14: Housing Demand Proxies - Heterogeneity in the Transmission of Monetary Policy

		House Price			Rent		
		h = 12	h = 24	h = 36	h = 12	h = 24	h = 36
Panel A: Population Growth							
β_D^h	Δ Shadow Rate $\times$ Population Growth	-0.00319	0.0515*	-0.0349	-0.00426	0.0140*	-0.00765
		(0.0304)	(0.0402)	(0.0413)	(0.00913)	(0.0104)	(0.0151)
Panel B: Young Age Share							
β_D^h	Δ Shadow Rate $\times$ Young Age Share	0.144*	0.408**	-0.0736	-0.0270	0.0303	-0.0999*
		(0.123)	(0.170)	(0.183)	(0.0530)	(0.0716)	(0.0855)
Panel C: Migration							
β_D^h	Δ Shadow Rate $\times$ Std(Net Migration, t-1)	0.105	0.543**	0.318	-0.0419	0.0862	0.00647
		(0.166)	(0.273)	(0.244)	(0.0678)	(0.105)	(0.125)
Panel D: Unemployment Rate							
β_D^h	Δ Shadow Rate $\times$ Unemployment Rate (t-1)	0.00410	-0.124	0.0952	-0.00316	-0.0754**	-0.0210
		(0.106)	(0.135)	(0.161)	(0.0411)	(0.0436)	(0.0628)
Panel E: Wage Quintile (Administrative Data)							
β_D^h	Δ Shadow Rate $\times$ 1st Wage Quintile	-0.170	-0.573	0.749	-0.0864	-0.00394	-0.0287
		(0.659)	(0.787)	(0.787)	(0.186)	(0.230)	(0.293)
β_D^h	Δ Shadow Rate $\times$ 2nd Wage Quintile	0.0353	0.445	0.239	-0.00834	0.122	0.216*
		(0.455)	(0.531)	(0.543)	(0.156)	(0.140)	(0.210)
β_D^h	Δ Shadow Rate $\times$ 4th Wage Quintile	0.307	0.554*	0.0463	0.0695	0.302*	-0.156
		(0.357)	(0.406)	(0.487)	(0.184)	(0.218)	(0.229)
β_D^h	Δ Shadow Rate $\times$ 5th Wage Quintile	0.487*	1.043**	0.428	-0.0352	0.468*	-0.385
		(0.386)	(0.518)	(0.598)	(0.185)	(0.297)	(0.335)
Panel F: East Germany							
β_D^h	Δ Shadow Rate $\times$ $\mathbb{1}$(East)	-0.216	-0.872*	0.628	-0.0780	-0.230*	0.0816
		(0.656)	(0.820)	(0.791)	(0.187)	(0.210)	(0.299)

Notes: The coefficients are reported in percent changes of house prices/rents. Conley standard errors (Conley, 1999, 2008) are in parentheses. Population growth represents the cumulative population growth per Kreis over the period 2007–2019. The young age share is the fraction of individuals aged 25 to 30 in each Kreis. Net migration represents the inflow minus the outflow of people across Kreis boarder in the last year (standarised). The lagged (last month) unemployment rate is used to capture labur market tightness. Wage quintiles are based on the average gross wage distribution in January 2007. $\mathbb{1}$(East) is a dummy variable indicating Eastern German regions. * $p < 0.32$, ** $p < 0.10$, *** $p < 0.01$.