

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

Martin Groiss¹ and Nicolas Syrichas²

¹University of Duisburg-Essen

²Freie Universität Berlin, Berlin School of Economics

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Abstract

Does monetary policy affect house prices and rents differently, and if so, how? We use 35 million property and rental listings across Germany and exploit exogenous variation in high-frequency monetary policy surprises in a local projection framework. We show that both house prices and rents increase significantly after expansionary monetary policy shocks. The effects are stronger and more persistent for house prices than for rents due to a relatively stronger increase in housing demand and a contraction in the supply for properties for sale. Better financing conditions and higher wages facilitate tenure transitions towards ownership. The findings imply that accommodative monetary policy disproportionately benefits homeowners, potentially widening wealth gaps between owners and renters.

Keywords: housing markets, monetary policy, house prices, rents, regional, housing tenure

JEL codes: E52, R21, R31

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Correspondence: University of Duisburg-Essen, Universitätsstraße 2, 45141 Essen, Germany; E-Mail: martin.groiss@uni-due.de, nicolas.syrichas@fu-berlin.de

1 Introduction

Over the past decade, significant increases in house prices and rents across and within countries have coincided with highly expansionary monetary policies. While there is extensive research on how monetary policy affects house prices, less attention has been paid to rental markets. Unlike house prices, the effects of monetary policy on rents are not clear *ex ante*. While higher house prices and wages could push up rents, cheaper financing conditions may reduce the demand for renting. Moreover, the transmission of monetary policy in rental markets may be quite different from that in the sales market. Understanding rental markets is important because they represent a large portion of the housing sector: more than a third of OECD households live in rented accommodation, and renters are on average poorer than home owners.

This paper fills the gap by providing comparative evidence on the causal effects of monetary policy shocks on residential property prices and rents.¹ Additionally, we examine the underlying supply and demand mechanisms that rationalise the differences between property and rental market responses. Addressing these gaps is essential for researchers and policy-makers alike, given the significant impact of housing on the transmission of monetary policy (Giuliodori, 2005), financial stability (Zhu et al., 2005) and overall economic welfare (Favilukis, Mabile, and Van Nieuwerburgh, 2023).

Identifying monetary policy effects in rental markets is more challenging than in property markets for a number of reasons. First, and most importantly, high-frequency data with sufficient geographical coverage that provide comparable information on property *and* rental markets are hard to obtain. Second, rental markets are often highly regulated, especially with regard to incumbent tenants, making it difficult to trace out policy effects. Finally, housing markets are inherently local and aggregating across regions may mask the heterogeneous effects of monetary policy. Existing studies on rental outcomes rely almost exclusively on country-level data (Dias and Duarte, 2019; Corsetti, Duarte, and Mann, 2022), ignoring the significant regional segmentation that characterises housing markets.²

We address these challenges by using a unique and comprehensive monthly dataset from Immobilienscout24, Germany’s leading online real estate platform. The dataset encompasses detailed, geo-referenced listings for owner-occupied and rental units in the period from January 2007 to June 2023. Notably, we observe rents advertised for vacant units, capturing the *flow* of rental prices rather than the rates from existing rental contracts. This distinction is

¹Throughout the paper, we use “property prices” and “house prices” interchangeably to refer to owner-occupied dwellings.

²An alternative way to obtain micro data on rents is via survey data that are often inferred and hence subject to measurement error.

crucial, as newly listed rents fall outside tenant-protection laws and are therefore far less affected by rent “stickiness”. Leveraging this dataset, we construct comparable inflation- and quality-adjusted price and rent indices at district level. With over 35 million observations – of which approximately half correspond to rental units – covering nearly all of Germany’s 401 administrative districts, our data provides an ideal setting to quantify and compare the transmission mechanisms of monetary policy shocks across regional sales and rental markets.

To achieve causal identification, we apply high-frequency monetary policy surprises (Altavilla, Brugnolini, Gürkaynak, Motto, and Ragusa, 2019) in a two-stage panel local projection framework (Jordà, Schularick, and Taylor, 2015). In our baseline specification, we instrument the Euro Area Shadow Rate (Krippner, 2013), a measure of the ECB’s overall monetary policy stance, with a linear combination of short-term policy rate, Forward Guidance (FG), and Quantitative Easing (QE) shocks to capture a *general* expansionary monetary shock. We estimate the impact of monetary policy on house prices and rents over a three-year horizon.

Our main finding is that an expansionary monetary policy shock leads to a positive and significant increase in both house prices and rents. However, the timing and magnitude of the response differ between the two markets. A one standard deviation reduction in the Euro Area Shadow Rate - equivalent to 27 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 and much smaller. The impact on rents materialises within the first few months, reaching a peak increase of around 1%. Our results are robust to changes in the time period, choice of interest rate, or the inclusion of additional financial and migration variables.

Moreover, we document substantial heterogeneity in the responses of house prices and rents to different policy instruments. Policy rate cuts have a temporary effect on house prices and rents, whereas forward guidance (FG) and quantitative easing (QE) have more substantial and lasting effects. For example, after two years, house prices rise by more than 2.4% in response to QE and by about 1.2% in response to a FG shock, whereas the reaction to policy rate cuts (amounting to 1%) is statistically insignificant. Rents, on the other side, 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.

We then ask whether housing supply constraints could magnify the sales and rental market responses to monetary policy. We exploit the regional granularity of our dataset and find temporarily stronger effects of monetary policy on house prices in urban regions, where housing supply is typically more constrained. We also use other measures of housing constraints and regulation, including the introduction of the German rental brake in 2015. Rent controls dampen the positive short-run effects of expansionary monetary policy on rents, whereas

stricter planning regulations slightly amplify the effects on house prices. We conclude that while these regulatory constraints are important, their effect on policy transmission is limited and generally short-lived.

We next turn to the underlying channels through which monetary policy affects house prices and rents. In the sales market the price effect is unambiguous, at least in theory: expansionary monetary policy increases property prices directly through improvements in financing conditions and indirectly through higher income. By contrast, the rental market faces two offsetting forces. On the one hand, higher wages raise tenants' willingness to pay, and higher house prices prompt landlords to pass on these higher costs to tenants. On the other hand, lower interest rates could encourage a fraction of tenants to switch from renting to owning, reducing rental demand and increase the supply of vacant rental units.

To capture these mechanisms empirically, we construct measures of housing demand and supply from our listings data. We measure demand by the average number of requests the seller receives per day, and capture supply by the total number of newly posted listings each month. In response to expansionary monetary policy, demand for properties for sale rises sharply and almost immediately, while rental requests rise only gradually. Using the German Socio-Economic Panel (SOEP), we confirm the results and show that expansionary monetary policy significantly increases the number of households transitioning from renting to owning, but not vice versa, leading to the observed upward pressure on house prices and muted effects on rents.

At the same time, we observe a decline in the number of listings for sale following an expansionary monetary policy shock, with the reduction in rental listings being more modest. Because newly built dwellings represent a small share of total listings and take time to complete, this reduction reflects existing owners' decisions to postpone market entry, rather than changes in construction activity. Thus, the more pronounced increase in house prices relative to rents is not only due to stronger demand, but also to a sharper contraction in the supply of units for sale.

Our empirical findings carry important policy implications. Accommodative monetary policy disproportionately benefits homeowners, exacerbating wealth disparities between owners and renters. Meanwhile, in many advanced economies, housing prices and rents have consistently outpaced income growth, tightening housing affordability for first-time buyers and lower-income households. This is especially relevant as only rents are considered in consumer price indices across Europe, which causes an underestimation of housing price dynamics. Policymakers should therefore account for these distributional effects when setting monetary policy especially in markets with large rental populations. In the short run, targeted rent-cap measures can help contain sharp increases in rents and over the long run, tax

incentives and other subsidies to encourage new construction are essential to expand housing stock and ease upward pressure on both property prices and rents.

1.1 Related Literature and Contribution

A large body of literature investigates how monetary policy affects house prices, but often overlooks the rental segment, e.g. [Kuttner \(2014\)](#), [Williams et al. \(2015\)](#), and [Jordà et al. \(2015\)](#), for early contributions, and [Kudlyak, Gorea, and Kryvtsov \(2022\)](#), [Hülsewig and Rottmann \(2021\)](#), [Aastveit and Anundsen \(2022\)](#), and [Flor and Klarl \(2023\)](#), for more recent studies using high-frequency identification approaches. [Kudlyak et al. \(2022\)](#), for example, combine micro-level listing data with high-frequency monetary policy shocks to document a pronounced, immediate rise in US house prices following conventional rate cuts, yet omit any analysis of rental responses.

A smaller but recent strand of the literature incorporates rental outcomes directly. [Dias and Duarte \(2019\)](#), [Corsetti et al. \(2022\)](#), and [Koeniger, Lennartz, and Ramelet \(2022\)](#) are the first to study rental outcomes, however they rely on country-level indicators or small-scale annual survey data. This limits their applicability, given that monetary policy decisions are made with high frequency *and* regional housing markets are highly segmented. In contrast, we use a district-level monthly dataset of both sales and rentals, which allows us to measure the impact of monetary policy on both market segments more precisely.

More recent research looks at the impact of unconventional monetary policy on real estate markets. [Kudlyak 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 in the Euro Area rise when the ECB embarks on accommodative unconventional measures. 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 fuelled urban house price booms. We extend the literature by tracking both house and rent responses to FG and QE shocks across Germany's administrative regions.

Our paper contributes to a third strand of the literature on rent regulation and housing markets. As reviewed by [Kholodilin \(2024\)](#), rent controls both temper rent increases and, in many cases, reduce overall housing supply. For example, [Diamond, McQuade, and Qian \(2019\)](#) find that while rent caps limit rent increases, they also discourage landlords to lend their properties. In the German context, [Mense, Michelsen, and Kholodilin \(2023\)](#) document that municipalities imposing a rent ceiling in tight markets saw rents rise in neighbouring unregulated areas as demand spilled over. Unlike these studies, our analysis asks how rent controls interact with monetary policy shocks. Specifically, we examine to what extent regulation affects

the pass through of expansionary monetary policy into rental markets.

Closest to our work are [Dias and Duarte \(2019\)](#) and [Dias and Duarte \(2022\)](#), who employ US data to show that, following a contractionary monetary policy shock, the home-ownership rate falls, housing rents rise, and house prices decline. Our analysis differs from theirs in two key respects. First, we leverage a granular, high-frequency dataset of listing-level prices and rents, rather than aggregate CPI measures. Second, we document qualitatively opposite rent dynamics: rents decline after a contractionary shock in our sample. These opposite findings could reflect institutional differences between the US and Germany and/or a different rent measure. Our focus is on the “flow” of newly listed rents, which are more responsive to policy shocks than the stock of existing rental contracts measured by CPI indices. Lastly, our results are corroborated by [Koeniger et al. \(2022\)](#), who use SOEP survey data to document similar renter-to-owner transitions in Germany following monetary policy shocks.

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 details the econometric framework and the monetary policy identification. Section 5 presents our main findings, before Section 6 distinguishes between policy instruments, and examines regional heterogeneity. Section 7 offers insights into the underlying supply and demand mechanisms, including tenure transitions. Finally, Section 8 concludes and discusses policy implications.

2 Institutional Background

Germany is one of Europe’s largest countries in terms of 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 100,000.³

Germany’s housing market offers a distinctive environment for examining the transmission of monetary policy changes to property prices and rents. Two key features are particularly relevant: Germany’s low home-ownership rate, compared to other rich countries, and the current regulation of the rental market. We briefly outline these features below.

Dominant Rental Market: The home-ownership rate in Germany is approximately 50%, significantly lower than the EU average of 69% ([Eurostat, 2018](#)) and the rates observed in

³Data source: Destatis 2023

the UK and the US. In Germany, renting is culturally accepted and institutionally supported (Kaas, Kocharkov, Preugschat, and Siassi, 2021; Huber and Schmidt, 2022). Similar dynamics are observed in other countries in continental Europe such as Austria, Switzerland, and Denmark. Consequently, changes in financing conditions are likely to affect not only the owner-occupied housing segment but also the rental sector, highlighting the dual sensitivity of Germany’s housing market to monetary policy. See Appendix A.1 for a more detailed description of home-ownership rates across censuses and regions in Germany.

Composition of the Housing Stock: Private individuals and commonhold owners account for the majority of residential units in Germany. Outside, homeowner-occupied units, over 60 percent of rental apartments are held by “mom-and-pop” landlords, while institutional and large corporate landlords hold significantly smaller shares (see Table A.2). Smaller segments include cooperatives, municipal housing companies, and government-owned entities. Given this market structure, private individuals and smaller landlords – who are generally more sensitive to economic conditions – play a central role in the housing market’s response to monetary policy. On the other hand, publicly owned units, including subsidized housing units, which are less sensitive to monetary policy changes, represent a relatively small fraction of the rental housing supply (around 4%) (Europe, 2017).

Rental Market Regulation: Germany has long standing tenant protection laws, first introduced in 1972, which strictly limit rent increases in *existing* contracts and protect tenants from evictions (Kholodilin, 2016; Mense et al., 2023). These protections apply only on existing tenants and do not constraint new rental agreements. However, a key shift occurred in 2015 with the introduction of the Mietpreisbremse (“rental brake”) in selected municipalities. This regulation caps the net cold rent on new contracts at 10% above the local reference rate. Tenants paying rents above this threshold are entitled to a reduction.⁴ In section 6.2 we explore the variation introduced by the “Mietpreisbremse” to examine whether rent controls dampen the transmission of monetary policy to house prices and rents.

3 Data

This section introduces our dataset of real estate listings. The primary advantage of employing this dataset lies in its comprehensive coverage across time and space. It provides detailed

⁴Exceptions 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). Moreover, 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. However, the law was later ruled unconstitutional by the German Federal Constitutional Court and abolished on April 15, 2021.

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, transaction-based spatial datasets for 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).⁵

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.⁶ This dataset comprises real estate listings posted in ImmobilienScout24, Germany’s largest platform for real estate advertisements. The dataset includes observations from January 2007 to June 2023, categorised into four segments: houses and apartments for sale or rent.

For each listing, we have information on the asking price or rent (both “warm” and “cold”),⁷ 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 whether a property was sold or withdrawn from the market. However, we restrict the sample to the last observation (listing price) when the same unit was re-posted multiple times within a short-interval (6 months). 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 the available variables.

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, the RWI 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).⁸ Throughout this paper, we use district-

⁵Kindermann et al. (2021) utilise annual-frequency, non-quality-adjusted data from Bulwiengesa across all regions. Amaral et al. (2023) compile a quarterly, quality-adjusted transaction-based dataset limited to several German cities.

⁶The dataset is compiled and provided by the Research Data Centre (*Forschungsdatenzentrum* or FDZ Ruhr) at the RWI – Leibniz-Institut für Wirtschaftsforschung (Klick and Schaffner, 2019).

⁷In Germany, “cold rent” refers to the base rent, while “warm rent” includes heating costs and sometimes other utilities.

⁸Several 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 consis-

level (Kreis) administrative boundaries and refer to them as regions.⁹

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 of rooms, or those identified as castles. We apply restrictions based on property size, excluding houses (apartments) smaller than 35 m² (20 m²) and those with more than 15 rooms (8 rooms). Finally, we limit the sample to dwellings with sale prices between €150/m² and €20,000/m², and rent prices between €2.50/m² and €45/m². Additionally, we remove ultra-popular listings by trimming entries at the 99th percentile based on the number of clicks they received.¹⁰

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 very few listings recorded. To minimise noise, we exclude any region-month pairs with fewer than 10 observations. For regions with sufficient entries, we impute the missing values after the hedonic regression using simple linear interpolation. Varying the cut-off point to 5 or 20 observations does not affect our results.

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.7 summarise key listing-level averages over our sample period.¹¹ Over time, the average duration of a listing on the market declines and (log) real prices and rents rise steadily. Email contacts per listing, a measure of market tightness, has increased markedly

tent 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.

⁹We 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. Nonetheless, in Figure G.16, we demonstrate that our main results remain robust when using a finer-level aggregation (municipality).

¹⁰Trimming is done separately for apartments and houses, and for sales and rentals.

¹¹The data quality for listing duration and contact requests was poor before 2009 and very volatile post 2018, so we do not report them.

in both sales and rental markets.¹² Finally, the total stock of active listings has fallen in both the sales and rental segments, reflecting the broader housing market boom in Germany over these years.

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. To assess this potential bias, we compare our listings prices with transaction-sale prices at the regional level (see Appendix B.7). Overall, both trends and levels align well, although some discrepancies emerge in smaller regions. Since our analysis focuses on growth rates rather than levels, any such bias is less concerning. To further alleviate doubts, Figure G.18 shows the Impulse Response Function (IRF) based on the transaction sales dataset, which yields estimates very similar to those from our listings data.¹³ Transaction data for rents at the regional level are not available. However, selection bias is arguably less pronounced in rental markets as shown by [Chapelle and Eyméoud \(2022\)](#).

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, websites 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 disproportionately skewed towards younger users 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.¹⁴ These statistics suggest that online postings well represent the overall German housing market both in terms of reach and user composition.

¹²The fact that the number of contacts increases over time may partly reflect the fact that platform usage increases over time.

¹³Note that due to the limited sample of only 16 cities, these IRFs are imprecisely estimated and not suitable for economic interpretation. They are included solely for comparison purposes.

¹⁴See Appendix B.2 for a more detail breakdown of users characteristics

3.4 Regional Hedonic Housing Indices

In this subsection, we use our cleaned dataset to construct regional house price and rent indices that account for *changes* in the composition of housing units over time. In particular, we employ the commonly used “time-dummy” approach that lies within the spectrum of hedonic regressions (Hill and Rambaldi, 2022).¹⁵

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:

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

where $\alpha^{l,\tau}$ is the constant and $X_{i,t}$ is a vector of housing characteristics of that property detailed in the Appendix. $F_{j(i)}$ is a full set of post-code dummies $j \in l$ to capture time-invariant neighbourhood differences such as parks and distance to the city centre. For the sales market, we include an indicator variable for properties sold with tenants in place,¹⁶ while for the rental market, we added 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.

The variable of interest 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 (January 2007) 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 $\gamma_t^{l,s}$ can be interpreted as the location-specific listed sales price index or rent index with respect to January 2007.

Our analysis distinguishes between listed property prices and rents. Importantly, our rental indices capture the **flow** of newly listed rents rather than the **stock** of existing rental contracts. This aligns with the institutional structure of the German rental market, where existing rents are heavily regulated, but new rental agreements are not (see Section 2), and allows for a direct comparison of currently listed housing prices.

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.

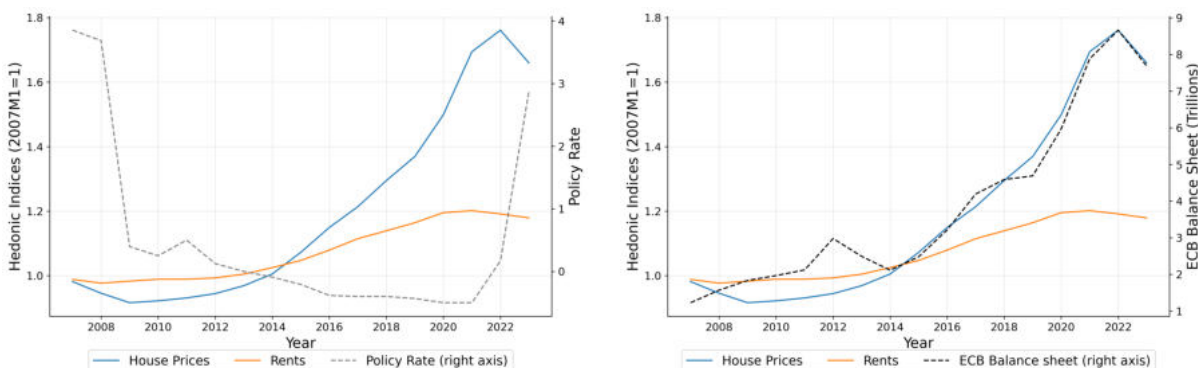
¹⁵Ideally, an house price index measures the price variation of a representative property over time, e.g., constructed by the repeat-sales method. However, this method is impractical at the regional level, especially in illiquid markets like Germany, and would require an housing object identifier.

¹⁶In Germany, selling a rented property does not terminate the lease; the new owner assumes it unless the owner terminate the tenancy for personal use.

3.5 Developments in monetary policy, property prices and rents

Before proceeding with our econometric analysis, we present descriptive evidence on the evolution of house prices and rents in Germany during a period of 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 development of hedonic house prices and rents in Germany at the national level from January 2007 to June 2023. Following the Global Financial crisis (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.¹⁷ Figure 1 also illustrates a strong correlation between the European Central Bank’s (ECB) monetary 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. This coincided with expansionary monetary policy, in particular, balance sheet expansion (see the right-hand panel of Figure 1).

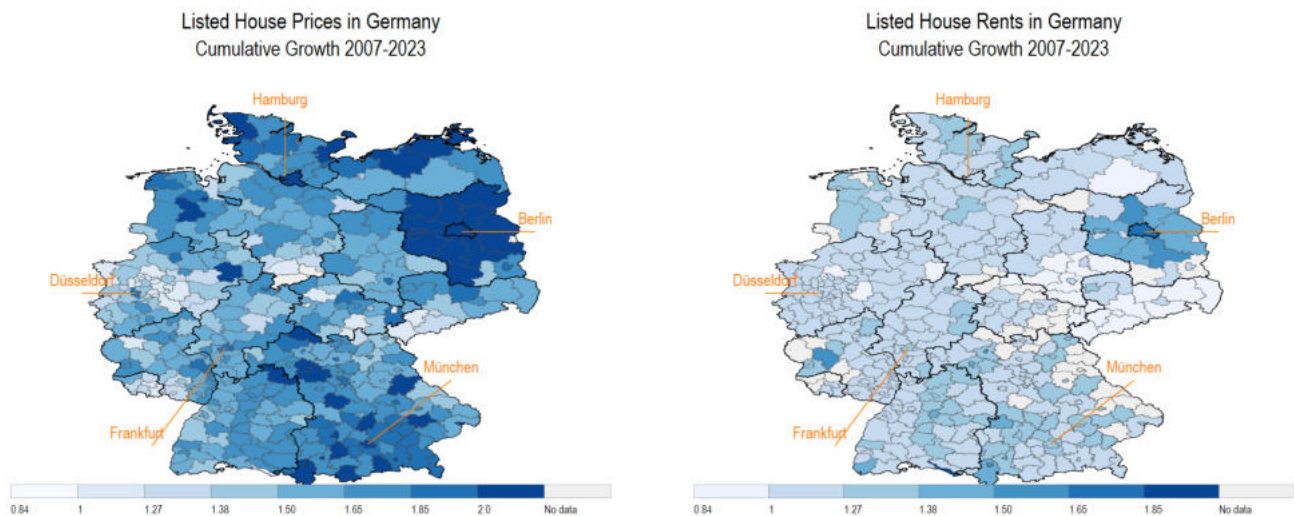
Interestingly, the price-to-rent ratio increased substantially until the monetary policy reversal in 2022. This pattern is consistent with a large body of empirical research demonstrating that housing booms often feature a rising price-to-rent ratio and a growing segmentation between

¹⁷Unlike 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. \(2021\)](#).

owner-occupied and rental markets (Amaral et al., 2023; Favilukis et al., 2023; Dong, Liu, Wang, and Zha, 2022).

Regional Developments 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, rents have increased by 50% or more in Berlin and Bavaria. Figure B.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.

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](#).

These descriptive patterns are not, of course, evidence of *causal* effects. In Section 4.2, we introduce a formal econometric framework to estimate the dynamic causal impact of monetary policy on property prices and rents.

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 a more detailed description see Appendix C.

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 (including government bond yields) are obtained from *Refinitiv* and the *ECB's Data Portal*. 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 at various frequencies such as the share of young cohorts and migration flows from *Destatis*. We also use the *SIAB* (Stichprobe Integrierter Arbeitsmarktbiographien) dataset from the *Institute for Employment Research (IAB)* to construct monthly average wage measures by district.

Housing Supply Constraints Land availability is measured by the *Leibniz Institute of Ecological Urban and Regional Development (IOER)* capturing the share of water and protected areas within each district (in 2006). The planning zone regulation intensity is constructed by [Pehlke and Siedentop \(2021\)](#) and reflects institutional differences in land use restrictions. Moreover, we track the implementation of the *Mietpreisbremse* (rental brake) using administrative decrees. Finally, we use the share of new dwellings listed on *ImmobilienScout24* as a proxy of new housing supply ([Mense et al., 2023](#)).

4 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) ([Jordà, 2005](#); [Jordà et al., 2015](#)). First, we regress the policy variable on high-frequency monetary policy shocks and control variables to extract the exogenous policy variation and tackle any endogeneity concerns. Then, we use the fitted policy values to compute impulse responses of prices and rents, which identifies the causal effect of a policy shock over time.

We choose panel LP instead of dynamic factor models (e.g. [Del Negro and Otrok, 2007](#); [Fischer, Huber, Pfarrhofer, and Staufer-Steinnocher, 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 6.2. 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.

4.1 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:

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

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.¹⁸ 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.¹⁹ 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 cyclical indicators at the local level, with $\phi^h(L)$ being a lag polynomial of order L . The policy indicators \widehat{policy}_t^p are the same for all regions. Hence, including time fixed effects is not possible, as it would absorb all variation and leave monetary policy unspecified. This might raise concerns that other concurrent shocks (not orthogonal to monetary policy) might be influencing house prices or rents. In Section 5.3, we address this issue by incorporating additional regional and national controls into our analysis and our main findings remain robust.

Our parameter of interest, β^h , measures the impact of an exogenous change in a monetary

¹⁸We 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).

¹⁹The 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 G.20, we plot the 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 small sample bias reported by Herbst and Johannsen (2024).

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 the next subsection, 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 of the intended shock, they are susceptible to measurement error (Stock and Watson, 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 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:

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

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

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

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).

4.2 Monetary Policy Identification

We employ monetary policy surprises derived from a high-frequency identification approach. 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 high-frequency approach yields exogenous policy shocks and separates conventional from unconventional monetary policy effects. We extend the approach by correcting for potential information effects embedded within the shocks (Jarociński and Karadi, 2020). For full details of how the shock series are built and what they look like, see Appendix D.

We aggregate surprises at the monthly level by summing individual surprises within each

calendar month. If there is no Governing Council monetary policy meeting in a given month, the shock is set to zero. 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. Positive shock values are interpreted as contractionary surprises. Importantly, even in months of rate cuts or QE, shocks may be positive if markets expected larger easing. The impact of the surprises on various financial assets are in line with expectations and can be found in Table D.9 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.

4.3 Econometric Specification

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 in line with Krippner (2013) to represent the overall stance of monetary policy.²⁰ 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 specification, 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.²¹ 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.²² Due to the weak relationship of the last policy-instrument combination 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 6.1, 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

²⁰Krippner (2013) builds upon a term structure model and uses non-negative forward rates in a factor model to estimate interest rates as if they could be negative.

²¹We 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.

²²By using the changes in the ECB's balance sheet, we capture the Asset Purchase Programme and the (targeted) Long-Term Refinancing Operations dominating the balance sheet development between 2007 and 2023.

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 lags of the 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. These controls improve the relationship between the policy tools and their instrumental variables, and 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 [G.19](#)).

Standard Errors To ensure robust inference, we estimate the first stage regression and the LP with Conley standard errors that account for heteroskedasticity, serial correlation and the spatial dependence between adjacent housing markets ([Conley, 1999, 2008](#)).²³ A spatial correlation cut-off 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 be found in Appendix [E.1](#).

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 [G.12](#)).

Diagnostic Tests Finally, we also perform a series of diagnostic tests to ensure the validity of our econometric strategy. Since we are not the first to use the shocks identified by [Altavilla et al. \(2019\)](#) as monetary policy instruments, we defer the detailed discussion to Appendix [E.2](#).

5 Monetary Policy Effects on House Prices and Rents

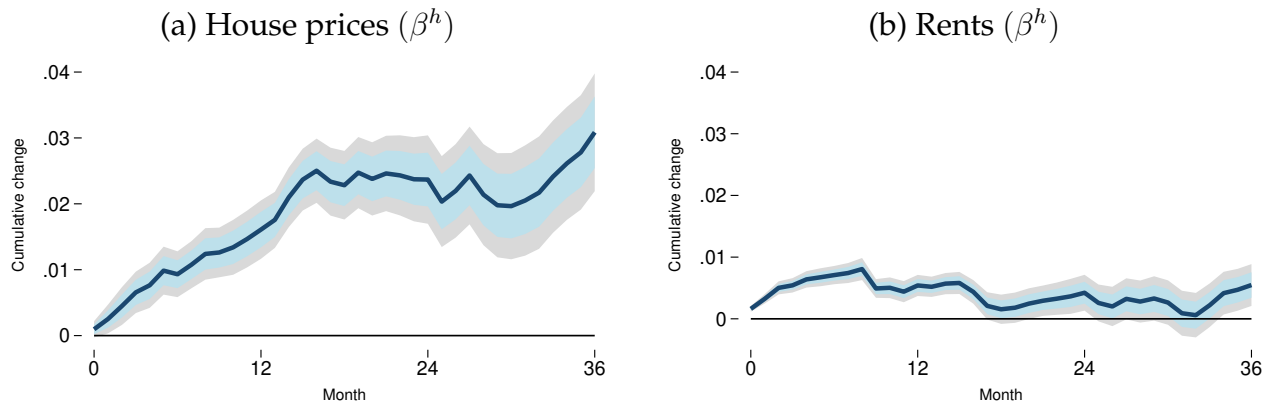
This section examines the effects of monetary policy shocks on house prices and rents. Subsection [5.1](#) analyses the impact of changes in the overall monetary policy stance, measured by the Shadow Rate. In subsection [5.2](#), we examine the transmission through long-term mortgage rates. Finally, subsection [5.3](#) discusses the robustness of our results along several dimensions.

²³We 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 \(2019\)](#).

5.1 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 (-0.27 percentage points) in the ECB’s Shadow Rate. Panels (a) and (b) of Figure 3 present the 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.

Figure 3: 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 (0.27 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 HAC and spatially robust Conley (1999, 2008) standard errors.

The average response of house prices and rents to expansionary monetary policy is positive and statistically significant across German regions. 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 also react immediately 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) 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:

$$\hat{f}_{i,t+h} = \alpha_0 \widehat{policy}_{t+h}^p + \alpha_1 \widehat{policy}_{t+h-1}^p + \dots + \alpha_h \widehat{policy}_t^p + \epsilon_{i,t+h} \quad (6)$$

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

Table 1 summarises the variance decomposition, highlighting the contribution of shifts in the Shadow Rate to fluctuations in both property prices and rents across regions. For house prices, the immediate influence is modest with 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.²⁴ These patterns suggest that while the short-run impact of monetary policy is relatively muted, it becomes an important 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 m	6 m	12 m	18 m	24 m	30 m	36 m
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).

At this point, it is useful to place our findings in the broader literature from Germany and abroad. The *direction* of the estimated house price responses is consistent with previous evidence from the US and other advanced economies, as surveyed by [Williams et al. \(2015\)](#). In terms of *magnitude*, our estimates align with recent studies that report larger housing market responses to monetary policy shocks, particularly those employing high-frequency identification strategies (e.g., [Aastveit and Anundsen, 2022](#); [Koeniger et al., 2022](#)).

Evidence for rental markets, by contrast, remains more limited. [Koeniger et al. \(2022\)](#) also report *positive* effects of expansionary monetary policy on housing rents using household

²⁴ Although these shares may appear modest, it is important to emphasize that regional housing markets are influenced by a myriad of local shocks. Since our identification strategy isolates the impact of aggregate monetary policy shocks, these region-specific disturbances enter as noise, and hence lowering the share of variance explained by the shadow rate.

survey data from Germany. On the other hand, [Dias and Duarte \(2019\)](#) and [Corsetti et al. \(2022\)](#) document a *negative* relationship between expansionary monetary policy and rents in the US and EU, respectively. A key distinction with these papers lies in the measurement of rents. The studies use CPI-based measures that mix existing rental contracts with new leases, which are often sticky and exhibit significantly lower rates ([Adams, Loewenstein, Montag, and Verbrugge, 2024](#)). In contrast, we focus exclusively on newly listed rents that are more adjustable to market changes. To benchmark against established CPI measures, we repeat our analysis using the rental component of the German Harmonized Index of Consumer Prices (HICP), which mirrors the rent definitions used in the aforementioned studies. [Figure G.14](#) shows that under this alternative measure, the positive effect of monetary policy on rents effectively disappears, but does not get significantly negative. The positive effects most likely stem from the strong positive demand effects for both property and rental objects as shown in [Section 7](#).

5.2 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.24](#)). Variable-rate mortgages, widespread in other parts of Europe, are very rare in Germany.²⁵ To understand how changes in mortgage rates driven by monetary policy affect the housing market, we re-estimate the IRFs and replace 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.²⁶

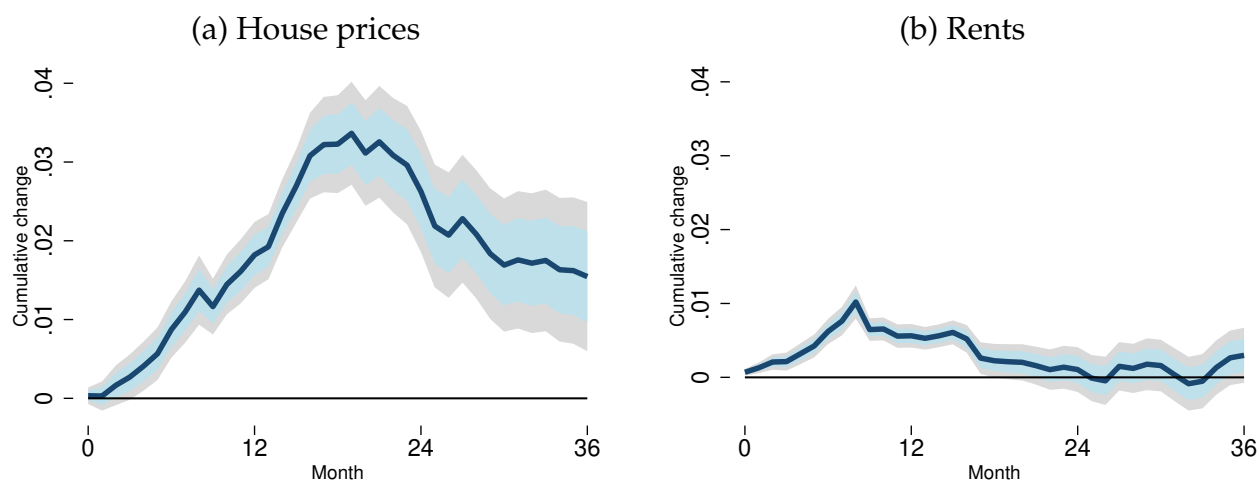
[Figure 4](#) reports the effects of a one standard deviation (0.11 percentage points) decline in the 10-year mortgage rate. House prices and rents climb quickly and significantly. Eighteen months after the shock, house prices are up by around 3%. The effect gradually declines but remains at about 2% after three years. Rents, by contrast, peak at just 1% after six months, and by the 36-month mark, the effect has disappeared entirely.

In the short to medium term, the results mirror the effects of a Shadow Rate cut, but in the long term, house price responses are somewhat smaller. Nonetheless, the effects are strong and significant highlighting how crucial financing costs are for understanding Germany's

²⁵Unlike in the US, refinancing is costly in Germany, and options for releasing home equity are limited.

²⁶We 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 [Kudlyak et al. \(2022\)](#).

Figure 4: 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.

housing market. In Section 7, we rationalise the results by the fact that expansionary monetary policy prompts a significant share of renters to become homeowners, and, over this horizon, reduce the incidence of renting relative to owning.

5.3 Robustness

We undertake a comprehensive set of robustness checks, three dimensions of which are presented here and the rest are detailed in Appendix G, to verify the consistency of our findings.

Since monetary policy shocks are common across all regions at each date, one cannot include time dummies as they would perfectly absorb the policy effect. While this avoids the “missing intercept” problem, it also means we do not directly control for other nationwide shocks that might co-move with both monetary policy surprises and housing prices. To mitigate this concern we follow [Kudlyak et al. \(2022\)](#) and [Bauer and Swanson \(2023\)](#), by adding several potential aggregates as controls: the 3-month growth rates of the S&P 500, the DAXX, the ECB’s commodity price index, and state-level population growth²⁷, 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 G.9, these additional variables slightly increase the estimated effects on house prices and rents, but do not alter them qualitatively.

²⁷State-level population data are reported quarterly so we linearly interpolate them to a monthly frequency.

The most noticeable difference is the more persistent response of rents.

A related concern points to migration pressures, particularly the large inflow of refugees in 2015/16 and 2022, which could potentially confound the housing market response — especially in the rental segment. While it is reasonable to assume that our monetary policy shocks are exogenous to demographic shifts, we augment our specification with (lagged) migration controls.²⁸ As depicted in Figure G.10, the inclusion of these controls does not attenuate the estimated IRFs.

Moreover, we control for spillover effects across housing segments. In particular, we include six lags of rent growth rates in the house price regressions and, conversely, six lags of the house price growth rates in the rent regressions. This allows us to capture potential feedback effects and temporal dependencies between these two housing markets. The IRFs depicted in Figure G.11, closely resemble those obtained from our baseline specification (Figure 3), confirming the exogeneity of our monetary policy surprises and the robustness of our findings.

Finally, we run a battery of additional robustness checks. In particular, we re-estimate our models (i) excluding the COVID-19 period, (ii) using a finer housing market aggregation i.e. municipality-level instead of district-level data, (iii) varying the minimum number of listings from 5 to 20 for the index construction, (iv) comparing our results to IRFs on transaction data, (v) altering the lag structure of our baseline specification, (vi) dropping fixed effects to address potential Nickell (1981) bias, (vii) expanding the spatial clustering radius from 100km to 200km, and (viii) using only large monetary policy shocks. Across all these specifications, the positive and significantly different effects of expansionary monetary policy shocks on house prices and rents remain unchanged, reinforcing our main conclusion that expansionary shifts in monetary conditions significantly increase property prices more than rents.

6 Heterogeneity in Monetary Policy Transmission

The increase in house prices and rents following monetary loosening documented in section 5 may mask important heterogeneity across policy instruments or housing regions. Understanding the heterogeneity in policy transmission is crucial for three reasons: (1) it helps to identify which monetary policy tool most significantly contribute to house price and rent appreciation, (2) it reveals potential distributional effects of monetary policy across regions, and (3) it assesses the effectiveness of regulatory policies to combat inflationary pressures, especially in the rental markets. In this section, we study heterogeneity along two key dimensions: differences across policy tools (subsection 6.1) and variation in responses among

²⁸Monthly regional migration data are not available in Germany. We use regional net migration data at annual frequency and interpolate linearly to obtain monthly changes.

different housing supply constraints (subsection 6.2).

6.1 Heterogeneity Across Policy Tools

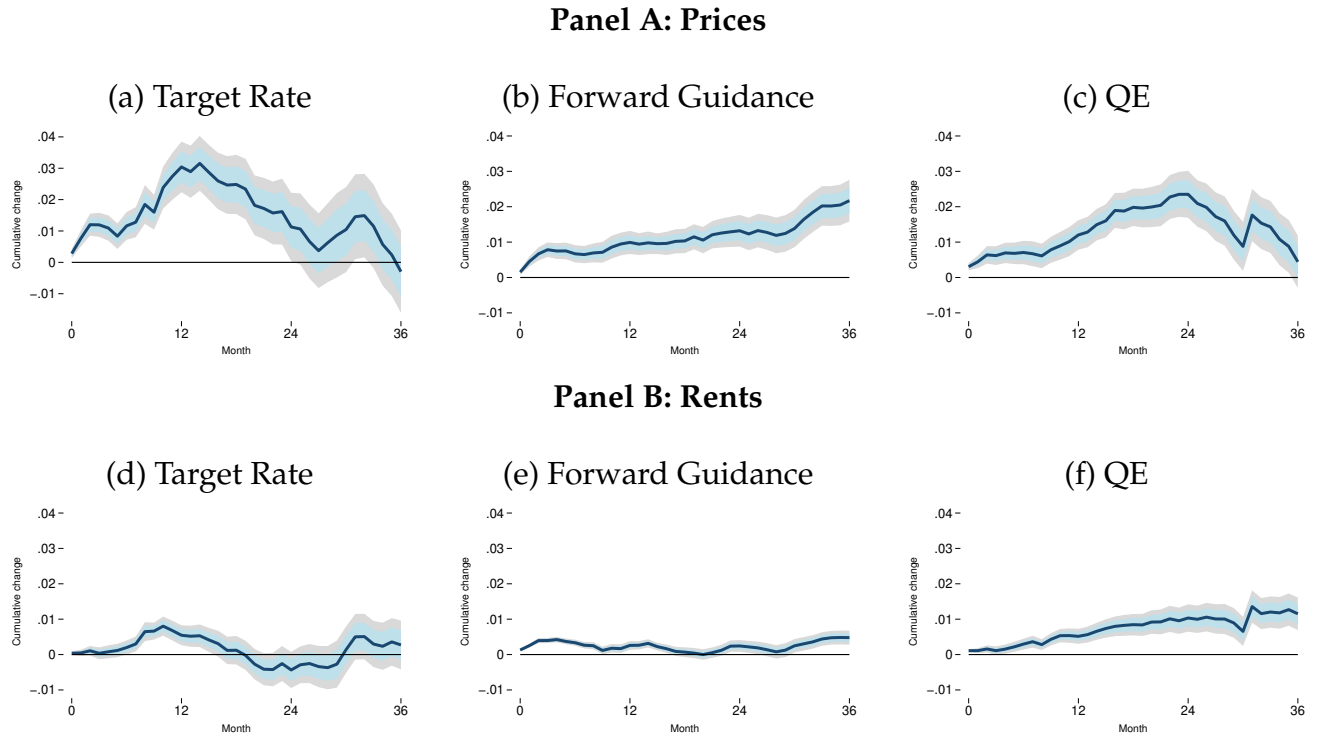
Shadow Rates serve as a useful indicator of the overall monetary policy stance, especially when the effective lower bound is binding. However, since the GFC, monetary policy has become multidimensional which likely induces different effects on house prices and rents, similar to other financial assets (Haitsma, Unalmis, and De Haan, 2016).

To differentiate between conventional and unconventional monetary policy, we employ distinct monetary policy surprises as instruments in our IV-LP framework. Specifically, we instrument the short-term nominal interest rate (proxied by the 1-month OIS rate) with the Target Rate shock. Forward guidance (FG), proxied by the 2-year OIS rate, is instrumented using the Forward Guidance shocks and quantitative easing, represented by changes in the ECB's balance sheet, is instrumented using the QE shocks and a QE announcement indicator. Including all policy tools and surprises simultaneously yields consistent results (see Figure G.23). All presented results correspond to a one SD shock to each respective policy tool.

House Prices (Panel A of Figure 5): A cut in short-term rates (-0.16 pp) 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. Conversely, unconventional policies exhibit more sustained impacts. Specifically, forward guidance, proxied by a (-0.2 pp) decline in the 2-year OIS rate, 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 (+ €117 billion), 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.

Rents (Panel B of Figure 5): The rent responses are generally more modest, but independent of the choice of policy tool, they are in the same direction as house prices. Conventional rate cuts lead to a mild and temporary increase in rents, with significance fading within two years. In contrast, 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. These findings suggest that unconventional monetary policies produce more durable effects on rents compared to conventional rate cuts, which induce only transitory impacts.

Figure 5: House price and rent responses - Policy decomposition



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 \(1999, 2008\)](#) standard errors.

6.2 Heterogeneity Across Housing Supply and Regulatory Constraints

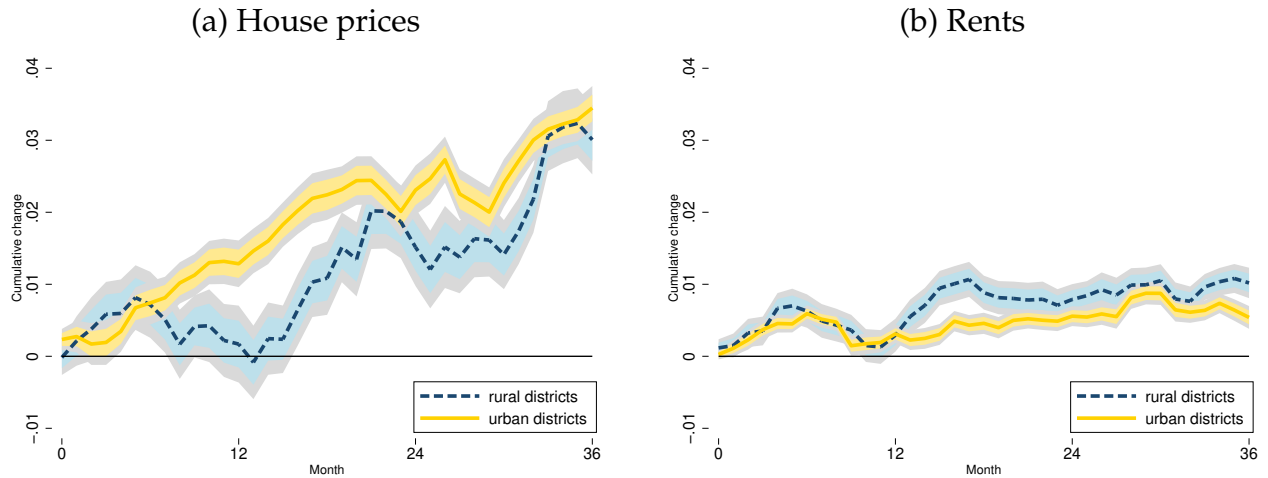
We next analyse whether specific regions respond differently to monetary policy loosening. A recent literature in the US has documented that local supply constraints can lead to asymmetric responses of monetary policy shocks on housing markets ([Aastveit and Anundsen, 2022](#)). In the German context, however, land constraints are unlikely to play a role given the country's generally flat terrain. On the other hand, zoning restrictions and rent regulation are more salient and may account for heterogeneous effects across regions. Leveraging the high granularity of our dataset, we investigate how these institutional and regulatory factors shape the transmission of monetary policy to local housing markets.

Urban-rural differences

Following the literature on spatial economics, a natural starting point is to split the sample into urban and rural regions, as rural regions are generally less subject to supply constraints

and regulation.²⁹ Figure 6 compares the IRFs of an expansionary monetary policy shock to housing prices separately for each type. Urban and rural regions see prices rise after an expansionary shock, but the timing varies. Urban areas react more sharply and immediately. However, rural districts eventually catch up in terms of price growth leaving no difference after three years. Interestingly, rents react slightly stronger to monetary policy shocks in rural regions suggesting that rent regulations, especially the rental brake introduced in urban areas, may help to contain rent increases.

Figure 6: 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 (0.27 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

Figure 6 suggests that supply constraints might amplify the short-term transmission of monetary policy to house prices and rents. However, since urban and rural areas differ in many dimensions beyond housing supply elasticity, we formalise this relationship by interacting monetary shocks with various proxies for local supply constraints.

We extend our baseline local projection model by estimating:

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

²⁹We classify regions (Kreis) according to Eurostat's definition of urban and rural regions at NUTS-3 level.

where β_S^h captures whether monetary policy has different effects in more supply constraint regions proxied by $Supply_{l,t-1}$. To identify this interaction effect we instrument it by the interaction of our high-frequency policy shocks and the supply constraint proxy. 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 absorbing macroeconomic shocks and tightening causal interpretation.³⁰

Table 2 reports the estimated coefficients β_S^h of equation 7 (in *percentage terms*) at 12, 24 and 36 months ahead. Each specification is estimated separately for different supply constraint measures, using data from January 2007 to December 2019 to avoid distortions from the COVID-19 period.³¹

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	0.009 (0.011)	0.014 (0.015)	0.001 (0.014)	-0.001 (0.004)	-0.004 (0.004)	-0.010* (0.006)
Panel B: Planning Zone - Regulation Intensity							
β_S^h	Δ Shadow Rate * Std(Regulation Int.)	0.253* (0.183)	0.249* (0.223)	0.171 (0.235)	0.062 (0.082)	0.010 (0.105)	-0.067 (0.132)
Panel C: Share of New Dwellings (inverse)							
β_S^h	Δ Shadow Rate * New Dwellings (-)	-0.060** (0.031)	-0.025 (0.033)	-0.091** (0.042)	-0.049** (0.021)	-0.056** (0.027)	-0.040* (0.031)
Panel D: Rental Brake							
β_S^h	Δ Shadow Rate * $\mathbb{1}$ (Rental brake)	0.159 (0.281)	-0.293 (0.394)	-0.158 (0.575)	-0.528*** (0.164)	-0.246* (0.205)	-0.323* (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 (-0.27 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. The regulation intensity is constructed by Pehlke and Siedentop (2021) for each regional planning zone in 2017. * $p < 0.32$, ** $p < 0.10$, *** $p < 0.01$.

Land unavailability Panel A of Table 2 shows that land scarcity across German regions does not significantly influence the transmission of monetary policy, likely due to limited regional variation (Bednarek, Kaat, Ma, and Rebucci, 2021).

³⁰While the proxy variables are potentially not exogenous, Borusyak, Hull, and Jaravel (2022) suggests that the exogeneity of the shock variable is sufficient for maintaining the causal interpretation of the policy effects in the IV setting. 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.

³¹We exclude the COVID-19 pandemic to mitigate outlier bias and address post-2020 data limitations.

Zoning regulation intensity Next, we use the planning zone regulation intensity constructed by [Pehlke and Siedentop \(2021\)](#) which reflects institutional differences in land use restrictions. Panel B shows that the increase in regulatory stringency by one standard deviation due to planning guidelines and limitations has effects on house prices and rents. Tighter regulations increase the pressure on house prices caused by monetary policy, but these effects are only weakly significant. The effects on rents are even weaker.

New dwellings To examine how new housing supply affects the transmission of monetary policy, we use the (inverse) of the share of new dwellings as a supply constraint. Exploiting exogenous variation in housing completions driven by adverse weather conditions, [Mense \(2025\)](#) show that an increase in new housing supply lowers average rents by 0.19. On top, Panel C indicates that a lower share 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 in Germany, a higher share leads to faster price dynamics.

Rental Brake Panel D exploits the staggered introduction of Germany's rental brake (*Mietpreisbremse*), a policy implemented in 2015 to contain increasing rents in overpopulated housing markets. The regulation caps new rental agreements at no more than 10% above the local reference rent and was gradually adopted across several municipalities, creating useful cross-sectional variation in rent regulation intensity (see also Section 2). We interact the shadow rate with a rental brake indicator (1 if active). Our results show that the rental brake significantly dampens the pass through of monetary easing into rents, reducing the effect by 0.52 pp after one year and by 0.32 pp after three years, relative to unregulated areas. Notably, we find no effect on house price dynamics, consistent with the regulation targeting only the rental segment.

These findings suggest that institutional frictions, particularly rent controls and construction activity can partially offset the inflationary effects of monetary easing on rents and house prices. Rent controls are more effective in the short run, as they directly constrain rent increases on new leases but the effect attenuates in the medium term. In contrast, supply-side measures like housing construction are more lasting but are typically slow moving and take longer to materialise.

Demand-side factors

A recent study from the US questions the conventional wisdom over the dominant role of supply factors in shaping house price dynamics (Louie, Mondragon, and Wieland, 2025). They argue that over the past 30 years, demand-side factors have played a more prominent role in housing markets. In Appendix I, we interact monetary policy shocks with demand side factors such as regional demographics, wage levels, and labour market tightness. While some patterns emerge, demand-side heterogeneity is generally weaker and less consistent than supply-side variation. These results support the view that in Germany institutional regulatory frictions play a more central role in shaping local housing responses to monetary shocks.

7 Mechanisms

So far, we have established that expansionary monetary policy raises house prices more strongly and persistently than rents. In this section, we seek to explore the forces behind these findings. We first examine the responses of housing demand and supply to monetary policy changes. We then use survey data to link these responses to household behaviour and housing tenure choices.

7.1 Housing Demand Responses

Monetary policy influences house prices and rents primarily by stimulating housing demand. To quantify this channel we use *contacts per listing-day* – defined as the total number of inquiries a seller received divided by the number of days the listing is active – as proxy for housing demand.³² To isolate demand-driven changes in contacts from shifts in the mix or quality of listings, we apply the same hedonic regression as for prices and rents. We regress contacts-per-listing-day separately for each region and tenure on the exact same set of covariates as described in Section 3.4.³³ In this exercise, we restrict our sample to January 2009 through December 2018 primarily due to the erratic behaviour of this series during the COVID-19 period and the limited availability of contact data prior to 2009.

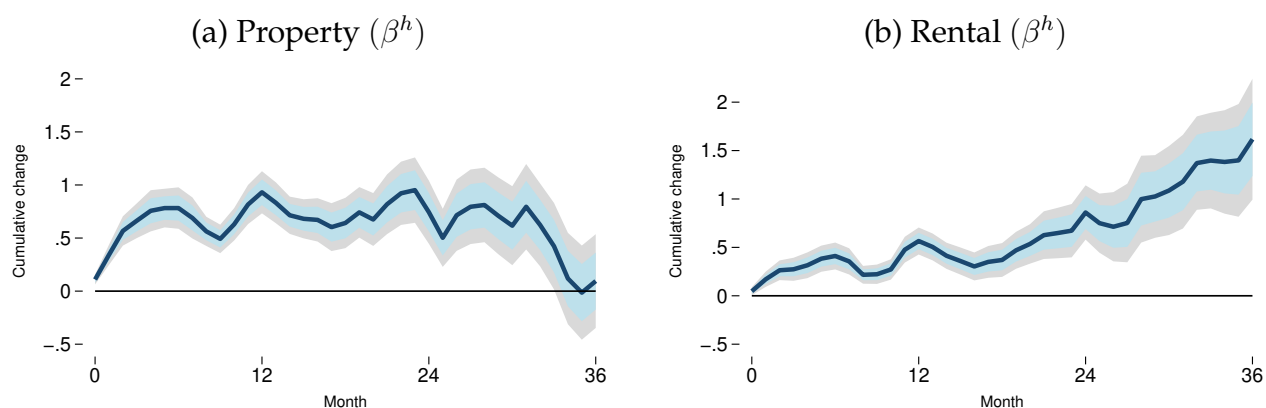
Figure 7 illustrates the IV-LP responses of housing demand to a one standard deviation reduc-

³²This measure is not equivalent to the number of clicks (hits) on a listing. To initiate contact, a prospective buyer must first click on the property listing on the Immobilienscout24 website and then select the “Contact Seller” option.

³³Unlike house prices and rents, contact per listing day exhibit several zero or near-zero values. Hence, the y variable in the hedonic regressions is in levels not logarithms. To reduce 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. We adjust for seasonality by X-13ARIMA-SEATS.

tion in the Shadow Rate. As expected, the housing demand proxy – contacts per listing-day – increases markedly for both the sales and rental markets. Initially, the rise in demand for purchases is approximately twice as large as for rentals, but this relationship reverses over longer horizons. Given average contacts per day of about 0.27 for purchases and 1.54 for rentals, these responses are economically substantial, particularly in the sales market. Thus, the relatively stronger response of demand in the sales market partly explains the stronger monetary policy effects on house prices found in the previous section.

Figure 7: 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 (0.27 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.

What might cause the increase in demand for house purchases? In theory, three main channels could rationalise the IRFs of Figure 7 (a). The first is direct and already discussed in Section 5.2. Expansionary monetary policy reduces long-term interest rates and make house financing more accessible, especially for first-time buyers. Moreover, a second indirect channel is at play – *the income channel*. Exploiting German administrative data, Groiss (2023) finds that monetary policy in the Euro Area led to an increase in employment and labour earnings during the same period. Increased earnings allow households to spend more money on housing and likely translate into higher housing demand. This is particularly relevant in Germany, where mortgage lenders typically require down payments of 20%-25% of the property’s value.

Aside from home-ownership choices, monetary policy also influences housing investment decisions. This mechanism is particularly relevant during periods of low interest rates, as institutional investors and wealthy households search for relatively higher yields in the buy-to-let market (Boddin et al., 2024; Berg et al., 2023). In Appendix F we further probe into this

mechanism. Rental yields are on average 5.3% in Germany and only fall 0.1 pp after a one SD Shadow Rate cut (see Figure F.8). This increases the attractiveness of housing investments relative to other more responsive financial products. In addition, capital gains on residential property rise by about 2 pp, boosting total returns and likely boosting purchase demand without affecting rental demand.

Turning to the rental market, the weaker demand responses compared to the property market are in line with theory. While indirect income effects might boost demand similar to the property market, cheaper financing conditions are arguably less relevant for renting than purchasing a house. In addition, landlords try to forward higher house prices to their tenants' rents to keep their investment profitable, as indicated by the stable rental yields (F.8). At the same time, the shift from renters to homeowners lowers demand. The portfolio rebalancing channel is only present at the sales market, where assets can be owned eventually. Beside theory, the developments shown here are also consistent with the monetary policy effects on housing transitions presented in Section 7.3.

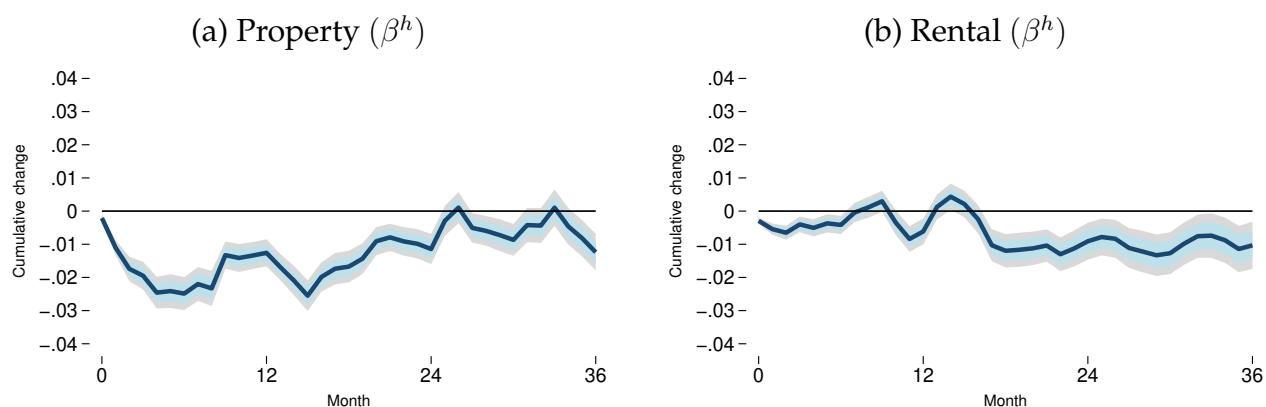
7.2 Housing Supply Responses

Aside from demand effects, monetary policy could influence housing supply. In order to capture the responses of housing supply, we count the average number of new listings per region and month for the period 2007-2023.³⁴ Figure 8 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 (Kudlyak et al., 2022; Fonseca and Liu, 2024). Kudlyak 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% 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.

At first glance, the findings on the number of listings may appear puzzling since aggregate statistics show that housing completion rates have increased markedly over this period as financing got cheaper. However, newly built properties account only for a small fraction of the new listings in the data. A more plausible explanation is that existing home sellers optimally delay listing to capture higher expected sale prices and rents. As transactions volumes are

³⁴In contrast to our demand variable, we do not have data issues, so we consider the whole sample period, but the results are similar for the period 2009-2018

Figure 8: 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 (0.27 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.

driven primarily by listing activity and less so by faster sales ([Ngai and Sheedy, 2020](#)), home movers are the key to understand the drop in listings as shown in the next sub-section.

A similar logic applies to the rental market, where listings also slightly decline following expansionary monetary policy shocks. 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, probably hoping for more favourable 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.

7.3 Household Mobility and Tenure Transitions

In this last section, we study the heterogeneous impact of monetary policy on household behaviour and how tenure decisions explain housing demand and supply dynamics. To rationalise the increase in housing demand and the contraction in housing supply, we expect renters and homeowners to respond differently to expansionary monetary policy shocks. While owners might postpone moving, hoping for a better deal for their house, renters seize the opportunity to become home owners. Likewise, higher labour earnings might induce renters to upsize their house, move to more expansive locations or even acquire their own house. Moreover, we use this section to validate our findings with a well known alternative

dataset.

Household survey data

We leverage household-level survey data from the Socio-Economic Panel (SOEP), a representative household survey administered by the German Institute for Economic Research (DIW Berlin). We use the survey waves 2005–2022 during which SOEP covers on average around 30,000 individuals in around 15,000 households each wave. While the survey is fielded annually, the interviews are conducted throughout the year, which allows us to assign the respective monetary policy changes at a quarterly frequency and avoid annual aggregation. The unit of observation is a household interviewed in a quarter of a given year. On average a household is interviewed 5 times (over 5 or more years). See Appendix J for descriptive statistics.

We use information from the calendar module in SOEP to construct annual transition rates between renting and owning. Table 3 presents the percentage of individuals with respect to their reference tenure that change housing (tenure) between two survey waves. As expected, the vast majority of movers are rent to rent transitions (roughly 8%) followed by rent to owner transition (3%). Younger households (< 45 years old) are generally more mobile. While transition rates from renting to renting are similar across the income spectrum, high income households are nine times more likely to become homeowners than low income households.

Table 3: Housing transition rates

	R → O (%R)	O → R (%O)	O → O (%O)	R → R (%R)
Overall transition rate (%)	2.23	1.28	1.21	8.64
among young (< 45 years)	2.97	1.84	1.73	13.2
among old (>= 45 years)	1.58	1.13	1.07	4.78
low income (first tercile)	0.62	2.75	0.86	8.55
middle income (second tercile)	2.39	1.24	1.12	8.65
high income (third tercile)	5.44	0.77	1.39	8.83
N (whole sample)	115,077	95,727	94,504	112,516

Notes: This table reports the transition rates between housing and housing tenure from one survey wave to another. The age is taken from the household head and the income from the whole household.

Econometric Analysis

We can now study how households tenure decisions are affected by changes in monetary policy. 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. Instead, we adopt the methodology proposed 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. We run the following regression:

$$Move_{iqy} = \beta z_{qy} + \gamma X_{iqy} + D_q + D_y + D_i + \epsilon_{iqy} \quad (8)$$

where $Move_{iqy}$ is a dummy variable that describes a change in the housing tenure or location 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 three 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. We differ from [Koeniger et al. \(2022\)](#), by including household fixed effects D_i in our regression to reduce any concerns about related 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 4.2 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.³⁵ 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. Summing over twelve monetary policy coefficients respectively, results in the three year cumulative effect on housing transitions.

Table 4 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 pp expansionary monetary policy shock increases the probability of transitioning from renting to ownership by 1.4% over three years and decreases the probability of owners to become a renter by 2.2%. In combination, these effects both boost demand for home-ownership and dampen turnover activity among incumbents.

³⁵First, 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.

Table 4: Monetary policy effects on housing tenure transitions

	R→O	O→R	O→O	R→R
Cum. 3y effect (0.25pp cut)	1.379*** (0.371)	-2.204** (1.168)	-2.642*** (0.756)	1.850* (1.416)
Lagged macro controls	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓
Fixed effects (household, year, quarter)	✓	✓	✓	✓
N	115,077	95,727	94,504	112,516

Notes: The dependent variable is 1 if a household changes housing (and tenure status) in the respective direction and 0 if it does not. Standard errors are clustered by quarter to capture cross-household effects by the aggregate monetary policy shocks. Macro controls include 3 lags of unemployment rate and inflation. Household controls include 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 all types of monetary policy shocks. * $p < 0.32$, ** $p < 0.10$, *** $p < 0.01$.

In the previous sub-sections, we have shown that the demand responses to monetary policy are relatively weaker in the rental market compared to the sales market. Table 4 helps to explain this observation. While the rent-to-rent mobility increases, the increase in rental demand is partly offset by tenants opting to purchase homes and by fewer owners becoming renters. Column 4 in Table 4 shows that expansionary monetary policy shocks lead to an 1.9% increase in tenants moving to new tenancies within a three-year period. New jobs and rising incomes associated with such policy shocks are likely the most important factor that facilitate this transition. 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.³⁶

Moreover, column 3 of Table 4 supports the finding of a significant reduction in housing supply after an expansionary monetary policy shock with a different dataset. The transitions of owners to new homes fall significantly by 2.6% following a Shadow Rate cut. This implies that less houses become vacant that could be posted on the market. In addition, less owners become renters (column 2), which has a similar effect on the sales listings.

Finally, we estimate equation (8), replacing the dependent variable with household income, separately for renters, owners and movers to shed some light on the role of income on housing decisions. Our goal is to uncover the “income effect” of monetary policy across tenure groups. We find that monetary loosening significantly increases incomes of renters and owners three years after an expansionary monetary policy shock (see Table 5). The effects on owning households are only a third of those of the renters, in line with the findings of [Groiss \(2023\)](#), who document that expansionary monetary policy during our sample period disproportionately

³⁶While the model specifically addresses ownership-to-ownership transitions, the implications are likely applicable to the rental market as well.

Table 5: Monetary policy effects on household income

	income (renters)	income (owner)	income (movers)
Cum. 3y effect (0.25pp cut)	1.756*** (0.233)	0.610*** (0.189)	3.502*** (0.731)
Lagged macro controls	✓	✓	✓
Household characteristics	✓	✓	✓
Fixed effects (household, quarter)	✓	✓	✓
N	115,077	95,727	13,725

Notes: The dependent variable is the real household income (in logs). Standard errors are clustered by quarter to capture cross-household effects by the aggregate monetary policy shocks. Macro controls include 3 lags of inflation. Household controls include age (squared), employment status, years of education, migration background, and gender of household reference person, household size, lagged permanent 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 all types of monetary policy shocks. * $p < 0.32$, ** $p < 0.10$, *** $p < 0.01$.

benefited younger, lower-income households that are mostly renters. Interestingly, the largest wage gains can be observed by those who move. This points to the relevance of income for moving decisions and the related increase in housing demand over the three year horizon.

8 Conclusion

In this paper, we establish how changes in monetary policy affect regional property prices and rents in a large European economy characterised by a liquid rental sector and historically stable house prices. Using an online dataset of 35 million real estate listings for both houses and apartments over 16 years, we demonstrate that expansionary monetary policies, both conventional rate cuts and unconventional interventions, 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. Although rents also respond positively to policy easing, these effects are smaller and less persistent than for house prices. Second, we find evidence that monetary policy exacerbates regional dispersion significantly in house prices or rents due to different regulatory stringency. However, these effects are small and short-lived and other supply constraints appear to propagate relatively uniformly across regions. Third, our analysis shed some light on the way expansionary monetary policy propagates into house prices and rents, through a reduction in mortgage financing costs, increasing wages, and changes in housing tenure. On the one hand, more favourable financing conditions and higher wages 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 pivotal in shaping how monetary policy shocks transmit through the housing market. A rich quantitative model that differentiates between owning and renting to quantify the welfare and general equilibrium effects could be beneficial but is left for future research.

These findings carry important policy implications for housing affordability and inflation dynamics. Central banks need to recognise that expansionary monetary policy, especially unconventional measures, have consequences for housing markets that might be stronger than intended. Not only do they significantly raise house prices, which are not included in the CPI, they may also have sizeable, more persistent effects on rental markets. The rental market predominantly consist of young and borrowing-constrained households, so that monetary easing increases the gap between property-owners and renters and has distributional consequences across cohorts.

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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 Homeownership Rates in Germany

Germany's owner occupancy rate is low and is often called the "land of renters". In 2022 only about 42% of the German households own the houses they live in, compared to the EU average of 69%. However, this ratio masks significant heterogeneity across regions and developments in the housing market in recent years.

There are large regional differences in homeownership across regions in Germany (see Figure A.1). In general, large cities have far lower ownership rates than smaller towns and rural areas. Among the German regions, the largest cities (Berlin, Hamburg, Munich) have some of the lowest ownership shares, while Saarland and other rural areas have the highest. Also note that East German areas generally show lower ownership rates than West German areas.^{37 38}

The number for housing units has also increased over time. Table A.1 compares the census statistics in 2011 and 2022. 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 faster growth in rental stock is driven largely by population inflows associated with migration after the Syrian civil war and the Russo-Ukrainian conflict. This fact explains why Germany's homeownership rate decreased slightly even though the number of owner-occupied dwellings grew over this period.

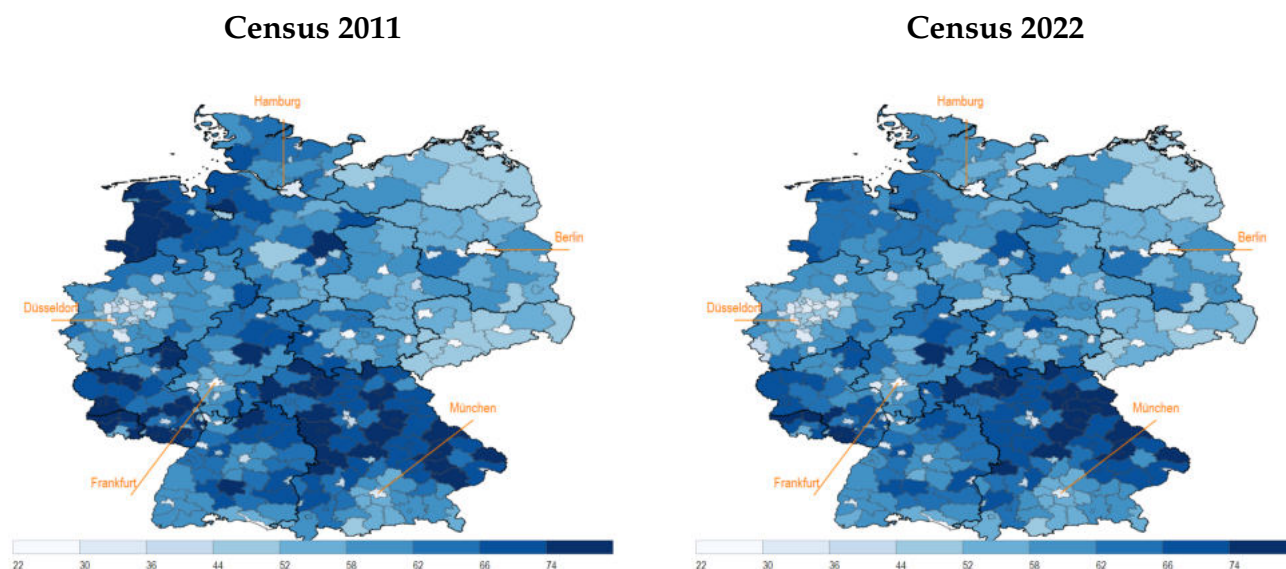
³⁷Our analysis relies on data from the 2011 and 2022 Census that can be accessed at [Zensus 2011](#). We exclude holiday/leisure and vacant dwellings from the total count. The homeownership rate is then calculated by taking the ratio of owner-occupied dwellings to the adjusted total number of dwellings.

³⁸As 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 that have merged since 2011, we calculated the homeownership rate by taking the unweighted average across the merged regions.

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: Homeownership 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

According to the 2022 Census, Germany's housing stock comprised roughly 19.4 million residential buildings and 43.1 million dwellings, up from 18.4 million buildings and 40.6 million dwellings in 2011. Of the 2.5 million net additional units, about one-fourth were owner-occupied and the remaining three-fourth entered the rental sector. Commonhold owners and

other private individuals collectively own nearly 80 percent of all dwellings, with cooperatives, municipal companies, non-profits, and public bodies sharing the remainder.

Ownership of that rental stock is highly fragmented. A back of the envelop calculation from Table A.2 indicates that outside of homeowner-occupied units, over 60 percent of rental apartments are held by “mom-and-pop” landlords many of whom rent out dwellings in the same buildings where they live, while institutional and large corporate landlords together account for less than 15% of the total.³⁹ Other public and state entities hold significantly smaller shares.

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 accessible at <https://ergebnisse.zensus2022.de/datenbank/online/variables>

³⁹Destatis and various other German reports corroborate this fact.

B Immobilienscout24 Data

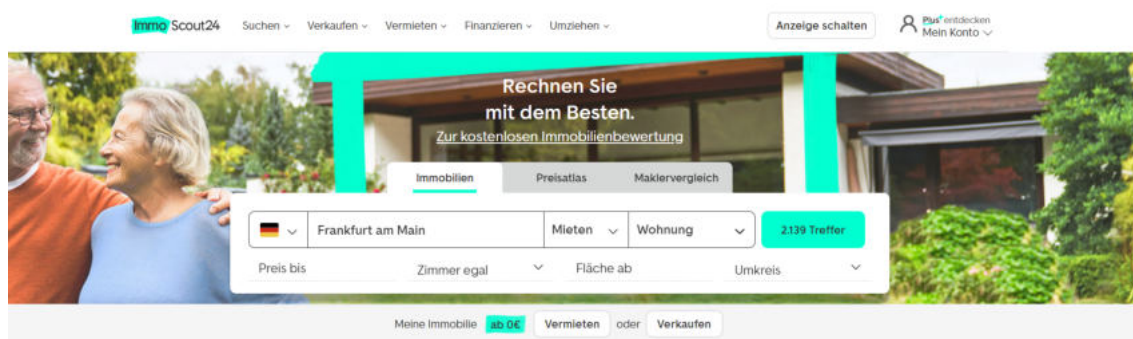
In this section of the Appendix, we provide comprehensive details about our housing listings dataset. Appendix B.1 offers an overview of the Immobilienscout24 online platform, while Appendix B.2 delves into the inferred user attributes of Immobilienscout24 visitors. The data cleaning procedures are thoroughly 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 ???. 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.⁴⁰ 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.

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
(-) 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
Final Dataset	17,807,089		18,182,468	

⁴⁰Similarweb Ltd. is a global company specializing in software development and data aggregation, with a focus on web analytics, traffic, and performance analysis.

Repeated entries Our raw dataset contains multiple duplicate entries for two reasons. First, Immobilienscout24 snapshots were taken roughly every six months beginning in November 2015. As a result, active listings from previous snapshots reappear as duplicates in subsequent retrievals. Second, certain properties are re-advertised multiple times within a six month window. To avoid double-counting we only retain the last occurrence or “spell” of each property in the dataset.⁴¹ 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 exclude listings with missing sale/rent price, post-code or implausible size values (as flagged by RWI). We then drop 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 €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 market.

Censoring Immobilienscout24 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.⁴² Lastly, we deflate the nominal values using the state specific CPI at the monthly frequency.⁴³

⁴¹If 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.

⁴²In 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-Fallingb.ostel* 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.

⁴³We 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](#).

B.4 Regional Mapping

The RWI Essen classify the regions according to the Amtlicher Gemeindeschlüssel (AGS).⁴⁴ 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.

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

⁴⁴The 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.

B.5 ImmobilienScout Variables

Table B.5: ImmobilienScout24 list of housing characteristics

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

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					
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					
Con/lis Day			0.06	0.11	0.14	0.15	0.18	0.32	0.40	0.41	0.42	0.48					
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 (count)	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 metre. **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: 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					
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					
Con/lis Day			0.54	0.65	0.99	1.11	1.38	1.77	2.75	4.17	5.20	5.39					
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 (count)	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 metre. **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.

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.

The hedonic regression is designed as follows:

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:

$$\ln(p_{i,t}^{l,\tau}) = \alpha^{l,\tau} + \gamma_t^{l,\tau} + \beta^{l,\tau} X_{i,t}^{l,\tau} + F_{j(i)} + \varepsilon_{i,t}^{l,\tau} \quad (9)$$

where $\alpha^{l,\tau}$ is the constant and $X_{i,t}$ is a vector of housing covariates. 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), $F_{j(i)}$ is a full set of post-code dummies $j \in l$ to capture time-invariant neighborhood differences such as parks and distance to the city center.

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.

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 indices 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 visit this link [GREIX project](#).

We use the transaction-based aggregate indices 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.

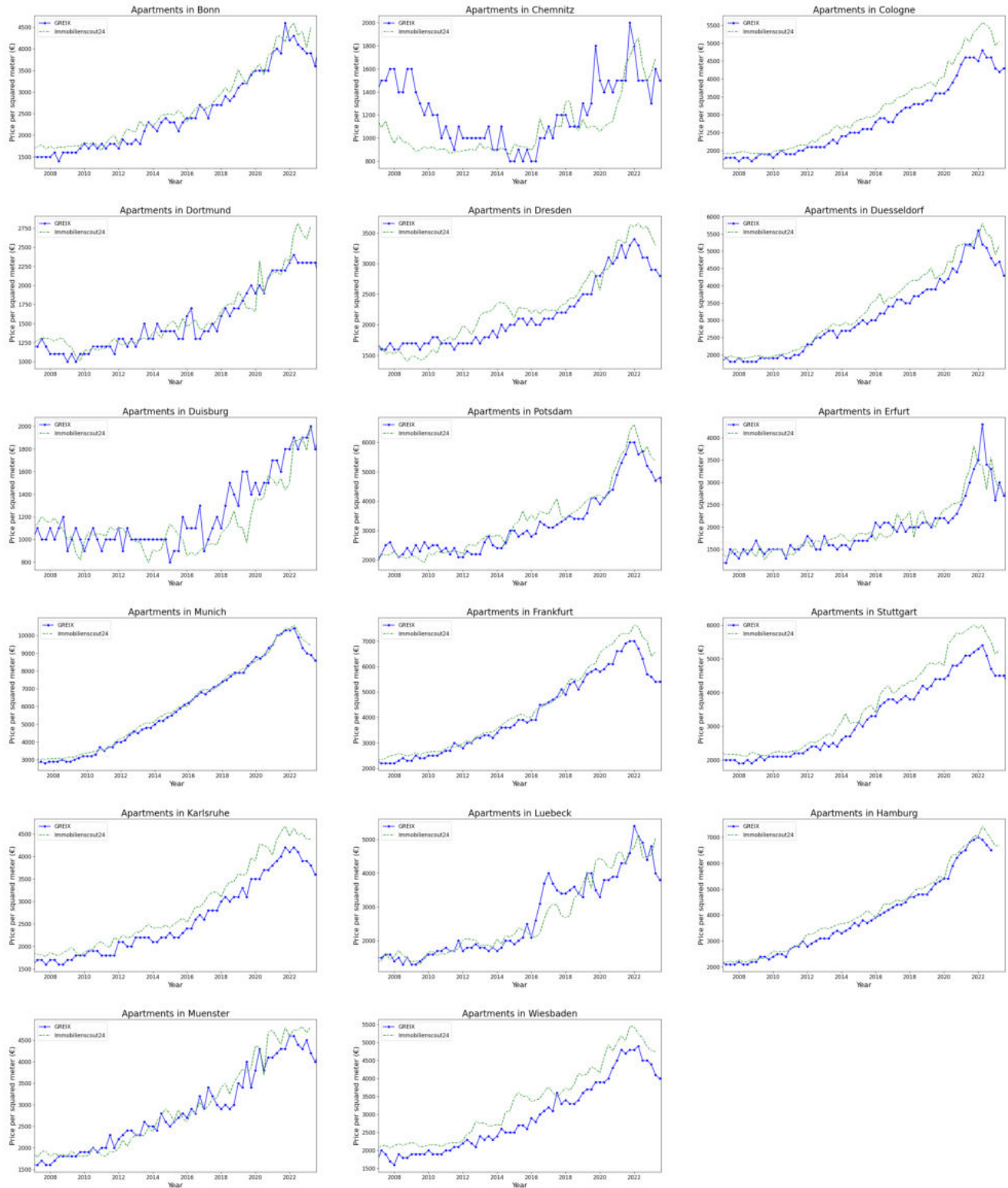
Single family houses The procedure for single family houses is more involved. We use the raw file “HK_SUF” that contains all listed houses for sale. We use the variable “kategorie_Haus” (house type) to identify the housing segment. We keep all the house types with entries a) Single-family house (detached), 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.⁴⁵ 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. Although there are some deviations, the trends and patterns are broadly similar. Figure [G.18](#) replicates the IRF of monetary policy shocks from Section 5 on apartment and family

⁴⁵We also replicate our analysis excluding missing entries and the final results appear almost identical.

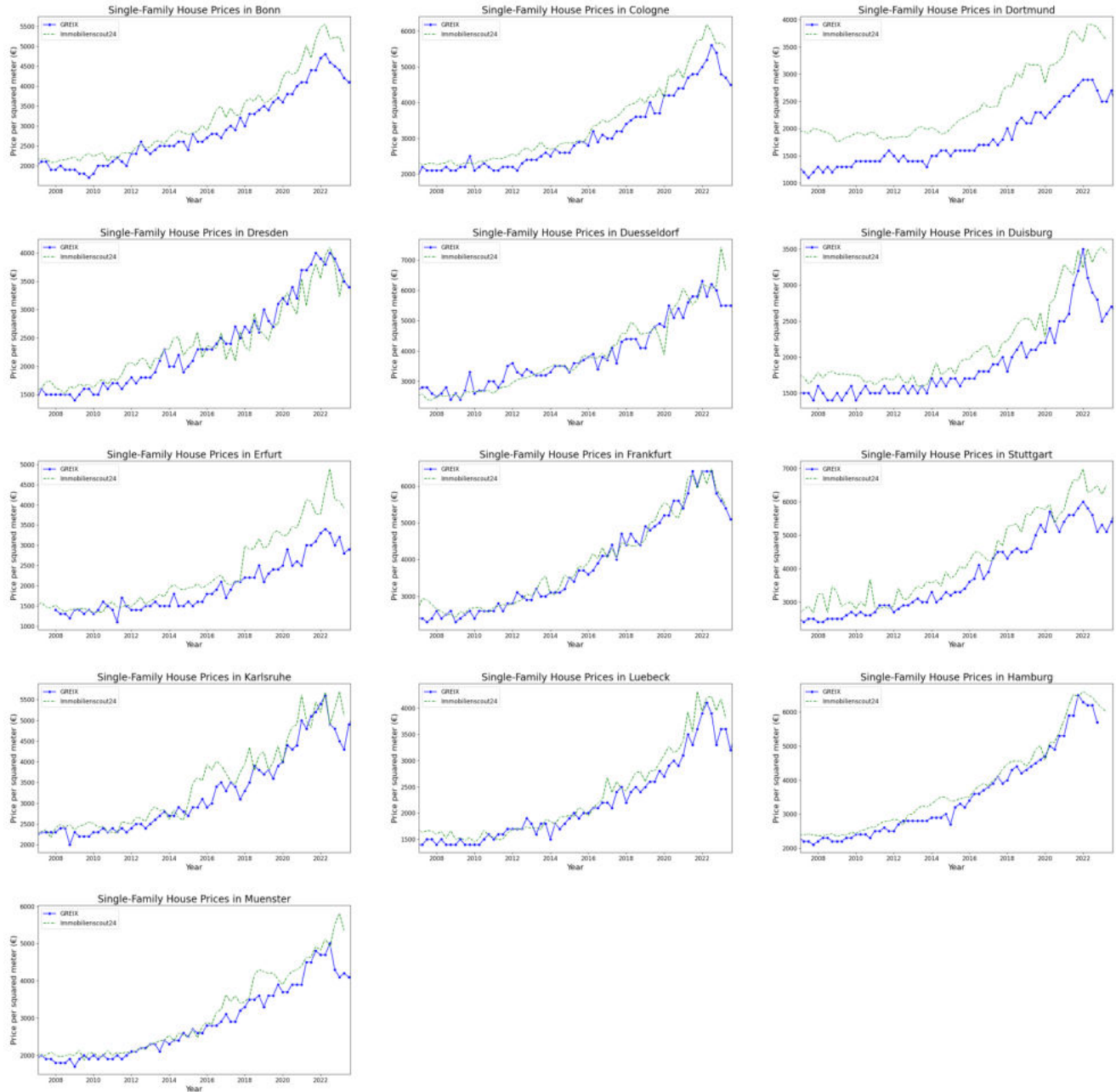
house prices at the quarterly frequency and shows that the responses of transaction prices to a Shadow Rate reduction are not significantly different from the responses of listing prices.

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.

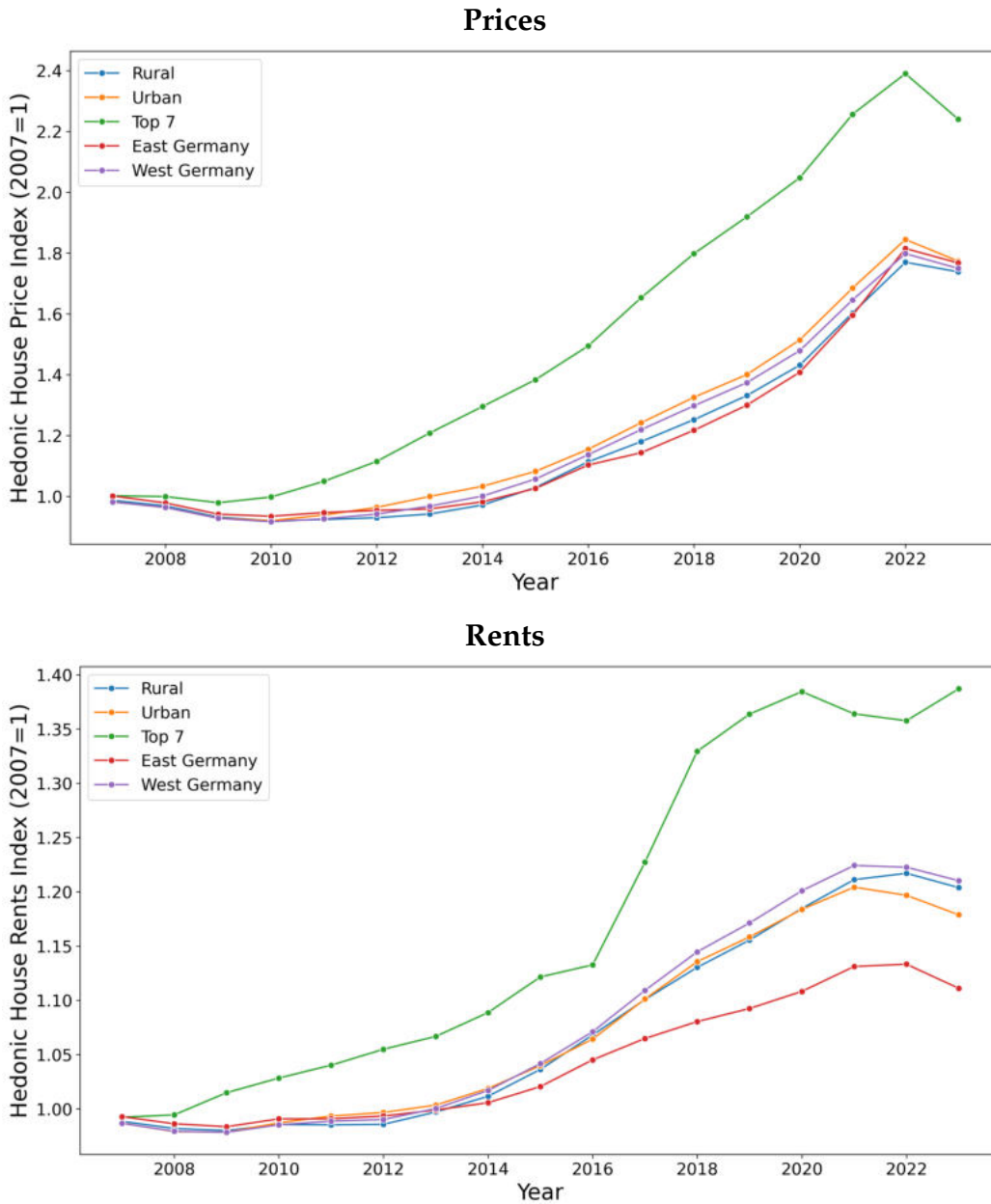
Figure B.4: Single Family house Sales Price - Transactions vs Listings



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.

B.8 Evolution of Hedonic House Prices and Rents Indices

Figure B.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.

C Data sources

In this section of the appendix, we provide details on additional data that we use in the empirical exercise. Table C.8 summarises the variables and the sources used. Data on the house prices and rents are additionally discussed in Appendix B.

Table C.8: 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
Rental yields	Kreis	Annual real rent divided by estimated house price of the same property (via Kreis-specific hedonic regressions), regional average	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 (2009-2018)	RWI-GEO-RED
Duration	Kreis	Days of availability of advertisements per month and Kreis, seasonal adjusted (2009-2018)	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 brake	Kreis	Indicator if Mietpreisbremse is in place in at least one municipality	Refrago.de
Regulation intensity	Kreis	Index that captures positive (guidelines) and negative (restrictions) regional planning regulations per planning zone in 2017 (Pehlke and Siedentop, 2021)	Pehlke/Siedentop
New construction	Kreis	Share of listings advertising housing that is less than one year old	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
Net migration	Kreis	Inflow minus outflow of people per Kreis, annual change	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 Portal
OIS rates	Country	Overnight Index Swap rates, maturities 1 month to 10 ten years	Refinitiv
Balance Sheet	Country	ECB Balance sheet volume	ECB Data Portal
Shadow Rate	Country	Euro Area Shadow Rate as constructed by Krippner (2013)	ljkma.com
10 year mortgage rate	Country	10-year mortgage interest rate, Germany	ECB Data Portal
S&P 500	Country	S&P 500 stock market index, 3 month growth rate	ECB Data Portal
Commodity price	Country	ECB Commodity Price Index, 3 month growth rate	ECB Data Portal
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.

D 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 changes 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.⁴⁶

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.⁴⁷ 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 [D.6a-D.6c](#). Notice that the series account for the possibility of information effects included in the shocks ([Jarociński and Karadi, 2020](#)). Specifically, 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. The final shock series are depicted by Figure [D.7](#).⁴⁸

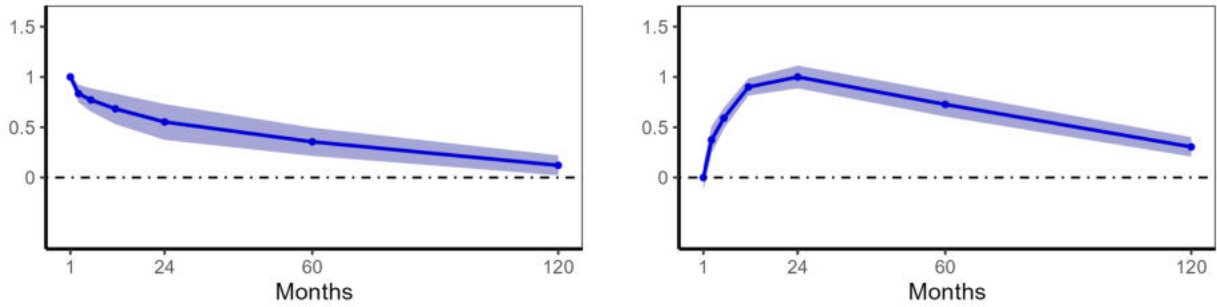
Table [D.9](#) presents the impact of aggregated monetary policy surprises, as measured by [Al-](#)

⁴⁶Following [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).

⁴⁷For maturities beyond one year prior to August 2011, intraday OIS data were unavailable, so German government bond yields data were used instead.

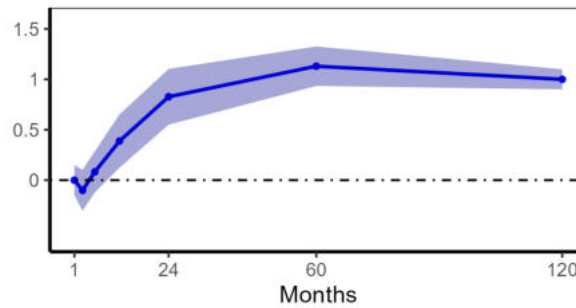
⁴⁸We decided against using the shock series provided by [Jarociński and Karadi \(2020\)](#) since they use the 3-month EONIA swap changes as shocks. As we want to compare the different policy tools and focus on a period where policy rates were little moving, it is not surprising that this shock series is not a strong instrument to the Shadow Rates by [Krippner \(2013\)](#) or balance sheet changes.

Figure D.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.

Figure D.7: 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 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.

E Methodological Details

E.1 Conley Standard Errors

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

Table D.9: High frequency shocks - Financial market responses

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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 cut-off 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:

$$\Sigma_{ij} = K \left(\frac{d(i, j)}{\lambda} \right) \cdot \hat{u}_i \hat{u}_j \quad (10)$$

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.

E.2 Diagnostic Tests

In this section, we discuss the series of diagnostic tests we perform to attest the validity of our econometric approach.

Relevance To establish instrument relevance, we first assess the strength of the monetary policy surprises as instruments for the endogenous policy variables. Table E.10 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. 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.⁴⁹

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 lags of these dependent variables have no significant explanatory power over the monetary policy shocks (see Table E.11), thereby supporting the assumption of lag exogeneity. Regarding lead exogeneity, it is satisfied by the definition of shocks as unexpected surprises, provided that 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.

⁴⁹While 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.

Table E.10: First Stage F-Statistic - House prices and Rents

	12 months	24 months	36 months		12 months	24 months	36 months
Shadow Rates	150.3	131.8	124.9	Shadow Rates	141.1	123.7	117.8
Policy Rate	100.4	104.8	106.0	Policy Rate	95.8	99.1	99.9
2y OIS Rate	497.1	972.1	962.0	2y OIS Rate	469.1	923.4	914.1
Balance Sheet	89.3	89.7	95.2	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 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

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 E.11: Lead-lag exogeneity test

	(1)	(2)	(3)	(4)	(5)	(6)
	Target	Forward	QE	Target	Forward	QE
House price index (t-1)	0.189 (0.18)	-1.072 (-0.96)	-1.577 (-1.43)			
House price index (t-2)	-0.576 (-0.98)	1.894 (0.98)	0.980 (1.17)			
House price index (t-3)	0.941 (0.79)	-0.504 (-0.46)	-0.167 (-0.17)			
House price index (t-4)	-1.102 (-0.82)	-1.841 (-0.93)	-0.489 (-0.60)			
House price index (t-5)	-0.0480 (-0.07)	2.996 (1.11)	1.190 (1.13)			
House price index (t-6)	0.275 (0.32)	-0.731 (-0.55)	0.0989 (0.10)			
Rent index (t-1)				-0.371 (-0.21)	-2.958 (-0.75)	-4.794 (-1.56)
Rent index (t-2)				-0.610 (-0.43)	1.591 (0.35)	1.655 (0.60)
Rent index (t-3)				-0.748 (-0.27)	2.988 (0.80)	2.135 (0.87)
Rent index (t-4)				-0.0983 (-0.03)	-0.0542 (-0.02)	0.189 (0.09)
Rent index (t-5)				2.523 (0.85)	-2.641 (-0.62)	-5.479* (-1.69)
Rent index (t-6)				-1.680 (-0.56)	3.186 (1.02)	6.210* (1.87)
Constant	0.331 (0.67)	-0.847 (-1.52)	0.0210 (0.03)	0.970 (0.77)	-2.177 (-1.54)	0.153 (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, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

F Rental Returns

Beside the purchase of housing for the own use, the property market also has an investment dimension that might matter for the understanding of house price dynamics. In addition to stocks, ETFs or other financial assets, real estate is an important part of the investment portfolios of wealthy households in Germany. Given these alternative investment opportunities, housing also needs to generate stable returns to remain attractive. To link our results to the recent financial literature on housing, we calculate the *total returns* on rented housing, its two components *rental yields* and *capital gains*, and their responses to changes in monetary policy.

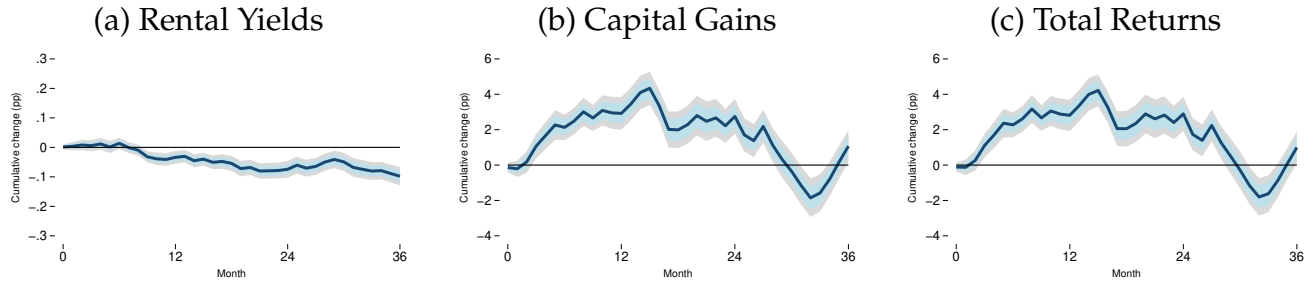
$$Total\ Returns_{l,t} = \underbrace{\sum_{i=1}^{N_{l,t}} \frac{1}{N_{l,t}} \frac{R_{i,t}}{\hat{P}_{i,t}}}_{rental\ yields} + \underbrace{\frac{P_{l,t} - P_{l,t-12}}{P_{l,t-12}}}_{capital\ gains} \quad (11)$$

To calculate rental yields, we follow the approach of [Hill and Syed \(2016\)](#) and estimate the sales prices of all houses and flats that are available for rent in our dataset. We make use of the estimated coefficients from the hedonic regressions of the regional sales markets and use them to estimate the expected (fitted) prices of rental objects. These prices are the denominators of the annual real rents to calculate real rental yields for each property. In order to remove outliers and prepare the data for our regional-monthly framework, we calculate the average rental yield for each Kreis and month (see equation 11). This panel dataset is then used in our LP framework as described in Section 4.

Figure F.8 (a) shows the IRF of an expansionary monetary policy shock (1 SD cut in the Shadow Rate) on rental yields. Rental yields fall only marginally by 0.1 pp over three years. Compared to the average yields observed on the German market of 5.3% (SD = 1.3), the decline is not economically relevant. While we observe that rents respond much less than house prices to expansionary monetary policy (see Section 5), this seems to be only partially transmitted to average rental yields. This is in line with the hypothesis that landlords try to keep their margins stable and adjust their rents as far as possible to increasing house prices.

In contrast, the responses of capital gains to expansionary monetary policy shocks are large and economically relevant (see Figure F.8 (b)). Defined as the twelve month growth rate of property prices, capital gains rise by 2 pp on average in the first two years before the effect fades. Consistent with our findings on house prices, the effects of monetary policy are largest in the sales market. These effects dominate the responses of the total returns of housing (Figure F.8 (c)). Due to the stability of rental yields, gains are mostly accelerated by the increased capital gains following expansionary policy shocks.

Figure F.8: House price and rent responses - Direct policy comparison

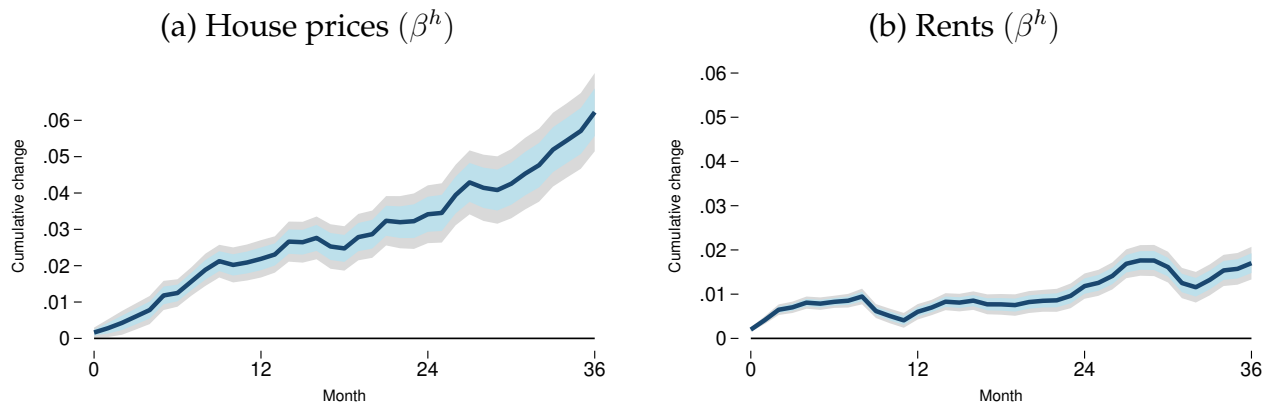


Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of rental yields, capital gains and total returns to a 1 SD (-0.27 pp) reduction in the Shadow Rate. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06. Confidence intervals are calculated using [Conley \(1999, 2008\)](#) standard errors.

G Robustness Exercises - IRF

This section presents several robustness exercises to verify the validity of the baseline results in Section 5. Figures [G.9-G.14](#) are explained in the main text in detail. The other figures are presented here for the interested reader.

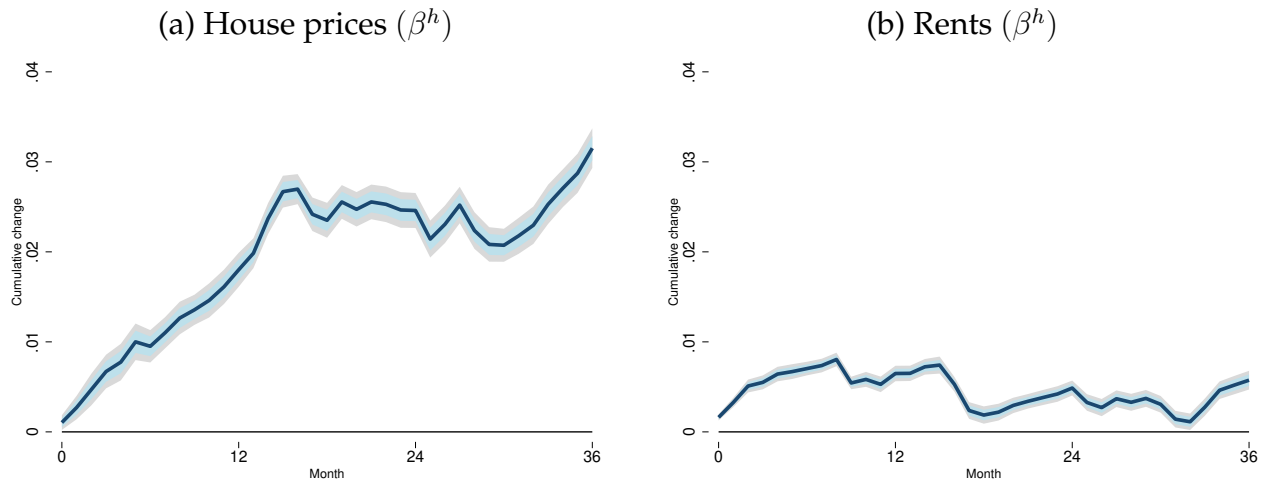
Figure G.9: House price and rent responses - additional controls



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.27 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.

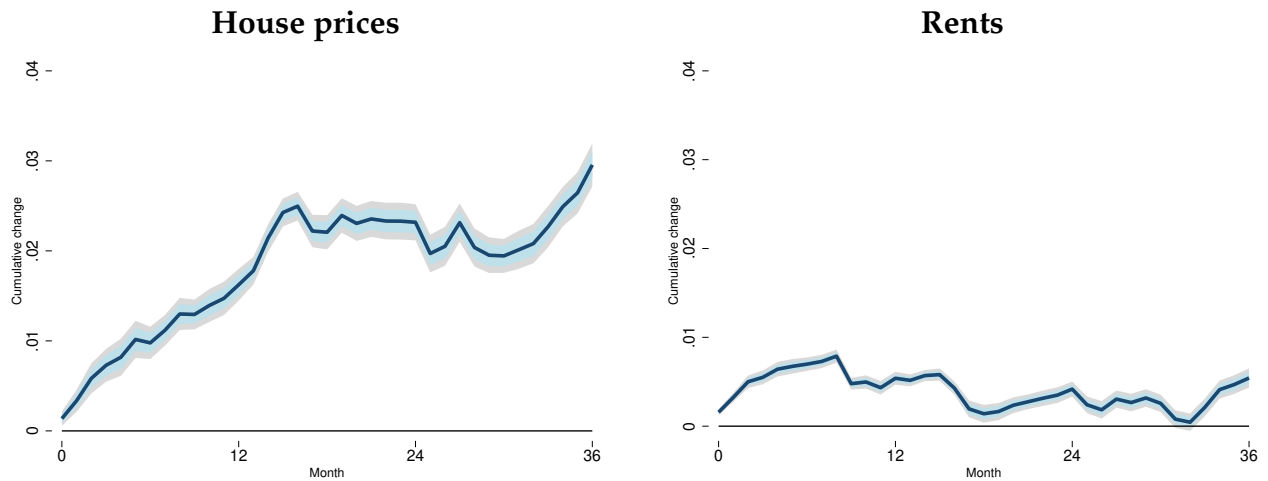
Excluding COVID-19 period Figure [G.15](#) reports the responses of house prices and rents to expansionary monetary policy shocks for a sample ending before the COVID-19 pandemic (2007:01–2019:12). While the pandemic period was associated with high uncertainty and unusual policy measures that could blur the identification of monetary shocks, our results remain similar in magnitude. The rent response is somewhat larger and more persistent, but

Figure G.10: House price and rent responses - Migration controls



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 (0.27 pp) reduction in the Shadow Rate of our baseline specification augmented with migration controls. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06.

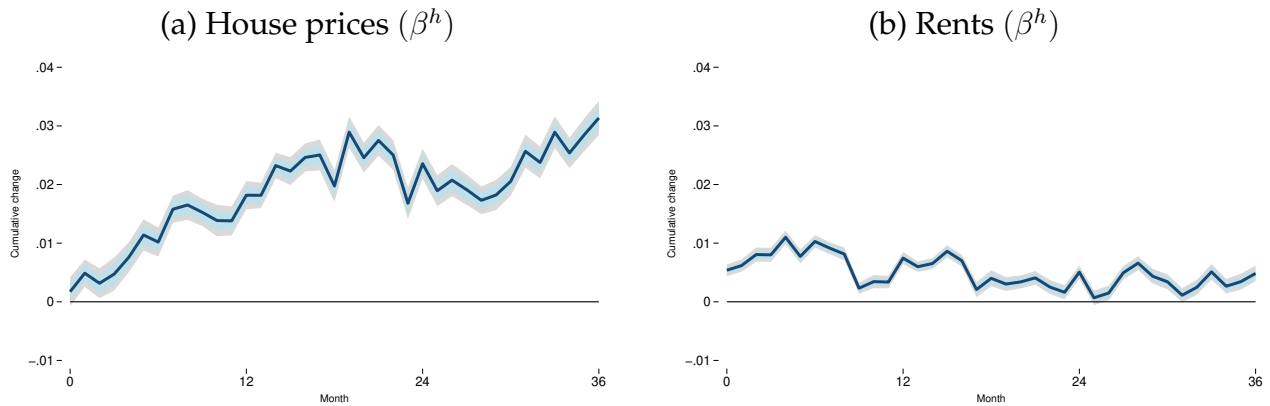
Figure G.11: House price and rent responses - lagged housing market dynamics



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 (0.27 pp) reduction in the Shadow Rate of our baseline specification augmented with lagged growth rates in house prices/rents. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06.

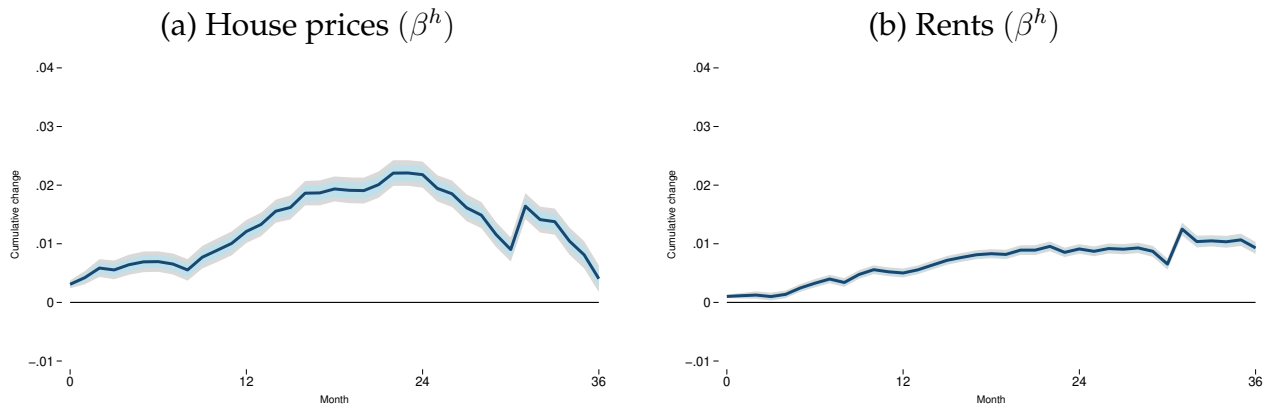
does not exceed 1%. To reduce the computational burden, we only show cluster robust standard errors, but the conclusions remain the same accounting for spatial correlation in the standard errors.

Figure G.12: House price and rent responses - without smoothing



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 (0.27 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 G.13: House price and rent responses - QE shock after 2009

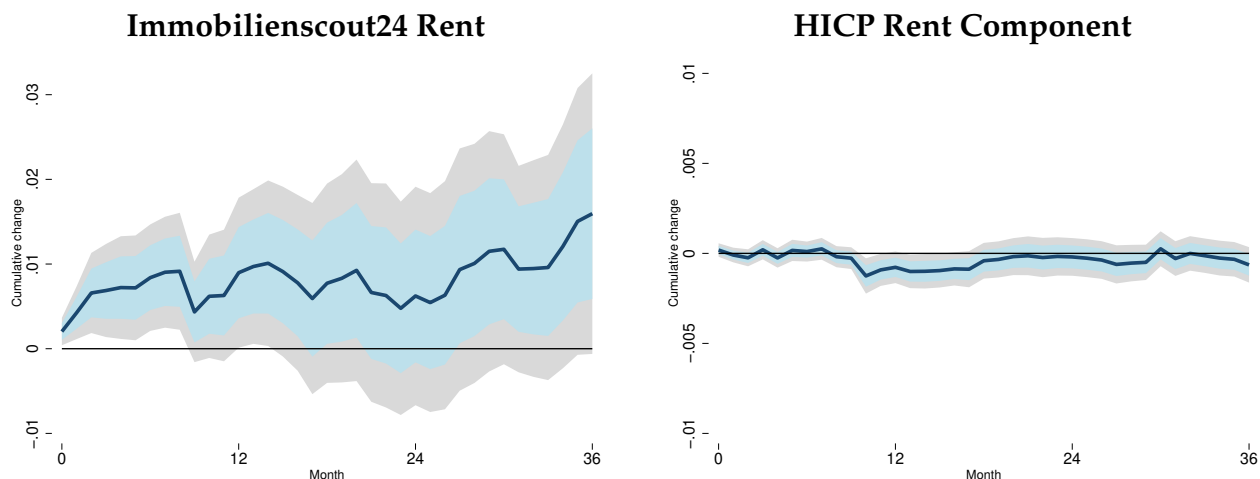


Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (117 billion €) expansion of the ECB's balance sheet. The QE shocks are set to zero before 2009:05. The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using cluster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

Finer Geographical Aggregation: Municipality Next, we assess whether the baseline estimates depend on the regional level of aggregation. Figure G.16 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.

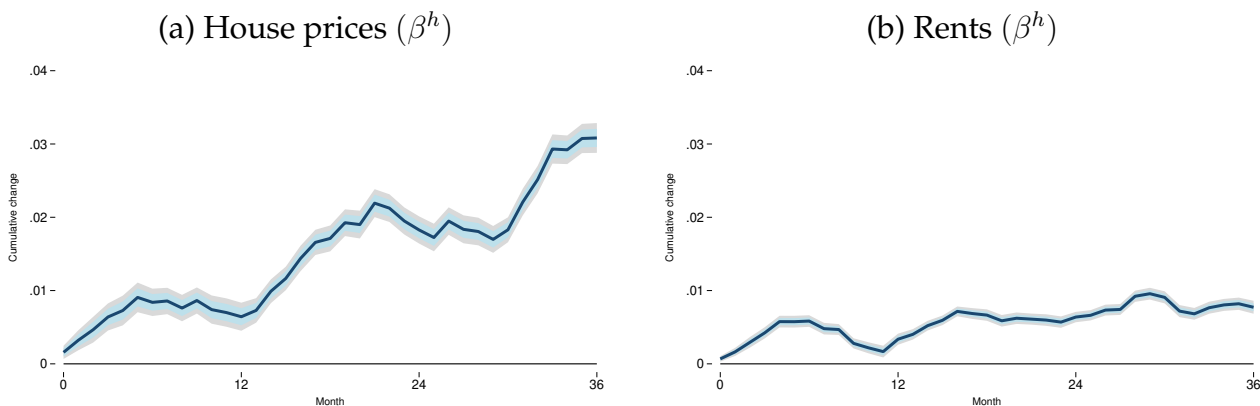
Minimum Listings Threshold To check whether sparsely populated regions with few list-

Figure G.14: Comparison Between Immobilienscout24 Rents and HICP Rental Component Responses



Notes: This figure compares the nationwide impulse response functions (IRFs) of rents to a 1 SD (0.27 percentage point) reduction in the Shadow Rate, using two different measures of rents. The left panel reports results based on the rental index from Immobilienscout24, while the right panel shows the response of the rental component of the Harmonised Index of Consumer Prices (HICP). Both IRFs are estimated at a monthly frequency using data from January 2007 to June 2023. Shaded areas represent Newey-West robust standard errors (68% and 90%).

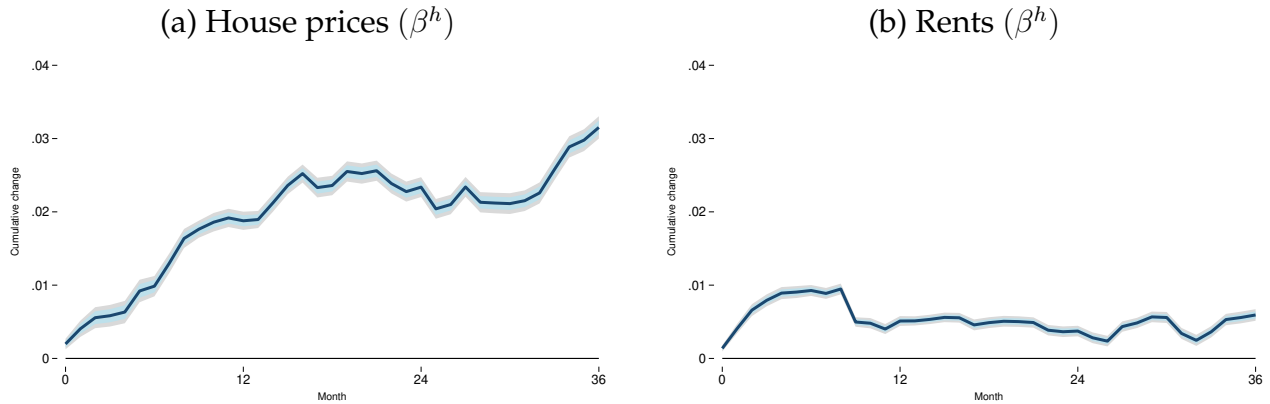
Figure G.15: House price and rent responses - Pre-Covid pandemic



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.27 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.

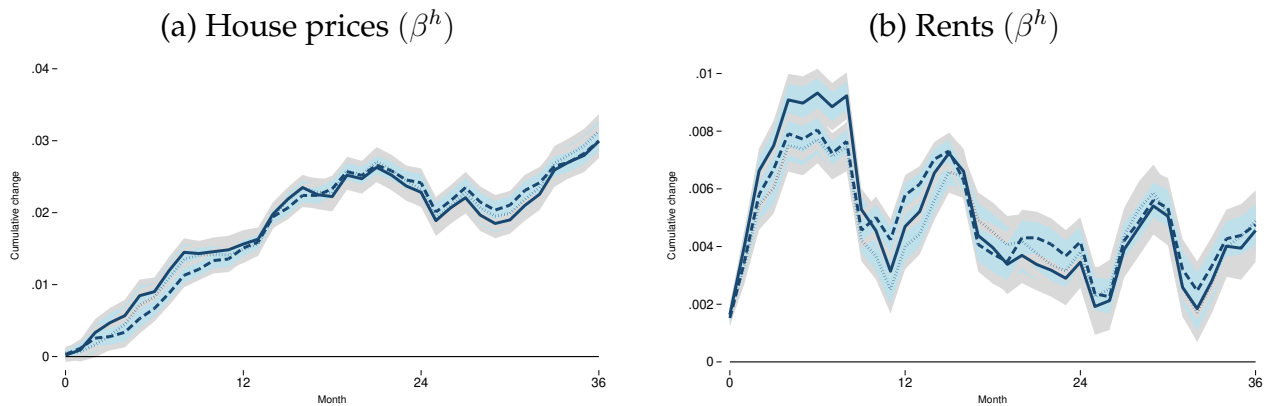
ings bias the results, we vary the threshold for the minimum number of monthly listings per district from 10 to 5 or 20. Figure G.17 indicates that although this modifies the number of districts in the sample, the IRFs remain unchanged.

Figure G.16: House price and rent responses - Municipality level



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.27 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.

Figure G.17: House price and rent responses - observation threshold

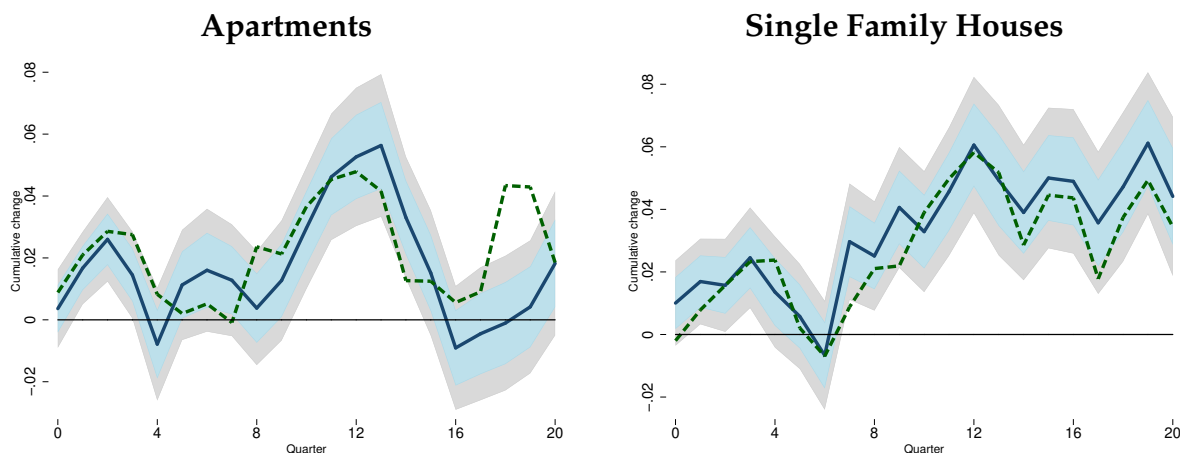


Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price and rent indices to a 1 SD (0.27 pp) reduction in the Shadow Rate. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06. The graph depicts cluster 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.

Comparison with Transaction Data We also consider whether our listing-based data yield 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 G.18 that the estimated responses remain positive and lie within the baseline confidence bands.

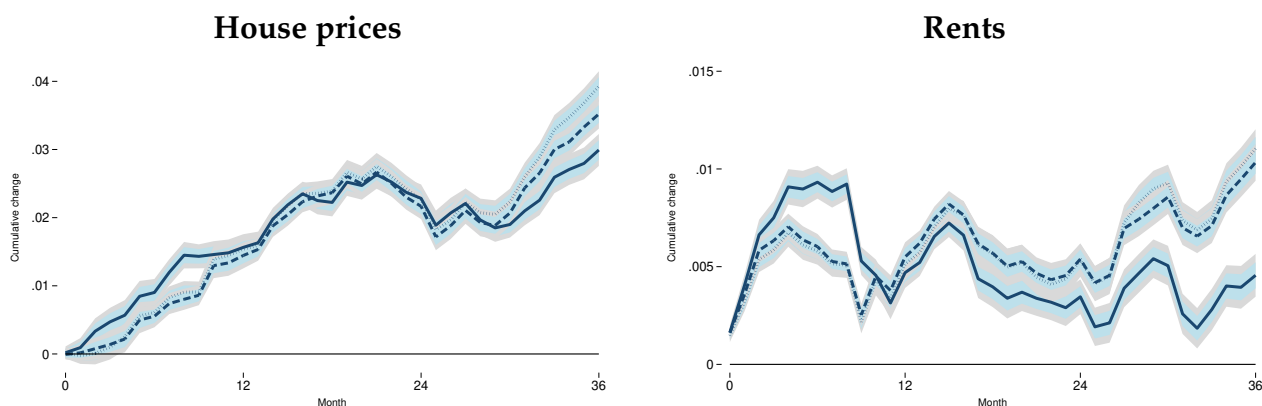
Lag Structure Our results are also robust to changes in the lag structure. Using 3 or 12 lags

Figure G.18: Shadow Rate responses - Transactions vs Listings



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.

Figure G.19: House price and rent responses - lag variation

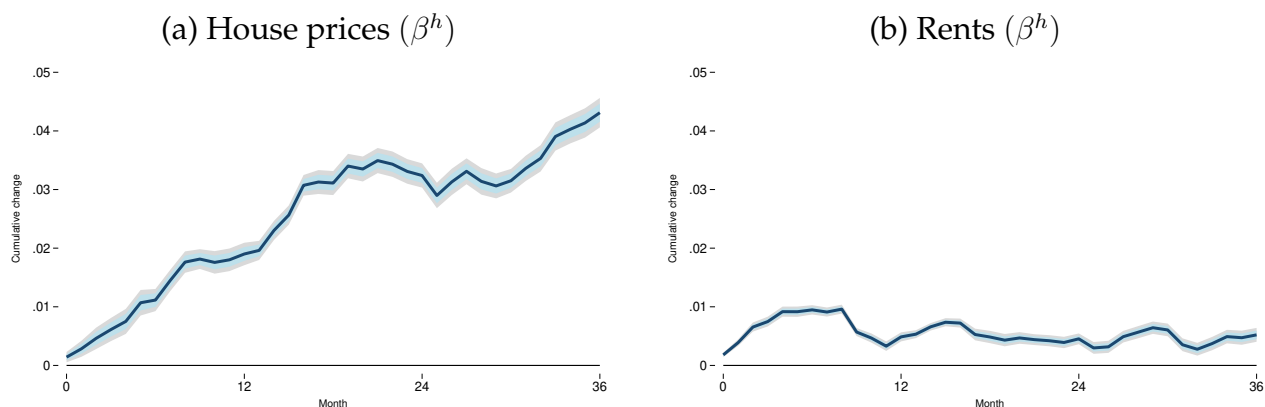


Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price and rent indices to a 1 SD (0.27 pp) reduction in the Shadow Rate. Impulse responses are at the monthly frequency using data from 2007:01 to 2023:06. Cluster robust standard errors. 3 lags of house price/rent growth = solid line, 6 lags = dashed line, 12 lags = dotted line

instead of 6 does not lead to meaningful changes in the IRFs. Figure G.19 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 G.20: House price and rent responses - without Fixed Effects



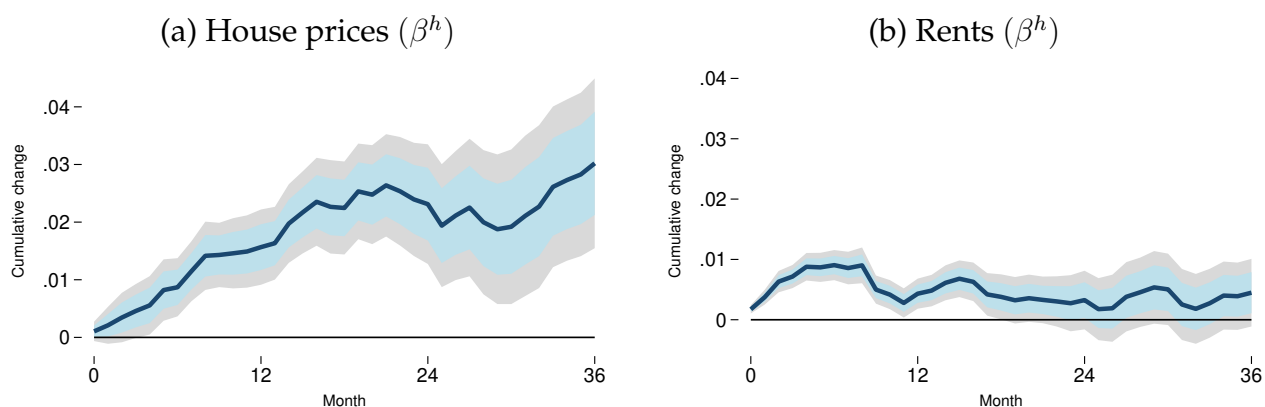
Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.27 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2007 to June 2023, without district fixed effects. The shaded areas represent the 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 G.20. The results are very similar to our baseline, only slightly larger for the house price responses.

Larger commuting zone Moreover, we check the sensitivity of our results to the assumptions made for the derivation of the Conley standard errors. Figure G.21 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.

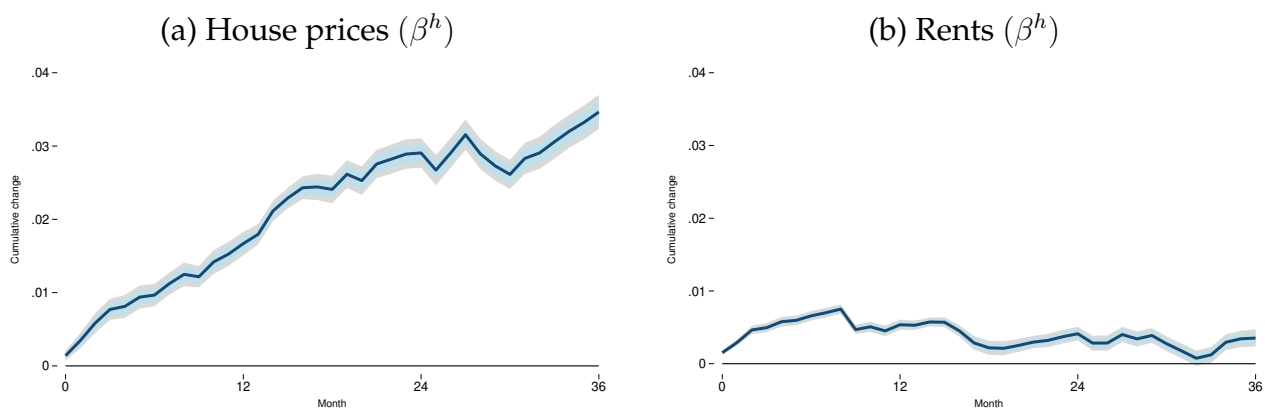
Larger Policy Surprises Finally, Figure G.22 depicts the IRFs for an alternative set of monetary policy shocks. Instead of using all shocks derived from the PCA and accounting for potential information effects, we only keep large and focal surprises observed between 2007 and 2023 (> 1 standard deviation). Thereby, we can account for noise and non-relevant changes in monetary policies. Excluding small surprises, keep our results mainly unchanged.

Figure G.21: House price and rent responses - larger SE cluster



Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.27 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 cut-off of 200km.

Figure G.22: House price and rent responses - Large policy surprises

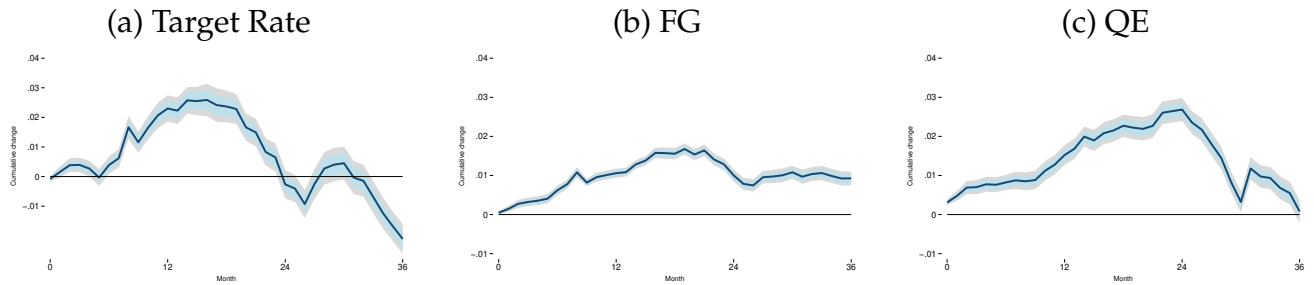


Notes: The figure displays the responses (β^h) of house prices (left) and rents (right) to a 1 SD (0.27 percentage points) reduction in the Shadow Rate. The responses are at a monthly frequency, using data from January 2007 to June 2023, only using large/focal monetary policy surprises as instruments (> 1 SD). The shaded areas represent the 68% (blue) and 90% (grey) confidence intervals, calculated using cluster robust standard errors.

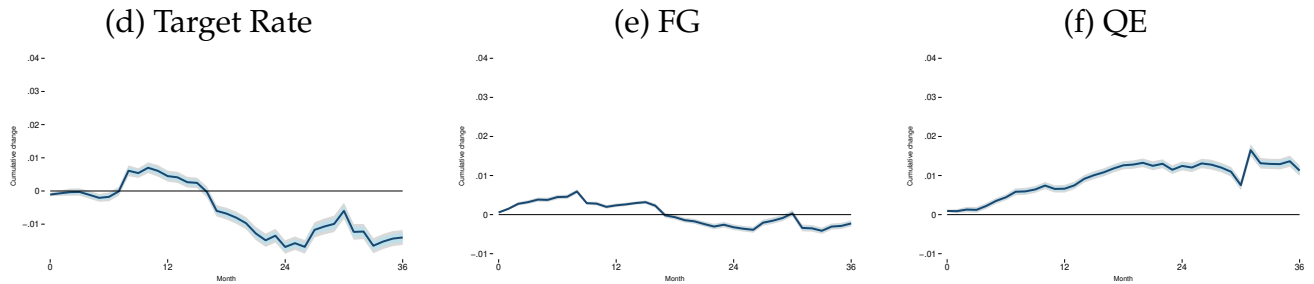
Adding Policy Tools as controls In Figure [G.23](#), we explore whether including all three monetary policy tools and their associated high-frequency instruments simultaneously changes the results. If anything, the differences become more pronounced: (i) QE exhibits the strongest impact on house prices, (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, be-

Figure G.23: House price and rent responses - Direct policy comparison

Panel A: Prices



Panel B: Rents



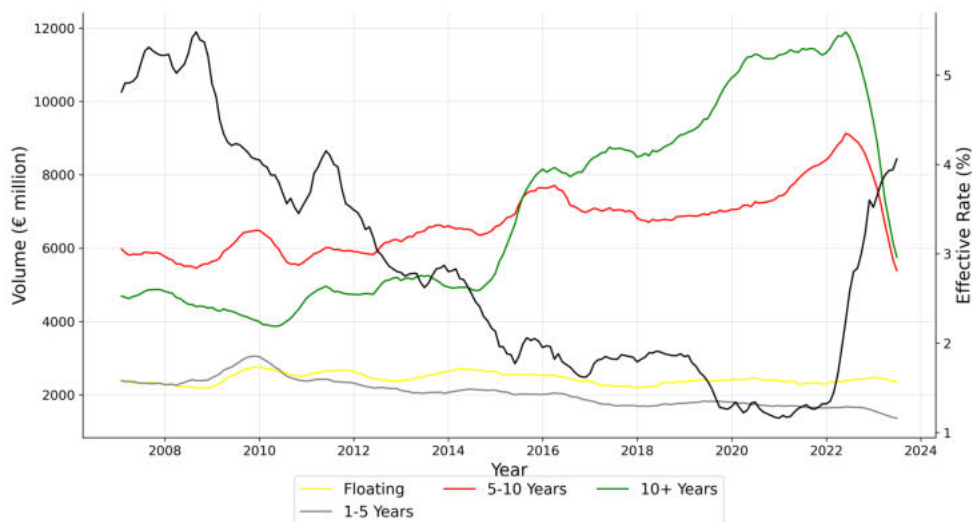
Notes: The figure plots impulse responses as well as 68% and 90% confidence intervals (blue and grey shaded areas) of house price indices to a 1 SD (0.16 pp) reduction in the 1-month OIS rate, a 1 SD (0.2 pp) reduction in the 2-year OIS rate, and a 1 SD (117 billion €) expansion of the ECB's balance sheet - 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.

cause the decomposition of policy tools is less clear when all exogenous instruments overlap, especially during the pre-QE period.

H Mortgage Loans Composition-Germany

Unlike homeownership rates, the composition of mortgage loans in Germany closely mirrors that of the United States.⁵⁰ As depicted in Figure H.24, 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.24: 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.

⁵⁰In 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 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:

$$\ln(y_{l,t+h}) - \ln(y_{l,t-1}) = c_l^h + c_t^h + \sum_{k=1}^K \alpha_k^h \Delta \ln(y_{l,t-k}) + \beta_D^h Demand_{l,t-1} \times \widehat{policy}_t^p + \phi^h(L) X_{l,t}^h + u_{l,t+h}^h, \quad h = 0, 1, \dots, H \quad (12)$$

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 I.12, 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 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, Griesemer, 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 I.12: 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 (0.0304)	0.0515* (0.0402)	-0.0349 (0.0413)	-0.00426 (0.00913)	0.0140* (0.0104)	-0.00765 (0.0151)
Panel B: Young Age Share							
β_D^h	Δ Shadow Rate \times Young Age Share	0.144* (0.123)	0.408** (0.170)	-0.0736 (0.183)	-0.0270 (0.0530)	0.0303 (0.0716)	-0.0999* (0.0855)
Panel C: Migration							
β_D^h	Δ Shadow Rate \times Std(Net Migration, t-1)	0.105 (0.166)	0.543** (0.273)	0.318 (0.244)	-0.0419 (0.0678)	0.0862 (0.105)	0.00647 (0.125)
Panel D: Unemployment Rate							
β_D^h	Δ Shadow Rate \times Unemployment Rate (t-1)	0.00410 (0.106)	-0.124 (0.135)	0.0952 (0.161)	-0.00316 (0.0411)	-0.0754** (0.0436)	-0.0210 (0.0628)
Panel E: Wage Quintile (Administrative Data)							
β_D^h	Δ Shadow Rate \times 1st Wage Quintile	-0.170 (0.659)	-0.573 (0.787)	0.749 (0.787)	-0.0864 (0.186)	-0.00394 (0.230)	-0.0287 (0.293)
β_D^h	Δ Shadow Rate \times 2nd Wage Quintile	0.0353 (0.455)	0.445 (0.531)	0.239 (0.543)	-0.00834 (0.156)	0.122 (0.140)	0.216* (0.210)
β_D^h	Δ Shadow Rate \times 4th Wage Quintile	0.307 (0.357)	0.554* (0.406)	0.0463 (0.487)	0.0695 (0.184)	0.302* (0.218)	-0.156 (0.229)
β_D^h	Δ Shadow Rate \times 5th Wage Quintile	0.487* (0.386)	1.043** (0.518)	0.428 (0.598)	-0.0352 (0.185)	0.468* (0.297)	-0.385 (0.335)
Panel F: East Germany							
β_D^h	Δ Shadow Rate \times $\mathbb{1}$ (East)	-0.216 (0.656)	-0.872* (0.820)	0.628 (0.791)	-0.0780 (0.187)	-0.230* (0.210)	0.0816 (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 labour 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. * $p < 0.32$, ** $p < 0.10$, *** $p < 0.01$.

J German Socio-Economic Panel (SOEP) - Details

To obtain transition rates between renters and homeowners, we use data from the German Socio-Economic Panel (SOEP). The SOEP is a widely used longitudinal survey of households in Germany, providing annual information on income, employment status, education, and housing tenure, among other topics (Goebel, Grabka, Liebig, Kroh, Richter, Schröder, and Schupp, 2019). We focus on the waves from 2005 to 2022 and construct quarterly household-level panels based on the timing of the interviews.

Overall, the socio demographic profile of our sample closely matches that of the German population during this period. Renters represent 56% of all observations and, on average, are younger with lower household incomes. Homeowners, by contrast, are older, more educated and more likely to be married, with slightly fewer children per household. Notably, only about half of homeowners hold an outstanding mortgage, implying that the remainder own their dwelling outright.

Table J.13: Descriptives SOEP 2005-2022

	Renters	Owners	Total
Age of Individual	45	54	49
Male	48.8%	59.6%	53.5%
No Migration Background	66.3%	87.3%	75.4%
Married	39.5%	71.3%	53.7%
Years of Education	11.9	12.9	12.3
HH Pre-Government Income	31,308	62,912	45,179
Mortgagors	-	50.2%	50.2%
N	179,846	139,375	319,221