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Macroeconomic Shocks and Housing Prices: Intra-Urban Submarket Asymmetries

Joao Victor Andrade

jvsantandrade@gmail.com

Universidade Federal de Minas Gerais

Renan Almeida

Universidade Federal de Minas Gerais

Rafael Ribeiro

Universidade Federal de Minas Gerais

Pedro Amaral

Universidade Federal de Minas Gerais

Research Article

Keywords: real estate, real estate cycles, spatial regimes, urban economics

Posted Date: March 4th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8971207/v1

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Additional Declarations: No competing interests reported.

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ABSTRACT

Drawing on debates about how the macroeconomy influences real estate markets and its cycles, we investigate whether the price dynamics of housing submarkets respond heterogeneously to macroeconomic shocks. Using 277k+ apartment transactions from Belo Horizonte (Brazil) for 2007–2023, we estimate a hedonic price model to predict values and delineate ten spatially contiguous housing submarkets via the SKATER regionalization algorithm. We then build monthly price indices for each submarket and, for tractability, focus our Local Projections impulse-response analysis on two contrasting areas: a centrally located high-end submarket and a low-end multiregional periphery. The macro set includes policy rate, mortgage credit, exchange rate, consumer and general inflation, construction standard class, regional activity, and economic confidence indicators. Results show clear macro-spatial asymmetries: in the high-end core, prices react significantly and negatively to monetary tightening and general inflation, whereas in the periphery, mortgage financing level exerts the strongest positive effect, with construction costs (low standard) and consumer confidence also mattering. We conclude that macroeconomic shocks transmit unevenly within cities, implying that housing-finance design and price-stability monitoring should be spatially sensitive, targeting credit access and cost pressures where they have the most significant impact.

Keywords: real estate; real estate cycles; spatial regimes; urban economics

1. Introduction

Understanding of property market cycles, a key topic in the real estate finance literature, has evolved through distinct phases. Initial advances in the late 1990s (Wheaton 1999; Kaiser 1997; Baffoe-Bonnie 1998) were followed by efforts in the 2000s to integrate housing within macroeconomic models (Edelstein e Kim 2004; Leung 2004; Shiller 2014). The Global Financial Crisis (GFC) subsequently returned the topic to prominence, especially concerning the dynamics of housing price cycles (Duca et al. 2021; Almeida 2025; Edelstein and Edelstein 2020). Among the drivers of housing price cycles, macroeconomic factors stand out. Key variables include financial conditions and interest rates, GDP, inflation, unemployment, balance of payments deficits, household income, and consumption (Aizenman and Jinjarak 2009; Grum and Govekar 2016; Duan et al. 2021; Zhang et al. 2016; Duca et al. 2021).

During the last few decades, however, the drivers of housing cycles have become increasingly complex (Duca et al., 2021), encompassing issues such as macroprudential policies, financial depth, and securitization (Ryan-Collins et al., 2017). Studies also vary in the spatial scale used to measure the effects of macroeconomic variables on housing prices, with some using city-level data (Zhang et al. 2016; Coën and Pourcelot 2024), while most of them use national housing price indexes (Aizenman and Jinjarak 2009; Iacoviello 2000; Časta 2024; Huang et al. 2020).

Within the academic body of literature that investigates housing cycles, studies considering the intra-urban scale are scarce. Studies has largely focused on national, metropolitan, or aggregate housing indices, while using a large micro-level dataset represent an important gap. Daams et al. (2024a and 2024b) investigate how real estate investments were differently affected by the GFC in the US and the UK, considering both inter- and intraurban data, and show how this heterogeneity is related to the economic growth spatial divergence these countries have faced. Therefore, the question arises whether these cycles might differ between centers and peripheries, for example, or in specific areas of an urban agglomeration, and if housing prices' sensitivity to macroeconomic shocks changes among housing submarkets. As housing becomes more important to the understanding of business cycles (Huang et al. 2020; Pérez-Montiel and Pariboni 2022), refining this knowledge in multiple spatial scales becomes critical. Intra-urban housing cycles provide useful information that enables planners and legislators to act in urban and regional planning processes; for housing policy and its adequate financing; for municipal tax authorities to promote fair and accurate taxation of properties; for financial stability monitoring; and to advance knowledge about the operating mechanisms of housing markets.

In this paper, we employ a novel four-step empirical framework to investigate the effects of macroeconomic variables on segmented housing markets. The first step involved a hedonic price model (HPM) to predict housing prices in the studied city. Secondly, based on these predicted prices, we run the SKATER (Spatial K'luster Analysis by Edge Tree Removal) algorithm (Assunção et al. 2006; Anselin and Amaral 2024) to create ten housing submarkets. Then, we used HPMs to construct monthly price time-series for each cluster, and selected the two most distinct submarkets for analysis: a high-end, centrally located submarket and a low-end, peripheral one. Finally, we employed the Local Projections (LP) technique (Jordá, 2005) to estimate the effects of changes in macroeconomic variables on these selected submarkets' housing prices.

With this approach, we aimed to cover some lacks in the literature. First, as mentioned, this approach captures the spatially heterogeneous effects of macroeconomic variables at a highly granular, intra-urban scale. We benefited from a rich dataset from apartments' transactions of the city of Belo Horizonte, Brazil's third biggest metropolitan area, with around six million inhabitants, which had a booming housing market with more than 315,000 sales in the last 15 years. This is a typical Global-South city, with dense and uneven housing markets. Second, by using hedonic price indexes to create time-series, we controlled for housing characteristics throughout the time. Third, we seek to contribute to the literature by empirically assessing the impact of a wide set of macroeconomic determinants on intra-urban house prices through a Local-Projection (LP) model. Vector Autoregressive models (VAR) have been largely used in the analyses of housing prices' response to macroeconomic shocks in the last decades (Fiorelli et al. 2024; Coën e Pourcelot 2024; Zhang et al. 2016; Baffoe-Bonnie 1998; Iacoviello 2000). However, studies using LP models are scant. We identified only one work using LP impulse-response functions to investigate this subject, a Bank of International Settlements' (BIS) report using US listing prices (Gorea et al. 2024). Our LP model included central bank policy rate, mortgage levels, exchange rate, consumer inflation, general inflation, construction costs of different sort of building materials, regional economic activity index, and expectations (consumer confidence index and business confidence index).

Results indicate that macroeconomic variables affect differently the selected submarkets. While policy interest rate and general inflation had statistically significant effects on housing prices (negative and positive, respectively) in the high-end submarket, mortgage levels and construction costs had positive statistically significant effects on housing prices in the low-end submarket. While elasticities to all these significant variables were relatively high in the low-end submarket, responses in the high-end market are inelastic. Mortgage was by far the variable with the highest estimated coefficient. Hence, these results suggest that what drives housing prices may differ socio-spatially, and highlight the importance of multiple and spatial-temporal methods to investigate housing market cycles and responses to shocks.

The remainder of this paper is organized as follows. Section 2 offers a literature review, focusing on the causal relationships between macroeconomic variables and housing prices. Section 3 describes the data and the three-step methodology: hedonic price model, SKATER clustering, and Local Projection impulse-response functions. Section 4 shows the empirical results for the relationships between the housing prices in the two selected clusters and macroeconomic variables, and discusses these results. Section 5 concludes.

2. Literature Review

2.1.Macroeconomics and housing cycles

Macroeconomic variables may produce different cycles in real estate market prices at different regional levels (Baffoe-Bonnie, 1998; Wheaton, 1999). Some of these most relevant macro determinants are: (i) interest rates; (ii) inflation; (iii) GDP; and (iv) exchange rate or current account deficits. We draw on Zhang et al. (2016) and Aizenman and Jinjarak (2009) summaries how each of these variables act in the housing market to dissect it:

1) From a demand perspective, there is a negative relationship between interest rates and real estate demand. When interest rates rise, the costs of purchasing a given property increase due to higher mortgage costs, lowering housing prices. Households with savings may prefer to allocate their wealth in Treasury bonds instead of buying real estate. In this study, as we do not use data of new development projects, we do not discuss supply side effects;

2) Considering inflation, a dual set of events can occur. First, there is the possibility that investors will increase their real estate investments because real estate is a good hedge against inflation. As investors increase their real estate investments, housing prices may rise. If this phenomenon occurs, it can be concluded that inflation increases real estate prices. However, the opposite situation can occur, as when inflation rises, consumers' ability to pay for a given good decrease due to the potential drop in purchasing power of consumer baskets, which includes housing. Therefore, inflation can both increase and decrease housing prices and requires specific empirical investigation;

3) When there is economic growth, and housing demand may follow suit, leading to an increase in property prices.

4) Exchange rate appreciation may have an effect of increasing national households' wealth and purchasing power, hence increasing housing demand. On the other hand, exchange rate depreciation may increase economic growth through the export channel (Marshall-Lerner condition) and may have inflationary effects. Therefore, its effects are not clear.

5) Confidence is a key variable in housing market decisions, as it involves a large sum of resources, liquidity constraints, and long-term financing. Therefore, higher confidence tends to push housing prices up.

Diverse results on the macro-determinants of housing prices can be found in various studies. Baffoe-Bonnie (1998) found that the housing market was found to be very sensitive to

shocks in employment growth and mortgage rates at both the national and regional levels, using US data. Aizenman and Jinjarak (2009) analyzed forty-three countries and found evidence that the current account balance is the main explanatory variable for real estate price dynamics in the OECD countries, followed by the base interest rate set by each country's Central Bank and the domestic inflation rate. Balance of payments deficits are associated with real estate price appreciation in all countries analyzed. Duan et al. (2018), using annual data between 1985 and 2015 for sixteen OECD countries in Europe, found that taxes on property prices and the unemployment rate have a negative effect on property prices and that real estate credit has a positive effect. They highlight that in the absence of 'space', macroeconomic effects are significantly over-estimated. Zhang et al. (2016) concluded that the macroeconomic growth rate has a positive effect on the increase in real estate prices in different cities in China, and the interest rate has a negative effect in the long run. Their results vary according to the position in the national urban network, with first-tier cities being more sensitive to macroeconomic shocks than lower-rank cities. Mou et al. (2017) also found that real estate prices in different regions in China respond differently when correlated with some variables, such as urbanization rate or wage level; that is, there is spatial heterogeneity in the relationship between real estate prices and macro-determinants. Aguiar (2014) used a VEC model to estimate the effects of macroeconomic variables on the Brazilian Central Bank's national residential price index. Her findings highlight the importance of the central bank policy rate, unemployment rate, and mortgage level. Pessoa et al. (2021) investigated the macroeconomic factors that determine housing prices in 13 Brazilian metropolitan regions, analyzing data from 2004 to 2016, also using the national residential price index provided by the Brazilian Central Bank. The authors employ panel data models to control for the specific characteristics of each region over time. The main results highlight that GDP has a positive and elastic relationship with housing prices, while the policy rate and the volume of housing credit demonstrate an inverse relationship, with interest rates being the monetary variable with the greatest impact.

What is clear is that different countries or regions present different results for the variables with the greatest explanatory power for real estate dynamics cycles. In other words, in each specific location, one variable becomes more relevant than another. At the same time, similarities were also found, such as unemployment rates and interest rates, which showed a negative relationship with property prices in the studies analyzed.

Just as the economy of many countries acts in a cyclical fashion, it is expected that the real estate market will also exhibit its own cyclical behaviors or, at least, follow economic

cycles, given that there is great interdependence between the two (Zabel 2015). Within the literature, we can find definitions of real estate cycles for different types of property. According to Trojanek (2021), based on a 1994 publication by The Royal Institution of Chartered Surveyors (RICS), real estate cycles are recurring and irregular fluctuations, with variable rises and falls in real estate activity indicators across all property types. Wheaton (1999) argues that investment levels in some property types, such as apartments and industrial areas, are highly correlated with economic factors.

Fluctuations in real estate prices across countries demonstrate that their cycles vary in terms of duration. Gottlieb (1976) studied more than 100 times series for different cities in different countries and found that local building cycles exhibit the mean periodicity of 19.7 years, and a mean standard deviation of 5.0 years. Wheaton (1987) and Ball et al. (2012) found property cycles of around 10 years for the US and UK, respectively. Trojanek (2021) points to cycles lasting 12 years. Therefore, our adoption of 14 year-period for this study is well grounded in the literature. For a review on housing cycles, see Leung (2004).

Authors such as Duca et al. (2021) point to synchronized international real estate cycles, in addition to the existence of a spillover effect. The GFC clearly illustrates this phenomenon, impacting real estate markets around the world. There is also strong evidence of price spillovers in national and metropolitan scales (DeFusco et al. 2018).

Table 1. Selected studies of the relationships between housing prices and macroeconomic factors

Author (years)	Method Utilized	City of Country of Study	Percentual Effect of Macroeconomic Variables on Housing Prices
Baffoe-Bonnie (1998)	Vector Autoregressive (VAR) model	United States (National and regional levels: Northeast, Midwest, South, West)	For national house prices, mortgage rate shocks explained **30.76%** of variance at 1 quarter and **44.92%** at 7 quarters. Employment growth explained **11.75%** at 1 quarter and **18.36%** at 7 quarters. (These are proportions of variance explained, not direct elasticities).
Iacoviello (2000)	Structural Vector Autoregression (SVAR) approach	Six European countries (France, Germany, Italy, Spain, Sweden, UK)	Six quarters after a one standard deviation monetary shock, real house prices in **Italy decreased by 1.8%**, and in **France, they decreased by 0.6%**.
Aizenman, Jinjarak (2009)	Dynamic Panel regressions	Cross-country (41 countries for panel estimation, 12 countries for cross-correlograms)	A one standard deviation increase in lagged current account deficits (4% increase) is associated with a **10% real appreciation** of real estate prices. A one standard deviation drop in the lagged real interest rate (2.5% drop) is associated with a **7% real appreciation** of real estate prices.
Aguiar (2014)	Vector Error Correction (VEC) model and VAR model	Brazil (National, implicitly; discussing Brazilian laws and	Not specified as a direct elasticity; the study analyzed **impacts of simulated shocks** on house prices and related series.

		government actions)	
Zhang, Li, Hui, Li (2016)	VAR	China (first-, second-, and third-tier cities)	For first-tier cities, a 1-percentage-point increase in the interest rate caused housing price **growth rate to decrease by 0.1-0.2 percentage points**. For inflation, a shock resulted in a max positive effect of **0.25 percentage points increase** in growth rate, and a max negative effect of **0.1-0.2 percentage points decrease** in growth rate. Macroeconomic growth had varying positive effects (e.g., **0.02 percentage point increase** for Guangzhou) depending on the city tier. (These are changes in the *growth rate* of house prices for a shock, not direct elasticities).
Pessoa, Rivero, Cerejeira (2021)	Static panel data model	Brazil (13 metropolitan regions)	For a 1% increase in Real GDP (Y), house prices increase by ~1.17%. For a 1% increase in Housing Credit Volume (F), house prices decrease by ~0.16%. For a 1% increase in Interest Rate (R), house prices decrease by ~0.28%. For a 1% increase in Job Market (L) index, house prices increase by ~0.0043%. For a 1% increase in Construction Cost (C), house prices increase by ~0.65%. (These are elasticities based on log-transformed variables)
Gorea, Kryvtsov, Kudlyak (2024)	Local Projections (LP)	U.S. (zip code level data)	A contractionary monetary policy shock **reduces list prices by 0.25%** after 2 weeks
Časta (2025)	Local Projections (LP)	United States (342 metropolitan areas, 81/74 MSAs)	The impact of mortgage rates on house prices varies depending on the index used: FHFA index yields estimates ranging from 10% to 25% (change in house prices), while Case-Shiller index yields estimates ranging from 2% to 10% (change in house prices). (These are implied percentage changes in house prices for a mortgage rate change, likely semi-elasticities)
Plakandaras et al. (2018)	Time-varying parameter VAR (TVP-VAR) model	US and UK	**US:** A unit increase in output **increases house prices by two units** after 2 years. (This indicates an elasticity of 2). Interest rate coefficients for the first lag are around -0.5, and for the second lag around -2 (post-1960).
Fiorelli et al. (2024)	VAR	Italy	For a positive shock of one standard deviation to the short-term interest rate (R): Real house prices (HP) show an approximate 0.6% decrease (log change) within 4-6 quarters [383, Fig. 3]. Residential transactions (TR) show an approximate 4-5% decrease (log change) within 2-4 quarters [383, Fig. 3]. (These are magnitudes of impulse responses to a 1 standard deviation shock).

Source: Authors' elaboration.

2.2.Housing Submarkets

Urban housing is often diverse, and housing market dynamics can directly reflect socioeconomic diversity, just as real estate market dynamics in general have significant impacts on local and regional development and national and international economic systems. To understand real estate market dynamics, it is first necessary to identify its homogeneous groups, after all, the market operates through a complex and spatially heterogeneous system (Keskin and Watkins, 2017; Wu and Sharma, 2012).

Although it is already well known within the real estate market that space matters, defining submarkets through clustering algorithms has potential for advancement (Anselin and

Amaral 2024). To obtain meaningful spatial interpretations consistent with the objective of this work (intra-urban analysis of a given city), methods for dividing the city into submarkets are essential, as most studies in the literature present more satisfactory results when this division is performed. In addition to submarkets serving as means to disaggregate territorial areas, it is believed that they also provide insights into how housing cycles behave at the intra-urban scale, that is, how housing prices of different parts of a city react to macroeconomic shocks.

While different approaches can be used to create housing submarkets, they all focus primarily on three distinct approaches: (i) exogenous or a priori structure; (ii) data-driven structure; and (iii) spatially constrained data-driven structure. The corresponding outcomes are geographic, non-geographic, and spatially constrained submarkets (Chen et al., 2023).

In the first approach, submarkets can be defined exogenously through areas demarcated by real estate appraisers (Bourassa et al. 2003; Keskin and Watkins 2017), division of areas of a city (Adair et al., 1996; Goodman, 1978; Schnare and Struyk, 1976), administrative area of a city (Helbich et al., 2013), or other division that provide spatial contiguity. Regarding the second approach, the logic behind it is that the structural attributes of the houses, together with the characteristics of the neighborhood, are used within an algorithm to find close substitutes for these houses, enabling the demarcation of submarkets. Bourassa et al. (1999), Bourassa et al. (2003) and Keskin and Watkins (2017) combined principal component analysis (PCA) with K-means clustering to group housing structures and neighborhoods together to create non-spatial submarkets. A counterpoint to the second approach is the lack of spatial consideration, which result in geographically fragmented submarkets that are difficult to interpret or understand (Chen et al., 2023). Finally, the third approach can be considered a crossover of the two previous approaches. According to Chen et al. (2023), prior methods tend to define spatially contiguous and meaningful boundaries, but often result in high variation within submarkets, and in contrast, data-driven statistical methods typically generate more homogeneous submarkets, although they lack spatial contiguity. To address these limitations, spatially constrained data-driven approaches have been proposed as a way to combine the strengths of both frameworks.

3. Methodology

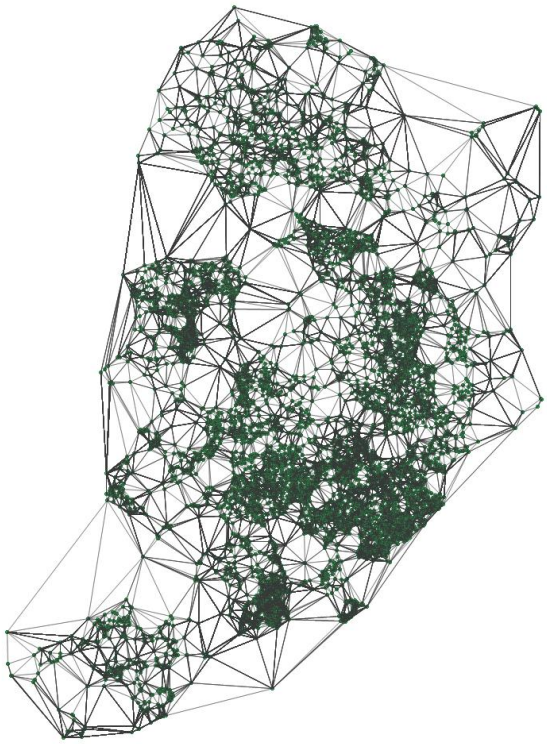
3.1. Generating housing submarkets – SKATER and Hedonic Price Model

The SKATER (Spatial K'luster Analysis by Edge Tree Removal) technique is used here to create the real estate submarkets within the city, which later is used to generate housing prices

time-series to each cluster. Proposed by Assunção et al. (2006), the SKATER regionalization technique is derived from approaches that include algorithms that use adjacency relations as constraints to the clustering process. Since spatially constrained clustering algorithms are computationally intensive, Assunção et al. (2006) implemented the SKATER, which is more efficient in this sense.

The first step of SKATER is to create an $n \times n$ spatial weighting matrix, W, whether it is a contiguous matrix, a geographic distance matrix, an inverse distance matrix, or one of the other possible methods (Anselin and Amaral 2024). In this paper, a first-order contiguous matrix of the Queen type was chosen. Weighted matrices provide the structure for a graph, where each observation is a node (or vertex) and the edges correspond to non-zero elements in the spatial weighting matrix. The second step of SKATER involves creating a connectivity graph. The graph is a key feature of SKATER, capturing the adjacency relations between objects, where each object is represented by a vertex and connected by edges to its neighbors, as shown in Figure 1.

Fig. 1. Connectivity graph of apartments' sales in 2022.



Source: Authors' elaboration.

Weighted matrices provide the structure for a graph, in which each observation is represented by a node (or vertex), and the edges correspond to non-zero elements in the spatial

weighting matrix. After creating the spatial weighting matrix and the connectivity graph, the continuity of SKATER is ensured by reducing the graph using the Minimum Spanning Tree technique. This technique involves generating a path that connects all spatial elements without a circuit occurring (a similar path between the first and last vertex of a graph). From the connectivity graph (Figure 1), in which the graph is a circuit, it will be transformed into a *Tree*, i.e., a connectivity graph in which no circuits occur. Thus, a *Spanning Tree T* of a graph *G* is a *Tree* that contains all the vertices of *G*, in which any two vertices are connected by a single path (Assunção et al. 2006). Since a *Spanning Tree* can traverse multiple paths, a *Minimum Spanning Tree* (MST) will be a *Spanning Tree* with the shortest possible path, that is, an optimal path (least cost path if we are talking about transportation cost from one location to another) based on the smallest sum of the dissimilarities (distance) of the edges (Assunção et al. 2006; Anselin and Amaral 2024). In other words, a path with the lowest possible cost that connects all spatial elements without a circuit occurring. Therefore, a *Minimum Spanning Tree* will have n vertices and $n - 1$ edge.

The last step to complete SKATER is a "pruning" of the MST, which is the removal of any edge of *T*, resulting in two subgraphs representing the final spatial cluster candidates. Since the graph is based on contiguity, each resulting subgraph will also contain spatially contiguous elements (Anselin and Amaral 2024).

As in any process of creating submarkets through SKATER or any other form of delimitation, it is first necessary to determine which variable or group of variables is used to inform its creation. Therefore, the SKATER present in this study was made using the GeoDA (Anselin et al. (2006), version 1.22.0.10) software, and the estimated apartment prices for 2009 (first year of database), obtained through Equation 1, were used as the key variable.

The HPM follows as:

$$\log(price_i) = \beta_0 + \beta_1 AREA_i + \beta_2 AGE_i + \sum_{j=2}^{17} \beta_j YEAR_{j,i} + \sum_{j=2}^{5} \beta_j STANDARD_{j,i} + \sum_{j=2}^{18} \beta_j ZONE_{j,i} + \sum_{j=2}^{257} \beta_j neighborhood_{j,i} + \varepsilon_i \quad (1)$$

The term $\log(price_i)$ represents the logarithm of the sale value of the apartment. The variable AREA indicates the constructed total area of the apartment. The variable AGE indicates how old the apartment was at the time of its transaction. The variable YEAR indicates the year in which the apartment was transacted. Furthermore, this is a variable that serves as a proxy for the economic cycle for each period present in the model (2007-2023). STANDARD is a 5-level categorical variable that classifies the quality of the building materials of each apartment. The variable ZONE refers to the zoning area where the apartment is located. The final variable, NEIGHBORHOOD, is a dummy variable indicating the neighborhood where the apartment is located. Most of the variables were statistically significant at 1% and showed the expected signs. Furthermore, the regression residuals are randomly distributed across space. With the estimated values from Equation 1, it was possible to create submarkets in the city of Belo Horizonte.

With these submarkets defined, we classified each housing transaction within a single submarket for the entire time-lapse of the database. This allowed the creation of a housing price time-series for each cluster.

3.2. Estimating the effects of macroeconomic shocks on submarkets housing prices: Local Projections' Impulse Response Functions

The methodology used to conduct the analysis of the impulse-response functions (IRFs) consists of the application of Local Projections (LP). This methodology was created by Jordà (2005), and has been gaining notoriety over the years for its simplicity in model specification, unlike Vector Autoregressive (VAR) models, which may contain problems in their specification. According to Barnichon and Brownlees (2019), as the assumptions of LP are weaker than those of VAR, their impulse-response function will be more flexible. Another important difference between VAR and LP is the way IRF are constructed. In VAR models, IRFs are obtained from

a single fitted model, that is, a single equation for all horizons. On the other hand, in Local Projections, each horizon has its own equation, and IRFs are estimated independently (Karlsson and Tchibalina 2023).

According to Jordà (2005), there are four main reasons to use Local Projections: i) they can be estimated using simpler techniques, such as Ordinary Least Squares (OLS); ii) they are robust to specification errors; iii) they have simple inference; iv) they easily accommodate experiments with flexible and linear specifications that may be inappropriate in a multivariate context. It is important to note that, for larger samples, Local Projections and VAR estimate the same IRFs (Plagborg-Møller and Wolf 2021).

For each horizon (h), an OLS regression is estimated for the equation below:

$$y_{t+h} = \alpha_h + \beta_h C_t + \delta_h y_{t-1} + \sum_{k=1}^{k} \gamma_{h,k}\, \chi_{t-k} + \varepsilon_{t+h} \quad (2)$$

Where t = 1, …, T represents the time indicator; y_{t+h} is the dependent variable at time t; α_h is a vector of constants; β_h is the coefficient that measures the impact of the shock at horizon h, that is, is represents the value of Impulse-Response Function; C_t is the shock on the chosen control variable; δ_h is the autoregressive coefficient; $\gamma_{h,k}$ is the vector of coefficients associated with the control variables; χ_{t-k} is the vector of control variables with lags; and ε_{t+h} is the error term for horizon t + h..

3.3. Data

Data used in this study originated from records of the Real Estate Transfer Tax (RETT) relating to real estate transactions in Belo Horizonte between 2007 and 2023. To ensure greater consistency and quality of information, the data underwent a refinement process. Initially, it contained 315,779 observations, which were reduced to 277,344 after filtering the data. We cleaned observations that fit to each of the following situations: (i) 1,170 observations from the Acquired Constructed Area variable, with values smaller than 10 m² and larger than 1000 m²; (ii) 1,095 observations from the Declared Value variable, with values smaller than BRL 999.00 and larger than BRL 30,000,000.00; (iii) 1,438 observations from the Value/m²; (iv) 33,281 observations from the Launch State variable, with values classified as “Null Value”, “Cancelled” or “Deactivated”; (v) 19 observations from the Year of Construction variable, with values smaller than 1,990; and (vi) 1386 observations with incorrect coordinates.

The data described above was used to create the Belo Horizonte submarkets and the monthly price index. To estimate the monthly price index, the following equation was used:

$$\begin{aligned}\log(price_i) = {} & \beta_0 + \beta_1 AREA_i + \beta_2 AGE_i \\ & + \sum_{j=2}^{176} \beta_j MONTHYEAR_{j,i} \\ & + \sum_{j=2}^{5} \beta_j STANDARD_{j,i} \\ & + \sum_{j=2}^{18} \beta_j ZONE_{j,i} + \sum_{j=2}^{257} \beta_j neighborhood_{j,i} + \varepsilon_i\end{aligned} \tag{3}$$

Through Equation 3, it was possible to capture the monthly prices of apartments from March 2010 to June 2023. Each submarket (cluster) was subjected to this regression, so each submarket has its own price index. Precisely, we chose the submarkets number 2 (centrally located high-end submarket), and number 3 (low-end, peripheral submarket). These two submarkets were chosen based on their descriptive statistics found in Table 3 (more details in the Submarket Description section).

Submarkets' monthly price indexes, in addition to the macroeconomic variables chosen for this study are part of the LP estimation. To ensure data accuracy, some variables underwent minor adjustments. The series for the IR, IBCR-MG, ER, FIN-BH, UPC (high and low standard), CCI, and BCI were transformed to a rate of change. On the other hand, the IPCA-BH and IGP-M series remained unchanged. Furthermore, it is important to note that all variables were seasonally adjusted using the X-13 Arima method. Consistent with the price index, these series also cover the period from March 2010 to June 2023. See Table 2 below:

Table 2. Variables of the empirical model

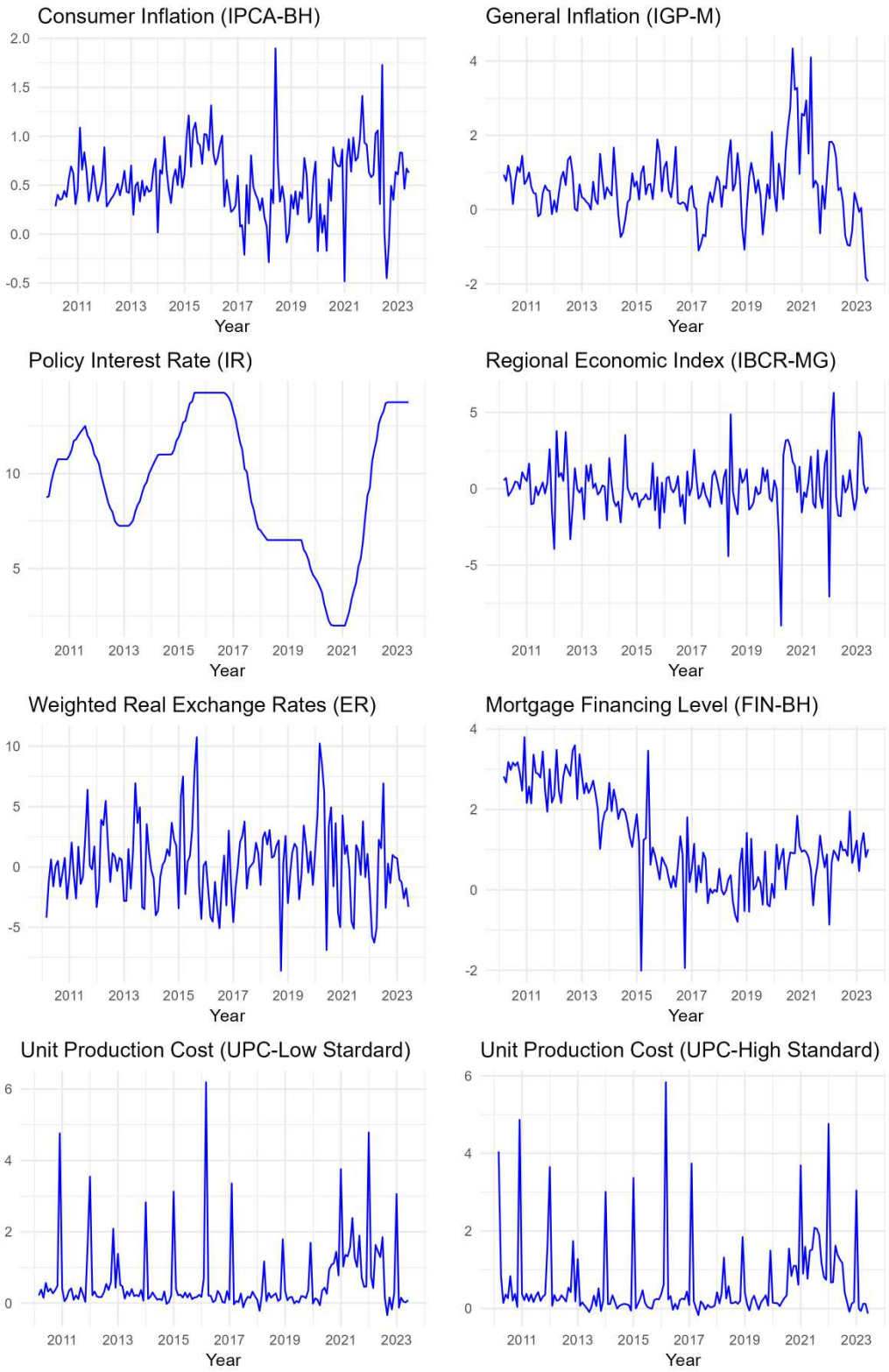
Variable Code	Variable Description	Source
	Dep. Variables - Submarket Indexes	
Price Index – Cluster 2	Monthly price indexes for high-end, centrally located submarket.	Authors' elaboration
Price Index – Cluster 3	Monthly price indexes for low-end, peripheral submarket.	Authors' elaboration

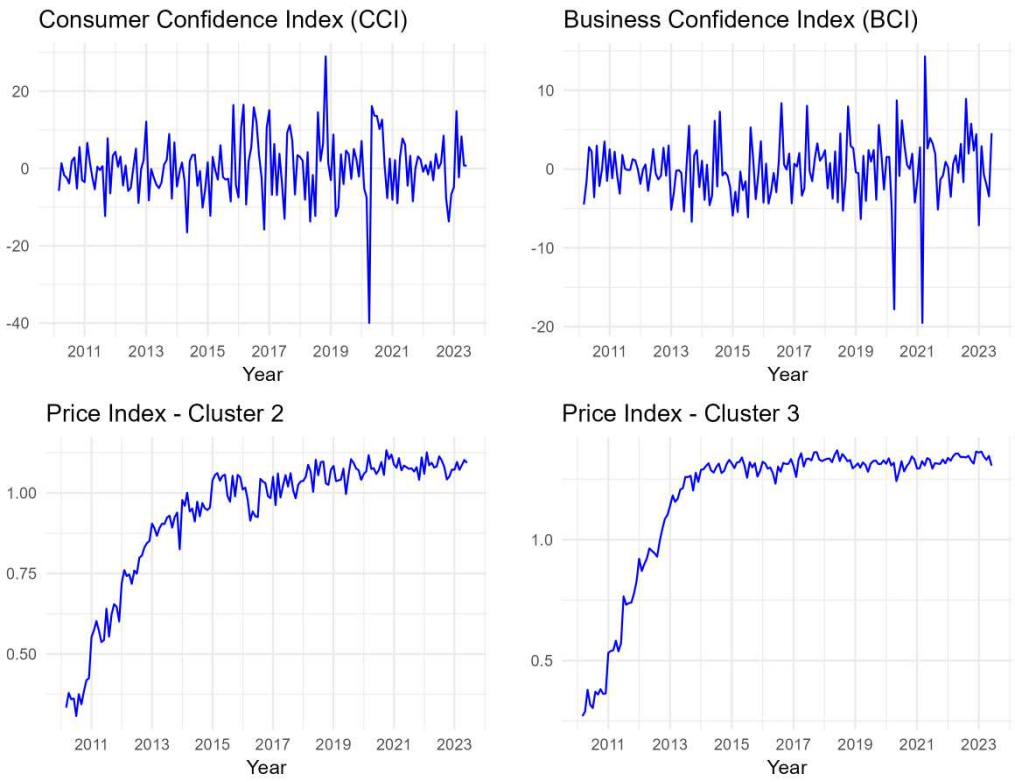
Indep. Variables - Macroeconomic Variables		
IPCA-BH	Monthly consumer price index for Belo Horizonte.	Institute of Economic and Administrative Research
IGP-M	General Market Price Index (Índice Geral de Preços - Mercado).	Getúlio Vargas Foundation
IR	Base interest rate for Brazil (e.g., SELIC rate).	Central Bank of Brazil
IBCR-MG	Economic activity index for the state of Minas Gerais (a proxy for regional GDP).	Central Bank of Brazil
ER	Weighted average of the Brazilian Real to US Dollar (BRL-USD) real exchange rate.	Central Bank of Brazil
FIN-BH	Mortgage financing level for Belo Horizonte.	Central Bank of Brazil
UPC	Unit production cost (for construction).	Civil Construction Industry Union
CCI	Consumer confidence index.	Institute of Economic and Administrative Research
BCI	Business confidence index.	Industries Federation of the State of Minas Gerais

Source: Authors' elaboration.

Figure 2 illustrates the time series data:

Fig. 2. Time series of used variables (Monthly data, 03/2010 to 06/2023).





Source: Authors' elaboration.

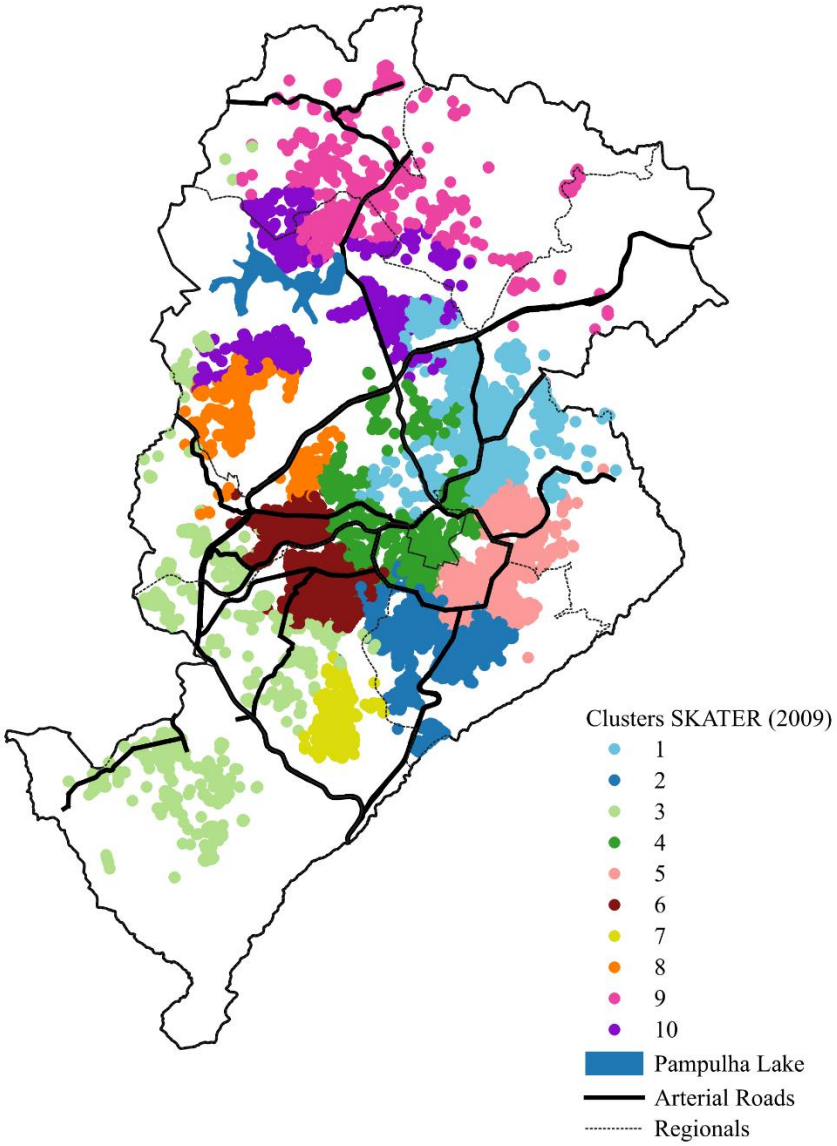
3.4. Submarkets Description

The city of Belo Horizonte was divided into ten submarkets, each with a minimum of 1,650 observations. This procedure aimed to ensure a high number of observations for each cluster on the one hand, and to have a spatially detailed number of submarkets on the other. It is important to note that a neighborhood or district does not necessarily have only one type of classification, given that a submarket does not necessarily follow political boundaries. Figure 3 depicts the submarkets created by SKATER.

The full description of each submarket is available upon request. Here we describe the two selected clusters. Cluster 2 (Expanded Submarket South Axis) is almost entirely located in the Center-South region. This submarket encompasses the highest-income areas of Belo Horizonte, including the city's key landmarks, the former seat of the state (Praça da Liberdade), and districts in the planned central area (within Contour Avenue, the city's first ring). Hence, it is the central place of the city, including well-paid job concentration, services, and opportunities (Cavalcante et al. 2016; Patrício et al. 2023). Furthermore, as local elites have been moving southwards (Almeida et al. 2022), it also includes the metropolitan edge city and skyscrapers in districts such as Belvedere, which has the city's highest per capita income. On the other hand, Cluster 3 (Multiregional Peripheral Submarket) has the largest territorial extension. It contains

transaction points in the city's Southeast, Northwest, West, and North regions, and it is home to the lowest-income households. These two submarkets were chosen due to their fundamentally distinct characteristics, which are confirmed by their average housing prices. In 2009, cluster 2 (Expanded Submarket South Axis) had the highest average price per square meter, with BRL 1,439.08. Cluster 3 (Multiregional Peripheral Submarket) had the lowest average, with BRL 825.56.

Fig. 3. Submarkets of Belo Horizonte (2009).



Source: Authors' elaboration.

Table 3 presents the descriptive statistics of the clusters formed through the SKATER method, based on the estimated prices for 2009.

Table 3. Descriptive statistics of clusters (price/m2) - nominal prices.

Cluster	Observations	Minimum (BRL/m²)	Maximum (BRL/m²)	Mean (BRL/m²)	Median (BRL/m²)
1	2702	84.86	4502.62	1030.95	923.84
2	2541	161.64	5738.03	1439.08	1228.57
3	2378	60.82	3306.00	825.56	726.72
4	2202	97.55	5151.85	1106.53	831.71
5	2020	107.06	5938.94	1171.12	1010.14
6	1920	131.54	3084.60	942.61	839.61
7	1725	245.59	4390.84	1187.22	1049.76
8	1718	119.73	2533.15	1074.25	910.27
9	1700	159.27	3085.19	858.69	735.82
10	1671	143.91	4500.60	1074.31	924.92

Source: Authors' elaboration. Note: 1 USD = 5.40 BRL on 08/14/2025.

This table was essential for selecting the submarkets included in the time series analysis. With the clusters formed, it was possible to create polygons from the transaction points of each grouping. This step is required to classify the points of the other years of the sample according to how they "fall within" the clusters created, so that the intra-urban dynamics of these clusters can be analyzed over time.

The criterion used was the cut-off based on the total area of the clusters in square kilometers. If two groups overlap, the group with the larger area will have its overlapping parts cut. It's worth mentioning that this heuristic was designed and implemented specifically for this study and is not directly based on methodologies previously known through literature.

Once the polygons are created, apartments from subsequent years in the database (2010-2023) can be associated with the cluster generated by the SKATER method. This association enables the tracking of the temporal behavior of the apartments over time, allowing for the construction of a time series for each cluster. Spatial "gaps" can be observed between polygons, resulting from the method used to delimit these areas. As time progressed and the real estate market expanded, new housing units were sold in areas of Belo Horizonte that previously had no transaction records – that is, areas located beyond the original polygons' boundaries. To address this spatial issue and prevent data loss, we employed a method of associating transaction points with the nearest polygon where these transactions were located.

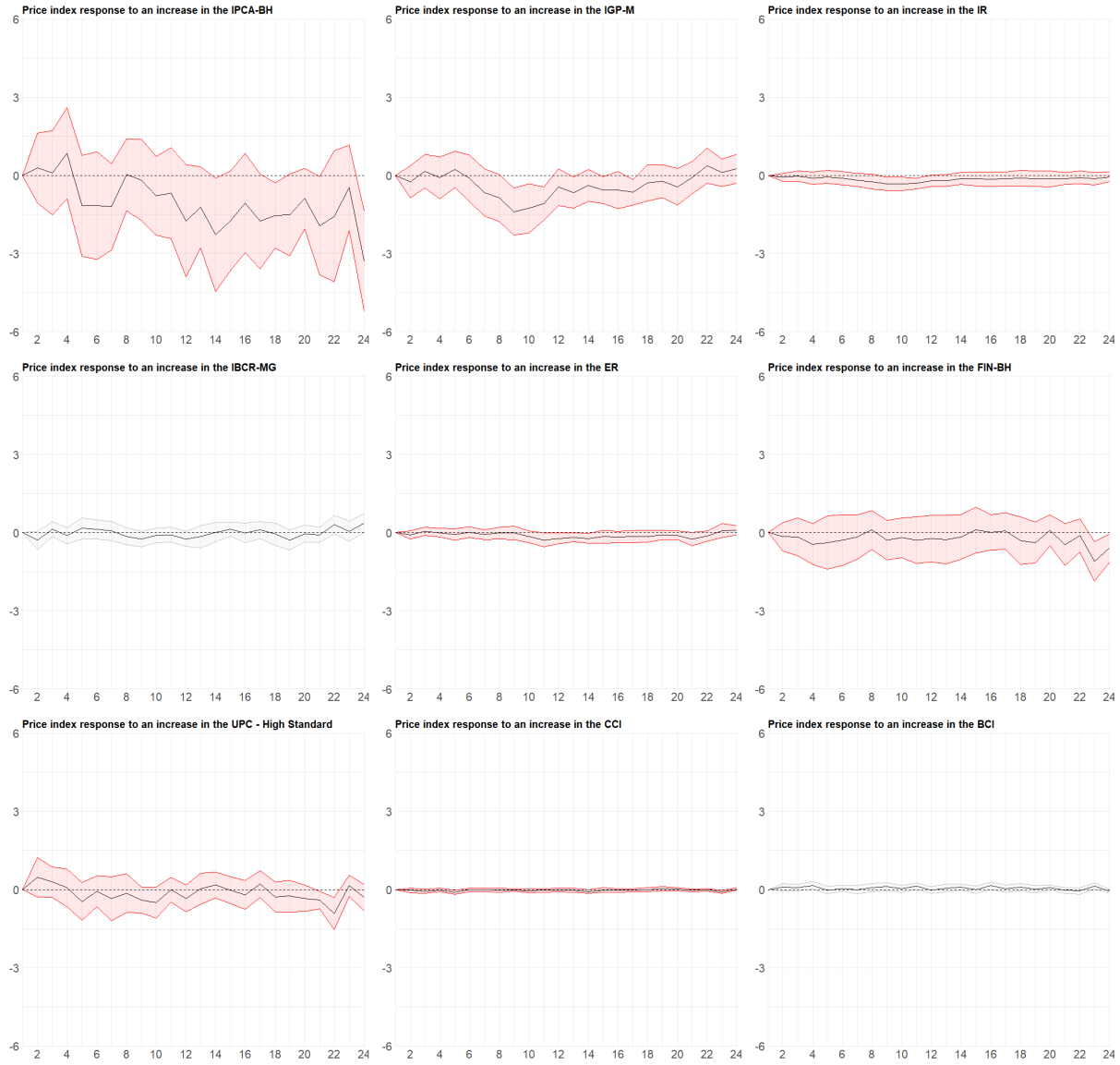
Based on this approach, we obtained the housing price time series for each cluster. Figure 2 depicts it for the two selected clusters. Employing the LP FIRs for all clusters is feasible, but that would be an exhaustive exercise for the limits of a single manuscript.

4. Results

This section presents estimates of the impacts of shocks from the selected macroeconomic variable on the price index of clusters 2 (high-end, high level of centrality) and 3 (low-end, peripheral and poorly serviced). The impact of macroeconomic shocks on the cluster 2 housing prices can be seen in Figure 4 through impulse-response functions (IRFs) graphs. As depicted, the most important variables for this submarket were the IGP-M (general inflation) and IR (policy interest rate). For the IGP-M, the index fluctuated during the first months of the series, alternating between positive and negative responses. Between months 9 and 11, the responses were significant and negative. A 1 percentage point increase in the general inflation index reduces housing prices by around 3% in this time-lapse. The price response to a shock to the IR was negative throughout the period analyzed. In the first months, the responses were modest but increased until reaching their peak in the 9th month. A 1 percentage point increase in policy interest rate reduces housing prices by around 0.75% after 9 months. As with the IGP-M, the significant months for the IR were between the 9th and 11th months.

The shock to the consumer inflation (IPCA-BH) initially shows a positive response in prices, peaking in the fourth month. However, the index shows a negative reaction after this initial period, remaining negative until the final horizon. The variable proved statistically significant only in the 24th month. In response to the mortgage level (FIN) shock, housing prices exhibited a predominantly negative reaction throughout most of the projection horizon. Their negative peak was in the 23rd month, the only significant horizon for this variable. For the construction costs index (UPC – High Standard), the response is initially positive, becoming negative after the 5th month. We can observe that positive responses occur sporadically, but they quickly converge back to negative responses. Regarding the statistical significance of this series, only the 23rd horizon was significant, and stood out as the negative peak response of the series. For consumer confidence, prices initially react negatively, remaining the 18th month, when fluctuations occur until the final horizon. There are two periods when consumer confidence is significant: in the 5th and 23rd months. Regarding business confidence, the initial response is positive and peaks in the 4th month. For practically the entire horizon, price responses are positive, but in the final horizon, they become negative. No significant horizons can be observed for this series. Exchange Rate (ER) was significant only in a short period around 13th and 14th months, with a very small negative effect on the exchange rate devaluation (BRL to USD).

Fig. 4. Apartment prices projection for 24 months after a 1 percentage point increase in selected variables (cluster 2).

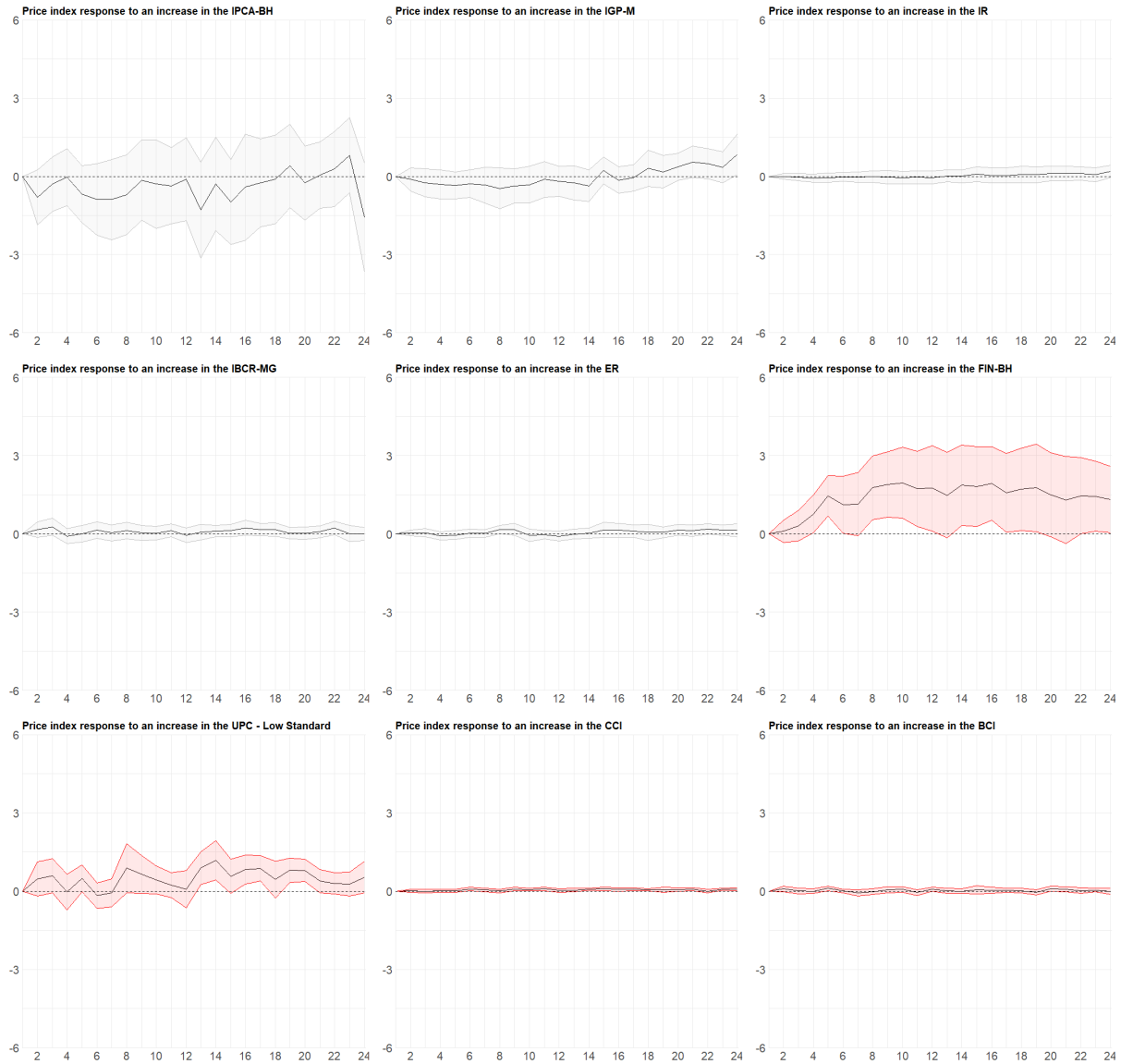


Source: Authors' elaboration. Note: The shaded areas represent 90% confidence intervals. The vertical axis represents the change in housing prices in percentage points, and the horizontal axis represents the 24-month horizon.
Note: Red shaded areas have at least one or more significant horizons. Gray shaded areas have no significant horizons.

Figure 5 shows the price index FIRs for cluster 3 (Multiregional Peripheral Submarket). In terms of significance, the most important variables were FIN, UPC – Low Standard, BCI, and the CCI. For the FIN variable, the price response is positive throughout the time series, standing out as the most sensitive of all the variables analyzed (and for both submarkets). The response exhibits an upward trajectory, achieving statistical significance by the 5th month. It is also clear that there are two significant moments for this shock: between months 8 and 11, and in month 16. For FIN, a shock resulted in a maximum positive effect of 1.5 percentage points.

For the UPC – Low Standard, the initial response is positive, becomes negative between months 6 and 7, and becomes positive again until the end of the horizon. Furthermore, it peaks in the 14th month. There are also months in which the shock is significant, more precisely, after month 12. A shock resulted in a maximum positive effect of 0.75 percentage points.

Fig. 5. Apartment prices projection for 24 months after a 1 percentage point increase in selected variables (cluster 3).



Source: Authors' elaboration. Note: The shaded areas represent 90% confidence intervals. The vertical axis represents the change in real estate prices in percentage points, and the horizontal axis represents the 24-month horizon.
Note: Red shaded areas have at least one or more significant horizons. Gray shaded areas have no significant horizons.

Regarding cluster 3, a shock to the CCI showed a positive price response. In the first few months, the response was not very sensitive, but from month 6 onwards, price sensitivity to this variable increased. Horizons such as the 14th and 23rd were significant. For a shock to

the IPCA-BH, the initial response was negative and remained so for much of the analysis period. No significant horizon was observed for this series. The price reaction to a shock to IGP-M is relatively similar of an IPCA shock, but the final horizons for these two variables are different. Between months 17 and 24, the reaction to the shock was positive. As with the IPCA-BH, there were no significant horizons for the series.

The response to the IR shock up to the 14th month is negative and very close to zero. From that month onward, prices become more sensitive and remain positive until the last horizon, without, however, the occurrence of significant horizons. The price response to the IBCR-MG is initially positive, peaks in the third month, and remains positive for much of the time series. Again, this variable was not significant. For an exchange rate shock, prices react positively in the first three months. From the 4th to the 7th month, fluctuations occur, and in months 8 and 9, the responses are positive. Between 10 and 12, the responses are negative, and from the 13th to the 24th month, the responses are positive. However, no horizon proved to be significant. A shock to the Business Confidence Index, however, revealed price fluctuations. At the beginning of the series, the response is positive, peaking in the 5th month, and is significant in this horizon. However, from the 7th month onward, the series fluctuates, with no significant horizons.

The 1 percentage point shocks revealed substantial differences in their response trajectories. In cluster 2, for example, a shock to the IPCA-BH led to a drop of nearly 3% in prices in the 24th horizon of the series. On the other hand, the price reactions to confidence indices – both consumer and business – were much lower, with magnitudes lower than 0.2% (whether positive or negative).

Regarding hypotheses for price trajectories in response to shocks, some results aligned with expectations, while others revealed patterns not initially expected. The IR, for example, although initially showing a similar trajectory for both submarkets, soon became quite distinct. In the Expanded Southern Axis Submarket (cluster 2), the price response is negative throughout the entire horizon. One possible explanation for this may be the substitution factor, as an increase in the interest rate allows families with greater purchasing power to choose to save their income and postpone consumption, thereby reducing demand for real estate. In the Multiregional Peripheral Submarket (cluster 3), the price response is much less sensitive to the shock, and from the 14th month onward, the responses are positive. Additionally, there was statistical significance in cluster 2, but not in cluster 3.

For the IPCA-BH, this variable was expected to be significant, either because real estate acts as a "defense" against rising inflation, thus increasing real estate prices, or because rising inflation reduces consumers' purchasing power or triggers higher interest rates, thus decreasing real estate prices. Based on the impact of interest rates on both submarkets, the latter hypothesis may be more plausible, given that in cluster 2, the shock proved to be more sensitive and negative compared to cluster 3. In any case, since this variable proved to be insignificant, it is likely that overall inflation, as captured by the IPCA, has a limited impact on real estate prices in both submarkets.

The IGP-M (General Market Price Index) showed a relatively similar response to the IPCA. The difference, however, was statistically significant for the Expanded Southern Axis Submarket (cluster 2). Considering the IGP-M as an index for rent adjustments, one possible explanation for this result is the difference in the search for new housing among consumers in the two submarkets. Occupants of properties in cluster 2 have greater purchasing power than those in cluster 3. Thus, consumers in cluster 2 would find it easier to seek housing alternatives when faced with rising rental costs, which would contribute to a reduction in price pressure. Another interpretation is that in this submarket, characterized by the formality of upscale areas and relationships based on contracts, as well as the involvement of real estate companies, the shock in the IGP-M makes a difference. In cluster 3, characterized by lower average income, residents tend to remain in their homes even with rising costs, given their limited relocation capacity. This would also explain the inertia of the Multiregional Peripheral Submarket, which is less sensitive to the shock. Furthermore, this sector is characterized by informality and a lower number of rental contracts.

A key finding was the difference in financing shocks between the two submarkets. It's clear how financing plays a significant role in the Multiregional Peripheral Submarket. Because families purchasing properties in this region have lower purchasing power, the ability to obtain financing is crucial to the viability of purchasing properties.

5. Final Remarks

This study aimed to analyze the dynamics of real estate cycles in Belo Horizonte, focusing on intra-urban segmentation, which remains underexplored in the literature, and the effects of macroeconomic shocks on apartment prices. To this end, methodological approaches were employed that enabled us to understand, on the one hand, the structural, accessibility, and

neighborhood factors that influence price formation, and on the other, how different submarkets react to variations in the macroeconomic scenario.

Although the property prices presented in this dissertation across different submarkets followed the same trend, their variations were quite distinct, reinforcing the argument that real estate cycles are not homogeneous across urban spaces. Real estate submarkets highlight the importance of understanding the heterogeneity of the housing market, its distinct structure, and the way it responds differently to economic stimuli.

Using a database of over 315,000 apartment transactions between 2007 and 2023, it was possible to create submarkets for the city of Belo Horizonte using the SKATER clustering technique, thereby identifying intra-urban differences within the municipality. In real terms, it was possible to observe two distinct periods in the real estate market in Belo Horizonte: a period of price boom until 2014, and a period of stagnation and decline starting in 2015. It is noted, however, that prices in 2022 remained higher than prices in 2009. As previously noted, significant heterogeneity in the patterns of appreciation and depreciation can be observed within the municipality, highlighting the role of submarkets in the intra-urban dynamics of real estate cycles.

Among the submarkets that grew the most, the Multiregional Peripheral Submarket (cluster 3) and the Northern Periphery Submarket (cluster 9) stand out. This result suggests that urban expansion, subsidized by public infrastructure investments, particularly in the North Vector, has boosted both property appreciation and transaction volume in these regions. It should be noted that, despite having the highest appreciation rate in the municipality, a notable price disparity still exists when compared to the Expanded South Axis Submarket (cluster 2) and the Hospital and Eastern Area Submarket (cluster 5), which have the highest prices. Regarding devaluations during the downturn (2015-2022), the Northern Periphery Submarket and the Southwest/Buritis Peripheral Submarket were the most resilient submarkets in Belo Horizonte, in contrast to the Central and Northern Pericentral Area Submarket (cluster 4) and the Northwest and Pampulha Submarket (cluster 8), which lost the most value. In summary, the results revealed that price dynamics in the Belo Horizonte real estate market cannot be interpreted homogeneously.

Finally, the analysis of the shocks in macroeconomic variables on real estate price revealed distinct sensitivities in the selected submarkets. In the Expanded Southern Axis Submarket (cluster 2), with higher prices, prices responded more intensely to shocks in the IR and IGP-M. In the Peripheral Multiregional Submarket (cluster 3), with lower prices, the impact

of financing stood out, with strong sensitivity and statistical significance at various points in time. This result reinforces the central role of real estate credit in enabling access to housing for low-income families.

Funding Declaration

Authors are grateful to the support received from the National Council of Scientific and Technological Development and the Brazilian Federal Agency for Support and Evaluation of Graduate Education.

Ethical Approval

This research did not require Ethical Approval.

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