Macroeconomic shocks and ripple effects in the Greater Paris Metropolis

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Abstract

The aim of this study is to show whether the Greater Paris housing market is integrated and can be defined globally or whether housing submarkets are present. Therefore, we analyze if macroeconomic shocks are homogeneous across the metropolis and check for the presence of ripple effects. For this purpose, we implement a panel vector autoregressive model at the metropolis and submarket levels to capture, through impulse response functions, the consequences of macroeconomic shocks on housing prices. In a second step, we perform a spatial panel vector autoregressive model to test for the presence of ripple effects and to check for robustness. We find the presence of housing submarkets and, hence, heterogeneous reactions of house prices to macroeconomic shocks across submarkets. Finally, we notice the presence of ripple effects in all submarkets with different spatial effects at play.

Keywords: house prices, spatial panel vector autoregressive model, spatial dependencies, ripple effects
JEL codes: C23, R31, R32

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1. Introduction

Since the Global Financial Crisis (GFC), a growing literature has been devoted to the analysis of asset price fluctuations, especially housing prices, and their impacts on business cycle dynamics. Here, we focus on the reverse link. We analyze the consequences of macroeconomic shocks on housing markets. Because the housing sector is influenced by macroeconomic policies and is subject to structural breaks and market imperfections, modeling house prices is obviously a challenge. These variations may have short- and long-term effects. Therefore, we use macroeconomic structural variables, such as demographic changes and vacancy rates, and cyclical variables, such as mortgage rates, inflation rates, income, and construction. The understanding of macroeconomic shocks and spillover effects across submarkets is fundamental for all the actors in the real estate sector, as well as policymakers. For instance, this point is important for real estate investors to define their investment strategies and diversify their portfolios. For real estate developers, it is useful for targeting locations and future hotspots and ensuring the liquidity and viability of their housing developments. Furthermore, policymakers are likely to be more involved in the housing market if they know the consequences of these shocks and their propagation effects from a neighbor city. A good understanding of the shocks' effects would enable policymakers to anticipate and to design affordable housing policies to protect low-income households from increases in house prices.

To shed new light on the effects of macroeconomic shocks and spillover effects across the housing submarkets, we have chosen the Greater Paris Metropolis. Including Paris, its neighboring three departments (or "petite couronne") and a few bordering cities in the departments beyond, the Greater Paris Metropolis presents a metropolitan area with administrative subdivisions (cities) exhibiting sharp differences in demographics, income, and wealth. These contrasted economic and hedonic characteristics explain the existence of submarkets and may explain why a hypothetical spatial arbitrage would not lead to price equalization across submarkets. As reported by Bourassa et al. (1999) (among others), dwellings are indeed poor substitutes in other submarkets.

In this article, we propose an investigation of housing submarkets to study the relative integration of the Greater Paris housing market. Likewise, we analyze the boom and bust cycles in the housing market during the period 1996-2019. Finally, we examine the spatial and temporal diffusion of macroeconomic shocks on house prices, with a particular focus on the presence of ripple effects. Therefore, we use a spatial panel vector autoregressive (SpVAR) approach and conventional impulse response functions that cover the period from 2006 to 2017.

The spatial dimension allows an understanding of the contagion effect between submarkets or cities. Furthermore, the presence of ripple effects explains, in part, why housing markets are not fully efficient. These ripple effects are not instantaneously integrated but spread out with certain delays.[3] Actually, the presence of a spatial effect tends to increase market dynamics that do not rely only on local factors, a phenomenon Meen (1999) explained well. A ripple effect is produced by structural differences between submarkets, inducing effects on housing demands and other house price fundamentals. Meen (1999) suggests four different explanations for the ripple effect: migration, equity conversion, spatial

[3] We would like to thank an anonymous referee for this relevant comment.

arbitrage, and exogenous shocks with different timing for spatial effects. Housing submarkets do not rely only on local factors. Trends in house prices and the presence of a spatial effect tend to trigger self-fulfilling expectations and, thus, the occurrence of boom-and-bust cycles.

The approach, in terms of housing submarkets, is particularly useful because it unveils relevant information for the analysis of house price dynamics that are not seeable at an aggregate, national, regional or metropolis level as a whole. In doing so, it enables investors, developers, credit institutions, households, and policymakers to anticipate and make informed decisions.

Our research fills the gap. Our results report that the housing market in the Greater Paris Metropolis is not integrated and cannot be seen as homogeneous. In fact, we show the existence of six housing submarkets by implementing principal component and clustering analysis. Furthermore, we demonstrate that macroeconomic shocks have heterogeneous effects on house prices across submarkets. Likewise, the integration of the spatial dimension provides evidence of ripple effects in the metropolis, but the effects are not present in all submarkets.

The paper is organized as follows. Section 2 develops the literature review on defining housing submarkets and the effects of macroeconomic shocks on house prices. Section 3 presents the empirical strategy and theoretical framework for macroeconomic shocks and ripple effects. Section 4 introduces the data and considers the housing cycles. Section 5 describes housing submarkets. Section 6 discusses the results, and Section 7 concludes the paper.

2. Literature review

2.1. Defining housing submarkets

Housing market dynamics reflect the status of socioeconomic diversity and socioeconomic conditions over time. We observe heterogeneous movements in housing prices in one economic area to identify homogeneous groups within one market. The delineation of housing submarkets, when they exist, presents several advantages. First, housing can be more relevantly described as a set of distinct but interrelated submarkets rather than a single homogeneous market, suggesting a more scrutinized analysis (Watkins, 2001). Second, delineating submarkets provides useful insights on the varying roles of property attributes, amenities, populations and neighborhood quality on the real estate market value. Third, delineation enables lenders and investors to understand housing dynamics better and to reduce risk exposure to homeownership. At the same time, delineations reduce search costs for housing consumers (Goodman & Thibodeau, 2007; Green & Malpezzi, 2003). Finally, submarket divisions substantially increase the accuracy of house price models and, thus, foster a more accurate price forecast (Goodman & Thibodeau, 2003).

The idea of defining submarkets has been widely researched, and the literature agrees, theoretically, on how to delineate housing submarkets. Rothenberg et al. (1991) put forward a description of housing based on four main characteristics: heterogeneity, durability, location fixity, and cost of supply. Bourassa et al. (1999) defined housing submarkets as sets of dwellings that are reasonably close substitutes of one another but relatively poor substitutes for dwellings in other submarkets. According to Bhattacharjee et al. (2016), three main criteria define submarkets: similarity in hedonic characteristics, similarity in

hedonic prices, and close substitutions of housing units. The pattern of substitution relies on structural characteristics of the property, location, prices, and neighborhood quality. Schnare and Struyk (1976) initial concept of a housing submarket was tested using Rosen (1974) hedonic approach.

The literature provides a large consensus on the theoretical framework of housing submarkets; however, in practice, methodologies vary across studies. The delineation methodologies can be divided into a priori and statistical classifications. A priori classifications are based on administrative boundaries, such as aggregated census blocks (Goodman & Thibodeau, 2003, 2007), postal codes (Goodman & Thibodeau, 2003; Watkins, 2001), and local government boundaries (Adair et al., 1996; Bourassa & Hoesli, 1999), or on real estate agents and experts' sentiments (Bourassa et al., 2003; Palm, 1978). The statistical approach relies on a multitude of data that covers a larger scope, such as demographic, economic, and social topics, as well as property attributes, distances and prices. These methodologies can result in spatially contiguous or noncontiguous housing submarket delimitations.

Principal component or factor analysis and cluster analysis techniques are the main statistical methods to capture housing submarkets. Principal component and factor analyses are used to reduce a large number of variables to fewer uncorrelated factors. These techniques extract a maximum common variance from all variables and assign them a common score. Clustering techniques introduce a distance measure between data to create homogeneous groups that are significantly different from other groups. These techniques enable minimization of intra-class variation while maximizing interclass variation.

For example, Dale-Johnson (1982) used factor analysis on 13 variables (including price) and extracted five factors to define 10 submarkets in Santa Clara. Maclennan and Tu (1996) investigated the structure of housing submarkets in Glasgow. They used principal component analysis to identify the individual variables that explain the highest proportion of the variation in the data. These variables become the basis for cluster analysis. Goodman and Thibodeau (1998) implemented hierarchical methods to define submarkets when focusing on the role of school districts in Dallas. Bourassa et al. (1999) applied principal component analysis to extract the relevant factors or dimensions of residential submarkets in Sydney and Melbourne, Australia. The significant factors were then used in a series of cluster analyses to form submarkets. Bourassa and Hoesli (1999) examined whether the structure of constrained submarkets, built according to three a priori classifications, differs from that of unconstrained submarkets, built by means of principal component and cluster analysis. The a priori classifications lead to submarkets in which the structures did not reflect the dimensions of housing submarkets in the metropolitan region of Auckland, New Zealand. Wu and Sharma (2012) employed principal component and clustering analyses and introduced a spatial contiguity matrix to define housing submarkets in the city of Milwaukee, Wisconsin. They indicated spatially contiguous submarkets could be obtained without compromising hedonic-housing model accuracy and attribute homogeneity.

2.2. Macroeconomic shocks on house prices

The last few decades have witnessed big movements in asset prices across industrialized countries. Among them, real estate was a leading sector that experienced rapid growth in prices until the Global Financial Crisis in 2008. Economists have studied the relationship between the real estate sector and the macroeconomy since the 1970s. However, the broader consequences of the crisis included rekindling strong interest in research that addresses the

short- and long-run effects of unanticipated macroeconomic shocks. The strong linkage between house prices and macroeconomic fundamentals has been widely underlined by the literature. Case and Shiller (1990) argued that population, real income, and house prices influence house price growth in the United States. Munro and Tu (1996) demonstrated that household income, mortgage rates, and housing completions affect house prices in the United Kingdom. Égert and Mihaljek (2007) studied the determinants of house prices in eight transition economies of Central and Eastern Europe and 19 OECD countries. They found GDP per capita, real interest rates, credit growth, demographic factors, and institutional developments are important determinants of house prices in Central and Eastern Europe.

Previous studies have focused on housing prices and their macroeconomic determinants at the national and subnational levels, such as census regions or metropolitan areas. Among national-level studies using vector autoregressive (VAR) models or panel VAR (PVAR) models, Iacoviello (2002) used a structural vector autoregressive model to identify the main macroeconomic determinants of house prices in France, Germany, Spain, Italy, Sweden, and the United Kingdom. He obtained a sizeable negative effect of adverse monetary shocks on real house prices. He explained that, across countries, the different responses of house prices to a monetary disturbance can be explained by different housing and financial market institutions. Apergis and Rezitis (2003) analyzed the dynamic effects of macroeconomic variables (i.e., housing loan rates, inflation, employment, and money supply) on the prices of new house properties sold in Greece. They found house prices respond to all macroeconomic variables. However, the housing loan rate is the variable with the highest explanatory power over the variation of housing prices, followed by inflation and employment, whereas money supply does not seem to show a substantial effect. Sari et al. (2007) examined relations between housing market activity and prices, interest rates, output, money stock, and employment. They argued that the monetary aggregate has a relatively more important and substantial effect on housing investment than employment does. Moreover, shocks to interest rates, output, and prices have noticeable effects on changes in the Turkish housing market. Using an identified Bayesian VAR, Jarocinski and Smets (2008) examined the role of housing investment and house prices in US business cycles since the second half of the 1980s. They obtained evidence that demand shocks have significant effects on residential investments and house prices and that an easy monetary policy designed to stave off perceived risks of deflation from 2002 to 2004 contributed to the boom in the housing market in 2004 and 2005. Finally, Goodhart and Hofmann (2008) investigated the linkages between money, credit, house prices, and economic activity. They based their analysis on a fixed-effect PVAR estimated for 17 industrialized countries during 1970-2006. They found evidence of a significant multidirectional link between house prices, monetary variables, and the macroeconomy. The link between house prices and monetary variables is stronger for a more recent subsample from 1985 to 2006, and the effects of shocks to money and credit are stronger when house prices are booming.

Among subnational-level studies, Vargas-Silva (2008) examined the influence of monetary policy shocks on the US housing market at a regional level. They observed housing starts and residential investment respond negatively to contractionary monetary policy shocks. However, the magnitude of the impact is sensitive to the selection of the horizon for which the restrictions hold. Miller and Peng (2006) used MSA-level data and a PVAR model to analyze the dynamic impact of the volatility of single-family home value

appreciation. They found the volatility is magnified by an exogenous increase in the home appreciation rate, responds to changes in the population growth rate, and is serially correlated. Moreover, an exogenous increase in the volatility raises the home appreciation rate, reduces personal income growth, and affects population growth. Gupta et al. (2012) looked at how monetary policy, specifically a federal funds rate shock, affected the dynamics of the US housing sector and whether the financial market liberalization of the early 1980s influenced those dynamics. Their analysis used a Bayesian VAR model at the national level and for four census regions. They noticed a 100-basis-point federal funds rate shock produces larger effects on real house prices at the regional and national levels in the post-liberalization period, when compared to the pre-liberalization era.

Numerous other studies have undertaken house price modeling at a subnational level. However, only a few include spatiotemporal analysis using all the improvements made in the topic of spatial econometrics. This latter is a subfield of econometrics that deals with spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression models for cross-sectional and panel data (Anselin & Griffith, 1988; LeSage, 1999a; Paelinck & Klaassen, 1979). Can (1992) indicated models that incorporate both types of externalities (spatial dependencies and spatial heterogeneity) were superior to those used in the mainstream literature, in which only neighborhood effects were considered.

Among the studies that include spatiotemporal effects on the housing market, Pollakowski and Ray (1997) examined the existence of price diffusion across US census division and metropolitan statistical areas using a VAR approach. They found evidence that housing price shocks in one area are likely to cause, in a Granger sense, subsequent shocks in the same area and in other areas. The metropolitan area analysis found evidence of diffusion between contiguous areas while the census division analysis shows a different pattern. Beenstock and Felsenstein (2007) applied SpVAR using annual data for Israel from 1987 to 2004. Kuethe and Pede (2011) studied the effects of macroeconomic shocks on housing prices in the western United States using quarterly state-level data from 1988 to 2007. They implemented a SpVAR model and reported that spillover Granger causes movements in housing prices. Moreover, they demonstrated, through impulse response functions, the effect of macroeconomic events in different neighboring locations. They also argued that including spatial information leads to significantly lower mean square forecast error. Holly et al. (2011) investigated spatial and temporal dispersions of shocks in nonstationary dynamic systems in the United Kingdom. They observed that house prices within each region respond directly to London shocks, and in turn the shock is amplified by the internal dynamics of each region and by interactions with contiguous regions. Furthermore, they identified an independent role for shocks to London coming from developments in New-York house prices. Brady (2011) and Brady (2014) estimated the spatial diffusion of house prices across California counties and US states using SpVAR. Through impulse response functions, he demonstrated that spatial diffusion of house prices is significant and persistent across regions and states. DeFusco et al. (2018) investigated the role of spillover effects in the recent housing boom. They looked at spillovers that followed a positive shock to a nearby housing market, which was identified by estimating structural breaks in house price growth. They found evidence that contagion played an important role in the recent housing boom. The contagion effect was found to be larger in smaller markets when the price shock began in a larger market. Moreover, they showed that the contagion effect is limited to markets with larger price elasticities in the housing supply. Öljemark and Egnell (2019) examined the

spatial and temporal diffusion of house prices in Sweden. They aimed to determine whether regional house prices responded to a shock in Stockholm house prices. Fischer et al. (2021) studied the microlevel evolution of residential house prices using data on repeat sales in Manhattan Island. They demonstrated that price comovement, even within a city, was a highly local and persistent phenomenon. Likewise, they highlighted that the strength of such co-movements vanished with spatial and temporal distance. Bangura and Lee (2020) examined the ripple effect of housing submarkets in the Greater Sydney metropolis. They defined two submarkets (low-priced and high-priced) and studied price diffusion using convergence tests, cointegration techniques, Granger causality, and a dynamic ordinary least square cointegration test. They found that a long-term relationship in house prices exists between these two submarkets and that a large degree of diffusion takes place from the less prosperous submarket to the high-end submarket. Their results support the equity transfer hypothesis suggested by Meen (1999). Cohen and Zabel (2020) investigated movements of house prices across time and space at three different levels: CBSA, town, and census tract in the United States. They used a fixed effect model and a split sample IV estimator to capture persistence and spillover effects. They found that persistence and spillover effects are significant in all aggregation levels but are much larger at the CBSA level than the local level.

Finally, our paper examines the effects of macroeconomic shocks on the Greater Paris housing submarkets. In our analysis, we include spatial econometrics to investigate the presence of a ripple effect. Moreover, as previously mentioned, spatial econometrics enables us to deal with spatial autocorrelation and to improve economic and econometric modeling. Therefore, we use SpVAR modeling to investigate macroeconomics shocks and spatiotemporal diffusion of residential prices on the Greater Paris Metropolis housing submarkets.

3. Theoretical framework and economic modeling

3.1. Macroeconomic framework and ripple effect

3.1.1. Macroeconomic framework

This section presents the theoretical framework of macroeconomic shocks and spatial autocorrelation in the Greater Paris housing submarkets. By examining macroeconomic shocks, we understand how the housing market reacts to an exogenous change in demand and supply. Furthermore, we are interested in how these shocks create spatial movements in the housing submarkets. Our aim is to shed light on the determinants of housing prices and to show how they react to a shock in demand and supply. In our framework, rents, mortgage rates, household income, households, and inflation represent the demand factors, housing starts and the vacancy rate are supply factors.

Regarding the demand side, we expect rents to have a positive influence on housing prices. In fact, when rents increase, the affordability of the rental market decreases, thus creating a trade-off situation between renting or buying a property. To protect themselves against rent inflation, households should be incentivized to buy property. Moreover, a rise in rent prices triggers investment opportunities because yields are more attractive enabling investors to increase their cash flows. The attractiveness of the rental housing market consequently produces an upward swing in prices.

The mortgage rate is a key variable in housing purchasing power. In fact, the mortgage rate represents the cost of the capital and, thus, the cost of indebtedness. A rise in the

mortgage rate reduces the housing purchasing power and, thus, reduces the demand for housing. Likewise, from an investor's perspective, low mortgage rates encourage people with excess funds to invest in the housing market to obtain a better rate of return rather than leaving their money in a bank account. This additional demand drives up housing prices. Hence, we expect a negative relationship between mortgage rates and housing prices.

Household income growth is also an important variable in housing purchasing power. Increases in income improve household solvency and enable purchasers to take on more debt to buy a property. However, a drop in income underlines a vulnerable financial situation that may lead to mortgage rejection. Hence, we expect a positive correlation between household incomes and housing prices.

Likewise, we expect a positive relationship between household growth and housing prices. A city's attractiveness stems from its ability to win new households, which ultimately creates a demand pressure on the housing market that triggers an increase in prices. Alternatively, an unattractive city drives people to leave, which decreases housing prices.

The literature shows the role of housing as a hedge against inflation. An inflation hedge typically involves investing in an asset expected to maintain or increase its value over a specified period. Therefore, housing is considered a hedge against inflation because home values and rents typically increase during times of inflation. Moreover, inflation is a proxy for the amount of money available in the economy. Hence, we can expect a positive relationship between inflation and housing prices.

Regarding supply-side factors, we take housing starts and the vacancy rate into account in our theoretical framework. Housing starts measure the number of new dwellings available in the market. Theoretically, an increase in housing supply should decrease housing prices because the number of dwellings available in the market is higher. However, in the short-term, housing prices are inelastic to the supply. The explanation can be found in the availability of land, the time required to obtain housing authorization, and the time it takes to build new houses. Moreover, in the long term, the availability of new dwellings leads to an improvement in the housing stock quality.[4] Hence, we expect no effect of housing starts on housing prices in the short-term and a mitigated effect in the long-term.

Finally, the vacancy rate, which is the number of dwellings available in the market relative to the total housing stock, can be structural or cyclical. The cyclical vacancy rate is considered transitory over short periods. In fact, this vacancy rate refers to the period between two tenants, a period for sale, or the renovation of a dwelling. This type of vacancy is normal and ensures good residential mobility. The structural vacancy rate refers to a vacancy period greater than a year.[5] This vacancy rate can be due to a slow housing market, a housing market that is no longer adequate relative to the demand (obsolescence) or an existing retention strategy. According to the economic theory, an increase in the vacancy rate or time on the market leads to a decrease in housing prices. However, the relationship can be more complex and the effect on housing prices mitigated.

[4] We use indeed a hedonic housing index for second-hand dwellings to control for housing quality.

[5] The period above one year follows the definition given by theCentre d'études et d'expertise sur les risques, l'environnement, la mobilité et l'aménagement (CEREMA). We may also mention that the structural vacancy includes the natural vacancy rate.

3.1.2. Ripple effect

This macroeconomic framework is classic in economics, but regarding the housing market, it must be completed by introducing a spatial dimension. Recently, the literature has provided evidence in support of the presence of ripple effects in the housing market. These effects relate to a disturbance in housing prices in a given market, which then spreads to other markets. This implies a divergence on housing prices in the short-term but a convergence in the long-term. The causes of the ripple effect are related to housing demand models and household behaviors. Meen (1999) explained that the ripple effect was produced by structural differences between regions that exhibit spatial dependence with effects on housing demand and other house price fundamentals. He suggested four explanations for the ripple effect: migration, equity conversion, spatial arbitrage, and exogenous shocks with different timing of spatial effects. For instance, Muellbauer and Murphy (1994) suggested equity transfer causes ripple effects when residents in a high value location purchased houses in lower-value locations.

In the case of Greater Paris, the migration effect is reflected in population movements. The Paris region is the most important economic area in France. It includes 18.2% of the French population, 23.3% of all jobs in France and 36% of all French executives. For several years, the Paris market has experienced a disequilibrium between demand and supply in the transaction sector. During the last 10 years, the average time on the market for an apartment has been 90 days in Paris, compared to 124 days in the whole country.[6] This suggests that the market is more competitive and, hence, very liquid. This competition in the Parisian housing market triggers population movement toward cities next to the capital that are more affordable.

We also notice a life cycle effect and structural differences. In the case of Paris, the homeownership rate stands at 33.1% and the housing stock is characterized as 78.2% for small residences (fewer than three rooms) and 71.3% for homes built before 1970. Consequently, we observe population movement toward the Paris suburbs where households can afford newer and bigger dwellings to build families. Couples with children represent between 16.9% and 17.4% of the total households in Paris but they represent a much higher share in the suburbs.[7]

Regarding equity transfer, owners from central cities or districts that are more expensive enjoy rising purchasing power, which they can exercise to take advantage in cheaper areas as well. Fiscal exemption programs in the new sector could also incentivize private investors. These new programs are mainly located in the suburbs where land is available and cheaper.[8] Finally, in the Greater Paris Metropolis, the price per square meter is higher in the western area, and the northeastern part of the metropolis is more affordable. In the spatial arbitrage explanation, a difference in prices and price changes leads to a potential opportunity that explains the spatial diffusion. Furthermore, in a city well connected by public transportation, a trade-off emerges between living in a small apartment near the central business district and living in a larger apartment or detached house away from the business area. In microeconomic theory, economic agents maximize their utility functions under budget constraints. Here, the utility function includes price and dwelling features,

[6] According to LPI Seloger.
[7] See Table A.9
[8] As suggested by Givord et al. (2013), and Briant et al. (2015), among others. Also see Table A.9

such as square meters. Moreover, public policies and transportation infrastructure projects, such as the greater Paris project, tend to have greater influence on investors' decisions in the presence of spatial arbitrage. For instance, the greater Paris project reinforces the connectedness in the metropolis, causing new spatial opportunity to arise. Likewise, the introduction of capped rent in Paris could incentivize investors to invest in the suburbs rather than in Paris.

3.2. Methodology

Developed by Sims (1980), VAR analysis is the most popular method for examining the dynamic relationship of several variables with total flexibility. A VAR analysis is a system regression model that can be considered a hybrid of the univariate time series model and the simultaneous equation model, in which the evolution of each variable is based on its previous values and previous observations of all other variables in the system. The VAR, which originated in macroeconometrics literature, has become a powerful instrument for examining macroeconomic shocks. An important feature of VAR model flexibility is that it is atheoretical; that is, it does not rely on theoretical structure but, instead, allows the irregularities in the data to tell the story (Lu, 2001). A VAR(p) of k endogenous variables is a system of k identical equations with p lags. A VAR model can be written as follows:

$$Y_t = \sum_{j=1}^{p} A_j Y_{t-j} + \epsilon_t \tag{1}$$

Where Y_t is a k-dimensional vector of endogenous variables, A is a $k \times k$ matrix of coefficients and ϵ_t is the error term.

Here we use panel VAR (PVAR) models. This modelling has indeed many advantages for our purpose to analyse housing submarkets.[9] Hence, a PVAR model of k endogenous variables and p lags can be written as follows:

$$Y_{i,t}^{c} = \sum_{j=1}^{p} A_j Y_{i,t-j}^{c} + u_i^{c} + \epsilon_{i,t}^{c} \tag{2}$$

Where $Y_{i,t}$ is a vector of endogenous variables for each cross-sectional unit i, A is a matrix of coefficients, u_i are city fixed effects and $\epsilon_{i,t}$ is the error term. The superscript c is an index for the cluster, with $c = 1, ..., 6$.

The improvements regarding spatial econometrics enable us to consider the spatial dimension in our modeling. A SpVAR is simply an extended version of the VAR framework. This approach includes spatial and temporal lags. The spatial extension is justified by the VAR framework's inability to consider the potential impacts of economic events in neighboring units. Ripple effects are completely excluded from the simple VAR framework. Hence, this technique combines the traditional VAR approach, which treats all the variables in the system as endogenous, with the panel data approach, which controls for unobserved individual heterogeneity. Likewise, the technique takes into account neighboring effects. The SpVAR model is written as follows:

$$Y_{i,t}^{c} = \sum_{j=1}^{p} A_j Y_{i,t-j}^{c} + \sum_{j=1}^{p} B_j W Y_{i,t-j}^{c} + u_i^{c} + \epsilon_{i,t}^{c} \tag{3}$$

[9] This modelling accounts for the time invariant unobservable factors at the city level.

Here, we estimate a first-order SpVAR model because our sample frequency is annual. For each cross-sectional unit i, $Y_{i,t}$ is a $(k \times 1)$ vector of endogenous variables. This vector includes six variables:[10] apartment prices growth, which is our variable of interest; mortgage rate is the cost of capital; household disposable income growth is our proxy for down-payment and the ability to take debt; household growth is our demand variable; inflation is a proxy for economic environment; and the vacancy rate is the share of available units in the housing stock. All variables are transformed using the Hodrick-Prescott filter. A is a matrix of coefficients for the lagged vector of endogenous variables. $WY_{i,t-j}$[11] is the lagged spatial term for each cross-sectional unit i with W a $n \times n$ matrix that defines the spatial relationship. B is a matrix of coefficients measuring the lagged spatial term effect, and u_i and $\epsilon_{i,t}$ are city fixed effects and the error term, respectively.

The introduction of spatial effects corrects for a possibly omitted variable (Brady, 2011; Elhorst, 2003; LeSage, 1999b). In fact, a spatial correlation arises due to market features shared by contiguous neighborhoods. For instance, housing market dynamics in one county or neighborhood may have a systematic feedback effect on surrounding areas.

The spatial weighting matrix W represents spatial correlations in our data. Conceptually, the spatial weighting matrix can be defined using several methods: distance, boundary, or distance–boundary. Likewise, Case and Rosen (1993) suggested an alternative to the spatial weighting matrix by considering a weighting matrix based on city similarities. In this paper, we use the boundary method (i.e., whether spatial units share a boundary) and the similarity approach, and we compare the results.

In the case of the boundary method, if the set of boundary points of unit i is denoted by $bnd(i)$, the so-called row normalized queen contiguity weights are defined by:

$$w_{i,j} = \begin{cases} \frac{1}{n}, & bnd(i) \cap bnd(j) \neq \emptyset \\ 0, & bnd(i) \cap bnd(j) = \emptyset \end{cases} \tag{4}$$

Such as $\sum_i^n w_{i,j} = 1$

In the case of the similarity matrix, we use the five scores drawn from the principal component analysis (explained in next section) to define the similarity weighting matrix between cities. The similarity weights are computed using a distance method written as follows:

$$w_{i,j} = \frac{\frac{1}{\sum_s^p \sum_i^n (Score_{s,i} - Score_{s,j})^2}}{\sum_1^n \frac{1}{\sum_s^p \sum_i^n (Score_{s,i} - Score_{s,j})^2}} \tag{5}$$

Finally, the queen contiguity and the similarity matrix can be written as follows:

$$W = \begin{pmatrix} 0 & w_{i,j} & \cdots & w_{i,n} \\ w_{j,i} & \ddots & & \vdots \\ \vdots & & \ddots & w_{n-1,n} \\ w_{n,i} & \cdots & w_{n-1,n} & 0 \end{pmatrix}$$

The SpVAR approach imposes the restriction that the underlying structure is the same for each cross-sectional unit. This restriction seems realistic because all cross-sectional units

[10] Table A.1, included in the Appendix section, provides a description of the data

[11] The SpVAR model differs slightly for the "Paris outside" submarket because of its small sample size. Consequently, we introduced only a spatial effect of housing prices for this submarket because we can not have fewer observations than parameters.

in each cluster have the same market profile according to the cluster analysis. However, this restriction is likely to be violated in practice; even if all cross sectional units share a similar profile, they still are idiosyncratic. Hence, introducing fixed effects to control for individual heterogeneity is a way to overcome this restriction. In doing so, fixed effects are correlated with the regressors due to lags in dependent variables. The mean differencing commonly used to eliminate fixed effects would create biased coefficients. To avoid this problem, we use the "Helmert procedure" (Arellano & Bover, 1995). This procedure removes only the forward mean (i.e., the mean of the future observations available for each city and year). This transformation preserves the orthogonality between transformed variables and the lagged regressors. In so doing, we use the lagged variables as instruments and estimate the coefficient using a system GMM.[12]

4. Data

4.1. Stylized facts

We built an annual dataset covering 2006-2017 for 119 cities in the Greater Paris Metropolis. Greater Paris notaries, in collaboration with the French Statistical and Economic Studies Institute (INSEE) provided prices per square meter for apartment dwellings, reported on a quarterly basis between 1996-2019, using hedonic models[13]. Figure 1 shows the house price cycles in the Greater Paris Metropolis. We clearly identify five periods—three periods of housing booms and two periods of housing busts.

The first boom period (1996-2008) occurred because of financial liberalization and loose credit conditions. Between 2001 and 2007, mortgage rates decreased from 5.7% to 3.9%, and mortgage durations increased by 4.5 years on average. Loose credit conditions increased households' housing purchasing power and, thus, the demand for housing. The second housing boom (2009-2011) was a two-year catch-up effect after the subprime crisis. The current housing boom began in 2015 and can be explained by the improvement in the economic conditions but also by the implementation of the non-conventional monetary policy from the European Central Bank, called quantitative easing.

We notice that the three cycles have different time horizons and magnitudes. The first cycle lasted 12 years; the second lasted only two years; and the latest cycle has lasted 4 years and is ongoing. Likewise, Figure 1's legend was standardized to compare cycles via magnitude. In the first cycle, the average annual increase in house prices was very high and spread across the region. However, the increase is higher in the Paris capital city and skewed to the east toward more affordable cities. In the second cycle, the average annual increase was very high in more cities than in the first cycle, but it skewed to the west toward less risky cities. We observe a flight-to-quality effect. The current cycle shows that the increase in house prices is considerably more moderated compared to previous cycles. Housing prices increase more in Paris districts, with a spillover effect toward cities that share a boundary with the capital.

In addition, we observe two periods of housing busts. The first housing bust (2008-2009) was the subprime crisis, and the second housing bust (2011-2015) was related to the sovereign debt crisis. The first cycle lasted only one year, but the second cycle lasted four

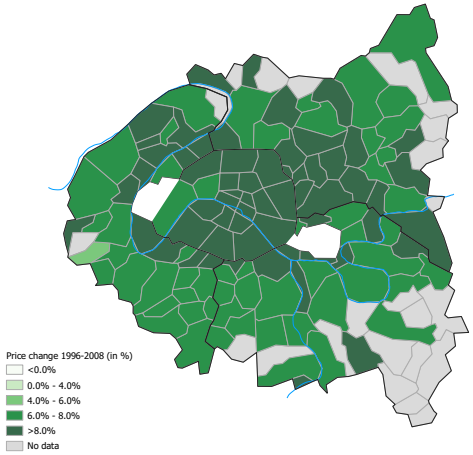
[12]We thank Abrigo and Love (2015) for their Stata programme for estimating the panel vector autoregression model.

[13]for more details on the hedonic methodology see https://www.insee.fr/fr/information/4175280

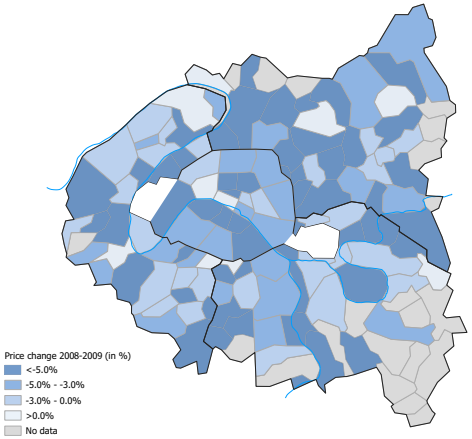
years. The first housing bust also hit the housing market more severely than the second housing bust did. Nevertheless, the housing market in Greater Paris showed strong resilience during the last housing bust. Housing prices decreased slightly compared to other metropolises in the United States and even in Europe. The Greater Paris housing market's resilience comes from its credit market structure and institutions. In fact, France's institutions strictly frame the credit market and protect the consumer. Moreover, social protection is relatively singular in France, with both a labor market law that protects employees and an unemployment insurance which secures a part of household incomes. The indebtedness ratio is defined as a 33% of a household's disposable income. Furthermore, according to the High Council for Financial Stability (HCSF), 94.6% of outstanding credits in 2018 were at fixed rates, even rising to 98.5% for new credits. Finally, credit market institutions protect households against a potential increase in mortgage rates. This regulation reduces the default risk, guaranteeing household solvency. Thus, the French housing market is less volatile than in other United States and European markets.

Other variables included in the analysis of the Greater Paris housing market are housing rents obtained from Clameur, the number of households, and household's disposable income, as obtained from the French Statistical and Economic Studies Institute (INSEE). We also include the number of new constructions and the vacancy rate from the Ministry of Territorial Cohesion and INSEE. In addition, we use country-level variables, such as mortgage and inflation rates, obtained from the housing credit observatory and INSEE.

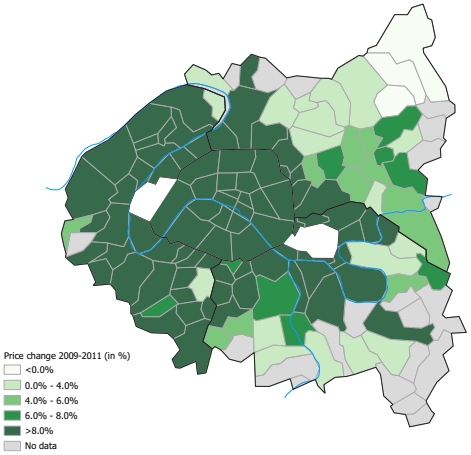
Figure 1: Housing price cycles in the Greater Paris



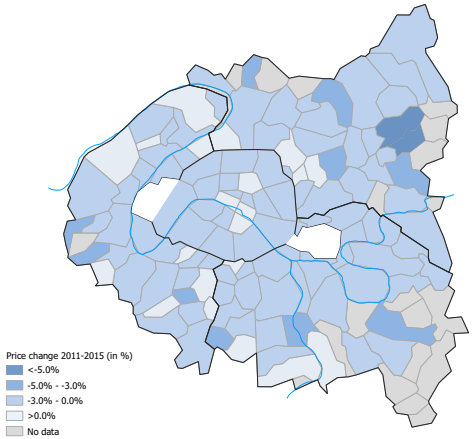
(a) Period 1996-2008



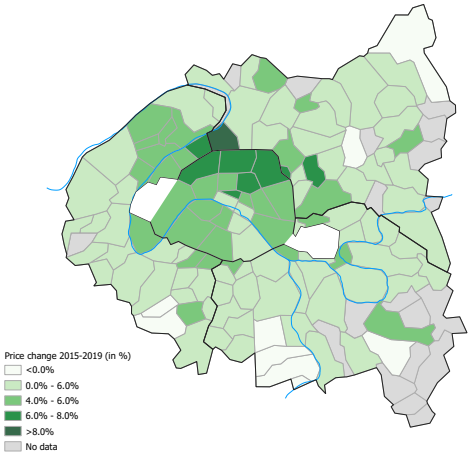
(b) Period 2008-2009



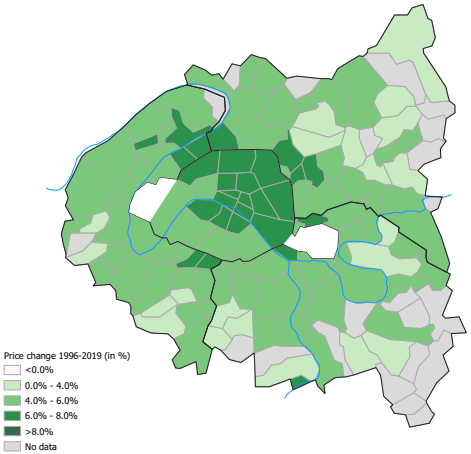
(c) Period 2009-2011



(d) Period 2011-2015



(e) Period 2015-2019



(f) Period 1996-2019

4.2. Panel unit root tests

Many economic and financial time series exhibit trending behaviors or nonstationary means. The leading examples are asset prices, exchange rates, and macroeconomic aggregates levels, such as real GDP. If the data are trending, some form of trend removal is required. Thus, data must be transformed into a stationary form. In our case, Table A.2 shows the results of panel unit root tests, which demonstrates that data are nonstationary in level but stationary in first difference. In this case, we could have used the first difference transformation for our analysis but we preferred to use the Hodrick-Prescott filter to detrend our series and keep the cyclical component of each series. Actually, this methodology, famous in business cycle topics, relates to the decomposition of time series y_t into three components, such as $y_t = \tau_t + c_t + \epsilon_t$. The first component is a trend component; the second is the cycle component; and the last is the error term. The Hodrick-Prescott formula appears as follows:

$$\min_{\tau} \Big(\sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \Big) \tag{6}$$

The equation's first term is the sum of the squared deviations, which penalizes the cyclical component. The second term is a multiple of the sum of the squares of the trend component's second differences. This second term penalizes variations in the trend component's growth rate. A larger λ value indicates a higher penalty. Hodrick and Prescott suggested 1600 as a value for λ for quarterly data. Ravn and Uhlig (2002) stated that λ should vary by the fourth power of the frequency observation ratio; thus, λ should equal 6.25 for annual data and 129,600 for monthly data. In our case, data are annual, thus, the value of λ we use is equal to 6.25.

After detrending our data, we again performed panel unit root tests on each time series. We conducted two tests: the augmented Dickey-Fuller test and the Phillips-Perron test. These tests have as a null hypothesis the presence of a unit root in all the panel's series. Table A.2 displays the results of these tests. We conclude that our time series are now stationary.

4.3. Spatial autocorrelation test

We investigate whether each variable follows a systematic pattern in its spatial distribution. We test for the presence of spatial autocorrelation in each series to motivate the use of spatial models. We conduct the test at the overall sample level and at the cluster level as well using the Moran's I statistic (Moran, 1950):

$$I = \frac{N}{\sum_i \sum_j W_{i,j}} \times \frac{\sum_i \sum_j W_{i,j}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \tag{7}$$

where X is a random variable, $\bar{X}$ is the mean value of X, N the total number of spatial units indexed by i and j and W is the spatial weights matrix. Indices i and j refer to each spatial units that are cities in our case. Finally, Moran's I values range between -1 and 1.

The Moran test statistics is computed using a normalized first-order contiguity weights matrix but also a normalized similarity weights matrix. As expected, the results of the

Moran's I statistic[14] reported in Table A.3 shows the presence of spatial autocorrelation[15]. Hence, we need to implement an econometric model that consider the spatial dimension to get a nonbiased estimation. Nevertheless, according to Anselin and Kelejian (1997), the Moran's I test is a powerful misspecification test because it does not provide any indication on the nature of the spatial process that causes the autocorrelation, specifically whether it is due to an error process or an omitted spatially lagged dependent variable. Likewise, the Moran's I test is typically considered in a context where all explanatory variables are exogenous. Hence, we decide to use the spatial autocorrelation test suggested by Anselin and Kelejian (1997) in Table A.4 for the contiguity approach, and in Table A.5 the similarity approach demonstrates the presence of spatial autocorrelation and, thus, the need to use spatial models. The next section explains our methodological approach to check for the presence of housing submarkets and provides stylized facts on each housing submarket.

5. Housing submarkets

The presence of spatial autocorrelation is unsurprising and even reassuring. In fact, the Greater Paris Metropolis is a large heterogeneous area. Looking at the housing market, however, we can distinguish a priori some homogeneity between cities. Urban housing seems as diverse as the people living in it, and the dynamics in housing prices across the Greater Paris Metropolis reflect diverse socioeconomic statuses and construction intensities. Therefore, the Metropolis could be divided into several submarkets that rely on demand and supply factors. We could thus improve the understanding of each submarket's features. Moreover, delineating housing submarkets can substantially increase the accuracy of housing-price modeling to provide accurate analyses of spillover effects (Wu & Sharma, 2012).

Housing submarkets refer to homogeneous groups that are significantly heterogeneous with respect to other groups. Our approach to building housing submarkets was not predetermined by some prior view; it let the data determine the structure of the submarkets.

To do so, we have a two-step approach. First, we implement a principal component analysis using a large dataset of nearly 30 variables,[16] including socio-eco-demographic and real estate characteristics. This approach can sum up and extract a small number of factors from a large dataset in which multicollinearity is a known problem. The procedure sum up the large dataset into five components. Figure A.6 shows the principal component analysis results with the variable's contribution to the two first components. Primarily, real estate factors describe the first component, and socio-economic factors describe the second component. Figure A.7 shows the cities repartition along the two first components via a color code at the department level. Real estate variables define the first component, and economic status determine the second component. Likewise, only the Paris department seems to form a group, even when points are quite spread out.

The second step implements a hierarchical agglomerative clustering on the score of the five components we drew from the principal component analysis. We use the ward linkage method in the clustering model to find the number of submarkets present in the Greater

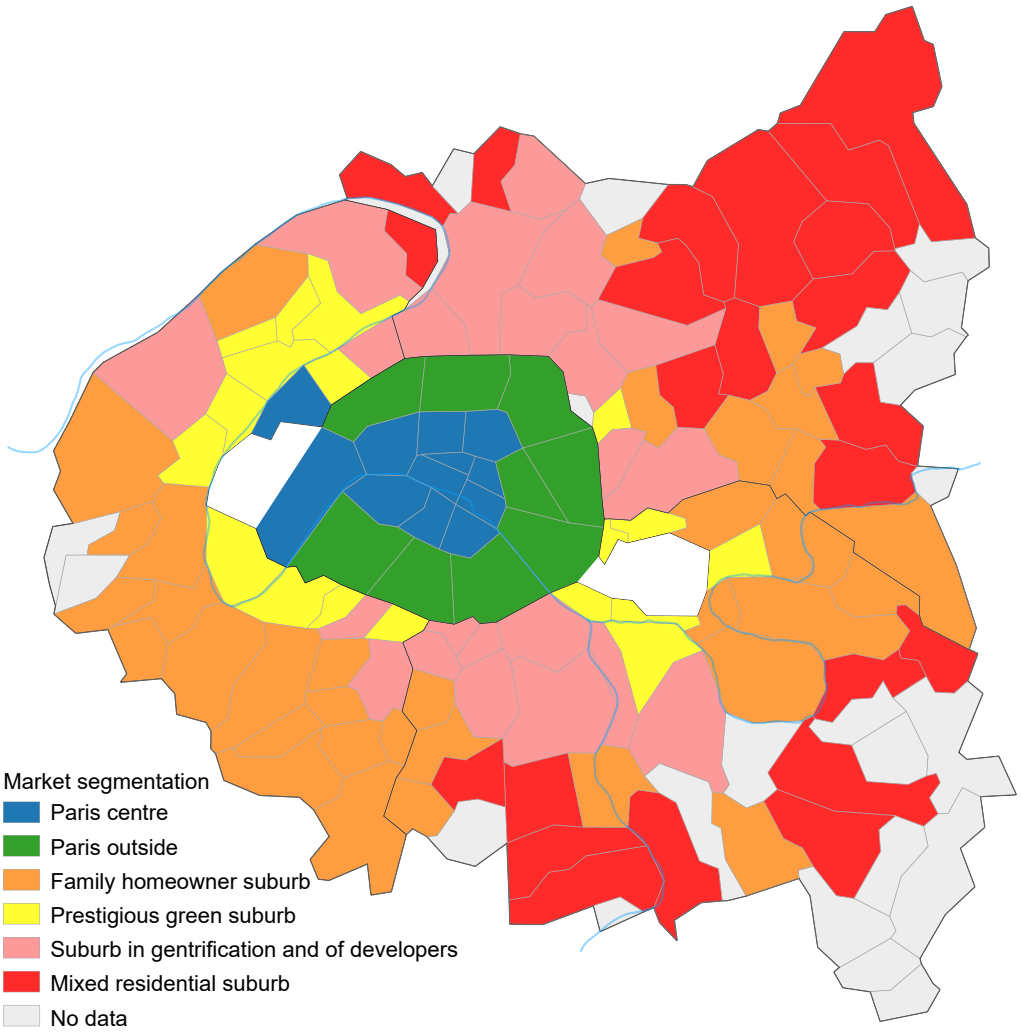
[14] A Moran test is not computed for the national level variables such as inflation and interest rate.

[15] We also use a Moran' I test for each cluster. Results confirm the presence of spatial autocorrelation and are available upon request.

[16] Table A.6 provides a list of the variables used in the principal component analysis.

Paris Metropolis.[17] This method minimizes the total within-cluster variance and maximizes the between-cluster variance assuring orthogonality between classes. Finally, we implement the Duda-Hart test in order to select the right cut-off. Results reported in Table A.7 show that there are six clusters in the Greater Paris Metropolis. The Je(2)/Je(1) is the second highest value after cut-off two but it has a significantly lower pseudo T-squared. Table A.8 lists each city's name in the six clusters. Figure A.8 shows the cities' repartitioning along the two first components, but this time the color code depends on the cluster analysis results. Figure 2 maps the six clusters in Greater Paris, and Table A.9 reports the summary statistics for each cluster.

Figure 2: Clusters in the Greater Paris Metropolis



5.1. Paris center

The Paris center's cluster comprises 11 Paris districts and one city in the west suburbs (Neuilly-sur-Seine) with a prestigious housing market. In fact, average housing prices per

[17] the Ward method is preferred to the K-means method because it does not require to define the number of clusters a priori.

square meter were €11,923 in 2019, and the average monthly rent per square meter reached €28.3 in 2018. House prices and rents increased by +21.3% and +3.2% respectively during the last three years. Hence, the average gross income return was 3.0% in 2018. The market is liquid, with a high level of transactions representing 14.8% of the total housing stock during the last five years (2014-2018).

Primary residences represent 76.4% of the total housing stock, and secondary residences and vacant dwellings represent a significant share of the total housing stock — 14.5% and 9.1%, respectively. The housing stock has been mainly built before 1970 (84.0%) and consists of apartments (96.6%) and small floor area (70.9%). The homeowner rate reaches 39.2%, and the private tenant rate is 47.2%. The public tenant rate is very low (6.3%).

Demand for housing comes from prosperous households with a high average disposable income (€55,771) in superior socio-professional categories (56.9%). The average number of households in each city is approximately 41,000, which decreased slightly (-2.4%) during the last three years (2014-2017). However, the share of superior socio-professional categories tends to increase during the same period (+7.5%). The share of one-person households is very high (51.2%), representing more than half of the total households. Finally, the construction activity is very low because only 0.6% of the total housing is under construction during the last five years (2014-2018). This low level of construction comes from the limited supply of land.

5.2. Paris outside

The cluster "Paris outside" comprises nine Paris districts with a high-end housing market. Table A.9 reports the average housing prices and monthly rents per square meter were approximately €9,576 in 2019 and €24.3 in 2018, respectively. The dynamic housing market shows a rise in house prices and rents, reaching +22% and +2.0%, respectively, during the last three years. However, the level of transactions during the last five years represents 11.6% of the total housing, which was less important compared to the Paris center's submarket. In 2018, the average gross income return was 3.3%.

Compared to the Paris center's cluster, primary residences represent a higher share of the total housing stock (85.5%). The share of secondary residences and vacant dwellings are still significant (6.3% and 8.2%, respectively) but lower compared to Paris center. The existing housing has been mainly built prior 1970 (64.5%) with mainly apartments (96.9%) and small floor area (80.5%). The homeowner rate is quite low, approximately 31.1%, and the private tenant rate is 42.8%. On the other hand, the public tenant rate is significantly higher (22.1%) than in the Paris center submarket.

Housing demand comes from superior socio-professional categories (53.0%) with an average disposable income of approximately €39,189, which is significantly lower than the average disposable income in the Paris center's cluster. Compared to Paris center, the average number of households in each arrondissement is higher, at 94,000, and it increased by +2.3% during the last three years. Furthermore, the share of superior socio-professional categories rose by +2.4%. The share of one-person households represents half of the total households (51.2%). Finally, the level of construction is also extremely scarce (1.6%).

5.3. Family-homeowner suburbs

The "family-homeowner suburbs" cluster is the biggest submarket, with 36 cities. The housing market is much more affordable compared to the two first clusters, with average

housing prices and rents of €4,463 and €17.4, respectively. The housing market is dynamic regarding of transactions, with 15.0% of the total housing stock involved in transactions during the last five years. However, the growth in housing prices and rents during the last three years is more moderate, at +12.1% and +1.2%, respectively. In 2018, the average gross income return was much more attractive at 5.1%.

This cluster is much more residential than the two first submarkets, with primary residences at 92.3% and secondary residences and vacant dwellings at 1.7% and 6.0%, respectively, of the total housing. Furthermore, this cluster records a high share of homeowners (50.3%), and the tenant rate is balanced between the private and public sectors at 24.4% and 23.2%, respectively. The shares of apartments and detached houses represent 74.3% and 24.4%, respectively, of the total housing stock. In addition, the housing units are larger and newer. Four-room and more units represent 42.1% of the total housing, and 48.1% of dwellings were built after 1970.

Demand for housing mainly comes from couples, with and without children (50.8%) neutralized between superior and other socio-professional statuses, with an average disposable income around €43,693. During the last three years, however, the number of households rose (+4.1%), similar to superior socio-professional statuses (+5.2%). On average, the number of households in each city is low — approximately 20,000. The cluster attracts new construction because new housing units represent 7.8% of the total housing during the last five years.

5.4. Prestigious green suburbs

There are 18 cities in the "prestigious green suburbs" cluster. Cities are split between the east and the west, next to the Boulogne and Vincennes forests and the Seine River. The housing market is expensive, with average housing prices and rents at approximately €7,000 and €20.4 per square meter, respectively. Furthermore, the market is dynamic, with 15.4% of the total housing market involved in transactions during the five last years and a rise in housing prices and rents of +17.7% and +1.4%, respectively, during the last three years. In 2018, the average gross income return grew closer to that of the Paris submarkets (3.8%).

Primary residences make up 88.5% of the total housing, and secondary residences and vacant dwellings represent 4.3% and 7.2%, respectively. This latter includes mainly apartments (92.4%) and small floor area (71.7%), with construction balanced between prior to 1970 and after 1970. The homeownership rate (42.8%) is high relative to Paris' clusters, despite high market prices. Moreover, the tenant ratio is higher in the private sector (35.5%) than it is in the public sector (18.8%).

Demand for housing comes from one-person households (42.6%) and from couples with and without children (25% and 20.3%, respectively). Households mainly belong to superior socio-professional categories (56%) with an average disposable income of approximately €48,000. This submarket corresponds to the prosperous Paris suburbs. The number of households in each city averages 30,000 and increased by +3.7% during the last three years. The share of superior socio-professional categories increased slightly (+4.3%) during the last three years. The construction activity is low compared to the other clusters because new housing units built over the last five years comprises 4.8% of the total housing stock.

5.5. Suburbs in gentrification and targeted by developers

The cluster "suburbs in gentrification and targeted by developers" includes 22 cities of the Paris suburbs. The housing market is the second-most affordable market in Greater Paris, with average housing prices and rents at €4,600 and €16.7 per square meter, respectively. However, even if the transactions there during the last five years represent only 11.6% of the total housing, the increase in housing prices during the last three years was high (+18.9%), and rents have remained rather stable. The average gross income return was higher compared to the Paris clusters and the "prestigious green suburbs", reaching 4.9% in 2018.

Primary residences represent 92.7% of the total housing stock, and secondary residences and vacant dwellings represent 1.5% and 5.8%, respectively. The housing stock consists mainly of apartments (86.5%), but the share of detached housing (11.2%) is more significant compared to those of the Paris clusters and the prestigious green suburbs. In addition, the housing units are rather small (71.2%), and the construction periods are balanced between prior to and after 1970. The homeowner rate is the lowest in the Metropolis (29.3%), and the share of tenants in the public sector is the highest (38.2%).

Demand for housing mainly comes from one-person households and couples with families who have little disposable income (€28,028) and who belong mainly to the working socio-professional class. However, as reported by Table A.9 (3 years of changes in SPC + ratio (2014-2017)), this cluster shows a high demand from new households, with a +7.5% increase during the last three years coming from people with a superior socio-professional status (+7.1%). This submarket is changing quickly due to its current gentrification. Furthermore, developers are targeting this cluster due to land availability, its low costs compared to other submarkets, and due to its potential for growing housing prices. As indicated by the variable construction/stock (2014-2018) in Table A.9, during the last five years, developers have put up numerous new housing programs for sale (i.e., 8.4% of the total housing stock).

5.6. Mixed residential suburbs

The "mixed residential suburbs" cluster is the last submarket. It brings together 23 cities. Its housing markets is the most affordable in Greater Paris, with average housing prices and rents of €2,779 and €14.8 per square meter, respectively. Likewise, this submarket is less dynamic, with 11.9% of the total housing being involved in transactions during the last five years. Housing prices increased by only +7.2% during the last three years (2016-2019). Rents remained stable between 2015 and 2018 (-0.5%). In 2018, the average gross income return was the highest in the metropolis (6.8%).

This cluster is the most residential submarket, comprising 94.0% primary residences and extremely low levels of second residences (0.9%) and vacant dwellings (5.2%). The housing stock includes apartments (65.4%) and an important share of detached housing (33.1%), balanced between small (55.1%) and large floor area (44.9%). The construction periods prior to and after 1970 are also balanced. The homeownership rate is the second highest (46.5%), with a higher tenant rate for the social sector (31.1%) than for the private sector (21.3%).

Housing demand comes from households with children (34.7%) belonging to the working socio-professional status with low disposable income (i.e., €30,734 on average). During the last three years, however, the population rose by +4.1%, and the population of those with a superior socio-professional status rose by +2.6%. Finally, new housing units represent 7.2% of the total housing stock during the last five years.

6. Results

6.1. Impulse response functions

Before estimating the consequences of accounting for spatial dependence using SpVAR, we estimate the panel VAR, assuming that spatial correlation is zero. We use only one lag in our model because our data are annual and most of other lags were insignificant. We control for individual fixed-effects by forward-mean-differencing (Helmert transformation) to preserve orthogonality between variables and their lags[18]. We begin the analysis looking at the macroeconomic shocks over the entire sample and then by submarket using city fixed-effects. Furthermore, we implement Granger causality tests and forecast error variance decomposition to explore the usefulness and explanatory power of each variable in the housing prices equation. Finally, we investigate the ripple effects by introducing spatial dependence using the contiguity and similarity matrices. In this SpVAR modeling, the impulse responses refer to the effects of shocks to a certain variable within a specific region. We investigate how house prices react according to past shocks in housing prices within each submarket. We also examined how house prices behave according to shocks in other variables within each respective submarket. Finally, we explore how housing prices in a given city within a submarket respond to shocks to house prices in the other cities within the same submarket. PVAR and SpVAR models are estimated using GMM.

6.1.1. Whole sample

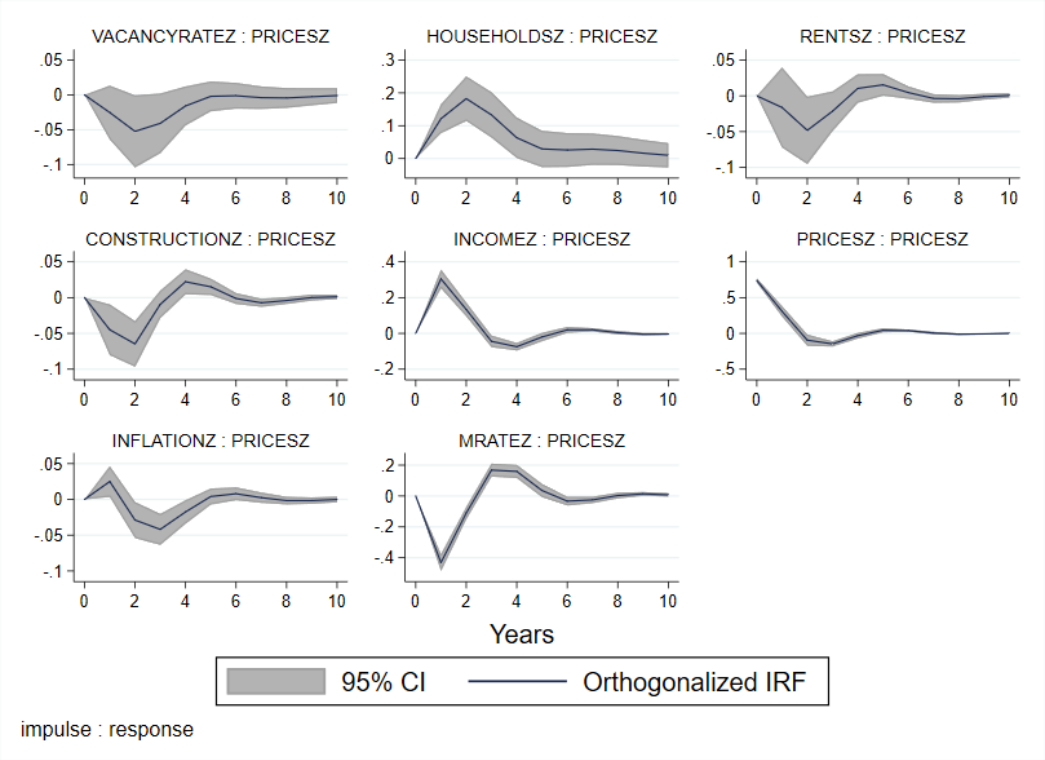
Figure 3 shows the impulse-response functions of housing prices to a shock of one-standard-deviation in housing prices, rents, interest rate, household disposable income, the number of households, inflation, housing starts and the vacancy rate. We also build a confidence interval corresponding to +/- 2 standard deviations of the shock and based on 500 Monte Carlo replications. We use the Choleski form to isolate the effects of each macroeconomic variable. Moreover, impulse responses can be sensitive to the ordering of the variables. We test different orderings to provide support to the robustness of our results.[19]

In Figure 3, we observe a strong temporal autocorrelation in house prices because a one-standard-deviation shock in lagged house prices increases actual housing prices significantly. The effect lasts two years before we observe a slight transitory mean reversion of housing prices and a return to the steady state. A rise in the mortgage rate indicates that the financing cost of a dwelling increases, thus reducing housing demand. A one-standard-deviation shock in the mortgage rate induces a sharp decrease in housing prices that lasts over two years. Then the effect dissipates before experiencing a slight mean reversion on year three and four. We expect household incomes to have a positive influence on housing prices because they contribute to increasing purchasing power for housing. The impulse-response functions confirm this positive effect on housing prices. We observe that housing prices react positively to a one-standard-deviation shock in household incomes. The effect lasts one year and then starts to decline and dissipate after three years. Regarding inflation, we observe that a shock of one-standard-deviation has a non significant positive impact on housing prices in the first year; then, inflation significantly decreases house prices during two years. After this period, house prices return to their steady state. The negative effect of

[18] In dynamic panel data, the first difference or Helmert transformation have often been used to eliminate the individual effects (see Anderson and Hsiao (1981) and Arellano and Bover (1995) among others).

[19] Results are available upon request.

Figure 3: Impulse responses for the whole sample (PVAR)



inflation on house prices is explained by the interest rate adjustment by the central bank to target inflation. This adjustment has a significant negative effect on house prices as we can see through the shock of mortgage rate. These demand shocks are economic, but housing also reacts to demographic demand shocks, such as changes to the number of households. In fact, everything else being equal, the growth in households places upward pressure on housing demand and, thus, increases prices. An impulse-response of one-standard-deviation in the number of households has a significant positive impact on housing prices that lasts four years before housing prices return to their steady state.

Regarding supply shocks, our panel vector autoregressive model accounts for housing starts and the vacancy rate. Theoretically, we could expect that a rise in construction would increase the number of units on the market and thus should decrease housing prices given a constant demand. However, a rise in construction in new dwellings tends to improve the quality of the total stock, thus increasing average housing prices. Furthermore, construction is a slow process that lasts for around two years. Impulse-response functions show that a one-standard-deviation shock in housing starts has a significant negative effect on housing prices. Regarding the vacancy rate, we observe that a shock of one-standard-deviation significantly decreases housing prices. The effect lasts for approximately four years and then dissipates. Finally, a one-standard deviation shock in rents does not have any significant effect on housing prices.

Now, we introduce the spatial effect through the SpVAR modeling. Figure 4 shows the impulse-response functions for the SpVAR model using the contiguity matrix, while Figure 5 reports the impulse-response functions for the SpVAR model using the similarity matrix. In both approaches, we decide to remove rent and construction. Indeed, these variables

Figure 4: Impulse responses for the whole sample (SpVAR contiguity matrix)

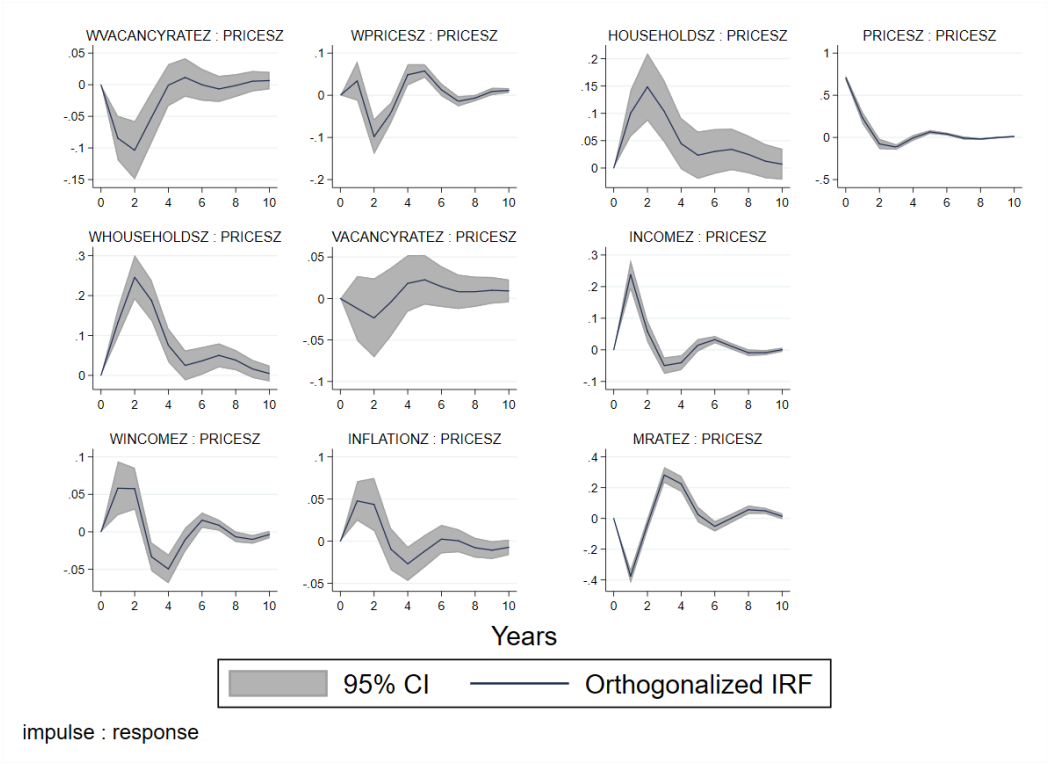
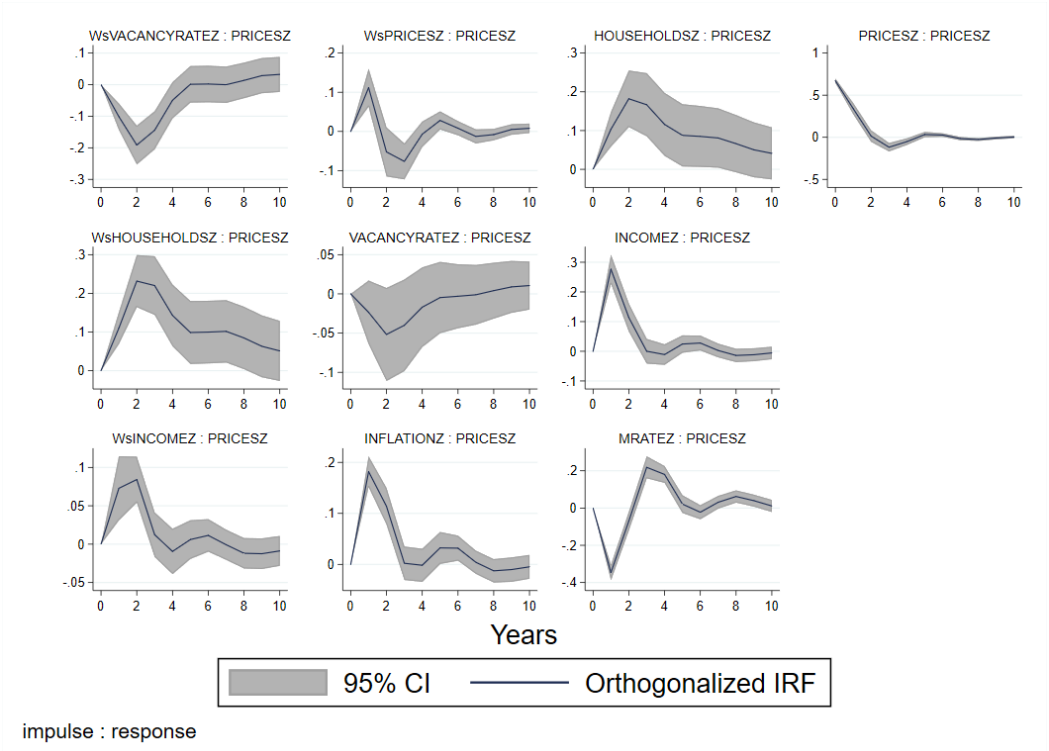


Figure 5: Impulse responses for the whole sample (SpVAR similarity matrix)



are either insignificant or barely significant at the submarket level, as suggested by Table

A.10. We observe that SpVAR results, using either the contiguity or similarity matrix, are similar to the PVAR results. Moreover, the lagged spatial lag of housing prices, income, number of households, and vacancy rate have significant impacts on actual housing prices. All variables except for vacancy rate have significant positive influences on housing price growth. Regarding vacancy rate, the local effect is not significant when we introduced its spatial effect. As expected, the vacancy rate has a significant negative influence on housing prices, with a global rather than a local impact. Taking into account spatial effects, we observe that inflation does have a significant positive influence on house prices. The SpVAR using the similarity matrix shows that spillover of housing prices is positive in year 1 and negative afterward, suggesting a slight mean reversion effect in period 3. Indeed, the comovements in housing prices tend to reverse after two years. The mean reversion is consistent with Glaeser et al. (2014), who showed mean reversion within five periods. The SpVAR using contiguity matrix shows that spillover of housing prices is postive but non significant in year 1 and become significantly negative in year 2 and 3. The mean reversion effect occurs in year 4 and during two years before spillover of housing prices return to its steady state. Overall, these results report a substitution and diffusion effects at the Greater Paris Metropolis level, as illustrated by Figure 4 and Figure 5. Table A.11 and Table A.12 suggest that the spatial variables affect housing prices significantly in the Granger causality tests. In the next section, we examine whether macroeconomic shocks have homogeneous effects on housing prices in each submarket. Moreover, we investigate whether spatial effects still affect housing prices within each submarket.

6.1.2. By submarket

We analyze impulse-response functions at the submarket level to understand whether macroeconomic shocks and spatial dependence have homogeneous impacts on housing prices. In doing so, we shed light on whether housing markets in the Metropolis are integrated and can be defined as a global market or as several submarkets. Panel VAR impulse responses for each submarket are shown in Figure A.9. The results in each submarket are similar to those for the whole sample. It takes several years for the shock to affect the housing market fully, given the slow process of choosing residences and conducting transactions in this sector.

A positive shock in the mortgage rate has a significantly negative impact on housing prices in all clusters. However, the effect is stronger for the "Paris center", "Paris outside" and the "prestigious green suburbs". Interestingly, expensive housing submarkets experience more sensitivity to mortgage rate increases as compared with cheaper housing submarkets. In fact, in markets where the price per square meter is high, households are more dependent on the financing market. Hence, given a shock in the mortgage rate, a larger number of vulnerable households are more likely to be excluded from the credit market. Therefore, we can expect spatial arbitrage and the migration effect toward spillover housing submarkets where the price is lower, to take advantage of affordable housing.

Regarding income, submarkets react homogeneously to a shock of one-standard-deviation on households' incomes. In fact, the effect is positive and significant. Therefore, a shock in household income triggers an increase in housing prices that lasts for around two or three years depending on the submarket. Moreover, the shock seems of higher magnitude in the Paris submarkets and the "Prestigious green suburbs". Housing prices are more sensitive to income shocks in expensive submarkets. The last economic variable is inflation, measured by the consumer price index. An inflation shock has a significantly positive influence on

housing prices in the "family-homeowner suburbs", the "prestigious green suburbs" and the "suburbs in gentrification targeted by developers". The effect on prices dies out between one and two years after the shock.

A shock in the number of households seems to have a heterogeneous influence on housing prices by submarket. In fact, an increase in households positively and significantly affects housing prices in Paris clusters but it has no significant impact on other submarkets. The effect dies out after three or four years in the Paris submarkets before returning to its steady state.

Regarding supply factors, a shock in housing starts appeared to have no significant impact on housing prices. This result is robust in all submarkets and suggests that housing prices are inelastic when it comes to the housing supply. However, a shock in the vacancy rate has a significantly negative impact on housing prices for the "Paris center" and the "prestigious green suburbs" but no significant impact on other clusters. Friction in the market is translated as an increase in the vacancy rate and incentivizes people to reduce the sale price to close the transaction. The effect is significant for clusters where the vacancy rate is already high, the housing market is expensive and the share of large housing units is high.

Figure A.10 introduces the impulse response for the SpVAR model using the contiguity matrix. In doing so, we control for omitted variable bias generated by spillover effects and check for robustness. The SpVAR model differs slightly for the "Paris outside" submarket because of its small sample size. Consequently, we only introduce a spatial effect of housing prices for this submarket because we can not have fewer observations than parameters. The spatial effect of housing prices has a positive and significant influence on housing prices for the "Paris center" cluster. However, the effect is negative and significant for "Paris outside", the "prestigious green suburbs" and the "family-homeowner suburbs". The former case show a positive diffusion effect while the latter cases show a substitution effect. The spatial effect of income growth has a positive and significant effect on housing prices in the "Paris center", the "prestigious green suburbs" and the "suburbs in gentrification and targeted by developers" but is not significant for the other clusters. The spatial effect of household growth also has a significant positive influence on housing prices in the "Paris center", the "prestigious green suburbs" and the "suburbs in gentrification and targeted by developers". Finally, the spatial effect of the vacancy rate has a significant negative influence on housing prices in all clusters except in the "family-homeowner suburbs" and the "mixed residential suburbs". In the SpVAR approach using the contiguity matrix, we observe that a shock in inflation produces a rise in house prices in all clusters except the "mixed residential suburbs" and the "Paris outside" clusters.

Figure A.11 introduces the impulse response for the SpVAR model using the similarity matrix. In doing so, we do not longer focus on the border effect but instead on the spillover effects between cities with similar market profiles. The spatial effect of housing prices has a negative and significant influence on actual housing prices for the "family-homeowner suburbs" and the "suburbs in gentrification and targeted by developers". Regarding other clusters, we observe no spillover effects on housing prices. The negative effect shows that housing markets are considered close substitutes rather than as spillover markets. The spatial effect of income growth has a positive and significant effect on prices for all clusters except the "mixed residential suburbs". Hence, local housing prices react positively to one-standard-deviation in income growth in cities that share similar market profiles. Household

growth has a significant positive spatial effect on housing prices in the "Paris center", the "family-homeowner suburbs" and the "suburbs in gentrification and targeted by developers". However, the effect is negative for the "prestigious green suburbs". In this case, cities with similar market profiles are competitors, and the results are seen as substitution effects on housing prices. Finally, the spatial effect of the vacancy rate has a significant negative influence on housing prices in all clusters but significant only for the "Paris center", the "family-homeowner suburbs" and the "Prestigious green suburbs".

To conclude, the SpVAR models using the contiguity or the similarity method exhibit similar results with the PVAR model. Moreover, the SpVAR models results show that some of the variables have more global effects than local effects when accounting for spatial autocorrelation. The comparison between the contiguity and the similarity matrices does not bring new conclusions but show that results are strongly similar. Nevertheless, the use of spatial models enables to show that different spatial effects are at play. For some variables, we observe a direct diffusion effects on house prices while for others we find substitution effects.

6.2. Forecast error variance decomposition

6.2.1. Forecast error variance decomposition for the SpVAR model using the contiguity matrix

Table A.13 shows the variance decomposition of housing prices for each submarket. The proportion of the variance in actual housing prices is mainly explained by its own lag. Previous variations in housing prices explain between 30.3% and 89.7% of the housing price variance. We observe a proportion greater than 50% in the short run but it drops significantly in the long-run. The proportion is higher for the "mixed residential suburbs" at 89.7% in the short-run and decreasing slightly to 83.1% in the long-run. The proportions in the "Paris center" submarket and the "prestigious green suburbs" are the lowest at 66.1% and 54.1% in the short-run and 30.3% and 39.9%, respectively, in the long-run. Regarding the cluster "Paris outside", the proportion stands at 72.1% in the short-run but drops to 39.0% in the long-run. The mortgage rate also plays a key role in housing price variance because it explains more than a third of total variance in housing prices except in the cluster "Paris outside" and the "mixed residential suburbs" where it explains around 25% and less than 10% respectively. The proportion tends to increase slightly over time. In addition, the demographic variables are the third most important variables in the housing price variance. Household growth plays a significant role of the variance in housing prices in "Paris outside" and "mixed residential suburbs", at 24.8% in the long-term for "Paris outside" and 8.9% for the "mixed residential suburbs". Moreover, the spatial effect of household growth has almost no effect in the short-run but has a striking influence on the variance of housing prices with a proportion ranging between 6% to 8% in the "Paris center", the "prestigious green suburbs" and the "suburbs in gentrification and targeted by developers. The other variables play a secondary role in the variance of housing prices, with marginal explanatory power. The explanatory power of the income growth is higher for the "family-homeowner suburbs", the "prestigious green suburbs" and the "Paris center" approximately 4%. The spatial effect of housing prices explain between 0% and 4.2% of the actual variation in housing prices. Finally, the spatial effect of the vacancy rate plays a greater role than the local vacancy rate did in the variation in housing prices, meaning that the vacancy rate must be considered at a more global level.

6.2.2. Forecast error variance decomposition for the SpVAR model using the similarity matrix

Table A.14 shows the variance decomposition of housing prices using the similarity matrix. The proportion of the variance in actual housing prices is mainly explained by its own lag. Previous variation in housing prices explains more than 50% in the short-run and at least 30% in the long-run. The proportion is higher for the "mixed residential suburbs", at 93.8% in the short-run and decreasing to 74.7% in the long-run. The proportions in the "Paris center" submarket and the "prestigious green suburbs" are the lowest, at 63.6% and 56.8% in the short-run and 30.8% and 33.9% in the long-run, respectively. The mortgage rate also plays a key role in housing price variance because it explains around a third of total variance in housing prices except in the "mixed residential suburbs", the cluster "Paris outside" and the "prestigious green suburbs" where it explains less than 10% around 25% and 20% respectively. The proportions are higher for "Paris center", the "family-homeowner suburbs", and the "suburbs in gentrification and targeted by developers", explaining more than 30% of the variance in housing prices in the long-run. The proportion tends to increase slightly over time. Compared to the contiguity matrix results, mortgage rate has a weaker influence on the variation in housing prices for the "Paris center" and the "prestigious green suburbs". The third most important factor in the variance of housing prices varies regarding submarkets. We observe households growth plays a significant role in the "Paris outside", at 26% in the long-term and around 6.9% in the long-term for the "mixed residential suburbs" while it has a marginal effect in the other submarkets. In the "Paris center" and the "prestigious green suburbs" income growth accounts for 14% and 11.6% in the long-term respectively while it stands at 6.5% in the "Paris outside and has a marginal effect in other clusters. Likewise, the spatial effect of income growth accounts for 4% in the "suburbs in gentrification and targeted by developers". The other variables have weaker influence on the variance of housing prices and are heterogeneous across submarkets. Lastly, the spatial effect of the vacancy rate plays a higher role than the local vacancy rate did in the variation in housing prices.

The forecast error variance decomposition shows that the results of both the contiguity and the similarity approaches are quite similar. Variables such as housing prices, mortgage rate, income growth, household growth and its spatial effect could be considered as core indicators explaining the variation in housing prices, while the other variables play secondary roles. The comparative analysis shows that the spatial effect of household growth plays a more important role in the contiguity matrix while income growth has a greater influence in the variance of housing prices using the similarity matrix. Nevertheless, as reported by Table A.13 and Table A.14, the spatial effects tend to play a relatively marginal role in the housing markets' dynamics.[20]

7. Conclusion

The purposes of this paper were to investigate the presence of housing submarkets in the Greater Paris Metropolis and to explore the outcomes of macroeconomics shocks, as well as the ripple effects on housing prices. Our empirical approach relies on the classical macroeconomic framework of supply and demand but introduces a spatial dimension as

[20] We may mention that household growth matters in a few submarkets.

well. To do so, we used a spatial panel vector autoregressive model to analyze and discuss the potential heterogeneous effects of macroeconomic shocks and ripple effects across housing submarkets.

The results indicate that the Greater Paris Metropolis cannot be seen as a single housing market but instead can be seen as several housing submarkets. We find the presence of six total submarkets. Furthermore, the investigation of macroeconomic shocks suggests that submarkets react differently to shocks and thus should be analyzed independently. In fact, an increase in lagged housing prices has a significant positive effect on actual prices. However, the effect is stronger for the Paris submarkets, whereas the effect is weaker in the "mixed residential" cluster. Likewise, a one-standard-deviation shock in the mortgage rate has a significant negative impact on housing prices. This effect is even more powerful in expensive submarkets. We also show the hedging effect of housing prices against inflation. One-standard-deviation increase in inflation has a significantly positive impact on housing prices in the "Paris center", the "family-homeowner suburbs", the "prestigious green suburbs" and the "suburbs in gentrification and targeted by developers". Regarding the demographic factor, housing prices react differently by submarket. The effect is positive and significant in the Paris clusters but has no effect in other clusters. Regarding supply factors, housing prices are inelastic to a one-standard-deviation shock in housing starts. This finding is homogeneous across clusters. However, an increase of one-standard-deviation in the vacancy rate pushes housing prices down in the "Paris center" cluster and the "prestigious green suburbs" where the vacancy rate is already high but has no significant effect in the other clusters.

Likewise, we investigated the presence of ripple effects in each submarket using the SpVAR method with contiguity and similarity matrices. The results show that non-spatial variables behave in the same way compared to the PVAR approach. Furthermore, the SpVAR approach demonstrate that some spatial autocorrelations are at play and have significant effects on housing prices in both the Greater Paris Metropolis and all of its submarkets. The implementation of two types of spatial matrices show that different spatial effects are at play. In the case of the contiguity matrix, a substitution effect exist between contiguous cities, while the similarity matrix exhibits some diffusion effects between cities that share similar market profiles. However, this phenomena is only observed at the global Metropolis level. At the submarket level, we observe that all spatial variables have a significant global diffusion effect on local housing prices. Nevertheless, the spatial effect of housing prices seems to display a substitution effect in the short-term. However, its magnitude is low and its explanatory power in the modeling is marginal. On the other hand, SpVAR results indicate that some of the variables become useless when considering spatial effects. This suggests that some of the variables have a global rather than a local effect; and thus, cities in the same cluster are interconnected and must be considered as part of a submarket, rather than alone.

In addition, the contribution of each variable to housing prices varies by submarket. However, the variables with the highest explanatory power are the lagged housing prices and the mortgage rates, followed by household growth and its spatial effect. Spatial effects play a secondary role because they explain marginal shares of the variation in housing prices except for the spatial household growth effect that has a relatively large influence on housing prices.

Finally, the analysis presents some caveats. Further research should investigate the directionality of lagged spatial lags as well as the ripple effect between submarkets. The annual frequency and the short time period of our data sample prevent us for undertaking such an analysis.

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Appendix A.

Table A.1: Data description

Variables	Description	Source
PRICESZ	Real hedonic house prices (€)	Notaries
MRATEZ	Real average mortgage rate for house purchase (%)	Housing credit observatory
INCOMEZ	Real household disposable income (€)	Insee
HOUSEHOLDSZ	Number of households	Insee
INFLATIONZ	Consumer price index	Insee
VACANCYRATEZ	Share of vacant dwellings in the housing stock (%)	Insee
RENTSZ	Real rent level in the rental private sector (€)	Clameur
CONSTRUCTIONZ	Number of dwellings under construction	Sitadel

Note: The letter Z means that variables have been standardized for the analysis.

Figure A.6: Principal Component Analysis

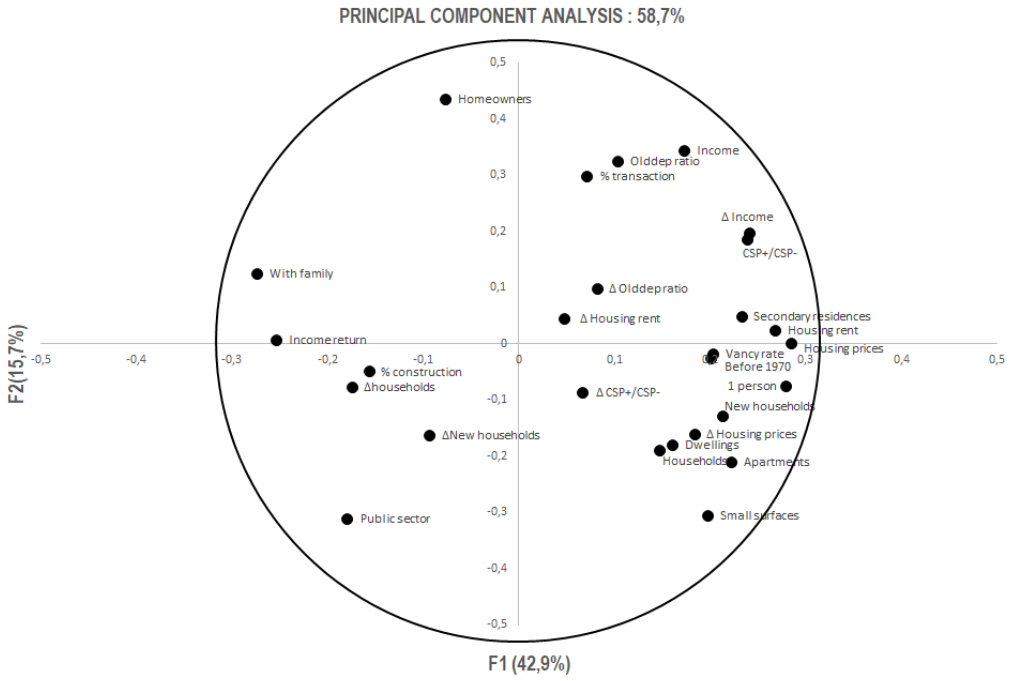


Table A.2: Panel unit root tests

	Level				First difference				HP-Filter			
	Augmented Dickey fuller		Phillips- Perron		Augmented Dickey fuller		Phillips- Perron		Augmented Dickey fuller		Phillips- Perron	
	Intercept	Trend	Intercept	Trend	Intercept	Trend	Intercept	Trend	Intercept	Trend	Intercept	Trend
	p-values				p-values				p-values			
HOUSE PRICES												
P	0.2842	0.0000	0.00023	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Z	0.7047	0.0000	0.0039	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.4953	0.0000	0.0017	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PM	0.2915	0.0000	0.0012	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
RENTS												
P	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Z	0.0055	0.0067	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0013	0.0019	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MRATE												
P	1.0000	0.0000	1.0000	0.9998	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9918
Z	0.8369	0.0000	0.9578	0.4377	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0958
L	0.8063	0.0000	0.9356	0.4451	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1251
PM	1.0000	0.0000	1.0000	0.9994	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9879
INCOME												
P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Z	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HOUSEHOLDS												
P	0.8000	0.0000	0.8003	0.3446	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1885
Z	1.0000	0.0002	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9907
L	1.0000	0.0000	1.0000	0.9998	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9605
PM	0.8022	0.0000	0.8024	0.3544	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1907
INFLATION												
P	0.0000	0.1628	0.1456	0.5047	0.0000	0.1547	0.0000	0.0000	0.0049	1.0000	0.0000	1.0000
Z	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0001	0.0000
L	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0005	1.0000
PM	0.0000	0.1633	0.1441	0.05168	0.0000	0.1547	0.0000	0.0000	0.0029	1.0000	0.4764	1.0000
CONSTRUCTION												
P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Z	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
VACANCYRATE												
P	0.0000	0.0001	0.0000	0.0192	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0033
Z	0.0658	0.8549	0.9281	0.9999	0.0000	0.0021	0.0000	0.0000	0.0000	0.3514	0.0000	0.9035
L	0.0161	0.5969	0.3464	0.9801	0.0000	0.0000	0.0000	0.0000	0.0000	0.1033	0.0000	0.4776
PM	0.0000	0.0000	0.0000	0.0150	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0018

Note: The capital letters P, Z, L and PM stand for: inverse chi-squared (P), inverse normal (Z), inverse logit t (L) and modified inverse chi-squared (PM).

Table A.3: Moran's test

Moran's I

Variables	I	E(I)	sd(I)	z	p-value
WPRICE	0.846	-0.008	0.059	14.389	0.000
WRENT	0.755	-0.008	0.059	12.843	0.000
WINCOME	0.610	-0.008	0.059	10.395	0.000
WHOUSEHOLDS	0.315	-0.008	0.058	5.560	0.000
WCONSTRUCTION	0.104	-0.008	0.058	1.955	0.025
WVACACYRATE	0.422	-0.008	0.059	7.283	0.000
WsPRICE	0.324	-0.008	0.018	18.295	0.000
WsRENT	0.319	-0.008	0.018	18.025	0.000
WsINCOME	0.116	-0.008	0.018	6.863	0.000
WsHOUSEHOLDS	0.240	-0.008	0.018	14.008	0.000
WsCONSTRUCTION	0.016	-0.008	0.018	1.335	0.091
WsVACACYRATE	0.109	-0.008	0.018	6.472	0.000

Note: W is the contiguity matrix and Ws is the similarity matrix

Table A.4: Spatial autocorrelation test using the contiguity matrix

Test	Value	P-Value
LM ERROR		
GLOBAL Moran I	0.5045	0.0000
GLOBAL Geary GC	0.4928	0.0000
GLOBAL Getis-Ords GO	-0.5045	0.0000
Moran MI Error test	29.2529	0.0000
LM Error (Burridge)	698.5154	0.0000
LM Error (Robust)	8.3004	0.0040
LM LAG		
LM LAG (Anselin)	731.0345	0.0000
LM LAG (Robust)	40.8195	0.0000
LM SAC		
LM SAC (LMError + LMLag_R)	739.3349	0.0000
LM SAC (LMLag + LMError_R)	739.3349	0.0000

Table A.5: Spatial autocorrelation test using the similarity matrix

Test	Value	P-Value
LM ERROR		
GLOBAL Moran I	0.3103	0.0000
GLOBAL Geary GC	0.6561	0.0000
GLOBAL Getis-Ords GO	-0.3103	0.0000
Moran MI Error test	52.0755	0.0000
LM Error (Burridge)	2012.9112	0.0000
LM Error (Robust)	8.0010	0.0047
LM LAG		
LM LAG (Anselin)	2029.3867	0.0000
LM LAG (Robust)	24.4765	0.0000
LM SAC		
LM SAC (LMError + LMLag_R)	2037.3877	0.0000
LM SAC (LMLag + LMError_R)	2037.3877	0.0000

Table A.6: PCA variables

List of variables	**Sources**	**List of variables**	**Sources**
Number of dwellings	Insee	3 rooms and less / stock (%)	Insee
Number of households	Insee	Construction before 1970 (%)	Insee
Household disposable income	Insee	New households (%)	Insee
Secondary residence (%)	Insee	3-years change in households (2014-2017)	Insee
Vacancy rate	Insee	3 years change in new households (2014-2017)	Insee
Apartments / stock (%)	Insee	3-years OLDDEP ratio change	Insee
Homeownership rate (%)	Insee	3-years change in households disposable income (2014-2017)	Insee
Public tenant ratio (%)	Insee	3-years change in SPC+ ratio (2014-2017)	Insee
1 person household (%)	Insee	Price/sqm 2019	Notaries
Couple with children (%)	Insee	3-years price change (2016-2019)	Notaries
SPC + ratio	Insee	Rent/sqm 2018	Clameur
Construction / stock (2014-2018)	Sitadel	3-years rent change (2015-2018)	Clameur
Transactions / stock (2014-2018)	Dvf / Insee	Income return 2018	Notaries / Clameur
Old ratio (%)	Insee		

Figure A.7: Score plot 1

Note: Colour code refers to administrative department boundaries. Pink: Paris; Orange: Hauts-de-Seine; Green: Val-de-Marne; Blue: Seine-Saint-Denis

Table A.7: Cut off rule test

	Duda / Hart	
Number of clusters	Je(2) / Je(1)	Pseudo T-squared
1	0.6354	67.70
2	0.7649	29.82
3	0.6004	28.62
4	0.6998	22.31
5	0.4356	24.61
6	**0.7346**	**12.29**
7	0.6017	13.90
8	0.6341	11.54
9	0.6365	10.85
10	0.4036	14.78
11	0.6604	5.14
12	0.6673	6.48
13	0.6370	6.27
14	0.4956	7.12
15	0.5221	6.41

Table A.8: Cities in each cluster

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Neuilly-sur-Seine	Paris 11e Arrondissement	Antony	Asnières-sur-Seine	Bagneux	Villeneuve-la-Garenne
Paris 1er Arrondissement	Paris 12e Arrondissement	Bourg-la-Reine	Bois-Colombes	Clichy	Aulnay-sous-Bois
Paris 2e Arrondissement	Paris 13e Arrondissement	Châtenay-Malabry	Boulogne-Billancourt	Gennevilliers	Le Blanc-Mesnil
Paris 3e Arrondissement	Paris 14e Arrondissement	Châtillon	Courbevoie	Malakoff	Bondy
Paris 4e Arrondissement	Paris 15e Arrondissement	Chaville	La Garenne-Colombes	Nanterre	Drancy
Paris 5e Arrondissement	Paris 17e Arrondissement	Clamart	Issy-les-Moulineaux	Aubervilliers	Épinay-sur-Seine
Paris 6e Arrondissement	Paris 18e Arrondissement	Colombes	Levallois-Perret	Bagnolet	Gagny
Paris 7e Arrondissement	Paris 19e Arrondissement	Fontenay-aux-Roses	Montrouge	Bobigny	Livry-Gargan
Paris 8e Arrondissement	Paris 20e Arrondissement	Garches	Puteaux	La Courneuve	Neuilly-sur-Marne
Paris 9e Arrondissement		Meudon	Suresnes	Montreuil	Noisy-le-Sec
Paris 10e Arrondissement		Le Plessis-Robinson	Vanves	Pantin	Pierrefitte-sur-Seine
Paris 16e Arrondissement		Rueil-Malmaison	Les Lilas	Saint-Denis	Sevran
		Saint-Cloud	Charenton-le-Pont	Saint-Ouen-sur-Seine	Tremblay-en-France
		Sceaux	Maisons-Alfort	Stains	Villepinte
		Sèvres	Nogent-sur-Marne	Alfortville	Boissy-Saint-Léger
		Ville-d'Avray	Saint-Mandé	Arcueil	Chennevières-sur-Marne
		Le Bourget	Saint-Maurice	Créteil	Chevilly-Larue
		Neuilly-Plaisance	Vincennes	Gentilly	Orly
		Noisy-le-Grand		Ivry-sur-Seine	Le Plessis-Trévise
		Les Pavillons-sous-Bois		Le Kremlin-Bicêtre	Sucy-en-Brie
		Le Raincy		Villejuif	Thiais
		Romainville		Vitry-sur-Seine	Villeneuve-le-Roi
		Rosny-sous-Bois			Villeneuve-Saint-Georges
		Villemomble			
		Bry-sur-Marne			
		Cachan			
		Champigny-sur-Marne			
		Choisy-le-Roi			
		Fontenay-sous-Bois			
		Fresnes			
		L'Haÿ-les-Roses			
		Joinville-le-Pont			
		Limeil-Brévannes			
		Le Perreux-sur-Marne			
		Saint-Maur-des-Fossés			
		Villiers-sur-Marne			

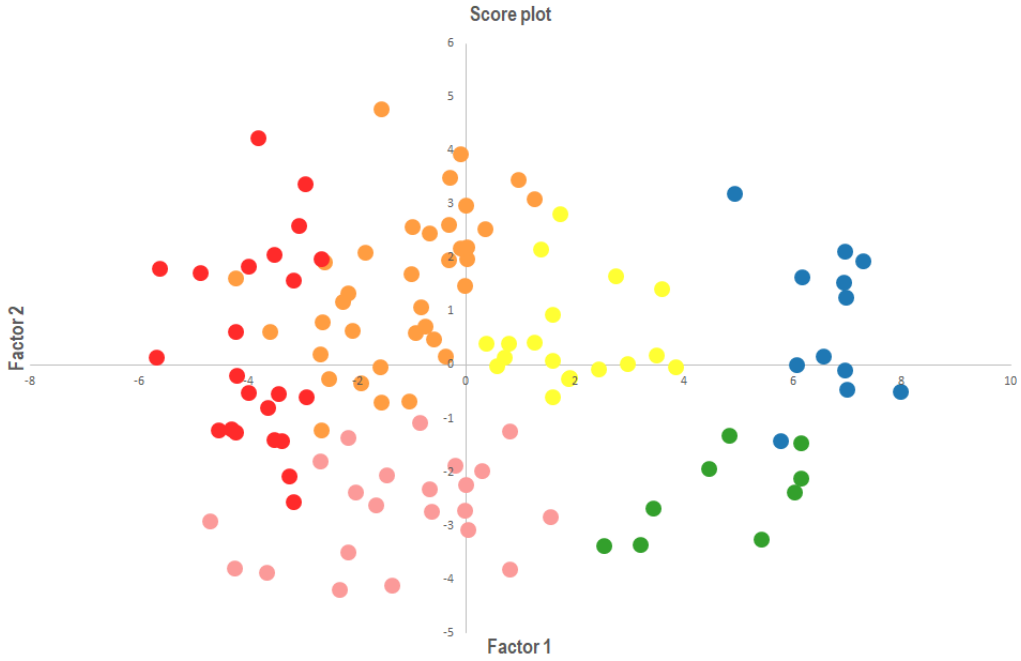
Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Table A.9: Summary statistics

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Price/sqm 2019	€11,923	€9,576	€4,463	€6,967	€4,600	€2,779
Rent/sqm 2018	€28.3	€24.3	€17.4	€20.4	€16.7	€14.8
3-years price change (2016-2019)	+21.8%	+22.0%	+12.1%	+17.7%	+18.9%	+7.2%
3-years rent change (2015-2018)	+3.2%	+2.0%	+1.2%	+1.4%	-0.1%	-0.5%
Income return 2018	3.0%	3.3%	5.1%	3.8%	4.9%	6.8%
Transactions/stock (2014-2018)	14.8%	11.6%	15.0%	15.4%	11.2%	11.9%
Homeownership rate	39.2%	31.1%	50.3%	42.8%	29.3%	46.5%
Private tenant ratio	47.2%	42.8%	24.4%	35.5%	30.3%	21.3%
Public tenant ratio	6.3%	22.1%	23.2%	18.8%	38.2%	31.1%
Primary residence	76.4%	85.5%	92.3%	88.5%	92.7%	94.0%
Secondary residence	14.5%	6.3%	1.7%	4.3%	1.5%	0.9%
Vacancy rate	9.1%	8.2%	6.0%	7.2%	5.8%	5.2%
Appartments/stock	96.6%	96.9%	74.3%	92.4%	86.5%	65.4%
Detached houses/stock	0.9%	0.9%	24.4%	6.2%	11.2%	33.1%
3 rooms and less/stock	70.9%	80.5%	57.9%	71.7%	71.2%	55.1%
4 rooms and more /stock	29.1%	19.5%	42.1%	28.3%	28.8%	44.9%
Construction before 1970	84.0%	64.5%	50.2%	49.5%	48.9%	48.7%
Construction after 1970	15.6%	34.8%	48.1%	49.4%	48.3%	49.6%
Household disposable income	€57,771	€39,189	€43,693	€48,114	€28,028	€30,734
SPC + ratio	56.9%	53.0%	46.7%	56.0%	36.4%	30.7%
3-years change in SPC+ ratio (2014-2017)	+7.5%	+2.4%	+5.2%	+5.6%	+7.1%	+2.6%
Number of households	41,479	94,006	19,798	30,021	28,968	16,847
3-years change in households (2014-2017)	-2.4%	+2.3%	+4.1%	+3.7%	+7.5%	+4.1%
1 person household	51.2%	51.2%	35.1%	42.6%	37.5%	29.8%
Couple without children	20.9%	18.9%	20.7%	20.3%	16.6%	18.5%
Couple with children	17.5%	16.9%	30.1%	25.0%	27.6%	34.7%
Construction/stock (2014-2018)	0.6%	1.6%	7.8%	4.8%	8.4%	7.2%

Note: Statistics refer to the weighted average of the latest available data in each cluster. In cluster 1 the average price per sqm in 2019 stands at €11,923.
Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Figure A.8: Score plot 2



Note: Colour code refers to housing submarkets. Blue: Paris center; Green: Paris outside; Orange: Family-homeowner suburbs; Yellow: Prestigious green suburbs; Pink: Suburbs in gentrification and targeted by developers; Red: Mixed residential markets

Table A.10: Granger causality test

	Whole sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
PRICESZ							
RENTSZ	0.149	0.211	**3.069**	0.091	0.001	0.490	2.423
	(0.699)	(0.646)	**(0.080)**	(0.764)	(0.977)	(0.484)	(0.120)
MRATEZ	**333.780**	**115.853**	**202.932**	**137.482**	**170.891**	**83.610**	**33.629**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
INCOMEZ	**133.257**	**52.009**	**43.619**	**24.342**	**43.100**	**7.990**	0.628
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.005)**	(0.428)
HOUSEHOLDSZ	**18.808**	0.143	**9.920**	1.758	0.089	0.544	2.205
	(0.000)	(0.705)	**(0.002)**	(0.185)	(0.765)	(0.461)	(0.138)
INFLATIONZ	**5.069**	2.345	1.217	**12.092**	**28.618**	**10.295**	0.003
	(0.024)	(0.126)	(0.270)	**(0.001)**	**(0.000)**	**(0.001)**	(0.958)
CONSTRUCTIONZ	**5.673**	0.154	0.112	0.910	0.361	0.748	0.163
	(0.017)	(0.694)	(0.738)	(0.340)	(0.548)	(0.387)	(0.686)
VACANCYRATEZ	1.593	1.732	0.690	0.289	2.527	2.424	0.008
	(0.207)	(0.188)	(0.406)	(0.591)	(0.112)	(0.119)	(0.928)
ALL	**595.421**	**294.730**	**769.405**	**228.059**	**350.433**	**95.226**	**44.815**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**

Note: The table reports heteroskedasticity robust test statistics for Granger causality (Ftests).
P-values are in parentheses. Significant test statistics are in bold.
Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Table A.11: Granger causality test (SpVAR contiguity)

	Whole sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6		Whole sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
→ ΔPRICESZ								→ ΔVACANCYRATEZ							
ΔMRATEZ → ΔPRICESZ	347.763 (0.000)	118.719 (0.000)	271.256 (0.000)	126.612 (0.000)	204.317 (0.000)	72.151 (0.000)	34.651 (0.000)	ΔPRICESZ → ΔVACANCYRATEZ	1.141 (0.286)	0.036 (0.849)	0.020 (0.889)	3.268 (0.071)	0.075 (0.784)	2.551 (0.110)	2.949 (0.086)
ΔINCOMEZ → ΔPRICESZ	16.530 (0.000)	7.540 (0.006)	36.841 (0.000)	1.084 (0.298)	3.218 (0.073)	0.650 (0.420)	0.001 (0.974)	ΔMRATEZ → ΔVACANCYRATEZ	1.902 (0.168)	0.079 (0.779)	0.029 (0.865)	1.011 (0.315)	0.180 (0.672)	0.368 (0.544)	1.610 (0.204)
ΔHOUSEHOLDSZ → ΔPRICESZ	7.973 (0.005)	0.027 (0.870)	11.485 (0.001)	1.219 (0.269)	0.522 (0.470)	0.100 (0.752)	1.322 (0.250)	ΔINCOMEZ → ΔVACANCYRATEZ	4.604 (0.032)	0.584 (0.445)	0.002 (0.966)	5.616 (0.018)	3.562 (0.059)	1.410 (0.235)	0.277 (0.599)
ΔINFLATIONZ → ΔPRICESZ	0.009 (0.923)	0.663 (0.415)	2.389 (0.122)	11.123 (0.001)	6.561 (0.010)	6.784 (0.009)	0.112 (0.738)	ΔHOUSEHOLDSZ → ΔVACANCYRATEZ	0.088 (0.767)	0.146 (0.702)	0.965 (0.326)	0.306 (0.580)	0.186 (0.667)	2.560 (0.110)	1.360 (0.243)
ΔVACANCYRATEZ → ΔPRICESZ	0.333 (0.564)	0.201 (0.654)	0.598 (0.439)	0.030 (0.862)	0.693 (0.405)	1.878 (0.171)	0.029 (0.866)	ΔINFLATIONZ → ΔVACANCYRATEZ	1.315 (0.252)	0.468 (0.494)	0.336 (0.562)	4.082 (0.043)	0.075 (0.784)	0.186 (0.666)	2.559 (0.110)
ΔWPRICESZ → ΔPRICESZ	0.276 (0.599)	1.446 (0.229)	4.503 (0.034)	0.415 (0.519)	1.365 (0.243)	2.236 (0.135)	0.456 (0.499)	ΔWPRICESZ → ΔVACANCYRATEZ	0.000 (0.989)	0.025 (0.875)	0.021 (0.886)	0.009 (0.925)	0.158 (0.691)	1.014 (0.314)	0.080 (0.777)
ΔWINCOMEZ → ΔPRICESZ	8.342 (0.004)	2.653 (0.103)		2.777 (0.096)	4.243 (0.039)	7.592 (0.006)	0.435 (0.510)	ΔWINCOMEZ → ΔVACANCYRATEZ	0.946 (0.331)	0.884 (0.347)		2.639 (0.104)	3.373 (0.066)	0.008 (0.927)	0.000 (0.996)
ΔWHOUSEHOLDSZ → ΔPRICESZ	13.940 (0.000)	0.296 (0.586)		0.353 (0.552)	0.440 (0.507)	0.057 (0.812)	2.576 (0.109)	ΔWHOUSEHOLDSZ → ΔVACANCYRATEZ	12.962 (0.000)	8.567 (0.003)		2.166 (0.141)	5.349 (0.021)	0.087 (0.768)	0.033 (0.856)
ΔWVACANCYRATEZ→ ΔPRICESZ	21.885 (0.000)	16.866 (0.000)		0.901 (0.342)	3.699 (0.054)	6.891 (0.009)	0.002 (0.968)	ΔWVACANCYRATEZ→ ΔVACANCYRATEZ	0.147 (0.701)	0.189 (0.664)		1.526 (0.217)	0.512 (0.474)	1.003 (0.316)	0.701 (0.402)
ΔALL → ΔPRICESZ	744.703 (0.000)	418.721 (0.000)	913.753 (0.000)	237.839 (0.000)	461.258 (0.000)	137.633 (0.000)	47.261 (0.000)	ΔALL → ΔVACANCYRATEZ	39.439 (0.000)	41.581 (0.000)	3.193 (0.784)	24.299 (0.004)	13.776 (0.131)	14.978 (0.092)	8.030 (0.531)
→ ΔMRATEZ								→ ΔWPRICESZ							
ΔPRICESZ → ΔMRATEZ	1.317 (0.251)	0.218 (0.681)	6.487 (0.011)	3.556 (0.059)	0.704 (0.402)	9.435 (0.002)	0.166 (0.684)	ΔPRICESZ → ΔWPRICESZ	1.178 (0.278)	2.099£ (0.147)	0.164 (0.685)	1.233 (0.267)	0.004 (0.952)	2.109 (0.146)	0.468 (0.494)
ΔINCOMEZ → ΔMRATEZ	0.355 (0.551)	2.276 (0.131)	6.609 (0.010)	3.993 (0.046)	0.229 (0.632)	0.013 (0.909)	7.294 (0.007)	ΔMRATEZ → ΔWPRICESZ	789.764 (0.000)	652.621 (0.000)	340.608 (0.000)	294.627 (0.000)	400.389 (0.000)	334.096 (0.000)	126.771 (0.000)
ΔHOUSEHOLDSZ → ΔMRATEZ	0.287 (0.592)	0.658 (0.417)	8.615 (0.003)	0.009 (0.924)	0.429 (0.513)	2.680 (0.102)	12.634 (0.000)	ΔINCOMEZ → ΔWPRICESZ	0.794 (0.373)	11.631 (0.001)	47.891 (0.000)	0.173 (0.677)	1.892 (0.169)	1.845 (0.174)	0.119 (0.730)
ΔINFLATIONZ → ΔMRATEZ	434.318 (0.000)	98.957 (0.000)	51.065 (0.000)	54.961 (0.000)	75.105 (0.000)	39.703 (0.000)	50.481 (0.000)	ΔHOUSEHOLDSZ → ΔWPRICESZ	4.087 (0.043)	0.007 (0.935)	9.487 (0.002)	2.241 (0.134)	0.039 (0.844)	1.374 (0.241)	2.307 (0.129)
ΔVACANCYRATEZ → ΔMRATEZ	1.508 (0.220)	2.476 (0.116)	0.179 (0.672)	0.104 (0.747)	4.986 (0.026)	0.055 (0.815)	0.712 (0.399)	ΔINFLATIONZ → ΔWPRICESZ	3.356 (0.067)	1.008 (0.315)	6.494 (0.011)	36.819 (0.000)	13.938 (0.000)	27.277 (0.000)	1.428 (0.232)
ΔWPRICESZ → ΔMRATEZ	12.234 (0.000)	1.329 (0.249)	5.919 (0.015)	12.528 (0.000)	0.460 (0.498)	2.093 (0.148)	21.985 (0.000)	ΔVACANCYRATEZ → ΔWPRICESZ	7.139 (0.008)	2.959 (0.085)	2.329 (0.127)	0.260 (0.610)	4.676 (0.031)	0.244 (0.621)	0.021 (0.884)
ΔWINCOMEZ → ΔMRATEZ	41.669 (0.000)	3.430 (0.064)		6.478 (0.011)	1.985 (0.159)	15.086 (0.000)	4.283 (0.038)	ΔWINCOMEZ → ΔWPRICESZ	82.528 (0.000)	34.622 (0.000)		23.777 (0.000)	23.634 (0.000)	85.118 (0.000)	2.220 (0.136)
ΔWHOUSEHOLDSZ → ΔMRATEZ	12.797 (0.000)	0.479 (0.489)		1.265 (0.261)	0.011 (0.918)	12.859 (0.000)	0.000 (0.982)	ΔWHOUSEHOLDSZ → ΔWPRICESZ	33.005 (0.000)	7.411 (0.006)		1.931 (0.165)	2.987 (0.084)	14.367 (0.000)	0.121 (0.728)
ΔWVACANCYRATEZ→ ΔMRATEZ	2.894 (0.089)	8.352 (0.004)		0.750 (0.387)	9.295 (0.002)	0.513 (0.474)	5.948 (0.015)	ΔWVACANCYRATEZ→ ΔWPRICESZ	15.555 (0.000)	8.014 (0.005)		2.017 (0.156)	4.048 (0.044)	0.128 (0.721)	3.959 (0.047)
ΔALL → ΔMRATEZ	3116.974 (0.000)	462.650 (0.000)	311.387 (0.000)	699.488 (0.000)	520.321 (0.000)	563.713 (0.000)	492.584 (0.000)	ΔALL → ΔWPRICESZ	1781.590 (0.000)	2402.296 (0.000)	949.733 (0.000)	630.067 (0.000)	1204.147 (0.000)	565.310 (0.000)	182.293 (0.000)
→ ΔINCOMEZ								→ ΔWINCOMEZ							
ΔPRICESZ → ΔINCOMEZ	29.333 (0.000)	17.107 (0.000)	1.020 (0.313)	20.324 (0.000)	4.896 (0.027)	2.439 (0.118)	0.453 (0.501)	ΔPRICESZ → ΔWINCOMEZ	15.647 (0.000)	6.829 (0.009)		17.937 (0.000)	0.845 (0.358)	3.658 (0.056)	0.046 (0.831)
ΔMRATEZ → ΔINCOMEZ	13.718 (0.00)	36.246 (0.000)	4.188 (0.041)	3.147 (0.076)	41.534 (0.000)	1.061 (0.303)	4.613 (0.032)	ΔMRATEZ → ΔWINCOMEZ	14.236 (0.000)	40.224 (0.000)		4.432 (0.035)	35.661 (0.000)	1.278 (0.258)	10.376 (0.001)
ΔHOUSEHOLDSZ → ΔINCOMEZ	6.828 (0.009)	2.126 (0.141)	3.376 (0.066)	1.310 (0.252)	0.226 (0.634)	1.051 (0.305)	2.635 (0.105)	ΔINCOMEZ → ΔWINCOMEZ	0.583 (0.445)	0.925 (0.336)		0.345 (0.557)	0.058 (0.810)	0.522 (0.470)	0.003 (0.955)
ΔINFLATIONZ → ΔINCOMEZ	75.046 (0.000)	3.435 (0.064)	12.254 (0.000)	60.496 (0.000)	17.556 (0.000)	6.206 (0.013)	3.181 (0.074)	ΔHOUSEHOLDSZ → ΔWINCOMEZ	12.499 (0.000)	0.658 (0.417)		4.878 (0.027)	1.287 (0.257)	0.001 (0.973)	2.875 (0.090)
ΔVACANCYRATEZ → ΔINCOMEZ	2.406 (0.121)	0.677 (0.411)	3.618 (0.057)	1.841 (0.175)	1.178 (0.278)	7.470 (0.006)	7.333 (0.007)	ΔINFLATIONZ → ΔWINCOMEZ	94.980 (0.000)	4.169 (0.041)		82.368 (0.000)	20.904 (0.000)	32.299 (0.000)	4.922 (0.027)
ΔWPRICESZ → ΔINCOMEZ	114.614 (0.000)	71.678 (0.000)	15.729 (0.000)	74.590 (0.000)	63.386 (0.000)	1.702 (0.192)	0.458 (0.499)	ΔVACANCYRATEZ → ΔWINCOMEZ	4.504 (0.034)	1.577 (0.209)		4.240 (0.039)	2.757 (0.097)	0.982 (0.322)	4.474 (0.034)
ΔWINCOMEZ → ΔINCOMEZ	4.916 (0.027)	0.889 (0.346)		0.365 (0.546)	2.056 (0.152)	0.002 (0.964)	0.006 (0.939)	ΔWPRICESZ → ΔWINCOMEZ	165.061 (0.000)	56.019 (0.000)		81.642 (0.000)	76.340 (0.000)	32.050 (0.000)	0.906 (0.341)
ΔWHOUSEHOLDSZ → ΔINCOMEZ	40.796 (0.000)	14.971 (0.000)		3.085 (0.079)	13.998 (0.000)	0.111 (0.739)	2.536 (0.111)	ΔWHOUSEHOLDSZ → ΔWINCOMEZ	66.726 (0.000)	8.128 (0.004)		5.326 (0.021)	32.980 (0.002)	8.857 (0.003)	5.949 (0.015)
ΔWVACANCYRATEZ→ ΔINCOMEZ	12.837 (0.000)	17.058 (0.000)		0.255 (0.614)	2.221 (0.136)	0.000 (0.993)	0.007 (0.933)	ΔWVACANCYRATEZ→ ΔWINCOMEZ	16.779 (0.000)	22.383 (0.000)		0.030 (0.862)	0.483 (0.487)	0.050 (0.822)	0.705 (0.401)
ΔALL → ΔINCOMEZ	244.987 (0.000)	224.967 (0.000)	33.415 (0.000)	132.037 (0.000)	146.003 (0.000)	26.699 (0.002)	21.581 (0.010)	ΔALL → ΔWINCOMEZ	414.014 (0.000)	242.422 (0.000)		147.812 (0.000)	218.017 (0.000)	62.923 (0.000)	31.575 (0.000)
→ ΔHOUSEHOLDSZ								→ ΔWHOUSEHOLDSZ							
ΔPRICESZ → ΔHOUSEHOLDSZ	1.113 (0.291)	0.189 (0.664)	1.010 (0.315)	0.003 (0.958)	0.458 (0.499)	0.884 (0.347)	0.373 (0.541)	ΔPRICESZ → ΔWHOUSEHOLDSZ	0.103 (0.748)	0.095 (0.757)		0.618 (0.432)	0.261 (0.610)	1.449 (0.229)	0.373 (0.541)
ΔMRATEZ → ΔHOUSEHOLDSZ	2.182 (0.140)	0801 (0.371)	0.040 (0.842)	0.834 (0.361)	0.160 (0.690)	1.788 (0.181)	0.088 (0.767)	ΔMRATEZ → ΔWHOUSEHOLDSZ	6.039 (0.014)	1.853 (0.173)		1.668 (0.197)	1.016 (0.313)	3.950 (0.047)	0.129 (0.719)
ΔINCOMEZ → ΔHOUSEHOLDSZ	0.000 (0.984)	0.257 (0.612)	0.077 (0.781)	0.701 (0.402)	2.724 (0.099)	0.014 (0.907)	0.507 (0.476)	ΔINCOMEZ → ΔWHOUSEHOLDSZ	0.390 (0.533)	0.033 (0.856)		1.253 (0.263)	1.937 (0.164)	0.021 (0.885)	0.097 (0.756)
ΔINFLATIONZ → ΔHOUSEHOLDSZ	4.371 (0.037)	1.706 (0.192)	4.086 (0.043)	0.349 (0.555)	1.433 (0.231)	4.246 (0.039)	3.736 (0.053)	ΔHOUSEHOLDSZ → ΔWHOUSEHOLDSZ	1.242 (0.265)	1.862 (0.172)		5.826 (0.016)	1.357 (0.244)	4.775 (0.029)	0.034 (0.853)
ΔVACANCYRATEZ → ΔHOUSEHOLDSZ	0.096 (0.757)	0.004 (0.952)	0.045 (0.832)	0.109 (0.742)	0.239 (0.625)	2.378 (0.123)	0.213 (0.645)	ΔINFLATIONZ → ΔWHOUSEHOLDSZ	21.497 (0.000)	2.580 (0.108)		9.570 (0.002)	1.543 (0.214)	3.334 (0.068)	5.100 (0.024)
ΔWPRICESZ → ΔHOUSEHOLDSZ	1.022 (0.312)	0.494 (0.482)	2.438 (0.118)	0.292 (0.589)	0.000 (0.987)	2.645 (0.104)	1.024 (0.312)	ΔVACANCYRATEZ → ΔWHOUSEHOLDSZ	2.581 (0.108)	0.647 (0.421)		3.545 (0.060)	2.996 (0.083)	0.511 (0.475)	1.047 (0.306)
ΔWINCOMEZ → ΔHOUSEHOLDSZ	0.252 (0.616)	0.483 (0.487)		0.796 (0.372)	0.056 (0.812)	0.218 (0.641)	0.540 (0.462)	ΔWPRICEZ → ΔWHOUSEHOLDSZ	0.011 (0.918)	1.921 (0.166)		0.669 (0.413)	0.032 (0.857)	0.675 (0.411)	0.067 (0.795)
ΔWHOUSEHOLDSZ → ΔHOUSEHOLDSZ	2.762 (0.097)	1.551 (0.213)		0.931 (0.335)	0.001 (0.972)	7.366 (0.007)	0.679 (0.410)	ΔWINCOMEZ → ΔWHOUSEHOLDSZ	0.016 (0.899)	0.211 (0.646)		0.940 (0.332)	1.037 (0.309)	0.006 (0.937)	0.281 (0.596)
ΔWVACANCYRATEZ→ ΔHOUSEHOLDSZ	0.964 (0.326)	0.021 (0.885)		1.703 (0.192)	1.363 (0.243)	0.028 (0.868)	0.000 (0.984)	ΔWVACANCYRATEZ→ ΔWHOUSEHOLDSZ	1.255 (0.263)	1.832 (0.176)		3.652 (0.056)	3.468 (0.063)	0.170 (0.680)	0.287 (0.592)
ΔALL → ΔHOUSEHOLDSZ	21.623 (0.010)	23.248 (0.006)	7.973 (0.240)	6.218 (0.718)	8.328 (0.502)	19.292 (0.023)	8.777 (0.458)	ΔALL → ΔWHOUSEHOLDSZ	74.034 (0.000)	15.774 (0.072)		40.683 (0.000)	18.925 (0.026)	14.975 (0.092)	9.219 (0.417)
→ ΔINFLATIONZ								→ ΔWVACANCYRATEZ							
ΔPRICESZ → ΔINFLATIONZ	0.719 (0.397)	0.002 (0.967)	4.111 (0.043)	1.050 (0.305)	0.533 (0.465)	4.337 (0.037)	0.048 (0.827)	ΔPRICESZ → ΔWVACANCYRATEZ	0.399 (0.527)	0.092 (0.762)		0.035 (0.852)	0.002 (0.961)	0.023 (0.878)	0.297 (0.586)
ΔMRATEZ → ΔINFLATIONZ	740.737 (0.000)	62.302 (0.000)	38.901 (0.000)	234.501 (0.000)	98.831 (0.000)	137.621 (0.000)	164.458 (0.000)	ΔMRATEZ → ΔWVACANCYRATEZ	6.038 (0.014)	1.161 (0.281)		6.974 (0.008)	1.732 (0.188)	4.566 (0.033)	4.642 (0.031)
ΔINCOMEZ → ΔINFLATIONZ	0.141 (0.707)	2.203 (0.138)	30.004 (0.000)	6.898 (0.009)	3.023 (0.082)	0.796 (0.372)	4.399 (0.036)	ΔINCOMEZ → ΔWVACANCYRATEZ	0.721 (0.396)	0.945 (0.331)		0.335 (0.562)	1.531 (0.216)	1.866 (0.172)	1.217 (0.270)
ΔHOUSEHOLDSZ → ΔINFLATIONZ	0.051 (0.822)	0.152 (0.697)	6.046 (0.014)	0.130 (0.719)	0.231 (0.630)	1.704 (0.192)	7.642 (0.006)	ΔHOUSEHOLDSZ → ΔWVACANCYRATEZ	3.693 (0.055)	1.153 (0.283)		0.532 (0.466)	2.760 (0.097)	0.002 (0.963)	0.354 (0.552)
ΔVACANCYRATEZ → ΔINFLATIONZ	0.371 (0.543)	0.886 (0.347)	0.101 (0.750)	0.337 (0.562)	2.910 (0.088)	0.258 (0.611)	0.900 (0.343)	ΔINFLATIONZ → ΔWVACANCYRATEZ	3.690 (0.055)	2.565 (0.109)		0.449 (0.503)	1.694 (0.193)	4.961 (0.026)	1.981 (0.159)
ΔWPRICESZ → ΔINFLATIONZ	0.589 (0.443)	3.178 (0.075)	1.501 (0.220)	1.276 (0.259)	0.110 (0.740)	0.009 (0.924)	4.716 (0.030)	ΔVACANCYRATEZ → ΔWVACANCYRATEZ	0.020 (0.889)	0.025 (0.875)		0.149 (0.699)	0.794 (0.373)	0.786 (0.375)	1.289 (0.256)
ΔWINCOMEZ → ΔINFLATIONZ	59.207 (0.000)	10.617 (0.001)		16.665 (0.000)	2.494 (0.114)	51.876 (0.000)	3.339 (0.068)	ΔWPRICESZ → ΔWVACANCYRATEZ	1.503 (0.220)	0.526 (0.468)		4.232 (0.040)	0.700 (0.403)	0.001 (0.979)	0.030 (0.863)
ΔWHOUSEHOLDSZ → ΔINFLATIONZ	8.214 (0.004)	0.515 (0.473)		0.713 (0.399)	0.106 (0.745)	8.340 (0.004)	0.043 (0.835)	ΔWINCOMEZ → ΔWVACANCYRATEZ	7.618 (0.006)	2.320 (0.128)		1.800 (0.180)	0.292 (0.589)	8.428 (0.004)	0.097 (0.756)
ΔWVACANCYRATEZ→ ΔINFLATIONZ	0.396 (0.529)	3.144 (0.076)		0.321 (0.571)	5.050 (0.025)	0.053 (0.818)	2.843 (0.092)	ΔWHOUSEHOLDSZ→ ΔWVACANCYRATEZ	10.084 (0.001)	3.945 (0.047)		0.887 (0.346)	7.797 (0.005)	3.355 (0.067)	0.504 (0.478)
ΔALL → ΔINFLATIONZ	2024.850 (0.000)	703.030 (0.000)	321.719 (0.000)	833.549 (0.000)	621.593 (0.000)	441.286 (0.000)	356.445 (0.000)	ΔALL → ΔWVACANCYRATEZ	55.995 (0.000)	28.611 (0.001)		27.948 (0.001)	24.911 (0.003)	38.056 (0.000)	13.486 (0.142)

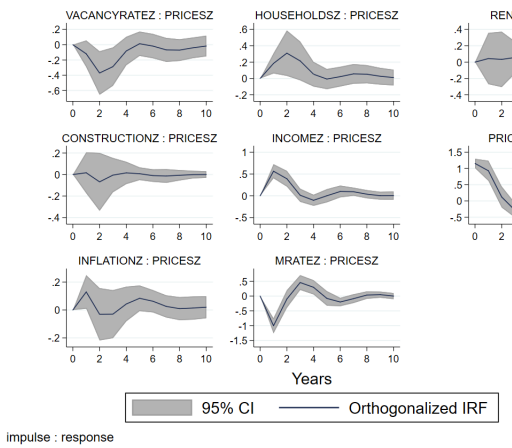
Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Table A.12: Granger causality test (SpVAR similarity)

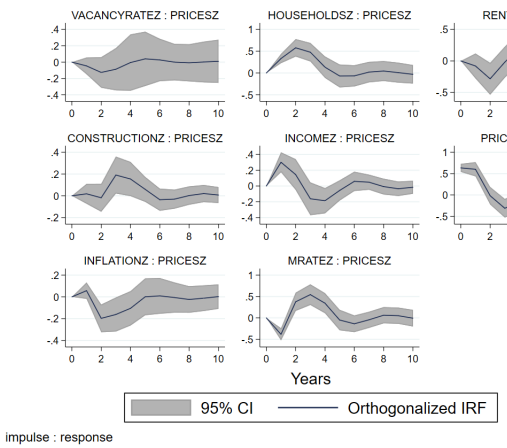
	Whole sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6		Whole sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
→ ΔPRICESZ								→ ΔVACANCYRATEZ							
ΔMRATEZ → ΔPRICESZ	15.317 (0.000)	74.519 (0.000)	229.627 (0.000)	182.499 (0.000)	175.114 (0.000)	71.950 (0.000)	37.451 (0.000)	ΔPRICESZ → ΔVACANCYRATEZ	0.850 (0.356)	0.217 (0.642)	0.019 (0.890)	2.546 (0.111)	0.713 (0.398)	3.216 (0.073)	2.450 (0.118)
ΔINCOMEZ → ΔPRICESZ	6.595 (0.010)	15.041 (0.000)	199.410 (0.000)	5.114 (0.024)	0.551 (0.458)	1.995 (0.158)	0.001 (0.975)	ΔMRATEZ → ΔVACANCYRATEZ	7.433 (0.006)	1.488 (0.223)	0.879 (0.349)	1.177 (0.278)	0.013 (0.910)	0.244 (0.621)	1.326 (0.250)
ΔHOUSEHOLDSZ → ΔPRICESZ	16.418 (0.000)	0.001 (0.974)	2.567 (0.109)	0.439 (0.508)	0.096 (0.756)	0.177 (0.674)	0.911 (0.340)	ΔINCOMEZ → ΔVACANCYRATEZ	7.062 (0.008)	1.489 (0.222)	1.345 (0.246)	2.827 (0.093)	0.023 (0.880)	2.554 (0.110)	0.907 (0.341)
ΔINFLATIONZ → ΔPRICESZ	0.037 (0.847)	3.803 (0.051)	1.393 (0.238)	24.274 (0.000)	0.117 (0.674)	12.243 (0.000)	1.075 (0.300)	ΔHOUSEHOLDSZ → ΔVACANCYRATEZ	0.924 (0.336)	0.438 (0.508)	0.166 (0.683)	0.493 (0.483)	1.064 (0.302)	1.722 (0.189)	1.084 (0.298)
ΔVACANCYRATEZ → ΔPRICESZ	0.473 (0.492)	0.830 (0.362)	0.022 (0.881)	0.023 (0.879)	1.870 (0.172)	1.555 (0.212)	0.000 (0.991)	ΔINFLATIONZ → ΔVACANCYRATEZ	0.967 (0.326)	1.291 (0.256)	0.103 (0.748)	4.404 (0.036)	0.267 (0.605)	0.005 (0.942)	0.251 (0.616)
ΔWsPRICESZ → ΔPRICESZ	0.443 (0.506)	0.472 (0.492)	0.735 (0.391)	19.389 (0.000)	9.815 (0.002)	18.061 (0.000)	0.099 (0.753)	ΔWsPRICESZ → ΔVACANCYRATEZ	0.010 (0.922)	0.012 (0.914)	1.174 (0.279)	0.092 (0.762)	0.797 (0.372)	2.055 (0.152)	1.055 (0.304)
ΔWsINCOMEZ → ΔPRICESZ	1.527 (0.217)	9.310 (0.002)		0.067 (0.796)	0.968 (0.325)	9.121 (0.003)	0.230 (0.631)	ΔWsINCOMEZ → ΔVACANCYRATEZ	0.316 (0.574)	0.154 (0.695)		0.288 (0.591)	0.264 (0.608)	0.015 (0.901)	0.641 (0.423)
ΔWsHOUSEHOLDSZ → ΔPRICESZ	6.243 (0.012)	0.014 (0.906)		0.043 (0.837)	0.193 (0.660)	1.491 (0.222)	1.839 (0.175)	ΔWsHOUSEHOLDSZ → ΔVACANCYRATEZ	5.509 (0.019)	2.501 (0.114)		0.308 (0.579)	10.697 (0.001)	2.663 (0.103)	1.791 (0.181)
ΔWsVACANCYRATEZ→ ΔPRICESZ	11.654 (0.001)	5.237 (0.022)		5.189 (0.023)	14.887 (0.000)	0.303 (0.582)	0.378 (0.539)	ΔWsVACANCYRATEZ→ ΔVACANCYRATEZ	0.087 (0.769)	0.085 (0.770)		0.330 (0.566)	1.076 (0.300)	0.532 (0.466)	0.318 (0.573)
ΔALL → ΔPRICESZ	163.412 (0.000)	601.903 (0.000)	9074.725 (0.000)	270.081 (0.000)	530.753 (0.000)	173.414 (0.000)	69.982 (0.000)	ΔALL → ΔVACANCYRATEZ	13.842 (0.017)	221.672 (0.000)	14.634 (0.023)	23.165 (0.006)	37.897 (0.000)	42.043 (0.000)	11.977 (0.215)
→ ΔMRATEZ								→ ΔWsPRICESZ							
ΔPRICESZ → ΔMRATEZ	0.423 (0.515)	0.540 (0.462)	0.526 (0.468)	0.692 (0.405)	1.833 (0.176)	0.244 (0.621)	0.475 (0.491)	ΔPRICESZ → ΔWsPRICESZ	0.289 (0.591)	1.311 (0.252)	0.648 (0.421)	0.143 (0.705)	0.101 (0.751)	0.125 (0.723)	0.020 (0.888)
ΔINCOMEZ → ΔMRATEZ	0.026 (0.872)	0.310 (0.578)	74.683 (0.000)	0.790 (0.374)	0.013 (0.908)	0.059 (0.808)	0.038 (0.845)	ΔMRATEZ → ΔWsPRICESZ	16.070 (0.000)	1778.514 (0.000)	286.262 (0.000)	3323.653 (0.000)	1782.331 (0.000)	1137.546 (0.000)	1221.056 (0.000)
ΔHOUSEHOLDSZ → ΔMRATEZ	0.437 (0.509)	2.886 (0.089)	12.521 (0.000)	0.626 (0.429)	2.509 (0.113)	0.003 (0.960)	4.203 (0.040)	ΔINCOMEZ → ΔWsPRICESZ	23.515 (0.000)	0.230 (0.631)	34.637 (0.000)	0.080 (0.778)	0.688 (0.407)	0.080 (0.777)	6.287 (0.012)
ΔINFLATIONZ → ΔMRATEZ	26.265 (0.000)	233.005 (0.000)	57.769 (0.000)	26.851 (0.000)	210.725 (0.000)	4.679 (0.031)	155.515 (0.000)	ΔHOUSEHOLDSZ → ΔWsPRICESZ	11.988 (0.001)	0.0240 (0.624)	5.704 (0.017)	0.215 (0.643)	0.129 (0.719)	0.037 (0.848)	0.153 (0.696)
ΔVACANCYRATEZ → ΔMRATEZ	2.006 (0.157)	6.029 (0.014)	0.715 (0.398)	0.208 (0.648)	6.047 (0.014)	0.246 (0.620)	4.451 (0.035)	ΔINFLATIONZ → ΔWsPRICESZ	0.040 (0.842)	12.442 (0.000)	3.325 (0.068)	349.320 (0.000)	0.225 (0.635)	76.434 (0.000)	34.411 (0.000)
ΔWsPRICESZ → ΔMRATEZ	4.085 (0.043)	2.170 (0.141)	17.988 (0.000)	99.795 (0.000)	6.532 (0.011)	79.442 (0.000)	56.978 (0.000)	ΔVACANCYRATEZ → ΔWsPRICESZ	3.757 (0.053)	2.666 (0.103)	0.523 (0.470)	4.144 (0.042)	2.744 (0.098)	0.610 (0.435)	1.051 (0.305)
ΔWsINCOMEZ → ΔMRATEZ	6.845 (0.009)	0.015 (0.901)		45.712 (0.000)	0.059 (0.807)	43.093 (0.000)	57.530 (0.000)	ΔWsINCOMEZ → ΔWsPRICESZ	29.303 (0.000)	8.664 (0.003)		56.787 (0.000)	17.577 (0.000)	88.318 (0.000)	0.736 (0.391)
ΔWsHOUSEHOLDSZ → ΔMRATEZ	0.027 (0.869)	12.937 (0.000)		0.686 (0.408)	11.125 (0.001)	0.125 (0.724)	138.268 (0.000)	ΔWsHOUSEHOLDSZ → ΔWsPRICESZ	7.714 (0.005)	0.003 (0.955)		1.385 (0.239)	0.749 (0.387)	12.924 (0.000)	219.428 (0.000)
ΔWsVACANCYRATEZ→ ΔMRATEZ	3.781 (0.052)	35.439 (0.000)		4.279 (0.039)	126.827 (0.000)	0.074 (0.785)	31.438 (0.000)	ΔWsVACANCYRATEZ→ ΔWsPRICESZ	7.031 (0.008)	18.802 (0.000)		4.210 (0.040)	44.369 (0.000)	1.578 (0.209)	8.993 (0.003)
ΔALL → ΔMRATEZ	182.360 (0.000)	61250.093 (0.000)	524.241 (0.000)	10030.581 (0.000)	5107.246 (0.000)	1909.816 (0.000)	2583.849 (0.000)	ΔALL → ΔWsPRICESZ	148.101 (0.000)	13904.608 (0.000)	7147.314 (0.000)	7662.857 (0.000)	4822.916 (0.000)	3838.854 (0.000)	2172.045 (0.000)
→ ΔINCOMEZ								→ ΔWsINCOMEZ							
ΔPRICESZ → ΔINCOMEZ	42.803 (0.000)	4.782 (0.029)	0.243 (0.622)	12.324 (0.000)	1.112 (0.292)	2.396 (0.122)	0.356 (0.551)	ΔPRICESZ → ΔWsINCOMEZ	13.930 (0.000)	6.477 (0.011)		5.565 (0.018)	0.368 (0.544)	7.287 (0.007)	4.495 (0.034)
ΔMRATEZ → ΔINCOMEZ	2.790 (0.095)	17.127 (0.000)	0.069 (0.793)	74.798 (0.000)	61.990 (0.000)	0.250 (0.617)	0.994 (0.319)	ΔMRATEZ → ΔWsINCOMEZ	2.333 (0.127)	10.942 (0.001)		106.893 (0.000)	240.974 (0.000)	20.746 (0.000)	3.416 (0.065)
ΔHOUSEHOLDSZ → ΔINCOMEZ	2.571 (0.109)	1.648 (0.199)	0.277 (0.599)	0.248 (0.618)	1.165 (0.280)	0.466 (0.495)	2.152 (0.142)	ΔINCOMEZ → ΔWsINCOMEZ	0.228 (0.633)	0.804 (0.370)		0.362 (0.547)	0.011 (0.917)	1.515 (0.218)	1.688 (0.194)
ΔINFLATIONZ → ΔINCOMEZ	4.004 (0.045)	2.235 (0.135)	0.403 (0.526)	204.632 (0.000)	2.510 (0.113)	0.505 (0.477)	9.088 (0.003)	ΔHOUSEHOLDSZ → ΔWsINCOMEZ	3.723 (0.054)	0.603 (0.437)		4.805 (0.028)	0.643 (0.423)	0.736 (0.391)	1.349 (0.246)
ΔVACANCYRATEZ → ΔINCOMEZ	1.643 (0.200)	0.801 (0.371)	0.136 (0.712)	1.171 (0.279)	2.474 (0.116)	18.001 (0.000)	10.776 (0.001)	ΔINFLATIONZ → ΔWsINCOMEZ	3.575 (0.059)	0.540 (0.462)		553.199 (0.000)	2.076 (0.150)	7.010 (0.008)	57.603 (0.000)
ΔWsPRICESZ → ΔINCOMEZ	44.114 (0.000)	78.350 (0.000)	0.814 (0.367)	209.511 (0.000)	78.257 (0.000)	1.465 (0.226)	3.858 (0.050)	ΔVACANCYRATEZ → ΔWsINCOMEZ	1.751 (0.186)	1.338 (0.247)		9.904 (0.002)	2.680 (0.102)	0.303 (0.582)	6.442 (0.011)
ΔWsINCOMEZ → ΔINCOMEZ	3.002 (0.083)	21.749 (0.000)		3.163 (0.075)	1.163 (0.281)	5.298 (0.021)	9.114 (0.003)	ΔWsPRICESZ → ΔWsINCOMEZ	48.557 (0.000)	81.692 (0.000)		378.702 (0.000)	140.211 (0.000)	49.819 (0.000)	31.155 (0.000)
ΔWsHOUSEHOLDSZ → ΔINCOMEZ	2.439 (0.118)	7.359 (0.007)		21.301 (0.000)	5.531 (0.019)	0.014 (0.904)	3.640 (0.056)	ΔWsHOUSEHOLDSZ → ΔWsINCOMEZ	2.577 (0.108)	11.940 (0.001)		20.158 (0.000)	2.836 (0.092)	2.126 (0.145)	60.096 (0.000)
ΔWsVACANCYRATEZ→ ΔINCOMEZ	10.367 (0.001)	3.448 (0.063)		12.442 (0.000)	35.075 (0.000)	0.081 (0.776)	7.045 (0.008)	ΔWsVACANCYRATEZ→ ΔWsINCOMEZ	9.241 (0.002)	4.485 (0.034)		15.364 (0.000)	43.682 (0.000)	1.989 (0.158)	60.093 (0.000)
ΔALL → ΔINCOMEZ	68.792 (0.000)	6572.315 (0.000)	5.037 (0.539)	647.479 (0.000)	727.322 (0.000)	198.632 (0.000)	47.058 (0.000)	ΔALL → ΔWsINCOMEZ	100.752 (0.000)	2253.061 (0.000)		3280.394 (0.000)	16004.540 (0.000)	1215.882 (0.000)	449.771 (0.000)
→ ΔHOUSEHOLDSZ								→ ΔWsHOUSEHOLDSZ							
ΔPRICESZ → ΔHOUSEHOLDSZ	5.241 (0.022)	0.174 (0.676)	1.107 (0.293)	0.138 (0.710)	0.417 (0.519)	0.719 (0.396)	0.156 (0.693)	ΔPRICESZ → ΔWsHOUSEHOLDSZ	0.211 (0.646)	0.188 (0.664)		0.150 (0.698)	0.540 (0.463)	0.435 (0.509)	2.040 (0.153)
ΔMRATEZ → ΔHOUSEHOLDSZ	2.277 (0.131)	4.661 (0.031)	0.040 (0.841)	0.003 (0.959)	0.490 (0.484)	3.194 (0.074)	0.242 (0.623)	ΔMRATEZ → ΔWsHOUSEHOLDSZ	2.551 (0.110)	59.741 (0.000)		17.850 (0.000)	21.866 (0.000)	52.007 (0.000)	15.158 (0.000)
ΔINCOMEZ → ΔHOUSEHOLDSZ	19.645 (0.000)	0.689 (0.406)	2.222 (0.136)	1.568 (0.210)	0.562 (0.453)	0.014 (0.907)	0.109 (0.741)	ΔINCOMEZ → ΔWsHOUSEHOLDSZ	4.442 (0.035)	0.168 (0.682)		19.812 (0.000)	4.903 (0.027)	0.000 (0.983)	1.897 (0.168)
ΔINFLATIONZ → ΔHOUSEHOLDSZ	2.332 (0.127)	1.652 (0.199)	2.221 (0.136)	0.028 (0.868)	0.941 (0.332)	1.957 (0.162)	0.409 (0.523)	ΔHOUSEHOLDSZ → ΔWsHOUSEHOLDSZ	7.466 (0.006)	0.072 (0.789)		0.051 (0.821)	0.007 (0.935)	0.394 (0.530)	14.403 (0.000)
ΔVACANCYRATEZ → ΔHOUSEHOLDSZ	0.001 (0.979)	0.328 (0.567)	0.028 (0.867)	0.324 (0.570)	0.128 (0.720)	1.733 (0.188)	0.220 (0.639)	ΔINFLATIONZ → ΔWsHOUSEHOLDSZ	1.447 (0.229)	10.525 (0.001)		0.068 (0.794)	7.933 (0.005)	37.468 (0.000)	5.325 (0.021)
ΔWsPRICESZ → ΔHOUSEHOLDSZ	0.130 (0.718)	1.029 (0.311)	0.024 (0.876)	4.438 (0.035)	0.576 (0.448)	3.721 (0.054)	0.103 (0.749)	ΔVACANCYRATEZ → ΔWsHOUSEHOLDSZ	0.001 (0.981)	0.568 (0.451)		1.645 (0.200)	2.256 (0.133)	1.703 (0.192)	2.262 (0.133)
ΔWsINCOMEZ → ΔHOUSEHOLDSZ	2.033 (0.154)	0.084 (0.772)		1.847 (0.174)	0.501 (0.479)	1.166 (0.280)	0.067 (0.796)	ΔWsPRICEZ → ΔWsHOUSEHOLDSZ	0.686 (0.407)	2.833 (0.092)		38.201 (0.000)	2.189 (0.139)	34.506 (0.000)	33.773 (0.000)
ΔWsHOUSEHOLDSZ → ΔHOUSEHOLDSZ	20.974 (0.000)	0.535 (0.464)		0.649 (0.421)	0.002 (0.969)	0.460 (0.498)	6.139 (0.013)	ΔWsINCOMEZ → ΔWsHOUSEHOLDSZ	0.036 (0.850)	3.131 (0.077)		51.907 (0.000)	1.371 (0.242)	13.250 (0.000)	9.552 (0.002)
ΔWsVACANCYRATEZ→ ΔHOUSEHOLDSZ	0.755 (0.385)	0.070 (0.792)		5.139 (0.023)	1.760 (0.185)	2.073 (0.150)	0.005 (0.944)	ΔWsVACANCYRATEZ→ ΔWsHOUSEHOLDSZ	1.677 (0.195)	0.261 (0.610)		3.184 (0.074)	1.514 (0.219)	8.731 (0.003)	6.284 (0.012)
ΔALL → ΔHOUSEHOLDSZ	81.808 (0.000)	352.977 (0.000)	25.495 (0.000)	18.001 (0.035)	21.205 (0.012)	50.686 (0.000)	24.804 (0.003)	ΔALL → ΔWsHOUSEHOLDSZ	7.942 (0.159)	8456.957 (0.000)		336.684 (0.000)	232.650 (0.000)	199.812 (0.000)	128.244 (0.000)
→ ΔINFLATIONZ								→ ΔWsVACANCYRATEZ							
ΔPRICESZ → ΔINFLATIONZ	0.011 (0.918)	0.062 (0.804)	0.525 (0.469)	0.703 (0.402)	2.249 (0.118)	0.000 (0.991)	0.085 (0.771)	ΔPRICESZ → ΔWsVACANCYRATEZ	0.000 (0.984)	0.700 (0.403)		0.036 (0.850)	1.178 (0.278)	4.484 (0.034)	2.040 (0.834)
ΔMRATEZ → ΔINFLATIONZ	513.951 (0.000)	586.965 (0.000)	93.700 (0.000)	3709.661 (0.000)	411.478 (0.000)	474.240 (0.000)	3860.710 (0.000)	ΔMRATEZ → ΔWsVACANCYRATEZ	4.422 (0.035)	77.200 (0.000)		31.753 (0.000)	2.295 (0.130)	5.052 (0.025)	15.158 (0.000)
ΔINCOMEZ → ΔINFLATIONZ	0.059 (0.809)	0.621 (0.431)	48.248 (0.000)	1.384 (0.239)	0.033 (0.855)	0.000 (0.987)	0.218 (0.640)	ΔINCOMEZ → ΔWsVACANCYRATEZ	0.334 (0.563)	0.058 (0.810)		3.592 (0.058)	0.011 (0.917)	0.650 (0.420)	1.897 (0.723)
ΔHOUSEHOLDSZ → ΔINFLATIONZ	0.725 (0.394)	2.185 (0.139)	1.885 (0.170)	0.359 (0.549)	3.193 (0.074)	0.000 (0.987)	9.655 (0.002)	ΔHOUSEHOLDSZ → ΔWsVACANCYRATEZ	14.175 (0.000)	0.598 (0.439)		1.478 (0.224)	1.872 (0.171)	2.864 (0.091)	14.403 (0.255)
ΔVACANCYRATEZ → ΔINFLATIONZ	0.546 (0.460)	5.475 (0.019)	0.002 (0.968)	0.013 (0.911)	6.483 (0.011)	1.220 (0.269)	12.418 (0.000)	ΔINFLATIONZ → ΔWsVACANCYRATEZ	1.017 (0.313)	32.902 (0.000)		64.872 (0.000)	0.012 (0.914)	0.001 (0.969)	5.325 (0.477)
ΔWsPRICESZ → ΔINFLATIONZ	1.671 (0.196)	11.191 (0.001)	32.967 (0.000)	33.349 (0.000)	19.517 (0.000)	44.062 (0.000)	0.701 (0.402)	ΔVACANCYRATEZ → ΔWsVACANCYRATEZ	1.389 (0.239)	0.724 (0.395)		1.603 (0.205)	2.244 (0.134)	0.166 (0.684)	2.262 (0.579)
ΔWsINCOMEZ → ΔINFLATIONZ	11.758 (0.001)	10.146 (0.001)		132.421 (0.000)	8.577 (0.003)	44.571 (0.000)	174.071 (0.000)	ΔWsPRICESZ → ΔWsVACANCYRATEZ	13.631 (0.000)	1.128 (0.288)		22.303 (0.000)	0.009 (0.926)	5.641 (0.018)	33.773 (0.461)
ΔWsHOUSEHOLDSZ → ΔINFLATIONZ	0.049 (0.825)	9.195 (0.002)		3.038 (0.081)	20.501 (0.000)	0.994 (0.319)	128.645 (0.000)	ΔWsINCOMEZ → ΔWsVACANCYRATEZ	13.257 (0.000)	2.961 (0.085)		0.415 (0.520)	1.241 (0.265)	4.584 (0.032)	9.552 (0.033)
ΔWsVACANCYRATEZ→ ΔINFLATIONZ	1.722 (0189)	27.109 (0.000)		2.274 (0.132)	127.889 (0.000)	2.586 (0.108)	109.430 (0.000)	ΔWsHOUSEHOLDSZ→ ΔWsVACANCYRATEZ	2.705 (0.100)	1.093 (0.296)		5.106 (0.024)	14.105 (0.000)	6.412 (0.011)	6.284 (0.001)
ΔALL → ΔINFLATIONZ	1830.964 (0.000)	152393.398 (0.000)	3642.240 (0.000)	56245.812 (0.000)	4840.190 (0.000)	3435.220 (0.000)	5848.506 (0.000)	ΔALL → ΔWsVACANCYRATEZ	34.564 (0.000)	1808.007 (0.000)		145.063 (0.000)	178.429 (0.000)	81.506 (0.000)	128.244 (0.000)

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

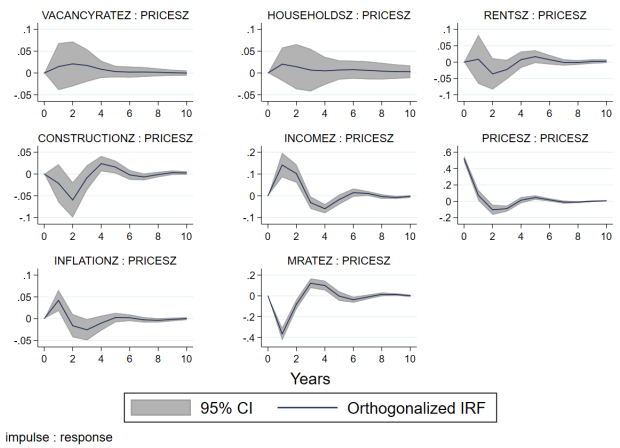
Figure A.9: Impulse responses Panel VAR



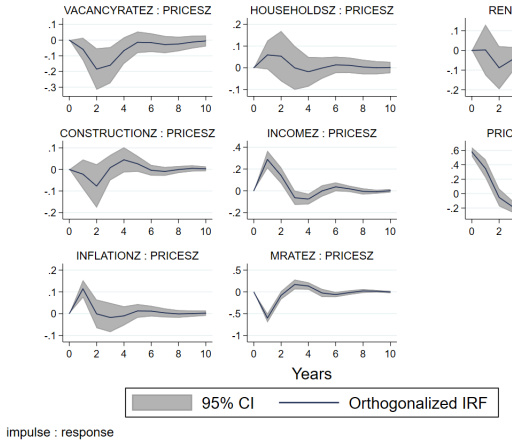
(a) Impulse responses for Cluster 1 (PVAR)



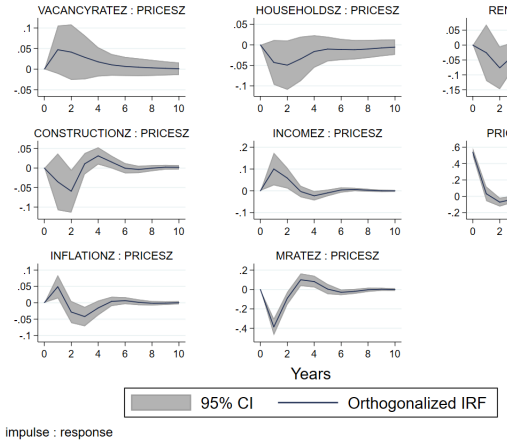
(b) Impulse responses for Cluster 2 (PVAR)



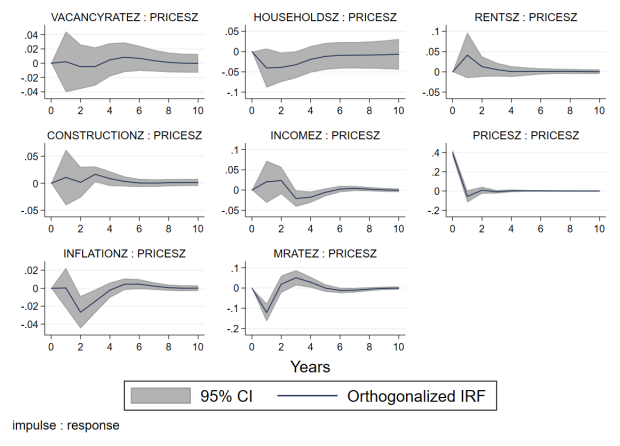
(c) Impulse responses for Cluster 3 (PVAR)



(d) Impulse responses for Cluster 4 (PVAR)



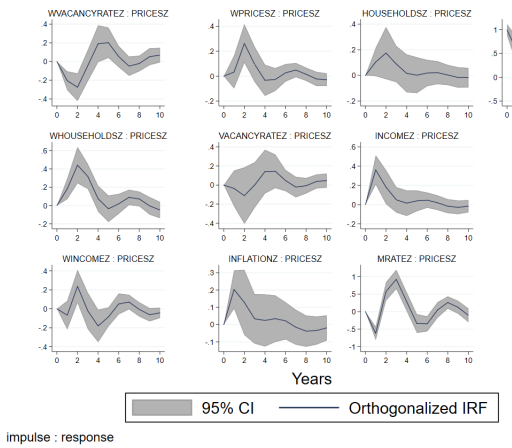
(e) Impulse responses for Cluster 5 (PVAR)



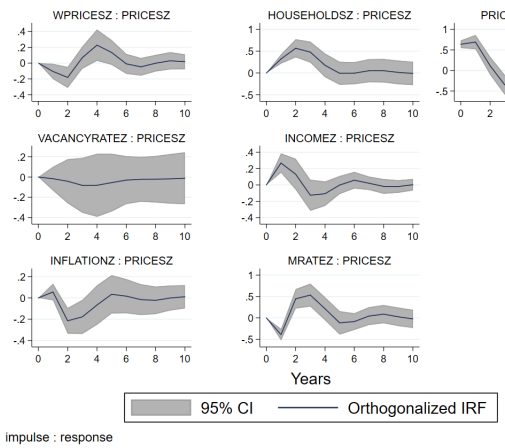
(f) Impulse responses for Cluster 6 (PVAR)

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

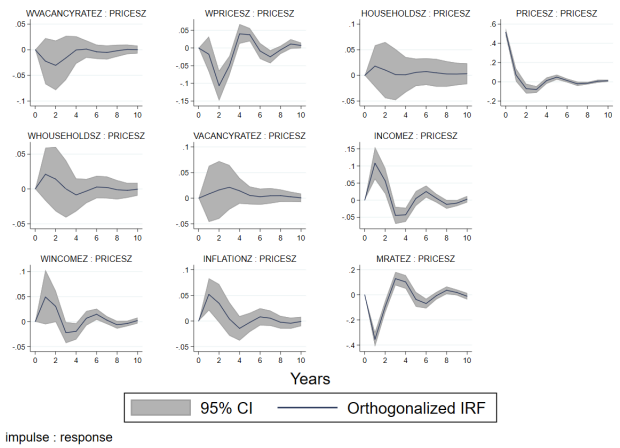
Figure A.10: Impulse responses Spatial Panel VAR (contiguity matrix)



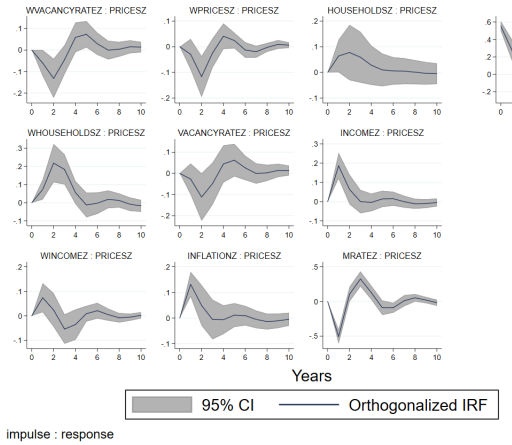
(a) Impulse responses for Cluster 1 (SpVAR)



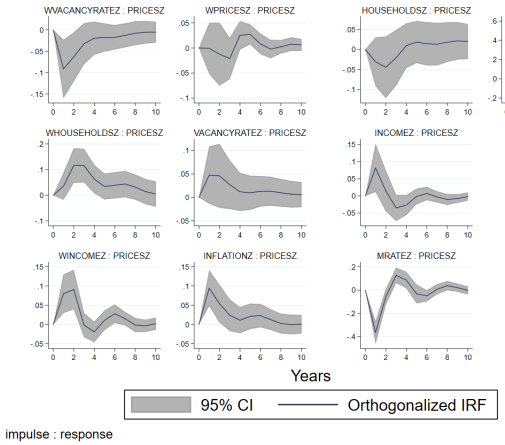
(b) Impulse responses for Cluster 2 (SpVAR)



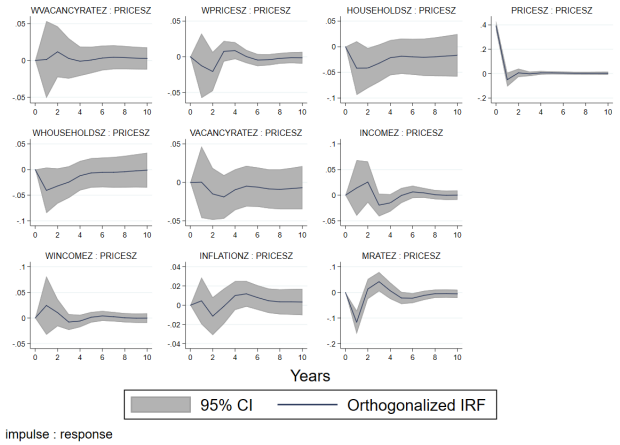
(c) Impulse responses for Cluster 3 (SpVAR)



(d) Impulse responses for Cluster 4 (SpVAR)



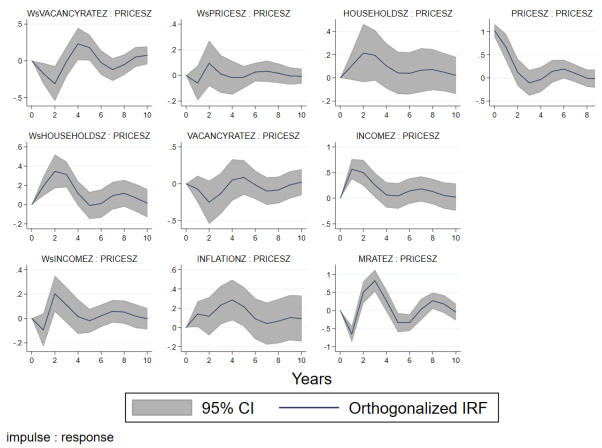
(e) Impulse responses for Cluster 5 (SpVAR)



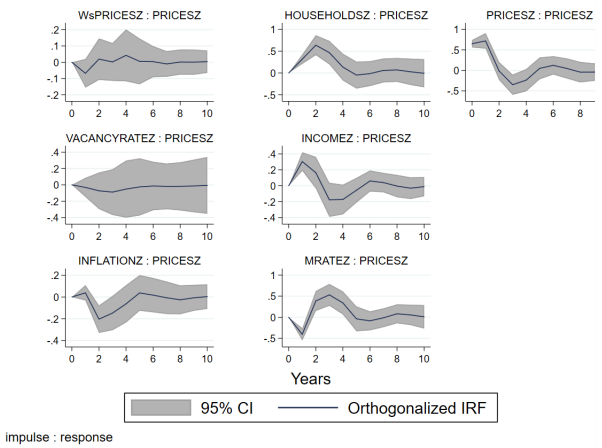
(f) Impulse responses for Cluster 6 (SpVAR)

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

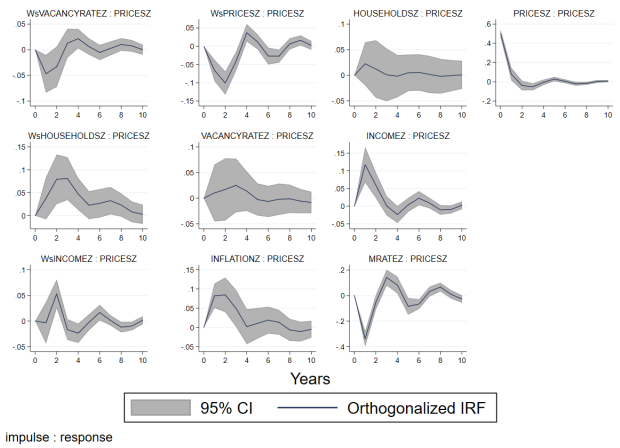
Figure A.11: Impulse responses Spatial Panel VAR (similarity matrix)



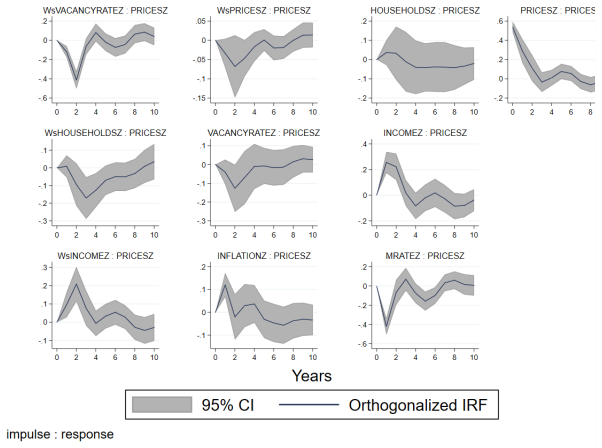
(a) Impulse responses for Cluster 1 (SpVAR)



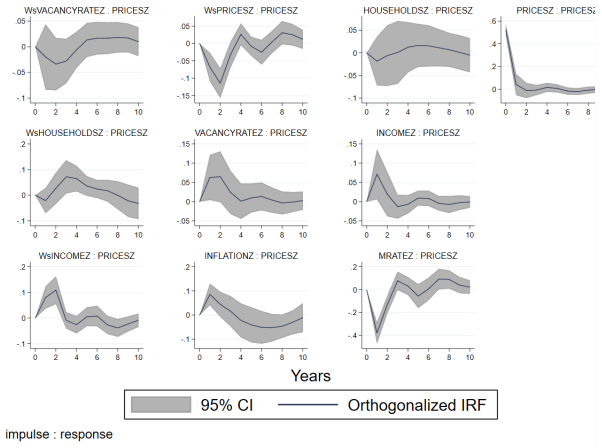
(b) Impulse responses for Cluster 2 (SpVAR)



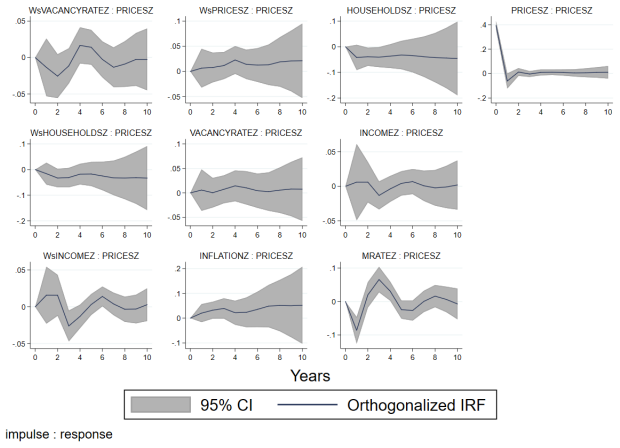
(c) Impulse responses for Cluster 3 (SpVAR)



(d) Impulse responses for Cluster 4 (SpVAR)



(e) Impulse responses for Cluster 5 (SpVAR)



(f) Impulse responses for Cluster 6 (SpVAR)

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Table A.13: Forecast error variance decomposition SpVAR (contiguity matrix)

		Impulse variables									
Clusters	Forecast horizon	PRICESZ	MRATEZ	INCOMEZ	HOUSEHOLDSZ	INFLATIONZ	VACANCYRATEZ	WPRICESZ	WINCOMEZ	WHOUSEHOLDSZ	WVACANCYRATEZ
Whole sample	2	69,8%	17,8%	7,2%	1,3%	0,3%	0,0%	0,1%	0,4%	2,2%	0,9%
	5	50,9%	24,3%	5,7%	4,0%	0,4%	0,1%	1,3%	0,9%	10,6%	1,8%
	10	50,0%	24,4%	5,7%	4,2%	0,5%	0,2%	1,6%	0,9%	10,8%	1,8%
Cluster 1	2	66,1%	20,0%	6,8%	0,6%	2,2%	0,1%	0,1%	0,2%	1,7%	2,2%
	5	33,4%	41,9%	4,2%	1,3%	1,5%	0,9%	2,0%	2,4%	8,5%	4,0%
	10	30,3%	44,8%	3,9%	1,1%	1,5%	1,3%	1,9%	2,6%	7,9%	4,7%
Cluster 2	2	72,1%	12,4%	5,8%	8,4%	0,3%	0,0%	0,9%			
	5	39,6%	24,4%	4,2%	24,6%	3,1%	0,6%	3,6%			
	10	39,0%	24,8%	4,2%	24,1%	3,1%	0,7%	4,2%			
Cluster 3	2	65,2%	30,3%	2,8%	0,1%	0,7%	0,0%	0,1%	0,6%	0,1%	0,1%
	5	57,5%	33,0%	3,8%	0,1%	0,8%	0,2%	3,2%	0,9%	0,1%	0,3%
	10	56,4%	33,6%	3,9%	0,1%	0,8%	0,2%	3,6%	0,9%	0,1%	0,3%
Cluster 4	2	54,1%	35,8%	4,8%	0,6%	2,4%	0,1%	0,1%	0,8%	0,7%	0,5%
	5	40,8%	37,0%	3,7%	1,4%	1,9%	1,7%	1,6%	1,0%	8,6%	2,5%
	10	39,9%	37,3%	3,6%	1,3%	1,9%	2,0%	1,6%	1,0%	8,3%	3,0%
Cluster 5	2	62,0%	30,1%	1,5%	0,2%	2,0%	0,5%	0,0%	1,4%	0,3%	1,9%
	5	52,5%	30,1%	1,7%	0,6%	2,4%	1,0%	0,2%	2,8%	6,0%	2,6%
	10	51,0%	30,0%	1,6%	0,9%	2,5%	1,1%	0,4%	2,9%	6,9%	2,7%
Cluster 6	2	89,7%	7,8%	0,1%	1,0%	0,0%	0,0%	0,1%	0,3%	0,9%	0,0%
	5	84,8%	8,4%	0,8%	2,7%	0,1%	0,4%	0,4%	0,4%	1,9%	0,1%
	10	83,1%	8,9%	0,8%	3,6%	0,3%	0,5%	0,4%	0,4%	1,9%	0,1%

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Table A.14: Forecast error variance decomposition SpVAR (similarity matrix)

		Impulse variables									
Clusters	Forecast horizon	PRICESZ	MRATEZ	INCOMEZ	HOUSEHOLDSZ	INFLATIONZ	VACANCYRATEZ	WsPRICESZ	WsINCOMEZ	WsHOUSEHOLDSZ	WsVACANCYRATEZ
Whole sample	2	67,4%	17,3%	9,5%	1,2%	0,3%	0,0%	0,5%	0,7%	1,8%	1,3%
	5	47,3%	20,9%	7,7%	6,2%	0,6%	0,3%	1,4%	1,2%	9,6%	4,9%
	10	43,9%	20,2%	7,4%	8,2%	0,6%	0,3%	1,7%	1,2%	12,0%	4,5%
Cluster 1	2	63,6%	17,9%	13,7%	0,5%	0,8%	0,2%	0,2%	0,4%	1,6%	1,3%
	5	34,0%	32,0%	14,3%	2,4%	3,7%	2,0%	0,3%	1,4%	6,0%	4,0%
	10	30,8%	34,2%	13,9%	2,4%	4,6%	2,2%	0,3%	1,4%	5,8%	4,5%
Cluster 2	2	72,1%	12,6%	7,1%	7,7%	0,1%	0,1%	0,4%			
	5	39,4%	24,9%	6,3%	26,2%	2,4%	0,6%	0,2%			
	10	39,3%	25,0%	6,5%	26,0%	2,4%	0,6%	0,2%			
Cluster 3	2	64,4%	28,4%	3,4%	0,1%	1,7%	0,0%	1,1%	0,0%	0,4%	0,5%
	5	54,4%	29,6%	3,7%	0,1%	3,4%	0,2%	3,6%	0,8%	3,4%	0,8%
	10	51,9%	31,4%	3,6%	0,1%	3,4%	0,3%	3,8%	0,8%	3,8%	0,8%
Cluster 4	2	56,8%	26,8%	10,0%	0,2%	2,2%	0,2%	0,2%	1,4%	0,0%	2,2%
	5	36,5%	18,1%	11,5%	0,4%	1,6%	2,1%	0,8%	5,5%	5,1%	18,4%
	10	33,9%	19,5%	11,6%	1,0%	2,2%	2,0%	0,8%	5,6%	5,5%	18,0%
Cluster 5	2	61,6%	32,1%	1,1%	0,1%	1,6%	0,9%	1,0%	1,4%	0,1%	0,1%
	5	53,1%	32,2%	1,1%	0,1%	1,9%	1,7%	3,7%	3,6%	2,0%	0,5%
	10	49,2%	33,6%	1,0%	0,2%	3,6%	1,6%	3,9%	3,9%	2,3%	0,7%
Cluster 6	2	93,9%	4,4%	0,0%	1,0%	0,2%	0,0%	0,0%	0,1%	0,1%	0,1%
	5	84,5%	6,9%	0,1%	3,3%	1,8%	0,2%	0,4%	0,7%	1,4%	0,7%
	10	74,7%	6,9%	0,2%	6,4%	5,9%	0,2%	1,0%	0,7%	3,1%	0,8%

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Table A.15: Panel VAR results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
PRICESZ							
L.PRICESZ	0.395***	0.166***	0.210***	0.185***	0.149***	0.147***	0.145***
	(9.69)	(4.30)	(5.04)	(4.52)	(2.85)	(2.80)	(2.78)
L.RENTSZ	-0.0518	0.00180	-0.00649	-0.00445	-0.00656	-0.00870	-0.0101
	(-1.59)	(0.06)	(-0.24)	(-0.17)	(-0.25)	(-0.33)	(-0.39)
L.MRATEZ		-0.555***	-0.435***	-0.440***	-0.449***	-0.449***	-0.450***
		(-18.96)	(-17.24)	(-17.65)	(-18.16)	(-18.24)	(-18.27)
L.INCOMEZ			0.362***	0.350***	0.362***	0.362***	0.360***
			(11.76)	(11.49)	(11.53)	(11.55)	(11.54)
L.HOUSEHOLDSZ				0.166***	0.169***	0.168***	0.149***
				(5.32)	(5.30)	(5.29)	(4.34)
L.INFLATIONZ					0.0692**	0.0767**	0.0701**
					(2.28)	(2.51)	(2.25)
L.CONSTRUCTIONZ						-0.0472**	-0.0470**
						(-2.39)	(-2.38)
L.VACANCYRATEZ							-0.0372
							(-1.26)
N	1190	1190	1190	1190	1190	1190	1190

t statistics in parentheses

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

Table A.16: Panel VAR results by cluster

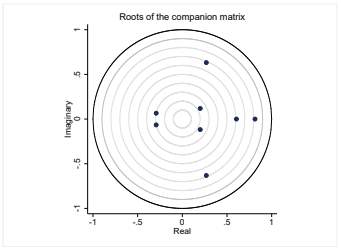
	Whole sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
PRICESZ							
L.PRICESZ	0.145***	0.0338	-0.151	-0.0619	-0.234***	-0.123	-0.198***
	(2.78)	(0.27)	(-1.62)	(-1.17)	(-3.34)	(-1.64)	(-2.74)
L.RENTSZ	-0.0101	0.0408	-0.171*	0.0118	-0.00120	-0.0284	0.0432
	(-0.39)	(0.46)	(-1.75)	(0.30)	(-0.03)	(-0.70)	(1.56)
L.MRATEZ	-0.450***	-1.199***	-1.108***	-0.392***	-0.679***	-0.419***	-0.146***
	(-18.27)	(-10.76)	(-14.25)	(-11.73)	(-13.07)	(-9.14)	(-5.80)
L.INCOMEZ	0.360***	0.399***	0.399***	0.190***	0.331***	0.196***	0.0562
	(11.54)	(7.21)	(6.60)	(4.93)	(6.57)	(2.83)	(0.79)
L.HOUSEHOLDSZ	0.149***	0.0294	0.199***	0.0845	0.0222	-0.0361	-0.140
	(4.34)	(0.38)	(3.15)	(1.33)	(0.30)	(-0.74)	(-1.49)
L.INFLATIONZ	0.0701**	0.300	0.143	0.128***	0.304***	0.162***	-0.00174
	(2.25)	(1.53)	(1.10)	(3.48)	(5.35)	(3.21)	(-0.05)
L.CONSTRUCTIONZ	-0.0470**	0.123	0.0162	-0.0280	-0.0203	-0.0238	0.0158
	(-2.38)	(0.39)	(0.33)	(-0.95)	(-0.60)	(-0.87)	(0.40)
L.VACANCYRATEZ	-0.0372	-0.160	-0.135	0.0212	-0.0874	0.0769	0.00360
	(-1.26)	(-1.32)	(-0.83)	(0.54)	(-1.59)	(1.56)	(0.09)
N	1190	120	90	360	180	210	230

t statistics in parentheses

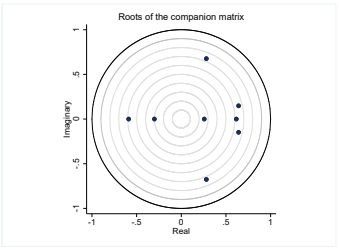
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

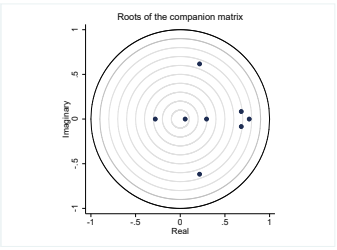
Figure A.12: Panel VAR Stability test



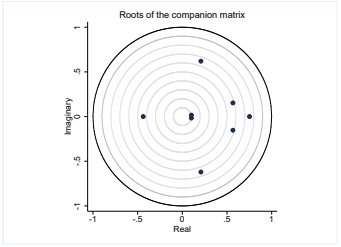
(a) Stability test for Cluster 1



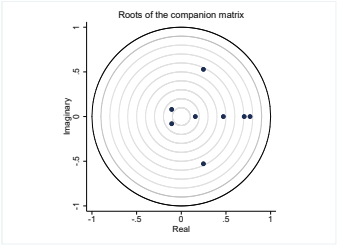
(b) Stability test for Cluster 2



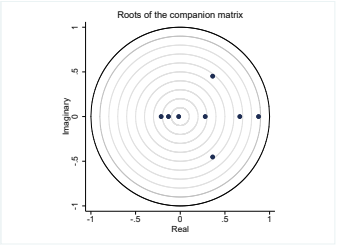
(c) Stability test for Cluster 3



(d) Stability test for Cluster 4



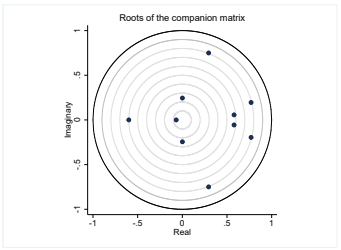
(e) Stability test for Cluster 5



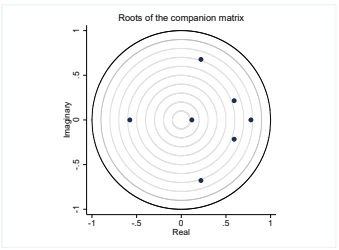
(f) Stability test for Cluster 6

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

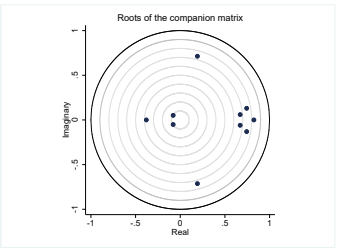
Figure A.13: Spatial Panel VAR Stability test (contiguity matrix)



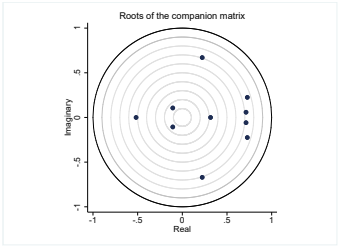
(a) Stability test for Cluster 1



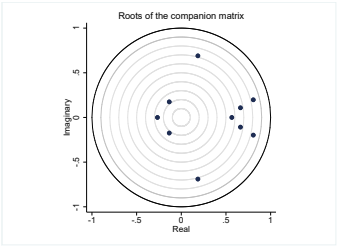
(b) Stability test for Cluster 2



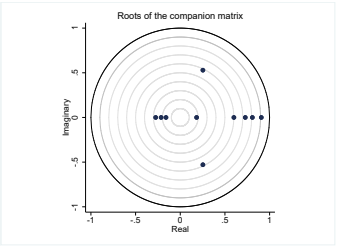
(c) Stability test for Cluster 3



(d) Stability test for Cluster 4



(e) Stability test for Cluster 5



(f) Stability test for Cluster 6

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Table A.17: SpVAR results contiguity matrix

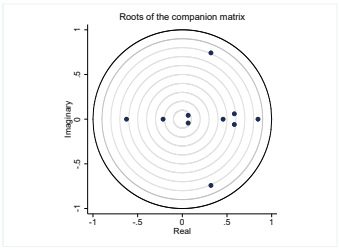
	Whole sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
PRICESZ							
L.PRICESZ	0.0799**	0.0844	0.181	-0.0477	-0.137	-0.108	-0.165***
	(2.06)	(0.51)	(1.52)	(-0.69)	(-1.29)	(-1.44)	(-2.89)
L.MRATEZ	-0.454***	-1.352***	-1.134***	-0.390***	-0.711***	-0.421***	-0.149***
	(-3.97)	(-9.12)	(-51.32)	(-11.97)	(-15.48)	(-7.76)	(-5.44)
L.INCOMEZ	0.199***	0.583***	0.382***	0.0736	0.134*	0.0644	0.00310
	(2.62)	(3.42)	(7.60)	(1.07)	(1.95)	(0.85)	(0.03)
L.HOUSEHOLDSZ	0.0926***	0.0103	0.214**	0.0726	0.0529	0.0177	-0.120
	(2.75)	(0.20)	(2.35)	(1.08)	(0.75)	(0.34)	(-1.13)
L.INFLATIONZ	0.00302	-0.151	0.211	0.143***	0.225***	0.177**	-0.0124
	(0.05)	(-1.44)	(1.33)	(2.85)	(4.16)	(2.34)	(-0.38)
L.VACANCYRATEZ	-0.0168	-0.0543	-0.129	0.00700	-0.0474	0.0717*	0.00713
	(-0.90)	(-0.61)	(-0.50)	(0.14)	(-0.67)	(1.77)	(0.22)
L.WPRICESZ	0.0328	-0.212	-0.455***	-0.0571	-0.132	-0.117	-0.0558
	(0.45)	(-1.21)	(-2.87)	(-0.53)	(-1.22)	(-1.45)	(-0.94)
L.WINCOMEZ	0.150**	-0.433**		0.145	0.183**	0.191***	0.0632
	(2.17)	(-2.17)		(1.64)	(2.22)	(3.30)	(0.80)
L.WHOUSEHOLDSZ	0.202***	0.0839		0.0626	0.0626	-0.0207	-0.132
	(3.08)	(1.19)		(0.54)	(0.69)	(-0.20)	(-1.45)
L.WVACANCYRATEZ	-0.263***	-0.747***		-0.0765	-0.268**	-0.325***	0.00286
	(-3.03)	(-5.08)		(-0.85)	(-2.22)	(-2.73)	(0.04)
N	1190	120	90	360	180	210	230

t statistics in parentheses

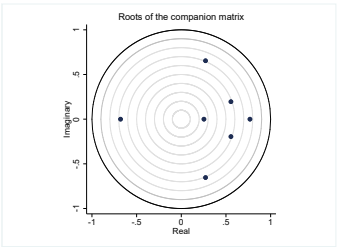
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

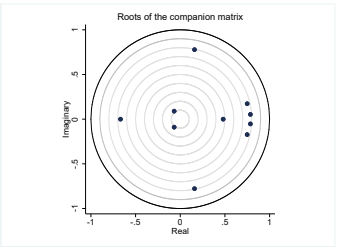
Figure A.14: Spatial Panel VAR Stability test (similarity matrix)



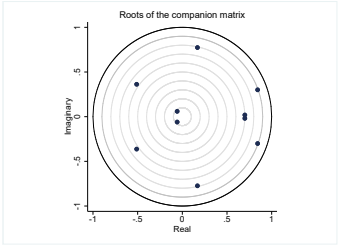
(a) Stability test for Cluster 1



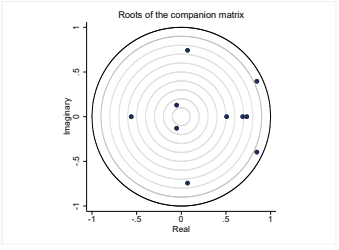
(b) Stability test for Cluster 2



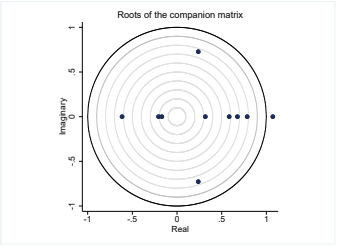
(c) Stability test for Cluster 3



(d) Stability test for Cluster 4



(e) Stability test for Cluster 5



(f) Stability test for Cluster 6

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Table A.18: SpVAR results similarity matrix

	Whole sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
PRICESZ							
L.PRICESZ	0.0477*	0.0764	0.0676	0.0497	-0.00442	-0.00937	-0.179***
	(1.76)	(0.51)	(0.44)	(0.79)	(-0.05)	(-0.12)	(-3.00)
L.MRATEZ	-0.452***	-1.262***	-1.180***	-0.453***	-0.706***	-0.443***	-0.148***
	(-3.91)	(-8.63)	(-33.81)	(-13.51)	(-13.23)	(-8.48)	(-6.12)
L.INCOMEZ	0.210**	0.711***	0.405***	0.190**	0.116	0.0902	0.00292
	(2.57)	(3.88)	(8.62)	(2.26)	(0.74)	(1.41)	(0.03)
L.HOUSEHOLDSZ	0.0564***	-0.00207	0.217**	0.0497	0.0173	0.0222	-0.115
	(4.05)	(-0.03)	(2.34)	(0.66)	(0.31)	(0.42)	(-0.95)
L.INFLATIONZ	-0.0165	-0.431*	0.219	0.250***	0.0509	0.312***	-0.0564
	(-0.19)	(-1.95)	(1.30)	(4.93)	(0.42)	(3.50)	(-1.04)
L.VACANCYRATEZ	-0.0164	-0.147	-0.102	0.00711	-0.0632	0.0571	-0.000388
	(-0.69)	(-0.91)	(-0.37)	(0.15)	(-1.37)	(1.25)	(-0.01)
L.WsPRICESZ	0.0593	-0.0967	-0.276	-0.454***	-0.292***	-0.424***	-0.0466
	(0.67)	(-0.69)	(-1.51)	(-4.40)	(-3.13)	(-4.25)	(-0.31)
L.WsINCOMEZ	0.133	-0.531***		-0.0237	0.143	0.503***	0.0833
	(1.24)	(-3.05)		(-0.26)	(0.98)	(3.02)	(0.48)
L.WsHOUSEHOLDSZ	0.162**	-0.0466		0.0743	-0.236	-0.242	-0.384
	(2.50)	(-0.12)		(0.21)	(-0.44)	(-1.22)	(-1.36)
L.WsVACANCYRATEZ	-0.479***	-0.926**		-0.385**	-0.760***	-0.144	-0.107
	(-3.41)	(-2.29)		(-2.28)	(-3.86)	(-0.55)	(-0.61)
N	1190	120	90	360	180	210	230

t statistics in parentheses

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

Note: Cluster 1: Paris center; Cluster 2: Paris outside; Cluster 3: Family-homeowner suburbs; Cluster 4: Prestigious green suburbs; Cluster 5: Suburbs in gentrification and targeted by developers; Cluster 6: Mixed residential suburbs

Table A.19: Moran's test: Cluster 1

Moran's I

Variables	I	E(I)	sd(I)	z	p-value
WPRICE	0.086	-0.091	0.118	1.507	0.066
WRENT	-0.016	-0.091	0.117	0.643	0.260
WINCOME	0.160	-0.091	0.117	2.155	0.016
WHOUSEHOLDS	0.004	-0.091	0.092	1.034	0.150
WCONSTRUCTION	-0.244	-0.091	0.112	-1.363	0.086
WVACACYRATE	0.081	-0.091	0.116	1.485	0.069
WsPRICE	0.086	-0.091	0.118	1.507	0.066
WsRENT	-0.016	-0.091	0.117	0.643	0.260
WsINCOME	0.160	-0.091	0.117	2.155	0.016
WsHOUSEHOLDS	0.004	-0.091	0.092	1.034	0.150
WsCONSTRUCTION	-0.244	-0.091	0.112	-1.363	0.086
WsVACACYRATE	0.081	-0.091	0.116	1.485	0.069

Note: W is the contiguity matrix and Ws is the similarity matrix

Table A.20: Moran's test: Cluster 2

Moran's I

Variables	I	E(I)	sd(I)	z	p-value
WPRICE	0.342	-0.125	0.172	2.712	0.003
WRENT	0.192	-0.125	0.165	1.918	0.028
WINCOME	0.173	-0.125	0.180	1.652	0.049
WHOUSEHOLDS	-0.027	-0.125	0.156	0.629	0.265
WCONSTRUCTION	-0.285	-0.125	0.162	-0.987	0.162
WVACACYRATE	0.309	-0.125	0.176	2.459	0.007
WsPRICE	0.342	-0.125	0.172	2.712	0.003
WsRENT	0.192	-0.125	0.165	1.918	0.028
WsINCOME	0.173	-0.125	0.180	1.652	0.049
WsHOUSEHOLDS	-0.027	-0.125	0.156	0.629	0.265
WsCONSTRUCTION	-0.285	-0.125	0.162	-0.987	0.162
WsVACACYRATE	0.309	-0.125	0.176	2.459	0.007

Note: W is the contiguity matrix and Ws is the similarity matrix

Table A.21: Moran's test: Cluster 3

Moran's I

Variables	I	E(I)	sd(I)	z	p-value
WPRICE	0.244	-0.029	0.037	7.378	0.000
WRENT	0.128	-0.029	0.037	4.244	0.000
WINCOME	0.279	-0.029	0.037	8.381	0.000
WHOUSEHOLDS	0.049	-0.029	0.036	2.127	0.017
WCONSTRUCTION	0.001	-0.029	0.035	0.833	0.203
WVACACYRATE	0.015	-0.029	0.036	1.202	0.115
WsPRICE	0.244	-0.029	0.037	7.378	0.000
WsRENT	0.128	-0.029	0.037	4.244	0.000
WsINCOME	0.279	-0.029	0.037	8.381	0.000
WsHOUSEHOLDS	0.049	-0.029	0.036	2.127	0.017
WsCONSTRUCTION	0.001	-0.029	0.035	0.833	0.203
WsVACACYRATE	0.015	-0.029	0.036	1.202	0.115

Note: W is the contiguity matrix and Ws is the similarity matrix

Table A.22: Moran's test: Cluster 4

Moran's I

Variables	I	E(I)	sd(I)	z	p-value
WPRICE	0.100	-0.059	0.054	2.951	0.002
WRENT	0.133	-0.059	0.055	3.506	0.000
WINCOME	0.061	-0.059	0.054	2.242	0.012
WHOUSEHOLDS	0.077	-0.059	0.051	2.691	0.004
WCONSTRUCTION	-0.046	-0.059	0.051	0.253	0.400
WVACACYRATE	-0.048	-0.059	0.055	0.199	0.421
WsPRICE	0.100	-0.059	0.054	2.951	0.002
WsRENT	0.133	-0.059	0.055	3.506	0.000
WsINCOME	0.061	-0.059	0.054	2.242	0.012
WsHOUSEHOLDS	0.077	-0.059	0.051	2.691	0.004
WsCONSTRUCTION	-0.046	-0.059	0.051	0.253	0.400
WsVACACYRATE	-0.048	-0.059	0.055	0.199	0.421

Note: W is the contiguity matrix and Ws is the similarity matrix

Table A.23: Moran's test: Cluster 5

Moran's I

Variables	I	E(I)	sd(I)	z	p-value
WPRICE	0.292	-0.050	0.066	5.173	0.000
WRENT	0.075	-0.050	0.065	1.919	0.028
WINCOME	0.199	-0.050	0.066	3.781	0.000
WHOUSEHOLDS	0.105	-0.050	0.066	2.349	0.009
WCONSTRUCTION	0.054	-0.050	0.059	1.775	0.038
WVACACYRATE	0.133	-0.050	0.064	2.846	0.002
WsPRICE	0.292	-0.050	0.066	5.173	0.000
WsRENT	0.075	-0.050	0.065	1.919	0.028
WsINCOME	0.199	-0.050	0.066	3.781	0.000
WsHOUSEHOLDS	0.105	-0.050	0.066	2.349	0.009
WsCONSTRUCTION	0.054	-0.050	0.059	1.775	0.038
WsVACACYRATE	0.133	-0.050	0.064	2.846	0.002

Note: W is the contiguity matrix and Ws is the similarity matrix

Table A.24: Moran's test: Cluster 6

Moran's I

Variables	I	E(I)	sd(I)	z	p-value
WPRICE	0.096	-0.045	0.060	2.363	0.009
WRENT	-0.087	-0.045	0.059	-0.703	0.241
WINCOME	0.278	-0.045	0.059	5.474	0.000
WHOUSEHOLDS	-0.021	-0.045	0.058	0.411	0.340
WCONSTRUCTION	0.011	-0.045	0.058	0.974	0.165
WVACACYRATE	-0.043	-0.045	0.056	0.045	0.482
WsPRICE	0.096	-0.045	0.060	2.363	0.009
WsRENT	-0.087	-0.045	0.059	-0.703	0.241
WsINCOME	0.278	-0.045	0.059	5.474	0.000
WsHOUSEHOLDS	-0.021	-0.045	0.058	0.411	0.340
WsCONSTRUCTION	0.011	-0.045	0.058	0.974	0.165
WsVACACYRATE	-0.043	-0.045	0.056	0.045	0.482

Note: W is the contiguity matrix and Ws is the similarity matrix