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SPATIAL AND TEMPORAL DIFFUSION OF FLAT PRICES IN LITHUANIA

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1. Introduction

This paper uses the approach introduced by Holly at al. (2011) to analyze the spatial and temporal diffusion of shocks in a dynamic system. I apply the approach to the Ober-Haus Lithuanian apartment price index data. The model allows for both spatial and city specific adjustment to shocks. Shocks to the dominant city are allowed to propagate spatially and contemporaneously to other cities. These spatial and contemporaneous effects are allowed to echo back to the dominant city. The effects of the shock are analyzed using generalized spatio-temporal impulse responses. This setup shows the diffusion of shocks both in the special dimension and the temporal dimension.

I show that Vilnius can be considered the dominant region however it may not be uniquely so. Kaunas may also be a dominant city, but Vilnius is still shown to be more dominant by the results. This intuitively seems to follow, according to The Lithuanian Department of Statistics data about 29% of residents in Lithuania live in Vilnius, 16% in Kaunas and about 43% of national GDP is generated in Vilnius, 21% in Kaunas (Statistikos departamentas, 2020). The results show that while Vilnius and Kaunas may be weakly exogenous to other cities, they are not necessarily weakly exogenous to each other. Results for other cities do not indicate them to be dominant for the whole of Lithuania. Approaches allowing multiple dominant regions exist.

Much work has been done trying to understand the determinants of house price fluctuations. This can be seen in some of the literature cited, however little work has been proceeding to analyze the dynamics of the Lithuanian housing market. A better understanding of the diffusion of fluctuations in a housing market could enable future research to identify bubbles and inform policy makers on how to respond to crashes in the housing market. This is especially relevant after the Great Recession.

My goal is to find how flat price changes in the assumed dominant city (Vilnius) affect flat prices in other cities in Lithuania. This work should be understood as a step in the direction for more comprehensive analyses of the Lithuanian housing market.

The work is structured into three objectives:

1. Adjust the Holly at al. (2011) approach to make it compatible with the aim of the thesis.
2. Estimate equations for the cities.
3. Construct the generalized impulse response functions.

The rest of the paper is set up as follows: Section 2 analyzes the relevant literature for my question while delving deeper into spatial analysis, Section 3 presents the model used for the price diffusion where the dominant region is distinguished from the others, I show how the results from individual estimations can be used to construct spatio-temporal generalized impulse response functions for analysis. Section 4 discusses empirical results using monthly price index data and different weight matrix specifications. Section 5 provides recommendations and Section 6 concludes.

2. Literature review

Anselin (2010) defines spatial econometrics as “a subset of econometric methods that is concerned with spatial aspects present in cross-sectional and space-time observations. Variables related to location, distance, and arrangement (topology) are treated explicitly in model specification; estimation; diagnostic checking and prediction”. The author argues that spatial modeling has come a long way since its inception and represents a shift in theoretical focus towards interactions among agents rather than individual behavior. This can be seen in works such as Glaeser et al. (1996). The question set out to answer is what explains the high variance of crime across time and space larger differences among the two being across space. The most obvious explanation for the differences is the varying economic and social conditions across space, however empirically these differences account for a small amount of the variation of crime. The authors apply an abstract spatial model of neighbors on a lattice to precinct and city-level for analysis.

There are two main ways of constructing the spatial model (Durbin, 1998). The first method are geostatic models that deal with spatially correlated data based on the theory of regionalized variables. The process uses coordinate data and the assumed functional form of the co-variance matrix. This approach is used by, for example, the mining industry to quantify mineral resources and to evaluate a projects economic feasibility. The second approach is based on an assumption of the spatial weight matrix, this approach is widely used in real estate literature, and it is regarded as well suited for this type of analysis (Pace et al., 1998). Though this type of model is used in this paper to analyze the geographical spatial interdependencies, these types of models are not limited to this application. This type of model has been used by epidemiologists and other specialists, for example, to analyze functional magnetic resonance images (Gössl at al., 2001). There has been work done in the research of spatial diffusion of housing prices.

Dijk et al. (2007) develop a panel model for quarterly regional house prices allowing for stochastic trends, cointegration, cross-equation corrections. They apply this model to regional house prices in the Netherlands and find two distinct classes of regions where price dynamics are similar, but different across classes. They find a ripple effect where shocks to house prices propagate to other regions. To find this ripple effect parameters of the difference between log price in relative to Amsterdam is considered.

Koramaz and Dokmeci (2012) use a semi-hedonic price model which is generated with a multiple regression model to investigate spatial determinants as one of the major explanatory domains for housing price values in Istanbul. They find that centrality, accessibility and distance to the coast are statistically significant spatial determinants for house prices.

Holly at al. (2011) present a method for analyzing spatial and temporal diffusion of shocks in a dynamic system. They apply this approach to house prices in the UK economy. Attention is given to the dominant region, which is allowed to have contemporaneous effects on other regions. The contemporaneous shocks effects can then propagate back to the dominant region in lagged effects thus creating echoes in the whole system. They also emphasize the importance of the difference in the time that shocks take to decay through different dimensions, they find that the effects of a shock decay more slowly along the geographical dimension and that the effects to regions further away from London take longer to dissipate. The paper highlights the varying importance of nodes on the spatial system with the distinction of London as the dominant region. Different nodes are most important for individual nodes through the spatial dimension, however one or a few nodes are most important for the whole system.

Pesaran, Yang (2021) allow for more flexible specifications of the matrix of spatial or network connections thus allowing multiple dominant units. In their empirical application to sectoral price changes in the US over the pre- and post-2008 financial crisis they show that the share of capital can be estimated reasonably well from the degree of sectoral interdependence using the input-output tables, despite the evidence of dominant sectors being present in the US economy.

Due to the importance of the weight matrix, there are many specifications of the matrix considered. Holly at al. (2011) use a simple 1/n for each neighbor of a particular region where n is the number of neighbors and 0 for all non-neighbors. They expand the definition of neighbor not only to geography but to centrality also. This is quite simplistic though; non-neighbors will have weight 0 despite their varying distance and importance for the node in question. These types of weight matrixes might be overly-restrictive for some applications as marginal effects are still effects.

Another specification is using distances between nodes and then adjusting them so that sum of each row (or column depending on model specification) of the weight matrix is equal to zero, travel time can also be used for this type of weight matrix. In contrast to these strictly positional approaches Cliff and Ord (1973) expand the definition of the weight matrix to include other spatial spillover effects. These spillover effects can include commuting (such as suggested by Holly at al. (2011)), migration patterns, demand and supply effects, competition between firms, tax competition between local governments and integration. Cliff and Ord (1973) also introduce interacting geographic properties to construct weight matrices, for example:

$$w_{ij} = (d_{ij})^a (x_{ij})^b$$

Where w_{ij} is the weight between objects i and j in the weight matrix, d_{ij} is the distance between objects i and j, x_{ij} is the proportion of border of i that is shared with j. This approach is not strictly geographical as it can include other factors.

Another way to construct the weight matrix is to move beyond geography and use economic distances. This approach is especially useful when the spatial interactions are determined by purely economic variables, which may have little to do with spatial configuration of boundaries or geographical distance *per se* (Corrado and Fingleton, 2011). Economic distance does not have a concrete definition and is used to mean possibly different things: a pseudo-metric summarizing international competitiveness, bilateral trade costs and comparative advantage (Fisher at al. 2015) GDP, growth rate gap (Choi at al. 2019) or the distances can be defined in terms of trade openness space, regulatory space, commercial space, industrial structure space, or product characteristics space (Corrado and Fingleton, 2011). In general, economic distance might be especially useful when modeling real estate prices. According to Fingleton and Le Gallo (2008) "the spillover between areas will not simply be a function of spatial propinquity", "it is more realistic to base it on relative 'economic distance.' Big towns and cities are less remote than their geographical separation would imply, whereas very small locations are often isolated from one another." So, the economic distance can reflect better integration of transportation and communication services and differences in employment legislation or similarity of demanded employability skills in regions. Lastly there are techniques developed to construct the weight matrix in a quantitative manner, optimizing the weight matrix endogenously, such as proposed by Lam and Souza (2020) and Bauman at al. (2018).

One spatially important component of economic distance is migration. Potepan (1994) investigates the extent to which migration and housing prices are simultaneously determined in metropolitan areas. Housing prices, emigration and immigration were simultaneously determined in his model. Two-stage least squares results indicate that higher net migration raises housing prices, while simultaneously, higher housing prices dampen further net migration.

Wu at al. (2021) analyze relationships between housing prices between cities using data from thirty-five large and medium-sized cities in China. They find that housing prices are mainly set by local demand and supply, however interactions between cities also have an effect. They also find that relationships in the housing price network change year-to-year especially in the presence of large external shocks and that cities have varying roles in the whole network, first-tier cities in the Chinese city tier system influence other cities greatly, while less developed cities interact and fluctuate together but do not have a big impact on the more developed cities. The authors attribute this effect to the development of regional economic integration.

There has been work done in analyzing the Lithuanian housing market. Ambrasas and Stankevicius (2007) used a simple regression model to analyze the difference in price between the cheapest and most expensive dwellings in different segments of real estate market in the capital. Egert and Mihaljek (2007) use panel DOLS techniques to study the determinants of house price dynamics in eight economies of eastern and central Europe. Ivanauskas at al. (2008) used contegration and granger causality tests to statistically analyze the housing market in Lithuania. They found no cointegration between income and housing costs using this and they suggest that a housing bubble might be forming. Jadevicius and Huston (2015) apply an ARIMA model on Ober-House Lithuanian House Price Index data to find that the model is good for forecasting index values.

However, these papers are factor based and do not consider the spatial dimension. This paper analyzes the spatial dimension, firstly using the central region (Vilnius) as the common factor and then modeling the remaining dependencies both contemporaneously and with a lag conditional in Vilnius prices. Solving the whole model allows to consistently estimate separate conditional error correcting models for each city which combined allow to solve for a full set of spatio-temporal generalized impulse response functions.

3. Methodology

Suppose we are interested in diffusion of prices in region i over time t: p_{it}, $i = 0, 1, 2, \dots N$, $t = 1, 2, \dots T$ and we have reason to believe that one region is dominant over others in the sense that shocks experienced by it will propagate to other regions over time and space, but shocks to other regions will have little effect on this dominant region, however the effects of the non-dominant regions can be non-zero. This dominant region will be denoted $i = 0$ and other regions will be $i = 1, 2, \dots N$. A first order linear error correction specification for the dominant region is given by:

$$\Delta p_{0t} = \varphi_{0s}\left(p_{0,t-1} - p^s_{0,t-1}\right) + a_0 + a_{01}\,\Delta p_{0,t-1} + b_{01}\Delta p^s_{0,t-1} + \varepsilon_{0t} \qquad (2.1)$$

And for other regions:

$$\Delta p_{it} = \varphi_{is}\left(p_{i,t-1} - p^s_{i,t-1}\right) + \varphi_{i0}\left(p_{i,t-1} - p_{0,t-1}\right) + a_i + a_{i1}\,\Delta p_{i,t-1} + b_{i1}\Delta p^s_{i,t-1} + c_{i0}\Delta p_{0t} + \varepsilon_{it} \qquad (2.2)$$

Where p^s_{it} denotes the spatial variable for region i denoted by:

$$p^s_{it} = \sum_{j=0}^{N} s_{ij}\, p_{jt} \text{ with } \sum_{j=0}^{N} s_{ij} = 1, \text{ for } i = 0, 1, \dots N \qquad (2.3)$$

The weights s_{ij} are set *a priori* based by one of the weight matrix specifications discussed previously with the following restrictions:

1. $\sum_{j=0}^{N} s_{ij} = 1$, for $i = 0, 1, \dots N$, the sum of weights in a single error correction formula for each region is equal to 1.
2. $s_{ii} = 0$, for $i = 0, 1, 2, \dots N$, a region price level will have no effect on the spatial component of that region.

All price equations are allowed to be error correcting; however, some restrictions are introduced to avoid over-parametrization, namely the central region is allowed to cointegrate with its weighted spatial price value p^s_{0t} while all other regions are allowed to cointegrate with the weighted spatial price value and the central region. According to Holly at al. (2011) this specification can be justified as a parsimonious representation of pairwise cointegration across regions.

Lastly, it is worth noting that the contemporaneous effect of the dominant region appears in the equations of other regions as $c_{i0}\Delta p_{0t}$, but there are no contemporaneous effects included in the equation of the central region. For the estimates to not be biased in the estimation, the assumption that same period price changes in the central region are weakly exogenous in the equations of non-dominant regions has to be established. This is done using the procedure advanced by Wu (1973), which can also be motivated using Hausman's (1978) type tests. Following Wu's approach denote the OLS residuals from the regression of the model for the dominant region by

$$\widehat{\varepsilon_{0t}} = \Delta p_{0t} - \widehat{\varphi_{0s}}\left(p_{0,t-1} - p_{0,t-1}^{s}\right) - \widehat{a_0} - \widehat{a_{01}}\,\Delta p_{0,t-1} - \widehat{b_{01}}\Delta p_{0,t-1}^{s},$$

And run the auxiliary regression:

$$\Delta p_{it} = \varphi_{is}\left(p_{i,t-1} - p_{i,t-1}^{s}\right) + \varphi_{i0}\left(p_{i,t-1} - p_{0,t-1}\right) + a_i + a_{i1}\,\Delta p_{i,t-1} + b_{i1}\Delta p_{i,t-1}^{s} + c_{i0}\Delta p_{0t} + \lambda_i\widehat{\varepsilon_{0t}} + \epsilon_t \qquad (2.4)$$

A standard t-test can be used to test hypothesis that $\lambda_i = 0$ for each i separately.

A significant difference from the estimation done by Holly at al. (2011) will be that I do not assume that the Wu Hausmann test is failed to be rejected for all regions. This addition to the model will have two main differences. Firstly, the estimation of the spatio-temporal impulse response functions will have to use a less restrictive form of the variance covariance matrix, this is covered in the next chapter. Secondly, with this assumption rejected it is not reasonable to conclude that c_{i0} will be unbiased in the (2.2) equation of the region for which the weak exogeneity test is rejected. This is solved by setting $c_{i0} = 0$ if the Wu Hausmann test of weak exogeneity rejects the null hypothesis for region i.

Lastly, following Holly at al. (2011) the error correcting terms φ_{is} and φ_{i0} are restricted such that if they are statistically significant at 5%, they take values that were estimated with OLS and are 0 otherwise. The full algorithm for the estimation of the whole model looks like this:

1. All (2.1) and (2.2) equations are estimated using OLS.
2. Terms φ_{is} and φ_{i0} are set to 0 if they are not statistically significant at 5% level and equations (2.1) and (2.2) are reestimated with these restrictions.
3. Wu Hausmann tests are conducted.
4. If Wu Hausmann test reject the null hypothesis for region i, c_{i0} is set to 0 and equation (2.2) is reestimated for i.

3.1 Spatio-temporal Impulse Response Functions

Although the equations for all equations in the previous section can be estimated with OLS, to interpret the results impulse response functions must be constructed. The above specified system of equations can be written in matrix form and solved to VAR form (matrix compositions can be found in Holly at al. (2011)

$$\Delta \boldsymbol{p_t} = \boldsymbol{a} + \mathbf{H}\boldsymbol{p_{t-1}} + (\boldsymbol{A} + \boldsymbol{G})\Delta \boldsymbol{p_{t-1}} + \boldsymbol{C_0}\Delta \boldsymbol{p_t} + \boldsymbol{\varepsilon_t} \tag{3.5}$$

$$\boldsymbol{p_t} - \boldsymbol{p_{t-1}} = \boldsymbol{a} + \mathbf{H}\boldsymbol{p_{t-1}} + (\boldsymbol{A} + \boldsymbol{G})(\boldsymbol{p_{t-1}} - \boldsymbol{p_{t-2}}) + \boldsymbol{C_0}(\boldsymbol{p_t} - \boldsymbol{p_{t-1}}) + \boldsymbol{\varepsilon_t}$$

$$(\boldsymbol{I} - \boldsymbol{C_0})\boldsymbol{p_t} = \boldsymbol{a} + (\mathbf{H} + \boldsymbol{A} + \boldsymbol{G} + \boldsymbol{I} - \boldsymbol{C_0})\boldsymbol{p_{t-1}} - (\boldsymbol{A} + \boldsymbol{G})\boldsymbol{p_{t-2}} + \boldsymbol{\varepsilon_t}$$

$$\boldsymbol{p_t} = \boldsymbol{\mu} + \boldsymbol{\Phi_1}\boldsymbol{p_{t-1}} + \boldsymbol{\Phi_2}\boldsymbol{p_{t-2}} + \boldsymbol{\epsilon_t} \tag{3.6}$$

Where $\boldsymbol{\mu} = (\boldsymbol{I} - \boldsymbol{C_0})^{-1}\boldsymbol{a}$, $\boldsymbol{\Phi_1} = (\boldsymbol{I} - \boldsymbol{C_0})^{-1}(\mathbf{H} + \boldsymbol{A} + \boldsymbol{G} + \boldsymbol{I} - \boldsymbol{C_0})$, $\boldsymbol{\Phi_2} = -(\boldsymbol{A} + \boldsymbol{G})$, and $\boldsymbol{\epsilon_t} = (\boldsymbol{I} - \boldsymbol{C_0})^{-1}\boldsymbol{\varepsilon_t}$. The temporal dependence is captured by $\boldsymbol{\Phi_1}$ and $\boldsymbol{\Phi_2}$, the spatial dependence by $(\boldsymbol{I} - \boldsymbol{C_0})^{-1}$ and error covariances. The temporal coefficients are also affected by the weight matrix. This VAR representation can be used to construct the impulse response functions.

For the impulse response analysis calculations, I will use the same approach as Holly at al. (2011) with a small difference. Using the same approach advanced by Pesaran and Shin (1998) adopted for this model:

$$g_i(h) = \frac{\boldsymbol{\Psi_h}(\boldsymbol{I} - \boldsymbol{C_0})^{-1} \sum \boldsymbol{e_i}}{\sqrt{\sigma_{ii}}}, \text{ for } h = 0, 1, \ldots, \mathrm{H} \tag{3.7}$$

Where $\boldsymbol{\Psi_h} = \boldsymbol{\Phi_1}\boldsymbol{\Psi_{h-1}} + \boldsymbol{\Phi_2}\boldsymbol{\Psi_{h-2}}$, for $h = 0, 1, ...$, with $\boldsymbol{\Psi_0} = \boldsymbol{I}$ and $\boldsymbol{\Psi_h} = \boldsymbol{0}$, for $h < 0$.

If the Wu test of the weak exogeneity of p_{0t} is not rejected, then it would be reasonable to assume that $Cov(\varepsilon_{0t}, \varepsilon_{it}) = 0$ for *i* that the weak exogeneity test was not rejected. However, if the result of the test was to reject, the covariance between that term and the dominant region residuals cannot be assumed to be 0. This means that the variance covariance matrix instead of taking a general form where the first column and row are populated with zeros:

$$\sum = \begin{pmatrix} \sigma_{00} & 0 & 0 & \dots & 0 \\ 0 & \sigma_{11} & \sigma_{12} & \dots & \sigma_{1N} \\ 0 & \sigma_{21} & \sigma_{22} & \dots & \sigma_{2N} \\ \dots & \dots & \dots & \dots & \dots \\ 0 & \sigma_{N1} & \sigma_{N2} & \dots & \sigma_{NN} \end{pmatrix}$$

Will take the form where some of the elements in the first row and column beside σ_{00} can take nonzero values, for example: in the case of five regions when the result of the Wu Hausmann test between regions $i = 0$ and $i = 1$ is rejection, but others are not the variance covariance matrix will take the following form:

$$\sum = \begin{pmatrix} \sigma_{00} & \sigma_{10} & 0 & 0 & 0 \\ \sigma_{01} & \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ 0 & \sigma_{21} & \sigma_{22} & \sigma_{23} & \sigma_{24} \\ 0 & \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} \\ 0 & \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{44} \end{pmatrix}$$

Where $\sigma_{ij} = E(\varepsilon_{it}\varepsilon_{jt})$ elements of $\sum$ are estimated using OLS residuals by $\widehat{\sigma_{ij}} = T^{-1}\sum_{t=1}^{T}\widehat{\varepsilon_{it}}\,\widehat{\varepsilon_{jt}}$, where $\widehat{\varepsilon_{it}}$ is the residual of the individual regression for region i. In this setup the Generalized impulse response function given by (3.7) with $\sum$ as described above will be applicable for the analysis for both the dominant and non-dominant regions alike.

3.2 Bootstrap GIRF Confidence Intervals

Bootstrapped confidence intervals are computed for the estimates of $g_i(h)$, over *h* and *i* to evaluate the statistical significance of the estimates. Estimated model from (3.6) is denoted as

$$\boldsymbol{p_t} = \boldsymbol{\hat{\mu}} + \widehat{\boldsymbol{\Phi}_1}\boldsymbol{p_{t-1}} + \widehat{\boldsymbol{\Phi}_2}\boldsymbol{p_{t-2}} + \left(\boldsymbol{I} - \widehat{\boldsymbol{C_0}}\right)^{-1}\boldsymbol{\hat{\varepsilon}_t} \tag{3.8}$$

and the estimated GIRF as

$$\widehat{\boldsymbol{g}_i}(h) = \frac{\widehat{\boldsymbol{\Psi}_h}\left(\boldsymbol{I} - \widehat{\boldsymbol{C_0}}\right)^{-1}\widehat{\sum}\ \boldsymbol{e_i}}{\sqrt{\widehat{\sigma_{ii}}}} \tag{3.9}$$

The generated *B* bootstraps are denoted by $\boldsymbol{p_t^{(b)}}$, *b* = 1, 2, …, *B*, then bootstrap GIRF $\boldsymbol{\hat{g}_t^{(b)}}$ are computed for each $\boldsymbol{p_t^{(b)}}$. Firstly, the b^{th} bootstrap samples are obtained recursively based on the data generating process

$$\boldsymbol{p}_{t}^{(b)} = \widehat{\boldsymbol{\mu}} + \widehat{\boldsymbol{\Phi}_1}\boldsymbol{p}_{t-1}^{(b)} + \widehat{\boldsymbol{\Phi}_2}\boldsymbol{p}_{t-2}^{(b)} + \left(\boldsymbol{I} - \widehat{\boldsymbol{C}_0}\right)^{-1}\widehat{\boldsymbol{\varepsilon}}_{t}^{(b)}$$

Where $\widehat{\boldsymbol{\varepsilon}}_{t}^{(b)} = \widehat{\sum}^{1/2} \boldsymbol{v}_{t}^{*(b)}$, where the elements of $\boldsymbol{v}_{t}^{*(b)}$ are random draws from the transformed residual matrix $\widehat{\sum}^{-\frac{1}{2}}(\widehat{\boldsymbol{\varepsilon}_1}, \widehat{\boldsymbol{\varepsilon}_2}, \dots, \widehat{\boldsymbol{\varepsilon}_T})$, with replacement, two initial observations are equated to the original data.

Secondly, using the obtained bootstrap samples $\boldsymbol{p}_{t}^{(b)}$, estimate the model and compute the individual GIRFs. 90% confidence interval is obtained as fifth and ninety fifth percentiles of $\widehat{\boldsymbol{g}}_{t}^{(b)}$ for each *h* and *i*.

3.3 Data

The Ober-House Lithuanian House Price Index (OHBI) is used in my analysis. It is the longest housing price index in Lithuania. It records the changes in apartment prices in 5 major Lithuanian cities (Vilnius, Kaunas, Klaipėda, Šiauliai and Panevėžys). The data for the five cities is monthly starting with January 1994 with a baseline value 100. When constructing the index following parameters are considered: the number of available apartments and the number of deals made in individual geographic segments (in the districts of individual cities and in district groups), and quality characteristics of apartments (a floor space, age, and completeness) (Ober-Haus, 2022). Both nominal and real values of the index are published.

Following Holly at al. (2011) I use the real values for my analysis, however since the actual price level data is unavailable or unreliable, I use the index values. This approach has some shortcomings. Mainly, the results will not be as interpretable or intuitive. However, the goal of my work is to identify the interrelationships and this goal is not impeded by the values of prices being interchanged with indexes as the fluctuations are still captured in the model. I use index values from January 1994 to December 2021 for the estimation of the model.

The OHBI index values and their monthly rates of change across the five cities are displayed in Figure 1. We can see three main stages in price development, firstly, the stagnant real prices from January 1994 to January 2003, secondly, the sharp increase and the subsequent fall of prices of the Great Recession from January 2003 to January 2013, prices firstly falling fast and then more gradually, and lastly the gradual increase from January 2013 to December 2021. It is also interesting to observe the changes in first differences of prices. Prices are generally volatile in the first period, extreme during the rise and fall and minimal after around January 2012. The plots suggest that the index series might be cointegrated, this is tested in further chapters.

Figure 1.

Source: Ober-Haus, prepared by the author.

4. Empirical results

The above-described methodology is applied on the Ober-House Lithuanian House Price Index data. Three different weight matrices are used and compared to show the flexibility and applicability of the model, also to find resulting differences between the specifications:

- Travel distance. The distance between city centers to be driven by car. This measure of distance may depend on the software being used to calculate it; however, the weights will generally be similar. These weights will all be positive. The advantages of this simple description of the weight matrix are that the actual matrix has no need to change with time and the price changes cannot change the distances thus preventing any simultaneity bias problems.
- Net internal migration by county. This data is taken from Statistikos departamentas (2020) and it is county level migration data. This is obviously not optimal as the index measures the price changes for flats in the cities and the migration data is for the whole county. Also, this migration data will be time sensitive and might be dependent on the price changes themselves. However, I still use this data as one of the weight matrix variants as migration could be responsible for housing price fluctuations (Potepan, 1994) and this migration weight matrix should be representative of larger long term migration patterns in Lithuania.
- Endogenous RSS minimizing weight matrix. This weight matrix was constructed by changing the weight matrix to minimize the residual sum of squares of all five OLS equations of the cities at once, meaning the objective function is:

$$\min \sum_{i=0}^{N} RSS_i$$

  Where RSS_i is the RSS of the individual OLS equation for each city. This approach allows to estimate a better fitting weight matrix to the data, while sacrificing the interpretability of the weight matrix itself.

The regression results of applying the described procedure to Ober-House Lithuanian House Price Index with the travel distance weight matrix are summarized in Table 1 with standard errors in the brackets. For Vilnius the error correcting terms are not estimated, and the flat price index changes are regressed on their lagged values and lagged values of the neighboring regions. For three regions the contemporaneous effects of Vilnius index change are included, for Kaunas they are not included.

Estimates for error correcting terms are in columns one and two. At least one error correcting term is significant for 3 cities. For Panevėžys both error correcting terms are insignificant and thus not estimated, according to Holly at al. (2011) this result might be due to the sample period being not informative enough or the error correcting properties might be different to the ones captured by the model. Three of the four estimated error correcting terms are negative as expected. However, one of the estimated error correcting terms is positive and statistically significant. This suggests that if the change in Klaipeda index values exceeds the increase of the weighted average of the other cities index values, then this will have a positive effect on the next period index increase against the weighted average. This might be due to speculating in real estate of Klaipėda, however if this is the case is a topic for future research.

Table 1

Estimation results of region specific flat price diffusion equation with Vilnius as a dominant region and travel distance weight specification.

Regions	EC1 (ϕ_{i0})	EC2 (ϕ_{is})	Intercept	Own Lag Effects	Neighbors Lag Effects	Vilnius Contemporaneous Effects	Wu-Hausman Statistics
Vilnius	-	-	0.126 (0.115)	0.233*** (0.058)	0.542*** (0.060)	-	-
Kaunas	-0.024*** (0.008)	-	-0.504** (0.220)	0.500*** (0.057)	0.194*** (0.060)	-	1.02 **
Klaipėda	-0.035*** (0.013)	0.026** (0.012)	-0.658*** (0.250)	0.169*** (0.059)	0.294*** (0.073)	0.423*** (0.060)	0.57
Šiauliai	-	-0.054*** (0.012)	-0.927*** (0.243)	0.271*** (0.052)	0.159* (0.085)	0.324** (0.063)	0.76
Panevėžys	-	-	0.017 (0.140)	0.579*** (0.047)	0.137* (0.081)	0.218*** (0.068)	1.01

*The table reports estimates based on equations (2.1) and (2.2). *** signifies that the rest rejects the null at the 1% significance level, ** at 5%, * at 10%. The error correction coefficients are restricted such that they are statistically significant at the 5% level. Source: prepared by the author on the basis of the research.*

Own lag effect estimates are presented in column 5. All these estimates are statistically significant at a 1% level. Column six shows the estimates of the neighbors' spatial effects. Estimates for the three largest cities neighbors lag effects are significant at 1% level, for Panevėžys and Šiauliai the neighbors lag effects are significant at the 10% level. This result might suggest that the spatial effects are not as important for the price determination as simple lagged effects of the same region.

The contemporaneous effects of Vilnius flat price index values are sizable and significant at least at a 5% significance level for Klaipėda, Šiauliai and Panevėžys, for Kaunas the contemporaneous effects are not estimated.

The results from applying the procedure to the migration weight matrix are not as significant. Results are presented in Table 2. In this case the Vilnius estimation includes one error correcting term, however it is positive, other error correcting terms are similar to the previous results. Klaipėda error correcting terms are both about twice as large, Kaunas and Šiauliai error correcting terms are very close to the previous results. Panevėžys equation again does not include any of the error correcting terms. All negative estimated error correction terms are significant at 1% level, the positive is significant at 5% level.

Table 2

Estimation results of region specific flat price diffusion equation with Vilnius as a dominant region and migration weight matrix specification.

Regions	EC1 (ϕ_{i0})	EC2 (ϕ_{is})	Intercept	Own Lag Effects	Neighbors Lag Effects	Vilnius Contemporaneous Effects	Wu-Hausman Statistics
Vilnius	-	0.018** (0.008)	-0.319 (0.233)	0.284*** (0.059)	0.421*** (0.060)	-	-
Kaunas	-0.026*** (0.008)	-	-0.580*** (0.201)	0.500*** (0.053)	-0.089 (0.060)	0.419*** (0.048)	0.35
Klaipėda	-0.069*** (0.018)	0.057*** (0.017)	-0.978*** (0.286)	0.350*** (0.061)	0.344*** (0.076)	-	-1.00**
Šiauliai	-	-0.041*** (0.010)	-0.889*** (0.254)	0.291*** (0.051)	0.125 (0.082)	0.344** (0.063)	-0.35
Panevėžys	-	-	0.050 (0.140)	0.565*** (0.047)	0.182** (0.079)	0.207*** (0.064)	0.10

*The table reports estimates based on equations (2.1) and (2.2). *** signifies that the rest rejects the null at the 1% significance level, ** at 5%, * at 10%. The error correction coefficients are restricted such that they are statistically significant at the 5% level. Source: prepared by the author on the basis of the research.*

Own lag effects are again very significant suggesting that these effects are the most important. Spatial effects of other cities index changes are less significant, only two of the five terms are statistically significant. Wu Hausmann test of weak exogeneity again resulted in one rejection, this time for Klaipėda. The terms that were estimated again have similar values to the previous results.

Overall, these results seem to suggest that both weight matrices have a good fit with the data, with the travel distance matrix capturing the spatial effect slightly better. Overall, the error correcting terms are smaller than the spatial and own lag effects. However, the computed GIRF for the net migration model variant shows that this choice of the weight matrix produces poor results.

Lastly, the results of the endogenously optimizing weight matrix are presented in Table 3. Five error correction terms are estimated, one for Kaunas, two for Klaipėda and Šiauliai, no error correction terms are estimated for Vilnius and Panevėžys. An interesting result is observed analogously to previous estimations: in equations where both error correction terms are estimated one is positive, one is negative.

Table 3

Estimation results of region specific flat price diffusion equation with Vilnius as a dominant region and endogenously optimizing weight matrix specification.

Regions	EC1 (ϕ_{i0})	EC2 (ϕ_{is})	Intercept	Own Lag Effects	Neighbors Lag Effects	Vilnius Contemporaneous Effects	Wu-Hausman Statistics
Vilnius	-	-	-0.136 (0.114)	0.207*** (0.058)	0.576*** (0.060)	-	-
Kaunas	-0.026*** (0.007)	-	-0.583*** (0.201)	0.443*** (0.050)	-0.092 (0.056)	0.428*** (0.050)	-0.19
Klaipėda	-0.032*** (0.012)	0.022** (0.010)	-0.691*** (0.251)	0.165*** (0.058)	0.292*** (0.069)	0.425*** (0.060)	0.12
Šiauliai	0.065*** (0.017)	-0.186*** (0.031)	-1.331*** (0.286)	0.254*** (0.049)	0.131* (0.074)	0.360*** (0.058)	-0.03
Panevėžys	-	-	0.014 (0.140)	0.552*** (0.049)	0.211** (0.087)	0.194*** (0.066)	0.32

*The table reports estimates based on equations (2.1) and (2.2). *** signifies that the rest rejects the null at the 1% significance level, ** at 5%, * at 10%. The error correction coefficients are restricted such that they are statistically significant at the 5% level. Source: prepared by the author on the basis of the research.*

Intercept term estimates are close to the results in Table 2. In the results for Vilnius and Panevėžys the intercepts are statistically insignificant, while for other cities the estimates are very significant. Own lagged effects are again very statistically significant.

Spatial neighbors' lagged effects are very similar to results is Table 2 both in significance and values.

The contemporaneous effects are estimated for all cities, and all are both sizable and statistically significant at the 1% level. This specification of the model seems to yield the best result in both RSS and in the fact that the contemporaneous effects are estimated analogously to Holly at al. (2011). With all three weight matrix specifications the contemporaneous effects and statistically significant neighbors lag effects are smallest for Panevėžys, this suggests that Panevėžys flat prices are less dependent on the effects of other large Lithuanian cities then these other large cities.

4.1 On the Choice of the Dominant Region

All the empirical analysis carried out this far has been done with the assumption that Vilnius is the dominant region and the results obtained seem to be compatible with this assumption. In the three applications of the model, Vilnius was not rejected by Wu-Hausman statistics to be weakly exogenous to most cities and in the best fitting application Vilnius was not rejected to be weakly exogenous for all other cities.

However, there is still a possibility that there might be other forms of pairwise dominance. This possibility is tested in Table 4 with the travel distance weight matrix specification. All cities are allowed to be the dominant and then whether the dominant city is weakly exogenous for other cities is tested using the Wu-Hausman statistic. Results in column 1 repeat the results shown in Table 1 that Vilnius can be regarded as weakly exogenous for three cities and cannot be regarded as weakly exogenous for Kaunas. Similar results are obtained with assuming Kaunas to be dominant, in this case Kaunas cannot be regarded as weakly exogenous for Vilnius. Assuming Klaipėda to be dominant results in two rejections of the null hypothesis. Interestingly both Šiauliai and Panevėžys can be regarded as weakly exogenous for all other cities.

These results do not directly show what city or cities are dominant, as the only test being done is whether the residuals from the assumed dominant region are a statistically significant predictor in the price equations of the other cities. So, this in effect tests the fit of the assumed dominant region to the whole model setup, so to choose a dominant region a wider consideration is needed. These results show that Šiauliai and Panevėžys, assumed to be dominant, would fit the model well, however they do not show if these setups effectively demonstrate the spatial and temporal diffusion of house prices in Lithuania, also Vilnius or Kaunas could possibly be shown to be more valid dominant regions with a higher lag order chosen.

Table 4

Wu-Hausman statistics for testing the exogeneity of house prices of the assumed dominant region with the travel distance weight matrix specification.

		Assumed Dominant region				
		Vilnius	Kaunas	Klaipėda	Šiauliai	Panevėžys
Price equation	Vilnius	-	0.30**	-1.06**	0.25	0.14
	Kaunas	1.02**	-	-1.15***	0.09	0.11
	Klaipėda	0.57	0.32*	-	-0.01	0.08
	Šiauliai	0.76	0.03	0.36	-	0.19 *
	Panevėžys	1.01	0.04	-1.44	0.11	-

*The Wu-Hausman statistic is computed with the procedure described above, H_0: $\lambda_i = 0$. *** signifies that the test is significant at the 1% level, ** at the 5% level, * at the 10% level. Source: prepared by the author on the basis of the research.*

Table 5

The Results of Johansen Cointegration Tests with Unrestricted Intercepts and Restricted Trend Coefficients, Real House Prices indexes of Five largest Lithuanian Cities.

	Johansen test statistic	
	H_0: $r = 0$ vs H_1: $r \geq 1$	H_0: $r \leq 1$ vs H_1: $r = 2$
Kaunas	28.1 **	7.07
Klaipėda	29.79 **	8.62
Šiauliai	25.43 **	9.94
Panevėžys	28.48 **	11.82 *

*The Johansen tests were done for each city individually. *** signifies that the test is significant at the 1% level, ** at the 5% level, * at the 10% level. Lag order chosen by Hannan–Quinn information criterion. Source: prepared by the author on the basis of the research.*

What is not shown in these results is that assuming Šiauliai to be dominant produces results where only one error correction term is estimated, that being in the equation of the dominant region itself and assuming Panevėžys to be dominant results in no error correction terms being estimated for Kaunas and Vilnius. Of course, assuming Vilnius to be dominant results are obtained where no error correction terms are estimated in the equation of Panevėžys. Overall, these results seem to suggest that comparatively, Panevėžys flat prices are more independent of the two biggest cities then other cities.

Cointegration was tested between Vilnius and the other cities, results are presented in Table 5. All 4 smaller cities' index values were found to be cointegrating with Vilnius, suggesting a long run relationship between the dynamics of the prices. However, if the Vilnius prices are long run causal for other cities is a question for future research. Granger causality tests were conducted to find Granger causality relationships between the prices, Vilnius real price index was found to be Granger causing real price indexes for all other cities. But all cities' real price indexes were found to be Granger causing all other cities' real price indexes. Granger causality test does not distinguish between long-term and short-term effects and does not allow for short term feedbacks from the non-causal to the causal regions. What the Granger causality test results showed is the possibility of spatial interconnectedness that the model used is designed to capture where all regions influence each other but have varying effects.

4.2 On the Choice of the Order of Lags

In the application described I use a one lag length description of the model. While this restricts the model when comparing with Holly at al. (2011), most of the lag orders chosen in Holly at al. (2011) were equal to one. To test if the predetermined lag order of one is incorrect for the model, I use the Durbin Watson statistic. The statistic is constructed between 0 and 4, with value of two indicating that there is no autocorrelation (Fox, 2016). Results are presented in Table 6. No statistic is found to be statistically significant at the 5% level meaning that higher order lags are not strictly necessary and the estimates for φ_{i0} are reliable.

Table 6

Durbin Watson statistics for the residuals of each equation of each model specification.

		Equation				
		Vilnius	Kaunas	Klaipėda	Šiauliai	Panevėžys
Model specification	Travel distance	2.22 *	2.18	1.83 *	1.98	2.14
	Migration	2.21 *	2.07	1.94	1.99	2.11
	Optimized	2.22 *	2.07	1.83 *	1.98	2.14

*Durbin-Watson statistics and their bootstrapped p-values. *** signifies that the test is significant at the 1% level, ** at the 5% level, * at the 10% level. "Travel distance" refers to Travel distance weight matrix specification, "Migration" refers to Net internal migration by county weight matrix specification, "Optimized" refers to Endogenously RSS minimizing weight matrix specification. Null hypothesis: First-order autocorrelation does not exist. Source: prepared by the author on the basis of the research.*

However, the Durbin Watson statistic only considers first-order autocorrelation, to test for higher order autocorrelation Breusch-Godfrey test can be used, conducting the test with lag order two, for travel distance weight matrix specification results of Vilnius equation shows that serial correlation of order up to two does not exist. Overall, higher order lags could be included for better fit, however I argue, they are not strictly necessary.

4.3 Spatial-temporal Impulse Responses

The results summarized in tables 1, 2, 3 present a complicated set of dynamic and interconnected relations with the actual estimates providing a narrow picture of the spatio-temporal nature of the relationships. For a wider view of the nature of these relationships we need to trace the profile of shocks both over time and across regions. Conventional impulse response analysis is influenced by past values of the variable in question and other variables. With a spatial dimension included dependence extends in both directions, spatially and temporally (Whittle, 1954).

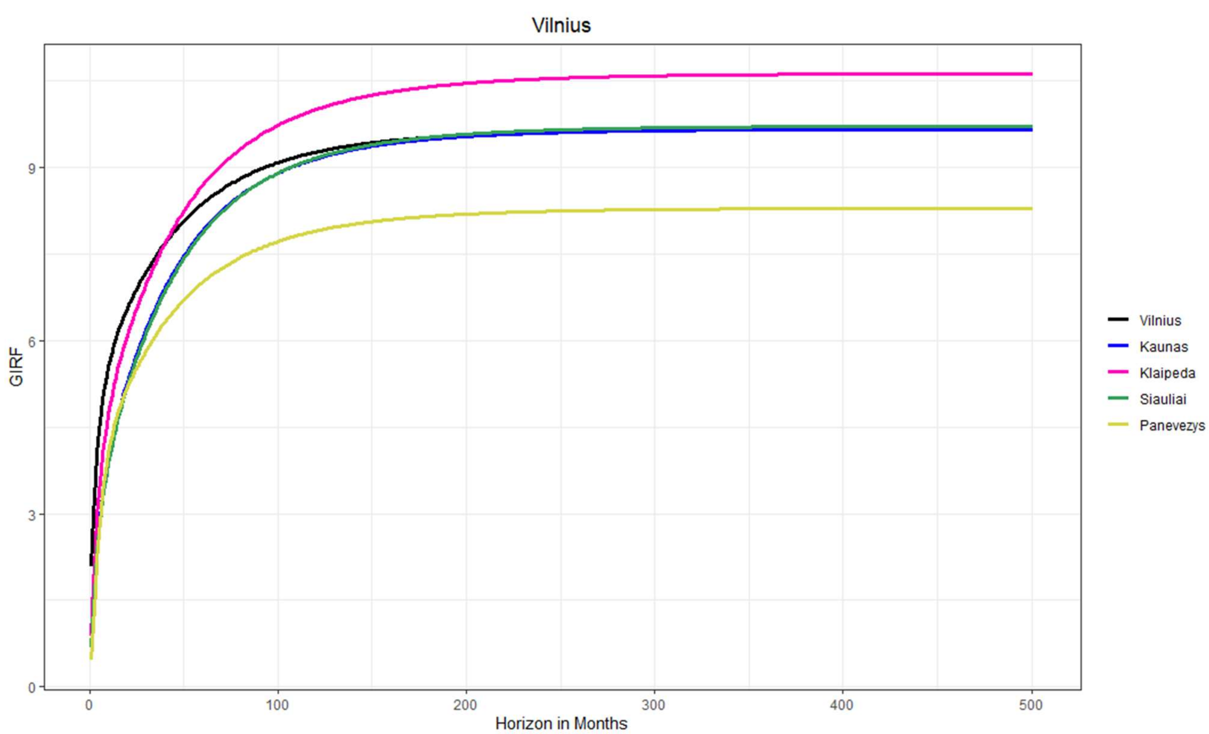
In Figure 2 generalized impulse responses of the effects of a positive unit shock to Vilnius flat price index are plotted with the distance weight matrix specification. Figure 3 presents the 90% bootstrapped error bounds for each region separately.

The positive shock to Vilnius flat price index spills over to other regions gradually, raising prices across the country. The effect is smallest for Panevėžys, highest for Klaipėda, the effects for other cities are very similar. The speed of the adjustment follows this pattern: Panevėžys adjusts the slowest, Klaipėda the fastest (excluding Vilnius itself). The speed of the convergence is similar across all regions. A delayed effect to more distant cities is not observed.

Figure 4 shows the impulse responses to shocks to non-dominant cities. Interestingly Panevėžys responds the most to each of the shocks in the distant responses. In the shock to Kaunas responses the story is similar to the one told by Table 1. Kaunas appears to be a dominant city also having an effect on all other cities, this effect is smaller than the one incurred by a shock to Vilnius price levels. The effect on average is about half of the effect from the capital. Shock to the three smallest cities price levels seem to yield no lasting effects. Klaipėda shock effects seem to be well behaved, having a substantial initial effect and fading. Šiauliai have a similar initial increase and gradual return to zero behavior. Panevėžys flat prices have a similar behavior, however the negative shock to Klaipėda prices and the positive shock to Panevėžys prices are substantial but are unlikely to be significant.

Figure 2

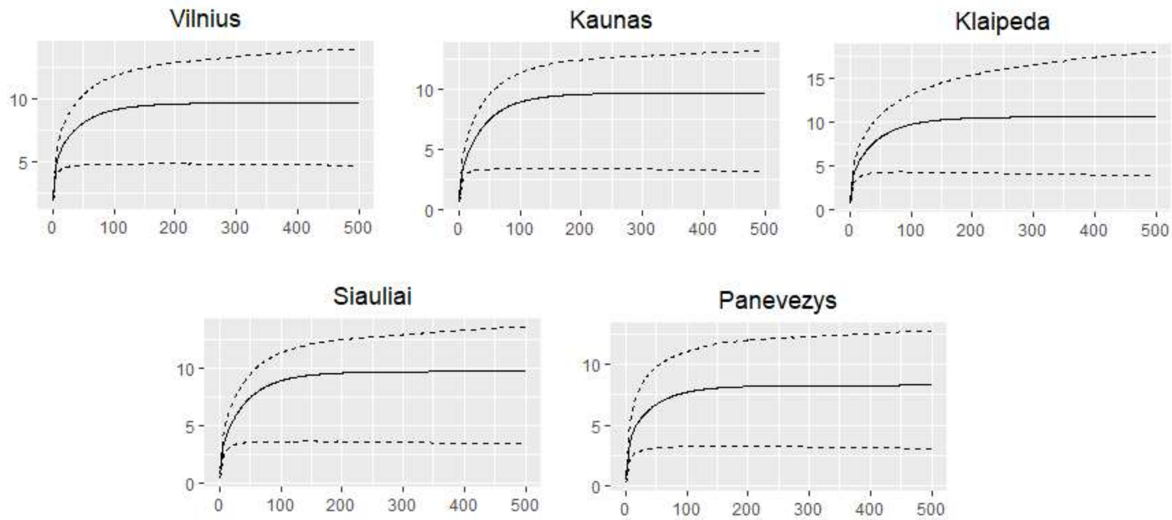
Generalized Impulse Responses of a Positive Unit (one s.e.) Shock to Vilnius House Prices (travel distance weight matrix).



Source: prepared by the author on the basis of the research.

Figure 3

GIRFs for Each Region with the 90% Bootstrap Error Bounds

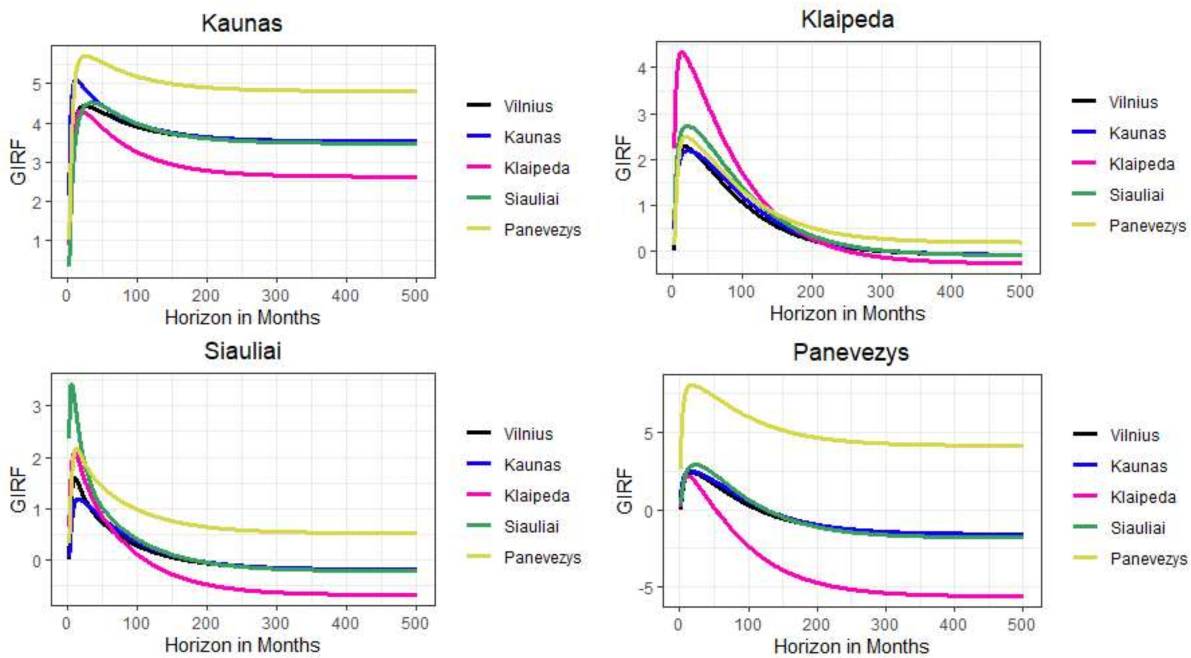


Figures show the mean estimates (solid line) with 90% bootstrap error bounds (broken line, based on 10000 bootstrap samples). Source: prepared by the author on the basis of the research.

The results from Figure 3, Figure 4 and Table 1 suggest a system where Vilnius is the dominant city in Lithuanian flat prices, shocks to the nations' capital have an effect on all other cities, Kaunas is not as dominant, however it is also dominating, the effects of shocks to Kaunas flat prices have a smaller, but still a substantial effect on other cities' flat prices. Klaipėda does not appear to be a dominant city, rather it is highly predictable of and dependent on the fluctuations in the two dominating cities. Šiauliai flat prices appear to be less dependent on the price levels in the capital (the dominant city error correction term is not estimated) than Klaipėda, but the shocks to the price levels in this city do not have a substantial lasting effect on other cities. Lastly, Panevėžys prices are the least impacted by shock to the capital prices and seem to be the most independent of the effects of the capital price fluctuations.

Figure 4

Generalized Impulse Responses of a Positive Unit (one s.e.) Shock to Other Cities' House Prices (travel distance weight matrix).

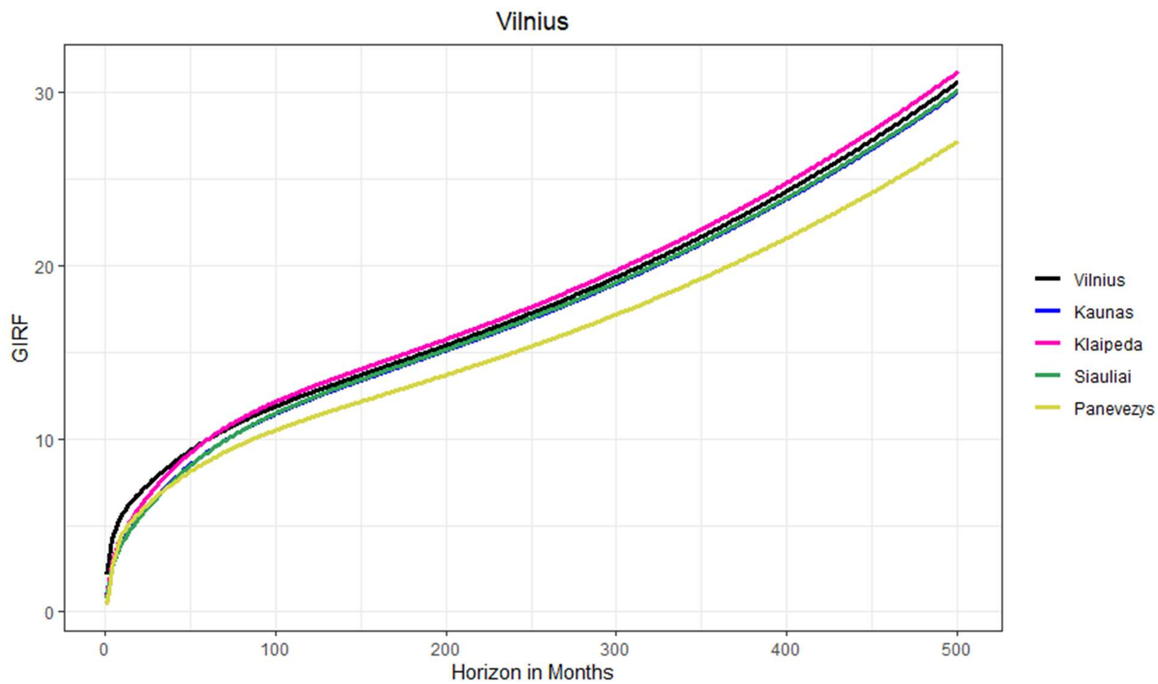


Source: prepared by the author on the basis of the research.

In Figure 5 generalized impulse responses of the effects of a positive unit shock to Vilnius flat price index are plotted with the migration weight matrix specification. The estimated impulse responses are not well behaved, having an upward trend. What causes this is unclear. Results in Table 2 are similar to the ones in Table 1, variance-covariance matrices are also similar, the whole applied procedure is the same, with the exception of the weight values. Estimating the contemporaneous effects disregarding the Wu-Hausman test results yields almost identical GIRF results. The conclusion is straightforward though, the weights used are a bad fit for the data with the procedure described above. The generalized impulse responses of the effects of a positive unit shock to other cities flat price indexes produce downward sloping results for all cities. I think these results are important as they show the sensitivity of the model of the weight matrix, producing varying and sometimes spurious results.

Figure 5

Generalized Impulse Responses of a Positive Unit (one s.e.) Shock to Vilnius House Prices (migration weight matrix).



Source: prepared by the author on the basis of the research.

In Figure 6 generalized impulse responses of the effects of a positive unit shock to Vilnius flat price index are plotted with the endogenously optimized weight matrix specification. Results are very similar to the ones in Figure 2; however, the responses seem to flatten out slightly faster and all the responses are higher compared to Figure 2. Figure 7 shows the impulse responses to shocks to non-dominant cities. Results for shocks to Klaipėda, Šiauliai and Panevėžys are very similar to the ones in Figure 4. Results for Kaunas are substantially different, they are more similar to Panevėžys instead of another dominant city besides Vilnius.

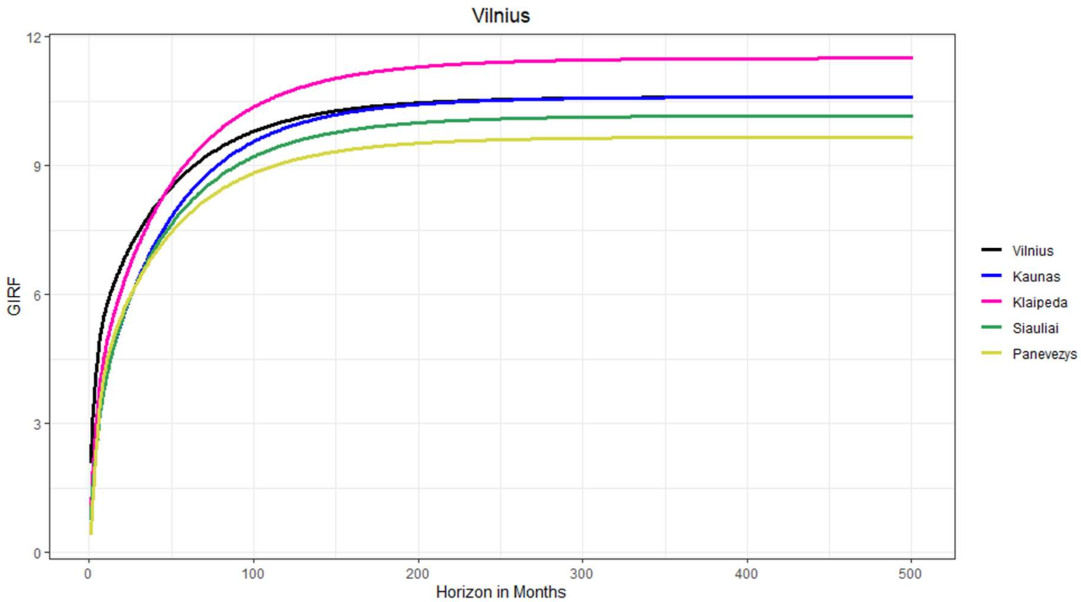
One more interesting result that can be seen in all estimated generalized impulse responses: responses from Kaunas and Vilnius are extremely close. Both cities flat prices respond very similarly to shocks in all five tested Lithuanian cities. Another result is the ranking of responses. The order of magnitude of response to shock to dominant city is flipped for all other cities' shocks. This is clear in Figures 6 and 7, not as clear, but still visible in Figures 2 and 4. Taking the Figures 6 and 7 as example: responses to Vilnius shock are ordered highest to lowest:

- Klaipėda, Vilnius and Kaunas, Šiauliai, Panevėžys.

However, this order is reversed for the other four GIRFs.

Figure 6

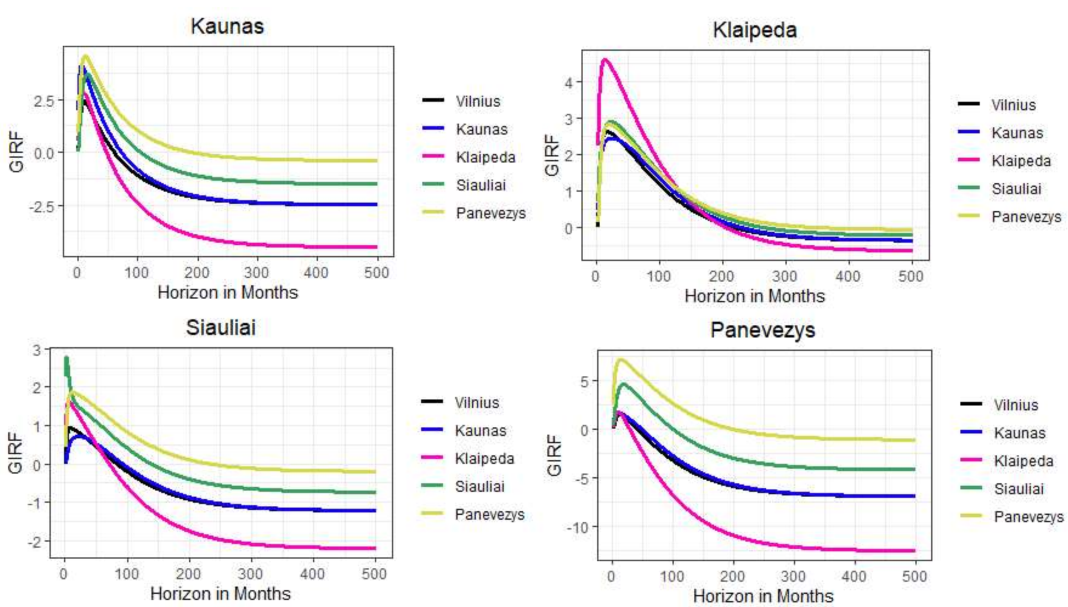
Generalized Impulse Responses of a Positive Unit (one s.e.) Shock to Vilnius House Prices (endogenously optimized weight matrix).



Source: prepared by the author on the basis of the research.

Figure 7

Generalized Impulse Responses of a Positive Unit (one s.e.) Shock to Other Cities' House Prices (endogenously optimized weight matrix).



Source: prepared by the author on the basis of the research.

5. Recommendations

I expand the model proposed by Holly at al. (2011) allowing for dominant cities to not dominate some of the cities. This approach makes this model more widely applicable for approaches where a unit is dominant, but not completely for all other units. Overall, the model fits systems with small N and confined areas well, for larger systems where multiple nearby area dominating cities might exist, for example a model of several countries where dominant regions or cities are the capitals, this approach could be expanded to create a system where dominant area regions or cities interact between each other and then the result from the interactions spills over to non-dominant regions or cities. The model can also be used for other questions, perhaps it could be used to analyze monopolistic markets.

For policymakers the results emphasize the relations between cities' housing prices and inform to consider the relationships as investment into a dominant region might produce better overall results for all regions then if spending was allocated to a non-dominant region.

6. Conclusion

This paper uses the approach proposed by Holly at a. (2010) to model spatial and temporal dispersion of shocks in non-stationary dynamic systems using the data for five largest Lithuanian cities. In the paper I show that Vilnius can be considered a dominant city for Lithuania. I estimate the house price equations with the Ober-Haus flat price index real values with Vilnius as the dominant city, I show that prices within each city respond to a shock to Vilnius prices and the shock is amplified both by internal dynamics of each region and by interactions with other cities using the spatio-temporal impulse response functions.

Results suggest that shocks to Vilnius have the highest effects on all cities, and the shocks decay about equally between cities. The effect of shocks to the capital is highest to Klaipėda and shocks to Klaipėda appear to have the smallest effect overall.

The housing market is an important field in economic research, this paper provides additional information on spatial interactions between city housing prices in Lithuania. Future research could focus on prediction capabilities when controlling the spatial effects or effects of local downturns for national economies.

7. References

Ambrasas, G. & Stankevicius, D. (2007). An analysis of dwelling market in Vilnius, Lithuania. *International Journal of Strategic Property Management*, 11, 243-262. https://www.tandfonline.com/doi/abs/10.1080/1648715X.2007.9637572

Anselin, L. (2010). Thirty years of spatial econometrics. *Papers in Regional Science*, 89, 3-25. https://doi.org/10.1111/j.1435-5957.2010.00279.x

Bauman, D. (2018). Optimizing the choice of a spatial weighting matrix in eigenvector-based methods. *Ecology*, 99, 2159-2166. https://doi.org/10.1002/ecy.2469

Choi, D., Chung, C.Y., Young, J. (2019). Are Economic Distance and Geographic Remoteness Important in Sustainable Trade? Evidence from the Bilateral Trade between China and Kazakhstan. *Sustainability* **2019**, 11(21), 6068. https://doi.org/10.3390/su11216068

Cliff, A. & Ord, K. (1973). *Spatial Autocorrelation*. Pion.

Corrado, L. & Fingleton, B. (2011). Where is the economics in spatial econometrics? *Journal of Regional Science*, 52, 210-239. https://doi.org/10.1111/j.1467-9787.2011.00726.x

Dijk, S., Franses, P.H., Paap, R., and van Dijk, D. (2007). Modeling Regional House Prices. *Tinbergen Institute, Erasmus University*, Report EI 2007-55. https://repub.eur.nl/pub/11723/ei2007-55.pdf

Dubin, R. (1998). Spatial Autocorrelation: A Primer. *Journal of Housing Economics*, 7, 304-327. https://doi.org/10.1006/jhec.1998.0236.

Egert, B. & Mihaljek, D. (2007). Determinants of house prices in central and eastern Europe. *Comparative Economic Studies*, 49, 367–388. http://dx.doi.org/10.1057/palgrave.ces.8100221

Fingleton, B. & Gallo, J. (2008). Estimating Spatial Models with Endogenous Variables, a Spatial Lag and Spatially Dependent Disturbances: Finite Sample Properties. *Papers in Regional Science*, 87, 319–339. https://doi.org/10.1111/j.1435-5957.2008.00187.x

Fisher, E., Gilbert, J., Marshall K.G., Oladi, R. (2015). A New Measure of Economic Distance. *CESifo Working Paper Series No. 5362.* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2613881

Fox, J. (2016). *Applied Regression Analysis and Generalized Linear Models*. Sage.

Glaeser, E., Sacerdote, B., and Scheinkman, J. (1996). Crime and Social Interactions. *The Quarterly Journal of Economics*, 111, 507-548. https://doi.org/10.2307/2946686

Gössl, C., Auer, D., Fahrmeir, L. (2001). Bayesian spatiotemporal inference in functional magnetic resonance imaging. *Biometrics*, 57(2):554-62. https://doi.org/10.1111/j.0006-341x.2001.00554.x

Hausman, J.A. (1978). Specifcation tests in econometrics. *Econometrica*, 46, 251-272. https://doi.org/10.2307/1913827

Holly, S., Pesaran, M.H. & Yamagata, T. (2011). The spatial and temporal diffusion of house prices in the UK. *Journal of Urban Economics*, 69, 2-23. https://doi.org/10.1016/j.jue.2010.08.002.

Ivanauskas, F., Eidukevicius, R., Marcinskas, A., and Galiniene, B. (2008). Analysis of the housing market in Lithuania. *International Journal of Strategic Property Management*, 12, 271-280. https://journals.vilniustech.lt/index.php/IJSPM/article/view/6770/5850

Jadevicius, A. & Houston, S. (2015). ARIMA modelling of Lithuanian house price index. *International Journal of Housing Markets and Analysis*, 8, 135-147. http://dx.doi.org/10.1108/IJHMA-04-2014-0010

Koramaz, T. K. & Dokmeci, V. (2012). Spatial Determinants of Housing Price Values in Istanbul. *European Planning Studies*, 20:7, 1221-1237. https://doi.org/10.1080/09654313.2012.673569

Lam, C. & Souza, P. (2020). Estimation and Selection of Spatial Weight Matrix in a Spatial Lag Model. *Journal of Business & Economic Statistics*, 38:3, 693-710. https://doi.org/10.1080/07350015.2019.1569526

Ober-Haus. (2022-01-20). *Lithuanian Apartment Price Index, December 2021*. https://www.ober-haus.lt/en/research/lithuanian-apartment-price-index-november-2021/

Pace, R. K., Barry, R., and Sirmans, C. F. (1998). Spatial statistics and real estate. *Journal of Real Estate Finance and Economics,* 17, 5–13. https://www.academia.edu/12912875

Pesaran, M.H. & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58, 17-29. https://doi.org/10.1016/S0165-1765(97)00214-0

Pesaran, M.H. & Yang, C. (2021). Estimation and inference in spatial models with dominant units. *Journal of Econometrics*, 221, 591-615. http://dx.doi.org/10.1016/j.jeconom.2020.04.045

Potepan, M.J. (1994). Intermetropolitan Migration and Housing Prices: Simultaneously Determined? *Journal of Housing Economics*, 3, 77-91. https://doi.org/10.1006/jhec.1994.1001.

Statistikos departamentas. (2022-03-01). *Population of Lithuania (edition 2020)*. https://osp.stat.gov.lt/en/lietuvos-gyventojai-2020/gyventoju-migracija/vidaus-migracija

Whitlle, P. (1954). On stationary processes in the plane. *Biometrika*, 41, 434-449. https://academic.oup.com/biomet/article-abstract/41/3-4/434/230856

Wu, D.M. (1973). Alternative tests of independence between stochastic regressors and disturbances. *Econometrica*, 41, 733-750. https://www.proquest.com/openview/82b9d87027ea95c5b40805fef07b06ba/1?pq-origsite=gscholar&cbl=48032

Wu, G., Li, J., Chong, D., and Niu, X. (2021). Analysis on the Housing Price Relationship Network of Large and Medium-Sized Cities in China Based on Gravity Model. *Sustainability* **2021**, *13*, 4071. https://doi.org/10.3390/su13074071

SPATIAL AND TEMPORAL DIFFUSION OF FLAT PRICES IN LITHUANIA

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Bachelor Thesis

Quantitative Economics programme

Faculty of Economics and Business Administration of Vilnius University

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Vilnius, 2022

Summary

34 pages, 7 figures, 6 tables, 27 references.

The main aim of this academic work was to determine how do flat price changes in the assumed dominant city (Vilnius) affect flat prices in other cities in Lithuania. The paper consists of three main parts: literature analysis, the methodology and data used and results, conclusions, and recommendations.

This paper uses a recently developed method to analyze the temporal and spatial characteristics of a dynamic system of house prices. Firstly, I discuss how the approach is conducted and what is changed so the model fits the data better, next I discuss how the results are used to construct generalized impulse response functions that are used to interpret the results. Next, the data used is described and the results are presented.

The results suggest that Vilnius has an important role for the flat prices in other cities. Shocks to the capital have lasting effects. All identified interrelationships have an important role to play in future policy and research.

ERDVINĖ IR LAIKINĖ BUTŲ KAINŲ SKLAIDA LIETUVOJE

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Vilnius Universiteto Ekonomikos ir verslo administravimo fakultetas

Darbo vadovas – Dr. Povilas Lastauskas

Vilnius, 2022

Santrauka

34 puslapiai, 7 paveikslai, 6 lentelės, 27 literatūros šaltiniai.

Pagrindinis šio akademinio darbo tikslas buvo nustatyti, kaip butų kainų pokyčiai tariamame dominuojančiame mieste (Vilniuje) veikia butų kainas kituose Lietuvos miestuose. Darbą sudaro trys pagrindinės dalys: literatūros analizė, panaudota metodika ir duomenys bei rezultatai, išvados ir rekomendacijos.

Šiame darbe naudojamas neseniai sukurtas metodas dinamiškos būsto kainų sistemos laiko ir erdvės charakteristikoms analizuoti. Pirmiausia aptariama, kaip taikomas metodas ir kas keičiama, kad modelis geriau atitiktų duomenis, toliau aptariama, kaip rezultatai naudojami kuriant apibendrintas impulsinio atsako funkcijas, kurios naudojamos rezultatams interpretuoti. Toliau aprašomi panaudoti duomenys ir pateikiami rezultatai.

Rezultatai rodo, kad Vilnius vaidina svarbų vaidmenį butų kainoms kituose miestuose. Šokai sostinėje turi ilgalaikį poveikį. Visi nustatyti tarpusavio ryšiai yra svarbūs būsimoje politikoje ir tyrimuose.