Lisbon School of Economics & Management
Universidade de Lisboa

MASTER

APPLIED ECONOMETRICS AND FORECASTING

MASTER´S FINAL WORK

DISSERTATION

A SPATIAL ECONOMETRIC APPROACH ABOUT THE HEDONIC HOUSE PRICES IN MAINLAND PORTUGAL

MARTA SOFIA LAURINDO CRUZ

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SUPERVISION:
PROFESSOR DOCTOR LUÍS FILIPE ÁVILA DA SILVEIRA DOS SANTOS

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To the loving memory of my grandparents.

ABSTRACT

The lack of stability that characterizes the house market encourage a discussion about the main drivers of real estate valuation. Modelling it has for long been recognized as a central investigation area. Using STATA software, this dissertation is based on an empirical analysis of the role of locational amenities and socioeconomic attributes of neighbourhoods that may affect and be responsible for the price that is attributed to residential houses. This study focuses on the median house price in the 278 municipalities of mainland Portugal, between 2016 and 2020. The housing market was modelled in a spatial econometric context using the Spatial Durbin Model and then examining the effect of contiguous municipalities using a weighting matrix. The results show evidence of spatial autocorrelation between real estate prices, proving that the placement of each region plays a critical role. The same results show that variables such as salary, the number of hospitals, the number of tourist accommodations and cultural spaces significantly increase housing prices.

KEYWORDS: Real estate; House prices; Spatial econometrics; Panel data; Spatial Durbin Model.

JEL CODES: C13; C33; R23; R30.

RESUMO

A falta de estabilidade que caracteriza o mercado imobiliário estimula a discussão sobre os principais fatores que afetam a sua valorização. Através do software STATA, este artigo faz uma análise empírica do papel das amenidades locais e atributos socioeconômicos das regiões que podem afetar e ser responsáveis pelo preço atribuído aos imóveis residenciais. Este estudo foca-se no preço mediano da habitação nos 278 concelhos de Portugal Continental, entre 2016 e 2020. O mercado da habitação foi modelado num contexto econométrico espacial utilizando o modelo espacial de Durbin e examinando o efeito de municípios contíguos através de uma matriz de ponderação. Os resultados mostraram evidências de autocorrelação espacial entre os preços das casas, comprovando que a localização desempenha um papel fundamental. Os mesmos resultados mostram que variáveis como o salário, a quantidade de hospitais, de alojamentos turísticos e espaços culturais, aumentam significativamente os preços da habitação.

PALAVRAS-CHAVE: Mercado imobiliário; Preços das casas; Econometria espacial; Dados em Painel; Modelo de Durbin Espacial.

CÓDIGOS JEL: C13; C33; R23; R30.

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GLOSSARY

Municipal Property Tax (IMI)

Municipal Tax on Real Estate Transfer (IMT)

INE – Statistics Portugal (Instituto Nacional de Estatística)

JEL – Journal of Economic Literature.

LISA – Local Indicators of Spatial Association.

LMA – Lisbon Metropolitan Area.

MFW – Master's Final Work.

MSA – Metropolitan Statistical Area.

OLS – Ordinary Least Squares.

OMA – Oporto Metropolitan Area.

SAR – Spatial Autoregression

SDM – Spatial Durbin Model.

SEM – Spatial Error Model.

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1. INTRODUCTION

The real estate market has a strong importance in the society in a way that everyone needs a house to live. Despite that, this kind of asset might be the most valuable of people's wealth and has been increasingly seen as a good kind of investment. Indeed, in the most developed countries the price of residential houses impacts in a great way both consumption and saving opportunities (Case, Clapp, Dubin & Rodriguez, 2004). Therefore, the prices practiced in the housing market are an important area of concern to financial institutions, lawmakers and, of course, all population as actual or potential homeowners (Schulz & Werwatz, 2004).

Having in mind that housing has as main characteristics durability and spatial fixity, when we come across the rushing of urbanization, the intensification of the inflow of people to the town, as well as the expansion of the extension of the city, easily seen in both Lisbon and Oporto metropolitan areas, with the peripheral municipalities showing very high population growth (Rosa, 2000), an adequate understanding of what motivates the prices that have been practiced in Portuguese houses is essential, even more due to the financial crisis experienced in recent times that makes a great amount of new habitants to be in the weakest border of financial circumstances, facing the high housing prices practiced in the cities.

The real estate market may suffer influence from macro-economic variables, amenities of the environment and municipal features (Kim, K., & Park, J., 2005), a simple example of the first are the credit booms, a really solid prediction of booms in the housing market (Ceruti et al., 2017). The 2008 financial recession declined the will of banks in lending, causing deteriorations mutually in house sales and their prices, particularly in nations where previously they have been rising, leading to inferior household wealth, and intensifying the crisis (Vale, S., & Snyder, T., 2022).

With nowadays incessant development of urbanization and socio-economic conditions, the right attention and improvement should be given to the issue of the real estate prices, as a community problem. In this line, the central concern of this research lies in the identification of which are the most important external factors and locational amenities, selected from a numerous of identified variables, affecting, and influencing the house prices in Portugal. This dissertation uses the median house values in the 278 municipalities of mainland Portugal as a proxy of valuation, between the years of 2016 and 2020.

Portugal, besides being a small country in terms of area, passed through a huge development of houses and infrastructures in the last decade. Given this, our country represents an exclusive case study for analysing the influence of a number of variables on the housing market in a countrywide framework (Januário J. et al., 2021).

To this regard, this paper applies the most recent spatial statistical methods and tools to the panel data, in order to properly analyse factors such as spatial dependence and heterogeneity, commonly observed in studies related to real estate econometrics. As a result, it is possible to correctly identify the importance of geography and spillover effects between housing prices and the external factors, not only in the Lisbon Metropolitan Area (LMA) and Oporto Metropolitan Area (OMA), but also in the surrounding municipalities. To analyse such effects, in combination with the study of spatial dependence using the global Moran´s I test, a spatial regression model is applied, the Spatial Durbin Model (SDM).

This thesis is organized in five chapters. After this introduction, chapter two presents the literature review. Chapter three presents the main methodologies used, as well as its advantages. The explanation of steps for building this work, the data, results, and relevant discussion are described in chapter four. Ultimately, the fifth chapter draws the conclusions of the study, together with its limitations and suggestions for future research.

2. Literature Review

2.1. The housing market

Housing goods stand out from other kind of goods because of its unique characteristics. The most common features of housing are the duration, - which leads to a low rate of substitution of goods - spatial fixity, - directly linked to location, has a great influence in its price – and heterogeneity - there are not two equal houses. This market is very distinct from the rest in a way that the liquidity of the goods is low, and it is a very regulated market, experiencing big government intervention namely legislation, taxation, rent control, price policies, transaction costs, subsidies, and limitations on the involvement of banks (Laskowska, 2016).

Domestic accommodation has a crucial role in the quality of life of any society, and the housing market in Portugal has experienced an improvement in the past three decades. With the abolition of certain controls in the financial market, and after joining the European Union, it became easier and cheaper to access credit, contributing to a movement of more transactions in construction and properties, in the long run (Januário J. et al., 2021).

Since 2006 that house prices in the EU have been fluctuating, experiencing annual growth rates of about 8% in 2007, right before the decline of 4% in 2009 due to the financial crisis. Despite that, it was in 2014 that real estate prices began to soar again. Generally, from 2010 until 2017, property prices increased by 11%. The proportion of the population with their own property remained stable, at around 70%, throughout the period from 2010 to 2016, with tenants remaining at around 30%, in fact, housing costs represent a burden for part of the population. In 2016, around 11% of the EU population spent 40% or more of their disposable income on housing, which is considered an excessive cost (INE, 2018).

In the particular case of Portugal, in the years from 2007 until 2013, house prices decreased 16.3% in nominal terms (22.0% in real terms). In 2014, with the beginning of the economic recovery, prices have risen on average 5.3% each year and in 2017 were at the same levels of pre-crisis years. This recovering occurred due to a number of factors that lead to a more favourable economic environment, such as the unemployment rate that fell from 17.3% to 8.5%, between 2013 and the 3rd quarter of 2017 (CaixaBank Research, 2017).

The recent event of COVID-19 pandemic has been affecting the entire world since March of 2020, causing severe global economic disruption. Many foreign buyers hesitate to invest in real estate business due to the result of Brexit and the COVID-19 pandemic. On the other hand, Portugal's housing market hardly fluctuated, considering other prices rising in 2020 such as basic food products like fruit, vegetables, and edible oils, but also liquid fuels and gas, along with banking and health insurance (INE, 2022). In Portugal, the soaring tendency of property prices during the past 10 years persisted in 2020, despite the pandemic. Housing prices grew, on average, 5.9% in 2020. In the 3rd quarter of 2020, when comparing with the homologous period, house prices in Portugal increased by 7.1% (Idealista, 2021).

Data for 2021 from the INE reveals that the Portuguese Housing Price Index showed an average annual change of 9.4%, more 0.6 percentage points than that recorded in 2020. The rise in prices was more intense in used houses (9.6%) compared with new ones (8.7%). 165,682 homes were traded, 20.5% more than in 2020. Existing dwellings showed an increase of 22.1% in number of transactions and 34.2%, in price. Regarding new housing, the number of transactions registered an increase of 12.9% and their price an increase of 21.7%.

According to Eurostat, for five consecutive years, the price of houses on the Portuguese market has annual changes of more than 6%, a value from which the European Commission considers that the market is at risk of a price bubble. In Portugal, the peak was recorded between 2018 and 2019 with annual increases of 6-8% in this index (Sousa, 2021).

Overall, the development of the housing market in Europe in the past ten years is notorious. Real estate prices have risen 30.9% from 2010 until the first quarter of 2021 in the EU, and in Portugal the rise was about 50% for 11 years. (Sousa, 2021).

The next chart shows the House Price Index for Portugal and the EU between 2006 and 2021.

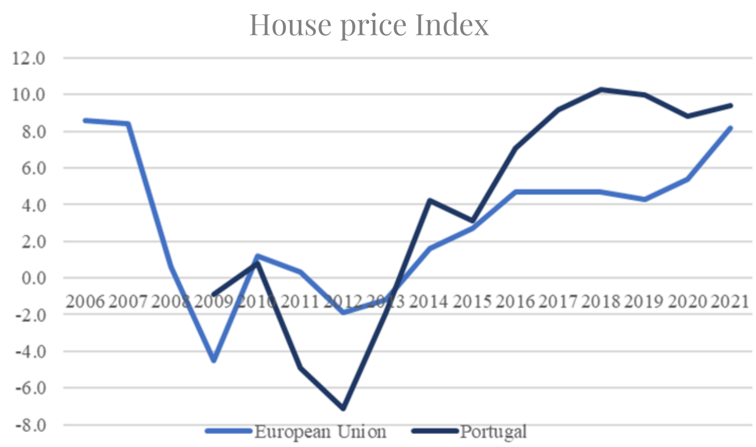

Figure 1 - House price index – annual average rate of change

Source: INE - Own elaboration; Software: Microsoft Excel.

2.2. The Hedonic Pricing approach

When constructing an index of “usefulness and desirability”, the term *hedonic* arises as it describes the weighting of the relative importance of various components that adjust the specification of the variable’s price under study (Goodman, 1998). Rosen (1974) definition of hedonic prices states that they are the inherent prices of products that are exposed to the economic agent by observing the prices of distinguished attributes, and the precise characteristics that they have associated.

It is on the Lancaster (1966)’s consumer theory that the hedonic price model is based. This idea has then been applied to the housing market by Rosen (1974), who placed theoretically how to calculate the hedonic price of a good, i.e., its implicit value (bid price, φ). It was specified as the maximum amount of money that an agent is willing to pay for a product beneath the condition that a specific level of utility is preserved. To do so, Rosen (1974) proposes considering the information that comes from the point where both consumers and producers have the same equilibrium condition, that is, the tangent of the market price curve. The function that establishes the minimum amount a producer might agree to sell a good, is the offer function. This relationship is shown in Figure 2 (Hidano, 2002).

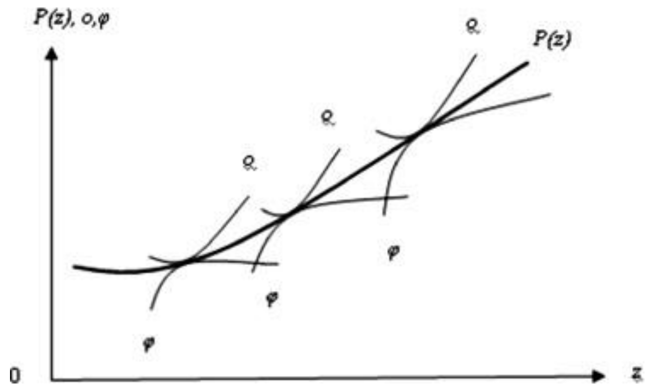

Figure 2 - Hedonic price function (Hidano, 2002)

When analysing distinguished goods, like houses, the functions of the hedonic price theory are useful due to the non-observable market values of its individual characteristics. In real estate researches, the hedonic model estimation has been used for doing inferences about values of different features that cannot be observed, namely the traveller access (e.g., railway and subway), airport noise, neighbourhood amenities, air quality (Janssen, Soderberg, & Zhou, 2001) and structural attributes that contains the tangible assets of the property, such as the dimension of the house, the year constructed, the number of bedrooms, bathrooms, that might outline the internal features of the houses (Can, 1992).

Under the hedonic pricing approach, the property is seen as a heterogeneous good in the sense that the utility of households is affected by the intrinsic and extrinsic characteristics of the property. In this way, consumers choose the asset based on quality and price, rather than quantity and price, evaluating each of the characteristics separately, despite the good being consumed together with all its features. Beneath the hypothesis that agents maximize utility, the implicit price is the maximum sum of money the agent wants to give for the attributes, whether referring to those of the property or of the municipality (Campos, 2018). The hedonic model is seen as a possible solution to know more about the determining factors of real estate prices in a way that it allows reducing the degree of subjectivity.

2.3. Real Estate determinants

The analysis of the housing market has had several contributions that resulted in abundant conclusions on the motivating influences of housing price. Beyond the characteristics of the property itself, that with no doubt influenced its price, the forces coming from the processes of urban agglomeration must be considered, which reflect in the configuration of urban space and in the prices of real estate (Loibl et al., 2018).

In this way, it is necessary to study the spatial factors capable of affecting the price of residential properties. With the aim of overcoming the limitation of traditional micro fundamentalist models (Alonso 1964; Mills 1967; Muth 1969), Brueckner et al. (1999) brings to the table the importance of amenities, i.e., qualities of the geographic space capable of altering the price of real estate. They are in fact demand-side factors based on economic fundamentals, - such as the salary, and the percentage of people unemployment – resident population, and living conditions services - education, and medical. (Zang et al., 2015; Fang et al., 2018; Lan et al., 2018; Wen et al., 2013). As pointed out by Gan et al. (2018), in those areas where the unemployment is higher, the demand for housing will be lower, essentially because it is linked to stronger credit conditions due to job uncertainty.

Another of those factors is the immigration, whose impact in housing prices has been an important area of study by a lot of investigators. Using data on American MSAs, it was estimated by Saiz (2007) that an 1% influx of immigration in a town's habitants were linked with rises in real estate prices of about 1%. Analogous findings were obtained in other nations. In Canada, Akbari and Aydede (2012) examined how immigration influenced housing prices and the findings indicated that when the immigrant share of population rises by 1% it increases property prices, although by only a portion of a percent. More related with the Portuguese reality are the dramatic findings stated by Gonzalez and Ortega (2013). They concluded that Spain's immigration in the 2000s was in charge for a rise of 52% in housing prices. They also pointed out that 37% of the recent construction were owed to immigrants because they contributed to the supply of labour in construction. Despite all that, there are a lot of reasons for hoping for the opposite effect, explaining the outcomes of some investigators such as Accetturo et al. (2014) who advocated that residents could observe a decline in amenities, directly linked to the arrival of immigrants, making the local escape from those regions with a high immigrant rate, and in consequence decelerating price growth.

Along the same line, the effects of property taxes were noticed to impact negatively housing investments as the rents and real estate prices decrease if the tax increases in the short run (Löffler & Siegloch, 2017).

Another significant influence on home prices is the purchasing power, as housing prices tend to fall when the consumer purchasing power drops (The Source of Home Price Movement, 2021). Therefore, property prices are positively correlated with the salary received and wealth level in the population, and negatively correlated with mortgage interest rates. Despite that, some studies indicate that the relationship between housing prices and income may well be negative at times. (Özmen et al., 2019, Case & Shiller, 1988). Holly et al. (2010) found that property prices and per capita income are cointegrated with coefficients (1, -β), meaning that they are strongly related in the long term, so, whether they grow or decrease, they do so in a synchronized way and maintain this relationship over time.

The reality is that threats to the price of what might seem an investment to increase the household wealth do exist and might reduce its demand. An example is criminality, which might decrease the attractiveness of proprietorship in impacted districts (Tita et al., 2006). A very significant factor to have in consideration when purchasing a property is the crime rate (Angelov, 2020).

The aging is also an aspect to be considered, in the way that the demography in Portugal has been shifting in the past decades. Portugal registers an old population and the second smallest birth rate in the EU (CaixaBank Research, 2019).

Other factors that might impact house prices are tourism, gross domestic product, domestic credit, and population density (Égert & Mihaljek, 2007; Paramati & Roca, 2019; Sutton, Mihaljek & Subelyte, 2017).

Following what was presented, and as panel data are frequently used to study the prompting reasons of the residential house price dynamics, the main focus will be on evaluating the impact of some factors - crime rate, resident population, remuneration, unemployment, number of hospitals, number of cultural properties, urban waste, mortality rate, volume of non-financial companies, tourist accommodation, IMT and IMI – on the Portuguese housing prices between 2016 and 2020.

3. Spatial Econometrics: Methodology

This chapter describes the methodology applied, presenting the details of the procedures and spatial panel econometric techniques used. In order to validate the spatio-temporal relationship and the spatial heterogeneity of houses selling prices, in this dissertation the econometric model selection acted in accordance. Having in mind the spatial autocorrelation of real estate prices amongst distinct municipalities, since the observations of the dependent variable are impacted by the adjacent ones, a spatial panel data model was chosen, in particular the Spatial Durbin Model.

3.1. Spatial Econometrics motivation

The record of efforts to account for spatial effects in housing prices evaluation is long. Back in the late 70's, Goodman (1978) and Li & Brown (1980) explored spatial effects at a neighbourhood level. The housing market, a market that has as mantra "location, location, location", is appropriate to profit from the developments of spatial econometrics (Cohen & Coughlin, 2008).

The first principle of geography determines that everything is connected to everything, although objects nearby are more connected than those who are far away (Tobler, 1970). This can be seen as the principal foundation of spatial autocorrelation and/or spatial dependence recognized as the absence of independence among observations (municipalities in this thesis). In practice, it is based on the relation between what occurs at a point (i) and what occurs in a different place (j), that is:

$$y_i = f(y_j), \qquad i = 1, 2, \ldots, n, \qquad j \neq i. \tag{1}$$

Positive spatial dependence implies that superior or inferior values of a variable have a tendency to gather in space, known by clustering, and negative spatial dependence occurs when locations manage to be bordered by neighbours with extremely different values.

Therefore, what characterizes Spatial Econometrics is spatial autocorrelation and spatial heterogeneity, (LeSage, 1998). Hubert et al. (1981) defines the concept of spatial autocorrelation,

"Given a set S containing n geographical units, spatial autocorrelation refers to the relationship between some variable observed in each of the n localities and a measure of geographical proximity defined for all n(n-1) pairs chosen from S."

(Hubert et al., 1981, p.224)

Anselin, L (1988) defined the term spatial heterogeneity as the aspects related to the regional science that leads to structural unsteadiness over space, in the form of unlike response functions or fluctuating parameters, as so, the association between y_i and y_j shifts depending on the place.

The last will not be studied in this dissertation because of its complexity and requirement for a Bayesian approach. In contrast, modelling spatial autocorrelation is possible by resorting to models that account for its presence, such as the Spatial Durbin Model (SDM) that will be discussed later.

3.2. Spatial Weights Matrix W

As defined by Anselin & Bera (1998), a spatial weights matrix is a *N*-by-*N* matrix, positive and symmetric, which specifies for every observation (row) the places (columns) that fit into its neighbourhood by setting them as nonzero elements. More formally, w_{ij}=1 when *i* and *j* are neighbours, and w_{ij}= 0 if not. Also, the elements of the weight matrix are nonstochastic and exogenous to the model, being defined *a priori* to avoid *spurious* relationships.

Over the last two decades spatial econometric methods have turn out to be strongly rooted in the literature of the valuation of the residential housing market, nevertheless, a troubling problem has dogged the area for ages: In what way can the appropriate spatial weights matrix be settled?

In spatial models, the spatial weight matrix (W_{ij}) is crucial, however, LeSage & Pace (2009) show that in the majority of cases its specification does not significantly modify the results of the model, deeming the prevalent idea that determining the best suited weight matrix is essential, calling it the “Biggest Myth in Spatial Econometrics”.

The geographic connection criterion of the spatial weight matrix lays on the idea of proximity, which can be defined according to contiguity or geographic distance. The contiguity measures rely on the knowledge that two districts are neighbours as long as they have physical boundary in common, while the distance approach is based on the idea that two geographically close regions have a greater spatial interaction. Regarding the contiguity idea, the problem lies in how the concept of geographic boundary is defined. There are three main criteria to define a geographic boundary, the queen criterion, which not only considers common physical boundaries but also common vertices. The tower criterion which only makes allowance to physical boundaries, and the bishop criterion where, in order to define contiguity, only vertices are considered (Almeida, 2012).

Usually, the most frequently used spatial weight matrices involve the Euclidean distance or the inverse distance. The latter might be the best representation of the arrangement of spatial interaction as it denotes the dampening of the effect of distance on the phenomenon under study, making what is closer to depend more on than what is more distant. That is, closer observations reveal a greater spatial autocorrelation than those that are further away (Almeida, 2012).

The choice of the weighting matrix in this dissertation fell on the inverse distance matrix because it is the one that, in our understanding, suits best the universe under study, by capturing the effect of municipalities that are not neighbours, since we consider that this effect is relevant given the small size of the country (mainland Portugal).

3.3 Dependence Indicator Tests

To analyse spatial dependence in the data, the Moran index suggested by Moran (1950) was undertaken. The Moran-I statistic for panel data is defined as:

$$I = \frac{\Sigma_{i=1}^{N}\Sigma_{j=1}^{N} w_{ij} Z_i Z_j}{S_0 m_2}, \qquad (2)$$

where *N* accounts for the number of observations, w_{ij} corresponds to the elements of the distance matrix **W** that express the spatial interaction between the i and *j*; $Z_i = Y_i - \bar{Y}$, where Y_i represents the value of *Y* at location *i* and $\bar{Y}$ the mean of *Y*; $S_0 = \Sigma_i \Sigma_j w_{ij}$ and $m_2 = \frac{\Sigma_i Z_i^2}{N}$.

The understanding of *I* is similar to the correlation coefficient of Pearson, where the values are limited to the interval [-1, 1]. As a result, when the values are negative an inverse relationship is obtained, that is an association amongst two variables in which one rises as the other declines, and vice versa. When positive, positive relationship comes along, meaning that two variables move together in the same direction. Results that are near to zero mean that no spatial dependence exists.

In this dissertation Moran Diagrams will be presented, with the objective of doing a comparison between the normalized values of a region and its neighbours mean. In this two-dimensional graph with four quadrants, the quadrant 1 (right and above) “high-high” and the quadrant 2 (left and below) “low-low”, reveal indication of positive spatial dependence (clusters), and quadrants 3 (right and below) and 4 (left and above), both “low-high” suggest negative spatial dependence (outliers).

Along the lines of the methodology of Anselin (1995), the allocation of Local Indicators of Spatial Association (LISA) was analysed, with the purpose of detecting potential clusters. LISA is an alternative to the Moran statistics and involves examining spatial association among a variable in a region and the mean of the same variable in neighbouring locations (Xavier, 2014). Generally, we can express a LISA for a variable y_i, observed at location *i*, as a statistic L_i, such that:

$$L_i = f(y_i, y_{Ji}), \tag{3}$$

where f is a function, and the y_{Ji} are the values observed in the neighbourhood J_i of i.

Other local measure of spatial autocorrelation, and an alternative to LISA, is the one introduced by Geary (1954), interesting as it is not reduced to linear relationships. The Geary *c* statistic is defined as (Anselin, 2017):

$$c = \frac{N-1}{4A} \frac{\Sigma_{i=1}^{N} \Sigma_{j=1}^{N} W_{ij} (z_i - z_j)^2}{\Sigma_{i=1}^{N} z_i^2}, \tag{4}$$

where *N* stands for points for which there are observations x_i $(i = 1, \dots, N)$. W_{ij} are the weights from the weight matrix **W**, indicating the existence of a relation between points *i* and j. z_i are the centered observations $z = x_i - \bar{x} = x_i - \Sigma_{j=1}^{N} x_j / N$ and the quantity *A* is defined as $A = \frac{1}{2} \Sigma_{i=1}^{N} \Sigma_{j=1}^{N} W_{ij}$.

Results lower than 1 suggest a slight distinction among an observation and its neighbours, indicating positive spatial dependence, on the other hand results bigger than 1 indicate huge discrepancies among an observation and its neighbours, implying negative spatial dependence.

3.4. Spatial Linear Regression Models

Many empirical studies have overlooked both the spatial and the temporal impacts, in addition to the spatial heterogeneity of real estate prices in neighbouring provinces (Liang et al., 2016). The OLS estimation usually used in the majority of studies is not suitable, because the observations near in the geographical area share the same underlying location characteristics (Tang et al., 2019). Works such as Osland (2010) about housing prices in Norway, and Brasington & Haurin (2006) about the effect of school expenditure on house prices, demonstrate the risks that might arise by disregarding the existence of spatial effects and carry on with the basic OLS – estimated models, once evaluating housing markets. If there is spatial dependence, and it is not taken into consideration when specifying the model, the estimates obtained with OLS will be biased and inconsistent (Anselin & Bera, 1998).

There are a couple of models that motivate efforts in modelling spatial autocorrelation, the spatial lag model, and the spatial error model, but if there is a suspicion of the presence of spatial dependence in both the dependent and independent variables, the Spatial Durbin Model (SDM), presented by LeSage & Pace, 2009, is the most appropriate specification. This model in not only more flexible in taking into account diverse features of spatial autocorrelation, but it is also very attractive because it admits a generic specification - spatial dependence on the dependent variable and on the regressors - stating greater flexibility.

The full Spatial Durbin Model with all types of interaction effects, for a panel of *N* observations over *T* time periods, can be given as (Elhorst, 2011):

$$Y_t = \rho W Y_t + \alpha \iota_N + X_t \beta + W X_t \theta + \mu + \mathrm{u}_t, \tag{5a}$$

$$u_t = \lambda W \mathrm{u}_t + \varepsilon_t, \tag{5b}$$

where **Y** designates an N×1 vector that consists of one observation on the dependent variable for every unit in the sample (i=1,…,N), ι_N is an N×1 vector of ones related with the constant term parameter α, **X** denotes an N×K matrix of exogenous explanatory variables, with the associated parameters β contained in a K×1 vector, and $\varepsilon = (\varepsilon_1, \dots, \varepsilon_N)^T$ is a vector of disturbance terms, where ε_i are independently and identically distributed (*i.i.d*) error terms for all *i* with zero mean and variance σ^2. **WY** denotes the endogenous interaction effects amongst the dependent variables, **WX** expresses the exogenous interaction effects between the independent variables, and **Wu** the interaction effects between the disturbance terms of the different units. ρ is known as the spatial autoregressive coefficient, λ as the spatial autocorrelation coefficient, and θ, like β, denotes a K×1 vector of fixed unknown parameters. **W** is a nonnegative N×N matrix of known constants illustrating the arrangements of the units in the sample. The diagonal elements of **W** are, by assumption, set to zero as long as no unit can be seen as its own neighbour. Finally, $\mu = (\mu_1, \dots, \mu_N)^T$. The spatial and time-period specific effects might be discussed as fixed or random effects. If the fixed effects model is the most suitable, a dummy variable must be introduced for each spatial unit and for each time period, but one to prevent multicollinearity. In contrast, if it is the random effects model, μ_i is handled as a random variable that is *i.i.d* with zero mean and variance σ_μ^2. Additionally, it is assumed that μ_i, and ε_{it} are independent of each other.

LeSage & Pace (2009) indicated that the SDM model is advantageous against Spatial Autoregressions (SAR) and Spatial Error Models (SEM). As stated by Floch & Saout (2018), the SDM model gives unbiased estimators (and the test statistics valid) even if we are in the presence of spatially auto-correlated errors (SEMs).

Regarding marginal effects, the effect of an independent variable's change for a specific unit will affect the unit itself and, potentially, all other units indirectly, implying the presence, and consequently the computation, of three different marginal effects: direct, indirect, and total marginal effects. The total effect of the independent variables is the sum of both the previous effects estimates.

The marginal effects of the independent variables can be obtained based on the following matrix **H** below:

$$\left[\frac{\partial Y}{\partial X_{1k}} \cdots \frac{\partial Y}{\partial X_{Nk}}\right] = \begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial x_{1k}} & \cdots & \frac{\partial y_N}{\partial x_{Nk}} \end{bmatrix} = (1 - \rho W)^{-1}[\beta_k I_N + \theta_k W] \ , \qquad (6)$$

This is a matrix of the partial derivatives of the dependent variable with respect to the kth independent variable in the different units (e.g., x_{ik} for $i = 1,\ldots,N$ and $t = 1,\ldots,T$).

In the context of the housing model, LeSage & Pace (2009) point out that the direct (feedback) effect records the impact of a housing price determinant on housing prices in that municipality and it is the mean of the diagonal elements of the matrix on the right-hand of Eq. (6). The indirect (spillover) effect measures the effect of the housing price determinant on real estate values in nearby municipalities and it is provided by both the mean of the rows sum or the mean of the columns sum of **H** (see Elhorst, 2010). The outcomes are independent from the time index, explaining why the right-hand side of the Eq. (6) do not contain the symbol t. The Eq. (6) also shows that short-term indirect effects do not occur if both ρ=0 and θ_k=0.

4. EMPIRICAL ANALYSIS

4.1. Overview

This empirical analysis focuses on the analysis of the factors that have influence on the spatial behaviour of the *median value of family accommodation sales per m^2*. The extensive literature on the housing market suggests a lot of explanatory variables impacting this market, as a result, the choice of the Data was made in accordance with the authors findings presented in *Sub section 2.3*. The results will be presented and analysed in this chapter through the usage of spatial techniques and interpretation of the Spatial Durbin Model results.

4.2. Data and Variables explanation

24 explanatory variables were chosen to measure house prices in mainland Portugal (dependent variable). The variables were taken from INE.pt and PORDATA.pt and the choice was made in accordance with the variables already used in similar studies and presented in the literature review section, as well as its economic interpretation.

Data processing was performed using STATA, Microsoft Excel, GeoDa and IpeaGeo software. The STATA software was used for all the modelling presented in this work. Microsoft Excel was applied to perform several calculations[1] in order to obtain the final variables used in the model. The GeoDa software was employed for the exploratory spatial data analysis, namely the performance of the LISA test, and IpeaGeo was utilized to carry out the dependence test statistics Moran's I and Geary's C.

4.2.1 Dependent variable – Median value of houses sales in mainland Portugal

The dependent variable was extracted from an annually updated database, and it reflects the median value of family dwellings sales per square meter. It is measured in Euros per square meter (€/m^2) and gives information according to the geographic localization based on the 278 municipalities of mainland Portugal, as so, the observation unit is the municipality, referring to the period between 2016 and 2020, inclusive, and the

[1] Calculation of averages and variations to obtain 2020 forecasts for some variables without information reported at that date.

sample used for this analysis consists of 1390 observations. This dependent variable will be used as a proxy to measure the house prices in mainland Portugal.

Figure 3 below shows the evolution of the annual average median value of houses sales in mainland Portugal in this sample. It is notorious that house prices have been growing in the last years (2016-2020), with a sales value in 2020 36.5% higher than in 2016, revealing that the growth pattern identified in the literature review remains.

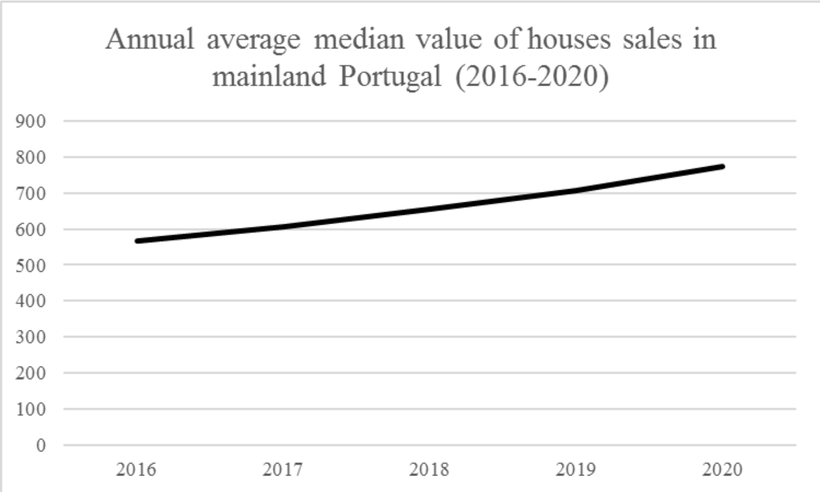

Figure 3 - Evolution of house prices between 2016 and 2020

Source: Own elaboration; Software: Microsoft Excel.

4.2.2 Explanatory variables

Regarding the explanatory variables, to conduct this analysis a classification was made, in line with what was presented in the Literature Review, allocating 24 neighbourhood amenities into economic fundamentals, population density and living condition services:

Economic Fundamentals: Crime rate (‰); Mortgage credit granted to individuals (€); Aging index; Average monthly base pay of employees (€); Number of unemployed; Birth rate (%); Mortality rate (‰); Number of retirees; Density of non-financial companies (Nº/Km^2); Volume of business of non-financial companies (€); Energy consumption per capita (kWh (quilowatt-hour)/ hab); Municipal Tax on Onerous Property Transfers – IMT (€); Property tax - IMI (€). **Population Density**: Resident population;

Foreign population. **Living Condition Services**: Number of licensed dwellings; Number of hospitals; Number of cultural spaces; Number of banks; Sanitation per capita (m^3/hab); Urban waste per capita (kg/hab); Number of higher education establishments; Number of pharmacies; Number of tourist accommodation. Too see more information about the computation of some of the variables, please refer to Appendix A.

Table VI of Appendix B presents the basic summary statistics for the data, such as the minimum, maximum and average values. It can be seen that between the years of 2016 and 2020, the median value of sales per m^2 of family accommodation (*val_med_vendas*) assumed values between 0 and 3,377 €/m^2, with a mean of approximately 661 €/m^2. The 0's (7 in the sample) correspond to 3 municipalities (Alvito, Barrancos and Penedono) with no values for house prices in some of the years in analysis, being the minimum median value of sales registered of 107 €/m^2. Municipalities in mainland Portugal have, on average, from 2016 until 2020 inclusive, a criminality rate of 27%, a resident population of 35,240, a monthly salary [2] of 807 €, 1,355 people unemployed, less than 1 hospital (despite the maximum number of hospital registered of 34 based in Lisbon), 15 cultural spaces [3], 483 kg/hab of urban waste collected, a mortality rate of 14.4%, non-financial companies making a volume of business [4] of 1,369.886 €, 17 tourist accommodations [5], an IMT of 57.7 € and an IMI of 120 € per resident population. Also, on average, between 2016 and 2020, the mortgage credit granted to individuals was 357.65 €/hab, the aging index [6] was 234%, foreign population with legal status of resident of 1,785, a number of licensed dwellings in new constructions for family housing of 66, 12 banking establishments, water distributed/consumed of 61.5 m^3/hab, a birth rate [7] of 6.9%, approximately 1 establishment of higher education, 11 pharmacies, 2,210 retirees

[2] Gross amount, before deduction of any discounts, in cash and/or in kind, paid on a regular basis and guaranteed to the employee in the reference period.

[3] Immovable property that integrates the cultural heritage such as monuments, ensembles and sites.

[4] Volume of business is the amount obtained by a company from the sale of goods and the provision of services, excluding taxes.

[5] Such as, agrotourism, tourist village, tourist apartment, country house, hotel establishment, inn, hotel, apartment hotel, rural hotel.

[6] Ratio between the elderly population and the young population, usually defined as the quotient between the number of people aged 65 or over and the number of people aged between 0 and 14 years old.

[7] Number of live births that occurred during a given period of time, usually a calendar year, referred to the average population for that period.

and pensioners, a density [8] of non-financial companies of 38, and electricity consumed per habitant of 5,022 kWh.

When building the model, it was found that most of the variables have shown not to be significant in explaining the behaviour of the housing market prices, as so, they were dropped from the model estimation. Table I below resumes the variables used to estimate the model after having used the general-to-particular approach in interpreting the significance of each variable in the estimation.

Table I – Regression Variables

Variable	***Description***
val_med_vendas	The dependent variable - Median value of sales per m^2 of family accommodation (€/m^2)
txcrime	Crime rate (‰)
popresid	Resident population (No)
remun	Average monthly base pay of employees (€)
total_desemp	Unemployed registered in employment and vocational training centers (No)
hosp	Hospitals (No)
cultura	Cultural real estate (No)
residuos	Urban waste collected per habitant (kg/hab)
tx_mortalidade	Crude mortality rate (‰)
volum_nao_finan	Volume of business of non-financial companies (€)
alojamento_tur	Tourist accommodation (No)
imt	Municipal Tax on Onerous Property Transfers – IMT (€)
imi	Property tax – IMI (€)

Source: Own elaboration; Software: Stata.

[8] Average number of companies per Km^2.

4.3 Spatial Data Analysis and Spatial Dependece Results

In Figure 4, the quantile distribution of the dependent variable, throughout the 5 years in analysis, allows us to visualize its spatial distribution and to conclude that the values are higher in the coastal area of mainland Portugal, represented in dark orange, and in all the neighbours of those coastal municipalities where the orange is turning lighter. With this initial analysis and the spatial dependence tests presented in Appendix C, we can conclude that the distribution shows spatial correlation between neighbouring regions, making sense to conduct a spatial analysis.

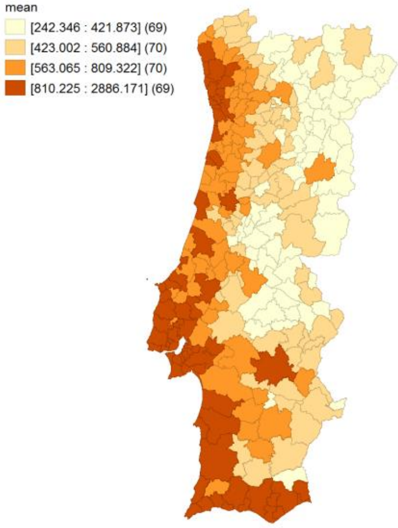

Figure 4 - Quantile distribution of housing prices from 2016 until 2020

Source: Own elaboration; Software: GeoDa.

As already mentioned, 12 of the 24 explanatory variables were dropped from the model estimation because they have shown not to be significant. Also, the spatial matrix used in this study was the inverse distance matrix as it captures the effect of municipalities that are not neighbours, so it captures the effects of each one of the 277 municipalities in the relevant municipality, and we consider this effect to be pertinent given the relatively small size of mainland Portugal. The imported matrix is a 278 panel-data units for 5 years.

In order to evaluate the presence of spatial dependence on the housing market of each municipality and to judge the appropriateness of a spatial model, the Moran's I and

Geary’s C tests were performed, being the null hypothesis the absence of spatial correlation. The tests were conducted for each of the five years and for all the years together. The results can be found in Tables VII and VIII of Appendix C together with the Moran dispersion diagrams of the dependent variable in Figure 7 of the same Appendix. All the *p-values* obtained allow for rejecting the null hypothesis (H0: the data is randomly distributed) against the alternative hypothesis (H1: the data is spatially clustered) at 1%, as well as all the dispersion diagrams present a positive slope, confirming the existence of positive spatial dependence in the dependent variable, meaning that the location of each region has a major impact on the valuation of real estate, and the need to use spatial econometric tools for the study of the housing market in mainland Portugal.

An analysis for Local Indicators of Spatial Associations (LISA) was conducted in order to study the local relationships in detail, and to find local clusters (Anselin, 1995) using a confidence interval of 95%. The results can be seen in Figure 8 of Appendix C. Given the value of each local statistic, each cluster can be designated to one of the following groups:

- High-High: High values bounded by high values (high value cluster);
- High-Low: High values bounded by low values (possible regional outlier);
- Low-Low: Low values bounded by low values (low value cluster);
- Low-High: Low values bounded by high values (possible regional outlier);
- Not significant: not statistically significant result.

About 60% of the population in mainland Portugal is situated in the areas near to the coast and in the two biggest metropolitan areas of Lisbon and Oporto (República Portuguesa, 2017). As a consequence, we expect higher prices in houses in these densely populated areas. The higher prices are registered for the municipalities of LMA, OMA, Algarve, and some of Baixo Alentejo. Alto Alentejo, and Northern-East are the ones with the lowest real estate prices in the years between 2016 and 2020.

To illustrate the spatial dependence between neighbors, LISA significance maps were also computed and can be seen in Figure 9 of Appendix C. The results show that the municipalities in darkest green have a high spatial dependence statistic, meaning that those are the ones contributing the most to the housing prices practiced in neighboring regions, being those the municipalities from the LMA and Algarve, and also Bragança, Guarda, Castelo Branco and Portalegre. Given this, and taking into account the analysis made above, the first two regions - LMA and Algarve - contribute to the high housing prices recorded, and the last - Alentejo and Northern-East - to the low ones, respectively.

4.4. Discussion of the Results

The individual test of significance was performed for each one of the 24 variables, and just as already mentioned, non-significant variables were successively removed from the Spatial Durbin Model until the final group of regressors was reached in which all but one of the independent variables were statistically significant at a level of 10% or inferior (Table IV).

The initial and final outputs are illustrated in Table II and III below.

Table II – SDM model with all the explanatory variables

Variables	**Coefficients**	**Std.Error**
txcrime	-0.833624	0.583553
credhipot_new	0.0300689	0.028164
popresid	0.0005848	0.000721
ienv	0.0078219	0.032955
popestrang	-0.000921	0.004830
remun	0.229505***	0.039021
total_desemp	-0.037261***	0.009970
nrfogoslic	0.086515	0.080776
hosp	9.413284	5.852147
cultura	1.52764***	0.549240
bancos	-1.305426***	0.422314
saneamento	0.239128	0.226042

residuos	0.015713	0.055151
tx_natalidade	14.26301***	3.135013
tx_mortalidade	-9.122735***	1.225830
num_estab_ens_superior	-3.002344	4.274110
num_farmacias	-0.562917	1.767137
num_reformados	0.026456***	0.004968
densidade_nao_finan	0.174000	0.133881
volum_nao_finan	-0.000015***	$4.89e^{-06}$
energia_per_capita	-0.000494	0.000594
alojamento_tur	1.011522***	0.390416
imt	0.648421***	0.122728
imi	1.304075***	0.119851

Source: Own elaboration; Software: Stata.

Table III – SDM model for the final explanatory variables

Variables	**Coefficients**	**Std.Error**
txcrime	-0. 986845	0.649327
popresid	0.001602***	0.000497
remun	0.104367***	0.039818
total_desemp	-0.051766***	0.008271
hosp	19.90116***	4.0711
cultura	1.819985***	0.497951
residuos	0.083956	0.057060
tx_mortalidade	-12.14735***	1.228788
volum_nao_finan	$3.08e^{-06}$	$2.88e^{-06}$

alojamento_tur	0.704659**	0.306263
imt	0.722459***	0.147992
imi	1.427098***	0.126410

Source: Own elaboration; Software: Stata.
Significance levels: ***1% and **5%.

In order to test and verify if the 12 chosen variables added value to the model, the F-test to overall significance was performed,

$$F = \frac{(SSR_R - SSR_U)/p}{SSR_U \,/\, N - p - 1} \quad \sim \quad \mathrm{F}\,(p, N - p - 1), \tag{7}$$

where SSR_R is the sum square of residuals of the restricted model, in this case the model with no explanatory variables, and SSR_U is the sum square of residuals of the unrestricted model, – the model with the 12 explanatory variables – p stands for the number of predictor variables, and *N* the number of observations. The null hypothesis of the F-test states that all the coefficients equal zero (H0: $\beta_1 = \beta_2 = \cdots = \beta_k = 0$), and the alternative hypothesis that at least one coefficient is different from zero (H1: $\exists_j^1 \beta_j \neq 0$, $j = 1,2, \dots, k$).

The result of our F-test was 518.48418 and the critical value for a significance level of 5% was 1.7592569. Given that the F statistic was higher than the critical value we can reject the null hypothesis and conclude that at least one of the explanatory variables is statistically significant, so our regression model fits the data better than the intercept-only model.

Also, in order to analyse the suspicions of endogeneity regarding the error term specific to the individual, the Hausman Mundlak test, proposed by Mundlak (1978), was carried out. The Mundlak approach consists in including the time means of the explanatory variables in the model as controls to capture the correlation between regressors and individual effects. In our model,

$$Y_t = \rho W Y_t + \alpha \iota_N + X_t \beta + W X_t \theta + \mu + \mathrm{u}_t. \tag{5a}$$

The objective is to determine if the individual effect (or individual heterogeneity) μ and X_t are correlated, so in this approach,

$\mu = \bar{X}_t\lambda + v_i$, $E(\mu|X_t) = \bar{X}_t\lambda$, $E(v|X_t) = 0$ and $Var(v|X_t) = \sigma_v^2$,

and the model will be represented as

$$Y_t = \rho W Y_t + \alpha \iota_N + X_t\beta + W X_t\theta + \bar{X}_t\lambda + v_i + u_t, \qquad (5c)$$

where $\bar{X}_t$ is the panel-level mean of X_t, and v_i the time-invariant unobservable that is not correlated with the explanatory variables. If $\lambda = 0$, X_t and the covariates are not correlated. The null hypothesis is the joint equality to zero of the coefficients associated with the time averages of the explanatory variables, so the test is given by H0: $\lambda = 0$ and H1: $\exists_j^1 \lambda_j \neq 0,\ j = 1,2,\ldots,k$.

The results of testing if the panel-level means generated are jointly zero can be seen in Output 1 of Appendix D, and as the test statistic result is 0, it leads to rejecting the null at a significance level of 5%, so there is statistical evidence for the presence of endogenous regressors. To model the endogeneity our Spatial Durbin Model was carried out along with the Chamberlain-Mundlak device presented above, although, in order to reach statistical significance in most of the variables, the spatial lag of 7 regressors had to be removed. The results can be found in Output 2 of Appendix D and also in Table IV below, and as it can be seen, only 4 out of the 12 regressors happen to be statistically significant in time and space at a significance level of 10%. Regarding the remaining 8 regressors, at a significance level of 10% or less, 1 is not significant in modelling the house prices in mainland Portugal (*residuos*), and 7 are significant, but just in time, not in space.

Table IV - SDM model with Chamberlain-Mundlak device for the final regressors

Variables	**Coefficients**	**Std.Error**
txcrime	-1.282109**	0.609322
popresid [(1)]	0. 031772**	0.013955
remun	0.108921***	0.039012
total_desemp	-0.032273***	0.007668
hosp	18.61386***	4.016617
cultura	1.363843***	0.481633
residuos	-0.014861	0.098386

tx_mortalidade	- 12.29991***	1.140484
volum_nao_finan (1)	$3.37e^{-06}$***	$9.19e^{-06}$
alojamento_tur	0.534099*	0.282632
imt (1)	0.530923***	0.179329
imi (1)	-0. 5866927*	0.329642

Source: Own elaboration; Software: Stata
(1) Spatially significant regressor
Significance levels: ***1%, **5%, and *10%.

This final model presents an R-Squared of 0.8435, meaning that 84.35% of the variation in housing prices in mainland Portugal is explained by the explanatory variables and the spatial autoregressive estimate for ρ was 0.801994 indicating strong spatial dependence in the sample data, meaning that the data is essentially guided by the spatial dynamic, supporting the reason why the non-observed individual heterogeneity term was only modelled for the spatially significant regressors.

In order to validate the literature, the OLS model was also estimated. Table V, below, presents the Log-Likelihood (LL) values for the two models. The SDM model is the one that achieves the best goodness of fit with the highest LL values.

Table V – OLS and SDM models comparison

	OLS	***SDM***
LL	-9076.7589	-8669.8151

Source: Own elaboration; Software: Stata.

Regarding the analysis of the independent variables, it cannot be performed using the coefficient values (β's) given by the SDM, in Output 3 of Appendix D, because they only show the direction of the impact of each explanatory variable in the dependent variable.

To start the coefficient analysis the marginal effects had to be computed and the coefficients presented in Table IX of Appendix D were obtained. All of the findings were consistent with the studies from other authors mentioned in the Literature Review carried out at the beginning of this dissertation. The marginal effects obtained are mostly positive, with the exception of the following variables: *total_desemp*: on average, an increase in the number of unemployed registered in employment and vocational training centers of a given municipality, that tends to happen when the economic conditions are not the most favourable, decreases the median house prices per square meter in the same municipality in 0.0318 p.p., *ceteris paribus*, as it happened during the 2008 crisis period. 0.0064 p.p. of this impact are explained by a direct impact (not statistically significative) and the remaining 0.0254 p.p. by an indirect impact (statistically significative at a significance level of 1%). Referring to Gan et al. (2018) in areas where unemployment is higher, the demand for houses will tend to be lower and therefore the price will be lower (law of demand and supply); *tx_mortalidade*: on average, an increase in the mortality rate of a given municipality, decreases the median house prices per square meter in the same municipality of mainland Portugal in the big amount of 12.1028 p.p., *ceteris paribus*, where 2.4355 p.p. are related to a direct effect, (statistically significative at 5%) and 9.6673 p.p. are related to an indirect effect (statistically significative at 1%). This indicator is largely related to aging, as the old population tends to buy less houses. At the same time, it is also related to criminality and lack of proximity to hospital services; *txcrime*: on average, an increase in the criminality rate of a given municipality, that represents a threat to the price of houses, could decrease the median house prices per square meter in the same municipality of mainland Portugal by 1.2616 p.p, *ceteris paribus*, by decreasing the attractiveness of the real estate in that location (Tita et al., 2006). Here the direct effect represents 0.2539 p.p. (not statistically significative) and the indirect effect 1.0077 p.p. (statistically significative at 10%); and *imi*: on average, an increase in the Municipal Property Tax of a given municipality, could decrease the median house prices per square meter in the same municipality and in the neighbour municipalities of mainland Portugal by 0.5773 p.p, *ceteris paribus*. Here the direct effect represents 0.1162 p.p. and the indirect effect 0.4611 p.p, neither of them statistically significant alone.

Regarding the remaining explanatory variables, we observe, on average, how inflows of the number of resident population (*popresid*) and an increase of the Municipal Tax on Real Estate Transfer (*imt*) influence the housing market in a positive way, as them increase in a given municipality will lead to an increase of the median house prices practiced in the respective municipality as well as in all the surrounding ones by 0.0313 p.p and 0.5224 p,p, respectively, *ceteris paribus*. In the same line, an increase in the average monthly base pay of employees (*remun*), the existence of more hospitals (*hosp*) and cultural spaces (*cultura*), and the increase of the number of tourist accommodations (*alojamento_tur*) in a given municipality will increase house prices in the same municipality by 0.1072 p.p., 18.3155 p.p., 1.3420 p.p., and 0.5255 p.p., respectively, *ceteris paribus*.

The population density, here represented by the resident population, is strongly related with immigration as shown by the findings of Gonzalez & Ortega (2013) who concluded that in the 2000's immigration was responsible for a rise of more than 50% in the real estate prices. This regressor is one of the 4 with a spatial component, where an increase in population leads to an increase of prices in the municipality under study and in the neighbour municipalities.

The remuneration, strongly linked to the purchasing power and wealth level, is the most relevant economic fundamental positively correlated with house prices, just like what was found by Holly et al. (2010).

Regarding the taxes, IMI and IMT, as have been evidenced by Löffler & Siegloch (2017), their increase could lead to a decrease in the price of houses in the short-run, as is shown in our model by the behaviour of IMI, because this Municipal Property Tax is paid every year from the moment the house is purchased and if they grew it is likely for the houses searching to fall, decreasing prices both in the municipality where the effect is noticed and in all the surrounding ones. On the other hand, the Municipal Tax on Real Estate Transfer is only paid once, when the purchase of a home is made, and it is applied to the Tax Asset Value, as so, the correlation between the house prices and this rate makes sense to be positive, as they are as higher as higher are the prices of houses practiced, because IMT is directly linked to the price of the property. Also, in this case the spatial effect is verified, where an increase in IMT in a municipality increases prices not only in that municipality but also in neighbouring ones.

The remaining variables are the ones that have the most positive impact in the decision to buy a house and therefore in the price charged in the municipality as pointed out by Lan et al. (2018), with the number of available hospitals being an undeniably important variable, given its impact on the price of real estate, revealing the appreciation of health by the population residing in mainland Portugal, and cultural properties and tourist accommodation trigger interest, demand, and the possibility of housing in certain municipalities, increasing real estate prices.

Regarding the volume of business of non-financial companies (*volum_nao_finan*), it has no statistically significant impact on in the dependent variable.

The disaggregated impact in direct and indirect effects can be also found in Table IX of Appendix D, where it is possible to see that all the respective indirect effects are significant, but two – *imi* and *alojamento_tur* – and that the only significant direct effects is the one related to the mortality rate (*tx_mortality*). This result provides evidence to affirm that the explanatory variables, with the exception of the mortality rate, do not directly impact the median house prices in mainland Portugal, in contrast, they impact the dependent variable through a mediator variable.

Postestimation was also performed by computing predicted values of the median house prices. A comparison between the real values and the predicted ones is presented in the Figure 5 below and we can conclude that the model is a good predictor of the outcome variable.

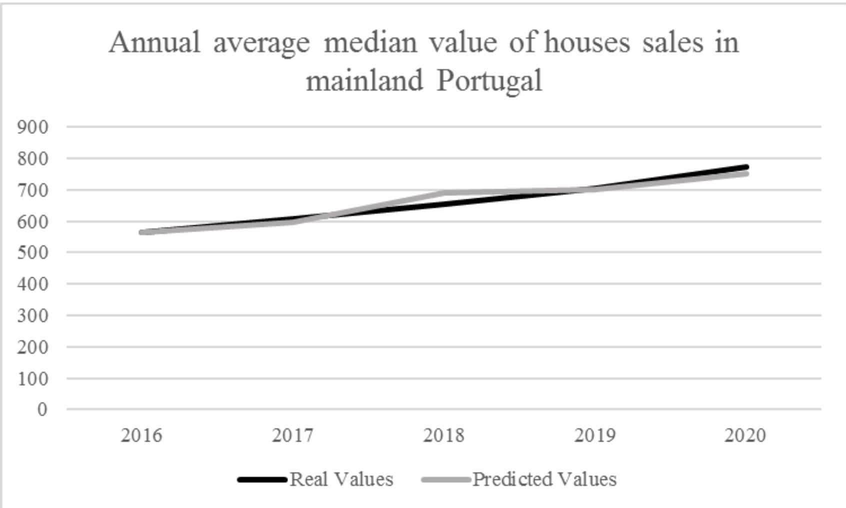

Figure 5 - Comparison between the real and predicted annual average median value of houses (€/m^2) between the years of 2016 and 2020

Source: Own elaboration; Software: Microsoft Excel.

For more details at the municipality level, please see Figure 10 of Appendix E. The average of the variation between the real values and the predicted values was 15%, and an interval of natural breaks was created, considering that variations greater or equal to 38% were a result of bad predictions, variations between 38% and 15% (inclusive) were reasonable predictions, and variations smaller than 15% were a result of good predictions. As so, we can see that the model is a very good predictor for 64% of the municipalities, among them, it predicts almost perfectly municipalities such as Alcácer do Sal, Caldas da Rainha, Guarda, Lagos, Leiria, Lisbon, Montijo, Pombal, Oporto, São Brás de Alportel and Viana do Castelo. It is a reasonable predictor for 28% of the municipalities, such as Amadora, Barreiro, Braga, Cascais, Covilhã, Évora, Grândola, Oeiras, Olhão, Portimão, Seixal, Setúbal, Tavira and Viseu, and a bad predictor for only 7%, such as, Castelo de Vide, Góis, Idanha-a-Nova, Mértola, Monforte, Sintra and Trancoso.

The overall spatial effect in the differences between the real and the predicted values is illustrated in the Natural Breaks Map below. This map uses a nonlinear algorithm to group the observations in a way that the within-group homogeneity is maximized. We can see that the 20 municipalities for which the model is not a good predictor, are essentially municipalities located in the inner regions of mainland Portugal, and as consequence, less populated and with fewer information and data available.

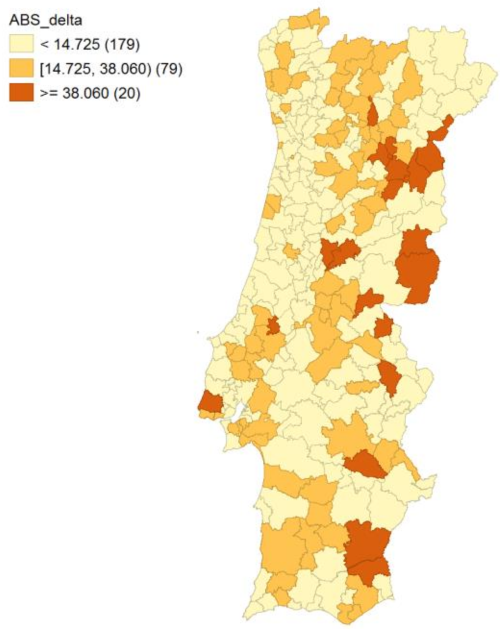

Figure 6 - Natural Breaks Map

Source: Own elaboration; Software: GeoDa

5. Final Remarks

5.1. Conclusion

This study investigated the influence of some determinants of housing prices in mainland Portugal between the years of 2016 and 2020, using data of 278 municipalities and a spatial modelling approach. Two main conclusions were obtained. First, it was found that there is a significant spatial and temporal dependence making housing prices in a given municipality to be influenced by the house prices practiced in neighbour municipalities, although just from few regressors. This impact is quite visible in LMA and OMA where the surrounding municipalities have been registering an increase in their house prices due to the population dispersion to neighbouring municipalities. Second, it was found that economic fundamentals were what impacted most negatively house prices, while living conditions were essentially what made house prices to rise. Development of the environment, reflected in this model by the number of cultural spaces and tourist accommodations, medical conditions, and salaries, along with the number of resident people, play a part in driving house prices to rationality. If there are more people to accommodate it is normal that the prices become more competitive, and so will the related taxes to those expensive houses.

From the 12 explanatory variables under study, only 4 were both spatial and time significant – *No of resident population*, *volume of business of non-financial companies*, *IMI* and *IMT*. Nevertheless, the *volume of business of non-financial companies* did not impact the median house prices in mainland Portugal. *Residuos* were not significant, and the remaining 7 regressors were significant, but only in time, not spatially, meaning that they only impacted real estate prices in the respective municipality.

The variables that more positively impacted house prices were the number of available hospitals, cultural properties, and tourist accommodation. On the other hand, the regressor with the greater negative impact was the mortality rate. Being also the only regressor that directly impacts the price of real estate, while the others only impact the price of houses through a mediator variable. In the same line, it is normal to expect that if there is a high number of unemployed people in a given, the house prices there will tend to be lower as people have no conditions to pay for expensive homes.

These findings might have two important policy implications for reducing Portuguese's rising house prices. First of all, it should be created a property supply system considering the soaring of population in order to avoid house prices from growing too fast. Second, policies related with the real estate market must emphasize municipality differences and come with matching supporting measures. As an example, the authorities of the LMA and OMA, must increase the support that is given to low-income families. Likewise, interior regions should improve their living conditions by investing in the natural environment, in quality of education and medical conditions, in order to become more attractive to migrants.

Overall, the results support the premise that real estate prices have been rising along with fundamentals (wages) and better living conditions and are align with the literature reviewed. Also, our model seems to be a good predictor of the real house prices in mainland Portugal as the average difference between the real and predicted values rises to 15%, and it predicts well 179 municipalities, representing more than 60% of the total number of municipalities in mainland Portugal.

5.2. Further Research and Limitations

Although this investigation offers meaningful insights, there are some limitations worth mentioning which should be addressed in future research. First, the geographic scale, since the validity of this study is the municipality, a sufficiently large scale if you want to study on a more micro one. Second, the speculation in the housing market do exist and was not taken into account in this investigation. As so, variables that can account for its measurement should be considered in further research to better assess real estate prices. Also, variables catching the small-scale municipalities conditions are not easy to find, so more variables must be considered in further studies.

In what concerns to the prediction ability of the estimated model, the less accurate predictions obtained might be related with the lack of information in the respective municipalities and this problem would be overcome by identifying that missing and relevant information and updating the data in order to properly predict the house prices in those 20 municipalities of mainland Portugal.

Also, regarding the zeros in the sample related to the dependent variable, in future work they should be removed, since they may be biasing the results.

Finally, the ongoing Russian-Ukraine war, and its impact in the world economy, led to the recent increase in the inflation and a subsequent increase in the interest rates charged by banks. These set of events will certainly impact the future of the real estate market in Portugal. Given this, and since these are quite recent happenings, we were not able to include them in the research, but we leave them as a relevant suggestion for future work.

Given the large sampling data available, further, and deeper investigation is expected to help the constant expansion of the Portuguese housing market, and also to allow international communities, mostly small countries, with real estate market attributes alike, to benefit from it.

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APPENDICES

APPENDIX A

$$txcrime = \left(\frac{\text{Number of crimes}}{\text{Resident populations}}\right) \times 1000$$

$$residuos = \frac{\text{Urban waste collected in the calendar year}}{\text{Annual average resident population}}$$

$$tx\_mortalidade = \left(\frac{\text{Deaths in the calendar year}}{\text{Annual average resident population}}\right) \times 1000$$

$$imi \text{ or } imt = \frac{\text{Revenues of Municipal Councils from IMI or IMT in the calendar year}}{\text{Average annual resident population}}$$

APPENDIX B

Table VI - Summary statistics of Regression Variables

stats	*val_med_vemdas*	*txcrime*	*popresid*	*remun*	*total_desemp*	*hosp*
N	1390	1390	1390	1390	1390	1390
min	0	8.7	1623	618.2	35.5	0
max	3377	85.6	509614	2133.5	26881.7	34
mean	660.7971	27.14281	35239.59	807.3085	1254.652	0.771223
sd	389.7501	9.301296	57174.42	134.8366	2517.371	2.585785
p50	578.5	25.4	14654.5	779.8	507.15	0

stats	*cultura*	*residuos*	*tx_mortalidade*	*volum_nao_finan*	*alojamento_tur*	*imt*	*imi*
N	1390	1390	1390	1390	1390	1390	1390
min	0	0	6.1	11364	0	0	8.2
max	301	1426.4	42	1.01e+08	713	798.634	555.6
mean	14.65612	483.0981	14.41532	1369886	17.25252	57.66816	120.113
sd	21.88118	150.2728	4.865901	5994034	39.51051	90.31166	71.13935
p50	11	447.2	13.7	286174.5	8	29.2	103.85

stats	*credhipot_new*	*ienv*	*popestrang*	*nrfogoslic*	*bancos*	*saneamento*	*tx_natalidade*
N	1390	1390	1390	1390	1390	1390	1390
min	1	84.3	10	0	0	13.4	1.5
max	783	760.1	106971	1254	575	349.1	12.2
mean	357.6489	233.7351	1784.964	65.80288	11.58561	61.50446	6.922014
sd	202.0096	106.4957	6153.025	125.3329	33.47702	30.36614	1.776445
p50	333	210.35	301.5	21.5	4	56.2813	6.9

stats	*num_estab_ens_superior*	*num_farmacias*	*num_reformados*	*densidade_nao_finan*	*energia_per_capita*
N	1390	1390	1390	1390	1390
min	0	1	136	0.5	1657.2
max	71	265	98890	1264.695	90858.4
mean	0.9841727	10.69568	2209.93	37.92819	5022.26
sd	4.920656	19.26901	6647.664	119.4572	7600.685
p50	0	5	715.159	7.7	3562.35

Source: Own elaboration; Software: Stata.

Appendix C

Table VII – Moran's I test

Year	*Statistic*	*P-value*
2016	0.7035	0.0000
2017	0.7287	0.0000
2018	0.7365	0.0000
2019	0.7224	0.0000
2020	0.7572	0.0000
Total	0.7297	0.0000

Source: Own elaboration; Software: IpeaGEO.

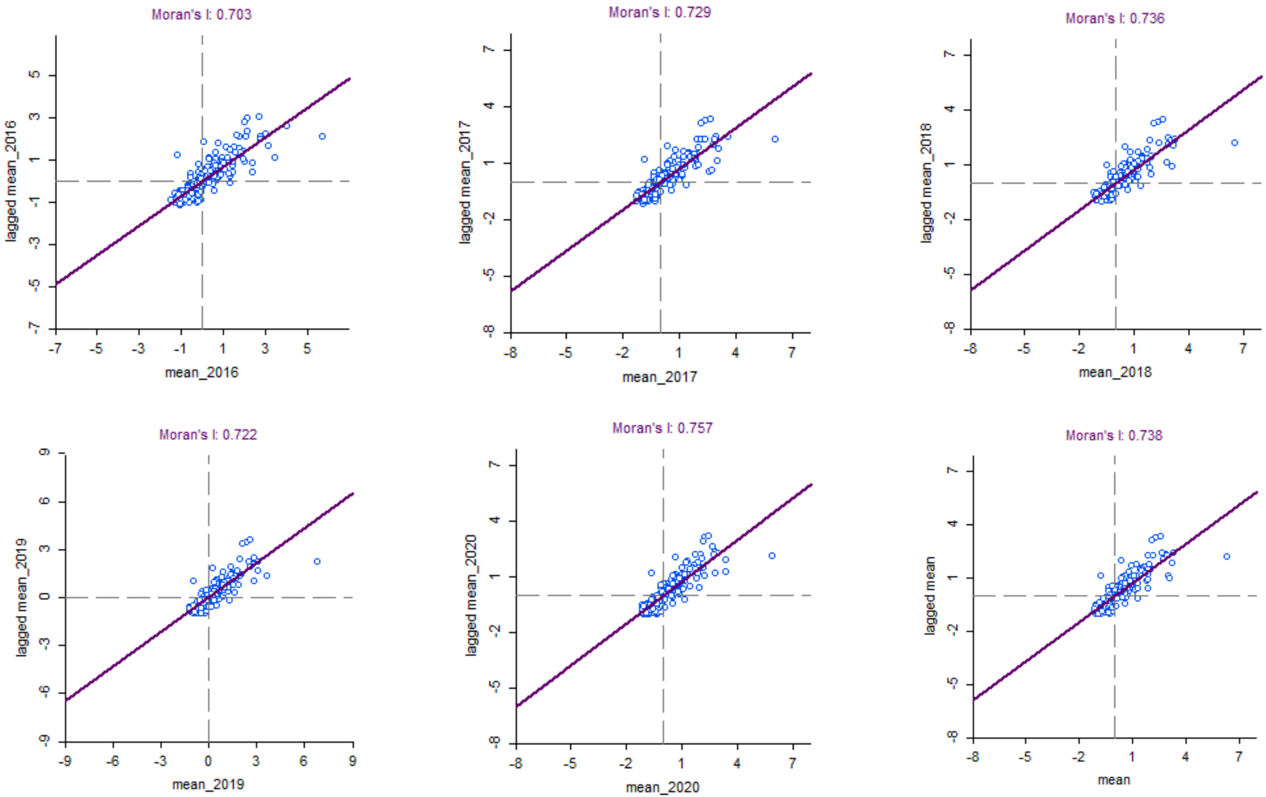

Figure 7 - Moran dispersion diagrams of the variable *val_med_vendas* in each of the 5 years and in all of the years together

Source: Own elaboration; Software: GeoDa.

Table VIII - Geary's C test

Year	*Statistic*	*P-value*
2016	0.2631	0.0000
2017	0.2377	0.0000
2018	0.2312	0.0000
2019	0.2486	0.0000
2020	0.2134	0.0000
Total	0,2388	0,0000

Source: Own elaboration; Software: IpeaGEO.

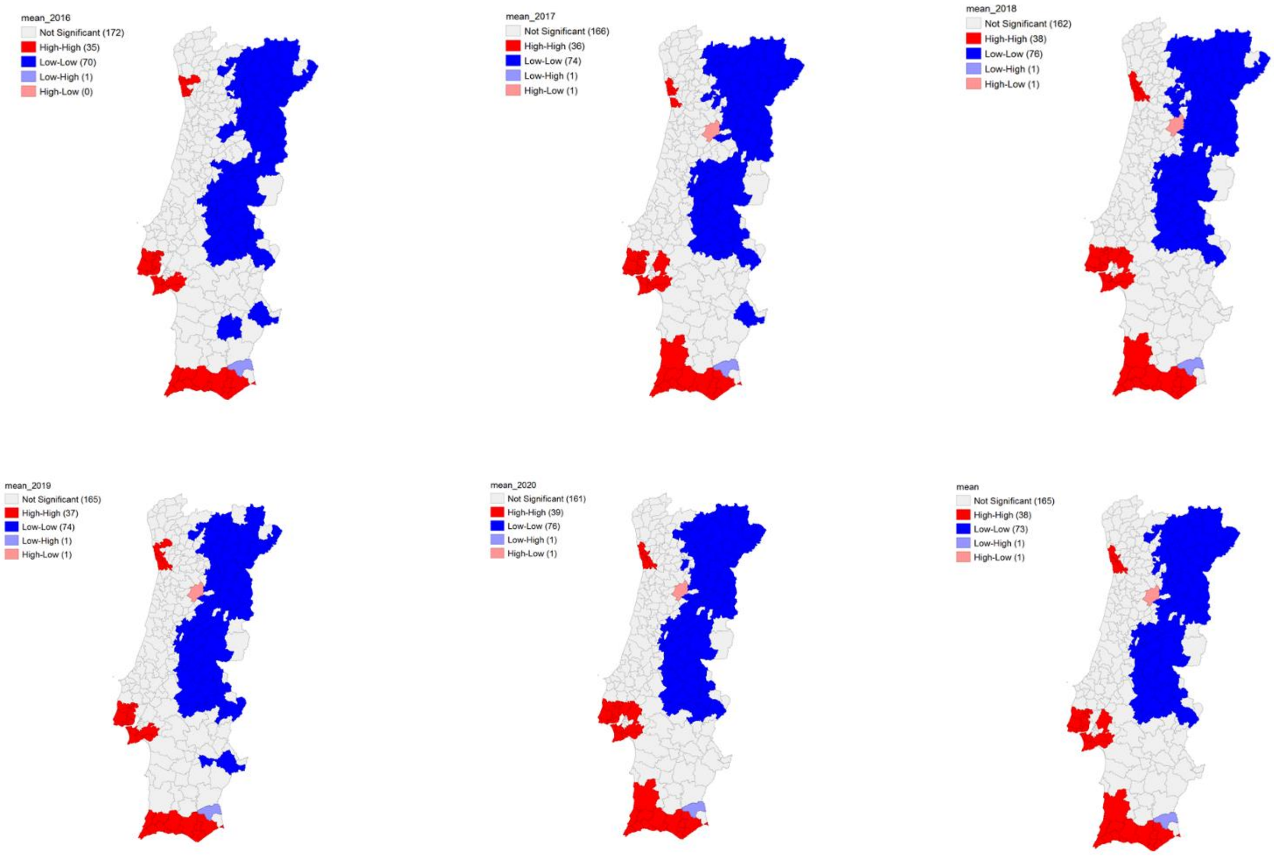

Figure 8 - LISA Cluster maps of the dependent variable from 2016 until 2020, and to all the years together

Source: Own elaboration; Software: GeoDa.

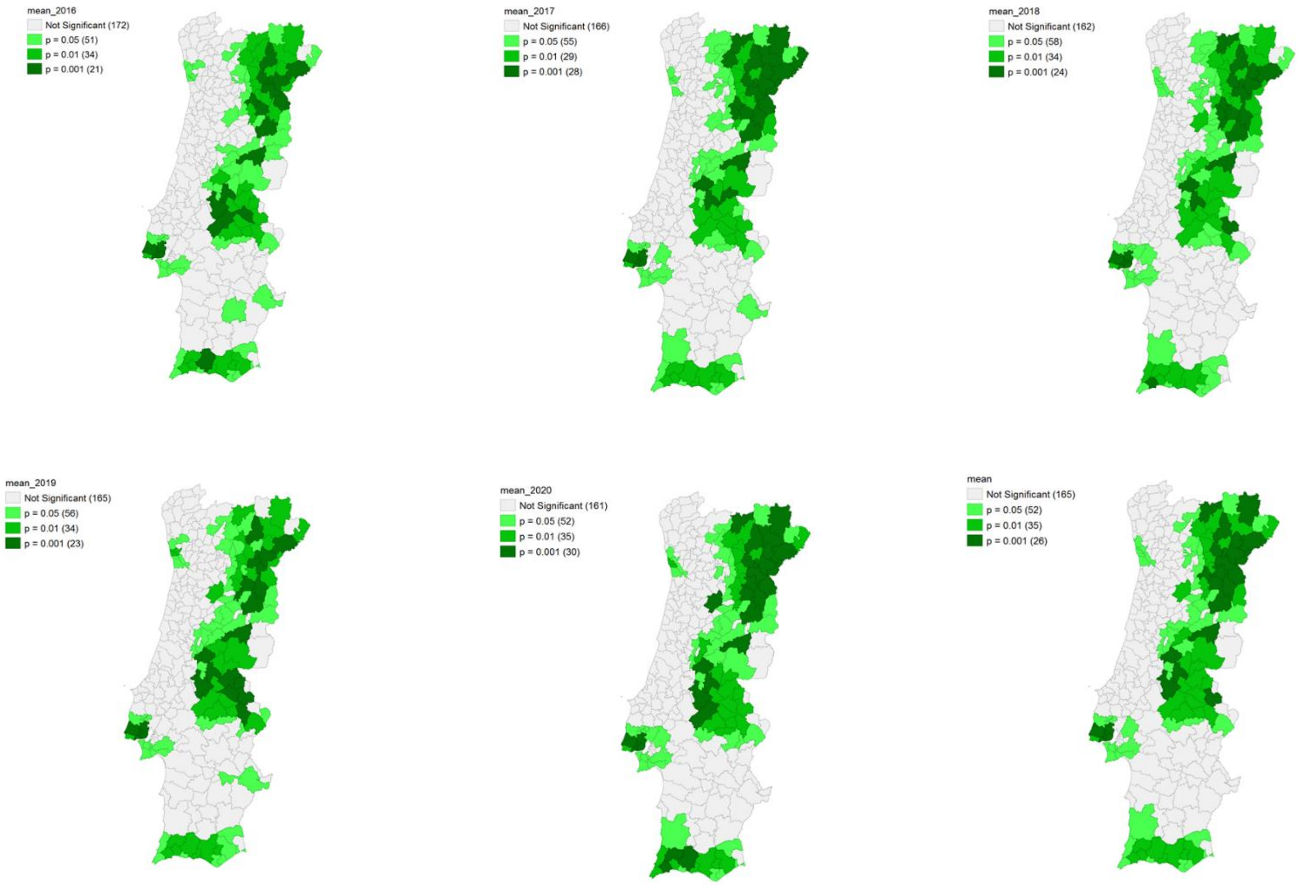

Figure 9 - LISA Significance map for the dependent variable from 2016 until 2020, and to all the years together

Source: Own elaboration; Software: GeoDa.

Appendix D

Output 1 - Hausman Mundlak test

```
. test $lxlistmean

 ( 1)  mean_txcrime = 0
 ( 2)  mean_popresid = 0
 ( 3)  mean_remun = 0
 ( 4)  mean_total_desemp = 0
 ( 5)  mean_hosp = 0
 ( 6)  mean_cultura = 0
 ( 7)  mean_residuos = 0
 ( 8)  mean_tx_mortalidade = 0
 ( 9)  mean_volum_nao_finan = 0
 (10)  mean_alojamento_tur = 0
 (11)  mean_imt = 0
 (12)  mean_imi = 0

           chi2( 12) =  380.08
         Prob > chi2 =    0.0000
```

Output 2 - Spatial Durbin Model (SDM) with Chamberlain-Mundlak device for the final variables

```
 Sample Size          =        1390   |   Cross Sections Number   =         278
 Wald Test            =   7367.2909   |   P-Value > Chi2(22)      =      0.0000
 F-Test               =    334.8769   |   P-Value > F(22 , 1090)  =      0.0000
 R2  (R-Squared)      =      0.8435   |   Raw Moments R2          =      0.4873
 R2a (Adjusted R2)    =      0.8006   |   Raw Moments R2 Adj      =      0.3467
 Root MSE (Sigma)     =    620.2697   |   Log Likelihood Function =  -8669.8151
------------------------------------------------------------------------------
- R2h= 0.8435   R2h Adj= 0.8006  F-Test =   334.88 P-Value > F(22 , 1090)0.0000
- R2r= 0.4873   R2r Adj= 0.3467  F-Test =    56.49 P-Value > F(23 , 1090)0.0000

---------------------------------------------------------------------------------
                    |               Robust
      val_med_vendas|      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------+------------------------------------------------------------
val_med_vendas      |
            popresid|   .0317719   .0139545     2.28   0.023     .0044217    .0591222
     volum_nao_finan|   .0000337   9.19e-06     3.67   0.000     .0000157    .0000517
                 imt|   .5309234   .1793291     2.96   0.003     .1794447     .882402
                 imi|  -.5866927   .3296421    -1.78   0.075    -1.232779    .0593939
            residuos|  -.0148605   .0983855    -0.15   0.880    -.2076927    .1779716
        w1x_popresid|   .0067165   .0011415     5.88   0.000     .0044792    .0089538
 w1x_volum_nao_finan|  -.0000381    .000016    -2.38   0.017    -.0000696   -6.70e-06
             w1x_imt|   1.561335   .6580096     2.37   0.018     .2716602    2.851011
             w1x_imi|   .7133746   .5506961     1.30   0.195      -.36597    1.792719
        w1x_residuos|  -.7999444   .2803343    -2.85   0.004    -1.349389   -.2504993
       mean_popresid|  -.0303969   .0138302    -2.20   0.028    -.0575036   -.0032903
mean_volum_nao_finan|  -.0000339   8.60e-06    -3.94   0.000    -.0000507    -.000017
            mean_imt|   .1873058   .1956021     0.96   0.338    -.1960673    .5706789
            mean_imi|   2.184181   .3638536     6.00   0.000     1.471041    2.897321
       mean_residuos|   .0731923   .1198269     0.61   0.541     -.161664    .3080487
             txcrime|  -1.282109   .6093221    -2.10   0.035    -2.476359   -.0878599
             cultura|   1.363843   .4816327     2.83   0.005       .41986    2.307826
        total_desemp|  -.0322727   .0076683    -4.21   0.000    -.0473022   -.0172432
      alojamento_tur|   .5340988    .282632     1.89   0.059    -.0198498    1.088047
                hosp|   18.61386   4.016617     4.63   0.000     10.74144    26.48629
      tx_mortalidade|  -12.29991   1.140484   -10.78   0.000    -14.53522    -10.0646
               remun|   .1089209    .039012     2.79   0.005     .0324588    .1853829
               _cons|  -28.36938   111.9554    -0.25   0.800    -247.7979    191.0591
--------------------+------------------------------------------------------------
                /Rho|   .8019938   .0707291    11.34   0.000     .6633673    .9406204
              /Sigma|   127.0701   3.838235    33.11   0.000     119.5473    134.5929
---------------------------------------------------------------------------------
 LR Test SDM vs. OLS (Rho=0):     128.5717   P-Value > Chi2(1)   0.0000
 LR Test (wX's =0):                73.4862   P-Value > Chi2(5)   0.0000
 Acceptable Range for Rho:         -5.1861   <  Rho  < 1.0000
------------------------------------------------------------------------------
```

Table IX– Marginal Effects

Variable	*Total*	*Direct*	*Indirect*
txcrime	-1.2616**	-0.2539	-1.0077*
popresid (1)	0.0313**	0.0063	0.0250*
remun	0.1072***	0.0216	0.0856**
total_desemp	-0.0318***	-0.0064	-0.0254***
hosp	18.3155***	3.6857	14.6299***
cultura	1.3420***	0.2700	1.0719**
residuos	-0.0146	-0.0029	-0.0117
tx_mortalidade	-12.1028***	-2.4355**	-9.6673***
volum_nao_finan (1)	0.0000***	0.0000	0.0000***
alojamento_tur	0.5255*	0.1058	0.4198
imt (1)	0.5224***	0.1051	0.4173**
imi (1)	-0.5773*	-0.1162	-0.4611

(1) Spatially significant regressor

Source: Own elaboration; Software: Stata.

Significance levels: ***1%, **5%, and *10%.

Appendix E

ID_Municipality	Name_Municipality	2016		2017		2018		2019		2020		Total		*Residual* (*e*=Y-Y')	|Δ|*
		Real	Predicted	Real	Predicted	Real	Predicted	Real	Predicted	Real	Predicted	Real (Y)	Predicted (Y')		
1	Abrantes	450	518	461	580	470	624	470	628	480	604	466	591	-125	27%
2	Águeda	592	581	658	637	679	702	716	734	755	721	680	675	5	1%
3	Aguiar da Beira	395	214	185	275	383	325	230	241	352	283	309	267	42	13%
4	Alandroal	422	343	411	447	398	503	303	506	464	470	400	454	-54	14%
5	Albergaria-a-Velha	612	562	661	636	682	670	749	705	800	689	701	652	49	7%
6	Albufeira	1381	1528	1572	1818	1709	1855	1914	1975	2026	2087	1720	1853	-132	8%
7	Alcácer do Sal	582	599	829	756	787	845	817	816	900	863	783	776	7	1%
8	Alcanena	390	529	444	665	479	734	451	714	475	762	448	681	-233	52%
9	Alcobaça	678	693	770	747	775	837	820	873	836	891	776	808	-32	4%
10	Alcochete	947	1136	1126	1298	1266	1444	1350	1438	1462	1487	1230	1361	-130	11%
11	Alcoutim	555	248	599	346	648	499	741	348	599	379	628	364	264	42%
12	Alenquer	611	766	716	890	733	989	773	1051	905	1087	748	957	-209	28%
13	Alfândega da Fé	221	309	283	341	584	406	323	403	506	347	383	361	22	6%
14	Alijó	400	322	455	361	290	432	361	459	400	449	381	405	-23	6%
15	Aljezur	1260	1022	1214	1168	1311	1319	1547	1294	1668	1452	1400	1251	149	11%
16	Aljustrel	455	432	592	578	380	678	552	609	488	675	493	594	-101	20%
17	Almada	1037	1073	1151	1263	1328	1410	1515	1504	1745	1502	1355	1350	5	0%
18	Almeida	267	247	241	276	203	333	361	318	251	327	265	300	-36	13%
19	Almeirim	558	502	564	625	573	665	665	672	682	679	608	628	-20	3%
20	Almodôvar	382	420	560	509	329	594	614	598	661	677	509	560	-50	10%
21	Alpiarça	565	459	504	592	543	613	577	614	582	611	554	578	-24	4%
22	Alter do Chão	277	211	339	321	388	384	313	339	315	410	326	333	-6	2%
23	Alvaiázere	418	314	395	411	373	455	466	494	442	491	419	433	-14	3%
24	Alvito	333	398	426	507	294	750	313	588	0	604	273	569	-296	-
25	Amadora	895	922	1037	1219	1247	1441	1499	1611	1667	1616	1269	1362	-93	7%

Figure 10 - Real and predicted values per municipality

26	Amarante	560	496	624	557	660	622	726	656	744	595	663	585	78	12%
27	Amares	555	588	591	669	647	718	677	741	720	718	638	687	-49	8%
28	Anadia	522	530	493	553	562	592	570	611	634	607	556	579	-22	4%
29	Ansião	473	441	419	473	447	523	452	551	486	559	455	509	-54	12%
30	Arcos de Valdevez	538	479	592	544	580	577	704	619	769	580	637	560	77	12%
31	Arganil	350	351	376	398	396	453	417	489	477	449	403	428	-25	6%
32	Armamar	321	325	355	377	427	411	283	484	358	437	349	407	-58	17%
33	Arouca	586	524	543	576	764	599	667	638	663	629	645	593	51	8%
34	Arraiolos	463	443	438	542	445	607	512	602	628	583	497	555	-58	12%
35	Arronches	212	237	356	264	411	285	257	281	389	433	325	300	25	8%
36	Arruda dos Vinhos	767	773	846	890	865	980	1016	1050	965	1076	892	954	-62	7%
37	Aveiro	895	836	989	943	1065	1055	1223	1123	1283	1149	1091	1021	70	6%
38	Avis	322	256	390	361	398	439	361	461	398	412	374	386	-12	3%
39	Azambuja	660	710	662	863	757	1052	832	1023	1035	1124	789	955	-165	21%
40	Baião	440	353	434	406	576	487	603	514	750	475	561	447	114	20%
41	Barcelos	641	758	679	841	708	913	830	953	897	894	751	872	-121	16%
42	Barrancos	0	255	0	434	0	454	0	487	0	527	0	431	-431	-
43	Barreiro	615	947	709	1089	795	1207	946	1251	1100	1225	833	1144	-311	37%
44	Batalha	620	588	651	673	621	726	735	761	699	773	665	704	-39	6%
45	Beja	598	511	645	613	682	662	699	656	737	665	672	621	51	8%
46	Belmonte	424	319	384	390	365	436	392	454	471	405	407	401	6	2%
47	Benavente	653	677	726	812	700	914	769	955	887	985	747	868	-121	16%
48	Bombarral	513	601	513	730	522	806	655	823	780	849	597	762	-165	28%
49	Borba	440	362	443	448	436	494	355	486	461	512	427	460	-33	8%
50	Boticas	150	331	177	356	452	403	354	433	462	421	319	389	-70	22%
51	Braga	642	740	678	906	801	1041	936	1142	1024	1126	816	991	-175	21%
52	Bragança	538	490	561	570	600	605	690	625	764	589	631	576	55	9%
53	Cabeceiras de Basto	498	389	519	450	541	504	675	552	699	503	586	479	107	18%
54	Cadaval	573	572	535	650	562	725	583	786	609	761	572	699	-126	22%
55	Caldas da Rainha	700	683	769	805	879	908	873	962	1006	973	845	866	-21	2%

56	Caminha	823	713	889	790	880	842	939	838	980	806	902	797	105	12%
57	Campo Maior	461	389	380	482	417	482	472	509	433	467	433	466	-33	8%
58	Cantanhede	657	613	621	663	714	719	678	725	748	716	684	687	-4	1%
59	Carrazeda de Ansiães	231	231	263	298	479	364	203	403	267	367	289	333	-44	15%
60	Carregal do Sal	450	340	463	408	378	475	479	471	484	449	451	429	22	5%
61	Cartaxo	601	598	637	707	626	770	658	792	749	807	654	735	-81	12%
62	Cascais	1688	1363	1922	1641	2333	1826	2596	1949	2787	1969	2265	1749	516	23%
63	Castanheira de Pêra	321	261	223	414	402	521	367	520	596	395	382	422	-40	11%
64	Castelo Branco	523	500	568	536	614	573	636	590	659	583	600	557	43	7%
65	Castelo de Paiva	507	457	399	523	441	593	623	620	603	584	515	556	-41	8%
66	Castelo de Vide	203	326	268	413	305	425	241	448	451	499	294	422	-128	44%
67	Castro Daire	299	360	257	450	397	437	459	470	500	441	382	432	-49	13%
68	Castro Marim	1105	1220	1237	1403	1342	1545	1399	1442	1470	1456	1311	1414	-103	8%
69	Castro Verde	469	466	663	543	422	653	483	645	545	698	516	601	-85	16%
70	Celorico da Beira	115	339	299	387	276	461	224	466	354	456	254	422	-168	66%
71	Celorico de Basto	482	407	583	435	458	476	545	530	672	469	548	463	85	15%
72	Chamusca	432	378	374	453	439	512	442	509	467	478	431	466	-35	8%
73	Chaves	600	445	625	520	718	585	679	606	806	575	686	546	139	20%
74	Cinfães	372	345	302	428	409	508	342	476	468	440	379	440	-61	16%
75	Coimbra	1092	944	1165	1056	1186	1174	1249	1245	1321	1265	1203	1137	66	5%
76	Condeixa-a-Nova	666	511	741	592	746	629	803	660	938	662	779	611	168	22%
77	Constância	532	454	468	530	532	584	583	602	441	567	511	547	-36	7%
78	Coruche	455	460	575	571	711	611	616	620	714	589	614	570	44	7%
79	Covilhã	592	463	544	529	639	578	691	576	709	579	635	545	90	14%
80	Crato	217	222	188	358	287	361	232	303	379	338	261	316	-56	21%
81	Cuba	507	294	479	415	578	481	280	474	460	447	461	422	39	8%
82	Elvas	488	444	509	528	445	574	457	553	553	568	490	533	-43	9%
83	Entroncamento	581	501	526	571	568	660	519	679	599	719	559	626	-67	12%
84	Espinho	824	672	1030	781	1084	853	1190	909	1344	889	1094	821	274	25%
85	Esposende	879	744	922	826	974	896	1098	947	1224	933	1019	869	150	15%

86	Estarreja	589	551	654	588	661	685	682	709	827	689	683	645	38	6%
87	Estremoz	442	366	463	411	534	523	544	474	634	491	523	453	70	13%
88	Évora	929	683	1034	801	1142	895	1187	895	1325	922	1123	839	284	25%
89	Fafe	598	531	648	598	676	633	721	670	766	621	682	611	71	10%
90	Faro	1032	950	1154	1099	1454	1237	1600	1271	1752	1334	1398	1178	220	16%
91	Felgueiras	578	599	597	654	619	710	694	735	755	672	649	674	-25	4%
92	Ferreira do Alentejo	528	444	420	591	405	623	445	614	454	679	450	590	-140	31%
93	Ferreira do Zêzere	561	454	621	484	527	578	633	572	571	538	583	525	57	10%
94	Figueira da Foz	867	768	808	841	831	897	897	919	1034	911	887	867	20	2%
95	Figueira de Castelo Rodrigo	107	261	161	219	229	359	193	324	167	358	171	304	-133	78%
96	Figueiró dos Vinhos	410	351	326	402	373	420	346	445	466	461	384	416	-32	8%
97	Fornos de Algodres	282	276	357	307	310	340	347	424	184	416	296	352	-56	19%
98	Freixo de Espada à Cinta	241	179	204	326	177	346	192	434	272	312	217	320	-102	47%
99	Fronteira	325	309	265	332	374	444	262	417	439	393	333	379	-46	14%
100	Fundão	473	470	443	544	538	588	608	592	600	626	532	564	-31	6%
101	Gavião	290	130	248	270	306	361	279	269	255	314	276	269	7	3%
102	Góis	211	324	229	356	297	391	303	467	348	378	278	383	-106	38%
103	Golegã	502	413	458	463	558	541	646	544	594	578	552	508	44	8%
104	Gondomar	685	542	739	702	828	848	964	982	1125	913	868	797	71	8%
105	Gouveia	265	353	273	368	262	392	255	425	376	393	286	386	-100	35%
106	Grândola	851	1043	981	1409	948	1422	1044	1435	1264	1520	1018	1366	-348	34%
107	Guarda	593	555	607	620	600	670	609	694	661	687	614	645	-31	5%
108	Guimarães	678	707	714	814	766	907	850	933	964	867	794	845	-51	6%
109	Idanha-a-Nova	234	323	224	414	276	431	261	491	262	437	251	419	-168	67%
110	Ílhavo	863	680	906	794	889	863	1058	939	1116	976	966	851	116	12%
111	Lagoa	1347	1516	1410	1660	1538	1791	1626	1802	1823	1953	1549	1744	-196	13%
112	Lagos	1452	1516	1687	1671	1787	1842	1923	1908	2016	2053	1773	1798	-25	1%
113	Lamego	538	458	550	547	600	601	593	617	661	590	588	563	26	4%
114	Leiria	727	728	773	833	837	912	947	952	1026	998	862	885	-23	3%
115	Lisboa	2065	1976	2438	2580	3010	3136	3247	3476	3377	3319	2827	2897	-70	2%

116	Loulé	1578	1476	1763	1721	1948	1791	2099	1862	2286	1922	1935	1755	180	9%
117	Loures	1129	978	1292	1257	1385	1481	1627	1636	1792	1608	1445	1392	53	4%
118	Lourinhã	777	732	814	857	874	933	977	983	1058	1014	900	904	-4	0%
119	Lousã	535	493	549	576	578	615	632	640	712	613	601	588	14	2%
120	Lousada	542	535	570	615	563	670	691	710	725	662	618	639	-20	3%
121	Mação	190	226	234	252	291	329	262	373	234	288	242	294	-51	21%
122	Macedo de Cavaleiros	442	347	421	418	543	447	470	471	577	454	491	427	63	13%
123	Mafra	966	1063	1082	1270	1208	1409	1348	1495	1557	1515	1232	1350	-118	10%
124	Maia	794	716	893	877	990	1044	1152	1172	1283	1190	1022	1000	23	2%
125	Mangualde	410	452	460	506	444	550	484	554	563	548	472	522	-50	11%
126	Manteigas	394	286	278	429	313	403	516	416	417	394	384	386	-2	1%
127	Marco de Canaveses	587	488	605	562	635	654	691	688	748	640	653	606	47	7%
128	Marinha Grande	581	620	618	697	674	772	726	761	798	777	679	725	-46	7%
129	Marvão	288	287	260	342	428	364	490	329	377	319	369	328	40	11%
130	Matosinhos	1020	784	1065	958	1255	1111	1471	1260	1637	1255	1290	1074	216	17%
131	Mealhada	631	523	647	587	695	644	771	654	661	652	681	612	69	10%
132	Mêda	234	304	333	370	327	409	404	429	179	390	295	380	-85	29%
133	Melgaço	330	410	299	439	386	543	512	554	454	513	396	492	-96	24%
134	Mértola	266	355	238	492	185	561	296	550	566	561	310	504	-194	62%
135	Mesão Frio	260	346	295	379	385	450	545	433	514	442	400	410	-10	3%
136	Mira	714	551	917	618	902	645	863	677	962	667	872	632	240	28%
137	Miranda do Corvo	500	398	514	411	535	454	480	518	553	457	516	448	69	13%
138	Miranda do Douro	275	308	364	336	427	455	463	464	399	433	386	399	-13	3%
139	Mirandela	563	418	542	465	635	528	728	569	714	529	636	502	135	21%
140	Mogadouro	291	290	257	363	368	410	429	420	374	386	344	374	-30	9%
141	Moimenta da Beira	353	373	446	462	247	495	388	513	386	487	364	466	-102	28%
142	Moita	591	754	587	894	654	1020	781	1049	900	1045	703	953	-250	36%
143	Monção	769	406	623	464	741	515	673	544	817	504	725	486	238	33%
144	Monchique	530	604	590	741	743	858	571	820	732	921	633	789	-156	25%
145	Mondim de Basto	306	383	300	426	347	507	452	505	370	460	355	456	-101	29%

146	Monforte	181	317	402	377	244	462	313	479	302	453	288	418	-129	45%
147	Montalegre	250	247	333	354	404	377	567	430	587	413	428	364	64	15%
148	Montemor-o-Novo	579	488	583	585	688	664	625	659	835	643	662	608	54	8%
149	Montemor-o-Velho	570	537	674	583	518	651	750	682	750	677	652	626	26	4%
150	Montijo	778	863	931	1014	1022	1178	1193	1231	1304	1288	1046	1115	-69	7%
151	Mora	291	282	372	388	309	435	472	485	540	394	397	397	0	0%
152	Mortágua	547	446	569	501	485	591	480	555	424	552	501	529	-28	6%
153	Moura	349	358	419	446	416	501	455	529	500	547	428	476	-48	11%
154	Mourão	352	408	260	483	478	574	385	555	600	568	415	518	-103	25%
155	Murça	326	274	278	334	350	385	387	429	305	322	329	349	-20	6%
156	Murtosa	664	556	714	657	686	699	768	727	840	729	734	674	61	8%
157	Nazaré	1007	974	1147	1060	1313	1135	1331	1110	1358	1171	1231	1090	141	11%
158	Nelas	464	441	472	493	467	556	507	577	496	555	481	524	-43	9%
159	Nisa	286	182	333	305	253	394	302	379	380	410	311	334	-23	7%
160	Óbidos	1098	978	1012	1086	1045	1149	1090	1220	1230	1242	1095	1135	-40	4%
161	Odemira	859	647	889	774	999	868	1172	872	1076	951	999	822	177	18%
162	Odivelas	1110	925	1305	1191	1523	1412	1781	1550	1999	1557	1544	1327	217	14%
163	Oeiras	1368	1142	1642	1449	2000	1691	2234	1809	2353	1839	1919	1586	334	17%
164	Oleiros	250	230	311	314	325	397	268	383	444	402	320	345	-26	8%
165	Olhão	1020	841	1078	945	1236	1032	1361	1077	1367	1100	1212	999	213	18%
166	Oliveira de Azeméis	574	650	613	734	617	796	721	814	805	770	666	753	-87	13%
167	Oliveira de Frades	567	489	397	540	577	613	679	583	696	538	583	552	31	5%
168	Oliveira do Bairro	581	523	615	576	640	659	700	715	731	701	653	635	19	3%
169	Oliveira do Hospital	394	435	470	502	514	535	544	565	584	526	501	513	-11	2%
170	Ourém	688	618	662	691	724	743	730	751	973	766	755	714	41	5%
171	Ourique	302	405	400	510	464	600	565	526	567	661	460	540	-81	18%
172	Ovar	735	677	800	771	882	839	939	892	1045	874	880	811	69	8%
173	Paços de Ferreira	592	582	602	655	553	740	673	794	791	747	642	704	-62	10%
174	Palmela	765	895	811	1064	858	1223	964	1282	1156	1300	911	1153	-242	27%
175	Pampilhosa da Serra	219	257	130	298	144	367	289	360	248	319	206	320	-114	55%

176	Paredes	608	559	657	675	674	769	736	821	849	776	705	720	-15	2%
177	Paredes de Coura	516	405	500	470	501	537	500	577	392	538	482	505	-24	5%
178	Pedrógão Grande	371	300	329	308	398	407	318	417	491	410	381	368	13	3%
179	Penacova	343	372	441	435	498	486	443	497	501	480	445	454	-9	2%
180	Penafiel	664	574	676	667	738	749	740	790	813	724	726	701	26	4%
181	Penalva do Castelo	211	296	238	362	438	380	306	424	330	447	305	382	-77	25%
182	Penamacor	166	196	182	322	175	368	253	329	225	337	200	310	-110	55%
183	Penedono	174	206	0	280	303	339	260	368	188	382	185	315	-130	70%
184	Penela	400	387	506	406	432	526	519	494	593	465	490	455	35	7%
185	Peniche	819	725	907	843	971	891	1031	933	1131	965	972	871	100	10%
186	Peso da Régua	447	396	629	463	546	512	693	555	677	539	598	493	105	18%
187	Pinhel	212	273	250	358	275	397	209	382	296	330	248	348	-99	40%
188	Pombal	566	563	613	621	702	650	692	665	778	687	670	637	33	5%
189	Ponte da Barca	483	465	584	494	588	556	571	601	660	553	577	534	44	8%
190	Ponte de Lima	665	605	779	679	847	748	915	780	1003	748	842	712	130	15%
191	Ponte de Sor	520	350	490	433	583	516	556	493	552	500	540	458	82	15%
192	Portalegre	648	491	666	562	640	608	634	568	649	580	647	562	86	13%
193	Portel	163	341	381	434	391	526	328	477	303	523	313	460	-147	47%
194	Portimão	1165	1381	1274	1574	1382	1770	1463	1745	1627	1896	1382	1673	-291	21%
195	Porto	1111	1209	1307	1524	1612	1803	1837	2112	2142	2063	1602	1742	-141	9%
196	Porto de Mós	475	545	511	640	505	711	575	696	615	717	536	662	-126	23%
197	Póvoa de Lanhoso	562	601	615	653	640	721	669	760	794	724	656	692	-36	5%
198	Póvoa de Varzim	944	799	1000	895	1068	993	1201	1043	1316	1029	1106	952	154	14%
199	Proença-a-Nova	409	255	301	302	432	386	392	348	505	325	408	323	85	21%
200	Redondo	437	328	519	424	482	508	386	510	568	525	478	459	19	4%
201	Reguengos de Monsaraz	496	500	510	572	425	672	492	676	578	702	500	624	-124	25%
202	Resende	302	438	400	460	344	496	356	529	458	495	372	484	-112	30%
203	Ribeira de Pena	343	291	318	372	344	419	347	479	605	485	391	409	-18	4%
204	Rio Maior	573	618	550	693	612	798	633	787	655	805	605	740	-136	22%
205	Sabrosa	294	368	309	447	327	487	212	504	400	486	308	458	-150	49%

206	Sabugal	311	269	237	312	277	333	288	325	349	328	292	313	-21	7%
207	Salvaterra de Magos	641	510	661	648	675	722	751	735	944	768	734	677	58	8%
208	Santa Comba Dão	428	458	581	542	454	572	467	586	601	549	506	542	-35	7%
209	Santa Maria da Feira	639	628	658	736	711	828	796	879	895	847	740	784	-44	6%
210	Santa Marta de Penaguião	357	288	356	341	318	399	400	411	479	425	382	373	9	2%
211	Santarém	556	681	588	814	650	881	673	888	729	906	639	834	-195	30%
212	Santiago do Cacém	675	675	894	810	850	890	976	916	990	939	877	846	31	4%
213	Santo Tirso	643	654	718	733	776	815	833	867	838	807	762	775	-14	2%
214	São Brás de Alportel	843	835	913	944	992	1038	1168	1110	1226	1161	1028	1018	11	1%
215	São João da Madeira	562	683	608	788	681	882	800	871	867	845	704	814	-110	16%
216	São João da Pesqueira	286	296	322	365	266	413	341	473	336	428	310	395	-85	27%
217	São Pedro do Sul	426	405	563	481	595	518	644	537	689	506	583	489	94	16%
218	Sardoal	223	308	237	394	272	400	390	446	349	334	294	376	-82	28%
219	Sátão	400	375	420	444	423	463	419	499	467	491	426	455	-29	7%
220	Seia	324	429	418	486	375	501	356	537	469	528	388	496	-108	28%
221	Seixal	772	980	863	1202	990	1379	1137	1473	1337	1486	1020	1304	-284	28%
222	Sernancelhe	278	326	215	340	196	420	286	472	357	418	266	395	-129	48%
223	Serpa	366	341	391	455	474	492	433	504	490	534	431	465	-34	8%
224	Sertã	475	315	535	421	542	450	608	432	590	417	550	407	143	26%
225	Sesimbra	1019	1032	1090	1173	1200	1316	1332	1357	1397	1381	1208	1252	-44	4%
226	Setúbal	746	997	808	1139	945	1284	1077	1318	1277	1305	971	1209	-238	25%
227	Sever do Vouga	523	457	607	528	480	605	432	602	676	533	544	545	-1	0%
228	Silves	1081	1037	1210	1152	1265	1284	1504	1300	1505	1418	1313	1238	75	6%
229	Sines	928	757	1065	910	1006	982	1102	1015	1319	1059	1084	945	139	13%
230	Sintra	791	942	879	1291	1002	1589	1192	1783	1396	1740	1052	1469	-417	40%
231	Sobral de Monte Agraço	549	680	737	826	718	912	850	950	964	960	764	865	-102	13%
232	Soure	455	470	449	504	519	568	634	582	581	578	528	541	-13	2%
233	Sousel	250	313	312	389	269	433	286	452	388	427	301	403	-102	34%
234	Tábua	383	334	420	414	508	432	519	440	586	437	483	411	72	15%
235	Tabuaço	350	369	354	415	298	455	277	527	438	503	343	454	-110	32%

236	Tarouca	492	397	335	449	450	506	380	522	577	505	447	476	-29	6%
237	Tavira	1307	1140	1423	1221	1686	1323	1806	1354	1963	1401	1637	1288	349	21%
238	Terras de Bouro	473	445	510	509	660	540	423	622	670	605	547	544	3	0%
239	Tomar	590	476	567	534	611	592	716	622	730	627	643	570	72	11%
240	Tondela	510	456	548	511	558	539	541	565	561	555	544	525	18	3%
241	Torre de Moncorvo	245	264	306	331	278	337	304	386	446	315	316	327	-11	3%
242	Torres Novas	483	510	562	585	582	650	619	669	647	703	579	624	-45	8%
243	Torres Vedras	809	847	877	985	943	1086	994	1172	1111	1202	947	1058	-112	12%
244	Trancoso	268	280	241	371	244	403	326	428	288	441	273	385	-111	41%
245	Trofa	654	772	698	867	764	944	791	1014	900	1006	761	921	-159	21%
246	Vagos	663	571	762	627	787	697	845	691	886	724	789	662	127	16%
247	Vale de Cambra	650	586	619	649	699	713	741	731	747	698	691	675	16	2%
248	Valença	608	498	531	499	653	614	609	654	683	625	617	578	39	6%
249	Valongo	678	649	724	775	812	894	944	1032	1128	993	857	869	-11	1%
250	Valpaços	289	272	313	314	385	369	537	395	440	356	393	341	52	13%
251	Vendas Novas	632	557	669	642	702	689	775	709	812	716	718	663	55	8%
252	Viana do Alentejo	469	403	513	451	393	600	533	548	609	543	503	509	-6	1%
253	Viana do Castelo	755	734	831	822	861	889	945	928	1011	913	881	857	23	3%
254	Vidigueira	409	301	364	403	448	520	395	483	464	484	416	438	-22	5%
255	Vieira do Minho	363	429	470	479	524	512	632	551	571	546	512	504	8	2%
256	Vila de Rei	326	163	451	234	277	371	285	360	521	343	372	294	78	21%
257	Vila do Bispo	1276	1354	1398	1470	1485	1666	1476	1652	1545	1706	1436	1570	-134	9%
258	Vila do Conde	892	819	951	914	1016	1000	1122	1076	1246	1069	1045	976	70	7%
259	Vila Flor	300	276	378	326	328	332	424	358	258	376	338	334	4	1%
260	Vila Franca de Xira	875	782	971	969	1046	1112	1183	1161	1346	1142	1084	1033	51	5%
261	Vila Nova da Barquinha	525	383	503	457	618	509	653	492	691	550	598	478	120	20%
262	Vila Nova de Cerveira	630	490	538	608	686	667	753	683	717	720	665	634	31	5%
263	Vila Nova de Famalicão	692	731	727	822	779	927	869	962	947	906	803	870	-67	8%
264	Vila Nova de Foz Côa	421	258	247	322	374	407	359	388	248	365	330	348	-18	5%
265	Vila Nova de Gaia	772	575	825	797	924	1075	1087	1323	1240	1320	970	1018	-48	5%

266	Vila Nova de Paiva	331	330	346	426	298	431	345	439	297	402	323	406	-82	25%
267	Vila Nova de Poiares	485	465	547	529	543	600	568	638	568	593	542	565	-23	4%
268	Vila Pouca de Aguiar	486	280	513	342	454	407	610	475	528	425	518	386	132	26%
269	Vila Real	725	518	741	576	773	651	875	731	946	692	812	634	178	22%
270	Vila Real de Santo António	1239	1232	1357	1367	1447	1431	1574	1405	1697	1489	1463	1385	78	5%
271	Vila Velha de Ródão	331	450	343	370	220	465	252	424	301	451	289	432	-142	49%
272	Vila Verde	527	537	578	608	674	665	740	708	805	660	665	636	29	4%
273	Vila Viçosa	558	383	545	493	464	543	488	504	510	506	513	486	27	5%
274	Vimioso	212	222	177	219	270	405	275	269	294	273	246	277	-32	13%
275	Vinhais	256	247	367	314	367	348	382	365	352	311	345	317	28	8%
276	Viseu	736	592	786	660	837	722	930	782	967	787	851	709	143	17%
277	Vizela	622	643	661	720	735	797	748	828	868	803	727	758	-31	4%
278	Vouzela	301	356	431	388	442	448	488	471	426	440	418	421	-3	1%

* $|\Delta|=\frac{(Y'-Y)}{Y}$;

If |Δ| is greater or equal to 38%;

If |Δ| is less than 15%;

If |Δ| is greater or equal to 15% but less than 38%.

Source: Own elaboration; Software: Microsoft Excel.