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Predicting housing prices. A long term housing price path for Spanish regions

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Abstract

This paper aims to forecast the long term trend of housing prices in the Spanish cities with more than 25 thousand inhabitants, a total of 275 individual municipalities. Based on a causal model explaining housing prices based on six fundamental variables (changes in population, income, number of mortgages, interest rates, vacant and housing prices), a pool VECM technique is used to estimate a housing price model and calculate the 'stable long term price', a central concept defined in the formal valuation process. The model covers the period 1995-2020, and the long term is approached from 2000 to 2026, so the prediction exercise includes backcast and forecast period allowing to extract the long term cycle housing price have followed during last 20 years and project it further six years. The analytical process follows three steps. Firstly, it identifies the cities following a common pattern in their housing market by clustering twice the cities: (1) using house price time series and (2) using a machine learning approach with the six fundamental variables. Results give a comprehensible evolution of the long term component of housing prices and the model also permits the understanding of the main drivers of housing prices in each Spanish region. Clustering cities with two statistical tools give pretty similar results in some cities but is different in others. The challenge of finding the correct grouping is critical to understanding the housing market and forecasting their prices.

Key words: housing prices, forecast, time series, housing valuation, Error correction models, machine learning

I. Introduction and Motivation

The interest in knowing the future evolution of residential prices has different motivations. On the one hand, anticipating future prices allows assessing the residential household wealth in an economy and its potential as a generator of consumption growth through the wealth effect (Case, Quigley and Shiller, 2005). On the other hand, predicting future prices reduces uncertainty in investment markets and facilitates the movement of capital and the decision to build.

Other relevant reasons support the interest in advancing housing prices, but one of them stands out for its great relevance to the economic system. Residential prices and their evolution are part of macro-prudential policy. To the extent that housing (and real estate in general) serves as collateral for the financing granted for its provision or purchase, an stable property value is part of the risk assumed by the financial system. In an economy with a developed mortgage market, correctly pricing real estate can be vital to keeping risk levels under control and avoiding situations that can lead to a loss of confidence with negative results for the institution or the financial system as a whole. The reason lies in the fact that the credits backing real estate are long term, and even if the financial institution acts correctly in granting them taking care of their risk levels, the economic situation can change completely during their lifetime so that operations that are robust at one point in time, would fail when the cycle changes. A massive fall in residential prices resulting from an economic or another shock would dramatically increase the risk level of the loans granted (and the financial assets issued on them). In contrast, a generalized increase in prices would generate the opposite effect, encouraging the financial system to grant more credit with very low-risk levels (at the moment), leading to increased exposure to real estate risk. Therefore, it is understandable that there is an interest in detecting real estate price bubbles or price corrections.

Predicting residential prices is not a simple matter. On the one hand, housing is a highly heterogeneous good, and its value depends on different groups of factors. The literature identifies the most relevant as location (AMM model, Brueckner, 1987); housing characteristics (Goodman, 1978); neighbourhood and demander characteristics (Hwang and Quigley, 2006); but also the evolution of a set of factors that have been so-called 'the fundamentals' (Kwan and Quigley, 2006, Case and Shiller, 2003; Case, Quigley and Shiller, 2001) that determine the existence of demand pressure (generally due to migratory movements, Saiz, 2007), and the payment capacities of potential demanders or their financial activity. It is considered the fundamentals that delimit the evolution of prices in the long run, although their local particularities determine the specific value levels of residential goods. Property heterogeneity and the bundle of variables affecting housing prices convert price prediction into a complex and challenging task.

Housing prices are critical for the financial system due to property acts as collateral of the loan. It is why appraisal techniques have been developed and embraced in most the developed countries. In the Spanish system, financial institutions take, as a reference value when granting mortgages, the value resulting from the appraisal of the property (so-called the mortgage price, ECO/805). Such calculation is under complex rules that include the precise measurement of the property, the location and certain adjustments that attempt to identify its market price independently of the price that has been offered in the transaction or declared. Valuations in Spain are calculated in real-time by institutions endorsed by the Bank of Spain and specialized training.

The financial crisis has globally shown how property values can be influenced by market shocks from stable levels (with precise valuations), towards scenarios of extreme risk, so that interest in anticipating these shocks is growing among institutions with macroprudential responsibility (see the alert mechanism of the EU's Macroeconomic Imbalance Procedure[1]). Institutions responsible for property valuation methodology (IVS- International Valuation Standards, white book; TEGoVA, European Valuations Standards, blue book; RICS, red book) agrees on the relevance of determining a stable value. Despite it, only some regulations in Europe, such as the Spanish ECO/805, include the obligation to estimate a long-term value to serve as a guide for the granular valuations carried out. This price concept is known as the 'Equilibrium Value' and would be the long-term value around which the observed price of the property evolves.

II. Theoretical basis

This paper adopts the fundamentals-based residential pricing approach to define the causal model used for housing price prediction. Housing markets experience a well-known pseudo-equilibrium situation derived from their characteristics that takes the form of a mismatch between prices in the short run and an adjustment over time so that the market is said to adjust prices in expansionary phases and quantities in contraction (DiPasquale and Wheaton, 1996). This imbalance manifests in a particular price reaction, which could lead to bubble situations (Glaeser et al., 2008, Quigley, 2002, Case and Shiller, 2003). There is an agreement that a bubble in housing prices would exist when the price increase is above than the one explained by fundamentals. The relevance of identifying the housing price shifts comes from the risk associated with the bubble burst experienced in some economies. However, the downwards correction seems to be a characteristic of the property price dynamics, as demonstrated by the literature of real estate cycles (Wheaton, 1999, Pyhrr, Roulac and Born, 1999).

The long-run price behaviour adopted in this paper is considered to depend on their fundamental factors, such as changes in population, income, financing flows, and interest rates (Ambrose et al., 2013, DiPasquale and Wheaton, 1996, Mayo, 1981, Hwang and Quigley, 2010, Case and Shiller, 2003, as relevant references), and adjusted for the supply response in each municipality. Supply responses to prices are captured here through the vacancies, according to the supply-literature. The model could be represented as in (1).

$$ph_{it}|Hs_{it} = \Psi(\Delta pop_{it}, Inc_{it}, h\_n_{it},\ ir_t,\ \mu_t) \tag{1}$$

Where Δpop is the change in the resident population in each municipality, Inc is the average income of the city, h_n captures capital flows for house purchases, Hs is an indicator of housing supply and corrects for the price reaction in each market adjusted for its idiosyncratic particularities, and ir represents the interest rate in nominal terms. The subscript 'i' refers to the municipality and t to the observed period. The function is a dynamic operator in panel environments, which allows the prediction of the dependent variable.

This approach defines a dynamic model representing causal relationships, used to forecast the housing price trend-cycle to approach the *'long-run price'*. It would approximate the stable long-run value associated with the residential market determinants in each market location.

[1] https://ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/eu-economic-governance-monitoring-prevention-correction/macroeconomic-imbalances-procedure_es

The prediction minimizes the difference between the observed and estimated price value with the long-term components at each point in time and location. The expression would be (2).

$$ph_i^{obs} - \widehat{ph}_i = \mu_i \qquad (2)$$

Where the first term, ph_i^{obs} refers to the observed price, $\widehat{ph}_i$ is the estimated price and μ is the error component representing the effects of short-run innovations that the model fails to capture (Riddel, 1999 called it a proxy of speculative component).

III. Data

The data used in this article comes from secondary sources of Spanish statistics. The six variables included in the long-term housing market model are: population changes (which are the proxy for potential new demand), municipality income (which is a proxy for the population's ability to pay and level of income in the city), investment flows for housing purchases (which are proxied by financial flows or mortgages reflecting new funds coming to the market to facilitate purchase), interest rates (which proxy for the user cost of capital) and housing supply which captures the idiosyncratic supply elasticity response (constraining the price reaction) in each market. House prices are measured using MITMA statistics on appraised prices. The average price per square metre is used. This information has been obtained for Spanish cities with more than 25 thousand inhabitants, 275 cities. The cities included in the analysis are listed in the appendix. The model uses annual data, and the time series covers 25 years, 1995-2020.

The whole period for some variables are not available, and the missing observations are extrapolated. The explanation of the data reconstruction process can be found in table 1 and their sources and basic statistics for each variable.

The variables allow constructing a panel with 275 cross-sections and 25 years (1995-2020) and six variables to analyze the causal relationships between house prices, four demand-oriented variables considered capturing the long-term fundamentals and controlling for housing supply. Representation of variables can be found in Figures 1-5.

IV. Methodology

- Housing markets mechanism patterns

Identifying the patterns of residential market price reaction is not straightforward. How the housing market reacts to fundamental changes is not observable, and closer responses assumptions are needed.

Three criteria have been followed in this work to find common patterns in grouping the municipalities. Firstly, proximity. The first classification is entirely arbitrary and classifies the cities regarding the location. Secondly, clustering methodology has been used to group cities to create consistent panels with closed patterns. The clusters of the 275 municipalities have been calculated considering the statistical behaviour of their residential prices during the whole available period. The methodology applied was based on clustering time series of prices by minimizing the distances between the centroids of the prices in each reference element (cities) following the works of Piccolo,1990, Corduas and Piccolo,2008, Xiong and Yeung, 2004 and Alonso and Peña, 2018. The clusters were calculated using different techniques (average linkage, distance and centroid) while also arbitrarily setting several numbers of clusters extraction (calculating 2,3,5,7,8,9 and 10 clusters) to select the best one. The equilibrium number was 8 clusters, and the municipalities included in each cluster are shown in Table 2.

In the second clustering, 16 clusters were calculated with Machine Learning (ML) methods that took into account all the available variables of the model when linking the cities. Two clustering techniques were applied within the Machine Learning tools. The first (based on the cumulative algorithm) consisted of grouping (based on 6 variables) the cities in close pairs, substituting their values for the centroid between the two, searching for the third nearby city in an iterative process until a cluster was reached. The second (K-means) consists of starting from several pre-determined centroids, adding others closer to them and recalculating the centroids in an iterative process that ends when the centroid value does not change. The ML techniques that were finally used were those of the first group (cumulative or agglomerative algorithm) because of their best results among a wide range of methods, from AdaBost, Catbost and linear regression, to Decision Trees with different accuracies and Random Forest (in total, 16 tools). The most accurate in minimizing distances between city price values was the CatBoost tool. The clustering of cities is shown in table 3[2].

With the three classifications, model (4) was applied on panels created according to the grouping of municipalities.

- **Empirical strategy to estimate the model**

The econometric strategy is developed through the following steps. The first step analyzes the stationarity properties of the variables through the panel unit root tests giving, as a result, that all of them show a unit root. Second step investigates the presence of a cointegration relationship between the variables. Pool unit root tests developed by Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003) are calculated to check the stationarity properties of the variables. LLC tests the existence of a common unit root process across the cross-sections against the null of no unit root, while IPS tests whether individual unit root processes exist across the cross-sections.

[2] The absence of a relationship between spatially proximate markets is surprising given that real estate theory has traditionally considered that proximity generated a transmission effect of influences on prices and construction. This is a principle that guides the classification of cities in exercise 1, although in exercises 2 and 3, the aggregation carried out with the statistical techniques does not associate proximity except in some cases. Results of the cluster exercise is not shown in this document. They are available under request.

The first test suggests a homogeneous autoregressive root, while IPS tests for the existence of heterogeneous autoregressive coefficient, both under the alternative hypothesis.

If cointegration relationships are identified, Pedroni (Engle-Granger Based) Cointegration Tests allowing for individual-specific fixed effects are applied to test for a long-run relationship among the variables contained in the model. The cointegration tests imply the existence of long-run relationships among variables. Thus, model (3) is estimated through a panel VECM approach developed by Engle and Granger (1987) to examine the causal relationship between the variables in which the error correction term (ECT) is included in the VAR system as an additional variable. The VECM approach, well known as the augmented Granger causality test, is able to investigate both long and short-run causal relationships. In this step, long and short-run causality are investigated and serves to define the final model.

The best model is chosen in the next step regarding its predictive capacity among those potential models that are stable (all roots inside the circle) and LM test rejecting the null of residual serial correlation.

Model (1) is fitted in this paper by error correction, i.e. using an environment (VAR) that calculates the interaction of all endogenous variables over the analyzed period as well as their cross-correlations association, so that it is possible to quantify a joint long-run behaviour (to which we call housing market pattern), to estimate the forecast. Error Correction Vectors (ECVs) quantify the stable relationship between variables in the long run (and identifies the components that permanently affect these price levels and hence their patterns) as well as the variations in the short run that cause deviations from that stable trend. Technically, the whole model captures the effects of residuals in the long-run relationship (ECT) and changes in its components in the short run. Formally, the models could be represented by (3).

$$\Delta X_t = A + X_{t-1}\Gamma_m + \Delta X_{t-j}\mathrm{B}_j + \mathrm{N}_t \qquad (3)$$

Extracting the price function from the endogenous system above, the functional form is (4).

$$\Delta Ph_{it} = \alpha_1 + \Omega_{1..6}\big[Ph_{it-1} + \delta_{1,1}d(Pop)_{it-1} + \delta_{1,2}In_{it-1} + \delta_{1,3}h_{n_{it-1}} + \delta_{1,4}ir_{it-1} + \delta_{1,5}d(Stock)_{it-1} + c_1\big] + \sum_{i=1}^{j}\beta_j\Delta X_{it-j} + \mu_{1,t} \qquad (4)$$

Where X is a matrix including the variables in the model so that X={ph, Δ(Pop), Inc, h_n, int, Δ(stock)}, the subscript 'i' refers to the city, *m* is the number of variables in the model (m=6). In specification (3), the matrix expression reflects the structure of the computed system of endogenous equations[3].

[3] Note that population and housing stock are computed in differences, i.e. they measure changes in the resident population in each municipality and changes in the residential stock; the mortgage indicator computes the number of mortgages granted for the purchase of houses to individuals and not their amount, thus avoiding

The first component on the right-hand side of equation (4) is the long-run relationship. If it exists (and is statistically significant), it is identified as the long-term causal pattern that quantifies how long-term prices contribute to equilibrium convergence in the short run. There can be more than one long-term relationship, so the omega parameter can take different values depending on calculated 'n' relationships. Each long-run relationship would be capturing an economic mechanism that acts autonomously on the evolution of prices in each cluster of cities. These mechanisms show permanent effects on the dependent variable. After the sigma parameter, the second component captures the short-run reactions; this block identifies and quantifies the factors that produce the deviations from equilibrium in the short run and have temporary effects. The number of lags is computed as 'j'.

The ECT coefficient indicates the presence of a long-run equilibrium relationship among the variables. We can determine the short-term causality when applying a joint test of the coefficients based on the F-test. Besides, the long-run causality is established through the significance of the lagged error correction term based on the t-test.

As the objective is to extend the long term cycle by forecasting the period further to the observed data (predicting the future), then in the case of multiple potential models, the choice is made by judgement approach (Hyndman and Athanasopoulos, 2018). The model is estimated starting in the earlier period as possible, seeking to identify whether the future model prediction is consistent with the previous long term cycle observed in the data. This decision is taken to reduce the subjectivity implicit in the judgement approach.

- Forecast methodology

Model (3) is fitted separately for each group of municipalities required, and the forecast is calculated as in (5).

$$\Delta\widehat{Ph_{t+k}} = \widehat{\alpha_1} + \widehat{\Omega_{1..n}}\left[Ph_{t+k-1} + \widehat{\delta_{1,1}}d(Pop)_{t+k-1} + \widehat{\delta_{1,2}}In_{t+k-1} + \widehat{\delta_{1,3}}h_{n_{t+k-1}} + \widehat{\delta_{1,4}}ir_{t+k-1} + \widehat{\delta_{1,5}}d(Stock)_{t+k-1} + \widehat{c_1}\right] + \sum_{i=1}^{j}\widehat{\beta_\iota}\Delta X_{t+k-j} \qquad (5)$$

Where 'k' is the number of future periods calculated, and the sign ^(hat) refers to the estimated value. Note that this methodology predicts all the variables and uses each of the predictions in one period to calculate the next period according to the estimated model, where the first prediction is the one made with the parameters set in the base period. These multiple predictions make it possible to assess whether the future quantification is according to the economic reasonability, as there is no possibility of calculating deviation errors as future specific values are not observable. The forecast method is multidirectional based on performing a dynamic-stochastic simulation using the estimated model, following Broyden solver with iterative calculations until reaching the convergence (allowed a máximum of 5000 iterations) at 95% of

what is known as the 'price-effect' in the computation of the mortgage flow, which is statistical noise and a repetitive (potential) reverse impact on the estimation of residential prices.

the confidence interval. The covariance matrix is scaled to equation specified variances, and the system allows for a máximum of 1000 repetitions converging to (1/1e^8).

The model is accepted depending on the forecast precision in two steps. First is the precision on the out-of-sample period (2017-2020) and have the larger R^2 and lowest AIC test. The second condition is when the backcast prediction from 2000 to 2020 gives a long term cycle with lower errors. The RMA measures errors.

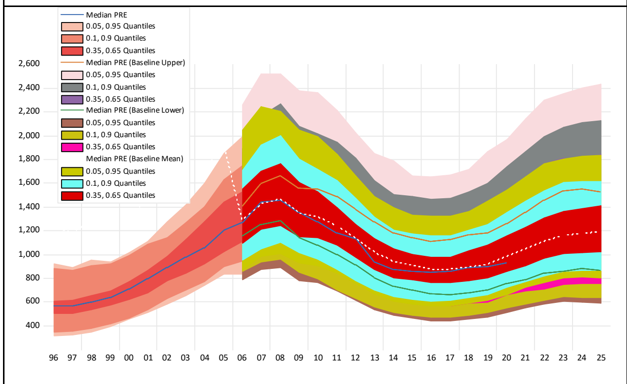
V. Results Empirical evidence

The full exercise has produced three groups of predictions. The first corresponds with the naïve forecast based on the chosen best model but with the arbitrary aggregation of cities. The second is made by using the first methodology of clustering based on housing prices time series, and the third corresponds with the second clustering based on machine learning methods.

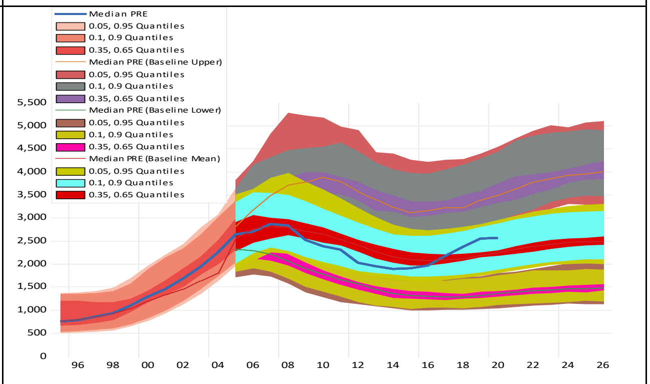
In the following panels, the forecasting results of the second and third group are presented through the aggregated estimation in fan-charts.

Panel 1. Fan-Charts in clustering number 1.

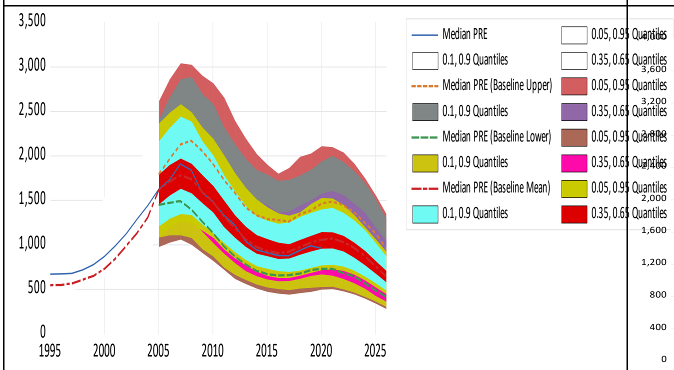
Cluster 1



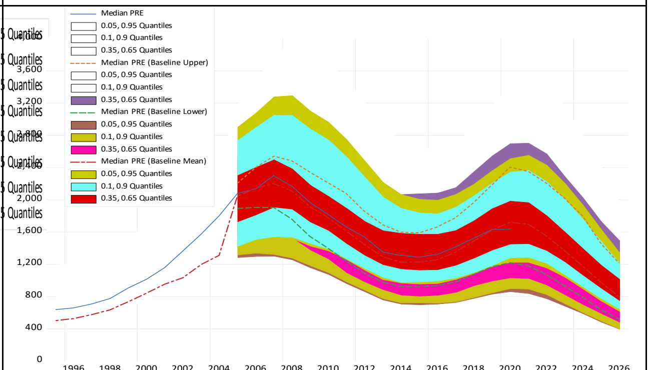
Cluster 2



Cluster 3

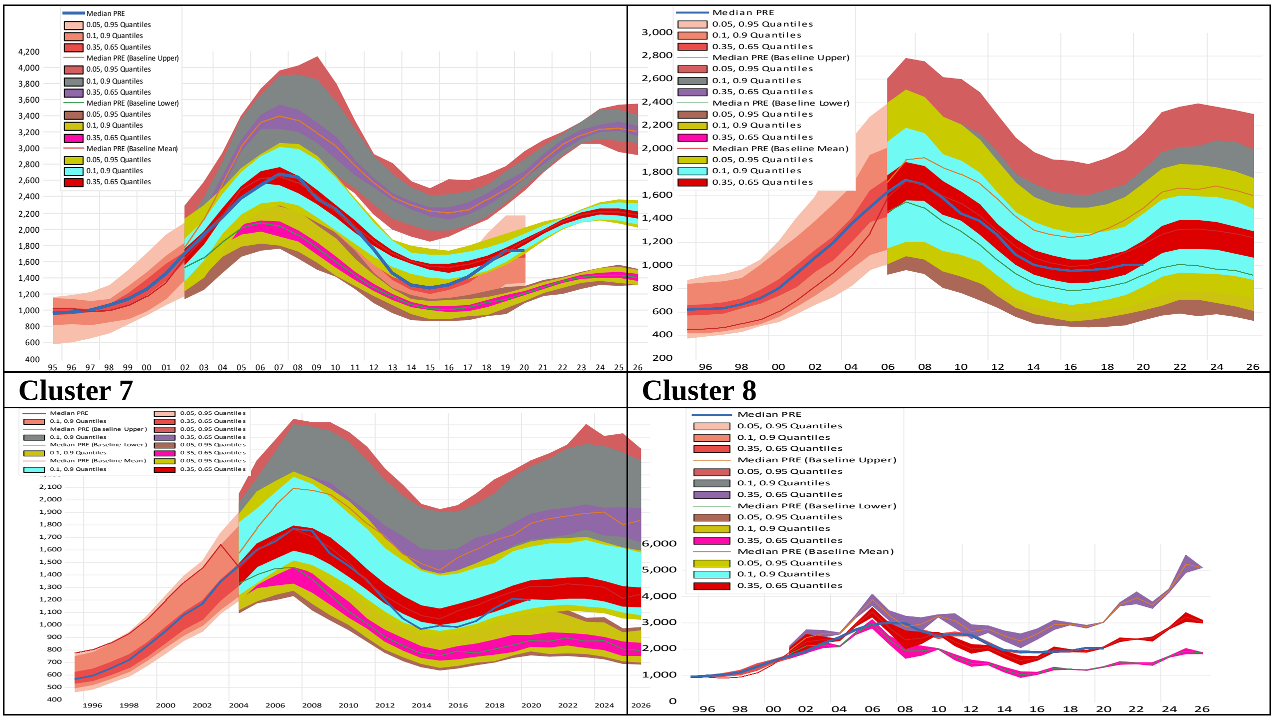


Cluster 4

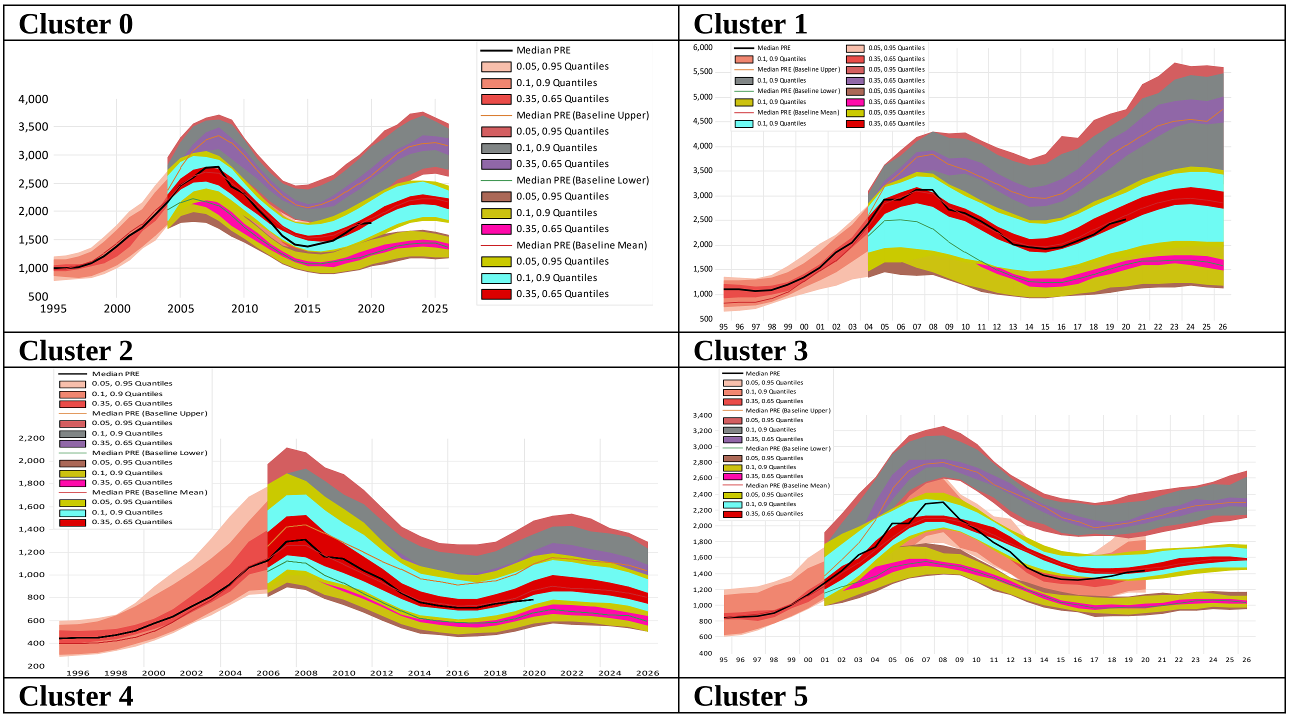


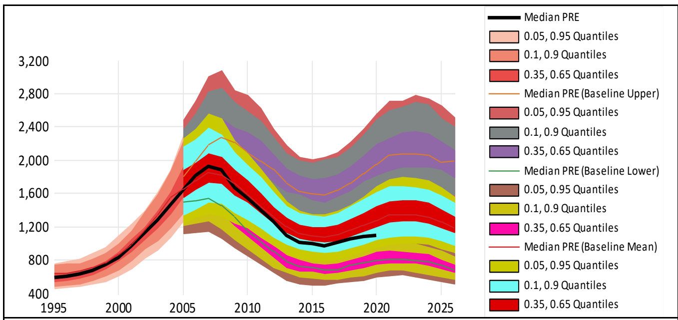
Cluster 5

Cluster 6

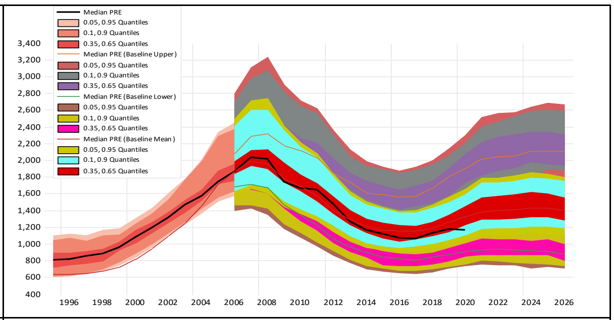


Panel 2. Fan-Charts in clustering number 2.

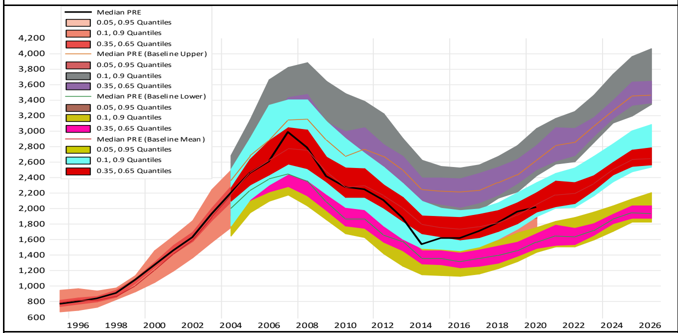




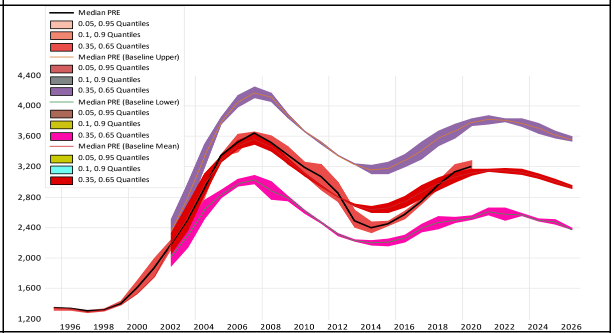
Cluster 6



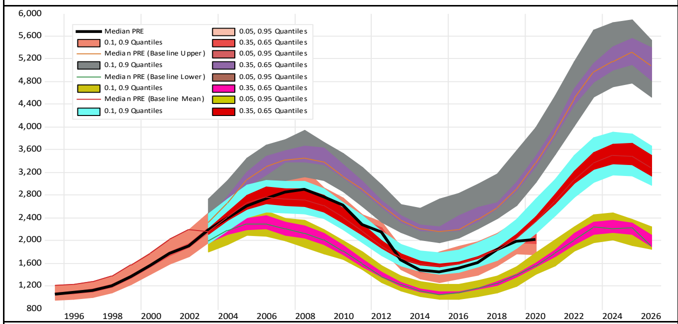
Cluster 7



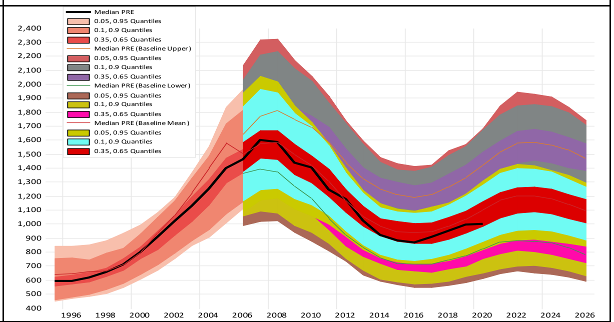
Cluster 8



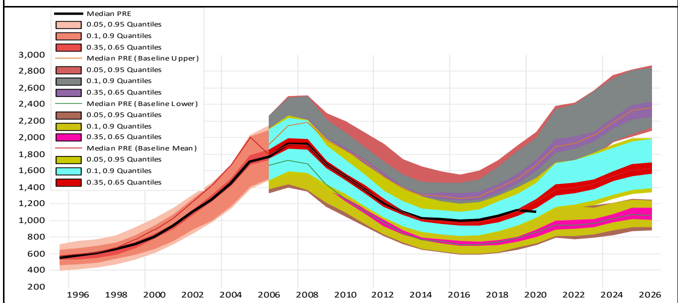
Cluster 9



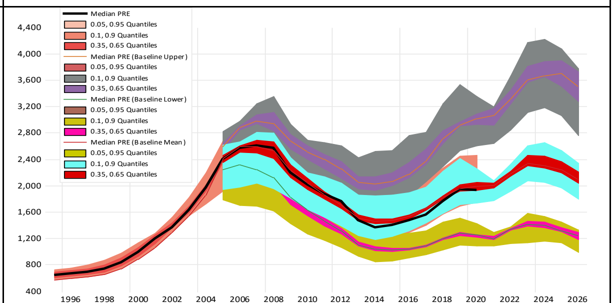
Cluster 10



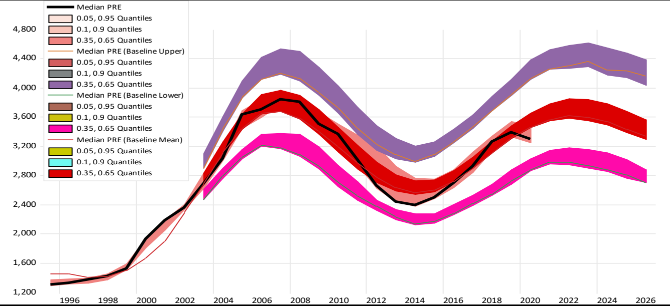
Cluster 11

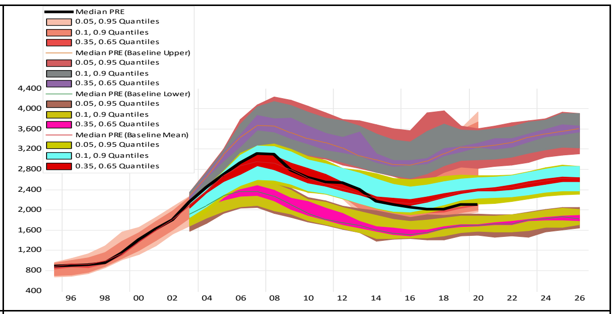


Cluster 12

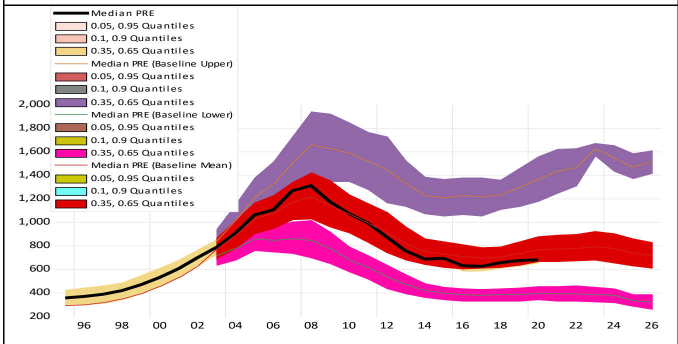


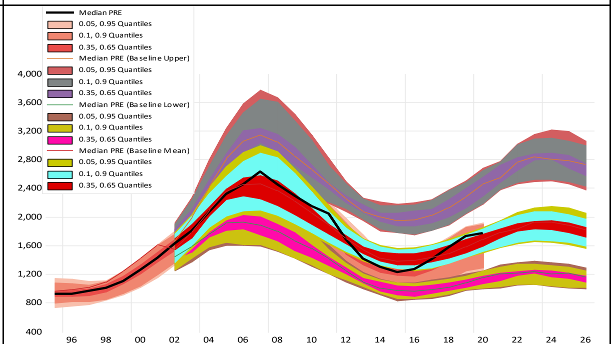
Cluster 13





Cluster 14 | **Cluster 15**

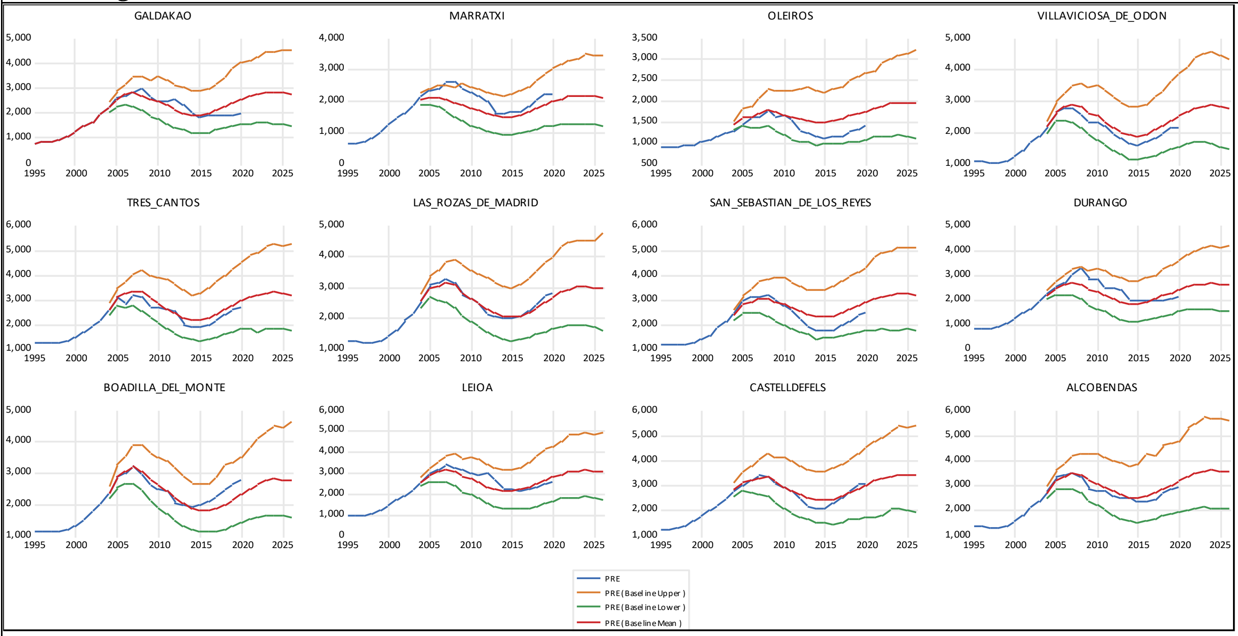




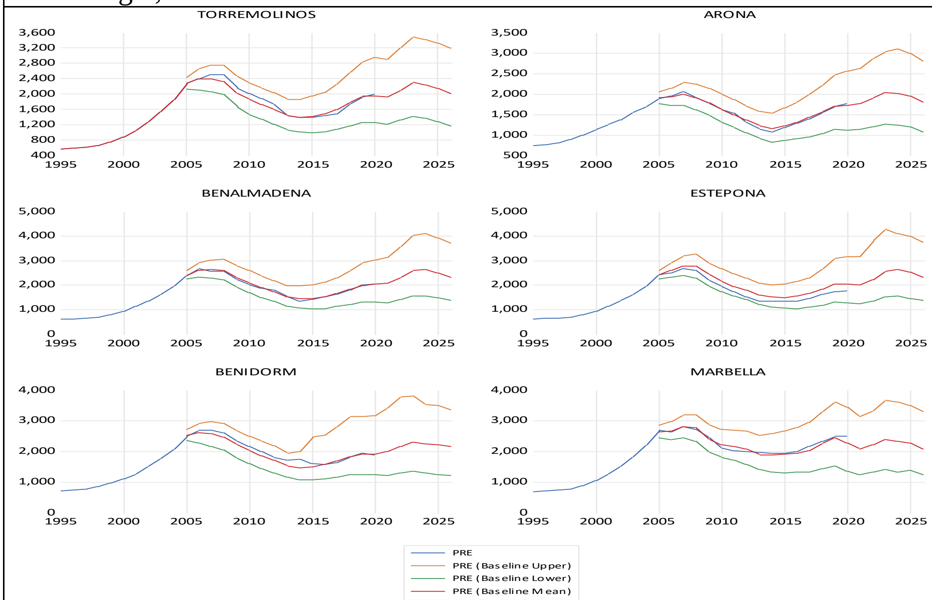
This method allows to forecast housing prices at the municipal level individually. Panel 3 represents a selected number of cities estimated in clustering 1 and 2. The dynamic prediction made for the model's backast and future period 2004-2026 are shown for each municipality.

Panel 3. Housing prices forecast by municipalities. Selected results

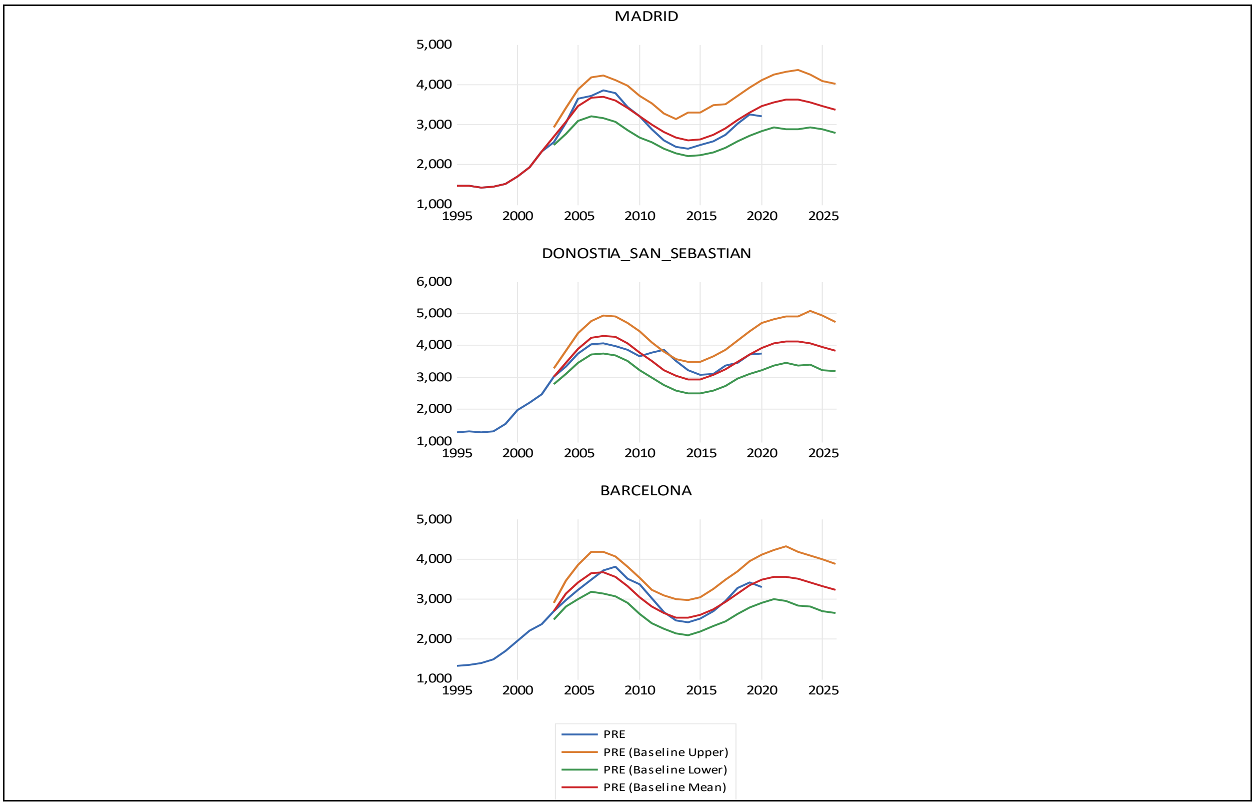
Clusering 2, cluster 1



Clusering 2, cluster 11. Main tourist cities



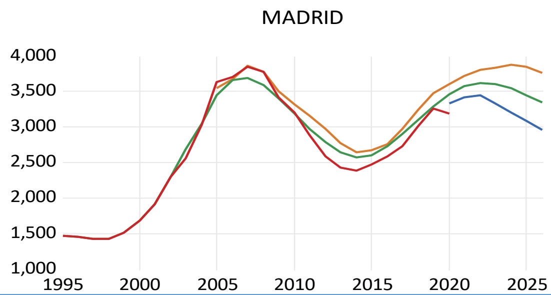
Clusering 2, cluster 12. Main capitals

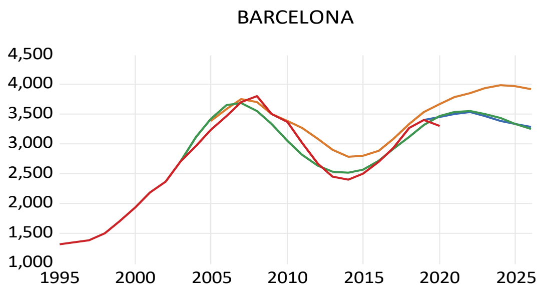


The comparison among the three forecast exercises, by city, is shown for selected cities in Panel 4.

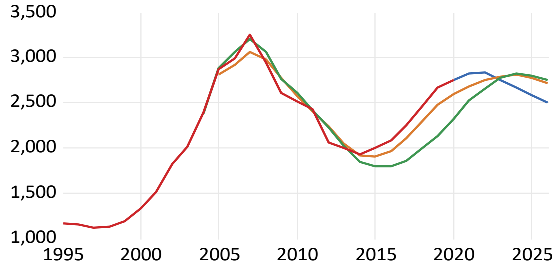
Panel 4. Forecasting comparison of housing prices in selected cities

MADRID	**BARCELONA**
	Observed values: ----------- Baseline prediction : ------------- Prediction- clustering 1: ------------- Prediction – clustering 2: --------------

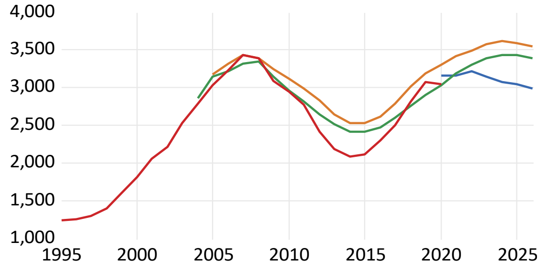




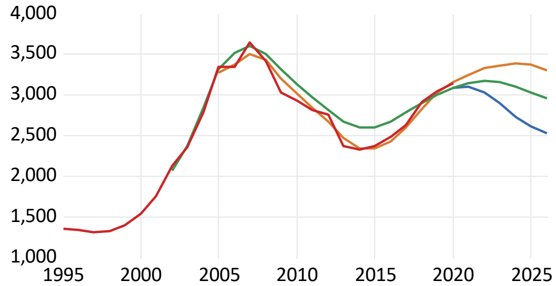
BOADILLA_DEL_MONTE



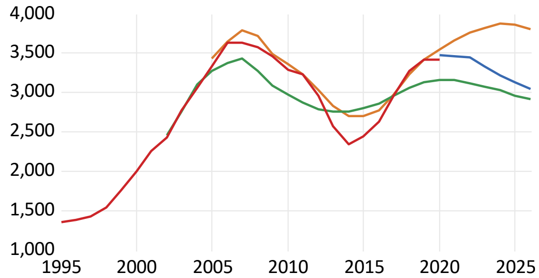
CASTELLDEFELS



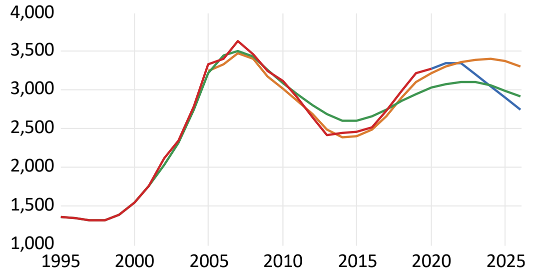
MAJADAHONDA



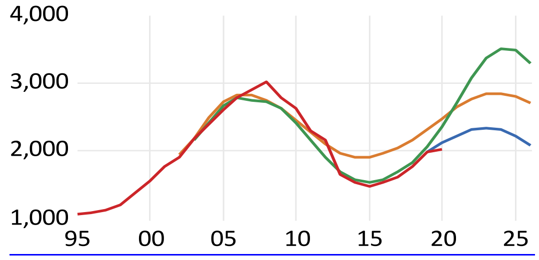
SANT_CUGAT_DEL_VALLES



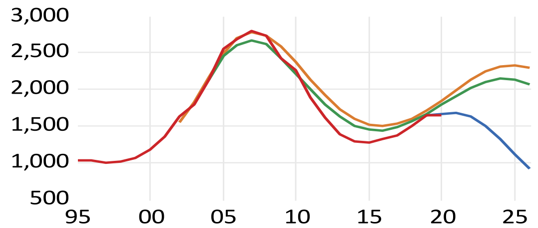
POZUELO_DE_ALARCON



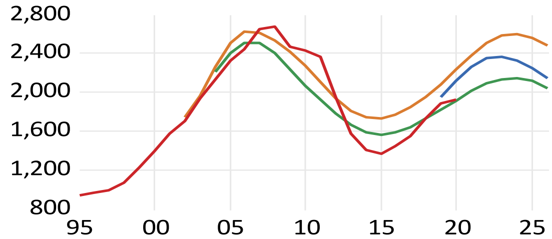
BADALONA



ALCALA_DE_HENARES



BARBERA_DEL_VALLES



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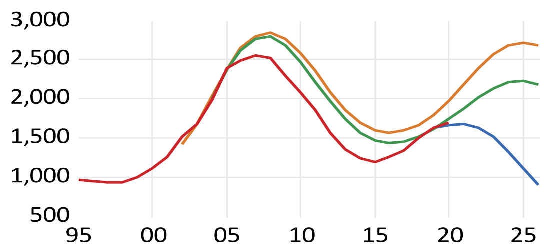
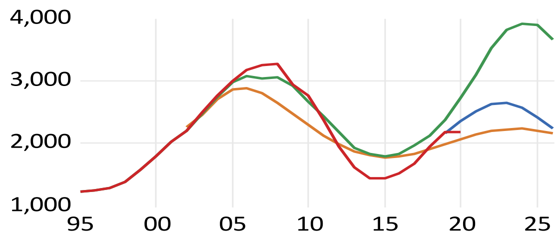
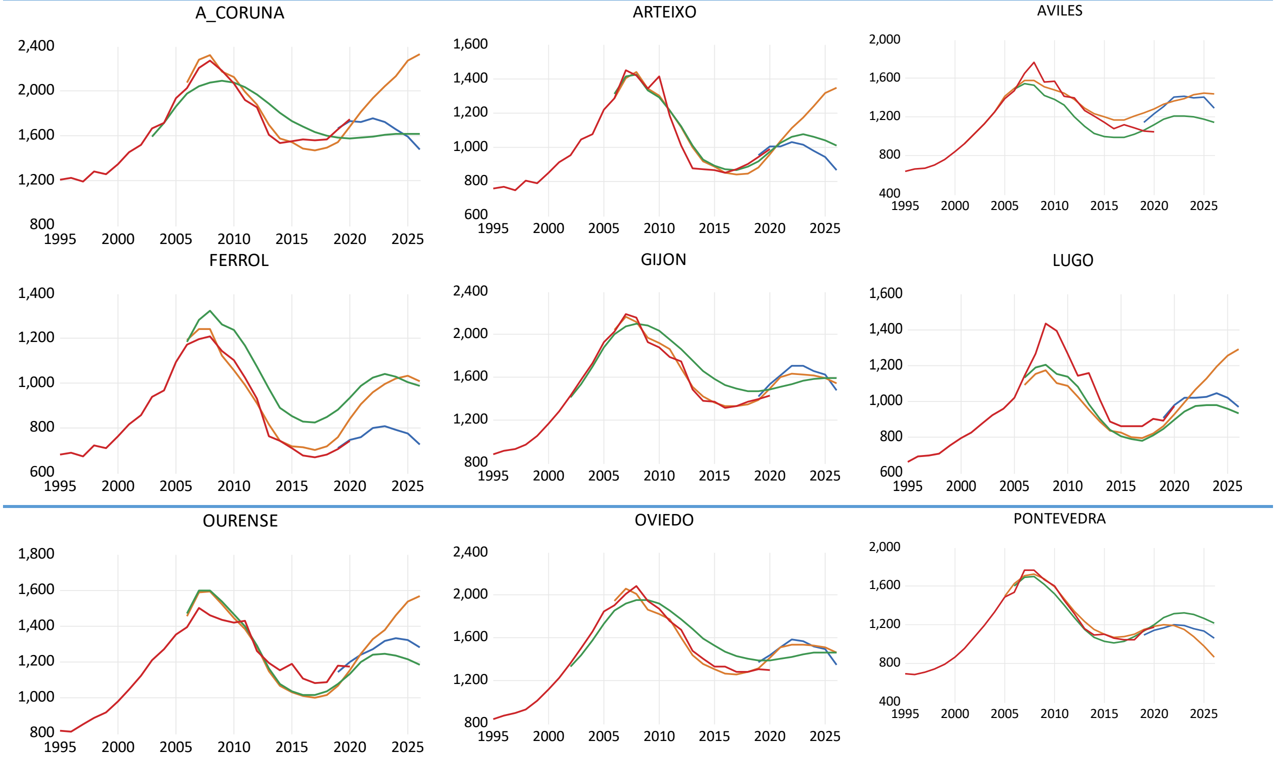


HOSPITALET_DE_LLOBREGAT



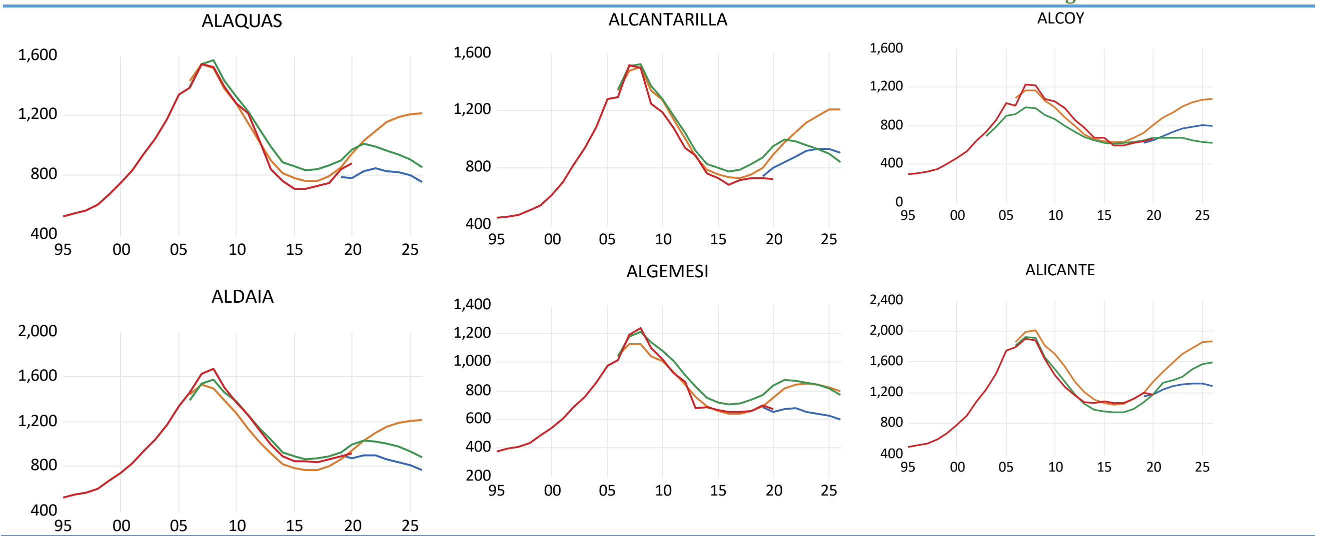
Galicia and Cantabrian Coast

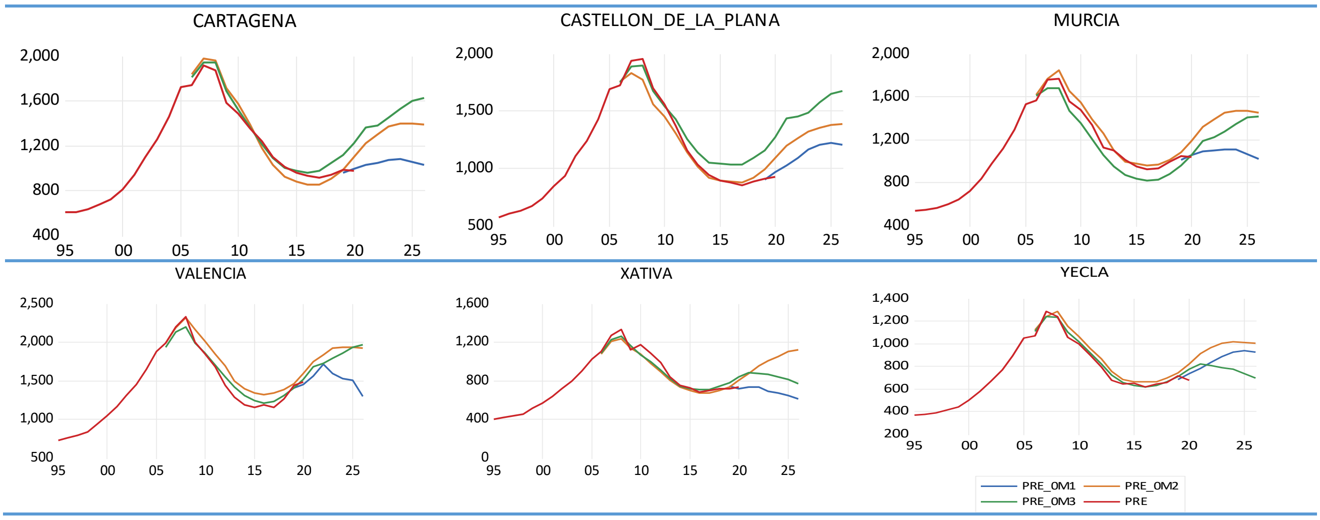
Observed values: -----------
Baseline prediction : -------------
Prediction- clustering 1: ------------
Prediction – clustering 2: --------------



Valencian Community and Murcia

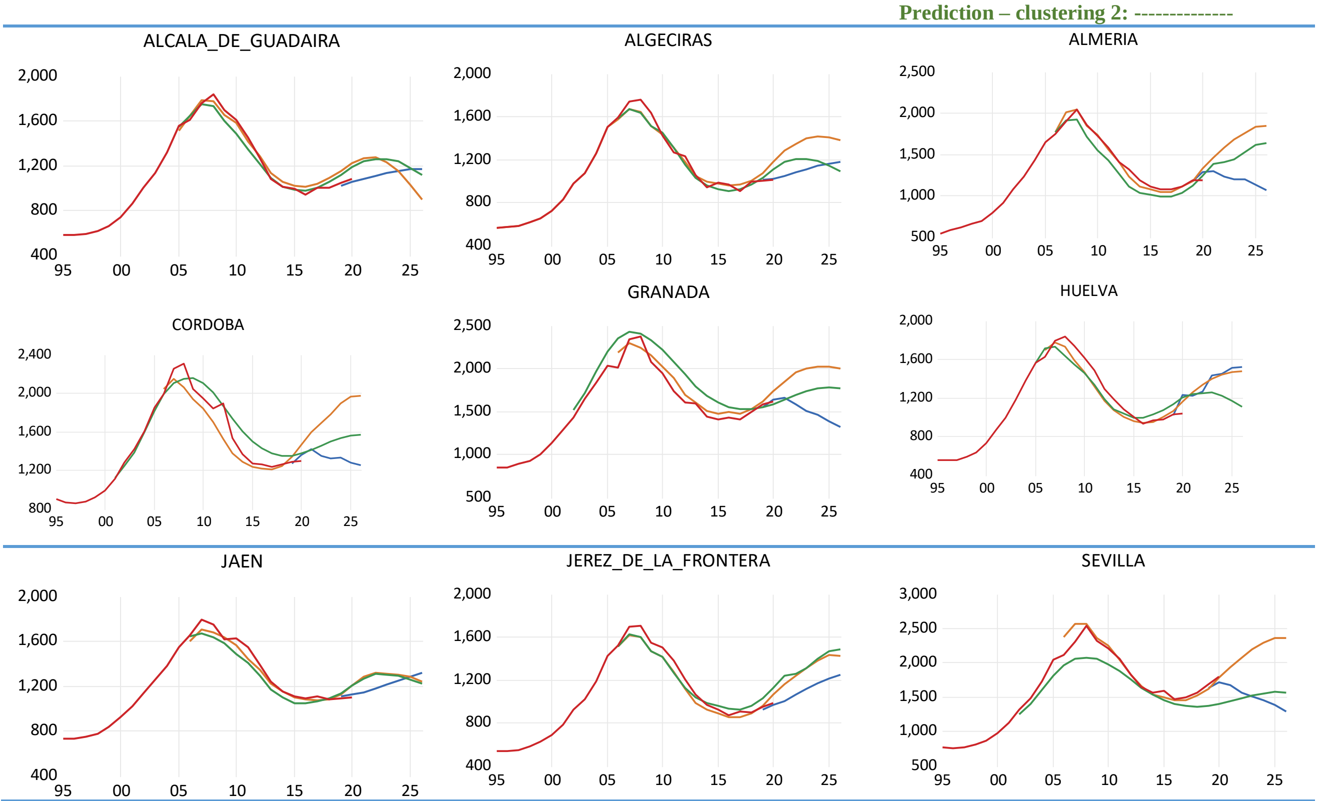
Observed values: -----------
Baseline prediction : -------------
Prediction- clustering 1: ------------
Prediction – clustering 2: --------------



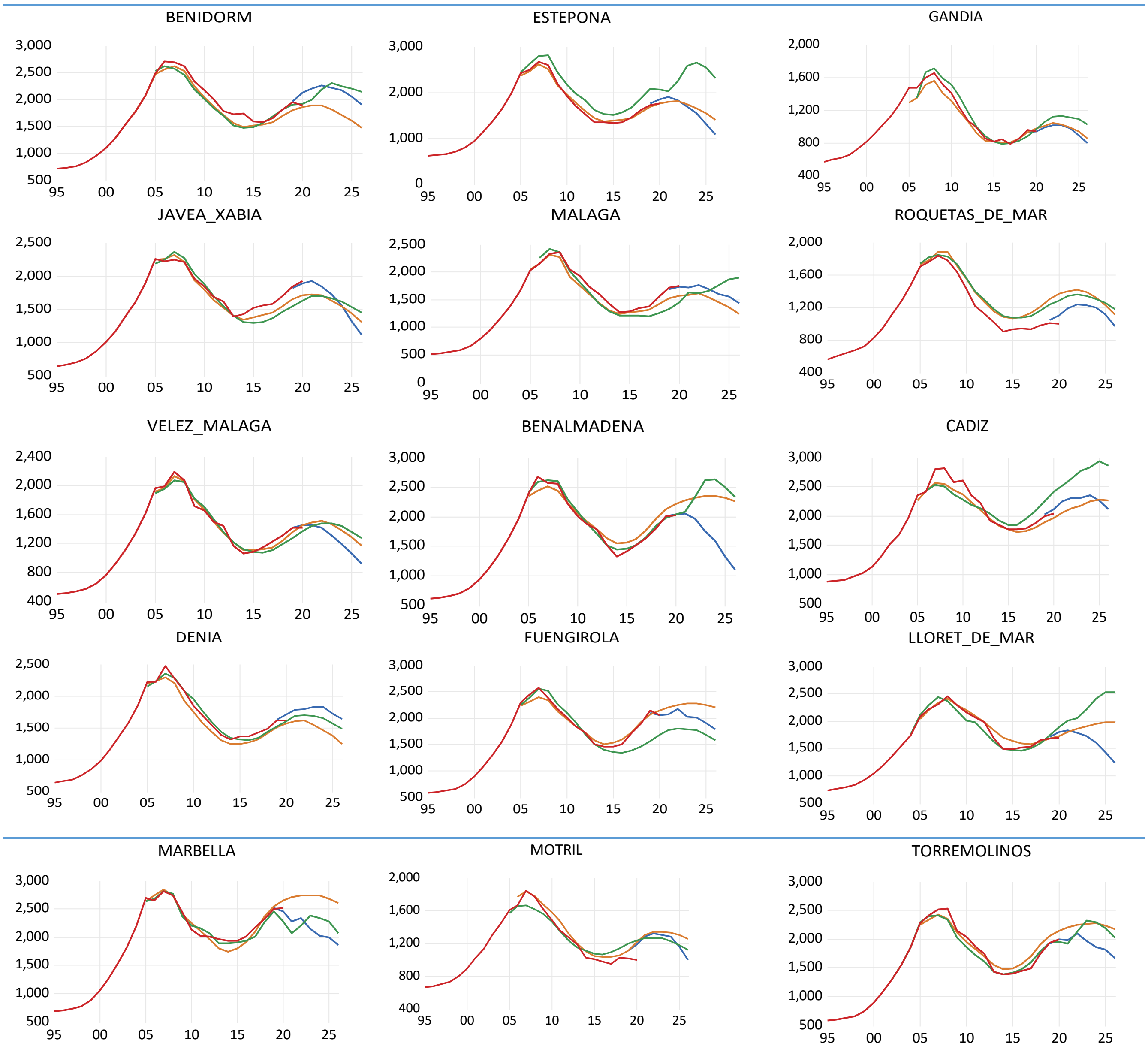


Andalusia

Observed values: -----------
Baseline prediction : -------------
Prediction- clustering 1: ------------
Prediction – clustering 2: -------------



Capitals and Tourist cities



- Discussion

Forecast housing prices requires a complex estimation. Firstly, the causal model explaining the long-term trend of housing prices identifies common housing price patterns in particular group of cities, suggesting that each market receives shocks from fundamental variables and generates the reaction of prices similarly but pretty closer in each group of cities. Those could be interpreted as that housing prices react to distinct stimuli from fundamentals following a long term pattern and that patterns represent both economic and idiosyncratic features combination. The exercise demonstrates similar patterns in the housing price reaction across Spain and not necessarily associated with physical proximity and that the prediction is feasible and very accurate in some areas. The prediction errors are found to be the lowest in the two Spanish archipelagos, Bask Country and central cities, which confirms the general belief that proximity (and accessibility as the ripple effect principles support) acts as a convergence channel in housing prices and fundamentals in particular areas with some degree of isolation, although not in others.

The two different types of clustering municipalities give different solutions in some of the cities. The aggregation of cities made through statistical tools does capture the common housing market patterns, allowing us to estimate the long term trend of housing prices and the potential deviations from the equilibrium in each city due to idiosyncratic features. However, it fails in classifying some of the cities in both cases.

In addition, the method is critical to determine the trend in the future. Clustering using the dependent variable time series fits better the data but tend to estimate an upward trend for prices. On the contrary, clustering using machine learning methods combining the six fundamental variables time series gives more smooth long term cycles. Both clustering methods produce more accurate and closed results than a baseline prediction in general.

This analysis represent the first attempt to estimate the long-term cycle for housing prices in Spain at the municipal level and their forecast, as well as it sets a methodology to advance the trend of prices allowing to prevent future shocks affecting housing prices, with its strong effects on the financial system. It serves to make decisions at a macroprudential policy level.

The critical issue to obtain accurate predictions is determining the standard pattern to which every city pertain which is the one offering the better precision.

Conclusions

This paper contains an empirical application of a method to forecast future evolution of residential prices for municipalities with more than 25,000 inhabitants in Spain, grouped according to relevant parameters. This paper is the first one providing a precise forecast of long term housing prices at the municipality level.

The estimation uses annual information up to 2019 and 2020 in residential prices, interest rates and mortgage concessions. It applies non-stationary time series forecasting methods based on a conventional long-run behavioural model. The model takes the main variables identified by the literature on residential markets as fundamental long-run drivers of housing prices.

The analysis strategy consists of the application of a Vector Error Correction models - VECM (within the Autoregressive Vector framework) on the time series based variables representing the housing price fundamentals, to obtain a housing price long term trend evolution through forecasting and backasting the observed data with the best chosen model. The model allows forecasting six years onwards based on the behavioural mechanisms that have been identified. The analysis period for fitting the models is 1995-2020, and each model adopts the best functional form that fits the actual data used.

This 'ad-hoc' modelling strategy used in this paper to estimate the model within the groups of municipalities highlight the form of endogenous relationship between the variables included, and cuantifying the hidden economic mechanisms of the residential market leading the price formation, which are called ‘housing market patterns’ in this paper.

For the modelling, municipalities are grouped. The groups are built, firstly arbitrarily (grouping by proximity), and secondly by calculating clusters based on (1) residential prices time-series clusters (estimated using the hierarchical clustering method, centroid clustering) and (2) machine learning approach, using six time-series variables. Eight clusters were chosen in the former case and 16 in the latter. The model is estimated by cluster obtaining a prediction of housing prices at municipality level.

In each estimated cluster model, the method identifies two types of influences, or effects, on housing prices. Long-run relationships are the first and are calculated as cointegrating relationships (linear combinations representing a stable and permanent long-run relationship between variables) that determine the fundamental evolution of prices in the long run. The second group of influences identify the effects that changes in the variables have on price developments and are responsible of the price deviation from the equilibrium. These short-run components are considered to have transitory effects.

The best model for the period 1995-2017 are selected for the forecast estimation step which is done in two steps. Firstly, forecasting out-of-sample 2017-2020 period and secondly, with a backast estimation from 2004-2026. As VECMs are a dynamic system of equations with endogenous variables, their structure allows predicting the actual data. Broyden algorithm has been used, with a maximum of 5000 iterations until convergence is reached in the parameters to obtain a dynamic solution. Results suggest:

- Less accuracy in the models resulting from the first grouping (grouping by proximity). The prediction is inaccurate in a more significant number of municipalities than the other two.

- The second prediction is more accurate than the third. In most municipalities, it can adjust the evolution of house prices with minor deviations and very low errors.

- There are some cities, however, where the third estimate is the best accurate. Nevertheless, the third prediction shows the long-term cycle better than the second one supporting the lower accuracy and larger errors in the results.

The forecasting exercise reveals the economic mechanisms leading housing markets in the groups of municipalities. In each of them, the behaviour of housing markets in the long and short term has been disentangled, identifying those patterns that act permanently and the sources of short-term price deviations.

The detailed analysis allows to identify two types of reactions across Spanish municipalities that lead the responses of residential prices. These reactions are found in different markets and allow us to understand the dynamics in cities. Interestingly, cities are grouped together with others far away, contradicting the principle of proximity to determine housing prices but supporting other evidence of ripple effect (Meen,1999).

The inference derived from the different mechanisms is consistent and reflects a heterogeneous group of responses that affect the diversity of the mechanisms at work in Spanish housing markets.

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TABLES AND FIGURES

Table 1. Variables and statistical description

VARIABLE	Population	Income	Mortgages	Interest rates	Stock	Housing prices
Description	Number of population registered.	Average household income in the city	Number of mortgage credits granted to buy a house at the province level.	Yearly average of mortgage interest rate in nominal terms	Number of existing housing units.	Housing price in euros, appraisal price
city level	yes	yes	no-province	no-national	yes	yes
Units	individuals	euros/year	number of credits	Percentage -%	houses	euros by m2, appraisal price
Source	INE	City Audit Eurostat and INE	INE	Bank of Spain	INE	MITMA
Available period	1995-2020	2011-2018; 2015-2018; 2019-2020	1995-2020	1995-2020	1991, 2001,2010, Census	2005-2020
Periodicity	anual	anual	monthly (aggregated at yearly basis)	monthly	total every 10 years	QUARTERLY
Extrapolation method	no. This variable is taken in differences to evaluate changes on population	Back forecasting./reconstruction. Guide indicator: GDP growth reate by province. Recovered from 1995-2010 and 2018-2020 in some cities	The variable serves as a proxy of number of mortgage granted in the city	no. The interest rates is the yearly average of montly mortgage rate.	This variable is taken in differences to evaluate vacancy rate in the market. It is recovered by using the starts lagged two years as a measure of completed which are added to the stock. Having starts, and taking the total amount of the stock differences from the census two years by city, the inter-year stock is estimated by sharing such difference according to the change rate of starts in each province.	We use the prices by province growth rate (1995-2020) to reconstruct the previous period of each city. Recalculation is made at quarterly level.

Basic statistics

VARIABLE	Population	Income	Mortgages	Interest rates	Stock	Housing prices
Mean	100369,5	23971,37	30355,89	4,083669	48498,89	1409,396
Median	47416,25	23807,92	15808	3,427167	24175,27	1271,985
Maximum	3273049	90334,42	164464	9,4535	1575484	4078,15
Minimum	13605	7164,415	321	1,910417	1592,975	283,552
Std. Dev.	226478,6	8134,153	35497,3	1,805062	107517,8	650,4112
Skewness	9,86069	1,302487	1,980493	1,039491	9,793845	0,915492
Kurtosis	121,7349	8,791829	6,688305	4,048857	119,6178	3,518695
Obs	6600	6600	6600	6600	6600	6600
Cross sections	275	275	275	275	275	275

Figure 1. Housing prices (euros/m2)

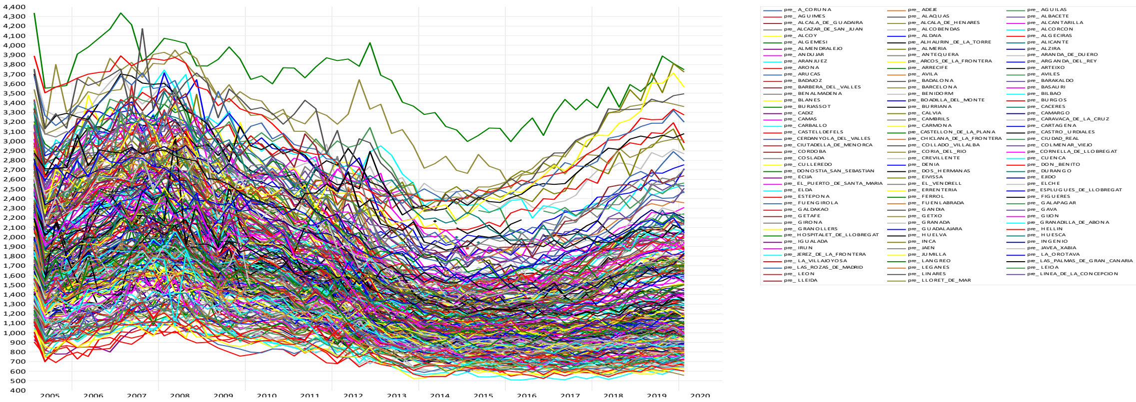

Figure 2. Population (yearly changes of registered residents)

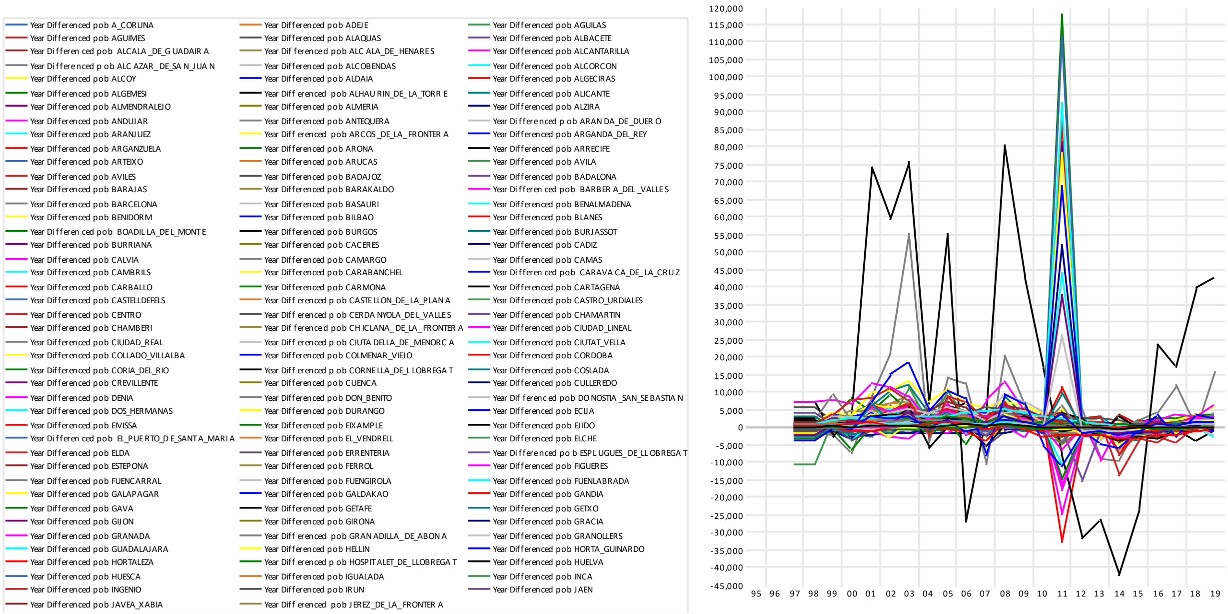

Figure 3. Income by household in the city (euros)

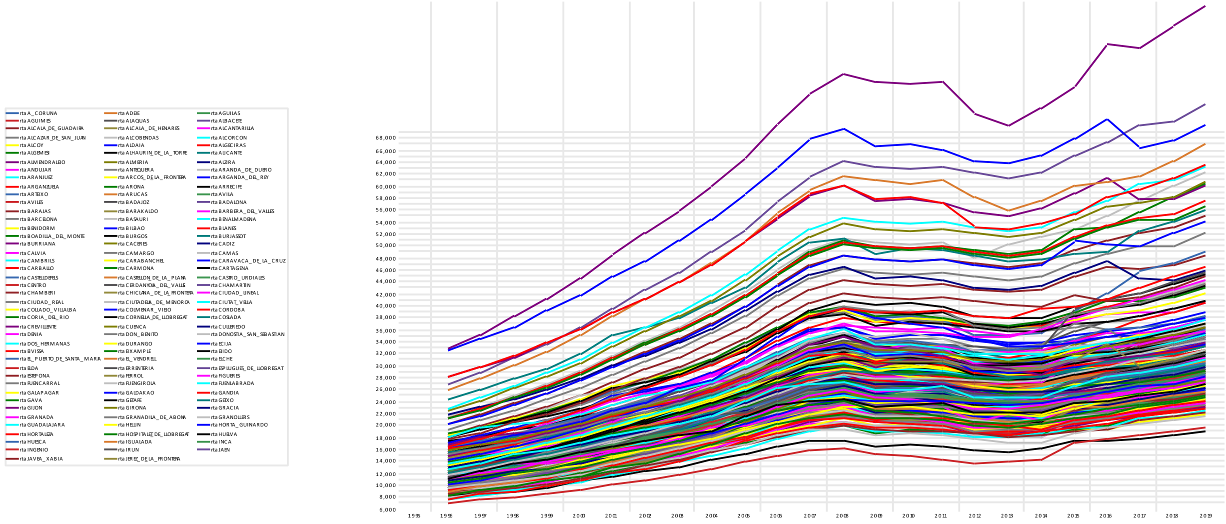

Figure 4. Number of Mortgage credits (nº)

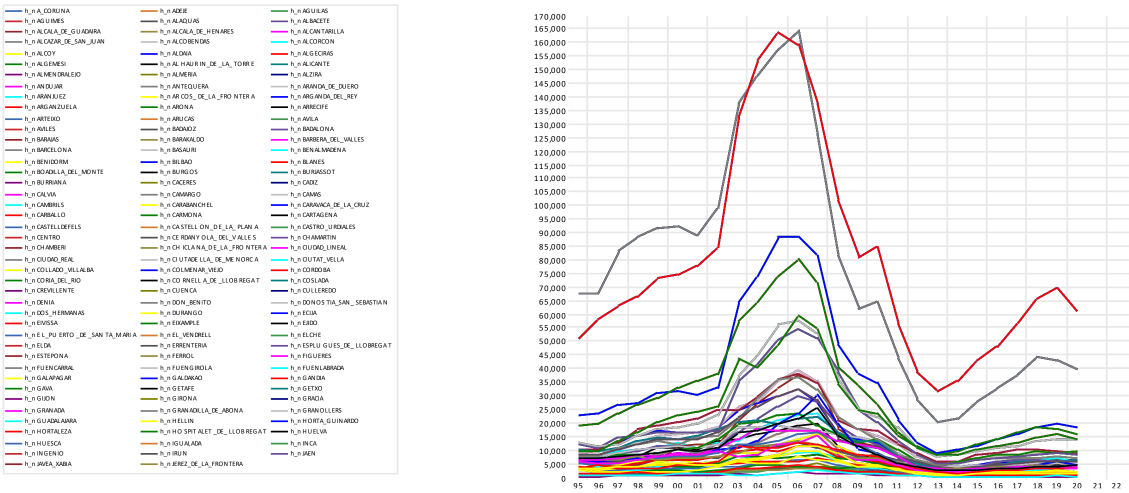

Figure 5. housing stock (yearly changes)

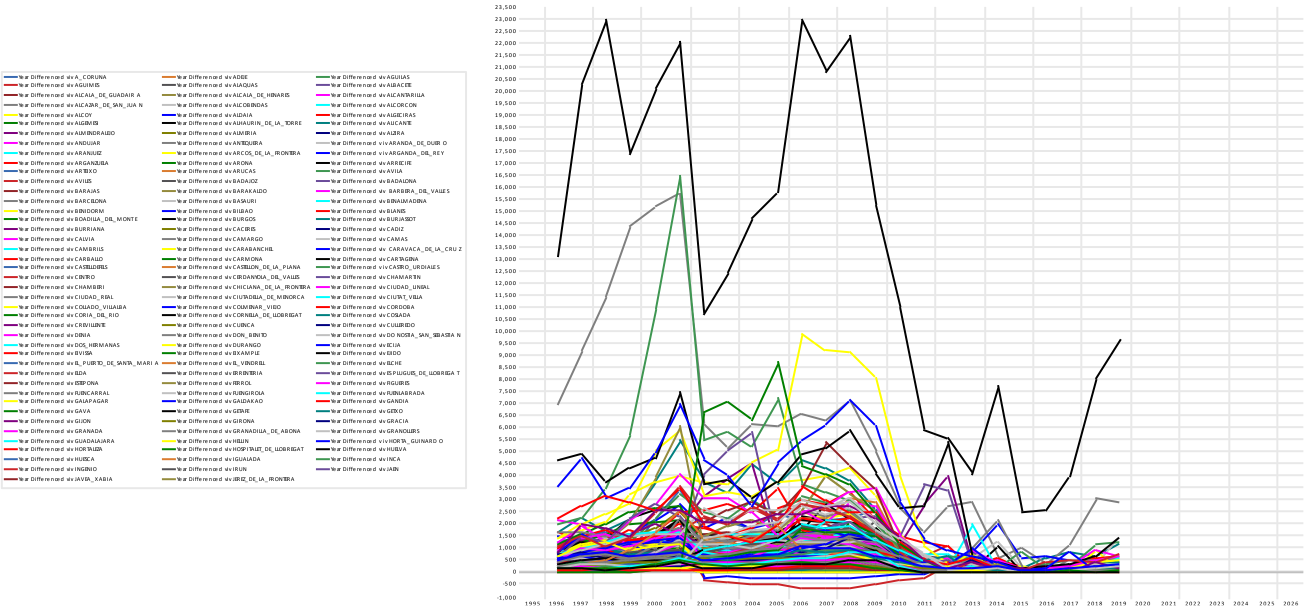
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Table 1. Groups of municipalities. Clustering 1, Time series clusters based on housing prices

20ª Conferência Internacional da LARES

06 e 07 de Outubro de 2021

	MUNICIPIOS								DISTRITOS	
CLUSTERS	1	2	3	4	5	6	7	8	MADRID	BARCELONA
1	A_CORUNA	ADEJE	AGUILAS	AGUIMES	ALCALA_DE_HENARES	ALCANTARILLA	ALGECIRAS	AVILES	Arganzuela	Ciutat_Vella
2	ALCALA_DE_GUADAIRA	ALCOBENDAS	ALAQUAS	ALICANTE	ALCORCON	ALGEMESI	ANTEQUERA	BADAJOZ	Barajas	Eixample
3	ALCOY	ALHAURIN_DE_LA_TORRE	ALBACETE	ARONA	ARANJUEZ	CACERES	BLANES	BARAKALDO	Carabanchel	Gracia
4	ALMENDRALEJO	BARCELONA	ALCAZAR_DE_SAN_JUAN	ARRECIFE	ARGANDA_DEL_REY	CAMARGO	CAMBRILS	BASAURI	Centro	Horta_Guinardo
5	ALMERIA	BENALMADENA	ALDAIA	ARUCAS	COLLADO_VILLALBA	CAMAS	CREVILLENTE	BILBAO	Chamartin	Les_Corts
6	ANDUJAR	BOADILLA_DEL_MONTE	ALZIRA	BADALONA	COLMENAR_VIEJO	CHICLANA_DE_LA_FRONTERA	DOS_HERMANAS	CADIZ	Chamberi	Nou_Barris
7	ARCOS_DE_LA_FRONTERA	CALVIA	ARANDA_DE_DUERO	BARBERA_DEL_VALLES	CORNELLA_DE_LLOBREGAT	CORIA_DEL_RIO	EL_VENDRELL	CARMONA	Ciudad_Lineal	Sant_Andreu
8	ARTEIXO	CASTELLDEFELS	AVILA	BENIDORM	COSLADA	EJIDO	ELCHE	CASTRO_URDIALES	Fuencarral	Sant_Marti
9	CARAVACA_DE_LA_CRUZ	DONOSTIA_SAN_SEBASTIAN	BURGOS	CERDANYOLA_DEL_VALLES	FUENLABRADA	GIJON	ELDA	DON_BENITO	Hortaleza	Sants_Montjuic
10	CARBALLO	EIVISSA	BURJASSOT	CIUTADELLA_DE_MENORCA	GALAPAGAR	JAEN	FIGUERES	DURANGO	Latina	Sarria_Sant_Gervasi
11	CORDOBA	FUENGIROLA	BURRIANA	DENIA	GETAFE	LINEA_DE_LA_CONCEPCION	GIRONA	ECIJA	Moncloa	
12	CULLEREDO	JAVEA_XABIA	CARTAGENA	ESPLUGUES_DE_LLOBREGAT	GRANOLLERS	LORCA	GRANADA	EL_PUERTO_DE_SANTA_MARIA	Moratalaz	
13	HUELVA	LAS_ROZAS_DE_MADRID	CASTELLON_DE_LA_PLANA	ESTEPONA	HOSPITALET_DE_LLOBREGAT	LOS_REALEJOS	LA_VILLAJOYOSA	ERRENTERIA	Puente_de_Vallecas	
14	JEREZ_DE_LA_FRONTERA	LLUCMAJOR	CUENCA	GAVA	LEGANES	MOTRIL	MOLINA_DE_SEGURA	GALDAKAO	Retiro	
15	JUMILLA	MADRID	FERROL	GRANADILLA_DE_ABONA	MARTORELL	OLIVA	MURCIA	GETXO	Salamanca	
16	LEON	MAJADAHONDA	GANDIA	INCA	MATARO	OLOT	NOVELDA	HELLIN	San_Blas	
17	LUGO	MALAGA	GUADALAJARA	INGENIO	MOLLET_DEL_VALLES	OVIEDO	PATERNA	IRUN	Tetuan	
18	MERIDA	MARBELLA	HUESCA	LA_OROTAVA	MONTCADA_I_REIXAC	PALENCIA	PETRER	LANGREO	Usera	
19	NARON	PALMA	IGUALADA	LAS_PALMAS_DE_GRAN_CANARIA	MOSTOLES	PLASENCIA	RINCONADA	LEIOA	Vicalvaro	
20	OLEIROS	POZUELO_DE_ALARCON	LINARES	MANACOR	PINTO	PONFERRADA	RONDA	LLORET_DE_MAR	Villa_de_Vallecas	
21	ONTINYENT	RINCON_DE_LA_VICTORIA	LLEIDA	MAO_MAHON	PUERTO_DEL_ROSARIO	REUS	ROTA	MAIRENA_DEL_ALJARAFE	Villaverde	
22	PONTEVEDRA	RIVAS_VACIAMADRID	LOGRONO	MARRATXI	RIPOLLET	SAN_ANDRES_DEL_RABANEDO	SAN_ROQUE	MORON_DE_LA_FRONTERA		
23	PUERTO_REAL	SAN_BARTOLOME_DE_TIRAJANA	LUCENA	MIJAS	ROQUETAS_DE_MAR	SANLUCAR_DE_BARRAMEDA	SANT_VICENT_DEL_RASPEIG	PALACIOS_Y_VILLAFRANCA		
24	PUERTOLLANO	SANT_CUGAT_DEL_VALLES	MANISES	ORIHUELA	RUBI	SANT_PERE_DE_RIBES	SANTA_POLA	PORTUGALETE		
25	REDONDELA	SANTA_EULARIA_DES_RIU	MANRESA	OURENSE	SABADELL	SESTAO	SANTANDER	PUENTE_GENIL		
26	RIBEIRA	TORREMOLINOS	MAZARRON	PRAT_DE_LLOBREGAT	SAN_FERNANDO_DE_HENARES	TARRAGONA	TORTOSA	SALAMANCA_CAP		
27	SAN_FERNANDO	TRES_CANTOS	MIERES	PREMIA_DE_MAR	SANTA_COLOMA_DE_GRAMENET	TORRELAVEGA	UTRERA	SANTIAGO_DE_COMPOSTELA		
28	SUECA	VILLAVICIOSA_DE_ODON	MIRANDA_DE_EBRO	PUERTO_DE_LA_CRUZ	TERRASSA	TOTANA	VALDEMORO	SANTURTZI		
29	VALDEPENAS		MISLATA	SAN_CRISTOBAL_DE_LA_LAGUNA	TORREJON_DE_ARDOZ	UBEDA	VALENCIA	SEVILLA		
30	XATIVA		PAMPLONA_IRUNA	SAN_SEBASTIAN_DE_LOS_REYES	VIC	VILLARROBLEDO	VIGO	SIERO		
31			PARLA	SANT_BOI_DE_LLOBREGAT		VILLENA	VINAROS	VILAGARCIA_DE_AROUSA		
32			SAGUNTO	SANT_FELIU_DE_LLOBREGAT		ZAMORA	YECLA	VITORIA_GASTEIZ		
33			SALT	SANT_JOAN_DESPI						
34			SAN_JAVIER	SANT_VICENC_DELS_HORTS						
35			SANT_ADRIA_DE_BESOS	SANTA_CRUZ_DE_TENERIFE						
36			SEGOVIA	SANTA_LUCIA_DE_TIRAJANA						
37			SORIA	TELDE						
38			TALAVERA_DE_LA_REINA	TORREVIEJA						
39			TERUEL	VELEZ_MALAGA						
40			TOLEDO	VILADECANS						
41			TOMELLOSO							
42			TORRE_PACHECO							
43			TORRENT							
44			TUDELA							
45			VALLADOLID							

Table 2. Groups of municipalities. Clustering 2, based on Machine Learning methodologies using six variables

0 MOSTOLES >0.005 |33|	1 ALCOBENDAS >0.008|12|	2 ANTEQUERA <0.003|38|	3 SEVILLA < 0.003 19|	4 HUELVA < 0.002 40|	5 TARRAGONA <0.003|20|	6 BARAKALDO >0.008 6|	7 GETXO >0.009 |4|	8 HOSPITALET_DE_LLOBREGAT>0.007 | 5|	9 BADAJOZ < 0.002|52|	10 VALENCIA > 0.005|12|	11 MARBELL >0.008 |6|	12MADRID >0.025|3|	13 BILBAO >0.006 |10|	14 ALCOY <0.000 | 4|	15 PARLA <0.002 |11|
MATARO	ALCOBENDAS	ALAQUAS	A_CORUNA	ADEJE	ARANDA_DE_DUERO	BARAKALDO	GETXO	BADALONA	AGUIMES	ALICANTE	ARONA	BARCELONA	BASAURI	ALCOY	ARGANDA_DEL_REY
ALCALA_DE_HENARES	BOADILLA_DEL_MONTE	ALCANTARILLA	ALBACETE	AGUILAS	CAMARGO	CIUTADELLA_DE_MENORCA	MAJADAHONDA	HOSPITALET_DE_LLOBREGAT	ALCAZAR_DE_SAN_JUAN	ALMERIA	BENALMADENA	DONOSTIA_SAN_SEBASTIAN	BILBAO	ALZIRA	IGUALADA
ALCORCON	CASTELLDEFELS	ALDAIA	BURGOS	ALCALA_DE_GUADAIRA	CIUDAD_REAL	ERRENTERIA	POZUELO_DE_ALARCON	PRAT_DE_LLOBREGAT	ALGECIRAS	CARTAGENA	BENIDORM	MADRID	CADIZ	ELDA	MARTORELL
ARANJUEZ	DURANGO	ALGEMESI	CORDOBA	ARCOS_DE_LA_FRONTERA	CUENCA	LLORET_DE_MAR	SANT_CUGAT_DEL_VALLES	SANT_ADRIA_DE_BESOS	ALHAURIN_DE_LA_TORRE	CASTELLON_DE_LA_PLANA	ESTEPONA		CALVIA	SUECA	MONTCADA_I_REIXAC
BARBERA_DEL_VALLES	GALDAKAO	ALMENDRALEJO	GIJON	ARRECIFE	GIRONA	SAN_BARTOLOME_DE_TIRAJANA		SANTA_COLOMA_DE_GRAMENET	ARTEIXO	ELCHE	MARBELLA		EIVISSA		PARLA
CERDANYOLA_DEL_VALLES	LAS_ROZAS_DE_MADRID	ANDUJAR	GRANADA	BLANES	GUADALAJARA	SESTAO			ARUCAS	JEREZ_DE_LA_FRONTERA	TORREMOLINOS		IRUN		PINTO
COLLADO_VILLALBA	LEIOA	ANTEQUERA	LAS_PALMAS_DE_GRAN_CANARIA	CAMBRILS	HUESCA				AVILA	LLEIDA			PORTUGALETE		RIPOLLET
COLMENAR_VIEJO	MARRATXI	BURJASSOT	LEON	CASTRO_URDIALES	LLUCMAJOR				AVILES	MALAGA			SANTA_EULARIA_DES_RIU		RUBI
CORNELLA_DE_LLOBREGAT	OLEIROS	CAMAS	LOGRONO	CHICLANA_DE_LA_FRONTERA	MAIRENA_DEL_ALJARAFE				BADAJOZ	MURCIA			SANTURTZI		SAN_FERNANDO_DE_HENARES
COSLADA	SAN_SEBASTIAN_DE_LOS_REYES	CARAVACA_DE_LA_CRUZ	OVIEDO	CORIA_DEL_RIO	MAO_MAHON				BURRIANA	SANTA_POLA			VITORIA_GASTEIZ		SANT_VICENC_DELS_HORTS
ESPLUGUES_DE_LLOBREGAT	TRES_CANTOS	CARBALLO	PALMA	DENIA	MIRANDA_DE_EBRO				CACERES	TORREVIEJA					VILAFRANCA_DEL_PENEDES
FUENLABRADA	VILLAVICIOSA_DE_ODON	CARMONA	PAMPLONA_IRUNA	EJIDO	OLOT				CULLEREDO	VALENCIA					
GALAPAGAR		CREVILLENTE	SALAMANCA_CAP	EL_VENDRELL	PALENCIA				DOS_HERMANAS						
GAVA		DON_BENITO	SANTA_CRUZ_DE_TENERIFE	FUENGIROLA	SANTIAGO_DE_COMPOSTELA				EL_PUERTO_DE_SANTA_MARIA						
GETAFE		ECIJA	SANTANDER	GRANADILLA_DE_ABONA	SEGOVIA				FERROL						
GRANOLLERS		HELLIN	SEVILLA	HUELVA	SORIA				FIGUERES						
LEGANES		INCA	VALLADOLID	JAVEA_XABIA	TARRAGONA				GANDIA						

20ª Conferência Internacional da LARES

06 e 07 de Outubro de 2021

MANRESA	JUMILLA	VIGO	LA_VILLAJOYOSA	TERUEL	INGENIO
MOLLET_DEL_VALLES	LA_OROTAVA	ZARAGOZA	LINEA_DE_LA_CONCEPCION	TOLEDO	JAEN
MOSTOLES	LOS_REALEJOS		LUCENA	TUDELA	LANGREO
PREMIA_DE_MAR	MANISES		MAZARRON		LINARES
RIVAS_VACIAMADRID	MORON_DE_LA_FRONTERA		MIJAS		LORCA
SABADELL	NOVELDA		MISLATA		LUGO
SANT_BOI_DE_LLOBREGAT	OLIVA		MOTRIL		MANACOR
SANT_FELIU_DE_LLOBREGAT	ONTINYENT		ORIHUELA		MERIDA
SANT_JOAN_DESPI	PETRER		PALACIOS_Y_ VILLAFRANCA		MIERES
SANT_PERE_DE_RIBES	PUENTE_GENIL		PUERTO_DE_ LA_CRUZ		MOLINA_DE_SEGURA
TERRASSA	RONDA		RINCONADA		NARON
TORREJON_DE_ARDOZ	SAN_ROQUE		ROQUETAS _DE_MAR		OURENSE
VALDEMORO	TOMELLOSO		ROTA		PATERNA
VIC	TOTANA		SAN_JAVIER		PLASENCIA
VILADECANS	UBEDA		SANLUCAR_ DE_BARRAMEDA		PONFERRADA
VILANOVA_I_LA_GELTRU	VALDEPENAS		SANT_VICENT _DEL_RASPEIG		PONTEVEDRA
	VILLARROBLEDO		SANTA_LUCIA _DE_TIRAJANA		PUERTO_DEL _ROSARIO
	VILLENA		TALAVERA_DE _LA_REINA		PUERTO_REAL
	XATIVA		TORRE_PACHECO		PUERTOLLANO
	XIRIVELLA		TORRENT		REDONDELA
	YECLA		UTRERA		REUS
			VELEZ_MALAGA		RIBEIRA
			VINAROS		RINCON_DE_LA_VICTORIA
					SAGUNTO
					SALT
					SAN_ANDRES_DEL_RABANEDO
					SAN_CRISTOBAL _DE_LA_LAGUNA
					SAN_FERNANDO
					SIERO
					TELDE
					TORRELAVEGA
					TORTOSA
					VILAGARCIA_DE_AROUSA
					VILLARREAL
					ZAMORA