House price forecasting and uncertainty: Examining Portugal and Spain

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Abstract
In this paper we apply dynamic model averaging (DMA) to forecast Portuguese and Spanish house prices. DMA is a useful method for forecasting because it inherently allows for uncertainty in both the combination of predictors (model uncertainty), as well as in the marginal effect of each predictor (parameter uncertainty). In doing so we are able to track which predictors are relevant over the forecast period. Besides fundamental macroeconomic determinants to house prices dynamics we also include as predictors business and consumer confidence and financial markets volatility. We find that different predictors have varying inclusion probabilities for both Portugal and Spain. In Portugal, most predictors appear to have some value when it comes to forecasting changes in house prices, including volatility and consumer confidence. Furthermore, each predictor's importance appears to increase over time. For Spain, most economic predictors appear to be useful for forecasting, and there appears to be less variation in each predictor's importance over time. However, volatility measures appear to be less important in Spain than in Portugal for predicting house prices. (JEL: C22, C53, R31)

1. Introduction

House prices have received considerable attention in recent years. The housing market and its developments can affect economic activity through the credit channel and through the impact that housing wealth has on consumption. Empirical evidence indicates that real estate is the main asset of households (Costa *et al.* (2020), ECB (2020) and EFF (2019)), and that changes in the value of wealth in housing can affect homeowners' consumption (Englund *et al.* (2002) and Case *et al.* (2005)). The impact on the economy resulting from changes in housing wealth may be greater than that resulting from movements in share prices (Helbling and Terrones (2003)). For an interesting overview of the dynamics of house prices in Europe, see e.g. Lourenço and Rodrigues (2015).

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Economic uncertainty is not observable and reflects the doubts that economic agents have, be they consumers, entrepreneurs or policy makers, about any future event, be it economic (e.g. GDP or house price growth) or non-economic (e.g. a natural disaster).[1] There is no consensus among economists on how to measure it and in the economic literature an extensive set of proxies have been used to measure economic uncertainty dynamics (Bloom (2013)). These include stock-market (or financial market) volatility, GDP and income volatility, forecaster disagreement (i.e. the standard-deviation across economic forecasts from a number of different institutions), news mentions of the term 'uncertainty' and other related terms (Baker *et al.* (2015)), and differences between the actual release values for variables such as GDP and their pre-release expected values. Other measures include unemployment expectations (Carroll and Dunn (1997)), sentiment indicators (Bachmann *et al.* (2013); Ling *et al.* (2015)), and internet searches for terms related to uncertainty (Dzielinski (2012)).

According to Bloom (2013), economic uncertainty is generally caused by the same events that cause recessions, such as oil-price shocks and credit crunches. This is further compounded by the fact that recessions themselves increase uncertainty, meaning that as economic growth deteriorates uncertainty is endogenously increased further. Pástor and Veronesi (2012) and Kozeniauskas *et al.* (2016) argue that it is the unfamiliarity of recessions which leads to an increase in uncertainty. In these situations, fiscal and monetary policy become more unpredictable as policy-makers attempt innovative ideas in order to boost economic growth, and find it more difficult to forecast something different from the usual pattern of positive growth.

The main link between uncertainty and house prices is that uncertainty leads consumers to be more cautious when making purchases. This is especially so for residential property, which involves a large outlay of money and in most cases a bank loan. Moreover, house purchases are very difficult to reverse, and, unlike purchases of necessities, can be delayed through a 'wait and see' approach. Consumers also tend to put away more savings as a precautionary measure in periods when uncertainty over their future income is high. Bertola *et al.* (2005) concluded that an increase in uncertainty reduces consumers' durable expenditure, while Ling *et al.* (2015) argued that house prices are affected by changes in sentiment among important market participants.

Identifying individual sources of uncertainty is difficult, and most commonly the total expected forecast uncertainty is reported. Typically this is presented as either standard deviations (usually with an underlying assumption of normality), or fan charts (densities). Calculation methods differ across the major forecasting institutions. Most common uncertainty measures are explicitly based on past forecasting errors and include those linked to mean-absolute forecast errors (MAFE) or root mean squared forecasting errors (RMSFE). These can be derived from a static specification, but are more commonly based on recursive model estimates and are usually simple to calculate and interpret. Such measures are used by a large number of forecasters – for example,

1. An economic distinction between uncertainty and risk was proposed by Knight (1921). According to Knight, 'risk is present when future events occur with measurable probability. Uncertainty is present when the likelihood of future events is indefinite or incalculable.'

OECD in their Interim Outlook, FOMC and FEDs, Bank of England, Bank of Canada, Sveriges Riksbank and ECB/ESCB or Bundesbank. The main limitations of the simplest approach are the normality assumption, proneness to large outliers (the ECB and OECD exclude some particularly large outliers from the calculations) and lack of relationship to most recent developments.

From the point of view of speculators, who purchase property solely for investment purposes, the return-risk ratio is negatively impacted by increased uncertainty over expected returns, and increased costs of financing from banks unwilling to lend in an environment of higher default risk.

The aim of this paper is to discuss forecasting models and the importance of variables proxying for economic uncertainty as predictors of residential property prices in Portugal and Spain. We use a forecasting methodology known as dynamic model averaging (DMA) applied to house price dynamics encompassing a wide set of variables. These include macroeconomic determinants, such as income, GDP, labor force, unemployment and interest rates but also shorter-term drivers, such as housing investment, housing loans, business and consumer confidence and financial markets volatility. DMA owes its success in part to its inherit flexibility, not only by incorporating uncertainty across different forecasting models, but also uncertainty pertaining to each parameter within any given forecasting model. This is done through the use of model averaging, and the usage of two forgetting factors that reflect uncertainty in both parameters and models.

The paper is organized as follows. Section 2 briefly describes the DMA methodology used in the forecasting exercise of house prices in Portugal and Spain. Section 3 discusses the data and evaluates the forecast performance of the DMA methodology. This evaluation includes a discussion on the usefulness of each predictor for forecasting at any given time; and provides a further analysis using factors extracted from the predictors using principal component analysis to forecast house prices, thereby reducing the dimension of the predictor set. Lastly, Section 4 concludes.

2. Methodology

The forecasting methodology employed in this analysis is known as dynamic model averaging (DMA). Initial work on the methodology was done by Raftery *et al.* (2010) who applied it to an industrial context. Later Koop and Korobilis (2012) adapted it to forecast inflation. Koop and Korobilis found evidence suggesting that DMA was a superior forecasting method when compared to several alternatives, including other time varying parameter models. Since then a number of studies have used the methodology in a variety of contexts. In terms of house price forecasting, Bork and Møller (2015) analyzed the performance of DMA to forecast average house prices of US states, Risse and Kern (2016) applied the method to European house prices, and Hill and Rodrigues (2020) used DMA to forecast house prices of major economies using a new dynamic forgetting (DF) strategy. Overall, DMA has been shown to be a valuable tool for macroeconomic forecasting. For other applications of the DMA methodology see, for instance, Moretti *et al.* (2019) and Nicoletti and Passaro (2012).

We will briefly discuss the DMA approach, emphasizing its relevance for uncertainty. We apply different tuning parameters to the DMA which reflect the flexibility that the methodology has in terms of model averaging and time variation of model coefficients. We also use dynamic model selection (DMS), which can be seen as a special case of the DMA approach described below. For more technical details the reader is referred to Raftery *et al.* (2010), Koop and Korobilis (2012) and Hill and Rodrigues (2020).

2.1. Between Model Uncertainty

The DMA procedure is initiated with the researcher specifying a set of potential models. In practice, this usually means selecting a group of predictor variables and generating a set of linear models with all possible combinations of predictors. For instance, for K predictors there would be 2^K different linear models. DMA then uses Bayesian model averaging of each model's forecast to generate the forecasts. The averaging is Bayesian in the sense that weights assigned to each model are based on how well each model performed in the past. Let $\hat{y}_t$ be the forecasted variable of interest, in our case house prices and let each of the 2^K models be labeled as M_k, $k \in (1, ..., 2^K)$. The weighted average is computed as,

$$\hat{y}_t = \sum_{k=1}^{2^K} P(model_t = M_k \mid \mathcal{F}_{t-1})\hat{y}_{t(k)} \tag{1}$$

where $\hat{y}_{t(k)}$ is the forecast from model k, $\mathcal{F}_{t-1}$ represents the information set available at the time of the forecast and $model_t$ refers to the forecasts generating model. The posterior probability weight $P(.)$ changes according to how well one of the k models forecasts in comparison with all the other available models. Weights are updated after each iteration. The update involves prior probabilities of model k, as well as a normal likelihood with mean $\hat{y}_{t(k)}$ and the predicted variance evaluated at the actual y_t. One important contribution of Raftery *et al.* (2010) was the use of a forgetting factor, labeled α, that reflects the degree of model uncertainty. The parameter α dictates how much uncertainty we wish to attach to the posterior weight as it is updated, i.e. becomes the prior in the next iteration. With fixed forgetting factors, the researcher can set α between 0 and 1, with lower values reflecting more model uncertainty. In practice α is usually set somewhere between 0.95 and 1. With $\alpha < 1$, models that perform better than the average receive proportionally less weight than they would if $\alpha = 1$, while weights of the models performing worse than average receive a higher weight. The lower α the stronger this effect. Therefore, DMA allows for initial uncertainty by allowing the researcher to be unsure of the data generating model, and α flattens the distribution over all possible models.

We also conduct analysis using a model selection framework based on dynamic model selection (DMS). This is shown in Table 1 below as dynamic model selection, or Bayesian model selection (DMS or BMS). In this setting there is no averaging over models as described above, instead the forecast comes from the model with the largest weight. This is a special case of DMA, in which the weights are 1 for $\max_k(P(model_t = M_k \mid \mathcal{F}_{t-1}))$ and 0 for all the other $K-1$ models. The model with the largest weight acts as the *selected* model and gives the exclusive forecast for a particular period. In the following period, weights are adjusted according to how well each model performed in the past, with α dictating, as indicated above, how much memory is involved in the process. This gives DMS an advantage when there appears to be one model that outperforms, while other models are confounding.

2.2. *Parameter Uncertainty*

Parameter uncertainty in the DMA framework is addressed through the use of state space methods, namely the Kalman filter. We can formulate this with a measurement and a state equation as,

$$y_t = \mathbf{x}'_{t-1}\boldsymbol{\theta}_t + \varepsilon_t \tag{2}$$

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\nu}_t \tag{3}$$

where ε_t and $\boldsymbol{\nu}_t$ are normally distributed error terms with ε_t being a scalar and $\boldsymbol{\nu}_t$ a vector of the same dimension as $\boldsymbol{\theta}_t$, $\boldsymbol{\theta}_t$ is a vectors of coefficients, and $\mathbf{x}_t$ a vectors of predictors. Raftery *et al.* (2010) provide a more detailed explanation, here we simply state that parameter uncertainty is accommodated via the coefficient vector $\boldsymbol{\theta}$, that evolves as a random walk. The Kalman filter can be thought of as a recursive least squares approach, which iteratively solves an OLS problem, thus giving a series of coefficient estimates. To avoid the filter converging on a specific $\boldsymbol{\theta}$, the DMA includes a second forgetting factor defined as λ, which effectively places more weight on recent observations of the recursive OLS problem, thereby allowing for some uncertainty in the coefficients. There are a number of ways of considering λ. Raftery *et al.* (2010) and others consider it to be a constant parameter which is set by the researcher *a priori*. As with α, λ in practice takes values between 0.95 and 1, with 1 indicating recursive OLS where recent and past observations carry the same weight. A lower λ increases the flatness of the coefficient covariance matrix implying more uncertainty over the generating process of $\boldsymbol{\theta}_t$. A drawback of a lower λ is that it makes the system more susceptible to noise which causes the filter to over-adjust.

Hill and Rodrigues (2020) explore a solution to the over-adjustment problem by employing predictor specific dynamic forgetting factors. This allows the filter to permit more uncertainty in the process, without over-fitting noise. The individual forgetting factors also decrease (originating more forgetting) when forecast errors are large, implying that, for instance, a structural break in the generating process will increase forgetting across all predictors. The main idea in Hill and Rodrigues is to limit the size of the covariance matrix from above and below, so as to allow forgetting, without the drawback of over-sensitivity (we present results using fixed as well as dynamic forgetting in Table 1). The role of the forgetting factor λ is the same under model averaging or model selection as its role is related to the rate of variation of parameters over time within each model.

3. Forecasting House Prices

3.1. Data

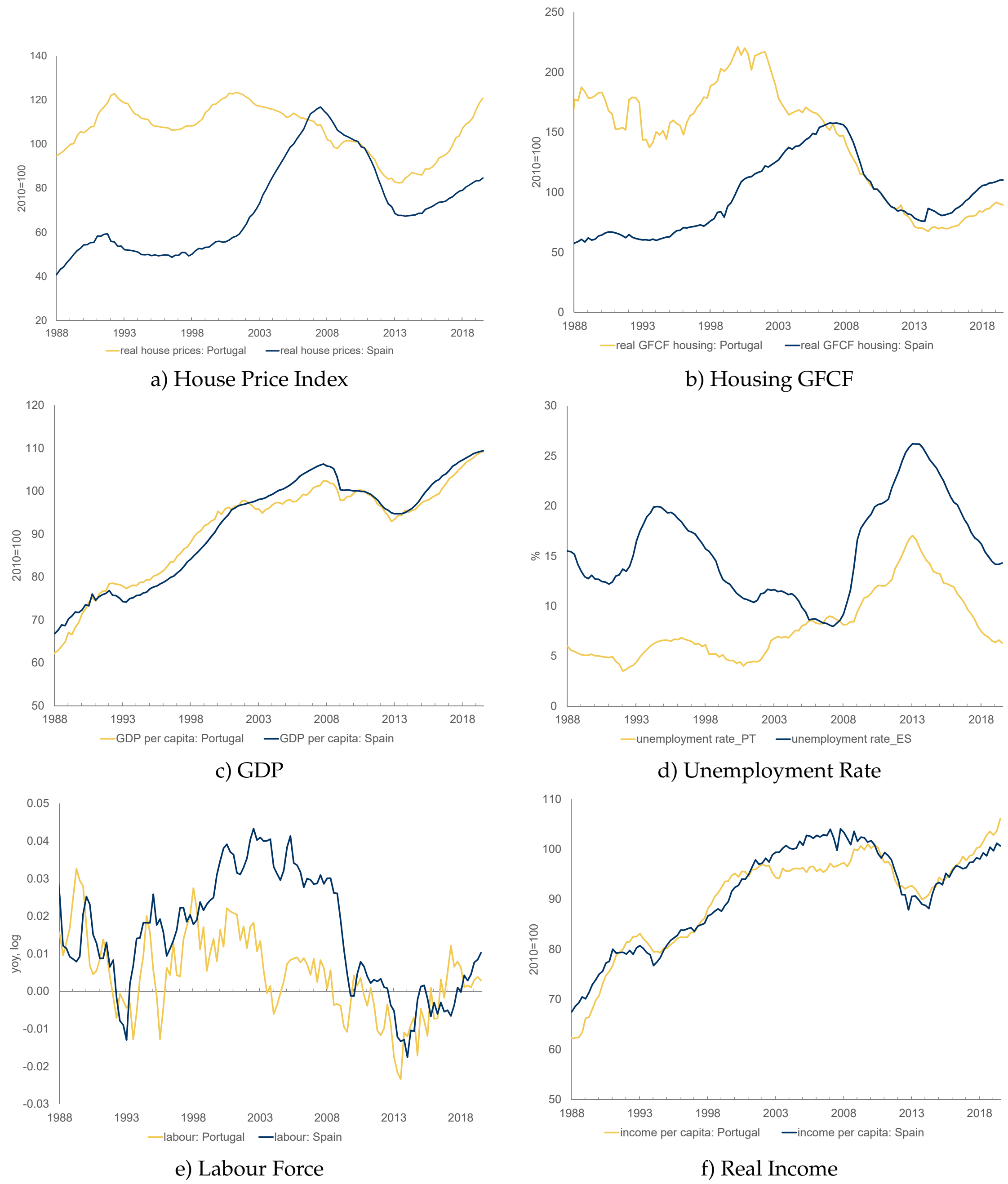
Real estate market dynamics have gained particular interest in recent years, following the US sub-prime collapse in 2007 which quickly spread worldwide and led to a significant impact of housing markets on the economy. Understanding the price determination process in real estate markets is of foremost importance if we want to forecast. Determinants of housing demand include growth in household disposable income and gradual shifts in demographics, such as the relative size of older and younger generations. Permanent features of the tax system that might encourage home ownership as opposed to other forms of wealth accumulation also matter, as well as the average level of interest rates possibly related to the long-term behavior of inflation. The availability and cost of land, as well as the cost of construction and investments in the improvement of the quality of existing housing stock are also relevant (Poterba *et al.* (1991) and Tsatsaronis and Zhu (2004)). For instance, the growth of the housing stock can be constrained in the short run as a result of a number of factors that include the length of the planning and construction. There could also be shorter-term drivers related to constraints in the growth of the housing stock, prevailing conditions in the provision of housing loans, or uncertainty about future prospects. Higher GDP and disposable income, more confidence in the economy, less unemployment, more labor and an increase in mortgage lending are expected to have a positive impact on the housing market. In contrast, higher interest rates are expected to drive borrowing costs up and demand down leading to a subsequent fall in house prices and make alternative applications of wealth more interesting. The same with residential investment, if it increases prices may go down.

The predictors we use in our analysis consist of fundamental macroeconomic covariates, such as real money market rate, labor force, real disposable income *per capita*, real GDP *per capita*, real mortgage rates, real gross fixed capital formation (GFCF) in housing, real loans for house purchases, and the unemployment rate. However, we also include other variables that attempt to gauge uncertainty, such as, business and consumer confidence and financial markets volatility which we also expect to have a positive impact on house prices.

Our data set comprises quarterly time series from 1988:Q1 to 2019:Q3 for Portugal and Spain. Data on house prices, real GDP, real GFCF in housing, disposable income, labor force, unemployment, population and private consumption deflator were collected from the OECD, the Eurostat, Statistics Portugal and Banco de Portugal, while loan for house purchases, short-term interest rates and mortgage rates were taken from the European Central Bank. Short-term interest rates correspond to 3-month inter-bank money market yield rates. Mortgage rates correspond to the interest rate on loans for house purchase. Confidence data refer to the Economic Sentiment Indicator of the European Commission Surveys. Historical volatility from the PSI-20 and IBEX 35 is the annualized standard deviation of 60-day average of daily volatility. The VIX, VDAX and

VSTOXX are market indexes representing the market's expectation of 30-day forward-looking volatility based on the price inputs of the S&P 500, DAX and EuroStoxx50 index options. These were taken from Refinitiv. All series in real terms were computed using the private consumption deflator. GDP and GFCF in housing are chain linked volume. House price indices correspond to seasonally unadjusted series constructed from national data from a variety of public and/or private sources, such as, national statistical services, mortgage lenders and real estate agents. House price series may differ in terms of dwelling types and geographical coverage. For Portugal and Spain they are country-wide and refer to newly and existing apartments. The house price indexes are based on hedonic approaches to price measurement characterized by valuing the houses in terms of their attributes (average square meter price, size of the dwellings involved in transactions and their location).

Before analyzing the empirical results it is important to briefly describe the evolution of the real estate markets, house prices and macroeconomic variables. During two decades, until the beginning of the financial crisis in 2007, house prices grew on average less than 1 per cent per year in real terms in Portugal and 7 per cent in Spain (Figure 1a)). Since the crisis and until the end of 2019 house prices fell 2 per cent on average in Spain and increased 1 per cent in Portugal. However, this masks a highly differentiated evolution over the past decade. House prices declined in both economies, though more in Spain, between 2008 and until the recovery in 2013, and increased in both countries over the past five years, especially so in Portugal. In terms of activity, there was a major difference between Portugal and Spain from the late 90's and until 2007, associated to the impact of immigration flows to Spain resulting in a significant increase of active population at the beginning of the XXI century, which probably contributed to an increase in housing demand (Lourenço and Rodrigues (2014)). During this period, Spanish residential investment grew at an average annual rate of about 8 per cent, while in Portugal it recorded a 2 per cent contraction (Figure 1b)). In turn, GDP accelerated slightly in both economies, although less in the Portuguese case (Figure 1c)). In the five years following the financial crisis and until the recovery in 2013, both countries saw a similar contraction in GDP and housing investment, although most strongly in terms of investment, over 11 per cent compared to 1 per cent in GDP. The unemployment rate increased sharply and labor force declined, which may be related to emigration flows (Figures 1d) and 1e)). Between 2014 and 2019, amidst increasing confidence, GDP accelerated 2 per cent in Portugal and in Spain and residential GFCF increased 4 and 6 per cent, respectively (Figure 2a)). Given its relevance for the housing sector and the impact it may have on the cost of financing it is also important to analyze credit in detail. Data on bank lending indicate the existence of episodes of very high growth in mortgage loans between the mid-1990s and 2007 (Figure 2b)). This annual growth was about 15 per cent on average in Portugal and in Spain, in the context of declining costs of bank loans and high and sustained growth in household disposable income, which was reflected in an increase of indebtedness of families (Figures 1f) 2b) and 2c)). The significant deceleration of credit to housing from 2010 onward should be seen in the context of the international financial crisis which had a negative impact on the supply, given a significant tightening in lending conditions, and on housing credit demand. The volatility variables (Figure 2d)) display spikes during the crises (e.g. subprime crisis followed by a recession and sovereign debt crisis).



a) House Price Index

b) Housing GFCF

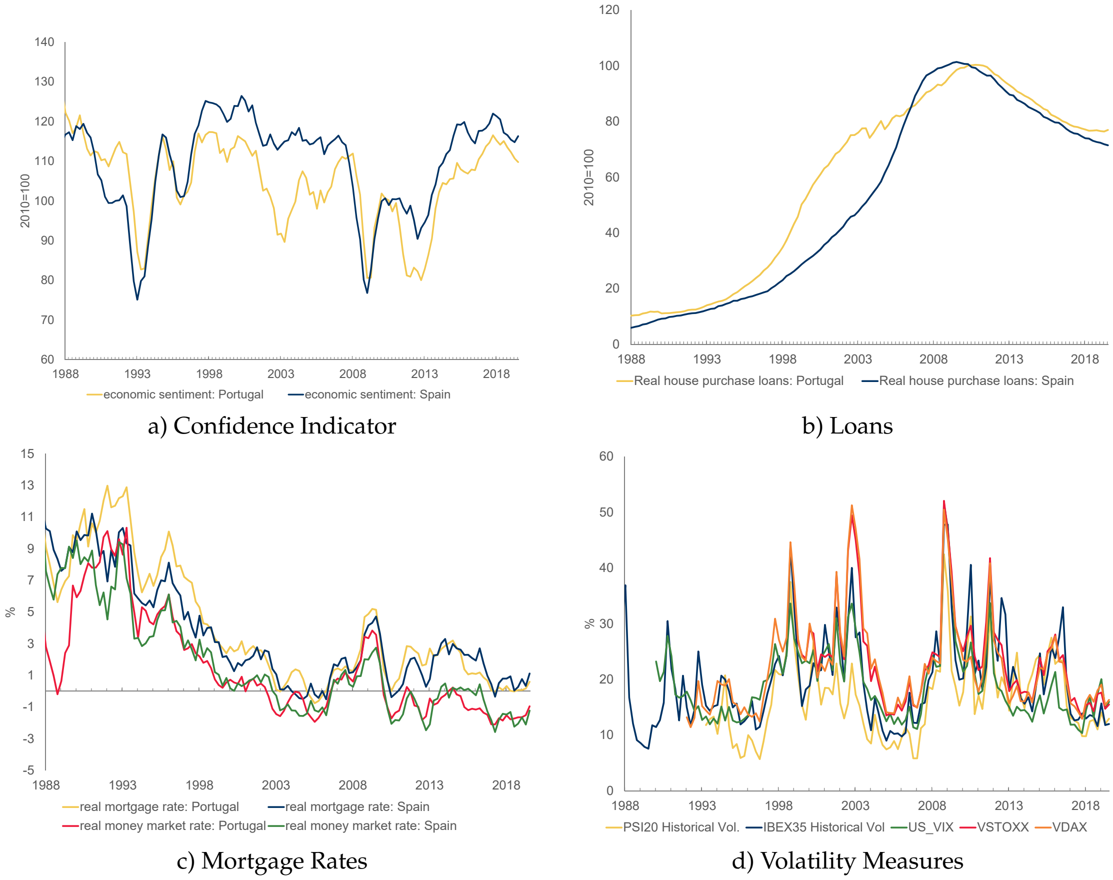
c) GDP

d) Unemployment Rate

e) Labour Force

f) Real Income

FIGURE 1: Plots of variables used in the analysis



a) Confidence Indicator

b) Loans

c) Mortgage Rates

d) Volatility Measures

FIGURE 2: Plots of variables used in the analysis

3.2. *Empirical Results - All Variables*

In our analysis we consider forecasts from a number of DMA specifications, from DMS and from a first order autoregressive model (AR(1)). The forgetting factor α is generally fixed between 0.95 and 1 in most applications of DMA in the literature. We find that varying α within this range does not alter forecasts significantly. Therefore for simplicity, we fix α at 0.97 in our analysis and allow λ to vary. We select four different specifications for λ; 0.95, 0.99, 1 and the dynamic forgetting of Hill and Rodrigues (2020), denoted by the superscript DF.

We measure the performance of each approach using the mean squared forecast error (MSFE), as well as the mean absolute forecast error (MAFE) for the pseudo out-of-sample period starting from T_0 =2009 Q1 to the end of the sample at T =2019 Q3. The MSFE is computed as $\sum_{t=T_0}^{T}(y_t - \hat{y}_t)^2/T_{os}$ and the MAFE as $\sum_{t=T_0}^{T}|y_t - \hat{y}_t|/T_{os}$, where T_{os} is the number of out-of-sample periods. We also report the p-values of the Clark and West (2007) test of equal predictability performance and the out-of-sample R^2 (R^2_{os}) given by

$$R^2_{os} = 1 - \frac{\sum_{t=T_0}^{T}(y_t - \hat{y}_t)^2}{\sum_{t=T_0}^{T}(y_t - \bar{y}_t)^2}$$

where $\bar{y}_t$ is the historical average of the y_t series and $\hat{y}_t$ is the forecast from our model in question. The R^2_{os} is positive if the forecasting model beats the historical average, while the opposite is true if the R^2_{os} is negative.

3.2.1. Forecast Performance

Table 1 shows that in general, across all time periods, the dynamic forgetting (DF) approach appears to have an advantage over fixed forgetting for the one period ahead forecasts. For longer periods, the results are mixed. For Spain the baseline AR(1) model seems to out-perform all competing models when $h = 4$ is considered. It is not clear which parametrization of λ offers the best forecast performance across both Portugal and Spain. This suggests the need for a forgetting scheme that is adaptable to different data generating processes.

Aside from the dynamic forgetting, at one period ahead, a low λ indicating more forgetting appears to have smaller forecast errors. This suggests that parameters in equation 3 provide better forecasts when we increase their variance, in other words increasing the uncertainty of the parameter estimates and thus preventing the Kalman filter from stabilizing provides us with lower forecast errors. In terms of discounting past data, a λ of 0.95 means that data at $t - 4$ carry about 80% of the weight as data at time t. For two periods ahead, the results for the two countries are more mixed. Dynamic model selection, in which the model weights are 1 for the best performing model and 0 otherwise, has the lowest forecast error for Spain, indicating that the data generating process may closely resemble one specific model, while other potential models tend to miss the mark. In this case the models that are selected for most of the out of sample period are the models that include only the lagged dependent variable and intercepts and the model that includes lagged real GDP *per capita* and loans for house purchases. In both Portugal and Spain, the two period ahead forecast horizon is not dominated by a single specification, instead both model selections with dynamic forgetting appear to do well. At four periods ahead, the high forgetting specification and dynamic forgetting do well in the case of Portugal, whereas in Spain, the AR(1) outperforms the DMA and DMS.

Portugal

	h=1				h=2				h=4			
forecasting method	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$
DMA $\alpha = 0.97, \lambda = 0.95$	0.2160	1.1123	**0.0000**	0.4141	0.2464	1.2520	0.0002	0.2724	**0.2994**	**1.4475**	0.0003	-0.0078
DMA $\alpha = 0.97, \lambda = 0.99$	0.2170	1.1131	0.0001	0.4086	0.2412	1.2152	0.0001	0.3027	0.3028	1.5247	0.0014	-0.0305
DMA $\alpha = 0.97, \lambda = 1$	0.2174	1.1107	0.0002	0.4062	0.2398	1.2025	0.0001	0.3106	0.3011	1.5231	0.0020	-0.0190
DMA $\alpha = 0.97, \lambda^{DF}$	**0.2149**	1.1104	0.0000	**0.4197**	0.2411	1.2146	0.0001	0.3034	0.2996	1.4949	0.0010	-0.0086
AR1	0.2225	1.1161	-	0.2654	0.2540	1.2574	-	0.1986	0.3207	1.6266	-	**0.0521**
DMS $\alpha = 0.97, \lambda = 0.95$	0.2188	1.1717	0.0002	0.3986	0.2314	**1.1214**	**0.0001**	0.3579	0.3132	1.5167	**0.0001**	-0.1026
DMS $\alpha = 0.97, \lambda = 0.99$	0.2192	1.1065	0.0031	0.3964	0.2378	1.1909	0.0030	0.3223	0.3087	1.5215	0.0035	-0.0714
DMS $\alpha = 0.97, \lambda = 1$	0.2163	**1.0885**	0.0043	0.4124	0.2426	1.2202	0.0061	0.2947	0.3045	1.5094	0.0049	-0.0425
DMS $\alpha = 0.97, \lambda^{DF}$	0.2154	1.0897	0.0009	0.4170	**0.2307**	1.1310	0.0008	**0.3622**	0.3099	1.5033	0.0013	-0.0793

Spain

	h=1				h=2				h=4			
forecasting method	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$
DMA $\alpha = 0.97, \lambda = 0.95$	0.1949	0.9768	0.0050	0.7160	0.2222	1.0400	0.0113	0.6394	0.3864	1.8016	**0.0072**	-0.0677
DMA $\alpha = 0.97, \lambda = 0.99$	0.1948	0.9820	0.0036	0.7163	0.2139	1.0333	0.0110	0.6660	0.3463	1.6295	0.0085	0.1426
DMA $\alpha = 0.97, \lambda = 1$	0.1980	0.9957	**0.0035**	0.7070	**0.2107**	1.0325	0.0095	**0.6758**	0.3330	1.5751	0.0089	**0.2069**
DMA $\alpha = 0.97, \lambda^{DF}$	**0.1935**	**0.9731**	0.0043	**0.7200**	0.2169	**1.0224**	0.0125	0.6566	0.3609	1.6834	0.0082	0.0683
AR1	0.2283	1.0577	-	0.1025	0.2213	1.0470	-	0.1382	**0.3212**	**1.3483**	-	0.0729
DMS $\alpha = 0.97, \lambda = 0.95$	0.2070	1.0206	0.0067	0.6798	0.2251	1.0359	0.0194	0.6299	0.4022	1.8920	0.0119	-0.1569
DMS $\alpha = 0.97, \lambda = 0.99$	0.2146	1.1079	0.0076	0.6557	0.2223	1.1120	0.0129	0.6391	0.3683	1.7581	0.0088	0.0299
DMS $\alpha = 0.97, \lambda = 1$	0.2092	1.0885	0.0084	0.6730	0.2129	1.0646	**0.0077**	0.6689	0.3643	1.7419	0.0097	0.0508
DMS $\alpha = 0.97, \lambda^{DF}$	0.2017	1.0204	0.0067	0.6958	0.2272	1.0884	0.0142	0.6232	0.3770	1.7803	0.0084	-0.0163

TABLE 1. Results when all predictors are considered

It is important to note that recent figures do not yet reflect the impact of the Covid-19 pandemic on the world economy. The unprecedented nature of this crisis makes it challenging to gauge its repercussions on the predictors used in this analysis, and of course on house prices themselves. The impact will, to a certain extent, depend on changes in fundamentals that support the housing market, such as, banks funding lines, interest rates, housing shortages within key locations, and unemployment, where particularly the latter may be one of the main stress factors in the coming months.

The pandemic will likely result in structural changes in the housing market and in the marginal effects of house price predictors. However, the model averaging as well as the time varying parameter characteristics of DMA should grant the forecasting method adequate flexibility to incorporate these structural changes. The speed at which DMA will be able to react to the changes brought on by the pandemic will depend on the tuning parameters α and λ, that represent the forecasters uncertainty pertaining to the set of predictors and the marginal effect of each predictor in this set.

3.2.2. *Posterior Probability of Inclusion Plots*

An interesting feature of the DMA approach is that using the posterior probability distributions (PIPs) from each model, one can construct inclusion probabilities for each predicting variable. Every model in the DMA model set that contains a particular variable is given a PIP upon propagation of the Kalman filter. The total probability attached to each of these models is then used as a posterior probability of inclusion for a given predictor. The PIPs are presented in Figures 3 and 4 for Portugal and Figures 5 and 6 for Spain. The inclusion probabilities have been divided between economic and financial/volatility predictors. The PIPs for the lagged autoregressive predictor, as well as for the constant are not included, given that these have been very high and relatively stable over the whole period considered. Each line represents the probability that the corresponding predictor is included in the applied model for a given period. In other words, each line represents the relative importance of a predictor for forecasting house prices. As shown in Figures 3 to 6 some of the variables change significantly over time. This indicates that a forecasting framework that incorporates model uncertainty is justified.

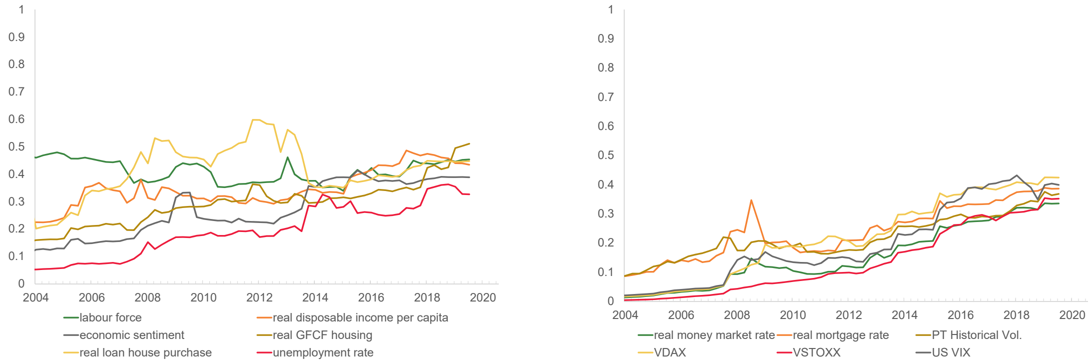


FIGURE 3: Portugal - one period ahead forecast horizon

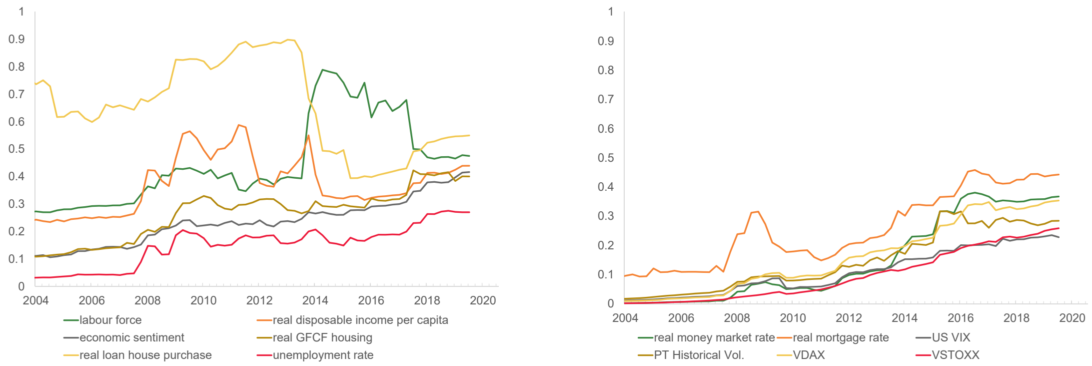


FIGURE 4: Portugal - four periods ahead forecast horizon

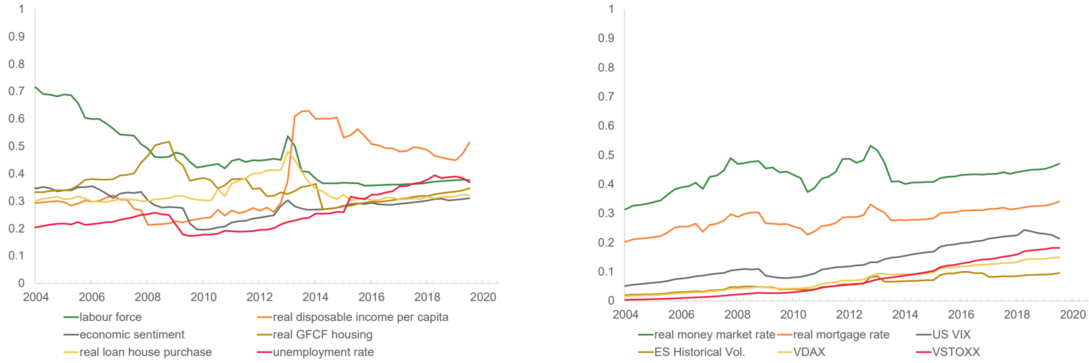


FIGURE 5: Spain - one period ahead forecast horizon

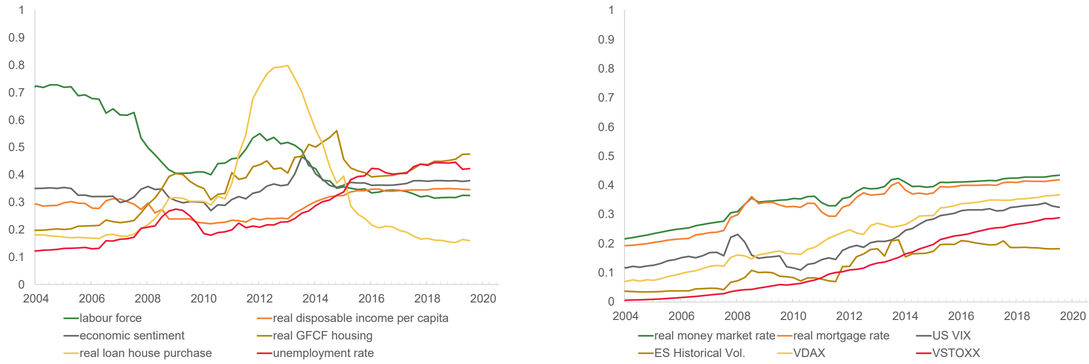


FIGURE 6: Spain - four periods ahead forecast horizon

The PIPs should be regarded as a measure of a particular predictor's importance for forecasting relative to other competing models. This is because the construction of the PIPs is based on the model weights used in the model averaging, which all sum to one and increase or decrease in proportion to the model's performance relative to the forecast performance of all other models. Therefore, when we see the financial and volatility predictors increasing over time as a group in Figures 3 and 4, this suggests a steady increase in importance of volatility and interest rate variables relative to other predictors. This includes the first lag of real house prices, which although has a PIP of 1, since it is included in all the models which contain other predictors, has a model averaging weight that could be decreasing in time and does not show up in the chart of PIPs.

For example, in the one period ahead PIPs for Portugal we notice the set of financial predictors all being relatively clustered together and increasing over time. The clustering of the PIPs for financial and volatility predictors likely stems from their strong correlation. We also see a slightly weaker increase in the PIPs of the real economic variables. Since all PIPs are increasing, they may be doing so at the expense of the lag of house prices. A possible interpretation of this is that the autoregressive property of the house price series is decreasing in favour of predictability from other variables, particularly financial/volatility variables.

For the four quarter forecast horizon, we notice more separation between the inclusion probabilities of predictors, particularly for housing loans. This predictor displays strong predictive power for the 2004 to 2013 period. It is later replaced by labour force in terms of significance after around 2013. The steady increase of PIPs for the financial/volatility predictors are, as per the one quarter ahead forecast, likely the result of the autoregressive property of the differenced house price series weakening. Given the DMA's lower performance for longer forecast horizons, it could be the case that the decrease in the autoregressive predictability of differenced real house prices is not being compensated by an improving predictive power of other predictors. Agents on the supply and demand side could be reacting quicker to changes in fundamentals and driving price changes in short horizons as opposed to longer ones.

Both sets of PIPs for Portugal suggest some volatility in terms of model switching around 2013. By itself, this is not sufficient evidence for a regime change in terms of the drivers of house prices, but it does suggest that dynamics may have shifted around this period. This question warrants further investigation; see e.g. Lourenço and Rodrigues (2017) and section 3.3.

The PIPS from Spain's one quarter ahead forecasts suggest that the labour force predictor was a relatively important variable for forecasting house prices up until 2013. This is the case for both one and four quarter ahead forecasts. However, after roughly 2013, in both forecast horizons the importance of labour force drops. Its importance is replaced by real disposable income for one quarter ahead, while for the four quarter ahead forecast there does not appear to be any variable that stands out aside from real house loans which jumps around 2013 but fall shortly afterwards. The financial and volatility predictors for Spain co-move over the forecast period, again likely due to the strong correlation of those predictors. Interestingly however, the real money market rate maintains a steady importance relative to other predictors over the forecast period. It is interesting to note that, similar to the case of Portugal, the shifts in the PIPs for one quarter ahead forecasts suggest some significance surrounding the year 2013. We also note that this coincides with the beginning of Spain's economic recovery. This corroborates work done on the subject of the Spanish housing market by Cuestas and Kukk (2019) who identify Q2 2013 as a break date in their analysis of drivers of house prices in Spain.

The differences in the dynamics of PIPs between Portugal and Spain is not clear. Both housing markets were affected by external factors over the sample period. However real loans for housing in Portugal appear to have played an important role pre-2013 for both long and short forecast horizons. Loans became an important driver in Spain during the bust period between 2008 and 2013. After that, real disposable income plays an important role. During the bust period, the availability of loans decreased as more restrictions were placed on lending thereby leading to a fall in housing loans observed in both countries, this also coincides with a fall in housing price and results in the increased importance of the housing loans predictor in both cases. The difference in the importance of the volatility predictors between the two countries is also interesting. Volatility, as a proxy for economic uncertainty, seems to play a bigger role in Portugal than in Spain. This could be due to a number of reasons. Portuguese lenders and buyers may be more cautious during higher volatility than their counterparts in Spain, and the composition of buyers could also be different.

3.2.3. *Posterior Size Plots*

A further interesting feature of the DMA methodology is the concept of posterior size probability. Each of the models which are averaged over in the DMA process contains a certain number of predictors. Taking the number of predictors of each model, and producing a weighted average using the posterior predictive probability of that model as a weight, provides an indication of the number of variables actually used to predict the change in real house prices (Koop and Korobilis (2011). For both Portugal and Spain, the number of predictors appears to increase over time. This is consistent with the posterior probability of inclusion plots, which show the probability of inclusion for most variables increasing over time. The distinct increase in the size of the best performing models indicates that they are changing over time. This suggests that the *a priori* model uncertainty was justified, since the 'optimal' model changes over time, i.e., it seems that there was not a single model specification that was appropriate over the whole sample. Hence, the implicit uncertainty, and updating in the DMA process was utilized in the forecasts. Had the lines in these charts been more or less constant, there would be less evidence for model change throughout the sample.

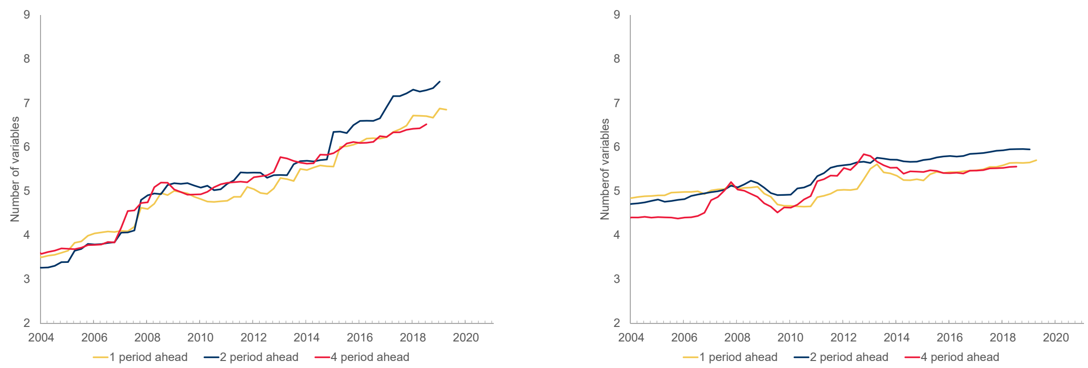


FIGURE 7: Left graph is for Portugal and the right graph for Spain

3.3. *Empirical Results - Factors*

Factor models have been used in a wide variety of forecast applications and have been found to be useful for dimension reduction which often improves out-of-sample forecasting. An added benefit is that the computational burden is drastically reduced when 12 predictors are replaced by 3 factors as we have done. We follow Koop and Korobilis (2011) and create block factors. We divide the predictors into three blocks; an economic uncertainty block consisting of the volatility indices; a financial block consisting of the real money market and mortgage rates, and a real economy block consisting of the remaining predictors. Thus, we extract the common variation in each predictor block, and use the resulting factor in place of the original predictors. This leaves us with $2^3 = 8$ models to average over in the DMA/DMS procedure. We extract factors using an eigenvalue decomposition of the standardized block predictor matrix. We confirm that one principal component captures most of the within block variation by examining the relative size of the largest eigenvalue and finally use these eigenvalues to extract the factors for the block matrix.

The analysis of the results suggests that there are gains in using factors instead of a large number of predictors. This is demonstrated by lower forecast errors in most cases across both countries and forecast horizons, in particular at longer forecast horizons. This suggests the there was perhaps some mild over fitting occurring in the DMA using all predictors, although the difference is not substantial enough to markedly alter the forecasts in this case.

Portugal

	h=1				h=2				h=4			
forecasting method	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$
DMA $\alpha = 0.97, \lambda = 0.95$	0.2142	1.1166	0.0000	0.4237	0.2401	1.1937	0.0000	0.3087	0.2826	1.4199	0.0018	0.1023
DMA $\alpha = 0.97, \lambda = 0.99$	0.2139	1.0834	0.0001	0.4250	0.2397	1.1827	0.0002	0.3113	0.2866	1.4499	**0.0006**	0.0771
DMA $\alpha = 0.97, \lambda = 1$	0.2138	1.0763	0.0002	0.4255	0.2388	1.1793	0.0008	0.3165	0.2853	1.4510	0.0009	0.0851
DMA $\alpha = 0.97, \lambda^{DF}$	0.2131	1.1186	**0.0000**	0.4293	0.2391	1.1972	**0.0000**	0.3146	0.2775	1.3671	0.0015	0.1343
AR1	0.2225	1.1161	-	0.2654	0.2540	1.2574	-	0.1986	0.3207	1.6266	-	0.0521
DMS $\alpha = 0.97, \lambda = 0.95$	0.2134	1.0926	0.0001	0.4282	0.2371	1.1641	0.0003	0.3259	0.2801	1.3958	0.0037	0.1180
DMS $\alpha = 0.97, \lambda = 0.99$	0.2128	**1.0706**	0.0002	0.4309	0.2371	1.1657	0.0000	0.3259	0.2870	1.4511	0.0018	0.0743
DMS $\alpha = 0.97, \lambda = 1$	0.2133	1.0719	0.0005	0.4286	0.2360	1.1690	0.0001	0.3323	0.2853	1.4400	0.0033	0.0854
DMS $\alpha = 0.97, \lambda^{DF}$	**0.2120**	1.0881	0.0001	**0.4353**	**0.2336**	**1.1502**	0.0002	**0.3460**	**0.2742**	**1.3543**	0.0028	**0.1548**

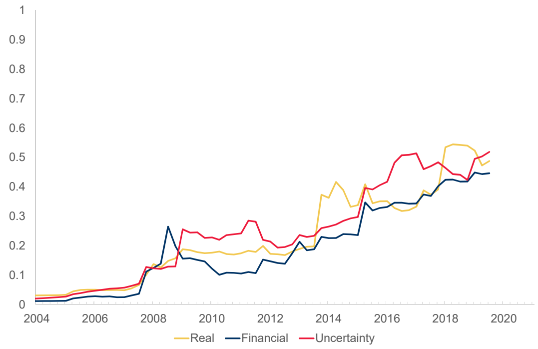
Spain

	h=1				h=2				h=4			
forecasting method	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$	**MSFE**	**MAFE**	**CW test**	$\mathbf{R^2_{os}}$
DMA $\alpha = 0.97, \lambda = 0.95$	0.1860	0.8860	0.0183	0.7414	0.2129	0.9550	0.0280	0.6690	0.3459	1.5850	0.0193	0.1445
DMA $\alpha = 0.97, \lambda = 0.99$	0.1912	0.9102	0.0227	0.7265	0.2090	0.9611	0.0367	0.6809	0.3170	1.4260	0.0294	0.2815
DMA $\alpha = 0.97, \lambda = 1$	0.1954	0.9403	0.0199	0.7146	0.2085	0.9687	0.0402	0.6826	0.3081	1.3816	0.0317	0.3211
DMA $\alpha = 0.97, \lambda^{DF}$	**0.1842**	**0.8756**	0.0166	**0.7463**	0.2119	0.9443	0.0275	0.6720	0.3543	1.6434	0.0133	0.1021
AR1	0.2283	1.0577	-	0.1025	0.2213	1.0470	-	0.1382	0.3212	**1.3483**	-	0.0729
DMS $\alpha = 0.97, \lambda = 0.95$	0.1867	0.9002	0.0149	0.7393	0.2087	0.9529	0.0290	0.6819	0.3384	1.5504	0.0160	0.1809
DMS $\alpha = 0.97, \lambda = 0.99$	0.1911	0.9140	0.0218	0.7270	**0.2080**	0.9812	0.0289	**0.6841**	0.3127	1.4165	0.0204	0.3008
DMS $\alpha = 0.97, \lambda = 1$	0.1995	0.9783	**0.0141**	0.7024	0.2094	1.0080	**0.0248**	0.6798	**0.3029**	1.3576	0.0223	**0.3439**
DMS $\alpha = 0.97, \lambda^{DF}$	0.1855	0.8904	0.0145	0.7426	0.2080	**0.9410**	0.0313	0.6840	0.3458	1.5962	**0.0117**	0.1448

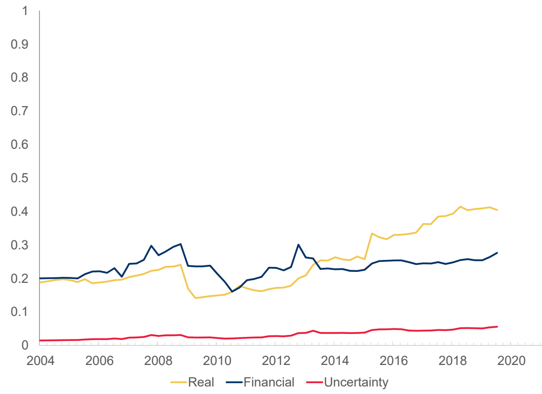
TABLE 2. Results when factors are used as predictors

3.3.1. *Posterior Probability of Inclusion Plots*

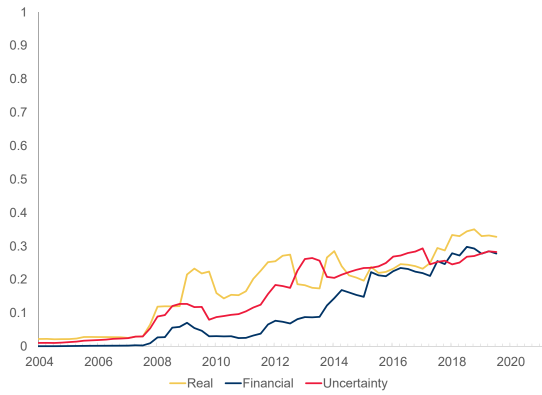
Regarding the posterior probability of inclusion plots (Figure 11), we see that extracting the common variance and reducing the dimensions changes some of the inclusion probabilities. We notice that for the 1 quarter ahead forecasts for Portugal, the uncertainty block factor becomes relatively more important towards the end of the sample, indicating that the common fluctuations of volatility indices have predictive power for house prices post 2012, albeit with a four quarter delay. Moreover, each factor has an increasing probability of being included in the data generating model, with a bump for each factor around the time of the financial crisis, across all forecast horizons. All factors tend to have roughly similar inclusion probabilities for Portugal, whereas in Spain we notice that the uncertainty block factor is less important for forecasting than the financial and real economy factors. The use of factors to reduce the dimension of the set of predictors is helpful as it illustrates clearly the usefulness of each set of factors for forecasting house prices.



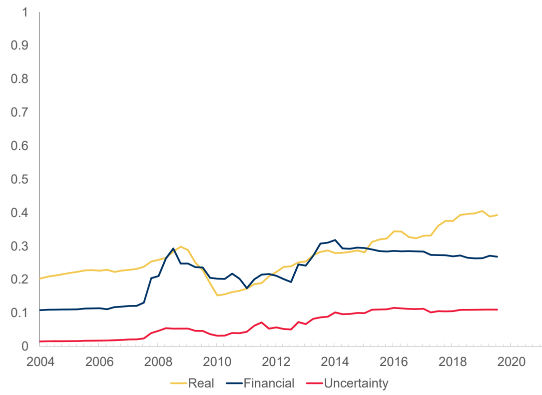
a) Portugal - one period ahead forecast horizon



b) Spain - one period ahead forecast horizon



c) Portugal - four periods ahead forecast horizon



d) Spain - four periods ahead forecast horizon

FIGURE 8: Posterior probability plots - Factors

In order to gain further insight we conduct a Quandt tests for each of the models in the factor model set and record the F test for a structural break. Although the limiting distribution of the Quandt test is not known precisely, we do see high values of the F statistics around 2013 for each of the models in the (factor predictor) model space. Although more research is needed in order to uncover what exactly is going on around 2013, we can say that there appears to be a structural break around that year.

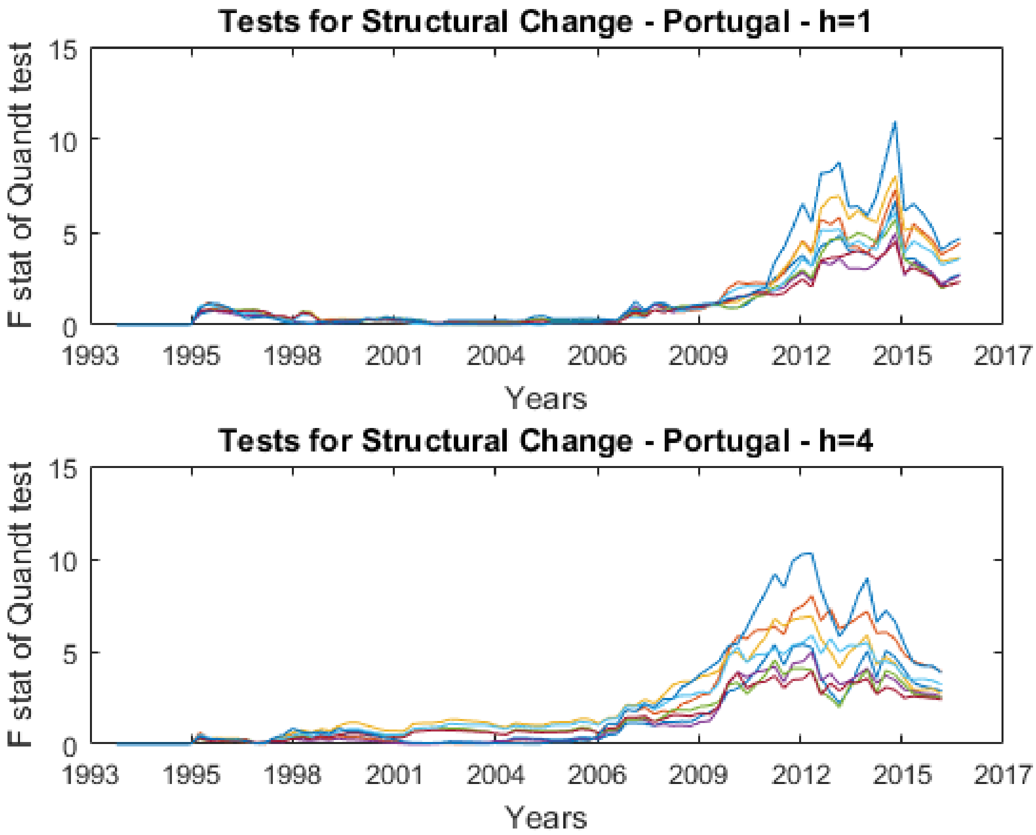


FIGURE 9: Portugal Quandt test - lines represent F statistics from a Quandt test at a given date for all 8 factor forecasting models. High values for the F statistic occur around the 2012 to 2014 period, suggesting a break date within that time frame.

4. Conclusion

Dynamic model averaging is a useful method for forecasting as it inherently permits uncertainty in both the combination of predictors as well as in the marginal effect of each predictor. Through the use of the two forgetting factors discussed above, DMA avoids converging onto a specific set of predictors and parameter estimates thereby allowing parameters and the predicting model to shift over time. These factors can be interpreted as mirroring the forecasters uncertainty towards estimated parameter and model distributions, with less 'forgetting' the forecaster is able to have more confidence in filtered parameter and model distributions. With more forgetting, the estimated distributions at each iteration of the filter are flattened reflecting the forecaster's uncertainty towards the estimates. This makes it a particularly useful approach for forecasting house prices for large out of sample periods, as we expect relevant predictors, and their marginal effects to change over time. In this paper, we applied DMA to forecast Portuguese and Spanish house prices, in doing so we are also able to track which predictors are relevant over the forecast period.

We experiment with different values for each forgetting factor and also apply a dynamic forgetting approach which attempts to minimize excess instability in estimating the coefficients of each model, while still permitting them to move quickly over time. We find that while there is no one-size-fits-all forgetting scheme, dynamic forgetting appears to offer lower forecast errors in most cases. We also carry out the analysis with block factors instead of a set of individual predictors. To acquire these factors, predictors were organized into real economy, financial, and volatility blocks. A specific factor was extracted from each block of predictors via the first principal component. We find that this dimension reduction technique provided gains in terms of forecast errors and should be considered in future forecasting exercises using DMA.

We find that different predictors have varying inclusion probabilities for both Portugal and Spain. The shifts in PIPs for Portugal (both sets) and Spain (one-quarter ahead) indicate some volatility in terms of model switching around 2013. Although by itself, this is not sufficient evidence for a regime change in terms of the drivers of house prices, nonetheless it does suggest that dynamics may have shifted around the beginning of the economic recovery. In Portugal, most predictors (including the economic uncertainty proxies) appear to have some value when it comes to forecasting changes in house prices. Furthermore, each predictor's importance appears to increase over time. For Spain, most real economy predictors appear to be useful for forecasting, and there appears to be less variation in each predictor's importance over time. Volatility measures appear to be more important in Portugal than in Spain for predicting house prices. This could be due to a number of reasons, for example it might be the case that Portuguese lenders and buyers may be more cautious during higher volatility than their counterparts in Spain or that the composition of buyers could also be different.

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