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FORECASTING HOUSE PRICES USING DYNAMIC MODEL AVERAGING

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ABSTRACT

This work project applies the Dynamic Model Averaging methodology to forecast quarterly house price growth in Portugal, Spain, Italy, Ireland, the Euro Area and the United States. This recent econometric technique uses the Kalman filter to recursively estimate dynamic models and ultimately produces a forecast by averaging these models using a prediction performance criterion. Results show the superior predictive ability of this methodology when compared to the usual autoregressive benchmarks. Furthermore, we make use of the model's outputs to provide a comparative analysis of the six series, concluding that there is no single predictor transversally important for all series.

Keywords: House prices, Dynamic Model Averaging, Kalman Filter, Forecasting

1. INTRODUCTION

The housing sector is an essential sector of the economy, primarily because it satisfies a basic need of the human being – shelter. In addition, the way most of our modern economies are built, put houses as one of the major assets in which people tend to invest their money. However, the role of the housing sector is larger and more complex than this. For instance, housing feeds mortgage markets, which are important drivers in the transmission of monetary policy and it is also argued that proper housing may facilitate labor mobility in the economy, helping it to adjust to adverse shocks. Furthermore, house prices have a significant positive impact on private consumption, residential investment and provide a useful indicator of demand pressures in the economy. Bottom line, "as economies develop one should expect a deepening and growth of housing markets" (Min Zhu speech at the *IMF Conference*, 2014).

The 2007/2008 recession urged the need to pay closer attention to this sector, which had until then been somewhat neglected by macroeconomists in general. Widely read textbooks in the field at the time, did not give real estate the due importance, as noted by Leamer (2007). Leamer explains that "Housing is the most important sector in our economic recessions, and any attempt to control the business cycle needs to focus especially on residential investment." A substantial increase in house prices contributes to an over-heating of the economy, whereas its opposite is usually associated with an economic slowdown. When the economy is growing, rising demand for housing pushes residential investment and construction employment upward, strengthening aggregate demand. On the other hand, contraction phases are characterized by falling income and job uncertainty, decreasing housing demand, reducing prices and the overall attractiveness of residential investment; see e.g. Risse and Kern (2016).

This sector has experienced several booms and busts over time and the close connection between sharp house price declines and financial recessions is well documented. In their famous book about financial crises, *This Time Is Different*, Reinhart and Rogoff (2007) call attention to the historical link between housing bubble bursts and banking crisis, both in advanced and emerging economies. The pattern that is highlighted by the authors and had already been addressed by Bordo and Jeanne (2002) refers that "a boom in real housing prices in the run-up to a crisis is followed by a marked decline in the year of the crisis and subsequent years." This statement shows, once again, the unquestionable importance of the housing market and the repercussions that its dynamics can have on the economy.

Considering all these facts, we can conclude that accurate house price forecasting is of great importance to extract valuable information on the business cycle and to help governments and policymakers to better regulate the real estate market, influencing the real economy. This paper intends to add to the existent literature of house price forecasting using Dynamic Model Averaging (DMA) and it closely relates with the works developed by both Wei and Cao (2017) and Risse and Kern (2016), as we aim to use DMA to forecast real house price growth in several European countries, namely peripheral countries such as Portugal, Spain and Italy, but also other economies strongly affected by the financial crisis of 2008 like Ireland and the US.

2. LITERATURE REVIEW

Predicting house prices is a problem addressed by a vast number of scholars, which have already produced quite extensive research on the topic, using a substantial quantity of different methods. DiPasquale and Wheaton (1994) were pioneers in the application of some macroeconomic variables to forecast house prices in the US and found that this approach led to improvements in the models' forecasting accuracy. Later, Brown et al. (1997) used time-varying coefficients (TVC) models to forecast UK's quarterly house price changes from 1968 to 1992, allowing for the introduction of a dynamic component inherent to markets in general that was being neglect until then. The methodology of these authors rivals with previous studies that assume that the underlying data generating process behind house price growth is stable and apply constant parameter techniques, which may not exactly match reality. The housing market tends to be exposed to structural shocks, such as institutional changes or government policies, thus coefficient stability is not present, and a methodology that incorporates this instability should be more appropriate to use. They show that the TVC model, in fact, yields better forecasting performance when compared to alternative constant parameter regressions, such as vector autoregressive (VAR) models, error correction mechanisms (ECM) and autoregressive models.

The historical boom and bust cyclical behavior of real estate markets drew researchers' attention, arousing the question of the existence of some heterogeneous regimes. Crawford and Fratantoni (2003), focusing on five US states from 1979 to 2001, tested regime-switching models, which also incorporate some instability by allowing the model to adapt itself to different states. The study aimed to forecast quarterly variations in house prices and the main conclusions were that despite achieving a good in-sample performance, the regime-switching model did not outperform the classical ARIMA in the out-of-sample evaluation. According to Miles (2008), some researchers have found in subsequent years that Markov-switching models are particularly "ill-suited for forecasting". Nevertheless, he also concludes that nonlinear models improve the forecasting performance in housing markets, particularly when these are subject to great volatility.

Rapach and Strauss (2009) use an autoregressive distributed lag (ARDL) model, considering 29-35 potential predictors including state and regional economic variables to forecast real house price growth in the 20 largest US states, in terms of population, from 1975 to 2006. They found substantial differences in forecasting house price growth in interior and coastal states. In interior states, there is evidence that combining models with different lag structures leads to accuracy improvements. However, in coastal states, house prices exhibit some disconnection in relation to economic variables, making forecasting an (even more) difficult task. This shows that there is no "one-size-fits-all" approach concerning house price forecasting, suggesting that each market and region may experience different dynamics, even if they belong to the same country.

Kouwenberg and Zwinkels (2015) rely on a different approach, as they try to exploit the short-term positive serial correlation and long-term mean reversion to fundamental values that real estate returns exhibit. These authors developed an econometric model (VECM with smooth transition between components) that dynamically weights these two stylized facts depending on the model's recent performance. Such balance implies an overweight of the positive serial correlation component in boom times when possible bubbles are gaining dimension and more weight to reversal to fundamental values during subsequent downturns. They found that the difference in forecasting performance is significantly better when compared to the fundamental mean reversion models and the random-walk benchmark, however it is not shown to outperform the classical AR(1). This result suggests that the problem with these models might lie in the correct estimation of the fundamental value of houses, which is not very consistent. The fundamental value estimate resembles the Gordon Model to value a stock's fundamental value based on dividends. This approach is based on a central assumption stating that the fundamental value is not conditional on any exogenous information, apart from rent and price data. Plus, it also requires the estimate of a constant discount and growth rates; and the assumption of an equilibrium relationship that implies that the long-run rate of capital gains is equal to the growth rate of rents. However, the characteristics of the real estate market, especially the lack of effective short-selling mechanisms, introduce some efficiency problems that can potentially undermine these assumptions and make fundamental value's estimation an onerous challenge.

With the revived interest in forecasting variables that have the power to undermine the entire economic stability, brought by the 2007 global financial crisis, novel methods and techniques have been applied to economic forecasting, particularly from the machine learning field. Jirong et al. (2011) presented a hybrid genetic algorithm and support vector machine (G-

SVM) approach to forecast the average selling house price in China, between 1993 and 2002. Their results are ambiguous since they only compare them with another genetic algorithm and do not provide a commonly used benchmark. Nonetheless, the support vector regressions (SVR) methodology is gaining some popularity among researchers and Plakandaras et al. (2014) propose a methodology that combines signal processing field tools with SVR. The results are quite interesting, as they found that the forecasting ability of their model outperforms the classical random walk, the Bayesian autoregressive and the Bayesian vector autoregressive models, both in and out-of-sample. Moreover, they also show that the model can be used as a warning system for sudden price drops, for instance, predicting the 2006-2009 US housing market decline, up to 2 years ahead.

Ghysels et al. (2013) make a thorough classification of the recent literature on house price forecasting, highlighting several problems with the more traditional models that motivate the use of dynamic models. First, it was found that the effects of the determinants of house prices change over time. As mentioned above, the relationships between fundamentals and house prices are subject to structural breaks and it may also be the case that the effect that certain variables have on the housing sector depend on time and market conditions. Second, research also points out that a model with a specific set of variables may not perform consistently over time, thus motivating the use of a model selection procedure that selects the best model at each point in time (Koop and Korobilis, 2012). The idea is that movements in house prices may be driven by different factors at different points in time, i.e. the best house price predictors during house price booms are different in boom and bust periods (Bork and Møller, 2015). The issue with the model selection procedure is that it comes with a huge computational task attached. To illustrate the point, take the following example: with n predictors, one would need to evaluate 2^n models at each point in time, which totalizes 2^{nT} models for a sample with T periods. With sufficiently large n and T, it becomes computationally demanding and unfeasible. The model averaging solution seems now compelling if one considers different sets of predictors as separate models and compute the weighted average of all possible combinations of predictors.

The challenge here is that the weights used to combine the different models cannot be constant over time, otherwise it will not be possible to have enough flexibility as to capture the time-varying contribution of each model. The classical Bayesian model averaging (BMA) fails at this point, as the weights assigned to each model over time are not time-varying (Próchniak and Witkowski, 2013; Man, 2015). Focusing on this issue, researchers developed several forecasting combination methods, namely the information-theoretic model averaging (ITMA) proposed by Kapetanios et al. (2008). The ITMA method takes the Akaike information criterion (AIC) of each individual model computed with respect to previous observations and then updates the model probability in the BMA. Their paper adopts this new averaging scheme to forecast inflation in the UK, concluding that it can be a powerful alternative to BMA and factor models.

Raftery et al. (2010) address some issues mentioned above with a new method named Dynamic Model Averaging (DMA). The methodology exposed in the paper is not directly related to economic forecasting, notwithstanding it has deserved the attention of some researchers. These authors aimed to solve the problem of online prediction when it is uncertain what is the best prediction model to use and was initially applied to the prediction of the output strip thickness for a cold rolling mill, where the output is measured with a time delay. The parallelism with economic forecasting is quite straightforward, as frequently there is a lot of uncertainty involved regarding which model to use and in the parameter estimation. Koop and Korobilis (2012) used this technique to forecast quarterly US inflation and found substantial improvements over both simple benchmark regressions and TVC models. The advantage of the DMA approach lies in the fact that it allows for the model to change and parameters to shift, adding the necessary flexibility to adapt to an ever-changing macroeconomic framework.

Additionally, this method combines the different models dynamically, using forgetting factors, which approximate the evolution of model parameters and model switching probabilities; see e.g. Wei and Cao (2017).

Bork and Møller (2015) were the first to apply DMA and Dynamic Model Selection (DMS) forecasting techniques to house prices. Their paper examined the house price forecast ability across the 50 US states and concluded that the accuracy of these new models' forecasts substantially improves in comparison with the usual OLS regressions and AR(1) model. They highlight that the states where the housing markets had been the most volatile, were the ones in which the model changes and parameter shifts were needed the most.

The focus of most research mentioned until now has been the US, where a state-specific approach is justified by the heterogeneity of house price dynamics between states. Though, other scholars have recently published research on the European and Chinese housing markets. Wei and Cao (2017) apply the DMA method to forecast the monthly growth rate of house prices in 30 major Chinese cities between 2007 and 2015. Their paper adds to the existent literature by using a model confidence set test (MCS) to statistically evaluate the forecasting efficiency of different models and by introducing a new predictor – the Google search index. This index was based on the popularity of the Google online search for the binomial "city name + house price". Their results proved once again the superior predictive power of these models and showed that the Google search index, in the last years of their sample, exhibits a greater importance than the macroeconomic or monetary indicators to predict house prices in China. This result should be taken into consideration in further studies on the housing market, as nowadays, people heavily use internet searches to make more informed purchasing decisions. The challenge here is to ensure the proper selection and quality of the data used to extract information about online searches related to the house-buying process.

Risse and Kern (2016) applied the same methodology (DMA) to the six largest countries of the European Monetary Union. Various macroeconomic, monetary and demographic fundamentals were used to forecast quarterly house-price growth for Belgium, France, Germany, Italy, the Netherlands and Spain in the period between 1975 and 2015. Their findings show that there is no predictor that is equally important in all countries, across all time periods. For instance, in France and Germany, house-price growth appears to be driven by macroeconomic fundamentals (such as e.g. unemployment and CPI), while the Belgian market is more influenced by industrial production and the term spread. The Italian market was found to be rather peculiar, as no set of predictors proved to have a significant effect. Interestingly, the Dutch market showed no influence from macroeconomic predictors, but solely the term spread and credit supply. Finally, the Spanish housing market displays a wider influence of variables, ranging from credit supply and industrial production to GDP and labor force. This dynamic averaging scheme allows us to obtain the evolution of each variables' probability of inclusion over time. This feature is quite useful in order to understand what are the drivers of each housing market and to see what is the behavior that they exhibit across time-periods.

The remaining sections of this paper are organized as follows: the econometric methodology is discussed in **Section 3**; the data is described in **Section 4** followed by the empirical results in **Section 5** and conclusion in **Section 6**.

3. ECONOMETRIC METHODOLOGY

3.1. Dynamic Model Averaging and Dynamic Model Selection

To better understand the methodology applied in this work project it is useful to consider the following: suppose that we have a set of K models that are built with different subsets of x_t as predictors, where $x^{(k)}$ for $k = 1, 2, \dots, K$, denotes the subset belonging to each model. Assume that the relation between the dependent variable and these predictors, can be written as

$$(1) \qquad y_t = x_{t-1}^{(k)'} \beta_t^{(k)} + \varepsilon_t^{(k)}, \qquad \beta_t^{(k)} = \beta_{t-1}^{(k)} + \eta_t^{(k)},$$

where, $x_{t-1}^{(k)'} \subseteq x'_{t-1}$ for $k = 1, 2, \dots, K$, denotes a specific predictor set, $\beta_t^{(k)}$ is the vector of parameters respective to each predictor set, $\varepsilon_t \sim i.i.d.N\left(0, V_t^{(k)}\right)$ and $\eta_t \sim i.i.d.N\left(0, W_t^{(k)}\right)$. Let $L_t \in \{1, 2, \dots, K\}$ identify the model that applies at time t, $\mathrm{B}_t = \left(\beta_t^{(1)'}, \dots, \beta_t^{(k)'}\right)'$ and $Y^t = \{y_1, \dots, y_t\}$. To produce a time t forecast using information conditional on $t-1$, DMA requires the computation of $\Pr(L_t = k | Y^{t-1})$, i.e. the conditional probability of selecting model k as the right one to forecast. Then, the final prediction is made by averaging forecasts across the different models, weighted by the respective probabilities. DMS follows a similar principle, but the final prediction is based on the model with the single highest probability, $\Pr(L_t = k | Y^{t-1})$.

The *dynamic* word in the methodology's name is merged with the *model averaging* feature, explained above, by allowing for different models to hold at different points in time. Such flexibility is important in macroeconomic modelling, as we can allow not only for the predictors of house prices but also their marginal impact to change over time. However, one should be careful, since the method still suffers from the usual risk of suggesting models which include many parameters – overparameterization. Attached to this, comes a great computational burden when forecasting with a large number of predictors. Note that the number of predictors increases exponentially the number of different forecasting models to be averaged, K. With n predictors in x_{t-1}, the total number of different forecasting models will be $K = 2^n$, at each point in time.

The application of the model described in (1) can only proceed if some specification for how predictors can get in and out of the model is modelled, in other words, a criterion for how transition between models would occur. An alternative would be to specify a transition matrix, P, with elements $p_{ij} = \Pr(L_t = i | L_t = j)$ for $i, j = 1, \dots, K$, using what is known as Markov switching processes. Once again, the computational effort arises as a barrier, since we add the additional estimation of the probability transition matrix, P, of dimensions $K \times K$. Thus, the number of predictors does not need to be that large for inference to be very imprecise due to the number of parameters in P. Bayesian inference through this alternative does not seem very attractive, motivating Raftery et al. (2010) to use an approximation that allows for the application of standard state space methods such as the Kalman filter.

The structure in (1) relates to the switching linear Gaussian state space models, which imply that the state vector, B_t, is broken into independent blocks, each one representing a different model. This independence means that the predictive density of B_t depends on $\beta_t^{(k)}$, but conditionally on $L_t = k$. By assuming this, it is possible to follow the accurate approximation of Raftery et al. (2010), where the Kalman filter is run K times.

The approximation mentioned above involves two parameters, λ and α, which the authors defined as *forgetting factors*, and which assume values slightly below 1. To properly understand these factors and how the algorithm works, let us consider the model in (1) ignoring the part of model uncertainty. With given values for $V_t^{(k)}$ and $W_t^{(k)}$, one can apply standard filtering results to recursively estimate or forecast. The Kalman filter's starting point assumes that the set of parameters on B_{t-1} conditional on $L_t = k$ and with information until $t-1$, (Y^{t-1}), follows a normal distribution with the following moments

(2) $$\mathrm{B}_{t-1}|\mathrm{L}_{t-1} = k, Y^{t-1} \sim N\left(\hat{\beta}_{t-1}^{(k)}, \Sigma_{t-1|t-1}^{(k)}\right).$$

It proceeds with parameter prediction for the subsequent period with information conditioned on the previous period,

(3) $$\mathrm{B}_t|\mathrm{L}_{t-1} = k,\ Y^{t-1} \sim N\left(\hat{\beta}_{t-1}^{(k)}, \Sigma_{t|t-1}^{(k)}\right),$$

where,

(4) $$\Sigma_{t|t-1}^{(k)} = \Sigma_{t-1|t-1}^{(k)} + W_t^{(k)}.$$

The first forgetting factor, λ, enters here. Raftery et al. (2010) simplify calculations by replacing equation (4) with

(5) $$\Sigma_{t|t-1}^{(k)} = \lambda^{-1}\Sigma_{t-1|t-1}^{(k)},$$

which is equivalent to $W_t^{(k)} = (\lambda^{-1} - 1)\Sigma_{t-1|t-1}^{(k)}$, where $0 < \lambda \leq 1$. This forgetting factor implies that data j time periods old is assigned with λ^j weight in comparison with the last period and it implies an effective window size of $\frac{1}{1-\lambda}$. Moreover, as it is set for the factor to assume a value slightly below one, coefficients in the model will experience a gradual evolution. Now, by applying this simplification, we can avoid the estimation or simulation of $W_t^{(k)}$. Then, the estimation of the parameters is achieved by the following *updating equation*:

$$\mathrm{B}_t|\mathrm{L}_t = k, Y^t \sim N\left(\hat{\beta}_t^{(k)}, \Sigma_{t|t}^{(k)}\right). \tag{6}$$

Equation (6) is the final stage of the Kalman filter. To properly detail the meaning of (6), the equations to estimate the first (6.1) and second (6.2) moments of the represented distribution are exhibited below.

(6.1) $\hat{\beta}_{t|t}^{(k)} = \hat{\beta}_{t|t-1}^{(k)} + K_t e_t$ (6.2) $\Sigma_{t|t}^{(k)} = \Sigma_{t|t-1}^{(k)} - K_t x_{t-1}^{(k)} \Sigma_{t|t-1}^{(k)}$

with $K_t = \Sigma_{t|t-1}^{(k)} x_{t-1}^{(k)\prime} \left(V_t^{(k)} + x_{t-1}^{(k)\prime} \Sigma_{t|t-1}^{(k)} x_{t-1}^{(k)}\right)^{-1}$, which corresponds to the Kalman gain and $e_t = \left(y_t - x_{t-1}^{(k)\prime} \hat{\beta}_{t-1}^{(k)}\right)$ to the one-step-ahead prediction error. The Kalman filter implements nothing more than an "average" between the one-step-ahead prediction and the measured value, weighted by the Kalman gain. The inference process is repeated recursively as we advance through time, nonetheless to start the process $\hat{\beta}_0^{(k)}$ and $\Sigma_0^{(k)}$ must be specified. Recursive forecasting is completed using the predictive distribution

$$y_t|Y^{t-1} \sim N\left(x_{t-1}^{(k)\prime} \hat{\beta}_{t-1}^{(k)}, V_t^{(k)} + x_{t-1}^{(k)\prime} \Sigma_{t|t-1}^{(k)} x_{t-1}^{(k)}\right). \tag{7}$$

It is important to reinforce the idea that the application of the previous results in (2), (3) and (6) is conditional on $\mathrm{L}_t = k$, consequently, the prediction and updating equations only provide information on $\beta_t^{(k)}$ and not on the full vector B_t. Therefore, we need a prediction method that is not conditional on a specific model k (unconditional prediction). As we have already discussed, the specification of a transition matrix and posterior use of MCMC algorithm to estimate the unconditional predictions is not suitable in practical terms, given its computational burden and parameter proliferation. We turn to another approximation as suggested by Raftery et al. (2010), adding an additional forgetting factor, α, with interpretation similar to λ. To solve the issue of being conditioned on a particular model, we would need to estimate the following equation:

(8) $$p(\mathrm{B}_{t-1}|Y^{t-1}) = \sum_{k=1}^{K} p\left(\beta_t^{(k)}\middle|\mathrm{L}_{t-1} = k, Y^{t-1}\right)\mathrm{Pr}(\mathrm{L}_{t-1} = k|Y^{t-1}),$$

where $p\left(\beta_t^{(k)}\middle|\mathrm{L}_{t-1} = k, Y^{t-1}\right)$ is given by (2). What (8) means is that the conditional distribution (predictive density) of all parameters derived from every possible combination of models, $p(\mathrm{B}_{t-1}|Y^{t-1})$, is given by an average of the distribution of the parameters of each specific model, $p\left(\beta_t^{(k)}\middle|\mathrm{L}_{t-1} = k, Y^{t-1}\right)$, weighted by the respective probability of each model, $\mathrm{Pr}(\mathrm{L}_{t-1} = k|Y^{t-1})$. All we have left to estimate is this last probability.

Let $\pi_{t|s,l} = \mathrm{Pr}(\mathrm{L}_t = l|Y^s)$, implying that $\mathrm{Pr}(\mathrm{L}_{t-1} = k|Y^{t-1}) = \pi_{t-1|t-1,k}$. If we used the transition probability matrix, P, with elements p_{kl} (probability of "jumping" from model k to model l), the model prediction equation would be

(9) $$\pi_{t|t-1,k} = \sum_{l=1}^{K} \pi_{t-1|t-1,l}\, p_{kl}.$$

Instead, with the approximation suggested by Raftery et al. (2010) we obtain

(10) $$\pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha}}$$

where $0 < \alpha \leq 1$ is set to a value slightly below 1. Following a Kalman filter type approach, the model updating equation is

(11) $$\pi_{t|t,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}\, p_k(y_t|Y^{t-1})}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha}\, p_l(y_t|Y^{t-1})},$$

where $p_l(y_t|Y^{t-1})$ is the predictive density of model l, i.e., the density of a $N\left(x_{t-1}^{(l)'}\hat{\beta}_{t-1}^{(l)}, V_t^{(l)} + x_{t-1}^{(l)'}\Sigma_{t|t-1}^{(l)}x_{t-1}^{(l)}\right)$ distribution evaluated at y_t.

Finally, the DMA and DMS one-step ahead recursive forecast, which dynamically incorporates the K models will be, respectively:

(12) $$\hat{y}_t^{DMA} = \sum_{k=1}^{K} \pi_{t|t-1,k}\, x_{t-1}^{(k)'}\hat{\beta}_{t-1}^{(k)},$$ and (13) $$\hat{y}_t^{DMS} = x_{t-1}^{(k^*)'}\hat{\beta}_{t-1}^{(k^*)}.$$

As mentioned above, the DMA forecast is a result of averaging all K models according to their historical performances, reflected in the probability $\pi_{t|t-1,k}$. The DMS forecast just considers the model with the *best* historical performance, k^*, thus the one with the highest probability $\pi_{(t|t-1,k^*)}$.

To correctly understand the interpretation of the forgetting factor, α, note that the weight of model k at time t is

(14) $$\pi_{t|t-1,k} \propto \left[\pi_{t-1|t-2,k} p_k(y_{t-1}|y^{t-2})\right]^{\alpha} = \prod_{i=1}^{t-1}\left[p_k\left(y_{t-i}\middle|y^{t-i-1}\right)\right]^{\alpha^i}.$$

Thus, model k is over weighted at time t if its forecasting performance, measured by the predictive density $p_k\left(y_{t-i}\middle|y^{t-i-1}\right)$, was good in the recent past. To control for "recent past", we rely on an exponential decay with rate α^i, for observations i periods ago. For instance, if $\alpha = 0.99$, the forecast performance 5 years ago with quarterly data receives 82% ($0.99^{5\times4} \cong 82\%$) as much weight as the forecasting performance last period. On the other hand, with $\alpha = 0.95$, this percentage drops to 36%, i.e. the lower the value of α, the faster information is forgotten. If $\lambda = \alpha = 1$, DMA is just the standard approach to BMA using conventional linear forecasting models with no time variation in coefficients, thus it is interesting to include this case as a competitive model of DMA in our empirical analysis.

To estimate the error variance $V_t^{(k)}$ the suggestion of Koop and Korobilis (2012) is followed. They avoid the computational burden of using a stochastic volatility or ARCH specification by applying an Exponentially Weighted Moving Average (EWMA) to estimate $V_t^{(k)}$, i. e.,

(15) $$\hat{V}_t^{(k)} = \sqrt{(1-\kappa)\sum_{j=1}^{t}\kappa^{j-1}\left(y_j - x_j^{(k)\prime}\hat{\beta}_{j-1}^{(k)}\right)^2}.$$

The use of EWMA estimators is common in finance applications and κ the decay factor is recommended to be set at 0.97 for monthly data and 0.94 for daily data. Just like these authors, in this paper, we use quarterly data and so the chosen κ is 0.98. To obtain the volatility forecasts $\hat{V}_{t+1|t}^{(k)}$ we recursively approximate and get

$$\hat{V}_{t+1|t}^{(k)} = \kappa \hat{V}_{t|t-1}^{(k)} + (1-\kappa)\left(y_t - x_t^{(k)\prime} \hat{\beta}_t^{(k)}\right)^2. \tag{16}$$

3.2. Evaluation of forecasts

Forecast evaluation is a crucial procedure in forecasting exercises, ultimately trying to answer the question: "Which is the best forecasting model?". The question is then what forecasting evaluation measures should be used. In this paper, two well-known loss functions are used: MAFE (Mean Absolute Forecast Error) and MSFE (Mean Squared Forecast Error), i.e.,

(17) $MAFE = N^{-1} \sum_{t=1}^{N} |y_t - \hat{y}_t|$, and (18) $MSFE = N^{-1} \sum_{t=1}^{N} (y_t - \hat{y}_t)^2$,

where y_t is the actual value of the real house price growth, $\hat{y}_t$ is the respective forecast and N is the number of forecasts. These criteria are quite similar, yet some differences are worth noting. Due to the quadratic loss function it uses, MSFE, assigns a relatively large weight to large errors, thus being more suitable when this kind of errors are particularly problematic. On the other hand, MAFE has the advantage of providing a real interpretation of its value, as it represents the average difference between the forecast and the actual value, something that cannot be achieved using MSFE.

3.2.1. The Clark and West Test

MAFE and MSFE are good measures to have a sense of how the forecasting accuracy compares between forecasts. However, if we are interested in knowing which alternative model presents the best predictive ability, considering the statistical significance of the forecasting losses between models, we must apply more advanced methods. We follow the method used by Bork and Møller (2015) and Risse and Kern (2016) that opt for the test proposed by Clark and West (2007). They reference a paper by Clark and McCracken (2001) that shows that the commonly used Diebold and Mariano (1995) statistic has a nonstandard distribution when testing for the equal accuracy of forecasts from nested models. As we are precisely working in a framework with nested models, we should use a methodology that is robust to this problem instead – the Clark and West test. The new statistic proposed is adjusted and it is approximately normally distributed in the case of nested models. The test statistic is defined as

$$f_{\boldsymbol{j},\boldsymbol{t}} = \left(y_t - \hat{y}_{MEAN,t}\right)^{\mathbf{2}} - \left[\left(y_t - \hat{y}_{j,t}\right)^{\mathbf{2}} - \left(y_{MEAN,t} - \hat{y}_{j,t}\right)^{\mathbf{2}}\right], \quad (19)$$

where $\hat{y}_{MEAN,t}$ represents the historical forecast of y_t using the historical mean benchmark and $\hat{y}_{j,t}$ represents the forecast of model $j = AR1,\ DMA,\ DMS$, for the different forgetting factor levels. The Clark and West test is completed by regressing $f_{\boldsymbol{j},\boldsymbol{t}}$ on a constant and then testing its significance using the underlying heteroscedasticity and autocorrelation corrected t-statistic. Rejection of the null hypothesis means that model j significantly overperforms the benchmark from a statistical stand point. We have statistical evidence to reject the null, at the 5% level, if the *t*-statistic is greater than 1.645, which is the corresponding critical value. For simplicity, the test hereby described uses the historical mean forecast as the benchmark against which we compare other models. Nonetheless, in this paper, we considered the AR(1) and AR(2) as benchmarks to conduct the Clark and West test, since it is straightforward that almost every model would outperform the historical mean forecast and in this way, we would be less demanding than what is required.

4. DATA

The data set used to conduct this analysis consists of quarterly observations of the real house price growth rate for Portugal, Italy, Spain, Ireland, the Euro Area and the US. Data was provided by *Banco de Portugal*, OECD, ECB and INE. The dependent variable is calculated as follows:

$$y_{i,t} = 100 \times \left[\ln\left(rhp_{i,t}\right) - \ln\left(rhp_{i,t-1}\right)\right] \quad (20)$$

where, $i = 1, \dots, 6$, stands for the country's index. The objective is to build forecasting models tailored to each of the countries, providing an analysis of European peripheral countries'

(Portugal, Spain and Italy) housing market, adding Ireland, the Euro Area and the US to establish comparisons. ***Table 1*** depicts the main descriptive statistics of the house price growth rate for the 5 countries considered, plus the Euro Area.

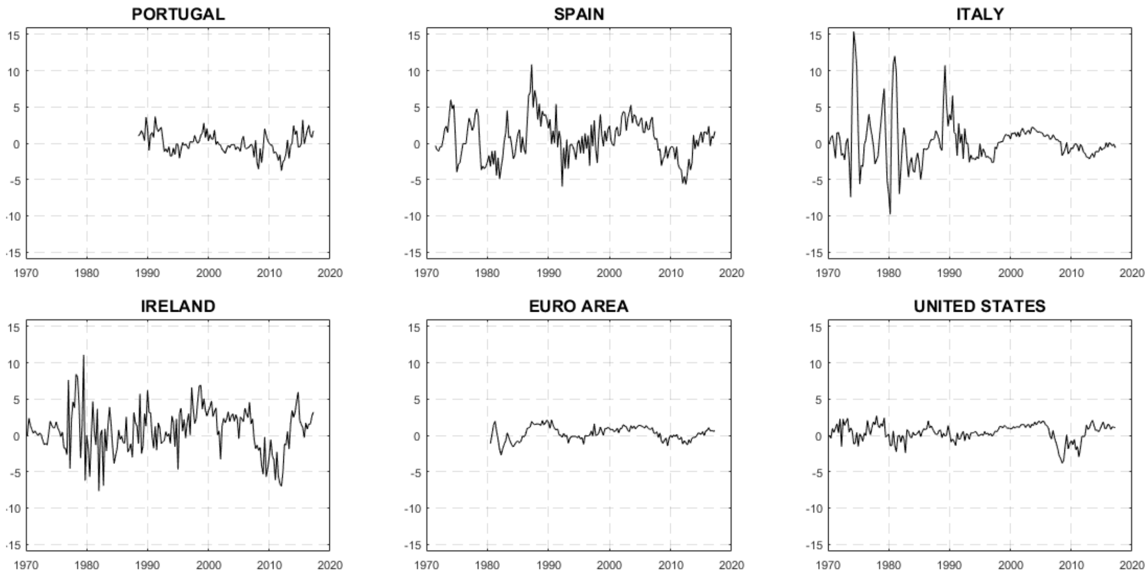
Table 1. Descriptive statistics of the dependent variable for each country.

Country	Obs.	Start	End	Mean	Min.	Max.	Std. Dev.	ADF
Portugal	116	1988.Q2	2017.Q1	0.0207	-3.7873	3.6691	1.4156	-5.4829***
Spain	184	1971.Q2	2017.Q1	0.5843	-5.9795	10.8534	2.7950	-5.4997***
Italy	188	1970.Q2	2017.Q1	0.2445	-9.8101	15.4302	3.3120	-6.1450***
Ireland	188	1970.Q2	2017.Q1	0.6908	-7.6876	11.0981	3.1086	-8.8122***
Euro Area	148	1980.Q2	2017.Q1	0.2739	-2.7273	2.1452	0.9353	-3.7228***
United States	188	1970.Q2	2017.Q1	0.3645	-3.8490	2.6937	1.1674	-5.7357***

Note: ADF stands for augmented Dickey-Fuller unit root test. The significance levels for the null hypothesis' rejection (unit root) are represented as follows: 10% '*', 5% '**' and 1% '***'

Four out of the six series used have data available since the 70's providing more than 180 observations each. However, Portugal and the Euro Area have shorter series counting with 116 and 148 observations, respectively. Regarding the behavior of the series, we can observe substantial disparities. Portugal figures as the country with the lowest quarterly average real house price growth (0.0207%), contrasting with the rest of the time series, where the average is at least 10 times above this. From this country set, only Portugal and Italy posted averages below the Euro Area. Ireland stands at the top of the six with a quarterly average growth rate of 0.6908%, followed by Spain and the United States. The largest quarterly drop occurred in Italy in the first quarter of 1980, where real house prices fell almost 10%, largely due to a surge in inflation at the time. Just a few years before, in 1973, the Italian real house prices increased more than 15%, which represents the largest quarterly growth among all the series. These huge ups and downs between the decade of 70 and 90 are a pattern that emerges in other countries as well, namely in Ireland and Spain, where volatility spiked in this period as one can observe from ***Figure 1***. These three countries stand out with standard deviations at least two times above the ones for Portugal, the Euro Area and the US, where movements went a lot smoother. A quick look at the plots does not suggest a great correlation between the six series, though we can see that from the end of 2007 until the end of 2013 real house prices fell, almost uninterruptedly, in all of them and the cause of this tumble is well-known. After the burst of the housing market bubble in the US in 2007/2008, the contagion effect spread the decline all over Europe. The dimension of this drop is remarkable, though quite heterogeneous. In the period between the end of 2007 and 2013, real house prices fell 63% in Ireland and 54% in Spain. Italy and Portugal experienced a fall of around 20% and the Euro Area and the US 13% and 17%, respectively. Additionally, ***Table 1*** also shows the test statistic of the Augmented Dickey-Fuller test for stationarity. The null hypothesis of the presence a unit root is rejected, at the 1% significance level, for all series (as expected).

Figure 1. Quarterly real house price growth.



For fair forecast evaluation, each individual sample was divided into in and out-of-sample data. Observations until and including the last quarter of 2006 were included in the training set, using these data points to compute the priors to input at the start of the recursive estimation. From the first quarter of 2007 onwards, the model does not include any forward-looking information and is recursively estimated in each quarter.

The DMA methodology allows for the inclusion of a set of predictors for the dependent variable, thus the model presented in this paper includes a group of 15 explanatory variables. One can subdivide the set in 4 types of variables: macroeconomic (LABOR, UNEMPLOYMENT, INCOME, GDP, GFCF and INFLATION), financial (SPREAD, MORTGAGE), housing market specific (RENT, RENTPRICE, LOAN, CONSTCOST and PERMITS) and lead sentiment indicators (CONSTCONF and CONFIDENCE). ***Table 2*** lists these regressors, briefly describing each of them and the transformations applied. The choice of these variables was based on the variables used in previous research on this topic, including also some new variables, namely RENTPRICE, MORTGAGE, GFCF, LOAN, CONSTCOST, CONSTCONF and CONFIDENCE, with the objective to test if they are relevant predictors of house prices.

Table 2. Description of the explanatory variables.

#	**ID**	**Tcode**	**Description**
1	LABOR	2	Total labor force in thousands
2	UNEMPLOYMENT	2	Unemployment rate
3	RENT	2	Rents index, calculated trough price-to-rent ratio
4	RENTPRICE	2	Rent to price ratio
5	SPREAD	2	10 years *versus* 3 months public debt spread
6	MORTGAGE	2	Real mortgage rate
7	INCOME	2	Real disposable income of households, in million euros
8	GDP	2	Real GDP, million euro or national currency (volume chained link and market prices)
9	GFCF	2	Real GFCF (housing), real gross fixed capital formation, million euros or national currency
10	LOAN	2	Loans to house purchase, base 2010
11	CONSTCOST	2	Construction costs index, base 2010
12	PERMITS	2	Number of housing permits, base 2010
13	CONSTCONF	2	Construction confidence index, base 2010 (Not available for Ireland)
14	CONFIDENCE	2	Economic sentiment indicator, base 2010 (Not available for Ireland)
15	PCD	2	Private consumption deflator, base 2010

Transformation Codes: 1 – No transformation, 2 – First difference of natural logarithm

5. EMPIRICAL RESULTS

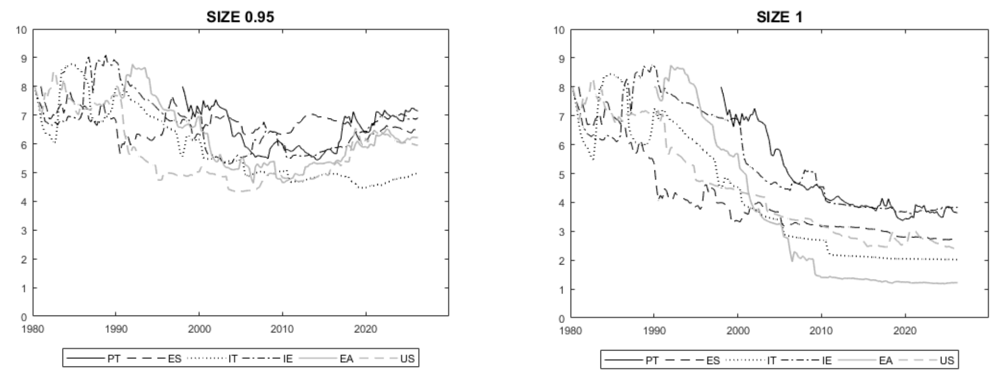
5.1. Average number of predictors

One of the remarkable advantages of the methodology used in this paper is its flexibility concerning the number of different explanatory variables included in the model over time. The inclusion or exclusion of each variable is conditioned on its recent past performance in terms of predictive ability, measured by π. It would be interesting to see if the model does capture the dynamic inclusion or exclusion of variables and how this number changes over time and across countries. Koop and Korobilis (2012) show that the expected number of predictors, at time t, will be

(21) $$E(size_t) = \sum_{k=1}^{K} \pi_{t|t-1,k} size_{(k)}$$

where $size_{(k)}$ is the number of explanatory variables in model k. ***Figure 2*** contains the expected number of coefficients in a historical time frame for the six series under analysis, for λ=α=0.95, on the left and λ=α=1, on the right, for a DMA with the 15 variables in our dataset. These plots show that the model size varies substantially across time. Additionally, it is possible to see a positive relation between the factor values and the expected number of coefficients. For the 0.95 case, expected size ranges from 9 to 4, whereas for the other it also starts at 9, but quickly decreases to values below 4. The conclusion is that the faster information is forgotten, the larger we expect models to be, possibly because in this way the algorithm can adapt more easily and allow for a larger number of predictors to input information on the final forecast.

Figure 2. Plot of the expected model size for DMA with (λ=α=0.95) and (λ=α=1)



5.2. Estimation process

To completely understand the results, it is important to know the process followed to achieve them, therefore, the inclusion probabilities are of utmost relevance for a detailed and correct perception of the empirical approach. Recall that in the DMA methodology these probabilities are the weights used in the averaging of the different model forecasts, thus they contain valuable information regarding the relative importance of each variable for the movements in aggregate housing prices. Plots of these probabilities for (λ=α=0.95) are available in the appendix. In addition to the variables included in ***Table 2***, we also tested the model with the inclusion of one lag of the dependent variable. The rationale for the inclusion of this lag is that house price growth tends to exhibit a strong correlation with the previous period, mainly at higher frequencies, like quarterly variations. Further evidence of this claim is reflected in the probability plots with and without the lag that can be found in the appendix. A closer look at these plots shows that in general, all probabilities decrease when the lag is included, which can be interpreted as a caption of information by the lag itself. By looking at the probability plots, some country independent conclusions can be taken. One of them is that sentiment variables are rarely of great importance to predict house prices, being assigned with low (below 0.5) probabilities of inclusion by the algorithm. The methodology itself can ignore less relevant variables, by assigning them low probabilities of inclusion, nevertheless they still have a considerable weight in the final forecast, especially if they produce extreme predictions, what introduces a lot of "noise" in the system. With this issue in mind, we opted to exclude less relevant variables (variables with historical inclusion probability below 0.5 during the training period) from the set, building models as parsimonious as possible. Our findings reinforce the idea of heterogeneity of the different housing markets and show that there is no single variable that is an important predictor across the countries under analysis. ***Table 3*** contains the models with variables that have shown relevance during the training period, i.e. with probabilities above 0.5 within the training period, plus a one-period lag (LAG) of the dependent variable.

Table 3. Forecasting model's composition.

Portugal	Spain	Italy	Ireland	Euro Area	United States
LAG	LAG	LAG	LAG	LAG	LAG
SPREAD	UNEMPLOYMENT	LABOR	RENT	MORTGAGE	RENTPRICE
INCOME	RENTPRICE	UNEMPLOYMENT	RENTPRICE	GDP	SPREAD
CONSTCONF	INCOME	RENT	GDP	GFCF	GDP
-	GDP	RENTPRICE	GFCF	PCD	LOAN
-	-	INCOME	LOAN	-	PERMITS
-	-	PCD	PCD	-	-

In Portugal, we find the term spread, income and construction confidence as the regressors with most importance in the training period. It is interesting to note that during the financial crisis specific variables instantly experienced increased probabilities, including variables that were previously disregarded. This can be seen in the plots of INCOME (2008), GFCF (2008), CONSTCOST (2008) and SPREAD (2011). The Spanish market displays different dynamics, with a dominance of macroeconomic variables, such as the unemployment rate, income and GDP, but also the rent-to-price ratio. The Italian house price growth series provides a clear example of regime switching series. It is possible to conclude this by observing its plot in ***Figure 1***, where we can see a highly volatile behavior with huge variations, roughly until 1995, and then volatility plummets, turning Italy into one of the most stable series of the sample. The probability plots are consistent with this since several variables have plots peaking at the beginning of the sample and then they abruptly decrease. This is the case for the unemployment rate, rents, rent-to-price and the deflator, only labor force and income exhibit a slower decrease of importance. In opposition to what we have seen above for Portugal, the financial turmoil lived in 2007-2011 did not have a great impact on the probabilities for the Spanish and Italian cases. The Irish housing market model is dominated by both housing market specific (RENT, RENTPRICE, LOAN) and macroeconomic variables (GDP, GFCF and PCD). Rents and the rent-to-price proved to have a great importance at the beginning of the sample that was rapidly lost at the time and has been approximating past levels again, along with the loan to house purchase series. Such as Portugal, the probability of inclusion of some variables spikes during the 2007-2011 period, namely for rents, rent-to-price, the term spread and loan. Regarding the Euro Area, the historical housing market growth rate displays very low volatility, mainly because it is an average of a considerable number of different markets, thus softening its behavior. The relevant variables in the in-sample period are all macroeconomic (GDP, GFCF and PCD), except for the mortgage rate. The four variables produce quite similar plots, with peaks at the beginning of the sample until mid-80's and then a sudden drop, remaining low until today. At present, these variables were surpassed in terms of probability of inclusion by the loan to house purchase series. Finally, the US housing market shows some similarities with the Euro Area, which makes sense as both are composed by smaller and heterogeneous housing markets. As in the previous case, the most relevant variables (RENTPRICE, SPREAD, GDP, LOAN and PERMITS), apart from GDP, have all very high probabilities of inclusion at the start of the sample and then they all drop in a short time, becoming less significant. Analyzing these probabilities as a whole, we could not disclose any pattern regarding the importance of predictors among peripheral and non-peripheral countries. Even so, some variables seem to be more relevant than others, for instance, the rent-to-price ratio appears to have substantial importance in Portugal, Spain, Italy and the in US. Quite surprisingly, the unemployment rate did not show a high probability of inclusion for any series, apart from Spain and, momentarily the US in 2008. Although, its probability still presented a slight increase in 2008 for every series, excluding Italy. Recently, we can observe that loan to house purchase describes a growing importance in every country except in the US, where it stands stable at low levels.

As mentioned in Section 3.1, the values for λ and α set the degree of past information that is considered at each point in time. Lower values for these factors mean a higher pace of information forgetting, introducing more flexibility in the model. In this forecasting exercise, λ and α were bound to the following set $\{0.95; 0.97; 0.99; 1\}$, which includes the optimal values suggested by Koop and Korobilis (2012) for output and inflation forecasting. According to these authors values below 0.95 may, sometimes, increase forecasting performance, though they increase the possibility of overfitting. Therefore, we tested four DMA and four DMS, one for each forecasting factor value. Additionally, to test our predictions, recursive AR(1) and AR(2) models were estimated. A summary of the forecasting performance, for a quarterly horizon, of the best models by country is depicted in ***Table 4*** (please see ***Table 5*** in the Appendix for detailed results).

Table 4. Forecasting performance summary.

Forecasting method	MAFE	MSFE	Rel. MSFE	CW AR1	CW AR2
	Portugal				
AR1	1.1550	2.1690	1	-	
AR2	**1.1304**	**2.0742**	**1.0457**		-
DMA (λ=α=0.95)	1.0898	2.1514	1.0082	2.8523***	2.7875***
	Spain				
AR1	1.1995	2.2989	1	-	
AR2	**1.0668**	**1.8589**	**1.2367**		-
DMA (λ=α=0.95)	1.0778	1.9136	1.2013	3.2059***	2.7084***
	Italy				
AR1	0.5193	0.4699	1	-	
AR2	0.6614	0.7208	0.6520		-
DMS (λ=α=0.95)	**0.4670**	**0.3719**	**1.2636**	2.8990***	4.0583***
	Ireland				
AR1	2.3736	8.8063	1	-	
AR2	2.1515	6.8913	1.2779		-
BMA (λ=α=1)	**1.8324**	**4.7660**	**1.8477**	4.2624***	3.2692***
	Euro Area				
AR1	0.3894	0.2325	1	-	
AR2	**0.3715**	**0.2086**	**1.1149**		-
DMA (λ=α=0.99)	0.3871	0.2207	1.0534	2.0189***	1.9343**
	United States				
AR1	0.7391	0.9763	1	-	
AR2	0.7453	0.9232	1.0576		-
DMS (λ=α=0.97)	**0.6699**	**0.7069**	**1.3810**	2.3621***	2.7102***

Note: The significance levels for the null hypothesis' rejection are represented as follows: 10% '*', 5% '**' and 1% '***'

Overall, the results of this estimation are quite satisfactory, as all the best models beat the MAFE and MSFE of the AR1 benchmark. The levels of improvement of the MSFE in relation to the AR1 can be seen in the column 'Relative MSFE', where Portugal stands in last with modest 0.82% and Ireland figures as the first with more than 80% improvement. When comparing the MAFE and MSFE with the AR2 benchmark results are less positive, though Italy, Ireland and US's best models still outperform the two-lag autoregressive model. Nonetheless, we are also interested in testing the differences in the forecasting performance of different models, because MAFE and MSFE are mere averages. As mentioned in Section 3.2.1 we can do this using the Clark and West test (CW). This test was applied to test whether the best model for each country was statistically better than the autoregressive benchmarks. Results were promising as each of dynamic models proved to outperform both AR1 and AR2 in forecasting house price growth, contradicting the MAFE and MSFE measures. The forecasting loss function of MAFE and MSFE is not the same as the one used in the CW test, motivating the different conclusions. Nonetheless, being specifically designed to be applied to nested models, the CW test is more reliable in this case.

6. CONCLUSION

This paper aimed to develop a comprehensive literature review of house price forecasting and to apply a recent methodology to peripheral countries' housing markets, as well as Ireland, the Euro Area and the US. As the results show, the final objective of producing valid forecasting models for this variable were met. However, some changes in the algorithm can potentially improve our results, for instance, with the introduction of clusters instead of using the whole span of forecasting models and with the use of dynamic processes to input optimal time-varying forecasting factors.

A thorough review and explanation of the Dynamic Model Averaging algorithm were made and the main advantages of it became clear, namely the way the econometrician can include several predictors inside the system, so that the algorithm chooses the most important ones at each point in time. This flexibility proved useful, not only to predict economic variables, but also to analyze their behavior through the inclusion of probability plots. Our results demonstrated the superior predictive ability of DMA and reinforced the idea that, despite the increased globalization of economies and financial markets, each individual housing market is subject to its own dynamic. The DMA methodology has already been applied to inflation and house prices, nevertheless, the potential of DMA can go beyond these applications and be tested with other macroeconomic variables, even outside of the economic scope. Possibly, pure financial applications like multifactor stock pricing models are one area for further research applying this method. Multifactor models can benefit from the model and parameter adaptation of DMA, as classic approaches fail to incorporate the break of linear relationships or are too slow to adapt to the new regimes.

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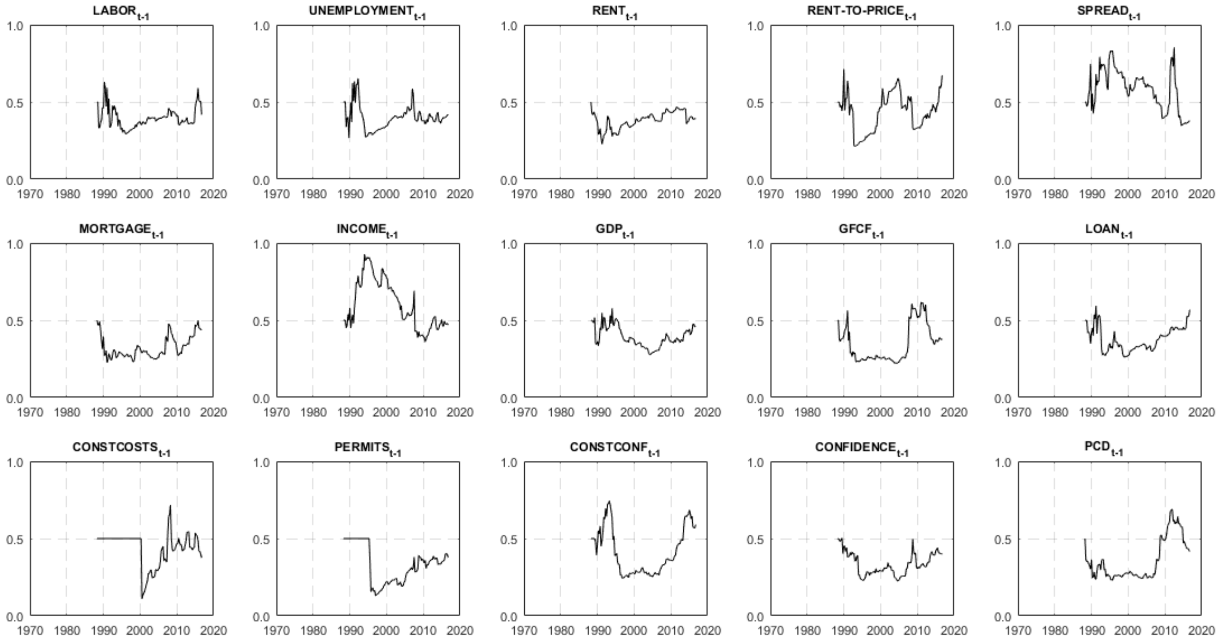
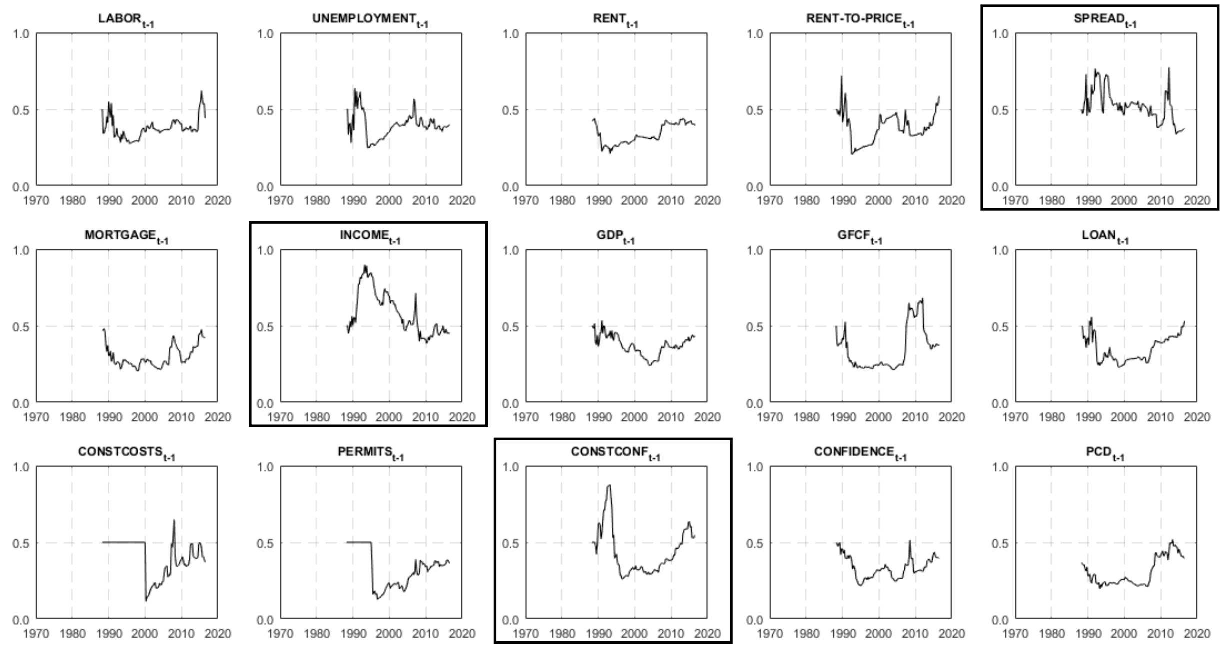
APPENDIX

Portugal

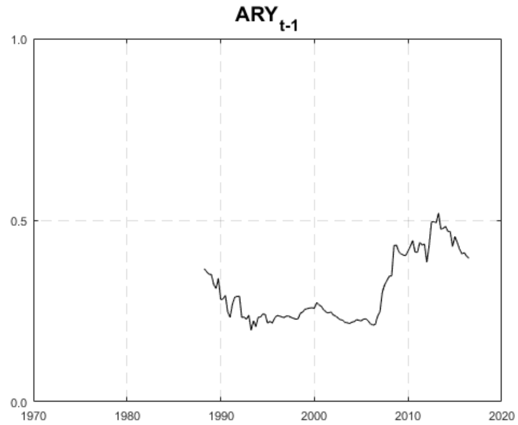
Probabilities



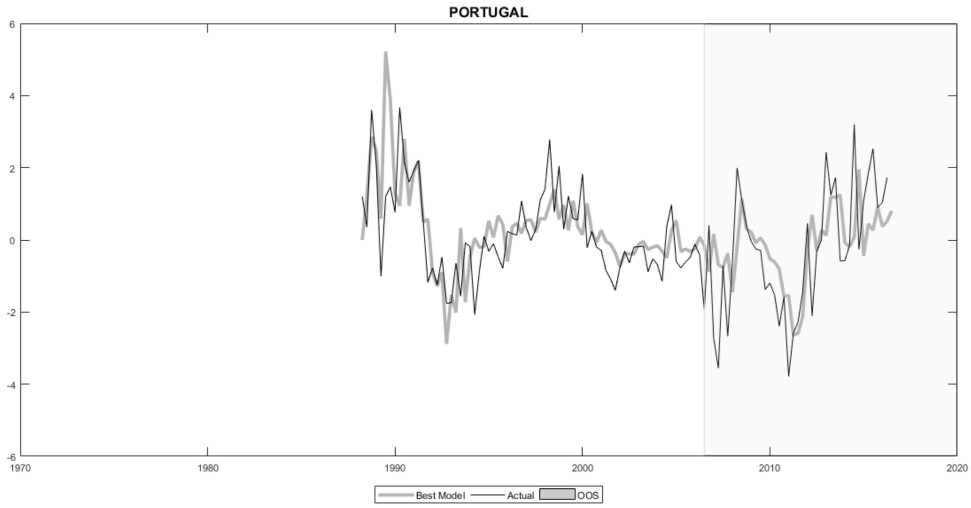
Probabilities with one lag



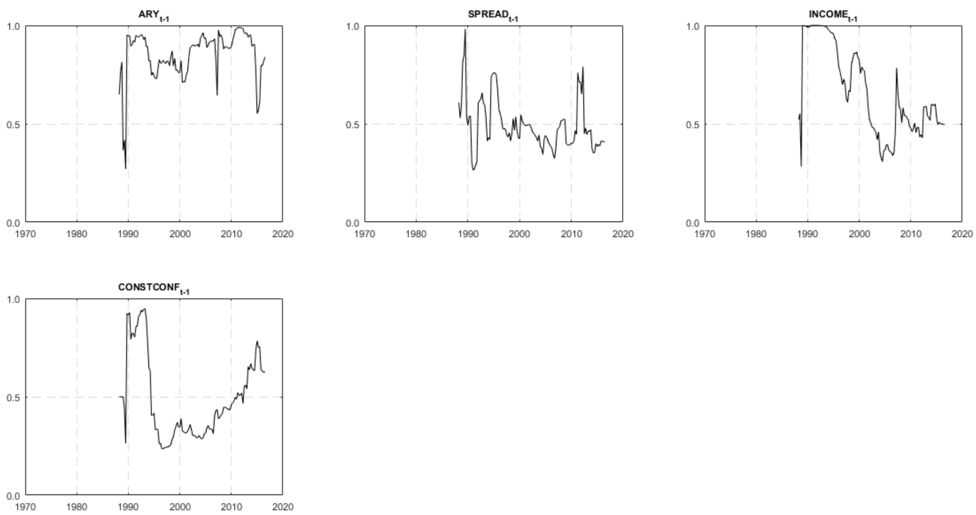
One-period lag



Actual vs Best model forecast

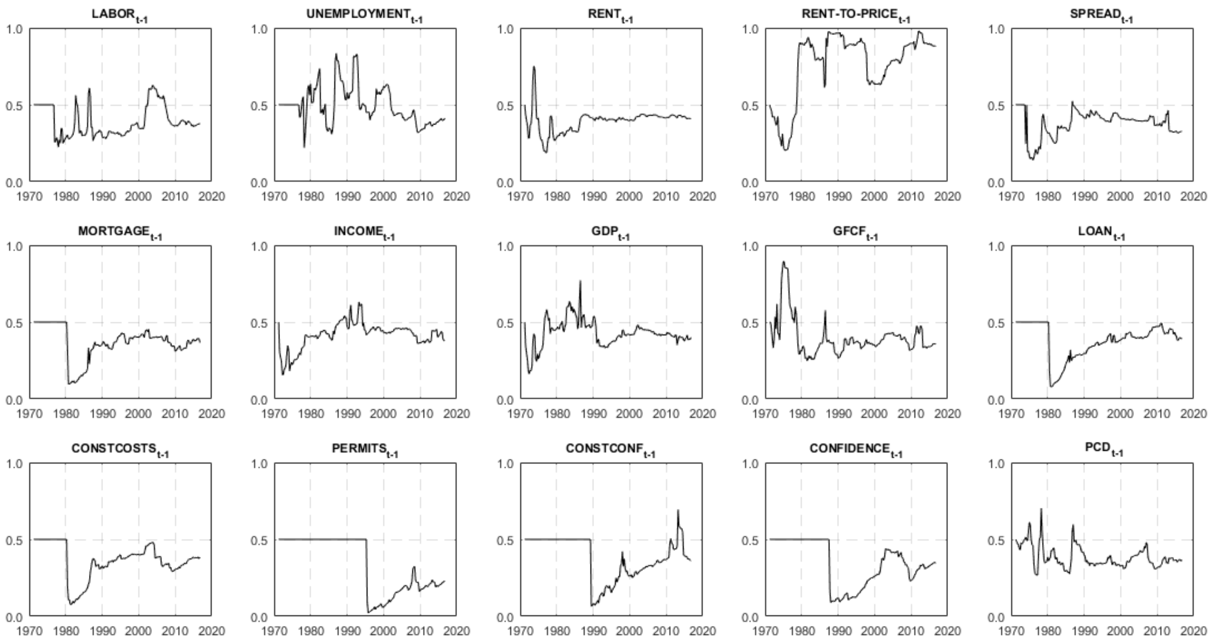


Probabilities

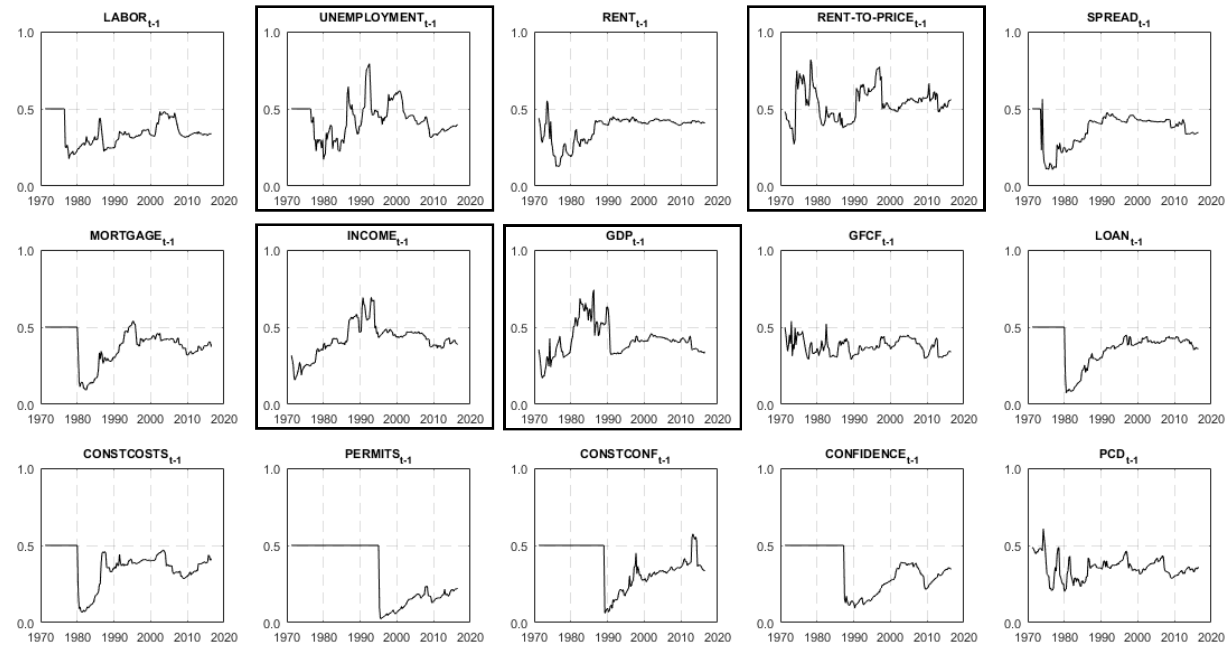


Spain

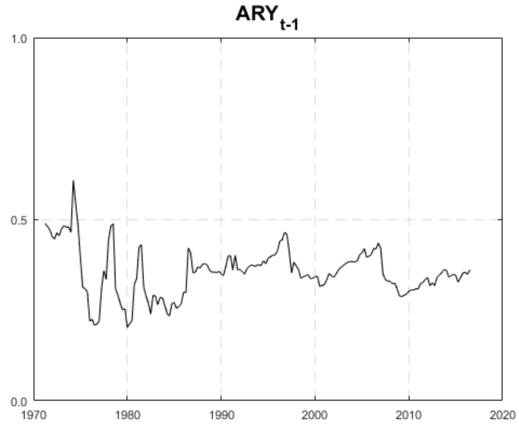
Probabilities



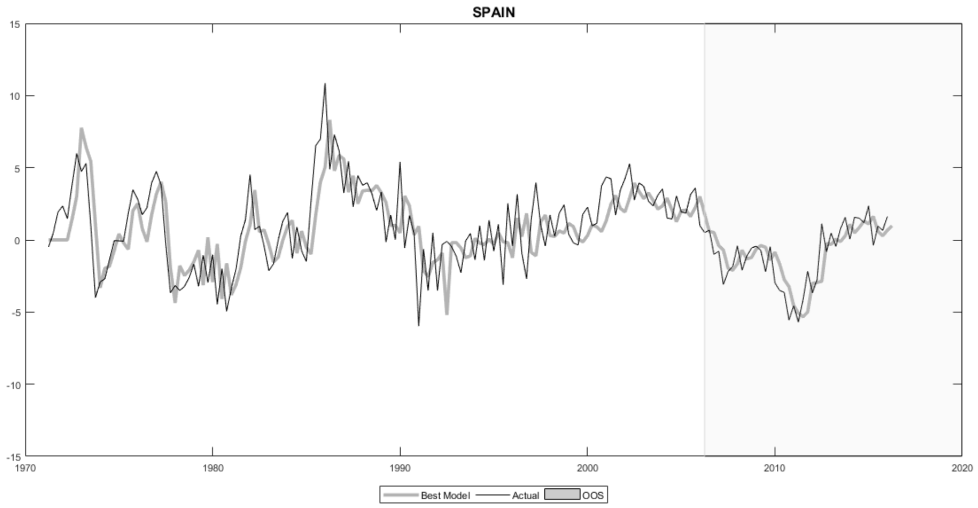
Probabilities with one lag



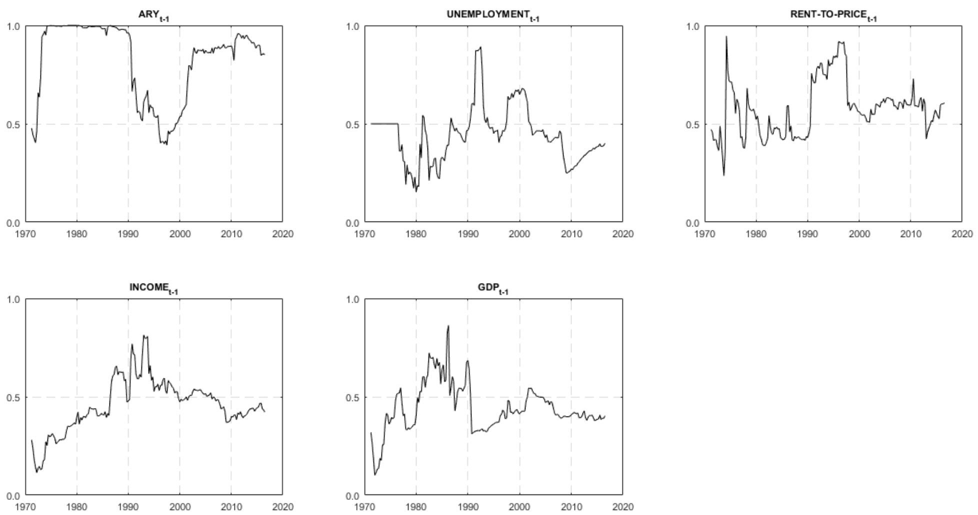
One-period lag



Actual vs Best model forecast

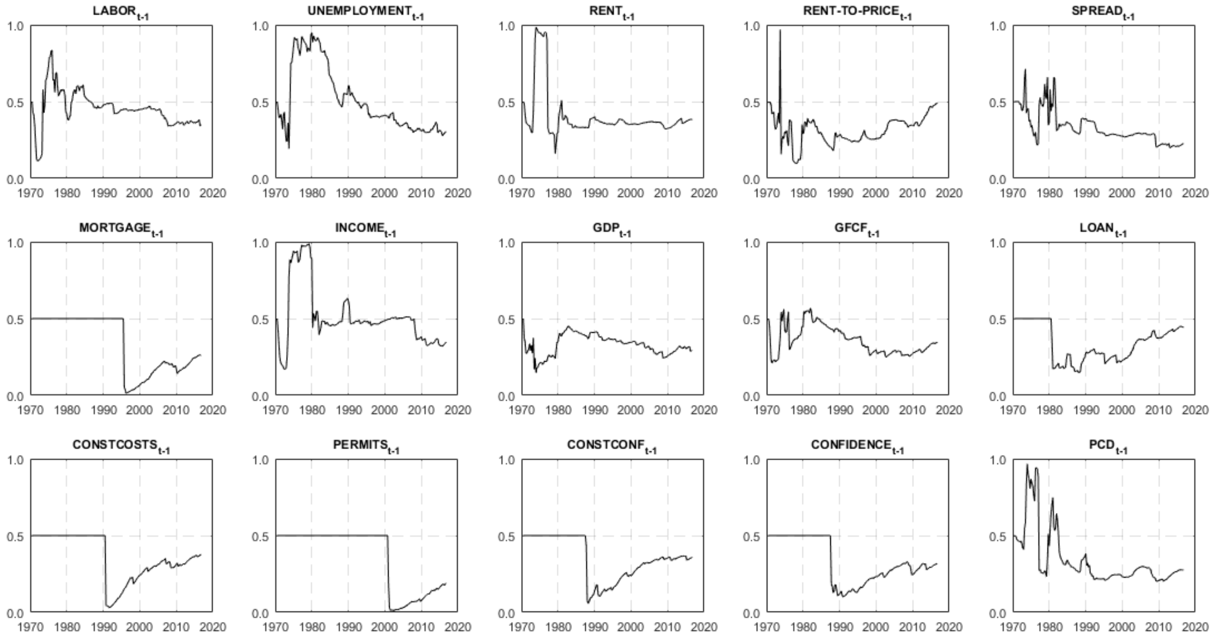


Probabilities

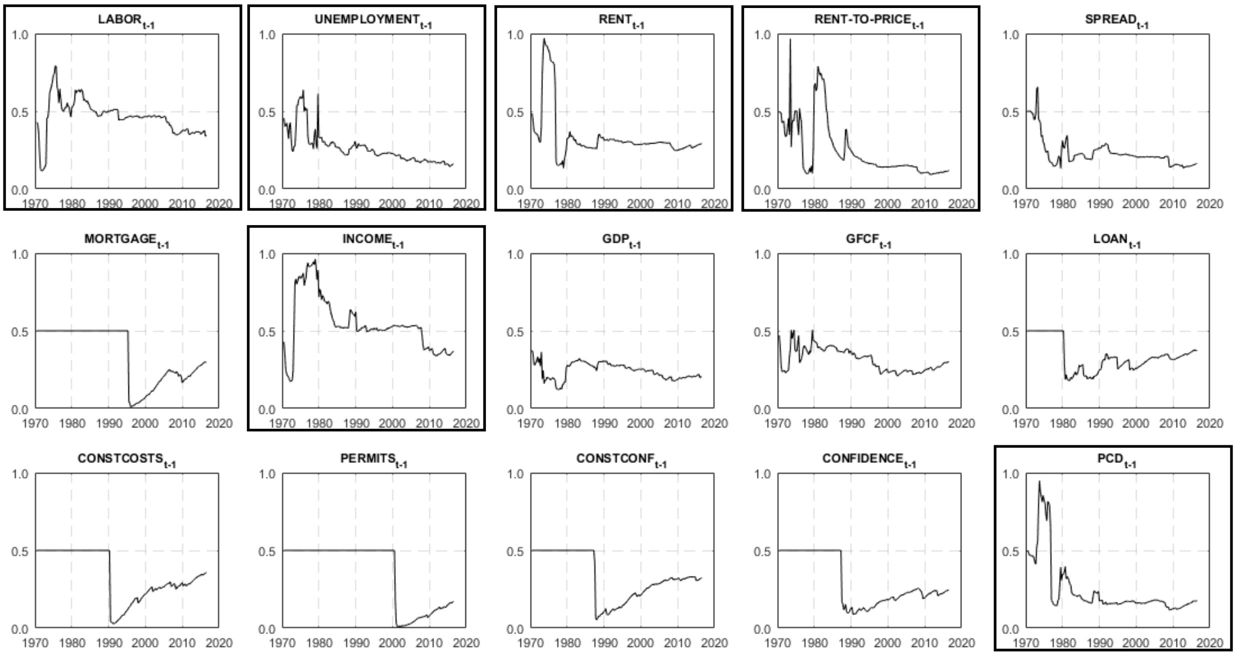


Italy

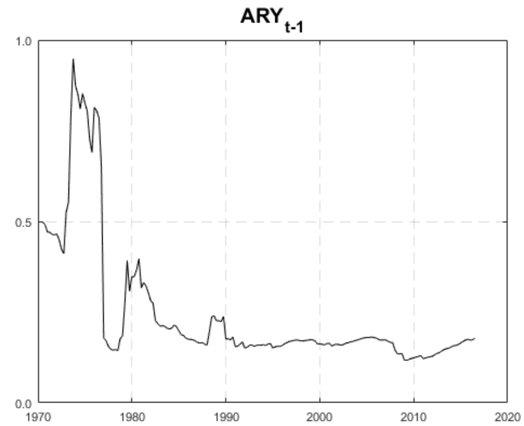
Probabilities



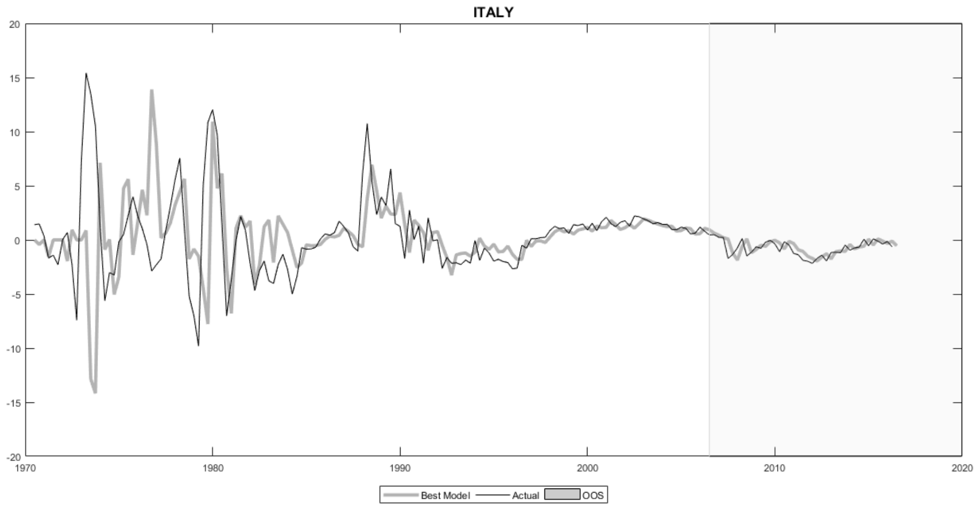
Probabilities with one lag



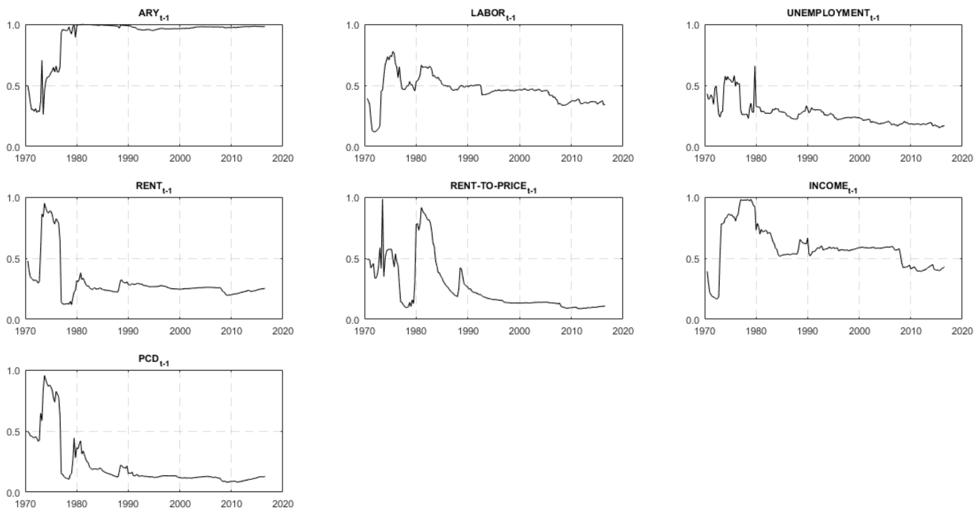
One-period lag



Actual vs Best model forecast

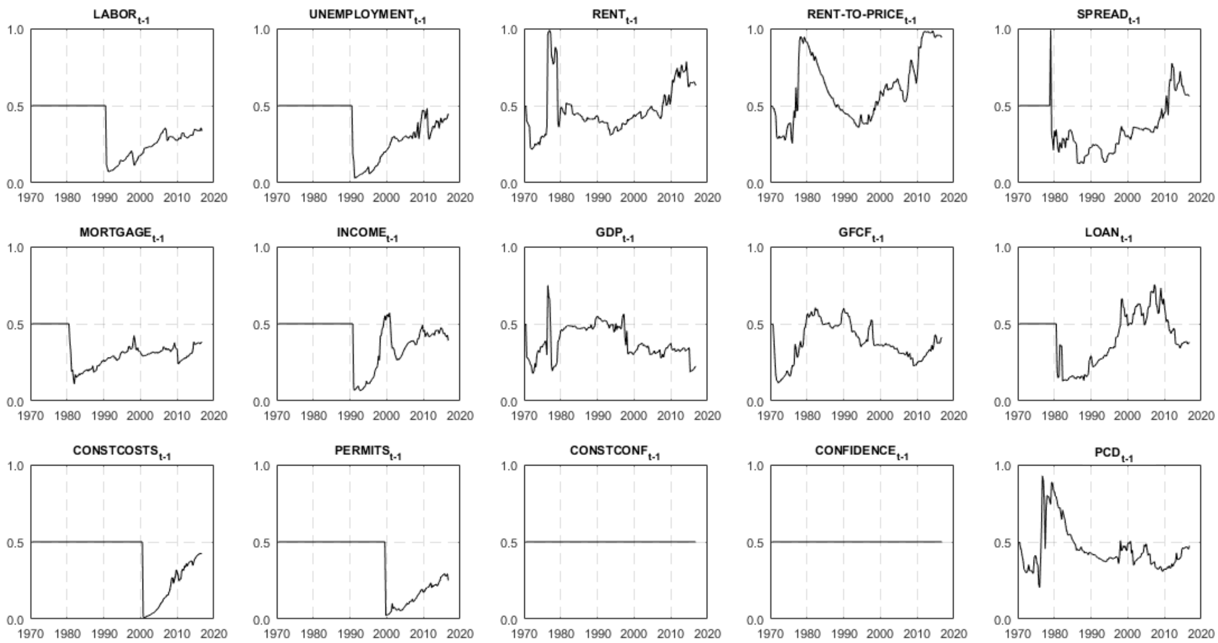


Probabilities

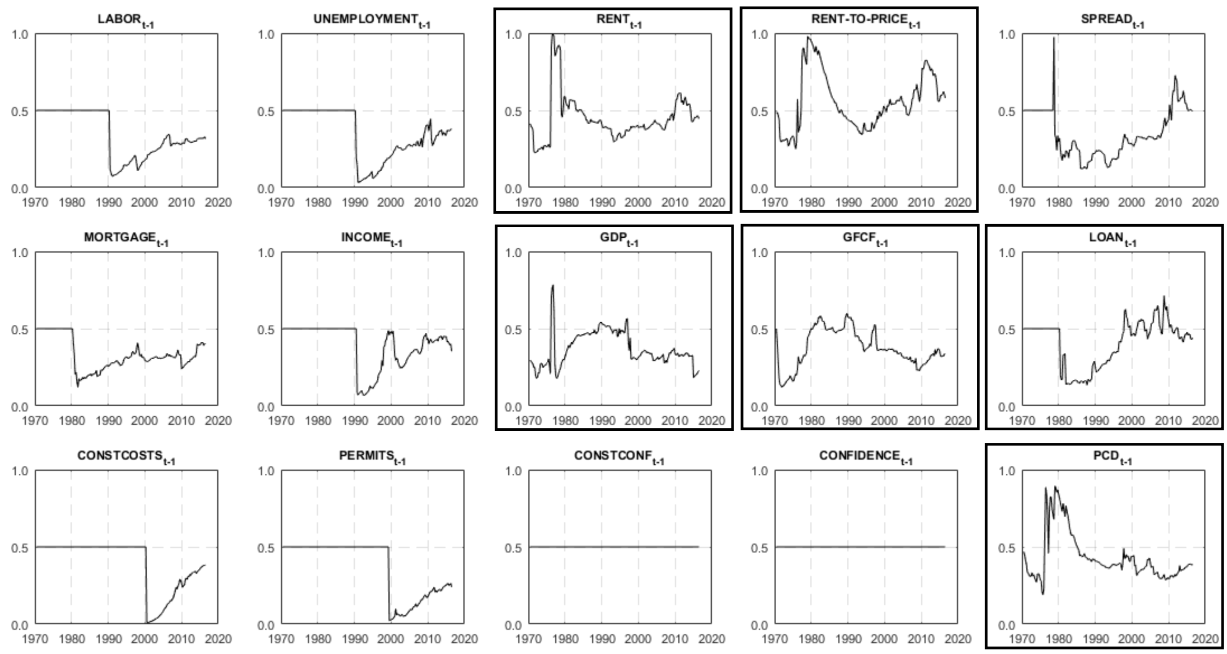


Ireland

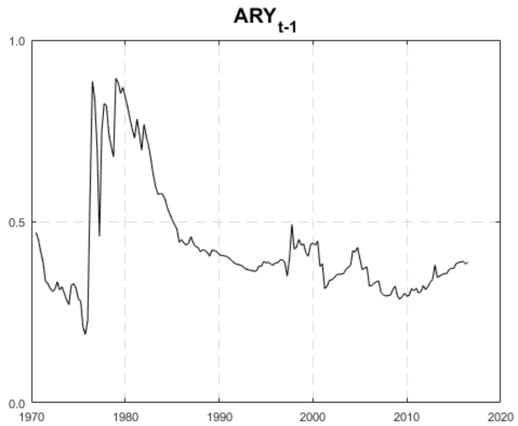
Probabilities



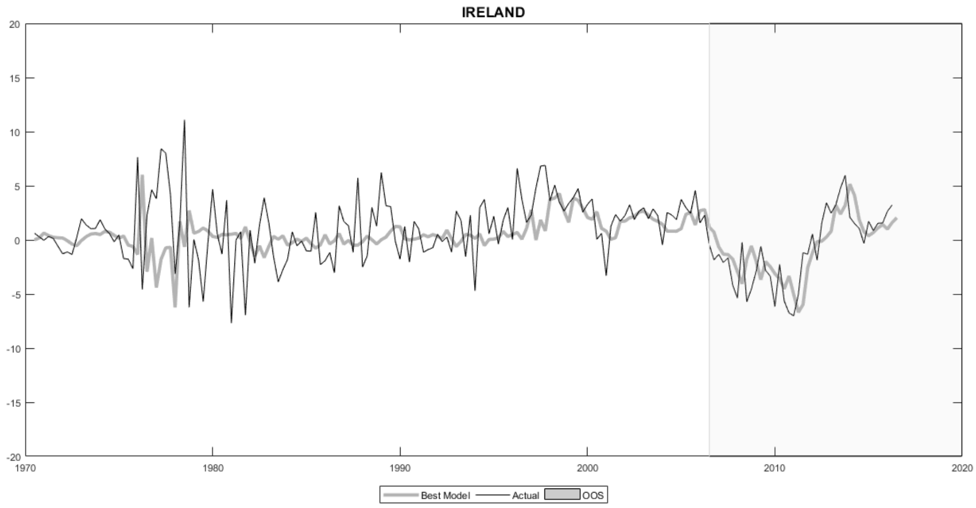
Probabilities with one lag



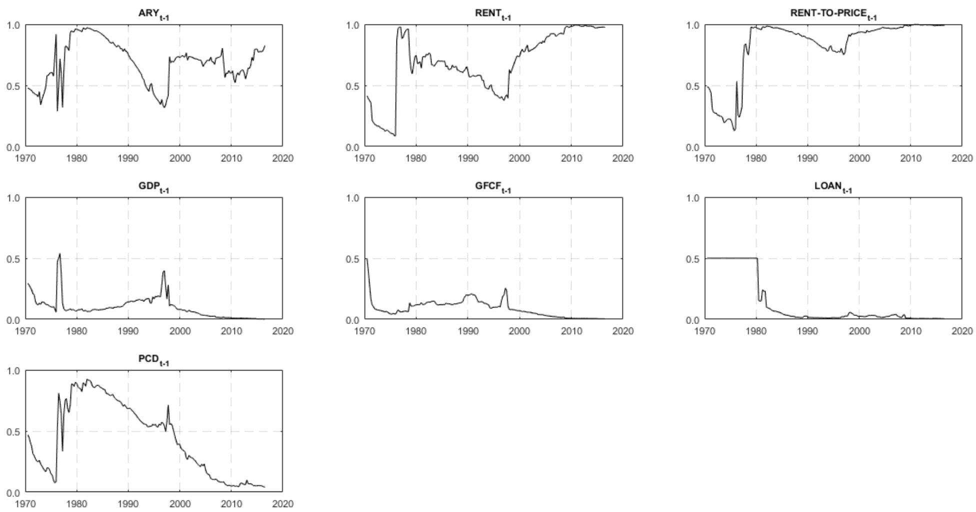
One-period lag



Actual vs Best model forecast

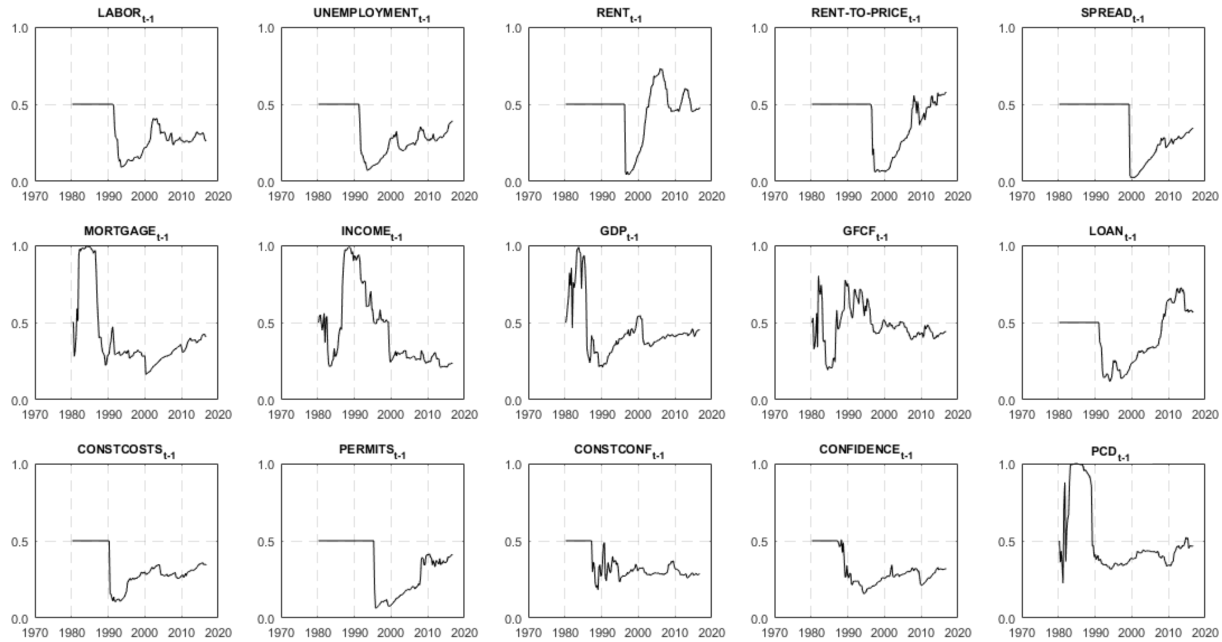


Probabilities

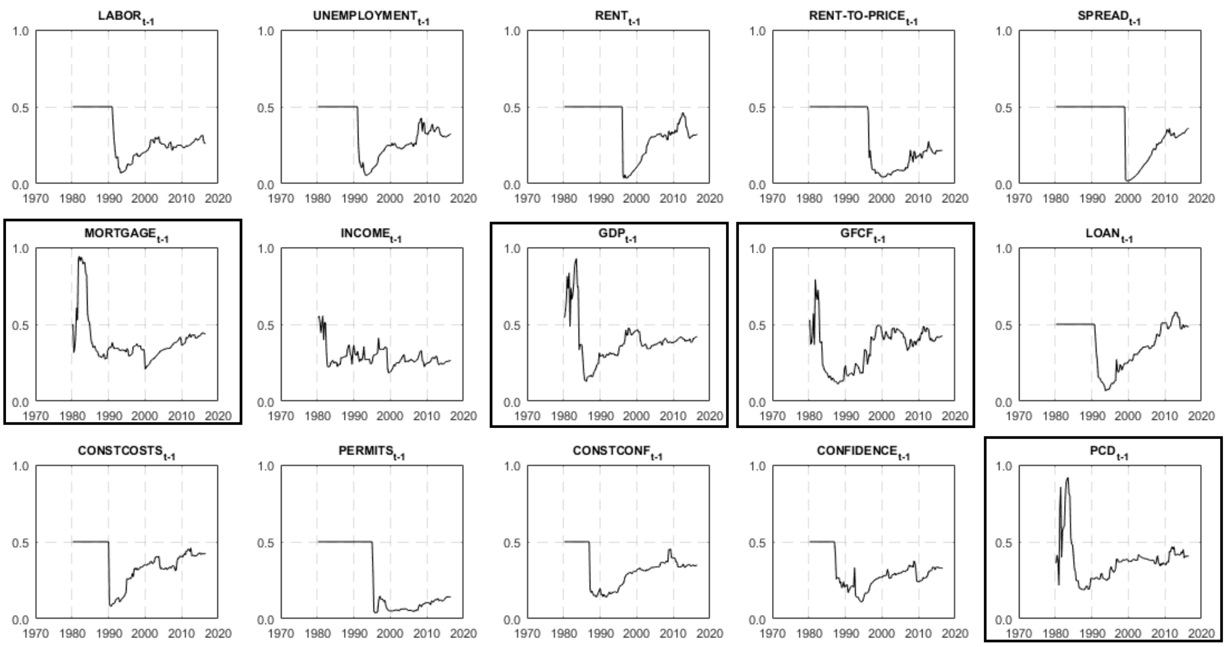


Euro Area

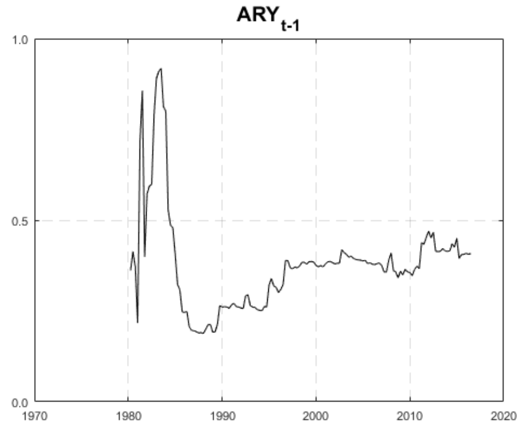
Probabilities



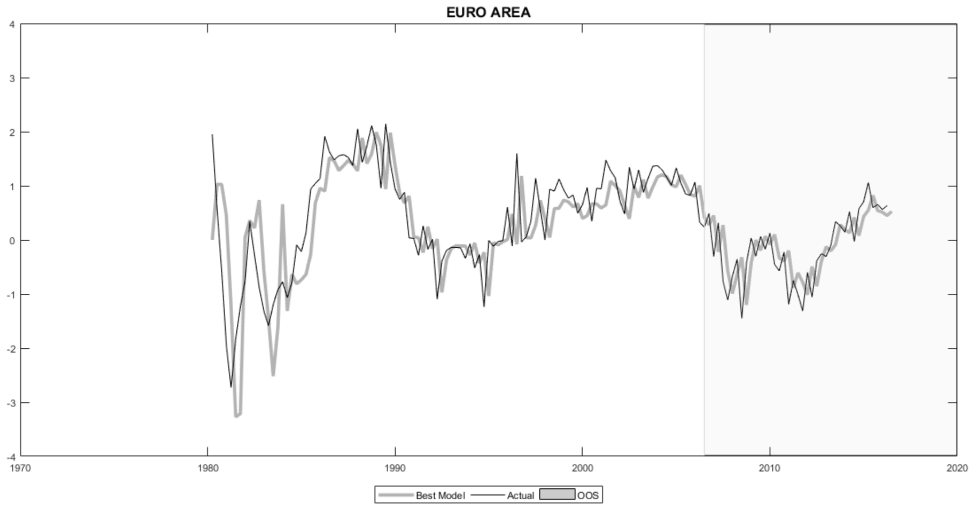
Probabilities with one lag



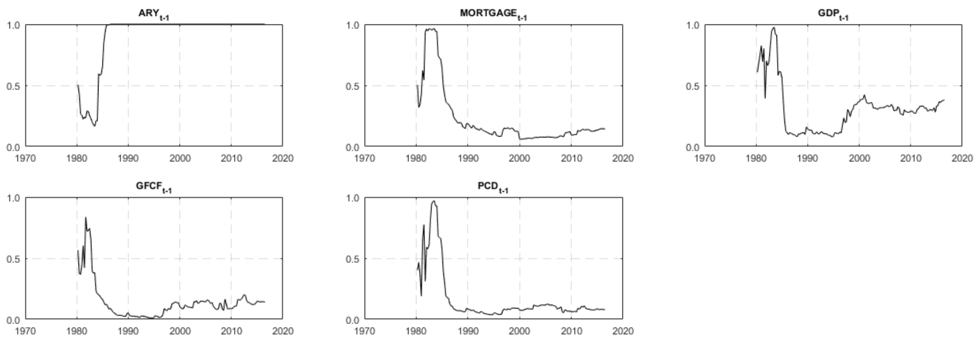
One-period lag



Actual vs Best model forecast

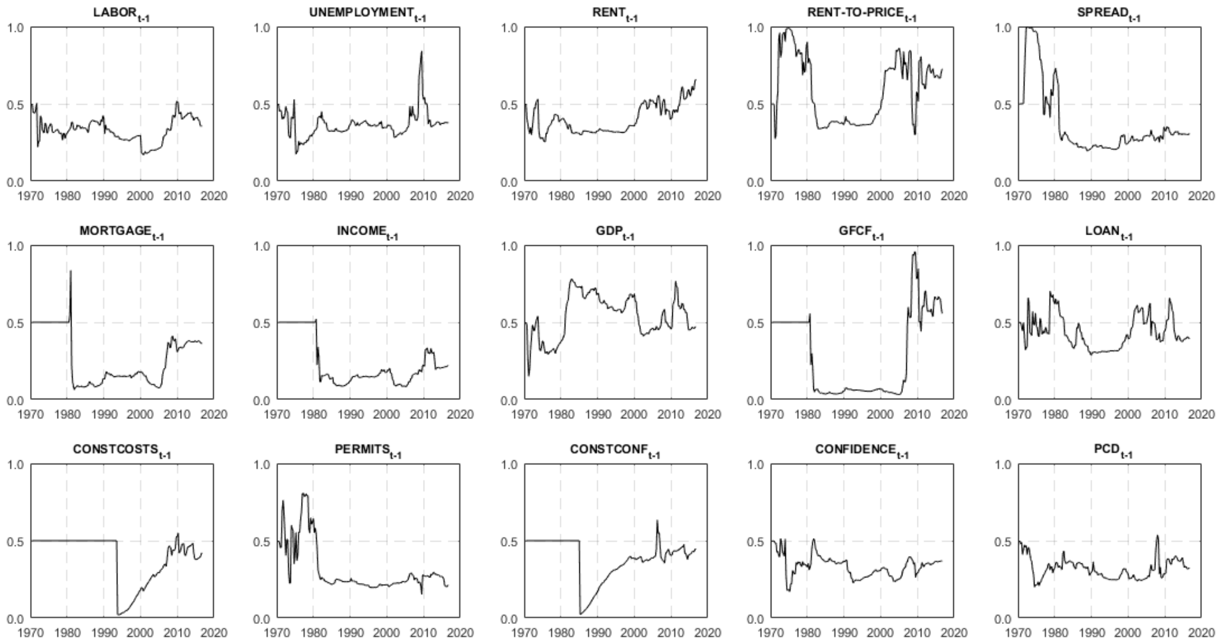


Probabilities

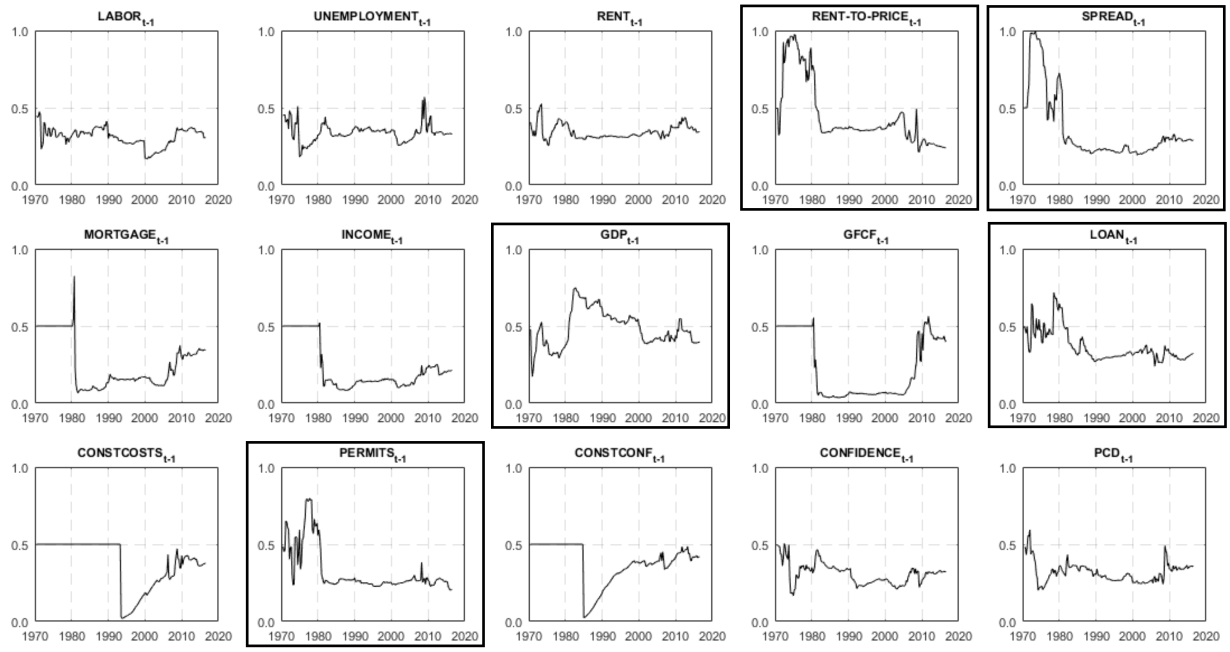


United States

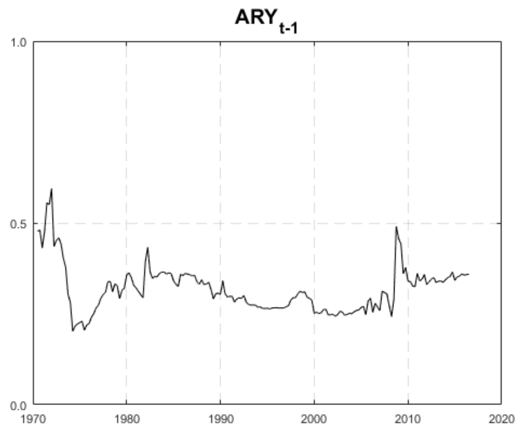
Probabilities



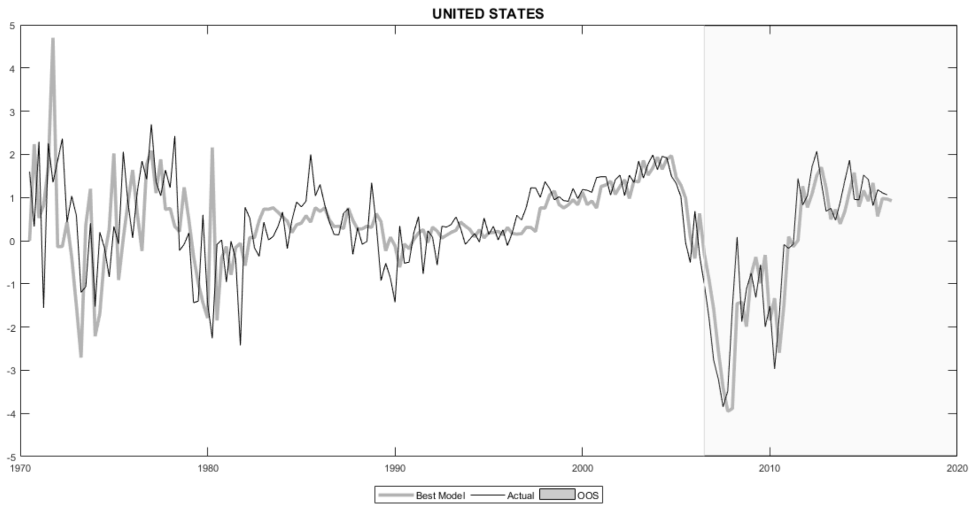
Probabilities with one lag



One-period lag



Actual vs Best model forecast



Probabilities

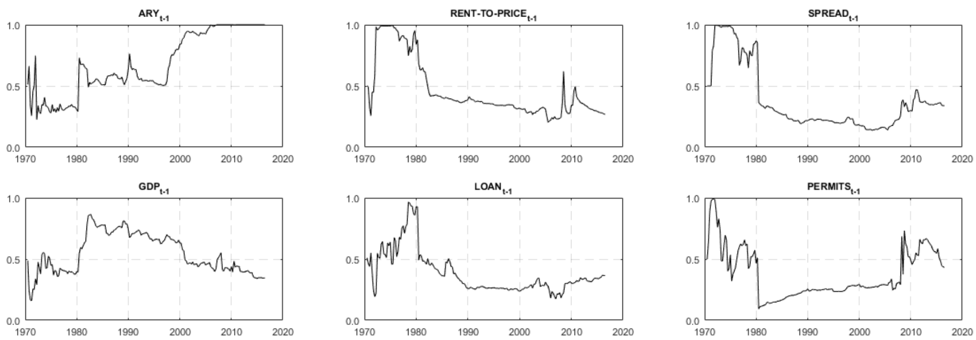


Table 4. Forecasting performance summary.

Forecasting method	MAFE	MSFE	Rel. MSFE	CW AR1	CW AR2
	Portugal				
AR1	1.1550	2.1690	1	-	
AR2	**1.1304**	**2.0742**	**1.0457**		-
DMA (λ=α=0.95)	1.0898	2.1514	1.0082	2.8523***	2.7875***
	Spain				
AR1	1.1995	2.2989	1	-	
AR2	**1.0668**	**1.8589**	**1.2367**		-
DMA (λ=α=0.95)	1.0778	1.9136	1.2013	3.2059***	2.7084***
	Italy				
AR1	0.5193	0.4699	1	-	
AR2	0.6614	0.7208	0.6520		-
DMS (λ=α=0.95)	**0.4670**	**0.3719**	**1.2636**	2.8990***	4.0583***
	Ireland				
AR1	2.3736	8.8063	1	-	
AR2	2.1515	6.8913	1.2779		-
BMA (λ=α=1)	**1.8324**	**4.7660**	**1.8477**	4.2624***	3.2692***
	Euro Area				
AR1	0.3894	0.2325	1	-	
AR2	**0.3715**	**0.2086**	**1.1149**		-
DMA (λ=α=0.99)	0.3871	0.2207	1.0534	2.0189***	1.9343**
	United States				
AR1	0.7391	0.9763	1	-	
AR2	0.7453	0.9232	1.0576		-
DMS (λ=α=0.97)	**0.6699**	**0.7069**	**1.3810**	2.3621***	2.7102***

Note: The significance levels for the null hypothesis' rejection are represented as follows: 10% '*', 5% '**' and 1% '***'

Table 5.a Forecasting performance (all models).

Forecasting method	MAFE	MSFE	Rel. MSFE	CW AR1	CW AR2
	Portugal				
AR1	1.1550	2.1690	1	-	
AR2	1.1304	**2.0742**	**1.0457**		-
DMA (λ=α=0.95)	1.0908	**2.2319**	**0.9718**	2.3074***	2.1185***
DMA (λ=α=0.97)	1.0900	2.2083	0.9822	0.6698	0.0690
DMA (λ=α=0.99)	1.0997	2.2167	0.9785	0.5531	0.0053
BMA (λ=α=1)	1.1119	2.2287	0.9732	0.5367	0.1078
DMS (λ=α=0.95)	**1.0714**	2.2952	0.9450	2.1407***	2.0407***
DMS (λ=α=0.97)	1.1214	2.3696	0.9153	0.3898	-0.1481
DMS (λ=α=0.99)	1.1702	2.4636	0.8804	0.0833	-0.4341
BMS (λ=α=1)	1.1354	2.3540	0.9214	0.4462	0.0448
	Spain				
AR1	1.1995	2.2989	1	-	
AR2	1.0668	1.8589	1.2367		-
DMA (λ=α=0.95)	1.0345	1.7803	1.2913	3.7039***	3.7108***
DMA (λ=α=0.97)	1.0346	1.7795	1.2919	3.6860***	3.6974***
DMA (λ=α=0.99)	1.0213	1.7662	1.3016	3.6387***	3.6308***
BMA (λ=α=1)	1.0290	1.7798	1.2916	3.5309***	3.5240***
DMS (λ=α=0.95)	**0.9965**	**1.7596**	**1.3065**	3.6157***	3.5451***
DMS (λ=α=0.97)	0.9991	1.7632	1.3038	3.6314***	3.5517***
DMS (λ=α=0.99)	1.0282	1.7849	1.2880	3.4967***	3.4952***
BMS (λ=α=1)	1.0282	1.7849	1.2880	3.5077***	3.5066***
	Italy				
AR1	0.5193	0.4699	1	-	
AR2	0.6614	0.7208	0.6520		-
DMA (λ=α=0.95)	**0.4653**	0.3776	1.2444	3.8966***	5.3754***
DMA (λ=α=0.97)	0.4653	0.3775	1.2447	3.8941***	5.3937***
DMA (λ=α=0.99)	0.4736	0.3884	1.2099	3.6015***	5.4095***
BMA (λ=α=1)	0.4734	0.3919	1.1991	3.4379***	5.3895***
DMS (λ=α=0.95)	0.4670	**0.3719**	**1.2636**	4.1849***	5.5104***
DMS (λ=α=0.97)	0.4819	0.4025	1.1675	3.6140***	5.5101***
DMS (λ=α=0.99)	0.4723	0.3907	1.2028	3.4384***	5.3911***
BMS (λ=α=1)	0.4723	0.3907	1.2028	3.4384***	5.3911***

Note: The significance levels for the null hypothesis' rejection are represented as follows: 10% '*', 5% '**' and 1% '***'

Table 5.b Forecasting performance (all models).

Forecasting method	**MAFE**	**MSFE**	**Rel. MSFE**	**CW AR1**	**CW AR2**
	Ireland				
AR1	2.3736	8.8063	1	-	
AR2	2.1515	6.8913	1.2779		-
DMA (λ=α=0.95)	**1.8050**	**4.8469**	**1.8169**	3.4653***	3.3375***
DMA (λ=α=0.97)	1.8333	4.9638	1.7741	3.1409***	2.6876***
DMA (λ=α=0.99)	1.9656	5.4493	1.6160	3.3439***	2.4607***
BMA (λ=α=1)	1.9562	5.5372	1.5904	3.6414***	2.6122***
DMS (λ=α=0.95)	2.0697	6.8086	1.2934	2.6624***	2.5394***
DMS (λ=α=0.97)	2.1879	7.0763	1.2445	2.3038***	1.9318**
DMS (λ=α=0.99)	2.2802	9.3070	0.9462	1.6979*	0.5653
BMS (λ=α=1)	1.9337	5.7863	1.5219	3.7146***	2.8781***
	Euro Area				
AR1	0.3894	0.2325	1	-	
AR2	0.3715	0.2086	1.1149		-
DMA (λ=α=0.95)	0.3569	0.1996	1.1652	2.5580***	2.8758***
DMA (λ=α=0.97)	0.3589	0.1991	1.1679	2.5829***	2.9004***
DMA (λ=α=0.99)	0.3575	0.1967	1.1822	2.6389***	2.9405***
BMA (λ=α=1)	0.3561	0.1958	1.1874	2.6545***	2.9504***
DMS (λ=α=0.95)	**0.3544**	**0.1952**	**1.1913**	2.6722***	2.9729***
DMS (λ=α=0.97)	0.3559	0.1957	1.1880	2.6582***	2.9541***
DMS (λ=α=0.99)	0.3559	0.1957	1.1880	2.6555***	2.9506***
BMS (λ=α=1)	0.3559	0.1957	1.1880	2.6555***	2.9506***
	United States				
AR1	0.7391	0.9763	1	-	
AR2	0.7453	0.9232	1.0576		-
DMA (λ=α=0.95)	0.6830	0.7326	1.3327	3.4114***	3.3298***
DMA (λ=α=0.97)	0.6795	0.7274	1.3422	2.2692***	2.5480***
DMA (λ=α=0.99)	0.6818	0.7517	1.2988	2.2192***	2.3037***
BMA (λ=α=1)	0.6975	0.8134	1.2003	1.9875***	1.8453**
DMS (λ=α=0.95)	0.6739	0.7188	1.3582	3.4851***	3.1733***
DMS (λ=α=0.97)	**0.6699**	**0.7069**	1.3810	2.3621***	2.7102***
DMS (λ=α=0.99)	0.6896	0.7855	1.2429	2.1059***	2.0668***
BMS (λ=α=1)	0.7110	0.8268	1.1809	2.0038***	1.8091**

Note: The significance levels for the null hypothesis' rejection are represented as follows: 10% '*', 5% '**' and 1% '***'