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FORECASTING HOUSE PRICES IN ITALY

by Simone Emiliozzi,[*] Elisa Guglielminetti[*] and Michele Loberto[*]

Abstract

Forecasting house prices is a difficult task given the strong relationship between real estate markets, economic activity and financial stability, but it is an important one. This paper evaluates the out-of-sample forecasting performance of various models of house prices in a quasi-real time setting. Focusing on Italy, we consider two structural models (using simultaneous equations) and a Bayesian VAR and compute both conditional and unconditional forecasts. We find that the models perform better than a simple autoregressive benchmark; however, the relative forecast accuracy depends on the forecast horizon and also changes over time. For the full sample period the simultaneous equation model, which takes into account credit supply restrictions and real estate taxation, shows the best performance measured in terms of root mean squared forecasting error (RMSFE). In the first part of the sample (2005-2010), medium-term forecasts of house prices greatly benefit from conditioning on the evolution of households' disposable income, whereas from 2010 onwards the path of the stock of mortgages becomes important.

JEL Classification: C32, C53, E37, R39.
Keywords: house prices, forecasting, structural model, BVAR.

Contents

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Introduction

Following the global financial crisis much more attention has been devoted to the link between housing markets and the macroeconomy. Dwellings are the main source of household wealth and, by affecting its value, house prices have an impact on household consumption (Mian et al., 2013). House prices are also relevant for activity in the construction sector: when house prices increase, firms find more profitable to build more dwellings (Glaeser and Gyourko, 2005), supporting via this channel also total employment and households' disposable income. Finally, the evolution of house prices is important also for the role of housing as collateral, both for households and small firms (Banerjee and Blickle, 2016).

Given these links, reliable forecasts of house prices are crucial for the assessment of the macroeconomic outlook and for the evaluation of potential risks to financial stability arising in the housing market. In this paper we consider and compare two different approaches to predict house prices: a structural approach (simultaneous equations) and a Bayesian vector autoregression model (BVAR). In our view, the first methodology is the best tool to obtain medium-term forecasts based on internally consistent "stories". Structural models gives the opportunity to understand how different channels affect the housing market; they thus allow to perform scenario analyses and to test their responsiveness to changes in key variables. Overall these features are particularly important for forecasting house prices and for assessing the risks to financial stability: the multifold interactions between the housing market, credit markets and the overall macroeconomic activity must be taken into account. Differently, the BVAR is a reduced-form model that in many empirical applications achieves a superior forecasting performance when compared to alternative approaches (Doan, Litterman and Sims, 1984; Karlsson, 2013): it can thus be regarded as a strong competitor of the structural models. When using the BVAR approach we test the performance of both unconditional and conditional forecasts, as in Banbura, Giannone and Lenza (2015). In summary, structural models are more suitable for policy purposes since they allow for a "storytelling" which rationalizes the forecasts; however, this comes at the risk of model misspecification when one imposes constraints which do not hold in the data. On the contrary, BVARs are flexible and parsimonious and may thus prove superior in forecasting when the reduced-form relationships between the data are sufficient to characterize their evolution over time. Clearly, the economic interpretation of the forecasting exercise is rather limited, instead.[1]

[1] A complementary approach would be represented by structural BVARs, in which the analyst imposes restrictions to identify some shocks of interest: this would allow an economic interpretation of house price dynamics. In this work,

We consider two structural models, presented in Loberto and Zollino (2016) and Nobili and Zollino (2017); such models consist of three blocks of equations, each of them describing the equilibrium in the market for dwellings, for mortgage loans to households and for loans to construction firms, respectively. Loberto and Zollino (2016) further takes into account credit supply restrictions and taxation on housing.

The BVAR estimation follows Giannone, Lenza and Primiceri (2015), who propose a new methodology for setting the informativeness of the prior for the model coefficients based on Bayesian hierarchical modeling (see Appendix B).

All models are estimated using samples starting in 1986Q1 with an expanding window[2] while their forecasting performance is assessed using a recursive exercise in quasi-real time (i.e. using the last vintage of data) on a period spanning from 2005Q1 up to 2016Q4 and looking to a projection horizon from 1 to 12 quarters ahead.

The first result is that all the models are useful in predicting house price dynamics and pass an important test (Breitung and Knuppel, 2017): for all the horizons, the root mean squared forecasting error (RMSFE) is lower than the unconditional standard deviation of the house price index.[3] Second, for horizons shorter than one year all models have a similar predictive accuracy and there is no clear winner. For the medium run (between one and three years), the forecasts of the structural models and those of the conditional BVAR have a superior accuracy with respect to the unconditional BVAR, indicating that at longer horizons house prices are strongly influenced by macroeconomic determinants. Lastly, a sub-sample analysis reveals that in order to have good projections for the Italian house price index before 2010 it is enough to condition on disposable income; conversely in the most recent years it is more important to further condition on the growth rate of the stock of mortgages to avoid systematic over-predictions of house prices during the crisis.

The rest of the paper is structured as follows. Section 1 reviews the related literature; Section 2 presents the data and the stylized facts; Section 3 describes the models; Section 4 illustrates the forecasting exercises and the results; Section 5 concludes.

however, we prefer to fully exploit the flexibility of the reduced-form BVARs against the tight structure imposed by the simultaneous equation models.

[2] The first estimation sample common to all models considered in the analysis ranges from 1986Q1 till 2004Q4 so that the out-of-sample exercise starts in 2005Q1.

[3] When the RMSFE is higher than the unconditional standard deviation of the target variable the forecasting model is totally misspecified.

1. Literature review

In this work we adopt a macroeconomic perspective to forecasting residential property prices. Since the outbreak of the Global Financial Crisis, the attention of central banks on modeling and forecasting the evolution of real estate variables has increased substantially because of their fundamental role in the assessment of macroeconomic and financial stability. Indeed macroprudential measures have been adopted by several European countries, following the recommendations of the European Systemic Risk Board (ESRB) about the vulnerabilities arising from the real estate market.[4]

For the ECB and the national central banks, the evaluation of the accuracy of house price forecasts is of primary importance given their use in the Eurosystem staff projections, stress testing exercises and the Financial Stability Report (FSR), which gauges the resilience of the whole financial system that is strongly interconnected with the real estate sector. The evolution of real estate markets is thus regularly and closely monitored; also, future dynamics of house prices are considered consistently with the broad macroeconomic scenario.

Forecasting house prices is a challenging task for a variety of reasons.

The first one is related to data availability: long time series of house prices with a reasonable coverage of the whole national market are relatively scant, especially for European countries. In addition, the data may capture different phenomena depending on the construction of the index and the aggregation method; a relevant issue, as explained in Section 2, is how to take into account dwellings' heterogeneity and changes in the quality of houses put on sale. Moreover, house price indexes are generally released with significant delays with respect to the reference period.

As pointed out by Ghysels *et al.* (2013), only few works have been able to study out-of-sample (OOS, henceforth) forecast accuracy of house prices because of limited availability of long time series. In this work we can go one step further: our Italian house price index, which is representative of the Italian real estate market, starts in 1986 and is computed at quarterly frequency, allowing us to rank the models based on OOS statistics. Since the Italian Statistical Institute (ISTAT) publishes a quarterly house price index based on actual transactions that starts in 2010, we use the reconstruction made by Muzzicato et al. (2008) that extends it back in time till 1986 based on average unit values per squared meters.

[4] ESRB, "Vulnerabilities in the EU residential real estate sector, November 2016".

The second difficulty in forecasting house prices emerges because the real estate market has wide and strong connections with the rest of the economy, but their relative importance may change over time. Demand factors – such as disposable income, interest rate on households' mortgages and the flow of household mortgages – are usually assumed to play the most important role, with the supply of housing being relatively inelastic to market conditions. However some contributions to the literature have stressed the importance of supply-side factors as well: Strauss (2012) finds that building permits improve the predictions of construction volumes and prices, while Spiegel (2001) shows in a theoretical model that construction cycles may arise in presence of credit constraints. Furthermore, there is no consensus in the literature on the importance of credit for house price forecasting. Many analyses find a strong positive effect of credit conditions on residential property prices (Igan and Loungali, 2012; Goodhart and Hofmann, 2008; Annett, 2005 and Tsatsaronis and Zhu, 2004). However Goodhart and Hofmann (2008) and Simigiannis and Hondroyiannis (2009) highlight the problem of reverse causality, which means that bank credit is itself driven by favorable conditions in the real estate market. Moreover, Annett (2005) shows that the relationship between credit and house prices is significant only in the long-run, whereas Gerdesmeier et al. (2011) find asymmetric effects depending on the state of the economy. This relationship may also be shaped by institutional characteristics, irrespective of the real economic outlook (Mian and Sufi, 2011). Our work is agnostic in this perspective since we rely on several approaches that can accommodate different views: the structural models take into account supply, demand and credit factors by imposing equilibrium relationships, whereas the BVARs are more parsimonious and capture only demand and financing conditions without any restriction on the short and long-run dependency between credit and house prices. The model in Loberto and Zollino (2016) also considers credit supply restrictions and changes in property taxation. Consistent with the literature on house prices' momentum, all the models we consider exploit the autocorrelation structure in the dependent variable. We do not explore the causes of the persistence in house price dynamics: however, several explanations have been provided by the theoretical literature, ranging from downpayment constraints (Stein, 1995), agency problems which affect banks' risk-taking behavior (Allen and Gale, 2000) and irrational exuberance (Shiller, 2005; 2009), to name a few.

From a methodological point of view, different models have been used in the literature to forecast house prices, depending on the quality and the time span of the available data as well as on the characteristics of the economic environment. Some studies have employed Error-Correction Models (ECMs) or Vector Error-Correction Models (VECMs), which distinguish between short and long-run determinants of house prices. These models implicitly assume the existence of a time-invariant long-run equilibrium of house prices and the forecasts are based on the assumption of reversion towards this equilibrium. This approach has been adopted, among others, by Gattini and Hiebert (2010) and Greiber and Setzer (2007) for the euro area, Malpezzi (1999), Painter and Redfearn (2002), McCarthy and Peach (2004) and Case et al. (2013) for the United States.

More recently, Jarocinski and Smets (2008), Carstensen et al. (2009) and Gupta, Kabundi and Miller (2011) have used Bayesian VARs with informative priors in order to improve their forecast accuracy; like the first authors, we test the forecasting performance of both unconditional and conditional BVAR forecasts. However, we also confront this technique with the predictive ability of two different simultaneous equations models, which should better take into account the multifold structural interactions of the Italian economy, though at the price of greater complexity. The literature has generally taken into account national and regional heterogeneity through panel models (e.g. Goodhart and Hofmann, 2008), which are however hard to apply for forecasting purposes due to data limitations. Other methods are more suited to extract information from large datasets, like dynamic factor models (Luciani, 2015) and Factor Augmented VARs (Eickmeier and Hofmann, 2013).

2. Data and stylized facts

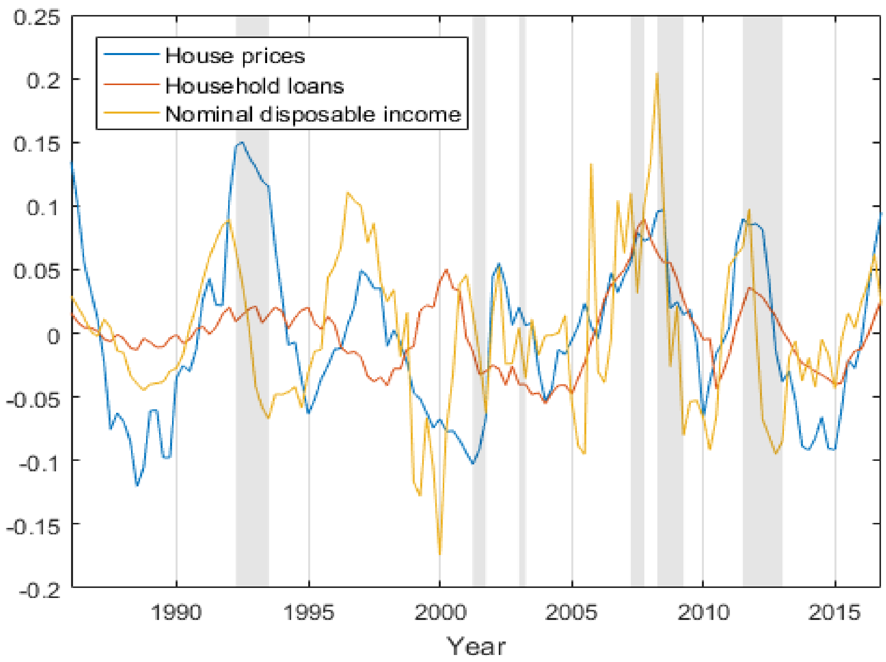
Reliable house price data are rarely available on a regular frequency and most of the times they cover only short time spans. The construction of house price measures entails many methodological difficulties. First, it is hard to gather representative data given the segmentation of the market at territorial level in relation to multiple characteristics (e.g. geography, income). Second, house price dynamics should be purged from composition effects due to changes in the quality of the dwellings put on the market. This issue is particularly relevant in the real estate market because of its extreme heterogeneity and the cyclical pattern of the quality of houses put on sale, which is imperfectly measurable.

The Italian Statistical Institute (ISTAT) publishes a quarterly house price index starting in 2010 and based on actual transactions taken from administrative sources. These data are highly representative at the geographical level; moreover, they contain information on house characteristics that allow to run hedonic regressions and to control for changes in the quality of dwellings.[5] For the years prior to 2010, we rely on the price index computed by Muzzicato et al. (2008), which combines several sources in order to estimate unit values of dwellings to extend the official house price index back in

[5] In July 2018 ISTAT disseminated a new revised series of the residential property price index, which is slightly different from the one used in our analysis.

time. This relatively long time series allows us to perform OOS exercises, whereas most of the literature has focused on in-sample properties of predictive regressions due to data limitations. We estimate models recursively starting from 1986Q1 and we evaluate the forecasting performance on the window 2005Q1-2016Q4.

Figure 1: House prices, household loans and nominal disposable income *(HP-filtered series)*



Note: The series are standardized and HP-filtered with smoothing parameter of 1600.

Figures 1 and 2 represent the cyclical component[6] and the annual growth rates of the Italian house price index together with the stock of loans for house purchases and nominal disposable income (shaded bars indicate Italian recessions).[7] The series display a strong co-movement both in their cyclical component and in annual growth rates, especially from 2002 onwards. In the late '90s and early 2000s the sizable increase in household loans was followed by a temporary acceleration in nominal disposable income and house prices. The strong credit dynamics during that period can be explained by two factors unrelated to both macroeconomic fundamentals and the outlook of the real estate market: i) the strong decrease in interest rates due to the incoming adoption of the euro and ii) the liberalization of the financial sector (see Angelini and Cetorelli, 2003 and Casolaro, Gambacorta and Guiso, 2006). In what follows we will see that this episode likely influences the estimate of the relationship between the variables of interests, leading to unsatisfactory predictive accuracy in the

[6] The series are first standardized to have mean zero and unitary standard deviation and then HP-filtered with a smoothing parameter of 1600.

[7] A recession is defined as two consecutive quarters of negative growth.

first part of the sample when we condition on the path of mortgages. This notwithstanding, over the full sample (1986Q1-2016Q4) the contemporaneous correlation of the annual growth rates of household loans and nominal disposable income with house prices remains strong (Table 1).

Figure 2: House prices, household loans and nominal disposable income *(annual growth rates)*

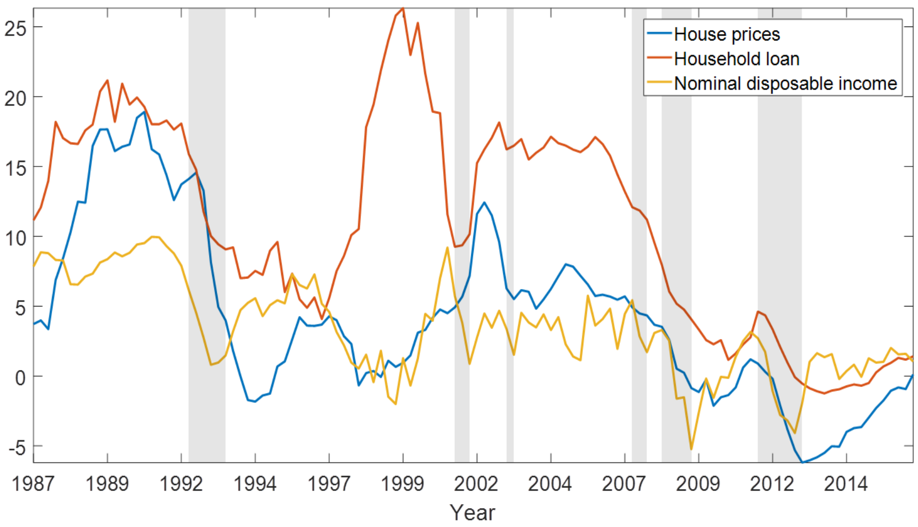


Table 1: Contemporaneous correlation annual growth rates (1986Q1-2016Q4)

	House prices	Household loan	Nominal disposable income
House prices	1.00		
Household loan	0.70	1.00	
Nominal disposable income	0.70	0.47	1.00

High forecast accuracy for house prices is of primary importance for mainly two reasons. First, reliable forecasts play a central role in policy making both for monetary policy and financial stability purposes. Second, house price data are generally characterized by long publication lags: in Italy they are released by ISTAT 95 days after the end of the reference quarter (see Table 2), in line with standards agreed at EU level. Given the difficulty of finding a unique model with high predictive accuracy in all states of the world, we consider more appropriate to rely on multiple approaches. In this exercise we thus investigate the properties and compare the performance of different models in order to exploit all the relevant information and get a deeper insight on the evolution of residential property prices.

Table 2: Publication lags of variables used in the models

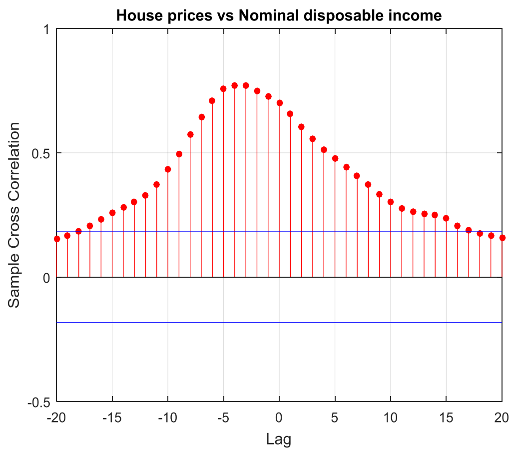
Key Variables	Publication Lag	Freq.
House prices (first release)	t+95	quarterly
Investments in Construction (National Accounts)	t+90	quarterly
Household loans	t+30	monthly
Nominal disposable income	t+90	quarterly

Figures 3a and 3b display the dynamic correlations of the annual growth rates of the house price index, household loans for house purchases and nominal disposable income in order to check their potential relevance in the forecasting exercise. House prices are strongly correlated with the other two variables not only contemporaneously but also at several leads and lags: at least five lags of both the mortages and the nominal disposable income growth contain valuable information (the cross-correlation is above 0.5) for predicting house prices. In particular, the peaks in the cross-correlations are achieved at the fourth lag of nominal disposable income and the first lag of credit growth (the correlation at the fifth lag, however, is only slightly below the peak). This information is fully exploited in both the structural and the BVAR models; the latter, however, relies on these three series only, while structural models are characterized by a richer information set. For a descriptive analysis of the properties of the underlying series we refer to Loberto and Zollino (2016).

Figure 3a Cross-correlation between house prices and household loans *(whole sample)*

Note: The cross-correlation is calculated on annual growth rates; positive values on the x-axis represent leads, while negative values represent lags.

Figure 3b Cross-correlation between house prices and nominal disposable income *(whole sample)*



Note: The cross-correlation is calculated on annual growth rates; positive values on the x-axis represent leads, while negative values represent lags.

3. Models

3.1 Structural models

The first approach to house price forecasting is based on simultaneous equations models. The main advantage of this methodology consists in obtaining medium-term forecasts on the basis of an internally consistent outlook for the real estate market as a whole, including the evolution of housing supply and the equilibrium on the market for mortgage loans and loans to construction firms. It is possible to understand how different channels (such as demographics, profitability of construction firms, monetary policy stance, etc.) affect the housing market and its sensibility to changes in key variables, thus allowing for a consistent "story-tellying". Overall these features are particularly important for house price forecasting and for financial stability analysis, where the interaction between the housing market, credit markets and the macroeconomic activity at large must be taken into account. We consider two different structural specifications[8] for the Italian housing market, borrowing from the work of Nobili and Zollino (2017, NZ hereafter) and extended in Loberto and Zollino (2016, LZ hereafter). In both models house prices are considered in nominal terms, as in the BVAR model described in the next section. In NZ the housing market is modeled as a dynamic system comprising three blocks of equations: i) the demand and supply schedules for housing; ii) the demand and supply schedules for mortgage loans to households; iii) the demand and supply schedules for loans to construction firms. In each equation the candidate regressors are considered up to 4 lags.

In the housing demand equation house prices are driven by households' disposable income, the flow of mortgage credit (approximated by the growth rate of the stock of outstanding loans) and the developments in population and housing stock. In the same equation are also included price expectations (current house prices may positively depend on future expected consumer prices), proxied by the expectations on general inflation collected by qualitative surveys across Italian households.[9] The housing supply is modeled by two equations. According to the first, the flow of residential investments over housing stock depends positively on house prices, which represent the

[8] Macro models for medium run forecasting used by the Eurosystem use both structural and reduced form models to generate house price scenarios to inform the prediction of other key macroeconomic variables used in the (B)MPE. In order to forecast real house prices the ECB uses both a VECM and a set of Bayesian VAR models (see ECB, 2016a). In the Bank of Italy quarterly econometric model (BIQM) house prices are obtained as the equilibrium between supply and demand for dwellings, with the latter determined on the basis of a portfolio allocation decision (see Bulligan et al., 2017).

[9] Data on expectations about future house prices developments are not currently available. Some attempts to produce reliable measures of such expectations have been carried out by the Bank of Italy's survey on the "*Italian housing market. Short-term outlook*", which starts in 2009. However the house price expectations time series is too short to be used in our models.

incentive for firms to build new houses, and the amount of loans granted to construction firms; residential investments are negatively affected by building costs. In the second equation, based on the perpetual inventory approach, housing stock changes are function of the flow of residential investments.

In the two credit blocks the identification of credit demand and supply schedules is achieved by assuming that the loan rate charged by the intermediaries is a mark-up over the cost of funding, which may fluctuate depending on the borrowers' creditworthiness and banks' balance sheets position; loan quantities do not enter the credit supply equation. The flow of mortgages for house purchases depends positively on house prices and negatively on the cost of credit and households' disposable income. In the market for loans to construction firms, the credit flow is positively related to residential investments and negatively to the opportunity cost of loan financing, measured by the spread between the bank interest rate and the long-term interest rate.

In LZ the previous model is extended to take into account developments that have characterized the Italian housing market during the financial and sovereign debt crisis. As a first innovation, the demand equation for housing includes a control for property taxation that, affecting the user cost of housing property, is a key determinant of the propensity to invest in dwellings. As a second innovation, the model accounts for possible disequilibria in the credit market: the empirical strategy adopted in order to model excess demand and supply is based on the "quantitative approach" developed by Fair and Jaffee (1972). This approach assumes that the observed amount of credit is the minimum between demand and supply, with the excess demand (supply) depending on banks' capital position. As pointed out by Del Giovane, Eramo and Nobili (2011), this factor became crucial during the sovereign debt crisis, when Italian banks participating in the Bank Lending Survey reported a tightening in credit standards due to the need of deleveraging.

We present in Appendix A the full description of the LZ structural model, which extends NZ. For a more comprehensive explanation of the modeling choices we refer to the original papers.

3.2 BVAR model

BVAR models are popular forecasting tools because they achieve high predictive accuracy though allowing for a parsimonious parameterization (Doan, Litterman and Sims, 1984; Karlsson, 2013 and Carriero, Clark and Marcellino, 2015). The BVAR model adopted in our exercise exploits the methodology put forward in Giannone, Lenza and Primiceri (2015).[10] They use a hierarchical

[10] See Appendix B for further details.

Bayesian approach to automatically select the tightness of the prior distribution for the model coefficients. The prior used in the estimation is a canonical and widely used Minnesota prior (Doan, Litterman and Sims, 1984; Litterman, 1979).

We started with a specification of the BVAR including five variables: the Italian house price index, the households' nominal disposable income, the stock of mortgages to households for house purchases, the HICP index and the average interest rate on outstanding loans for house purchases. However, we observed that the last two variables do not help in forecasting house prices[11]: we thus present the results of a more parsimonious specification based on the first three variables only. The model is specified in log-levels with four lags of the endogenous variables. We estimate the model recursively over an expanding window, using quarterly data starting from 1986Q1.

For the BVAR we evaluate both unconditional forecasts and predictions conditional on the future paths of some key variables. For generating conditional forecasts we use the methodology proposed in Banbura Giannone and Lenza (2015) based on Kalman filter recursions.[12] Unlike unconditional forecasts, where the econometrician is agnostic about the subsequent evolution of the variables included in the model, conditional forecasts assume to have some knowledge on the future path of one or more series that could be relevant for the target variable. Even if not directly useful in a real-time forecasting exercise, in our work conditional forecasts serve two scopes. The first is to deliver projections that are consistent with the dynamics of other variables included in the vector autoregression. For instance it is possible to trace different paths for house prices, conditioning on different dynamics of the nominal disposable income. The second is to indirectly test the goodness of the model ex-post: since conditional forecasts contain superior information (in our case the true future path of the conditioning variables) they should perform better than their unconditional counterparts. The failure of such validation exercise could be related to two problems: i) misspecification of the forecasting model or ii) a structural break in one or more variables included in the conditioning set.

[11] Extending the benchmark BVAR with three variables with the HICP series does not improve forecast accuracy of the unconditional forecasts. Instead the forecast precision of the unconditional forecasts slightly deteriorates when the average interest rate on outstanding loans for house purchases is included both in the benchmark specification and in the one with the HICP.

[12] More details can be found in Appendix B.

4. Quasi-real time forecasting design and out-of-sample evaluation

4.1 Whole sample exercise (2005Q1 – 2016Q4)

Our goal is to evaluate the out-of-sample forecasting performance for the Italian house prices of two structural models (the NZ and LZ models) and a BVAR model, which is used to produce unconditional forecasts (labeled as BVAR), as well as two conditional projections:

- the first one is obtained by conditioning on the true evolution of one variable, namely the nominal disposable income (we label this approach as BVARc);
- the second one uses information on the actual path of two variables: the nominal disposable income and the stock of mortgages for house purchases (this approach is labeled BVARc2).[13]

Moreover we compare their forecasting performance to an autoregressive model of order 4 (labeled as AR) as a naïve benchmark.[14] Our analysis is conducted in quasi real time, meaning that we use the last vintage of the data but never take into account the path of the endogenous variables beyond the estimation sample (as in a real time setting). We thus do not consider data revisions and use the true path of the exogenous variables for the conditional forecasts.

As pointed out by Clark and McCracken (2017), the quality of conditional forecasts in reduced form models (e.g. VARs) depends on two main factors: i) the goodness of the model and ii) the informativeness of the conditioning set. We choose to use the actual path of the variables in order to set to zero the second source of uncertainty and focus entirely on the first one. As regards the effects of increasing the length of the future path of the variables used in the conditional forecast, the improvement in the projection precision is expected only if the model is well specified. If the model performance worsens after conditioning on a long path of actual values this could be due to two main reasons: i) the in-sample fit of the model is poor because the model is severely misspecified; ii) there could have been a structural break in the relationship between the target and the conditioning variable.

Our models are estimated using the last vintage of data available up to 2016Q4 over an expanding window starting in 1986Q1 that increases as new observations become available. The out-of-sample (OOS henceforth) forecasting exercise starts in 2005Q1 in order to have a large enough sample (48 observations where the maximum forecast horizon is set to 12). In the table we report statistics for

[13] We do not report the results of conditioning only on the future path of mortgages for house purchases since they are very close to those obtained through the BVARc2; they are available upon request.

[14] We also use the Random-Walk model as naïve benchmark, constructed using the mean q-o-q growth rate in the estimation sample; however results are not reported given its poor forecasting performance.

accuracy for 1, 4, and 12 step ahead predictions. In order to investigate how the forecasting performance evolves with the housing and the macroeconomic cycle, we split the OOS period in two parts. The first subsample ranges from 2005Q1 to 2010Q4 (25 observations) while the second starts in 2011Q1 and runs till the end of the sample (23 data points). The two sub-samples correspond to different phases of the residential real estate market. The first one comprises the deceleration of house prices from the strong growth at the beginning of 2005 (almost 8%) until the outbreak of the Global financial crisis which engendered a modest decline in prices. The second sub-sample coincides with the sovereign debt crisis and its long-lasting consequences on the real estate market: prices declined by 10% in 2 years and continued to decrease, though at slower pace, until recently. Furthermore, we can fairly compare the forecast accuracy in the two sub-samples since they have approximately the same size.[15]

Given the shorter subsample length, a caveat must be raised: finding statistically significant differences in forecasting performance between different models becomes more difficult. Furthermore, part of the difference in forecasting accuracy between the structural models and the BVAR forecasts could depend on the difference in the number of estimated parameters: the first class of models is more heavily parameterized than the BVAR. Hence estimating the models on samples with the same number of observations can generate an efficiency loss in the OOS performance for the NZ and LZ models due to less degrees of freedom.

The OOS performance of the point forecasts is assessed through the Root Mean Squared Forecast Error (RMSFE).[16] In order to test if a model has a superior forecast accuracy we use the Diebold and Mariano (1995) t-statistics (DM hereafter), by adopting as loss function the squared prediction errors. We define $e_{1,t+k}$ and $e_{2,t+k}$ as the prediction errors of model 1 and model 2 made in quarter t at forecast horizon k and define $d_{t+k} = e_{1,t+k}^2 - e_{2,t+k}^2$ the difference in their squared errors. The null hypothesis of the test posits that the two models under investigation have the same forecast accuracy, so that $E(d_{t+k}) = 0$. The DM test statistic follows in equation (1):

$$DM_k = (T-k)^{1/2} \frac{\overline{d_k}}{\widehat{V_k}^{1/2}}, \qquad (1)$$

[15] As an alternative we can also run a statistical test of break in forecast accuracy (like Bai and Perron, 1998, as proposed by Martins and Perron, 2016): we leave this possibility for future research.
[16] Density forecast accuracy exercises are left for future research.

where T is the number of forecasts, $\overline{d_k} = (T-k)^{-1} \sum_{t=1}^{P-k} d_{t+k}$ and $\widehat{V_k} = \hat{\gamma}_{k,0} + 2\sum_{j=1}^{k-1} \hat{\gamma}_{k,j}$ is the asymptotic variance with $\hat{\gamma}_{k,j} = (P-k)^{-1} \sum_{j=1+j}^{P-k-j} \left(d_{t+k} - \overline{d_k}\right)\left(d_{t+k-j} - \overline{d_k}\right)$.[17]

Tables 3a and 3b display the results of the OOS forecast evaluation exercise on the whole sample (2005Q1-2016Q4). Table 3a contains the RMSFE of the six models described so far (NZ, LZ, BVAR, BVARc, BVARc2, AR) evaluated over 1, 4 and 12 step-ahead horizons, together with the unconditional standard deviation of the Italian house price index (bottom line of Table 3a). The RMSFE is the most important statistic in order to judge the performance of the models considered in the analysis, because the lower its value the smaller the forecast error. While the BVAR employs past and present information, the rest of the models (except the benchmark) use also the ex-post realization of some conditioning variables. Table 3a shows that both the structural and reduced-form approaches pass a first important test, since their RMSFE is lower than the unconditional standard deviation of the house price index at all horizons. Following Breitung and Knuppel (2017) this implies that such models do improve our knowledge about the future path of the Italian house price index; conversely, when a model generate forecasts that do not meet this basic condition it proves to be useless.

In order to assess whether differences in RMSFEs are statistically significant the results of pairwise Diebold-Mariano tests are reported in Table 3b. Lastly, we report evidence of the forecast bias (Figure 4); this is informative about the tendency of the models to systematically under-predict or over-predict house prices.[18] As first evidence we can notice in Table 3b that significant differences are rarely obtained one and four-steps ahead; in many cases this is due to the strong autocorrelation of forecast errors, which inflates the estimated variance of the DM statistics. Let us now describe in details the results for each forecast horizon.

All models are characterized by comparable predictive accuracy one-quarter ahead. This result could be explained by the fact that the DM test tends to be conservative when evaluating the predictive accuracy over short horizons. However, the first column of Table 3a shows that the lowest RMSFE is reached by the LZ model, followed, in order, by the BVARc, the BVAR and the NZ models. Even if the BVARc exploits the true value of the disposable income realized in the quarter of the one-step ahead forecast, it does not significantly outperform its competitors. The

[17] The lags for the estimation of the asymptotic variance $\widehat{V_k}$ are selected according to the criteria suggested in Newey and West (1994).

[18] Notice that a model can display a superior forecasting performance (i.e. a significantly lower RMSFE) even in presence of a larger bias; the intuition is that forecast errors may be very large, thus generating a high RMSFE, though having a zero mean (i.e. a null bias).

BVARc2 has the worst performance (worse than the AR) even if its projections are obtained by conditioning on the true values of both households' nominal disposable income and mortgages for house purchases. However, we will show that this result does not hold in all periods. For the one-step horizon, over the whole sample the LZ and the BVARc2 show a positive bias: they have the tendency to under-predict the true path of the Italian house price index (Figure 4). For the BVARc2 this tendency to under-predict is generated by the slow recovery of credit to households on which we condition: in fact the unconditional forecasts of the BVAR for this short horizon display a bias close to zero.

Table 3a: RMSFE for the period 2005Q1-2016Q4

	T+1	T+4	T+12
NZ	2.79	2.04	2.79
LZ	2.55	2.04	1.83
BVAR	2.64	2.12	3.22
BVARc	2.63	1.56	1.88
BVARc2	2.88	2.43	2.75
AR	2.82	2.51	3.41
House prices unc. Std	7.34	6.16	5.66

Note: Percentage points. The RMSFE relate to forecast errors based on annualized average growth rates over the forecast horizon. Because of averaging the RMSFE may decrease as the forecast horizon gets longer.

NZ: Nobili and Zollino (2017); LZ: Loberto and Zollino (2016); BVAR: unconditional BVAR's forecasts; BVARc: BVAR's forecasts conditional on income; BVARc2: BVAR's forecasts conditional on income and mortgages.

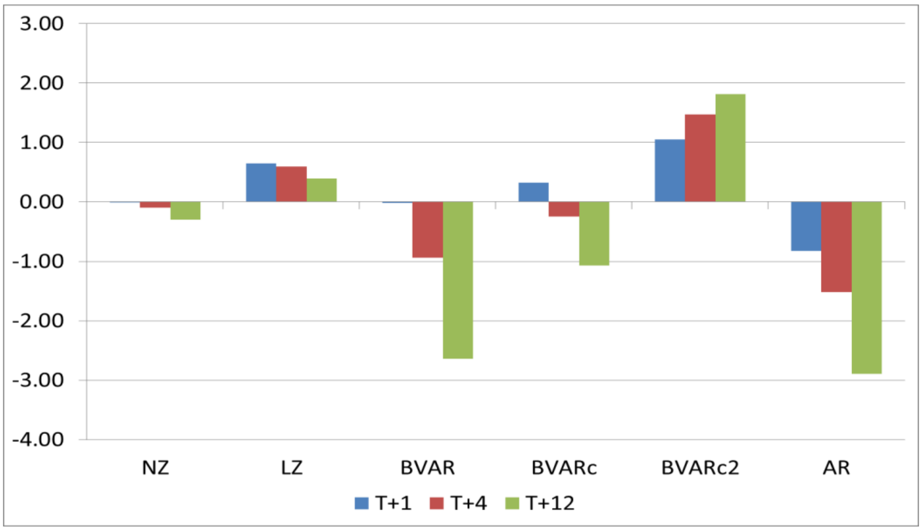
Table 3b: DM test for the period 2005Q1-2016Q4. Pairwise comparisons between models.

	T+1	T+4	T+12
NZ vs LZ	0.88	0.00	2.62***
NZ vs BVAR	0.84	-0.18	-1.29
NZ vs BVARc	0.90	1.45	4.97***
NZ vs BVARc2	-0.35	-0.87	0.07
NZ vs Ar	-0.10	-0.92	-1.86*
LZ vs BVAR	-0.39	-0.16	-2.32**
LZ vs BVARc	-0.36	1.03	-0.11
LZ vs BVARc2	-1.04	-0.72	-1.37
LZ vs AR	-0.88	-0.79	-2.72***
BVAR vs BVARc	0.05	1.58	3.14***
BVAR vs BVARc2	-1.00	-0.57	0.70
BVAR vs AR	-1.10	-2.08**	-1.65*
BVARc vs BVARc2	-1.33	-1.52	-1.12
BVARc vs AR	-0.85	-2.33**	-4.01***
BVARc2 vs AR	0.21	-0.13	-0.94

Note: Positive values denote that the second model has higher forecast accuracy than the first. Stars "" ,"**", "***" denote the significance level at 10, 5 and 1%, respectively. The DM statistic is confronted with the quantiles of a standard normal distribution.*

At the one-year horizon, the BVARc has a superior performance in terms of RMSFE, followed by the two structural models. Based on the DM test, however, the only two models that significantly outperform the AR benchmark are the BVAR and the BVARc. Despite the lower RMSFE, the structural models fail to yield significantly better forecasts than their competitors. This is due to the large estimated variance of the DM test ($\widehat{V_k}$), determined by the strong autocorrelation of forecast errors at this horizon. For the one-year ahead predictions we thus conclude that the better performance of the BVARc is explained by the significant amount of relevant information that it incorporates (one year of data on nominal disposable income). However, despite this great advantage, its 4-step ahead forecast accuracy is not significantly different from the one of NZ, LZ and the unconditional BVAR. At this horizon, the bias of NZ and BVARc models is close to zero on the whole sample.

Figure 4: Bias for the period 2005Q1-2016Q4



Note: The figure shows the bias of the six models. Positive values imply that the model systematically under-predicts the Italian house price index.

Over the three-year horizon the LZ model is the most accurate since it displays the lowest RMSFE and, according to the DM test, it beats the NZ, the BVAR and the AR. Only the BVARc and the BVARc2 have a comparable performance, but the first one displays a much lower RMSFE than the second. In interpreting these results we should consider that our aim is to forecast the average annual growth rate of house prices over a relatively long time span (3 years); this is more likely to be determined by macroeconomic fundamentals rather than by temporary factors. Hence it is of primary importance to properly take into account the evolution of macroeconomic fundamentals in order to obtain accurate house price forecasts. Our results indicate that structural economic linkages between the housing market and the rest of the economy are better captured by LZ model and by conditioning on the true path of the nominal disposable income as in the BVARc: these two models are thus able to achieve a better forecasting performance in the medium-long term. Over this relatively long forecast horizon, the structural models present lower bias while the BVAR and the BVARc tend to over-predict the average growth rate of the house price index. Notice that, as explained above, the negative bias displayed by the BVARc does not prevent it to rank very high in terms of forecasting performance (RMSFE).

In summary, for short-term forecasts all models are statistically equivalent, given that forecast errors are slightly inflated by the high volatility of the target series in the short run. For medium-term forecasting (1 and 3 years ahead) the DM test signals a superior forecast accuracy of the LZ model and the BVARc, which better capture macroeconomic fundamentals.

4.2 First subsample exercise (2005Q1 – 2010Q4)

In order to shed further light on the OOS forecasting performance of our models we split the sample into two sub-periods and compute the same statistics. The first period ranges from 2005Q1 to 2010Q4, and consists of 25 observations: it includes an initial phase of sustained but decelerating growth of house prices till 2009, when the consequences of the Great Recession negatively affected the real estate market for a couple of years.

Tables 4a and 4b present the RMSFE and the DM tests. As on the whole sample, modeling the Italian house price index produces gains since the RMSFE at all horizons is lower than the unconditional standard deviation of the target variable. As regards the predictive accuracy 1-step ahead, no model displays a significantly better performance according to the DM test, even if the BVAR shows the lowest RMSFE, followed by the AR and the structural models. By conditioning on the paths of both disposable income and mortgages the performance worsens with respect to the unconditional BVAR. In this first sub-sample we find particularly poor results when conditioning on the realized path of mortgages, contrary to prior expectations of a positive and strong correlation with house prices. This finding is related to the presence of a structural break in the series of households' mortgages that occurred in the second half of 1996, when Italy was joining the European Monetary Union and interest rates decreased substantially. Over the same period the Italian financial market was liberalized and increased competition put additional downward pressure on interest rates further expanding the supply of mortgages (see Angelini and Cetorelli, 2003 and Casolaro, Gambacorta and Guiso, 2006). This boom in mortgage activity caused a strong reduction in the historical positive correlation between loans to households and house prices (see evidence in Figure 2) and reduced its predictive ability as conditioning variable.[19] The problem is more severe in the first sub-sample because the temporary but sizeable disconnect between house prices and credit dynamics influences a large part of the estimation period.

At 1-year horizon the best performing model in terms of RMSFE is the BVARc, which ranks above the BVAR and the NZ models. Again, this result is driven by the large amount of information

[19] Using a rolling correlation with a 10 year backward-looking window we detect a structural break in the contemporaneous correlation between house prices and mortgages: historically, the correlation was close to one but, after the boom in mortgages in the second half of 1996, it fell dramatically from 2001Q1 to 2009Q3. Afterwards it increased again, thus restoring the forecasting power of mortgages.

exploited in the estimation process. In this part of the sample, the performance of the BVARc2 is particularly poor.

Table 4a: RMSFE for the period 2005Q1-2010Q4

	T+1	T+4	T+12
NZ	3.04	1.94	2.44
LZ	2.94	2.27	1.64
BVAR	2.77	1.70	2.79
BVARc	2.88	1.11	0.93
BVARc2	3.30	3.08	3.31
AR	2.89	1.93	2.85
House prices unc. Std	7.34	6.16	5.66

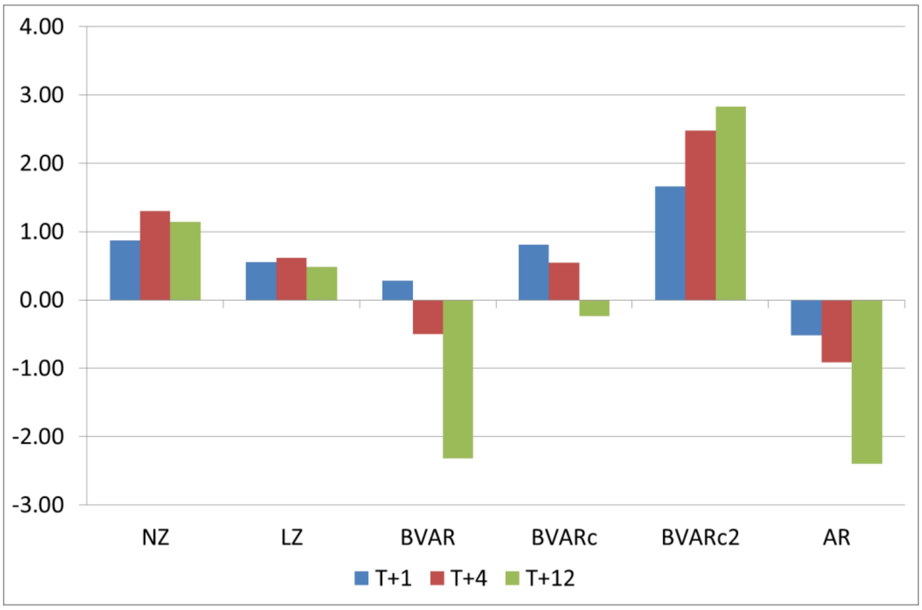
Note: Percentage points. The RMSFE relate to forecast errors based on annualized average growth rates over the forecast horizon. Because of averaging the RMSFE may decrease as the forecast horizon gets longer.
NZ: Nobili and Zollino (2017); LZ: Loberto and Zollino (2016); BVAR: unconditional BVAR's forecasts; BVARc: BVAR's forecasts conditional on income; BVARc2: BVAR's forecasts conditional on income and mortgages.

Table 4b: DM test for the period 2005Q1-2010Q4. Pairwise comparisons between models

	T+1	T+4	T+12
NZ vs LZ	0.26	-0.44	1.80*
NZ vs BVAR	1.05	0.53	-1.32
NZ vs BVARc	0.70	1.72*	4.72***
NZ vs BVARc2	-0.64	-2.19**	-1.75*
NZ vs AR	0.44	0.04	-1.26
LZ vs BVAR	0.50	0.86	-2.28**
LZ vs BVARc	0.17	1.64	1.81*
LZ vs BVARc2	-0.67	-1.04	-2.17**
LZ vs AR	0.14	0.49	-2.71***
BVAR vs BVARc	-0.49	1.81*	3.95***
BVAR vs BVARc2	-1.41	-2.70***	-1.13
BVAR vs AR	-0.73	-1.13	-0.52
BVARc vs BVARc2	-1.42	-2.76***	-2.83***
BVARc vs AR	-0.01	-2.00**	-4.11***
BVARc2 vs AR	0.98	2.54**	0.86

Note: Positive values denote that the second model has higher forecast accuracy than the first. Stars "" ,"**", "***" denote the significance level at 10, 5 and 1%, respectively. The DM statistic is confronted with the quantiles of a standard normal distribution.*

Figure 5: Bias for the period 2005Q1-2010Q4



Note: The figure shows the bias of the six models. Positive values imply that the model systematically under-predicts the Italian house price index.

The BVARc wins the forecasting competition also at longer horizons, followed by the LZ model. The structural models tend to have a positive bias in the first part of the sample over all horizons (Figure 5). The poor performance of the BVARc2 can be largely traced back to its strong positive bias. A possible explanation could be that, since mortgages shrank at a faster pace than house prices for large part of the subsample, conditioning on their true path generate a forecast that is strongly downward biased. To conclude, in this first subsample the highest predictive accuracy is achieved by the BVARc, closely followed by the LZ model especially at the 3-year horizon.

4.3 Second subsample exercise (2011Q1 – 2016Q4)

The second subsample goes from 2011Q1 until 2016Q4 (23 observations): this period includes the sovereign debt crisis and its long-lasting consequences on the real estate sector. After an initial recovery, house prices markedly dropped in 2012 and 2013 and continued to decrease at a slowing pace for the following years.

Table 5a and 5b analyze the forecasting performance in the second subsample where house prices decreased to levels previously recorded in 2001.

Table 5a: RMSFE for the period 2011Q1-2016Q4

	T+1	T+4	T+12
NZ	2.49	2.16	3.41
LZ	2.03	1.71	2.18
BVAR	2.49	2.56	3.98
BVARc	2.33	1.98	3.01
BVARc2	2.34	1.21	0.74
AR	2.74	3.09	4.36
House prices unc. Std	7.34	6.16	5.66

Note: Percentage points. The RMSFE relate to forecast errors based on annualized average growth rates over the forecast horizon. Because of averaging the RMSFE may decrease as the forecast horizon gets longer.
NZ: Nobili and Zollino (2017); LZ: Loberto and Zollino (2016); BVAR: unconditional BVAR's forecasts; BVARc: BVAR's forecasts conditional on income; BVARc2: BVAR's forecasts conditional on income and mortgages.

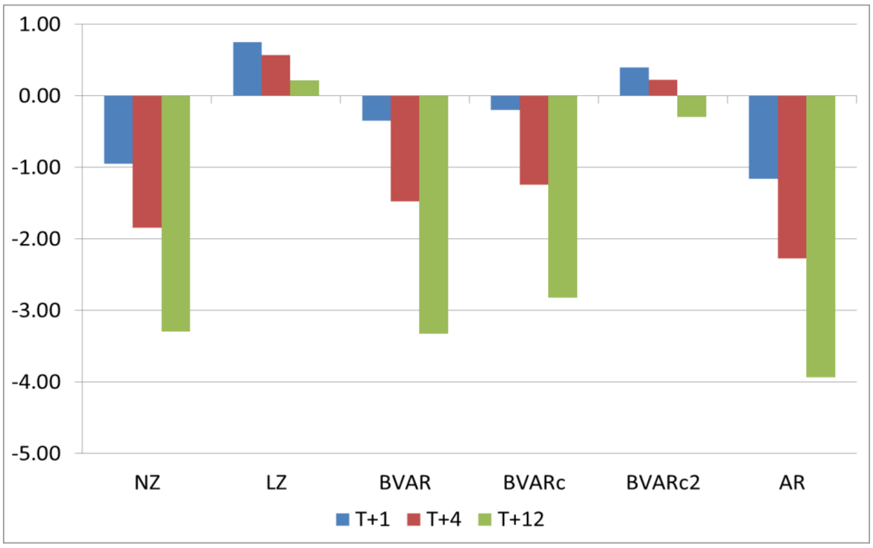
Table 5b: DM test for the period 2011Q1-2016Q4. Pairwise comparison between models.

	T+1	T+4	T+12
NZ vs LZ	1.17	0.83	2.33**
NZ vs BVAR	-0.03	-0.51	-0.90
NZ vs BVARc	0.56	0.37	2.53**
NZ vs BVARc2	0.52	1.91*	5.53***
NZ vs AR	-0.61	-1.04	-1.76*
LZ vs BVAR	-2.06**	-1.15	-1.68*
LZ vs BVARc	-1.31	-0.50	-1.38
LZ vs BVARc2	-1.91*	1.88*	3.27***
LZ vs AR	-1.72*	-1.52	-2.20**
BVAR vs BVARc	1.32	0.93	1.38
BVAR vs BVARc2	1.14	1.60	2.46**
BVAR vs AR	-0.82	-1.86*	-2.33**
BVARc vs BVARc2	-0.09	1.45	4.09***
BVARc vs AR	-1.44	-1.66*	-2.33**
BVARc2 vs AR	-1.14	-1.87*	-3.13***

Note: Positive values denote that the second model has higher forecast accuracy than the first. Stars "", "**", "***" denote the significance level at 10, 5 and 1%, respectively. The DM statistic is confronted with the quantiles of a standard normal distribution.*

In this subsample, the LZ model has a superior forecasting performance in the short run. One reason is that it explicitly models credit supply restrictions and it controls for the evolution of real estate property taxation, that since the end of 2011 was characterized by several legislative changes. This model performs remarkably well also over long horizons, together with the BVARc2. While four-step ahead only the BVARc2 has a marginally significant better forecast accuracy with respect to other competitors, 12-step ahead also the LZ model performs well. The pairwise comparison between the LZ model and the BVARc2 is won by the structural model in 1-quarter ahead forecasts, and by the latter over longer horizons. In this part of the sample conditioning on the true path of the stock of mortgages for house purchases strongly improves the forecasts: during this period the correlation between house prices and mortgages is very strong. This increased synchronization between the evolution of mortgages and house prices could have been generated by the extremely accommodative monetary policy stance via a strong reduction in the cost of credit for house purchases (see Loberto and Zollino, 2016 for a more detailed explanation of the link between monetary prices and house price dynamics). Alternative hypotheses may be advanced but we not discuss them here since the time-varying relationship between credit supply to households and house price dynamics is beyond the scope of the paper. Conditioning only on nominal disposable income does not improve the forecasting performance. In this sub-sample the two best performing models, namely the LZ and the BVARc2, display very little bias; on the contrary, the others tend to over-predict house prices across all horizons, meaning that they were constantly surprised by the slow recovery of house prices in this period (Figure 6).

Figure 6: Bias for the period 2011Q1-2016Q4



Note: The figure shows the bias of the six models. Positive values imply that the model systematically under-predicts the Italian house price index.

5. Conclusions

In this paper we compare the out-of-sample accuracy of structural and BVAR models in forecasting the Italian house price index. All the models under examination have a RMSFE lower than the unconditional standard deviation of the Italian house price index. Up to one year ahead we also find limited evidence of a systematic bias in the predictions provided by the different models.

Considering a short-term forecast horizon (less than one year), we find no significant differences in the forecasting performance across conditional and unconditional models. Conditional forecasts prove to be definitely more accurate over longer horizons, when the evolution of house prices is mostly driven by economic fundamentals and short-lived factors play a secondary role. Forecasts of house prices obtained through conditional models are quite close to their realizations, provided that we have good predictions for the determinants. Related to this point, an important caveat is warranted: in our exercise we condition on the true actual path of some of the variables included in the models. In such a way we do not address the issue of reliability of the forecasts of the determinants of house prices, in particular those related to households' nominal disposable income. Also, we do not take into account data revisions; the preliminary estimate of the house price index is often revised markedly. A real-time analysis is left for future research.

Looking instead at the comparisons between structural and conditional BVAR models, we find that over a long evaluation period there is no single winner, although some models prove more accurate in sub-samples. For these reasons, we face the trade-off between the parsimonious structure of the BVAR and the possibility of taking into account the multifold interactions between housing, credit and construction sectors, which is guaranteed by the structural models at the expense of maintaining a bigger dataset and periodically revising the equations in line with economic developments. Structural models further allow to build a picture of the evolution of the real estate market as a whole (including the mortgage credit market) and this can be particular useful for judgement, while BVARs are designed to return good predictions only for the target variable.

Lastly, we find that structural breaks in the relationship between mortgages and house prices, reflecting the credit boom in the late '90s[20], strongly affect the forecasting performance of the BVAR conditional on this series. Once this confounding factor fades away, conditioning on credit variables proves very useful in predicting house price dynamics.

[20] The credit boom in the late '90s was generated by the combination of two factors: i) a strong decrease in mortgage rates caused by the incoming adoption of the euro ii) an important institutional change in the Italian banking system carefully explained in Angelini and Cetorelli (2003) and Casolaro, Gambacorta and Guiso (2006).

Appendix

Appendix A. Stylized specification of Loberto and Zollino (2016)

Housing block

$$\begin{pmatrix}\text{Housing}\\ \text{market}\end{pmatrix}:\begin{cases}\text{Demand}: \textit{House prices} = \text{F (disposable income (+), demographic trends (+), } \textit{Mortgage loans} \text{ (+),}\\ \qquad\qquad\qquad\qquad \text{Housing stock (-), property tax rate (-))}\\ \text{Supply a)}: \quad \textit{Investments / Housing stock} = \text{F (building cost (}-\text{), } \textit{House prices} \text{ (+), } \textit{Loans} \text{ (+))}\\ \text{Supply b)}: \quad \textit{Housing stock} = \text{F (} \textit{Investments} \text{ (+), depreciation (-))}\end{cases}$$

Credit blocks

$$\begin{pmatrix}\text{Mortgage loans}\\ \text{to households}\end{pmatrix}:\begin{cases}\text{Demand}: \textit{Mortgage loans} = \text{F (} \textit{House prices} \text{ (+), disposable income (+/-), financial wealth (+/-),}\\ \qquad\qquad\qquad\qquad \textit{Mortgage rate} \text{ (-), bank capital ratio increase (-))}\\ \text{Supply}: \quad \textit{Mortgage rate} = \text{F (money market rate (+), bank capital ratio (+/-), financial wealth (-),}\\ \qquad\qquad\qquad\qquad \textit{House prices} \text{ (-), bank capital ratio decrease (-), sovereign spread (+))}\end{cases}$$

$$\begin{pmatrix}\text{Loans to}\\ \text{construction firms}\end{pmatrix}:\begin{cases}\text{Demand}: \textit{Loans} = \text{F (} \textit{Investments} \text{ (+), building cost (-), } \textit{Loan rate} \text{ (-), firms' gross value (-),}\\ \qquad\qquad\qquad\qquad \text{bank capital ratio increase (-))}\\ \text{Supply}: \quad \textit{Loan rate} = \text{F (money market rate (+), bank capital ratio (+/-), business cycle (-),}\\ \qquad\qquad\qquad\qquad \textit{House prices} \text{ (-), bank capital ratio decrease (-), sovereign spread (+))}\end{cases}$$

Appendix B. BVAR and conditional forecasts

The BVAR(p) model, where p is the number of lags, can be written as:

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} + \ldots + A_p X_{t-p} + \varepsilon_t$$

Where X_t is a vector with n variables expressed in log-levels, ε_t is a normally distributed multivariate white noise process with covariance matrix $\sum$. We use the hierarchical procedure developed by Giannone, Lenza and Primiceri (2015) with a Minnesota prior where all the variables are assumed to follow a random-walk plus drift. A first advantage of this method is that the tightness of the prior distribution on the VAR parameters is entirely data-driven and it is set by maximizing the marginal likelihood of the prior parameters. Further, the hierarchical structure makes inference more robust since it can be shown that the unconditional prior distribution of the parameters has fat tails. When the prior has fatter tails than the likelihood, the posterior distribution is less sensitive to discrepancies between the prior and the likelihood. In our application, where variables display abrupt changes in their growth rates, this robustness of the posterior helps in improving the estimation. Using BIC information criteria we select four lags for all the VARs used in the paper.

Conditional forecasts are produced using the methodology developed in Banbura et al. (2015). Putting the BVAR model in state-space form and using the simulation smoother proposed by Carter and Kohn (1994) the conditional forecasts are computed using the realized path of some of the variables in the model from 1 to 12 step ahead (the longest forecast horizon in our exercise). Even if not really useful for real-time analysis, conditional forecasts serve two scopes: the first is to deliver forecasts that are consistent with the dynamics of the other variables included in the vector autoregression. The second is to indirectly test the goodness of the model: when the BVAR is informed with good information regarding the variables in the conditioning set (in our case the realized path for the time series considered) it should perform better than unconditional forecasts. If this is not the case, one should think of setting up a better econometric specification.

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