



Forecasting the US real house price index: Structural and non-structural models with and without fundamentals[☆]

Rangan Gupta^a, Alain Kabundi^b, Stephen M. Miller^{c,*}

^a Department of Economics, University of Pretoria, Pretoria, 0002, South Africa

^b Department of Economics and Econometrics, University of Johannesburg, Johannesburg, 2006, South Africa

^c Department of Economics, University of Nevada, Las Vegas, Las Vegas, Nevada, USA 89154-6005

ARTICLE INFO

Article history:
Accepted 5 April 2011

JEL classification:
C32
R31

Keywords:
US House prices
Forecasting
DSGE models
Factor augmented models
Large-scale BVAR models

ABSTRACT

We employ a 10-variable dynamic structural general equilibrium model to forecast the US real house price index as well as its downturn in 2006:Q2. We also examine various Bayesian and classical time-series models in our forecasting exercise to compare to the dynamic stochastic general equilibrium model, estimated using Bayesian methods. In addition to standard vector-autoregressive and Bayesian vector autoregressive models, we also include the information content of either 10 or 120 quarterly series in some models to capture the influence of fundamentals. We consider two approaches for including information from large data sets – extracting common factors (principle components) in factor-augmented vector autoregressive or Bayesian factor-augmented vector autoregressive models as well as Bayesian shrinkage in a large-scale Bayesian vector autoregressive model. We compare the out-of-sample forecast performance of the alternative models, using the average root mean squared error for the forecasts. We find that the small-scale Bayesian-shrinkage model (10 variables) outperforms the other models, including the large-scale Bayesian-shrinkage model (120 variables). In addition, when we use simple average forecast combinations, the combination forecast using the 10 best *atheoretical* models produces the minimum RMSEs compared to each of the individual models, followed closely by the combination forecast using the 10 *atheoretical* models and the DSGE model. Finally, we use each model to forecast the downturn point in 2006:Q2, using the estimated model through 2005:Q2. Only the dynamic stochastic general equilibrium model actually forecasts a downturn with any accuracy, suggesting that forward-looking microfounded dynamic stochastic general equilibrium models of the housing market may prove crucial in forecasting turning points.

© 2011 Elsevier B.V. All rights reserved.

1. Introduction

This paper considers the dynamics of the US real house price index and the ability of a dynamic stochastic general equilibrium (DSGE) model and different time-series models to forecast this price index. In the analysis, we consider how the researcher can incorporate large data sets into forecasting equations, using dynamic factor analysis or Bayesian-shrinkage vector autoregressive (VAR) models. The main focus, however, compares the relative effectiveness of the DSGE and various time-series models, including simple average forecast combination methods, in out-of-sample forecasting and turning-point identification.

Policy makers and academics desire accurate forecasts of economic variables. Economic theorists exploit the recent development in computation to write simple and complex models that can closely

simulate reality. As such, an increasing need exists for large information sets to mimic economic relationships. Traditional econometric models, such as univariate time-series and multivariate VAR models, cannot easily accommodate large numbers of variables. Although popular when compared to traditional structural macroeconomic models for forecasting purposes, the VAR model exhibits a serious limitation – the issue of overparametrization. Thus, the main problem of small-scale models lies in choosing the correct variables to include. In practice, however, forecasters and policymakers believe that information from many series, which cannot be included simultaneously in a VAR model, can prove important in the forecasting exercise.

Bernanke and Boivin (2003) argue that central banks monitor and analyze literally thousands of variables to inform their monetary policy decisions. Therefore, econometricians should consider the marginal benefits and marginal costs associated with increasing the amount of information brought to the forecasting exercise. The use of factor models significantly advances the accommodation of large panels of variables in forecasting exercises. Sargent and Sims (1977) and Geweke (1977) introduce the dynamic factor approach to macroeconomics. They exploit the dynamic interrelationship of variables and then reduce the number of common factors even further. The method employed by

[☆] We gratefully acknowledge an anonymous referee, M. Balcilar, M. Iacoviello and S. Neri for many helpful comments. All remaining errors are ours.

* Corresponding author.

E-mail addresses: rangan.gupta@up.ac.za (R. Gupta), akabundi@uj.ac.za (A. Kabundi), stephen.miller@unlv.edu (S.M. Miller).

Sargent and Sims (1977) and Geweke (1977), however, proves too restrictive, since it imposes orthogonality on the idiosyncratic components. Chamberlain (1983) and Chamberlain and Rothschild (1983) allow weak cross-sectional correlation of the idiosyncratic components.

Recently, Stock and Watson (2002b), Kapetanios and Marcellino (2009) and Forni et al. (2005) propose improved methods to account for serial correlation and weak cross-sectional correlation of the idiosyncratic components. Since this innovation can accommodate a large panel of variables in the forecasting exercise, increasing professional and practitioner interest arises in the usage of these models. Much divergence in opinion remains as to whether factor models with large cross-section of time series will outperform traditional econometric models with a limited number of variables. Giannone and Matheson (2007), Van Nieuwenhuyze (2006), Cristadoro et al. (2005), Forni et al. (2005), Schneider and Spitzer (2004), Kabundi (2004), Forni et al. (2001), Stock and Watson (1989, 1991, 1999, 2002a, 2002b), and Gupta et al. (2009) provide evidence of improvement in forecasting performance of macroeconomic variables using such factor analysis. Schumacher (2007), Schumacher and Dreger (2004), Gosselin and Tkacz (2001) and Angelini et al. (2001) find little or no improvements in forecasting ability.

What explains this difference in outcomes? Banerjee et al. (2005), for example, find that small models forecast macroeconomic variables better than factor-augmented models. In addition, they also report that the performance of factor-augmented models differs across countries. Factor-augmented models perform better at forecasting real variables but worse at nominal variables in the US compared to the euro area. Furthermore, Boivin and Ng (2006) claim that the composition of the dataset and the size of the cross-section dimension matter in producing better forecasts with factor-augmented models. In sum, the existing research suggests that idiosyncratic factors determine the best performing model.

This paper uses a DSGE model developed by Iacoviello and Neri (2010) to forecast the US real house price index and its downturn in 2006:Q2 and compares its performance to a series of time-series models. The Iacoviello and Neri (2010) model employs 10 variables in their DSGE specification. We also exploit the information content of 120 quarterly time-series variables, including the 10 variables in Iacoviello and Neri (2010) and the 110 macroeconomic variables in Boivin et al. (2009), in some of our other forecasting models.¹ We evaluate the out-of-sample forecasting performance of the random walk (RW) model and various time-series models, including average forecast combination methods, relative to the root-mean-squared error (RMSE) of the DSGE model. Moreover, with the exception of Wang (2008) and Gupta and Kabundi (forthcoming), the comparisons of factor-augmented and DSGE models occur rarely and deserve more attention. Also using a DSGE model to forecast introduces the comparison of “atheoretical” models, such as factor-augmented VAR and Bayesian VAR (BVAR) models, to a microfounded theoretical model.

We next examine the explanatory power of including information from a large set of economic variables, using dynamic factor or Bayesian shrinkage approaches. More specifically, we compare the out-of-sample forecasting performance of various time-series models – VAR, FAVAR, and various Bayesian time-series models. For the Bayesian models, we estimate BVAR, Bayesian factor augmented VAR (BFAVAR), and small- and large-scale BVAR (SBVAR and LBVAR) models. Based on the average RMSE for the one-, two-, three-, and four-quarters-ahead forecasts, we find that the small-scale Bayesian-shrinkage model (10 variables) outperforms the other models, even outperforming the large-scale Bayesian-shrinkage model. When we use simple average forecast combinations, however, the combination forecast using the 10 best

atheoretical models produces the minimum RMSEs compared to each individual model, followed closely by the forecast combination using the 10 atheoretical models and the DSGE model. Finally, we calculate *ex ante* forecasts of each model to identify the downturn in 2006:Q2, using the estimated model through 2005:Q2. Only the DSGE model actually forecasts a downturn with any accuracy, suggesting that attention to fundamentals and their interactions may prove crucial in forecasting downturns.

We organize the rest of the paper as follows. Section 2 outlines the DSGE model of Iacoviello and Neri (2010). Section 3 provides a brief review on the use of large data sets in forecasting models. Section 4 discusses the literature on forecasting house prices. Section 5 specifies the various time-series models estimated and used for forecasting. Section 6 discusses the data and the results. Section 7 concludes.

2. The DSGE model of Iacoviello and Neri (2010)

Iacoviello and Neri (2010) develop a DSGE model of the US economy to consider how shocks in the macroeconomy affect events in the housing market and then how housing market adjustments spill over and affect the macroeconomy. We adopt their structural model of the macroeconomy to determine how this model performs with respect to various time-series models in forecasting real house prices as well as predicting the downturn in real house prices that occurred in 2006:Q2.

The model differentiates between housing and non-housing goods. The household sector divides into patient (lenders) and impatient (borrowers) households. Both types of households work, consume, and accumulate housing. Impatient households face a binding collateral constraint in equilibrium, because they only accumulate the minimum down payment to obtain the financing to buy their housing consumption. The production process for housing combines capital, labor, and land to produce new homes.

Wholesale firms operate under competitive flexible prices and produce both housing and non-housing goods, using separable production technologies. Nominal rigidities exist in the non-housing goods market with the assumption of monopolistic competition. The housing market, on the other hand, operates with flexible prices (Barsky et al., 2007). The labor markets also adopt rigidities similar to the non-housing good market. Monetary policy uses a Taylor rule that adapts gradually to inflation and GDP growth.

Heterogeneous trends exist in productivity across the consumption, non-residential, and housing sectors. Random shocks to productivity conform to first-order auto-correlated processes. Market equilibrium includes the consumption, housing, and loan markets, where goods market equilibrium includes consumption, business investment (accumulation of capital for consumption and housing production), and intermediate inputs.

The final model includes 36 equations.² The data for construction of the model requires 10 variables – aggregate consumption, business fixed investment, residential investment, inflation, the nominal short-run interest rate, real house prices, hours in the consumption and housing sectors, and wage inflation in the consumption and housing sectors as well as a series of parameter choices. We adopt the same model, including the prior distributions on the parameters,³ in our analysis.

3. Forecasting with large data sets

For forecasting purposes, time-series models generally perform as well as or better than dynamic structural econometric specifications.

¹ Boivin et al. (2009) report 111 macroeconomic variables. One variable, the Treasury bill rate, also appears in the 10 variables in Iacoviello and Neri (2010).

² See Appendix B of Iacoviello and Neri (2010).

³ See Tables 3 and 4 in Iacoviello and Neri (2010).

Zellner and Palm (1974) provide the theoretical rationalization.⁴ An important issue involves determining how additional information can or cannot improve the forecasting performance over a simple univariate autoregressive or autoregressive-moving-average representation.

One method uses “atheoretical” VAR models.⁵ These models do not impose exogeneity assumptions on the included variables. Unlike the single-equation autoregressive distributed-lag (ARDL) model, the VAR approach assumes that lagged values of each variable may provide valuable information in forecasting each endogenous variable. VAR models, however, face problems of over-parameterization, since the number of parameters to estimate increases dramatically with additional variables or additional lags in the system.⁶ Given this problem, one method to include more information in the VAR model involves the extraction of common factors from a large data set that researchers can then add to the VAR specification (Bernanke et al., 2005; Stock and Watson, 2002a, 2002b, 2005). Adding several common factors from the large dataset to a VAR system economizes on the number of new parameters to estimate.

BVAR models address the over-parameterization problem by specifying a small number of hyper-parameters that defines the relationships between all the parameters in the system. Since the Bayesian approach already solves the over-parameterization problem, researchers can add a large set of variables to the estimation of a BVAR system, obviating the need to extract common factors. Nothing prevents, however, the extraction of common factors from the large set of macroeconomic variables to include in a factor-augmented VAR and BVAR systems, which we also do.

In the factor-augmented approach, the researcher potentially leaves information on the table by only extracting the common factor information and leaving the remaining information out of the analysis. On the other hand, the Bayesian approach, includes all the information from the large set of data, but restricts the estimation by imposing conditions on the parameters of the estimating equation. In sum, all methods introduce restrictions on the way information from the large dataset affects the estimation process. Thus, any of the individual approaches may lead to better forecasts a priori.

In this paper, we consider the factor-augmented and large-scale Bayesian methods for incorporating the information from a large dataset.⁷ These methods provide the natural extension of the VAR and BVAR models.⁸

⁴ Any dynamic structural model implicitly generates a series of univariate time-series models for each endogenous variable. The dynamic structural model, however, imposes restrictions on the parameters in the reduced-form time-series specification. Dynamic structural models prove most effective in performing policy analysis, albeit subject to the Lucas critique. Time-series models prove most effective at forecasting. That is, in both cases errors creep in whenever the researcher makes a decision about the specification. Clearly, more researcher decisions relate to a dynamic structural model than a univariate time-series model, suggesting that fewer errors enter the time-series model and allowing the model to produce generally better forecasts.

⁵ A simple approach, which we do not adopt in this paper, uses an autoregressive distributed-lag (ARDL) model (Stock and Watson, 1999, 2003, 2004). That is, the researcher runs an ARDL, or transfer function, model, where the variable to forecast enters as an autoregressive process and one driver variable enters as a distributed lag. The researcher compares the baseline model, the pure autoregressive specification forecasts with the forecasts for the ARDL specification. Extending this further, the researcher can repeat the process for a whole series of potential driver variables. In this extended case, one aggregates across all of the individual forecasts to generate the combined forecast. Combination forecasts range from simple means or medians to more complicated principal-components- or mean-square-forecast-error-weighted forecasts.

⁶ The implementation of the ARDL approach avoids the problem by only using bivariate transfer function models and then combining the forecasts from the different bivariate analyses.

⁷ We also include a small-scale Bayesian-shrinkage model that includes the 10 variables in the Iacoviello and Neri (2010) DSGE model.

⁸ The ARDL model involves a single-equation, whereas the VAR and BVAR models involve multiple equations. Thus, we exclude the ARDL approach from our analysis.

4. Forecasting house prices

Traditionally, the housing market and its cycle played an important role in understanding the business cycle. More recently, several authors argue that asset prices help forecast both inflation and output (Forni et al., 2003; Das et al., 2009, 2010, 2011; Gupta and Das, 2008, 2010; Stock and Watson, 2003). Since homes imbued much individual wealth, house price movements may provide important signals for consumption, output, and inflation. That is, housing market adjustments play an important role in the business cycle (Iacoviello and Neri, 2010), not only because housing investment proves a volatile component of demand (Bernanke and Gertler, 1995), but also because house price changes generate important wealth effects on consumption (International Monetary Fund, 2000) and investment (Topel and Rosen, 1988).

In sum, models that forecast real house price inflation can give policy makers an idea about the future direction of the overall macroeconomy and, hence, can provide important information for designing better and more-appropriate policies. In other words, the housing sector acts as a leading indicator for the real sector of the economy. The recent world-wide credit crunch began with the end of the run-up in the US real house price index with a dramatic fall in that index, which, in turn, led the real sector of the world's economy into a severe economic slump.

The existing literature on forecasting house prices considers whether economic fundamentals provide sufficient information. A large number of economic variables affect house price growth (Abraham and Hendershott, 1996; Cho, 1996; Johnes and Hyclak, 1999; Rapach and Strauss, 2007, 2009). For instance, income, interest rates, construction costs, labor market variables, stock prices, industrial production, consumer confidence index, and so on act as potential predictors. On these issues, Quigley (1999) and Wheaton and Nechayev (2008) compare the forecasting performance of models with and without fundamentals. Quigley (1999) concludes that models including only fundamentals explain less than half of the movement in house prices. Further, he argues that explaining turning points in house prices improves in models that include fundamentals, but still does not predict such turning points well. Wheaton and Nechayev (2008) also consider the role of fundamentals in explaining house price movements. They estimate autoregressive models in the house price augmented by fundamentals. They conclude that in all 59 housing markets, the models that include fundamentals underpredict the house price run up from 1998 to 2005.

Most models that forecast US house prices focus on regional, state, or MSA levels of analysis and do not consider the national house price index. Several papers implement techniques that relate to our paper. Rapach and Strauss (2007, 2009) consider forecasting house prices in states, using a large data set of economic variables. Rapach and Strauss (2007) use an autoregressive distributed lag (ARDL) model framework, containing 25 determinants, to forecast real house price growth for the individual states of the Federal Reserve's Eighth District — Arkansas, Illinois, Indiana, Kentucky, Missouri, Mississippi, and Tennessee. Given the difficulty in determining a priori the particular variables that prove the most important in forecasting real house price growth, the authors also use various methods to combine the individual ARDL model forecasts, which result in better forecast of real house price growth. Rapach and Strauss (2009) perform the same analysis for the 20 largest US states based on ARDL models containing large number of potential predictors, including state, regional and national level variables. Once again, the authors reach similar conclusions on the importance of combining forecasts.

Das et al. (2010) consider the forecasting performance of regional real house price growth rates in the nine US census regions, using FAVAR and LBVAR models. They find that the FAVAR models generally outperform the LBVAR models. Gupta et al. (2009) consider the forecasting performance of time-series models with and without 308

monthly variables and spatial specifications for the 20 largest US states and corroborate the general findings of Das et al. (2010) in that factor augmented models generally outperform large-scale Bayesian models. Finally, based on principal component analysis and Bayesian regression, Gupta and Kabundi (2010) reach similar conclusions when forecasting the aggregate US real house price using 112 monthly variables.

Our paper extends the abovementioned studies by considering a DSGE model in addition to various time-series models with and without fundamentals to forecast the US real house price index out of sample and to forecast the downturn of the run-up of the US real house price index.

5. VAR, BVAR, FAVAR, FABVAR, and LBVAR specifications and estimation⁹

5.1. VAR, BVAR, and LBVAR

Following Sims (1980), we can write an unrestricted VAR model as follows:

$$y_t = A_0 + A(L)y_t + \varepsilon_t, \quad (1)$$

where y equals a $(n \times 1)$ vector of variables to forecast; A_0 equals an $(n \times 1)$ vector of constant terms; $A(L)$ equals an $(n \times n)$ polynomial matrix in the backshift operator L with lag length p ,¹⁰ and ε equals an $(n \times 1)$ vector of error terms. In our case, we assume that $\varepsilon \sim N(0, \sigma^2 I_n)$, where I_n equals an $(n \times n)$ identity matrix.

The VAR method typically uses equal lag lengths for all variables, which implies that the researcher must estimate many parameters, including many that prove statistically insignificant. This over-parameterization problem can create multicollinearity and a loss of degrees of freedom, leading to inefficient estimates, and possibly large out-of-sample forecasting errors. Some researchers exclude lags with statistically insignificant coefficients. Alternatively, researchers use near VAR models, which specify unequal lag lengths for the variables and equations.

Litterman (1981), Doan et al. (1984), Todd (1984), Litterman (1986), and Spencer (1993) use the BVAR model to overcome the over-parameterization problem. Rather than eliminating lags, the Bayesian method imposes restrictions on the coefficients across different lag lengths, assuming that the coefficients of longer lags may more closely approach zero than the coefficients on shorter lags. If, however, stronger effects come from longer lags, the data can override this initial restriction. Researchers impose the constraints by specifying normal prior distributions with zero means and small standard deviations for the most coefficients, where the standard deviation decreases as the lag length increases and implies that the zero-mean prior holds with more certainty. The first own-lag coefficient in each equation proves the exception with a unitary mean. Finally, Litterman (1981) imposes a diffuse prior for the constant. We employ this “Minnesota prior” in our analysis, where we implement Bayesian variants of the classical VAR models.

Formally, the means of the Minnesota prior take the following form:

$$\beta_i \sim N(1, \sigma_{\beta_i}^2) \text{ and } \beta_j \sim N(0, \sigma_{\beta_j}^2) \quad (2)$$

where β_i equals the coefficients associated with the lagged dependent variables in each equation of the VAR model (i.e., the first own-lag coefficient), while β_j equals any other coefficient. In sum, the prior

specification reduces to a random-walk with drift model for each variable, if we set all variances to zero. The prior variances, $\sigma_{\beta_i}^2$ and $\sigma_{\beta_j}^2$, specify uncertainty about the prior means, $\beta_i = 1$, and $\beta_j = 0$. We also adopt the specification in Banbura et al. (2010) and Bloor and Matheson (2010), whereby we set a white-noise prior (i.e., $\bar{\beta}_i = 0$) for those variables in the data sets (i.e., comprising 10 or 120 variables) that exhibit mean-reversion. Otherwise, we impose the random walk prior, described above.

Doan et al. (1984) propose a formula to generate standard deviations that depend on small numbers of hyper-parameters: w , d , and a weighting matrix $f(i, j)$ to reduce the over-parameterization in the VAR models. This approach specifies individual prior variances for a large number of coefficients, using only a few hyper-parameters. The specification of the standard deviation of the distribution of the prior imposed on variable j in equation i at lag m , for all i, j and m , equals $S(i, j, m)$, is defined as follows:

$$S(i, j, m) = [w \times g(m) \times f(i, j)] \frac{\hat{\sigma}_i}{\hat{\sigma}_j}, \quad (3)$$

where $f(i, j) = 1$, if $i = j$ and k_{ij} otherwise, with $(0 \leq k_{ij} \leq 1)$, and $g(m) = m^{-d}$, with $d > 0$. The estimated standard error of the univariate autoregression for variable i equals $\hat{\sigma}_i$. The ratio $[\hat{\sigma}_i / \hat{\sigma}_j]$ scales the variables to account for differences in the units of measurement and, hence, causes the specification of the prior without consideration of the magnitudes of the variables. The term w indicates the overall tightness, with the prior getting tighter as the value falls. The parameter $g(m)$ measures the tightness on lag m with respect to lag 1, and equals a harmonic shape with decay factor d , which tightens the prior at longer lags. The parameter $f(i, j)$ equals the tightness of variable j in equation i relative to variable i , and by increasing the interaction (i.e., k_{ij}), we loosen the prior.¹¹

We estimate the alternative BVARs using Theil's (1971) mixed estimation technique. Essentially, the method involves supplementing the data with prior information on the distribution of the coefficients. The number of observations and degrees of freedom increase artificially by one for each restriction imposed on the parameter estimates. Thus, the loss of degrees of freedom from over-parameterization in the classical VAR models does not emerge as a concern in the alternative BVAR specifications. We consider the following VAR specifications:

VAR	In addition to the random walk (RW) and univariate autoregressive (AR) ¹² models with eight lags ¹³ in the US real house price index, we also run a 10-variable VAR, incorporating the 10 variables in Iacoviello and Neri (2010);
UBVAR	This benchmark univariate BVAR model uses only the US real house price index;
SBVAR	The small-scale BVAR model includes only the 10 variables in Iacoviello and Neri (2010); and
LBVAR	The large-scale BVAR model includes the 10 variables in Iacoviello and Neri (2010) plus the 110 additional variables from Boivin et al. (2009).

¹¹ For an illustration, see Dua and Ray (1995).

¹² As an anonymous referee requested, we also estimated an ARIMA model, specifically an ARIMA(8,1,3), which performed worse than the AR model. Thus, we omit these results, which are available from the authors.

¹³ The choice of 8 lags reflects the unanimity of the sequential modified LR test statistic as well as the Akaike information criterion (AIC), the final prediction error (FPE) criterion, and the Hannan–Quinn (HQ) information criterion applied to the stable small-scale VAR estimated with 10 variables. Stability, as usual, implies that no roots lie outside the unit circle. We retain the eight lags for all the “atheoretical” models.

⁹ The discussion in this section relies heavily on LeSage (1999), Gupta and Sichei (2006), Gupta (2006), Gupta and Miller (forthcoming a, b), and Das et al. (2009).

¹⁰ That is, $A(L) = A_1L + A_2L^2 + \dots + A_pL^p$;

5.2. FAVAR and BFAVAR

This study also uses the Dynamic Factor Model (DFM) to extract common components between macroeconomic series and then uses these common components to forecast the US real house price index, adding the extracted factors to univariate and multivariate VAR and BVAR models to create FAVAR and BFAVAR models in the process. Furthermore, we estimate the idiosyncratic components (see below) with AR(p) processes as suggested by Boivin and Ng (2005).

The DFM expresses individual times series as the sum of two unobserved components: a common component driven by a small number of common factors and an idiosyncratic component for each variable. The DFM extracts the few factors that explain the comovement of the US economy. Forni et al. (2005) demonstrate that for a small number of factors relative to the number of variables and a heterogeneous panel, we can recover the factors from present and past observations.

Consider a $n \times 1$ covariance stationary process $Y_t = (y_{1t}, \dots, y_{nt})'$. Suppose that X_t equals the standardized version of Y_t . Under DFM, we write X_t as the sum of two orthogonal components as follows:

$$X_t = \lambda F_t + \xi_t \quad (4)$$

where F_t equals a $r \times 1$ vector of static factors, λ equals an $n \times r$ matrix of factor loadings, and ξ_t equals a $n \times 1$ vector of idiosyncratic components. In a DFM, F_t and ξ_t are mutually orthogonal stationary process, while, $\chi_t = \lambda F_t$ equals the common component.

Since dynamic common factors are latent, we must estimate them. We note that the estimation technique used matters for factor forecasts. This paper adopts the Stock and Watson (2002b) method, which employs the static principal component approach (PCA) on X_t . The factor estimates, therefore, equal the first principal components of X_t , (i.e., $\hat{F}_t = \hat{\Lambda}' X_t$, where $\hat{\Lambda}$ equals the $n \times r$ matrix of the eigenvectors corresponding to the r largest eigenvalues of the sample covariance matrix $\hat{\Sigma}$).

For forecasting purposes, we use univariate and multivariate VAR models augmented by extracted common factors using the Stock and Watson (2002a) approach. This approach is similar to the univariate static, unrestricted approach of Boivin and Ng (2005). Therefore, the forecasting equation to predict Y_t is given by

$$\begin{bmatrix} \hat{Y}_{t+h} \\ \hat{F}_{t+h} \end{bmatrix} = \hat{\Phi}(L) \begin{bmatrix} Y_t \\ F_t \end{bmatrix}, \quad (5)$$

where h equals the forecasting horizon and $\hat{\Phi}(L)$ equal lag polynomials, which we estimate with and without restrictions. As Boivin and Ng (2005) note, VAR models are special cases of Eq. (5). With known factors and the parameters, the FAVAR approach should produce smaller mean squared errors. In practice, however, we do not observe the factors and must estimate them. Moreover, the forecasting equation should reflect a correct specification. We consider the following DFM specifications:

- UFAVAR Single equation model that includes the US real house price index and the common static factors¹⁴;
- MFAVAR Multiple equation model that includes the 10 variables in Iacoviello and Neri (2010) and the common static factors;
- BUFAVAR The Bayesian version that includes the US real house price index and the common static factors; and
- BMFAVAR The Bayesian version that includes the 10 variables in Iacoviello and Neri (2010) and the common static factors.

¹⁴ We also confirm the choice of the four factors by the cumulative variance share, under which, the fifth eigenvalue fell below the threshold of 5%.

6. Data description, model estimation, and results

6.1. Data

While the univariate VARs, both the classical and Bayesian variants, only include the annualized US real house price index, the large-scale BVAR and the factor-augmented models also include the 120 quarterly series. In between, we estimate small-scale VARs and BVARs in the 10 variables employed by Iacoviello and Neri (2010), including the US real house price index. The nominal US house price index comes from the Census Bureau House Price Index deflated by the implicit price deflator for the nonfarm business sector. In addition, we also employ the other nine variables identified in Iacoviello and Neri (2010). See Appendix A in their paper for a discussion of sources of data as well as the transformations made to these 10 variables.

For the remaining 110 quarterly macroeconomic series of the US economy, we use the data set constructed by Boivin et al. (2009) that covers the period of 1976:Q1 to 2005:Q2. The data set includes measures of industrial production, several price indices, interest rates, employment as well as other key macroeconomic and financial variables. To this data set, we add 10 of the variables used by Iacoviello and Neri (2010), implying a total of 120 variables. We drop the Treasury bill rate from the original 111 variables in the Boivin et al. (2009) data set, since it appears in the Iacoviello and Neri data set. Moreover, since the Boivin et al. (2009) data set appears at a monthly frequency, we convert it into a quarterly frequency by taking averages for flow variables and the last month observation for the stock variables (i.e., we use temporal aggregation and systematic sampling, respectively, as suggested by the literature on frequency conversions). We seasonally adjust and transform all series to induce stationarity for the FAVAR.¹⁵ Since this data set ends in 2005:Q2, our sample also ends at the same point.

6.2. Estimation and results

This section reports our econometric findings. First, we select the optimal model for forecasting the US real house price index, using the minimum average root mean squared error (RMSE) across the one-, two-, three-, and four-quarter-ahead out-of-sample forecasts. Second, we consider the ability of the best models to predict the downturn in 2006:Q2, using *ex ante* and recursive forecasts.

6.2.1. One- to four-quarter-ahead forecast accuracy

Following the existing literature on estimation of DSGE models and, of course, Iacoviello and Neri (2010), we consider the linearized DSGE model describing the equilibrium around the balanced growth path. Given the parameters, we represent the solution to the DSGE model in a state-space form that is used to compute the likelihood function. The estimation strategy follows a Bayesian approach, which involves transforming the data into a form suitable for computing the likelihood function, choosing prior distributions for the parameters of the DSGE model, and estimating their posterior distribution using the random-walk version of the Metropolis–Hastings algorithm. We estimate the DSGE model over the in-sample of 1976:Q1 to 2000:Q4 and then recursively over the out-of-sample horizon of 2001:Q1 to 2005:Q2, based on a sample of 500,000 draws. We use a normal jump distribution with the covariance matrix equal to the Hessian of the

¹⁵ Using non-stationary data, however, is not required with the BVAR. Sims et al. (1990) indicate that since the Bayesian approach is entirely based on the likelihood function, the associated inference does not require special treatment for non-stationarity, since the likelihood function exhibits the same Gaussian shape regardless of the presence of non-stationarity. As an anonymous referee requested, we also estimated both the classical and Bayesian variants of the small-scale vector error-correction (VEC) model to account for possible cointegration among the 10 variables. These models, however, performed poorly and we do not report those findings. The results are available from the authors.

posterior density evaluated at the maximum. We choose the scale factor to obtain an acceptance rate of about 25%. We assessed convergence by comparing the moments computed by splitting the draws of the Metropolis into two halves.¹⁶

Given the specification of priors in Section 4, we estimate the alternative univariate, small-, and large-scale models in our sample over the period 1976:Q1 to 2000:Q4 using quarterly data. We then compute out-of-sample one- to four-quarters-ahead forecasts for the period of 2001:Q1 to 2005:Q2, and compare the forecast accuracy relative to the forecasts generated by the DSGE model. Note that the choice of the in-sample period, especially the starting date, depends on data availability. The starting point of the out-of-sample period precedes the rapid run-up and then collapse of the house price index experienced over the last decade. As indicated above, the end-point of the horizon is 2005:Q2, since the Boivin et al. (2009) data on the 110 macroeconomic variables ends there.

We estimate the univariate and multivariate versions of the classical VAR, the small-scale BVARs, the large-scale BVARs, and the classical and Bayesian FAVARs over the period 1976:Q1 to 2000:Q4, and then forecast from 2001:Q1 through 2005:Q2. Since we use eight lags, the initial eight quarters from 1976:Q1 to 1976:Q4 feed the lags. We re-estimate the models each quarter over the out-of-sample forecast horizon in order to update the estimate of the coefficients, before producing the four-quarters-ahead forecasts. We implemented this iterative estimation and the four-quarters-ahead forecast procedure for 15 quarters, with the first forecast beginning in 2001:Q1. This produced a total of 15 one-quarter-ahead forecasts, ..., up to 15 four-quarters-ahead forecasts.¹⁷ We calculate the root mean squared errors (RMSE)¹⁸ for the 15 one-, two-, three-, and four-quarters-ahead forecasts for the real house price index of the models. We then examine the average of the RMSE statistic for one-, two-, three-, and four-quarters ahead forecasts over 2001:Q1 to 2005:Q2.

Why do we use the RMSE? Zellner (1986) argues that the “optimal” Bayesian forecasts will differ depending upon the loss function employed and the form of predictive probability density function. In other words, Bayesian forecasts are sensitive to the choice of the measure used to evaluate the out-of-sample forecast errors. Zellner (1986) also notes that the mean of the predictive probability density function for a series is optimal relative to the squared error loss function and the mean squared error (MSE). Hence, the RMSE is an appropriate measure to evaluate performance of forecasts, when using the mean of the predictive probability density function.¹⁹

For the various Bayesian time-series models, we start with a value of $w=0.1$ and $d=1.0$, and then increase the value to $w=0.2$ to account for more influences from variables other than the first own lags of the dependant variables. In addition, as in Dua and Ray (1995), Gupta and Sichei (2006), Gupta (2006), and Gupta and Miller (forthcoming a, b), we also estimate the BVARs and BFAVARs with $w=0.3$ and $d=0.5$. We also introduce $d=2$ to increase the tightness on lag m . In addition, we follow Banbura et al. (2010), Bloor and Matheson (2010), and De Mol et al. (2008) in setting the value of the overall tightness parameter to obtain a desired average fit for the variable of interest (i.e., real US house price, in the in-sample period from 1976:Q1 to 2000:Q4). We retain the optimal value of $w(Fit)$

(=0.006)²⁰ obtained in this fashion for the entire evaluation period. Specifically, for a desired *Fit*, w comes from the following optimization:

$$w(Fit) = \arg \min_w \left| Fit - \frac{MSE_i^w}{MSE_i^0} \right| \quad (6)$$

where $MSE_i^w = \frac{1}{T_0-p-1} \sum_{t=p}^{T_0-2} (y_{i,t+1}^w - y_{i,t+1})^2$. MSE_i^w equals the one-step-ahead MSE evaluated using the training sample $t=1, \dots, T_0-1$, where T_0 equals the beginning of the sample period and p equals the order of the AR model of the real US house price. MSE_i^0 equals the MSE of variable i with the prior restriction imposed exactly ($w=0$). Finally, the baseline *Fit* equals the relative MSE from the OLS-estimated AR model as follows:

$$Fit = \frac{MSE_i^\infty}{MSE_i^0} \quad (7)$$

We select the model that produces the lowest average RMSE values as the ‘optimal’ specification.

Table 1 reports the average of the one-, two-, three-, and four-quarter-ahead RMSEs across the various specifications relative to the RMSE of the DSGE model. Thus, the 0.6004 entry for the UFAVAR model for the four-quarter-ahead forecast means that the UFAVAR model experienced a forecast RMSE of only 60.04% of the forecast RMSE for the DSGE model.

Several observations emerge. First, the Bayesian models, excluding the DSGE model, forecast better than the RW model, on average, whereas the non-Bayesian models, except for the UFAVAR, generally do not, on average. As can be seen, the VAR and MFAVAR models perform worse on average than the RW model. Although, the AR(8) and UFAVAR models do perform better than the RW model, on average, they perform worse than every Bayesian model, on average, save two – the LBVAR models with ($w=0.3, d=0.5$) and ($w=0.2, d=1$), when considering the average values across all horizons.

Second, the SBVAR model with ($w=0.3, d=0.5$) posts the best forecasting performance at all horizons, including the overall average, except for the four-quarter-ahead forecasts, where the LBVAR model with ($w=0.006, d=2$) does the best. In other words, the Bayesian models that include fundamentals utilized by Iacoviello and Neri (2010) in their DSGE model do the best job of forecasting out of sample. The average relative RMSE shows the SBVAR model improving over the DSGE model by 54.61%.

We also examined average forecast combinations across the best performing individual models. Rows FCOMB1 and FCOMB2 report these findings. FCOMB1 combines the 10 *atheoretical* models, while FCOMB2 combines the DSGE model and the 10 *atheoretical* models. FCOMB1 produces the best forecasts across all the individual models over all horizons. FCOMB2 ranks second to FCOMB1 at all horizons. These results, thus, indicate the gains of combining information across models.

Table 1 also compares whether the gain or loss in RMSE of a specific model and forecast combination significantly differs from the RMSEs obtained from the DSGE model based on the *ENC-t* test of Clark and McCracken (2001), which was designed for nested models. The test statistic is defined as follows:

$$ENC-t = (P-1)^{1/2} \frac{\bar{c}}{\left(P^{-1} \sum_{t=R}^{T-1} (c_{t+h} - \bar{c})^2 \right)^{1/2}} \quad (8)$$

where $c_{t+h} = \hat{v}_{0,t+h}(\hat{v}_{0,t+h} - \hat{v}_{1,t+h})$, $\bar{c} = \sum_{t=R}^{T-1} c_{t+h}$, R denotes the estimation period, P is the prediction period, f is some generic loss

¹⁶ See Appendix C of Iacoviello and Neri (2010) for more details.

¹⁷ For this, we used the Kalman filter algorithm in RATS, version 7.1.

¹⁸ If A_{t+n} denotes the actual value of a specific variable in period $t+n$ and F_{t+n} denotes the forecast made in period t for $t+n$, the RMSE statistic equals the following:

$\sqrt{\left[\sum_{t=1}^N (F_{t+n} - A_{t+n})^2 / N \right]}$, where N equals the number of forecasts.

¹⁹ In addition to the RMSE, we also used the mean absolute percentage error (MAPE) statistic, a statistic also used widely in the Bayesian forecasting literature (LeSage, 1999) to evaluate our forecasts. The ordering of the models remained the same as with the RMSE. These results are available from the authors.

²⁰ Note that, in this case, $d=2$ and $k_{ij}=0.5$.

Table 1
One to four-quarters-ahead RMSEs for the real US house price index.

	Models	Relative RMSE				
		1	2	3	4	Average
Parameters	RW	0.8572	0.8412	0.8430	0.8934	0.8587
	AR(8)	0.7692†	0.6709†	0.6220*	0.6954†	0.6894
	VAR	1.1628	1.0274	0.8598	0.7940†	0.9610
	UFAVAR	0.8126	0.7344†	0.6078*	0.6004*	0.6888
	MFAVAR	1.3774*	1.0341	0.9707	0.8207	1.0507
$w = 0.3, d = 0.5$	UBVAR	0.7320†	0.6201*	0.5508**	0.6145*	0.6294
	BUFAVAR	0.6872*	0.5631**	0.4570**	0.5102**	0.5544
	BMFAVAR	0.6497*	0.5330**	0.3741**	0.3995**	0.4891
	SBVAR	0.6319*	0.4887**	0.3271**	0.3680**	0.4539
	LBVAR	0.7673†	0.8025	0.6334*	0.6054*	0.7021
$w = 0.2, d = 1$	UBVAR	0.7398†	0.6323*	0.5591**	0.6166*	0.6370
	BUFAVAR	0.7418†	0.6426*	0.5659**	0.6243*	0.6437
	BMFAVAR	0.6610*	0.5594**	0.4262**	0.4855**	0.5330
	SBVAR	0.6627*	0.5392**	0.4104**	0.4680**	0.5201
	LBVAR	0.7769†	0.7699†	0.6085*	0.6365*	0.6979
$w = 0.1, d = 1$	UBVAR	0.7454†	0.6365*	0.5569**	0.6068*	0.6364
	BUFAVAR	0.7550†	0.6537*	0.5789**	0.6333*	0.6552
	BMFAVAR	0.7313†	0.6403*	0.5483**	0.6041*	0.6310
	SBVAR	0.7246†	0.6198*	0.5244**	0.5756**	0.6111
	LBVAR	0.7999†	0.7480†	0.5708**	0.6152*	0.6835
$w = 0.2, d = 0.2$	UBVAR	0.7384†	0.6207*	0.5313**	0.5723**	0.6157
	BUFAVAR	0.7737†	0.6705*	0.5936**	0.6365*	0.6686
	BMFAVAR	0.6910*	0.6148*	0.4970**	0.5539**	0.5892
	SBVAR	0.6989*	0.6049*	0.4952**	0.5482**	0.5868
	LBVAR	0.7795†	0.7217†	0.5768**	0.6357*	0.6784
$w = 0.1, d = 2$	UBVAR	0.7370†	0.6181*	0.5284**	0.5670*	0.6126
	BUFAVAR	0.7550†	0.6430*	0.5614**	0.6060*	0.6414
	BMFAVAR	0.7426†	0.6577*	0.5697**	0.6196*	0.6474
	SBVAR	0.7381†	0.6420*	0.5525**	0.5978**	0.6326
	LBVAR	0.7833†	0.6940*	0.5201**	0.5798**	0.6443
$w(\text{Fit}) = 0.006, d = 2$	LBVAR	0.7007†	0.5257**	0.3489**	0.3492**	0.4811
	FCOMB1	0.4924**	0.3474**	0.2344**	0.2218**	0.3240
	FCOMB2	0.5386**	0.4067**	0.3040**	0.2925**	0.3855

Note: The numbers equal the ratio of the root-mean square error (RMSE) of the model in the row divided by the RMSE of the dynamic stochastic general equilibrium (DSGE) model. The bolded numbers equal the minimum values in each column. RW is the random walk model. AR(8) is the autoregressive model with 8 lags. VAR is the vector autoregressive model. UFAVAR is the univariate factor-augmented VAR model. MFAVAR is the multivariate FAVAR model. UBVAR is the univariate Bayesian VAR model. BUFAVAR is the Bayesian univariate FAVAR model. BMFAVAR is the Bayesian multivariate FAVAR. SBVAR is the small Bayesian VAR model, and the LBVAR is the large BVAR model. FCOMB1 equals the simple average forecast combination of all the models except the DSGE model. FCOMB2 equals simple average forecast combinations for all the models including the DSGE model. The average column computes the average RMSE of the one-, two-, three-, and four-quarter-ahead RMSE reported in columns 1, 2, 3 and 4. †(*)[**] Indicates 10%, [(5%), [1%] level of significance for the *ENC-t* test statistic.

function, $h \geq 1$ is the forecast horizon, and $\hat{v}_{0,t+h}$ and $\hat{v}_{1,t+h}$ are h -step ahead prediction errors for models 0 and 1 (where model 0 equals the DSGE model), constructed using Newey and West (1987) type consistent estimators.

The hypotheses of interest are:

$$H_0 : E(f(v_{0,t+h}) - f(v_{1,t+h})) = 0, \quad (9)$$

and

$$H_A : E(f(v_{0,t+h}) - f(v_{1,t+h})) > 0. \quad (10)$$

The limiting distribution for $h = 1$ is $N(0, 1)$: The limiting distribution for $h > 1$ is non-standard. See Clark and McCracken (2001). Bhardwaj and Swanson (2006) argue that as long as we use a Newey and West (1987) type estimator when $h > 1$, the tabulated critical values close approximate the $N(0, 1)$ values. Significant values of *ENC-t* indicate the superiority or inferiority of the alternative models over the DSGE model in forecasting the real US house price at all horizons. In general, except for the RW and the MFAVAR models where the ratio of the RMSE of a specific model with respect to the

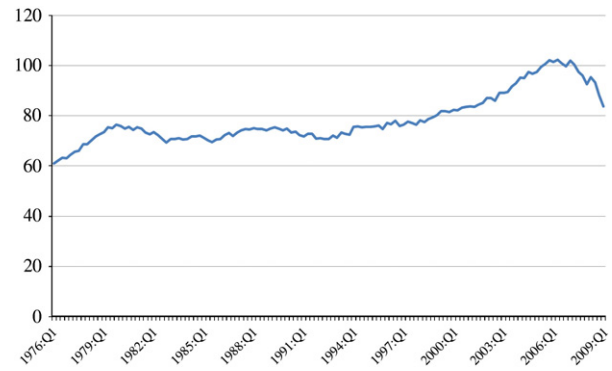


Fig. 1. The US real house price index.

RMSE from the DSGE model was less than 1, the *ENC-t* test statistic proved significant at least at the 10% level. In addition, when we carried out the *ENC-t* test between FCOMB1 and FCOMB2, we did not observe a statistical difference between the forecasts, as we did find when we compared SBVAR ($w = 0.3, d = 0.5$) to LBVAR ($w = 0.006$ and $d = 2$). Both forecast combination methods produced significantly better forecasts than the SBVAR ($w = 0.3, d = 0.5$) and LBVAR ($w = 0.006$ and $d = 2$) models.²¹

6.2.2. Forecasting the downturn

Fig. 1 illustrates that the US housing market experienced a marked reversal of the real house price index after the peaks in 2006:Q2. That is, the run-up in the house price index reverses itself in 2006:Q2 and then proceeds to fall. We expose our optimal forecast models to the acid test – predicting this downturn. We estimate the optimal models based on the average relative RMSE from Table 1, using data through 2005:Q2. Next, we forecast prices from 2005:Q3 through the end of the sample period in 2009:Q1, the last equal to a 15-quarter-ahead forecast. We do not recursively update the data set after each forecast and re-estimate the model. Rather, we use the model estimated through 2005:Q2 to forecasts all 15 quarters through 2009:Q1.

Table 2 reports the results of this forecasting experiment. Examining the actual data, we see that the US real house price index peaked in 2006:Q2 at 102.41, but we also see secondary peaks in 2005:Q4 at 102.22 and 2007:Q1 at 102.08. After 2007:Q1, the index falls monotonically through the end of the sample in 2009:Q1, reaching a level of 83.72.

The *ex ante* forecasting results produce several observations. First, most of the optimal forecasting models, including the two forecast combination methods, do not predict a downturn, but rather forecast a continual rise in the index through the end of the sample in 2009:Q1. Two exceptions exist – the DSGE model and the optimal MFAVAR model. Only the DSGE model, however, forecasts a downturn (i.e., 2006:Q3) close to the actual downturn. Moreover, the MFAVAR model forecasts exceed the actual data by large margins (e.g., 130.73 versus 83.72 in 2009:Q1).

Second, examining the correlations between that actual series and each of the forecast series, we see that only the DSGE model exhibits a positive correlation (i.e., 0.81). All other forecasts report a negative correlation with the actual series. In sum, the DSGE model performs better than the other models in forecasting the actual series, which includes the downturn in 2006:Q2. On the other hand, while the DSGE model shows a downturn one quarter after the actual downturn, its forecasts uniformly over-predict the actual index numbers after the downturn (e.g., 100.67 versus 83.72 in 2009:Q1). This evidence, possibly limited, suggests that we need more research on using structural models to forecast turning points.

²¹ These additional *ENC-t* test results are available from the authors.

Table 2

Ex ante forecasts for the real US house price index.

Date	Actual	RW	AR(8)	VAR	DSGE	UFAVAR	MFAVAR	UBVAR	BUFAVAR	SBVAR	BMFAVAR	LBVAR	FCOMB1	FCOMB2
2005:Q2	99.59	99.59	99.59	99.59	99.59	99.59	99.59	99.59	99.59	99.59	99.59	99.59	99.59	99.59
2005:Q3	100.74	101.88	101.77	104.47	101.04	101.97	110.92	101.97	103.51	103.91	102.50	102.31	103.52	103.30
2005:Q4	102.22	102.71	102.42	103.16	101.36	102.53	105.38	102.47	102.88	105.12	103.18	103.48	103.33	103.15
2006:Q1	101.58	103.52	103.88	104.96	101.70	103.64	105.95	103.58	104.64	106.58	104.49	104.62	104.58	104.32
2006:Q2	102.41*	104.34	104.97	105.67	101.92	104.81	115.66	104.86	105.21	107.45	105.27	105.73	106.39	105.98
2006:Q3	101.07	105.17	105.94	104.27	102.01*	105.37	116.64	105.29	104.31	106.84	105.59	106.85	106.63	106.20
2006:Q4	99.75	105.98	106.84	107.62	101.95	105.98	124.36	106.02	106.92	109.10	106.99	108.01	108.78	108.15
2007:Q1	102.08	106.80	107.52	107.25	101.81	106.95	127.76	106.98	106.85	111.46	107.73	109.21	109.85	109.11
2007:Q2	100.54	107.63	108.35	105.78	101.63	107.69	123.78	107.52	106.15	111.77	108.18	110.47	109.73	108.99
2007:Q3	97.51	108.46	109.19	108.35	101.45	108.41	130.48	108.43	108.15	113.90	109.26	111.79	111.64	110.71
2007:Q4	96.22	109.29	109.89	108.13	101.26	109.48	122.66	109.55	108.23	113.65	110.14	113.15	111.41	110.49
2008:Q1	92.61	110.13	110.59	108.89	101.10	110.20	113.17	110.40	108.78	114.40	111.01	114.56	111.21	110.29
2008:Q2	95.39	110.97	111.29	109.90	100.94	111.21	132.24*	111.59	109.70	116.77	111.91	115.99	114.16	112.95
2008:Q3	93.39	111.81	111.99	109.66	100.81	112.48	127.87	112.86	109.96	118.47	112.86	117.47	114.53	113.28
2008:Q4	88.29	112.67	112.67	111.15	100.72	113.56	123.91	114.06	111.10	120.34	113.75	118.94	115.21	113.90
2009:Q1	83.72	113.52*	113.35*	111.61*	100.67	115.13*	130.73	115.71*	116.69*	121.65*	114.74*	120.43*	116.85*	115.38*
Correlation		−0.88	−0.84	−0.88	0.81	−0.90	−0.49	−0.91	−0.89	−0.89	−0.89	−0.90	−0.85	−0.84

Note: The starred and bolded numbers equal the maximum values in each column. The correlation measures the correlation between the column's forecasted values and the actual values.

Fig. 2 plots the actual series from 2005:Q2 to 2009:Q1 along with the forecasted values from the DSGE model and the optimal MFAVAR model. The DSGE forecasts conform more to the actual series than the optimal MFAVAR model forecasts. The DSGE forecasts, however, do not fall as significantly as the actual series does after its peak in 2006:Q2.

7. Conclusion

We forecast the US real house price index, using various time-series models, both with and without the information content of 10 or 120 additional quarterly macroeconomic series. Two approaches exist for incorporating information from a large number of data series – extracting common factors (principle components) in a factor-augmented vector autoregressive (FAVAR), factor-augmented Bayesian vector autoregressive (FABVAR) models, or Bayesian shrinkage in a large-scale Bayesian vector autoregressive (LBVAR) models. We also use the estimated DSGE model of Iacoviello and Neri (2010) as a dynamic structural method of forecasting the US real house price index. In addition, we also look at average forecast combination across the best performing individual *atheoretical* and DSGE models.

Using the period of 1976:Q1 to 2000:Q4 as the in-sample period and 2001:Q1 to 2005:Q2 as the out-of-sample horizon, we compare the forecast performance of the alternative models for one- to four-quarters ahead forecasts. Based on the root mean squared error (RMSE) for the one-, two-, three-, and four-quarter-ahead forecasts, we find that the SBVAR model performs the best for the one-, two-, and three-quarter-ahead forecasts as well as for the average across all four horizons. The LBVAR model performs the best only at the four-quarter-ahead forecast horizon. The DSGE model performs poorly,

never beating the RW model at any horizon, though the differences are not statistically significant. When we calculate simple average forecast combinations of individual models, forecast combination of the 10 best *atheoretical* models produces the minimum RMSEs compared to all individual models. The forecast combination of the 10 best *atheoretical* models and the DSGE model comes in as the second best forecasting method, based on the RMSE.

Finally, we also report *ex ante* forecasts of the actual US real house price index from 2005:Q3 to 2009:Q1. Interestingly, now the DSGE model performs better than the other forecasting models, even though the DSGE model exhibit a one- to four-quarter ahead forecasting performance that does not beat the RW model.

In sum, we conjecture that the utilization of fundamental economic variables may improve the forecasting performance over models that do not use such data. Interestingly, this conclusion seems to hold more strongly for the 10 fundamental economic variables in the DSGE model of Iacoviello and Neri (2010), compared to a large data set of 120 macroeconomic variables. These gains, however, do not prove statistically significant. In addition, even though difficult to interpret intuitively, forecast combinations based on simple averages across models yield exceptionally favorable results. But, our findings suggest that to forecast the peak of a house price run-up may require a forward-looking microfounded dynamic stochastic (DSGE) model in the fundamental variables. Our suggestive findings call for additional research to determine if our conjecture holds true.

References

- Abraham, J.M., Hendershott, P.H., 1996. Bubbles in metropolitan housing markets. *Journal of Housing Research* 7 (2), 191–207.
- Angelini, E., Henry, J., Mestre, R., 2001. Diffusion index-based inflation forecasts for the euro area. Working Paper No. 61 ECB.
- Banbura, M., Gianonne, D., Reichlin, L., 2010. Bayesian VARs with large panels. *Journal of Applied Econometrics* 25 (1), 71–92.
- Banerjee, A., Marcellino, M., Masten, I., 2005. Leading indicators for Euro-area inflation and GDP growth. *Oxford Bulletin of Economics and Statistics* 67 (1), 785–814.
- Barsky, R.B., House, C.L., Kimball, M.S., 2007. Sticky-price models and durable goods. *The American Economic Review* 97 (3), 984–998.
- Bernanke, B., Boivin, J., 2003. Monetary policy in a data-rich environment. *Journal of Monetary Economics* 50 (3), 525–546.
- Bernanke, B., Gertler, M., 1995. Inside the black box: the credit channel of monetary transmission. *The Journal of Economic Perspectives* 9 (4), 27–48.
- Bernanke, B.S., Boivin, J., Eliasz, P., 2005. Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly Journal of Economics* 120 (1), 387–422.
- Bhardwaj, G., Swanson, N.R., 2006. An empirical investigation of the usefulness of ARFIMA models for predicting macroeconomic and financial time series. *Journal of Econometrics* 131 (1–2), 539–578.
- Bloor, C., Matheson, T., 2010. Analysing shock transmission in a data-rich environment: a large BVAR for New Zealand. *Empirical Economics* 39 (2), 537–558.

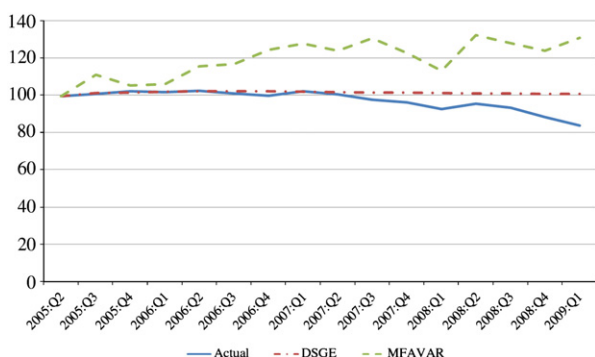


Fig. 2. Out-of-sample *ex ante* forecasts: US real house price index.

- Boivin, J., Ng, S., 2005. Understanding and comparing factor based forecasts. *International Journal of Central Banking* 1 (3), 117–152.
- Boivin, J., Ng, S., 2006. Are more data always better for factor analysis? *Journal of Econometrics* 132 (1), 169–194.
- Boivin, J., Giannoni, M.P., Mihov, I., 2009. Sticky prices and monetary policy: evidence from disaggregated us data. *The American Economic Review* 99 (1), 350–384.
- Chamberlain, G., 1983. Funds, factors, and diversification in arbitrage pricing models. *Econometrica* 51 (5), 1281–1304.
- Chamberlain, G., Rothschild, M., 1983. Arbitrage, factor structure and mean-variance analysis in large markets. *Econometrica* 51 (5), 1305–1324.
- Cho, M., 1996. House price dynamics: a survey of theoretical and empirical issues. *Journal of Housing Research* 7 (2), 145–172.
- Clark, T.E., McCracken, M.W., 2001. Tests of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics* 105 (1), 85–110.
- Cristadoro, R., Forni, M., Reichlin, L., Veronese, G., 2005. A core inflation indicator for the Euro area. *Journal of Money, Credit and Banking* 37 (3), 539–560.
- Das, S., Gupta, R., Kabundi, A., 2009. Could we have predicted the recent downturn in the South African housing market? *Journal of Housing Economics* 18 (4), 325–335.
- Das, S., Gupta, R., Kabundi, A., 2010. The blessing of dimensionality in forecasting real house price growth in the nine census divisions of the US. *Journal of Housing Research* 19 (1), 89–109.
- Das, S., Gupta, R., Kabundi, A., 2011. Forecasting regional house price inflation: a comparison between dynamic factor models and vector autoregressive models. *Journal of Forecasting* 30 (2), 288–302.
- De Mol, C., Giannone, Reichlin, L., 2008. Forecasting using a large number of predictors: is Bayesian regression a valid alternative to principal components? *Journal of Econometrics* 146 (2), 318–328.
- Doan, T.A., Litterman, R.B., Sims, C.A., 1984. Forecasting and conditional projections using realistic prior distributions. *Econometric Reviews* 3 (1), 1–100.
- Dua, P., Ray, S.C., 1995. A BVAR model for the Connecticut economy. *Journal of Forecasting* 14 (3), 167–180.
- Forni, M., Hallin, M., Lippi, M., Reichlin, L., 2001. Coincident and leading indicators for the EURO area. *The Economic Journal* 111 (471), 62–85.
- Forni, M., Hallin, M., Lippi, M., Reichlin, L., 2003. Do financial variables help forecasting inflation and real activity in the EURO area? *Journal of Monetary Economics* 50 (6), 1243–1255.
- Forni, M., Hallin, M., Lippi, M., Reichlin, L., 2005. The generalized dynamic factor model, one sided estimation and forecasting. *Journal of the American Statistical Association* 100 (471), 830–840.
- Geweke, J., 1977. The dynamic factor analysis of economic time series. In: Aigner, Goldberger, A. (Eds.), *Latent Variables in Socio-Economic Models*. North Holland, Amsterdam, pp. 365–383.
- Giannone, D., Matheson, T.D., 2007. A new core inflation indicator for New Zealand. *International Journal of Central Banking* 3 (4), 145–180.
- Gosselin, M.-A., Tkacz, G., 2001. Evaluating factor models: an application to forecasting inflation in Canada. Working Paper No. 18 Bank of Canada.
- Gupta, R., 2006. Forecasting the South African Economy with VARs and VECMs. *South African Journal of Economics* 74 (4), 611–628.
- Gupta, R., Das, S., 2008. Spatial Bayesian methods for forecasting house prices in six metropolitan areas of South Africa. *South African Journal of Economics* 76 (2), 298–313.
- Gupta, R., Das, S., 2010. Predicting downturns in the US housing market: a Bayesian approach. *Journal of Real Estate Finance and Economics* 41 (3), 294–319.
- Gupta, R., Kabundi, A., 2010. Forecasting real US house price: principal components versus Bayesian regressions. *International Business and Economics Research Journal* 9 (7), 141–152.
- Gupta, R., Kabundi, A. A Large Factor Model for Forecasting Macroeconomic Variables in South Africa. *International Journal of Forecasting*, forthcoming (available online, January 2011).
- Gupta, R., Miller, S.M. forthcoming-a. “Ripple Effects” and Forecasting Home Prices in Los Angeles, Las Vegas, and Phoenix. *Annals of Regional Science* (available online, November 2010).
- Gupta, R., Miller, S.M. forthcoming-b. The Time-Series Properties on Housing Prices: A Case Study of the Southern California Market. *Journal of Real Estate Finance and Economics* (available online, March 2010).
- Gupta, R., Sichei, M.M., 2006. A BVAR model for the South African economy. *South African Journal of Economics* 74 (3), 391–409.
- Gupta, R., Kabundi, A., Miller, S.M., 2009. Using large data sets to forecast housing prices: a case study of twenty US States. Working Paper No. 0912. University of Nevada, Las Vegas. <http://ideas.repec.org/p/nlv/wpaper/0916.html>.
- Iacoviello, M., Neri, S., 2010. Housing market spillovers: evidence from an estimated DSGE model. *American Economic Journal: Macroeconomics* 2, 125–164.
- International Monetary Fund, 2000. *World Economic Outlook: Asset Prices and the Business Cycle*.
- Johnes, G., Hyclak, T., 1999. House prices and regional labor markets. *Annals of Regional Science* 33 (1), 33–49.
- Kabundi, A., 2004. Estimation of Economic Growth Using Business Survey Data. *International Monetary Fund. Working Paper No. 04/69*.
- Kapetanios, G., Marcellino, M., 2009. A parametric estimation method for dynamic factor models of large dimensions. *Journal of Time Series Analysis* 30 (2), 208–238.
- LeSage, J.P., 1999. Applied econometrics using MATLAB. www.spatial-econometrics.com.
- Litterman, R.B., 1981. A Bayesian procedure for forecasting with vector autoregressions. Working Paper. Federal Reserve Bank of Minneapolis.
- Litterman, R.B., 1986. Forecasting with Bayesian vector autoregressions — five years of experience. *Journal of Business and Economic Statistics* 4 (1), 25–38.
- Newey, W.K., West, K.D., 1987. A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55 (3), 703–708.
- Quigley, J.M., 1999. Real estate prices and economic cycles. *International Real Estate Review* 2 (1), 1–20.
- Rapach, D.E., Strauss, J.K., 2007. Forecasting real housing price growth in the eighth district states. Federal Reserve Bank of St. Louis. *Regional Economic Development* 3 (2), 33–42.
- Rapach, D.E., Strauss, J.K., 2009. Differences in housing price forecast ability across U.S. states. *International Journal of Forecasting* 25 (2), 351–372.
- Sargent, T.J., Sims, C.A., 1977. Business cycle modelling without precluding to have too much a priori economic theory. In: Sims, C. (Ed.), *New Methods in Business Research*. Federal Reserve Bank of Minneapolis.
- Schneider, M., Spitzer, M., 2004. Forecasting Austrian GDP Using the Generalized Dynamic Factor Model. *Oesterreichische National Bank. Working Paper No. 89*.
- Schumacher, C., 2007. Forecasting German GDP using alternative factor models based on large datasets. *Journal of Forecasting* 26 (4), 271–302.
- Schumacher, C., Dreger, C., 2004. Estimating large-scale factor models for economic activity in Germany: do they outperform simpler models? *Jahrbücher für Nationalökonomie und Statistik* 224 (6), 731–750.
- Sims, C.A., 1980. Macroeconomics and reality. *Econometrica* 48 (1), 1–48.
- Spencer, D.E., 1993. Developing a Bayesian vector autoregression model. *International Journal of Forecasting* 9 (3), 407–421.
- Stock, J.H., Watson, M.W., 1989. New indexes of coincident and leading economic indicators. *NBER Macroeconomics Annual* 10, 351–393.
- Stock, J.H., Watson, M.W., 1991. A probability model of the coincident indicators. In: Lahiri, K., Moore, G. (Eds.), *Leading Economic Indicators: New Approaches and Forecasting Record*. Cambridge University Press, Cambridge, pp. 63–95.
- Stock, James H., Watson, M.W., 1999. Forecasting inflation. *Journal of Monetary Economics* 44 (2), 293–335.
- Stock, J.H., Watson, M.W., 2002a. Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association* 97 (460), 147–162.
- Stock, J.H., Watson, M.W., 2002b. Macroeconomics forecasting using diffusion indexes. *Journal of Business and Economic Statistics* 20 (2), 147–162.
- Stock, J.H., Watson, M.W., 2003. Forecasting output and inflation: the role of asset prices. *Journal of Economic Literature* 41 (3), 788–829.
- Stock, J.H., Watson, M.W., 2004. Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting* 23 (6), 405–430.
- Stock, J.H., Watson, M.W., 2005. Implications of dynamic factor models for VAR analysis. NBER Working Paper No. 11467.
- Theil, H., 1971. *Principles of Econometrics*. John Wiley, New York.
- Todd, R.M., 1984. Improving economic forecasting with Bayesian vector autoregression. *Quarterly Review*, Federal Reserve Bank of Minneapolis 18–29 (Fall).
- Topel, R.H., Rosen, S., 1988. Housing investment in the United States. *Journal of Political Economy* 96 (4), 718–740.
- Van Nieuwenhuize, C., 2006. A generalized dynamic factor model for the Belgian economy identification of the business cycle and GDP growth forecasts. *Journal of Business Cycle Measurement and Analysis* 2005 (2), 213–248.
- Wang, T., 2008. Comparing the DSGE model with the factor model: an out-of-sample forecasting experiment. *Deutsche Bundesbank Discussion Paper Series 1: Economic Studies* 2008/04.
- Wheaton, W.C., Nechayev, G., 2008. The 1998–2005 housing “bubble” and the current “correction”: what’s different this time? *Journal of Real Estate Research* 30 (1), 1–26.
- Zellner, A., 1986. A tale of forecasting 1001 series: the Bayesian knight strikes again. *International Journal of Forecasting* (2), 494.
- Zellner, A., Palm, F., 1974. Time series analysis and simultaneous equation econometric models. *Journal of Econometrics* 2 (1), 17–54.