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# Using Large Data Sets to Forecast House Prices: A Case Study of Twenty U.S. States

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## Abstract

Several Bayesian and classical models are used to forecast house prices in 20 states in the United States. There are two approaches: extracting common factors (principle components) in a factor-augmented vector autoregressive or factor-augmented Bayesian vector autoregressive models or Bayesian shrinkage in a large-scale Bayesian vector autoregressive models. The study compares the forecast performance of the 1976:Q1 to 1994:Q4 in-sample period to the out-of-sample horizon 1995:Q1 to 2009:Q1 period. The findings provide mixed evidence on the role of macroeconomic fundamentals in improving the forecasting performance of time-series models. For 13 states, models that include the information of macroeconomic fundamentals improve the forecasting performance, while for seven states they do not.

This paper considers the dynamics of real house prices and the ability of different pure time-series models to forecast real house prices with two main foci. First, it considers how the researcher can incorporate large data sets into forecasting equations, using dynamic factor analysis or shrinking large-scale Bayesian vector autoregressive (BVAR) models. Second, it also considers the role of spatial priors in the BVAR models. The process is illustrated using house prices from the 20 most-populous states in the United States: Arizona, California, Florida, Georgia, Illinois, Indiana, Massachusetts, Maryland, Michigan, Missouri, North Carolina, New Jersey, New York, Ohio, Pennsylvania, Tennessee, Texas, Virginia, Washington, and Wisconsin.[1]

While the paper focuses largely on forecast performance of various time-series models, the specific application proves important for macro and regional economists when considering the business cycle. That is, the housing sector provides a key factor in predicting the business cycle in the post World War II period. Leamer (2007, p. 149) argues that ''Housing *is* the Business Cycle.'' He performs a battery of empirical analyses on the business cycle, which he calls the consumer cycle because of the importance of residential investment and durable consumption spending in explaining the onset of recessions. Excluding the most recent Great Recession that he did not consider, residential investment and durable consumption experienced significant problems before the beginning of eight of the ten post World War II recessions.

Leamer (2007) argues that the characteristics of the housing market make it a crucial factor in explaining recessions. Basically, the stock-flow nature of the housing market and the reluctance of home owners to lower their prices in a weak market provide the setting for cyclical movement in sales volume. And the cyclical movement in sales volume implies cyclical movements in housing construction and employment. When the economy booms, construction and employment in the housing sector expand, along with increases in nominal house prices. During the contraction, nominal house prices fall sluggishly and most of the adjustment arises through decreases in sales volume and, thus, construction and employment activity in housing. The Great Recession proved the exception as nominal house prices dropped dramatically around the U.S. Although nominal house prices typically fall sluggishly, real house prices do fall during recessions as general inflationary trends reduce real house prices even with sticky nominal house prices. The analysis here focuses on forecasting real house prices.

In sum, during a boom period, developers overbuild the supply of new housing. The size of the excess building, which depends on the strength and length of the boom, will help to determine the length of the next recession. Good monetary policy requires action before the overbuilding goes too far and necessitates central bank intervention early in the boom period, when political pressure probably weighs against monetary policy restraint. That is, understanding and forecasting movements in the housing market plays a critical role for monetary policy authorities.

Further, movements in real housing prices at the regional level can provide important information regarding the regional business cycle, as well as can assist in predicting shifts in housing construction and employment activity between regions due to changes in relative regional house price. Regions with rising relative housing prices will attract construction and employment resources from regions with falling relative house prices.[2] Developers and builders can benefit from good information on the future movements in house prices.

This paper examines the explanatory power of including information from a large set of economic variables that potentially affect house prices, using dynamic factors or Bayesian shrinkage approaches. It compares the out-of-sample forecasting performance of various time-series models: vector autoregressive (VAR), factor-augmented VAR (FAVAR), and various Bayesian time-series models with spatial priors. The spatial priors assume that spillover effects between contiguous states exert more influence than spillover effects between non-contiguous states. Spatial Bayesian VAR (SBVAR), spatial Bayesian FAVAR (SFABVAR), and spatial large-scale BVAR (SLBVAR) models are estimated (LeSage, 2004; Gupta and Miller, forthcoming b). The first set of tests compares the out-of-sample forecasting performance of the various models, using the root-mean-squared-error (RMSE) criteria. The second set of tests performs recursive forecasts to see if the best models can forecast the turning points—peaks and troughs—observed in most states over the 2005 to 2009 period at the end of the sample.

The spatial factor-augmented models perform the best across the half of the 20 states, using the average root-mean-squared-error (RMSE) criteria. The models that exclude the information from the large data set (i.e., SBVAR models) perform the best in seven states. Large-scale models perform the best in the final three states. The FAVAR models do not achieve the best forecasting performance for any of the 20 states. The recursive forecasts mimic the movement in actual house prices, but generally do not anticipate turning points (peaks or troughs).

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature on using large data sets in forecasting models. Section 3 discusses the literature on forecasting house prices. Section 4 specifies the various time-series models estimated and used for forecasting. Section 5 discusses the data and the results. Section 6 concludes.

## Forecasting with Large Data Sets

Time-series models generally perform as well as or better for forecasting purposes than dynamic structural econometric specifications. Zellner and Palm (1974) provide the theoretical rationalization.[3] 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.

A simple approach 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.

Another method uses ''atheoretical'' VAR models. These models do not impose exogeneity assumptions on the included variables. Unlike the single-equation ARDL model, the VAR approach assumes that the 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 used in the estimation increases dramatically with additional variables or additional lags in the system. Given this problem, one approach for using more data in the VAR model involves the extraction of common factors from a large data set that researchers can then add to a more compact VAR specification (Bernanke, Boivin, and Eliazs, 2005; Stock and Watson, 2002, 2005). Adding a couple of 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 provide linkages 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 system, which is done in models presented here.

The ADRL method uses information in the large dataset one variable at a time and then aggregates across all forecasts. As a result, this approach does not differentiate between common factors and non-common factors in the large dataset. Each exhibits the same effect on the forecast, over and above the autoregressive part of the model. Different weighting schemes for the combination forecasts can increase or decrease the relative importance of the variables, however. 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.

This paper considers the factor-augmented and large-scale Bayesian methods for incorporating the information from a large dataset. These methods provide the natural extension of the VAR and BVAR models. The ARDL model involves a single-equation, whereas the VAR and BVAR models involve multiple equations. Thus, the ARDL approach is excluded from the analysis.

Note that the use of fundamentals in the factor-augmented (FAVAR and SFABVAR) and SLBVAR models does not imply structural modeling. Rather, the factor-augmented approach extracts principle components from the large data set that is used in a time-series modeling exercise. The large scale model takes advantage of Bayesian shrinkage to estimate huge numbers of variables that the standard VAR model cannot handle because of degrees of freedom issues. In sum, this paper compares the forecasting performance of different time-series models that include a large set of macroeconomic variables and use spatial priors.

## Forecasting House Prices

The housing market and its cycle play important roles in understanding the business cycle. Several authors argue that asset prices help forecast both inflation and output (Forni, Hallin, Lippi, and Reichlin, 2003; Stock and Watson, 2003; Gupta and Das, 2008, 2010; and Das, Gupta, and Kabundi, 2009, 2010, 2011). Since homes imbed much individual wealth, house price movements may provide important signals for consumption, output, and inflation. Thus, 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). Leamer (2007) states an even stronger case, as we noted above, arguing that housing is the business cycle.

Models that forecast real house prices can give policymakers and other stake holders an idea about the future direction of the overall macro or regional economies, and hence, can provide important information for designing better and more-appropriate policies. Leamer (2007) notes that the housing market predicted 8 of the 10 post World War II recessions. If he wrote his paper today, the analysis probably would argue that the housing market predicted 9 of the 11 post World War II recessions. 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 collapse of the house-price bubble, which, in turn, led the real sector of the world's economy toward an economic slump.

A large number of economic variables affect house prices (Abraham and Hendershott, 1996; Cho, 1996; Johnes and Hyclak, 1999; and 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.

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 U.S. states based on ARDL models containing 29 to 35 potential predictors, including state, regional, and national level variables. Once again, the authors reach similar conclusions on the importance of combining forecasts.

Vargas-Silva (2008a) uses a FAVAR model, containing 120 monthly series, to analyze the effect of monetary policy actions on the housing sector of four different regions of the U.S. This is the first attempt to look into the ability of FAVARs in forecasting regional real house prices.[4] Das, Gupta, and Kabundi (2010) consider the forecasting performance of regional real house price growth rates in the nine U.S. Census regions, using FAVAR and LBVAR models. They find that the FAVAR models generally outperform the LBVAR models.

The current paper extends the above mentioned studies, in the sense that it uses large-scale models that allow for not only the role of a wide possible set of fundamentals to affect the housing sector, but also spatial influences amongst the prices of the 20 largest U.S. states. The forecasting exercise includes the dramatic run up and collapse in house prices in recent years.

### *VAR, BVAR, FAVAR, BFAVAR, and LBVAR Specifications and Estimation*[5]

***VAR, BVAR, and LBVAR.*** An unrestricted VAR model, following Sims (1980), is written as follows:

$$y_t = A_0 + A(L)y_t + \varepsilon_t, \tag{1}$$

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 $p$,[6] and $\varepsilon$ equals an $(n \times 1)$ vector of error terms. It is assumed 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, Litterman, and Sims (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 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 typically proves the exception with a unitary mean. Finally, Litterman (1981) imposes a diffuse prior for the constant. The ‘‘Minnesota prior’’ is used in the analysis discussed here, where Bayesian variants of the classical VAR models are employed.[7]

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

$$\beta_i \sim N(1, \sigma^2_{\beta i}) \text{ and } \beta_j \sim N(0, \sigma^2_{\beta j}), \tag{2}$$

where $\beta_i$ equals the coefficients associated with the lagged dependent variables in each equation of the VAR model (i.e., the first own-lag coefficient), while $\beta_j$ equals any other coefficient. The prior specification reduces to a random walk with a drift model for each variable, if all variances are set to zero. The prior variances, $\sigma^2_{\beta i}$ and $\sigma^2_{\beta j}$, specify uncertainty about the prior means, $\overline{\beta}_i = 1$, and $\overline{\beta}_j = 0$.

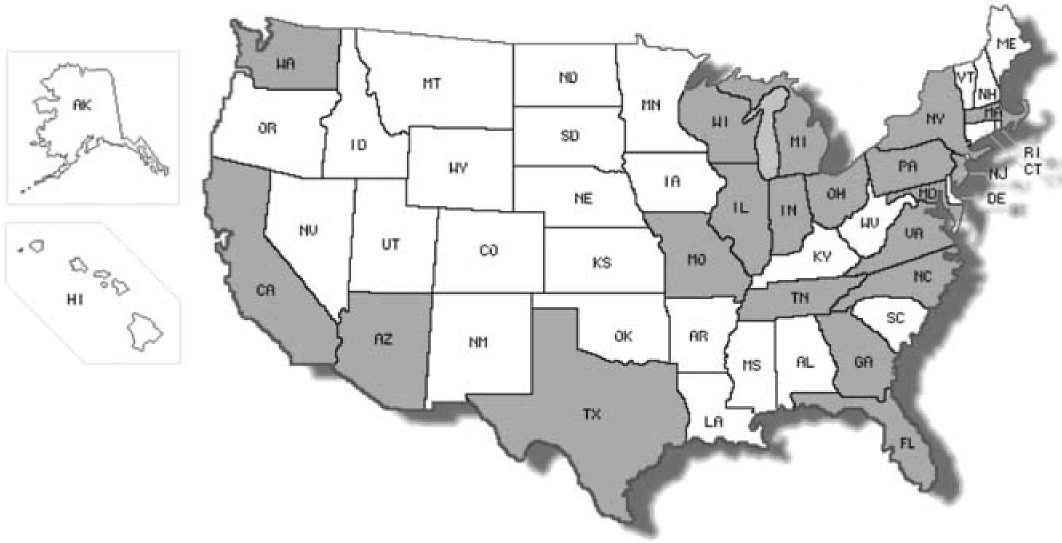
Doan, Litterman, and Sims (1984) propose a formula to generate standard deviations that depend on a small numbers of hyper-parameters: $w$, $d$, and a weighting matrix $f(i, j)$ to reduce the over-parameterization in the VAR models. This approach specifies individual prior variances for a large number 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 (3) at lag $m$, for all $i$, $j$, and $m$, equals $S(i, j, m)$, defined as follows:

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

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., the value of $k_{ij}$), the prior is loosened.[8] The overall tightness ($w$) and the lag decay ($d$) hyper-parameters equal 0.1 and 1.0, respectively, in the standard Minnesota prior, while $k_{ij} = 0.5$, implying a $20 \times 20$ weighting matrix ($F$) for the 20 states with ones down the diagonal and 0.5 in all the off-diagonal positions.

Since researchers believe that the lagged dependant variable in each equation proves most important, the diagonal elements of $F$ impose $\overline{\beta}_i = 1$ loosely. The $\beta_j$ coefficients, however,

**Exhibit 1. United States**




that associate with less-important variables receive off-diagonal elements (i.e., $k_{ij} = 0.5$) in the weighting matrix ($F$) that impose prior means of zero more tightly. Since the Minnesota prior treats all variables in the VAR, except for the first own-lag of the dependent variable, in an identical manner, several researchers attempt to alter this fact. Usually, this means increasing the value for the overall tightness ($w$) hyper-parameter from 0.10 to 0.20, so that more influence comes from other variables in the model. In addition, Dua and Ray (1995) introduce a prior that imposes fewer restrictions on the other variables in the VAR model (i.e., $w = 0.30$ and $d = 0.50$).

Alternatively, LeSage and Pan (1995) propose spatial BVAR (SBVAR) models. They adopt a weight matrix that uses the first-order spatial contiguity (FOSC) prior, implying a non-symmetric $F$ matrix with more importance given to variables from neighboring states than those from non-neighboring states. Exhibit 1 maps the locations of the 20 states. They impose a value of one for both the diagonal elements of the weight matrix, as in the Minnesota prior, as well as for place(s) that correspond to variable(s) from states with which the specific state shares a common border(s). For the elements in the $F$ matrix that correspond to variable(s) from states that do not share common borders, Lesage and Pan (1995) impose a weight of 0.1. The 0.5 weights in the specification of the $20 \times 20$ weighting matrix ($F$) become 1.0 for neighbors and 0.1 for non-neighbors.

In the current application, the large data set of national and regional variables includes 171 quarterly series, house prices in the 20 largest states, as well as 151 macroeconomic variables.[9] Logic and prior research argues that state-level variables should exert minimal, if any, effect on national indicators, while the latter set of variables surely influences the former. Thus, setting $k_{ij} = 0.5$ seems unrealistic. Hence, borrowing from the BVAR models used for regional forecasting, involving both regional and national variables, such as Kinal and Ratner (1986), Shoesmith (1992), Dua and Ray (1995), Das, Gupta, and

Kabundi (2009, 2010), and Gupta and Kabundi (2010, forthcoming), the weight of a national variable is set in a national equation, as well as a state equation, at 0.6. The weight of a state variable is set in other state equation at 0.1 and in a national equation at 0.01. Finally, the weight of the state variable is set in its own equation at 1.0. These weights implement Litterman's circle-star structure. Star (national) variables affect both star and circle (state) variables, while circle variables primarily influence only other circle variables.[10] Thus, the large-scale BVARs are estimated with asymmetric priors, incorporating spatial influences, as well as unequal influences amongst the state- and national-level variables.

The alternative BVARs are estimated, based on 20 or 171 variables, 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.

***FAVAR and BFAVAR.*** This paper also uses the Dynamic Factor Model (DFM) to extract common components between macroeconomic series and then uses these common components to forecast real house prices of the 20 largest U.S. states, adding the extracted factors to the 20-variable VAR model to create a FAVAR in the process. Furthermore, an idiosyncratic component is estimated (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 co-movement of the U.S. economy. Forni, Hallin, Lippi, and Reichlin (2005) demonstrate that for a small number of factors relative to the number of variables and a heterogeneous panel, the factors can be recovered from present and past observations.

Consider a $n \times 1$ covariance stationary process $Y_t = (y_{1t}, \ldots, y_{nt})'$. Suppose that $X_t$ equals the standardized version of $Y_t$ (i.e., $X_t$ possesses a mean zero and a variance equal to one). Under DFM, $X_t$ can be written as the sum of two orthogonal components as follows:

$$X_t = \lambda P_t + \xi_t, \tag{4}$$

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

Since dynamic common factors are latent, they must be estimated. The estimation technique used matters for factor forecasts. This paper adopts the Stock and Watson (2002a) 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., $\hat{P}_t = \hat{\Lambda}' X_t$, where $\hat{\Lambda}$ equals the $n \times r$ matrix of the eigenvectors corresponding to the $r$ largest eigenvalues of the sample covariance matrix $\hat{\Sigma}$).

A 20-variable VAR augmented by extracted common factors using the Stock and Watson (2002b) approach is used for forecasting purposes. This approach is similar to the univariate Static and Unrestricted (SU) approach of Bovin and Ng (2005). Therefore, the forecasting equation to predict $Y_t$ is given by:

$$\begin{bmatrix} \hat{Y}_{t+h} \\ \hat{P}_{t+h} \end{bmatrix} = \hat{\Phi}(L) \begin{bmatrix} Y_t \\ P_t \end{bmatrix}, \tag{5}$$

where $h$ equals the forecasting horizon and $\hat{\Phi}(L)$ equal lag polynomials, which are estimated with and without restrictions. VAR models are special cases of equation (5), as Boivin and Ng (2005) clearly note. The FAVAR approach should produce smaller mean squared errors with the known factors and parameters. In practice, however, one does not observe the factors and they must be estimated. Moreover, the forecasting equation should reflect a correct specification. Two DFM specifications are considered: (1) FAVAR, which includes the real house prices of the 20 states and the common static factors; and (2) BFAVAR, which is the FAVAR specification with Bayesian restrictions on lags of the real house prices based on the alternative types of priors outlined above.

## Data Description, Model Estimation, and Results

### Data

While the small-scale VAR model includes data of only the annualized real house prices of the 20 largest U.S. states, the large-scale BVAR models and the DFMs also include the 151 quarterly national and regional series. Nominal house prices come from the Freddie Mac database, the Conventional Mortgage Home Price Index (CMHPI). The CMHPI uses matched transactions on the same property over time to account for quality changes and consists of both purchase and refinance-appraisal transactions on over 33 million homes. The state-level nominal CMHPI house price is deflated by the personal consumption expenditure (PCE) deflator from the Bureau of Economic Analysis (BEA) to generate the real house price series.

The remaining 151 macroeconomic variables include national and regional series.[11] The data series was collected from various sources such as the Bureau of Labor Statistics, the Conference Board, the Global Insight database, the FREDII database of the St. Louis Federal Reserve Bank, the U.S. Census Bureau, and the National Association of Realtors.[12]

All data were transformed to induce stationarity for the FAVAR-type models before extracting the four factors, with the number of factors determined by tests suggested by Bai and Ng (2002) and Alessi, Barigozzi, and Capasso (2010). Non-stationary data, however, can be used with the BVAR. Sims, Stock, and Watson (1990) indicate that with the Bayesian approach entirely based on the likelihood function, the associated inferences do not require special treatment for non-stationarity, since the likelihood function exhibits the same Gaussian shape regardless of the presence of non-stationarity. Following Banbura, Giannone, and Reichlin (2010) for the variables in the panel that are characterized by mean-reversion, however, a white-noise prior is established (i.e., $\overline{\beta}_i = 0$); otherwise, the random walk prior (i.e., $\overline{\beta}_i = 1$) is used. In the data set, including the 20 real house prices, there are 143 I(1) variables, which are transformed to induce stationarity, while the remaining 28 variables are left untransformed, since they are I(0). The Appendix lists these variables, as well as the transformations used prior to analyzing the data.

The real activity group consists of variables such as industrial production, capacity utilization, retail sales, real personal consumption, real personal income, new orders, inventories, new housing starts (national and regional), housing sales (national and regional), employment, average working hours, and so on. The price and inflation group consists of variables such as the consumer price index, the producer price index, real housing prices (national and regional), the personal consumption expenditure deflator, average hourly earnings, exchange rates, and so on. The monetary sector group consists of variables such as monetary aggregates, various interest rates, credit outstanding, and so on. Amongst the 151 national and regional macroeconomic indicators, 87 variables relate to real activity, 36 relate to prices or inflation, and 28 relate to the monetary sector. Finally, in addition to the 20 state real house prices, the large data set also includes national and regional (i.e., the Northeast, South, Midwest, and West) data on housing starts and permits, home sales, real house prices, and national mobile home manufacturer shipments.

## Estimation and Results

This section reports the econometric findings. The optimal model for forecasting each market's house price is selected, using the minimum average root mean squared error (RMSE) across the one-, two-, three-, and four-quarter-ahead out-of-sample forecasts.

The data sample for all 20 states runs from 1975:Q1 through 2009:Q1. First, the out-of-sample forecasting experiment covers 1995:Q1 through 2009:Q1. Second, the recursive forecasts begin four quarters before the peak in the house price in the 2005 to 2008 period in each state and continue to the end of the sample in 2009:Q1.

***One- to Four-Quarter-Ahead Forecast Accuracy*** Given the specification of priors in Section 4, the alternative small- and large-scale models are estimated for the 20 states in the sample over the period 1976:Q1 to 1994:Q4 using quarterly data. Out-of-sample one- to four-quarters-ahead forecasts are then created for the period of 1995:Q1 to 2009:Q1, and then forecast accuracy relative to the forecasts generated by an unrestricted 20-variable VAR is examined. 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 follows Rapach and Strauss (2007, 2009), who observe marked differences in house price growth across U.S. regions since the mid-1990s.

The multivariate versions of the classical VAR, spatial versions of the classical and Bayesian FAVARs, and spatial versions of the large-scale spatial BVARs are estimated over the period 1976:Q1 to 1994:Q4, and then a forecast is created for 1995:Q1 through 2009:Q1. Since there are two lags, the initial two quarters from 1976:Q1 to 1976:Q2 feed the lags. The models are re-estimated for 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. This iterative estimation and the four-quarters-ahead forecast procedure is iterated for 57 quarters, with the first forecast beginning in 1995:Q1. This produced a total of 57 one-quarter-ahead forecasts, ..., up to 57 four-quarters-ahead forecasts.[13] Root mean squared errors (RMSE)[14] were calculated for the 57 one-, two-, three-, and four-quarters-ahead forecasts for the 20 annualized real house prices of the models. The average of the RMSE statistic for one-, two-, three-, and four-quarters ahead forecasts are examined over the 1995:Q1 to 2009:Q1 period.

The SBVAR, SFABVAR, and SLBVAR models are initially examined using a value of $w = 0.1$ and $d = 1.0$, and then the value is increased to $w = 0.2$ to account for more influences from variables other than the first own lags of the dependant variables of the model. In addition, as in Dua and Ray (1995), Gupta and Sichei (2006), Gupta (2006), and Gupta and Miller (forthcoming a, forthcoming b), the SBVAR, SFABVAR, and SLBVAR models are also estimated with $w = 0.3$ and $d = 0.5$; $d = 2$ is introduced to increase the tightness on lag $m$. The model that produces the lowest average RMSE values is selected as the 'optimal' specification for a specific state.

Exhibit 2 reports the average of the one-, two-, three-, and four-quarter-ahead RMSEs across all 20 states. The benchmark for all forecast evaluations is the VAR model forecast RMSEs. Thus, the average RMSE for the Arizona FAVAR model of 0.973 means that the RMSE for the FAVAR model equals only 97.3% of the RMSE for the VAR model. Several observations emerge. First, based on the average performance across the 20 states, the spatial Bayesian VAR models (SBVAR) exhibit the steadiest performance. They achieve the lowest average RMSE, falling just under one, across all specifications. Moreover, the standard deviation of the RMSEs across states also achieves the lowest values, except for the FAVAR model. Second, although the SFABVAR models do not achieve performance on average better than the VAR models, they do achieve the best performance in 10 of the 20 states. The SBVAR models provide the best performance in seven states. The SLBVAR model performs the best in three states and the FAVAR model never achieves the best performance in any of the 20 states.[15]

Second, although the spatial BVAR models show the best performance on average across the 20 states as well as the lowest standard deviation, these models only provide the best performance in seven states: Massachusetts, Michigan, Missouri, New Jersey, New York, Texas, and Wisconsin. The spatial factor-augmented BVAR models produce the best performance in minimum average RMSEs in 10 states: California, Florida, Georgia, Illinois, Indiana, North Carolina, Ohio, Pennsylvania, Tennessee, and Virginia. Although the worst performing on average of the various models, the spatial large-scale BVAR models still provide the best performance in three states: Arizona, Maryland, and Washington. Finally, the factor-augmented VAR model performs almost in exact synchronization with the VAR model; however, this model never achieves the best forecast performance for any of the 20 states.[16]

Overall, different specifications yield the lowest RMSE in different states. No common pattern emerges. Comparing the forecasting performance across states, however, the five best performing forecast models in order from best to worst include Arizona (9.8% of the VAR RMSE), Pennsylvania (13.7%), California (17.3%), Georgia (30.5%), and Indiana (13.7%). The five worst performing forecast models, although the best in each state, in order from worst to best include Missouri (97.5% of the VAR RMSE), New York (94.7%), New Jersey (90.2%), Massachusetts (79.0%), and Michigan (73.1%). The five worst performing forecast models are spatial BVAR models while four of the best performing models are spatial factor-augmented BVAR models.

**Exhibit 2. One-to-Four-Quarter Ahead RMSE Forecast Errors**

| **Model** | | | **SBVAR** | | | | | **SFABVAR** | | | | | **SLBVAR** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Parameters** | **VAR** | **FAVAR** | $w$ = 0.3, $d$ = 0.5 | $w$ = 0.2, $d$ = 1 | $w$ = 0.1, $d$ = 1 | $w$ = 0.2, $d$ = 2 | $w$ = 0.1, $d$ = 2 | $w$ = 0.3, $d$ = 0.5 | $w$ = 0.2, $d$ = 1 | $w$ = 0.1, $d$ = 1 | $w$ = 0.2, $d$ = 2 | $w$ = 0.1, $d$ = 2 | $w$ = 0.3, $d$ = 0.5 | $w$ = 0.2, $d$ = 1 | $w$ = 0.1, $d$ = 1 | $w$ = 0.2, $d$ = 2 | $w$ = 0.1, $d$ = 2 |
| AZ | 0.028 | 0.973 | 1.039 | 1.017 | 1.046 | 1.039 | 1.078 | 0.294 | 0.324 | 0.313 | 0.395 | 0.318 | 0.098[a] | 0.166 | 0.153 | 0.353 | 0.332 |
| CA | 0.021 | 0.954 | 0.936 | 0.996 | 1.134 | 1.123 | 1.317 | 0.173[a] | 0.267 | 0.254 | 0.319 | 0.306 | 0.174 | 0.196 | 0.205 | 0.197 | 0.218 |
| FL | 0.023 | 0.848 | 1.003 | 1.058 | 1.085 | 1.107 | 1.120 | 1.099 | 0.416 | 0.402[a] | 0.436 | 0.586 | 5.256 | 5.656 | 5.550 | 6.324 | 6.113 |
| GA | 0.007 | 0.978 | 1.201 | 1.285 | 1.290 | 1.335 | 1.298 | 0.305[a] | 0.486 | 0.861 | 0.832 | 1.095 | 1.371 | 1.661 | 1.661 | 1.826 | 1.855 |
| IL | 0.008 | 0.998 | 1.217 | 1.354 | 1.387 | 1.468 | 1.461 | 0.797 | 0.688 | 0.609 | 0.439[a] | 0.570 | 3.472 | 3.738 | 3.738 | 4.350 | 4.233 |
| IN | 0.006 | 1.038 | 1.123 | 1.103 | 1.074 | 1.033 | 0.984 | 0.518 | 0.535 | 0.465 | 0.484 | 0.342[a] | 3.747 | 3.685 | 3.662 | 3.167 | 3.286 |
| MA | 0.015 | 0.990 | 0.790[a] | 0.807 | 0.944 | 0.811 | 0.984 | 1.198 | 1.526 | 1.563 | 1.510 | 1.547 | 4.880 | 5.005 | 4.943 | 5.875 | 5.583 |
| MD | 0.016 | 0.977 | 1.033 | 1.064 | 1.124 | 1.110 | 1.219 | 1.745 | 2.323 | 2.864 | 2.040 | 2.803 | 1.188 | 0.862 | 0.651[a] | 1.879 | 1.887 |
| MI | 0.010 | 1.035 | 0.731[a] | 0.807 | 0.820 | 0.897 | 0.865 | 1.607 | 1.607 | 1.107 | 1.857 | 1.571 | 7.571 | 7.500 | 7.750 | 7.357 | 7.929 |
| MO | 0.010 | 1.039 | 1.000 | 1.023 | 0.975[a] | 1.053 | 0.981 | 2.336 | 2.528 | 2.701 | 2.484 | 2.496 | 6.551 | 4.823 | 4.605 | 3.876 | 3.659 |
| NC | 0.007 | 0.881 | 1.041 | 1.122 | 1.147 | 1.133 | 1.156 | 0.857 | 0.954 | 0.906 | 0.718 | 0.686[a] | 1.022 | 1.188 | 1.238 | 1.416 | 1.416 |
| NJ | 0.013 | 1.049 | 0.924 | 0.895 | 0.902[a] | 0.905 | 0.929 | 1.974 | 1.705 | 1.629 | 1.612 | 1.504 | 6.530 | 6.543 | 6.480 | 7.131 | 7.082 |
| NY | 0.016 | 1.003 | 0.947[a] | 0.983 | 1.027 | 0.987 | 1.029 | 1.649 | 1.049 | 1.114 | 1.598 | 1.549 | 4.475 | 5.042 | 4.768 | 6.150 | 5.376 |
| OH | 0.009 | 0.998 | 0.790 | 0.799 | 0.748 | 0.790 | 0.723 | 0.699 | 0.620[a] | 0.651 | 0.658 | 0.631 | 0.731 | 0.771 | 0.665 | 0.790 | 0.693 |
| PA | 0.013 | 1.051 | 0.694 | 0.679 | 0.683 | 0.662 | 0.677 | 0.137[a] | 0.218 | 0.275 | 0.316 | 0.312 | 0.837 | 0.945 | 0.964 | 0.957 | 0.975 |
| TN | 0.010 | 1.023 | 0.946 | 0.979 | 0.927 | 0.968 | 0.894 | 0.544 | 0.555 | 0.519 | 0.442[a] | 0.445 | 1.764 | 2.097 | 2.124 | 2.275 | 2.279 |
| TX | 0.014 | 1.073 | 0.788 | 0.730 | 0.680 | 0.727 | 0.676[a] | 5.333 | 4.646 | 3.640 | 3.676 | 2.458 | 6.217 | 4.974 | 4.992 | 4.213 | 4.224 |
| VA | 0.014 | 1.000 | 0.879 | 0.908 | 0.909 | 0.928 | 0.937 | 0.778 | 0.630 | 0.673 | 0.509[a] | 0.570 | 0.696 | 0.692 | 0.717 | 1.147 | 1.092 |
| WA | 0.012 | 1.035 | 0.979 | 0.932 | 0.843 | 0.936 | 0.865 | 1.177 | 1.276 | 1.378 | 1.263 | 1.275 | 0.542[a] | 0.979 | 0.947 | 1.366 | 1.335 |
| WI | 0.020 | 1.091 | 0.708 | 0.703 | 0.607 | 0.695 | 0.581[a] | 0.807 | 4.211 | 6.209 | 7.345 | 7.494 | 8.668 | 8.838 | 7.786 | 12.346 | 9.939 |
| Average | 0.014 | 1.002 | 0.938 | 0.962 | 0.968 | 0.985 | 0.989 | 1.201 | 1.328 | 1.407 | 1.447 | 1.428 | 3.290 | 3.268 | 3.180 | 3.650 | 3.475 |
| Std. Dev. | 0.006 | 0.059 | 0.153 | 0.180 | 0.204 | 0.203 | 0.231 | 1.152 | 1.252 | 1.467 | 1.646 | 1.628 | 2.784 | 2.655 | 2.555 | 3.112 | 2.776 |

Notes: Prior to forecasting, the variables were transformed by taking the base 10 logarithm of the price index divided by the personal consumption deflator from the national income and product accounts. The average value of the transformed variable across all states and time equals 0.242. The actual RMSE appears in the VAR column. All other columns report the RMSE of the model forecasts relative to the RMSE of the VAR model. Thus, the value of 0.973 for Arizona and the FAVAR model means that the FAVAR model's RMSE equals 97.3% of the RMSE of the VAR (i.e., 0.028).

[a]The minimum relative root mean square error (RMSE) across the various specifications.

Finally, if researchers want to adopt a common methodology to forecast, then the best performing model, on average, across the 20 states is the spatial BVAR model with $w$ = 0.3 and $d$ = 0.5. On average, it performs at 93.8% of the VAR model, but does not achieve the lowest variability across states. The factor-augmented VAR achieves the lowest variability, but on average does not outperform the VAR model. That is, a common methodology choice could choose either the VAR, factor-augmented VAR, or spatial BVAR model. But different models achieve the best performance in different states.

***Recursive Turning Point Forecasts.*** Nearly all of the housing markets in the 20 states experienced a dramatic run up in prices followed by an equally dramatic fall near the end of the sample period. In addition, near the end of the sample period most states experienced a trough in the real house price and saw house prices rise for a few quarters. Texas provides the exception to this pattern, where its real house price rose modestly through the end of the sample period. The optimal forecast models were exposed to the acid test—predicting these specific turning points (peaks and troughs), in each of the 20 states. The findings in this section are exploratory and illustrative, since only two turning points are examined in each real house price series. More definitive turning point analysis requires many more actual turning points to determine a success rate with some statistical confidence.

The optimal models in Exhibit 3 use data through the fourth quarter prior to the peak in house prices in each state and then house prices are forecasted one-quarter ahead. The data were then updated with the new quarter and then forecasted again one-quarter ahead. This updating and forecasting one-quarter ahead is continued through the end of the sample in 2009:Q1.[17] The results of this forecasting experiment appear in Exhibit 3. Exhibit 4 plots the forecast and actual real house prices in the 20 states over the recursive forecasting period for each state.

North Carolina and Texas are excluded from an examination of the forecasting results for the peaks in the real house price series because they experienced peaks too near the end of the sample to draw inferences. Nevertheless, the actual and forecast values for these states are reported in Exhibit 3 and the graphs are included in Exhibit 4. Of the remaining 18 states, five states (Arizona, Florida, New Jersey, Tennessee, and Virginia) saw the forecast peak occur ahead of the actual peak, usually by one quarter. Another five states (Massachusetts. New York, Ohio, Pennsylvania, and Washington) experienced the forecast peak simultaneously with the peak in the actual real house price. Finally, the remaining eight states (California, Georgia, Illinois, Indiana, Maryland, Michigan, Missouri, and Wisconsin) identified the forecast peak after the peak in the actual real house price, usually one-quarter after.[18]

Turning now to the troughs in the real house price series, Maryland, North Carolina, and Texas are excluded either because they did not experience a trough before the end of the sample period (Maryland) or their peaks occurred too near the end of the sample period (North Carolina and Texas). Arizona, California, and Washington saw the forecast of the trough occur at the same quarter as the trough in the actual house price series. For the remaining 15 states (Florida, Georgia, Illinois, Indiana, Massachusetts, Michigan, Missouri, New Jersey, New York, Ohio, Pennsylvania, Tennessee, Virginia, and Wisconsin), the forecasted trough came after the actual trough in the house price series, typically one quarter later.

**Exhibit 3. Recursive Forecasts**

| | Arizona | | California | | Florida | | Georgia | | Illinois | | Indiana | | Massachusetts | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Date | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast |
| 2004:Q4 | | | | | | | | | | | 211.6 | 210.3 | 249.0 | 256.8 |
| 2005:Q1 | | | | | | | | | | | 211.8 | 211.3 | 252.9 | 253.9 |
| 2005:Q2 | | | | | | | | | | | 212.7 | 210.5 | 257.0 | 258.3 |
| 2005:Q3 | | | 439.1 | 439.6 | | | | | | | 213.7[a] | 211.5 | 258.1[a] | 261.8[a] |
| 2005:Q4 | | | 455.5 | 453.2 | | | | | | | 212.6 | 212.4[a] | 258.0 | 260.6 |
| 2006:Q1 | 311.0 | 326.1 | 463.8 | 469.7 | 358.8 | 365.8 | 225.9 | 225.9 | 308.2 | 307.2 | 211.8 | 211.3 | 257.5 | 259.5 |
| 2006:Q2 | 316.4 | 318.6 | 465.6[a] | 470.9 | 364.3 | 381.4 | 226.2 | 228.2 | 309.4 | 311.8 | 210.3 | 210.5 | 253.0 | 258.9 |
| 2006:Q3 | 317.2 | 329.2[a] | 465.1 | 471.3[a] | 365.5 | 383.0[a] | 227.0 | 228.6 | 310.3 | 311.2 | 210.4 | 208.8 | 249.4 | 252.6 |
| 2006:Q4 | 319.9[a] | 320.5 | 462.5 | 464.1 | 368.6[a] | 374.5 | 231.4[a] | 228.3 | 314.5[a] | 311.9 | 212.5 | 208.2 | 250.2 | 247.5 |
| 2007:Q1 | 316.4 | 326.3 | 453.2 | 455.5 | 363.6 | 373.9 | 231.4 | 230.9 | 314.1 | 316.8[a] | 211.5 | 211.0 | 246.0 | 251.4 |
| 2007:Q2 | 311.3 | 319.4 | 444.2 | 442.3 | 356.7 | 360.1 | 230.9 | 228.8 | 311.4 | 314.8 | 210.5 | 209.8 | 240.8 | 245.8 |
| 2007:Q3 | 303.8 | 314.9 | 430.0 | 432.0 | 344.1 | 349.9 | 229.0 | 231.7[a] | 308.5 | 310.8 | 208.8 | 208.7 | 235.4 | 238.9 |
| 2007:Q4 | 296.7 | 295.9 | 409.3 | 407.6 | 333.7 | 329.5 | 228.7 | 227.8 | 307.2 | 303.7 | 207.3 | 206.7 | 233.1 | 231.7 |
| 2008:Q1 | 285.1 | 288.5 | 381.8 | 387.9 | 317.5 | 319.2 | 228.0 | 226.5 | 304.0 | 304.8 | 207.7 | 204.6 | 230.2 | 229.5 |
| 2008:Q2 | 267.4 | 266.0 | 349.6 | 355.1 | 294.8 | 301.1 | 223.5 | 224.9 | 296.6 | 301.4 | 204.6 | 206.1 | 220.8 | 226.0 |
| 2008:Q3 | 246.7 | 236.4 | 320.5 | 319.2 | 271.0 | 272.0 | 216.8[b] | 219.4 | 286.0[b] | 287.1 | 199.6[b] | 202.1 | 213.5[b] | 214.0 |
| 2008:Q4 | 243.0[b] | 231.3[b] | 315.4[b] | 290.9[b] | 261.2[b] | 244.9 | 219.6 | 213.5[b] | 290.6 | 275.4[b] | 202.7 | 196.0[b] | 217.6 | 207.6[b] |
| 2009:Q1 | 243.8 | 244.9 | 319.5 | 305.4 | 268.2 | 239.3[b] | 225.7 | 226.5 | 292.7 | 289.5 | 207.1 | 208.7 | 219.8 | 216.4 |

**Exhibit 3. Recursive Forecasts (continued)**

| | Maryland | | Michigan | | Missouri | | North Carolina | | New Jersey | | New York | | Ohio | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Date | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast |
| 2004:Q2 | | | 273.2 | 271.2 | | | | | | | | | | |
| 2004:Q3 | | | 275.4 | 273.2 | | | | | | | | | | |
| 2004:Q4 | | | 276.3 | 273.4 | | | | | | | | | 235.4 | 235.3 |
| 2005:Q1 | | | 276.9[a] | 272.6 | | | | | | | | | 236.3 | 234.3 |
| 2005:Q2 | | | 276.8 | 277.1[a] | | | | | | | | | 237.1 | 235.5 |
| 2005:Q3 | | | 276.6 | 277.1[a] | | | | | | | | | 237.1[a] | 237.5[a] |
| 2005:Q4 | | | 273.4 | 273.8 | | | | | | | | | 235.8 | 236.9 |
| 2006:Q1 | 350.4 | 361.4 | 271.6 | 269.8 | 224.4 | 226.4 | | | 285.7 | 287.8 | | | 235.2 | 233.2 |
| 2006:Q2 | 355.5 | 352.0 | 265.7 | 268.3 | 223.6 | 228.0 | | | 287.7 | 291.1[a] | 299.0 | 308.2 | 233.0 | 232.9 |
| 2006:Q3 | 358.2 | 364.5 | 262.1 | 261.8 | 224.5 | 227.5 | | | 288.0 | 290.1 | 298.0 | 307.3 | 231.3 | 230.0 |
| 2006:Q4 | 362.5[a] | 356.6 | 263.7 | 256.7 | 227.1[a] | 228.4 | | | 290.0[a] | 288.3 | 302.9 | 303.3 | 232.5 | 229.1 |
| 2007:Q1 | 360.7 | 370.9[a] | 259.6 | 261.3 | 226.6 | 231.8[a] | | | 288.0 | 290.8 | 303.0[a] | 308.7[a] | 230.5 | 231.8 |
| 2007:Q2 | 358.9 | 361.4 | 253.1 | 255.9 | 225.2 | 230.7 | | | 284.0 | 285.7 | 300.4 | 305.8 | 228.1 | 229.5 |
| 2007:Q3 | 353.4 | 359.3 | 244.8 | 249.1 | 223.5 | 229.1 | | | 280.4 | 280.3 | 295.5 | 302.0 | 224.9 | 228.1 |
| 2007:Q4 | 347.9 | 341.0 | 242.2 | 239.5 | 222.7 | 226.4 | | | 276.8 | 275.5 | 295.2 | 294.4 | 223.0 | 223.5 |
| 2008:Q1 | 338.9 | 343.6 | 240.6 | 237.4 | 221.1 | 224.2 | | | 272.5 | 272.0 | 294.0 | 292.5 | 223.3 | 220.6 |
| 2008:Q2 | 325.8 | 321.1 | 229.7 | 236.3 | 216.9 | 222.6 | 232.4 | 232.9[a] | 263.0 | 267.4 | 287.3 | 289.8 | 218.2 | 221.7 |
| 2008:Q3 | 311.1 | 317.2 | 219.3[b] | 224.6 | 211.7[b] | 216.6 | 228.1[b] | 230.9 | 253.7[b] | 254.7 | 277.9[b] | 279.3 | 211.4[b] | 217.1 |
| 2008:Q4 | 311.2 | 293.6 | 221.1 | 210.9[b] | 216.0 | 209.4[b] | 232.1 | 225.0[b] | 255.8 | 244.3[b] | 280.8 | 271.3[b] | 215.6 | 208.8[b] |
| 2009:Q1 | 309.9[b] | 279.4[b] | 228.2 | 219.3 | 219.2 | 218.2 | 235.1[a] | 228.9 | 256.1 | 253.5 | 284.7 | 281.4 | 221.6 | 215.8 |

**Exhibit 3. Recursive Forecasts (continued)**

| | Pennsylvania | | Tennessee | | Texas | | Virginia | | Washington | | Wisconsin | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Date | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast | Actual | Forecast |
| 2006:Q1 | | | | | | | 319.4 | 322.2 | | | 287.7 | 292.6 |
| 2006:Q2 | 274.2 | 273.1 | | | | | 323.1 | 327.7 | | | 285.8 | 295.9 |
| 2006:Q3 | 275.8 | 272.9 | 219.3 | 217.7 | | | 323.4 | 331.1[a] | | | 285.5 | 294.8 |
| 2006:Q4 | 279.4 | 273.8 | 223.9 | 220.1 | | | 328.0[a] | 327.0 | 430.5 | 423.0 | 289.4[a] | 296.1 |
| 2007:Q1 | 279.9[a] | 279.6[a] | 223.7 | 223.6[a] | | | 326.4 | 330.3 | 434.5 | 436.7 | 287.8 | 301.6[a] |
| 2007:Q2 | 279.2 | 276.6 | 225.1[a] | 223.2 | | | 325.0 | 325.8 | 436.9 | 434.3 | 285.4 | 298.5 |
| 2007:Q3 | 277.4 | 274.5 | 224.5 | 223.6[a] | | | 320.6 | 323.7 | 437.3[a] | 444.6[a] | 283.1 | 295.4 |
| 2007:Q4 | 276.0 | 270.3 | 224.0 | 223.3 | | | 316.4 | 313.9 | 436.0 | 428.0 | 282.1 | 290.2 |
| 2008:Q1 | 275.8 | 271.1 | 223.9 | 221.5 | | | 312.0 | 311.7 | 430.7 | 426.3 | 280.8 | 288.1 |
| 2008:Q2 | 270.2 | 272.5 | 221.2 | 219.7 | 178.0 | 177.5 | 301.6 | 303.7 | 420.2 | 414.7 | 274.6 | 286.2 |
| 2008:Q3 | 264.0[b] | 264.5 | 216.3[b] | 217.4 | 176.2 | 175.8 | 292.1[b] | 289.6 | 406.1[b] | 399.9[b] | 267.8[b] | 276.4 |
| 2008:Q4 | 268.5 | 256.3[b] | 221.5 | 210.8[b] | 179.9 | 173.1 | 294.7 | 279.7[b] | 409.1 | 402.6 | 273.0 | 265.6[b] |
| 2009:Q1 | 271.6 | 268.6 | 224.0 | 219.4 | 182.6[a] | 178.3[a] | 297.1 | 287.6 | 405.9 | 421.6 | 276.2 | 274.3 |

Notes: The forecasts begin four quarters prior to the actual peak in the house price series in each state and continues through 2009:Q1. Plots of the actual and recursive forecasts appear in Exhibit 4.

[a] The peak in the real house price index.

[b] The trough in the real house price index.

**Exhibit 4. Recursive Forecasts**

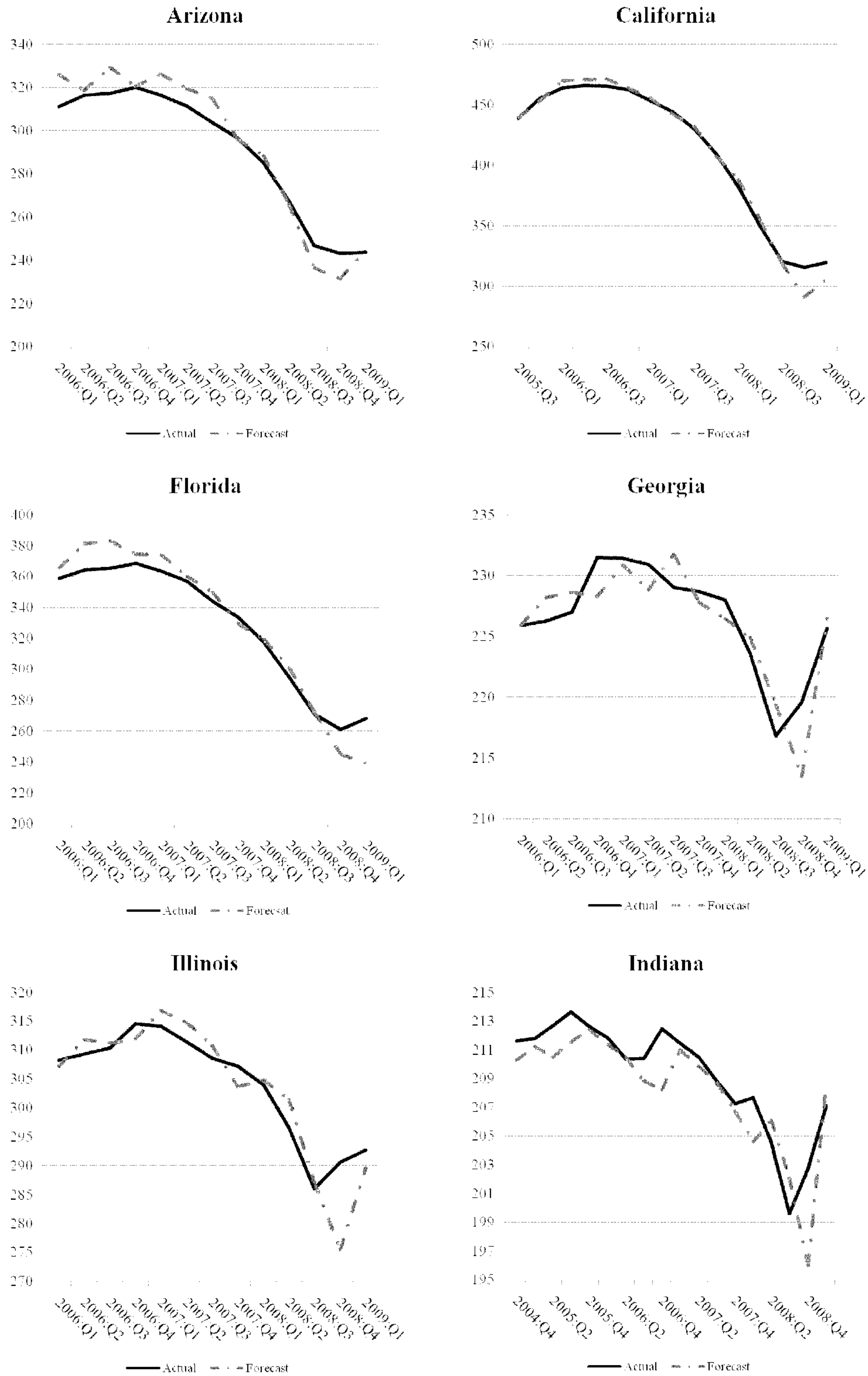


**Exhibit 4. Recursive Forecasts (continued)**

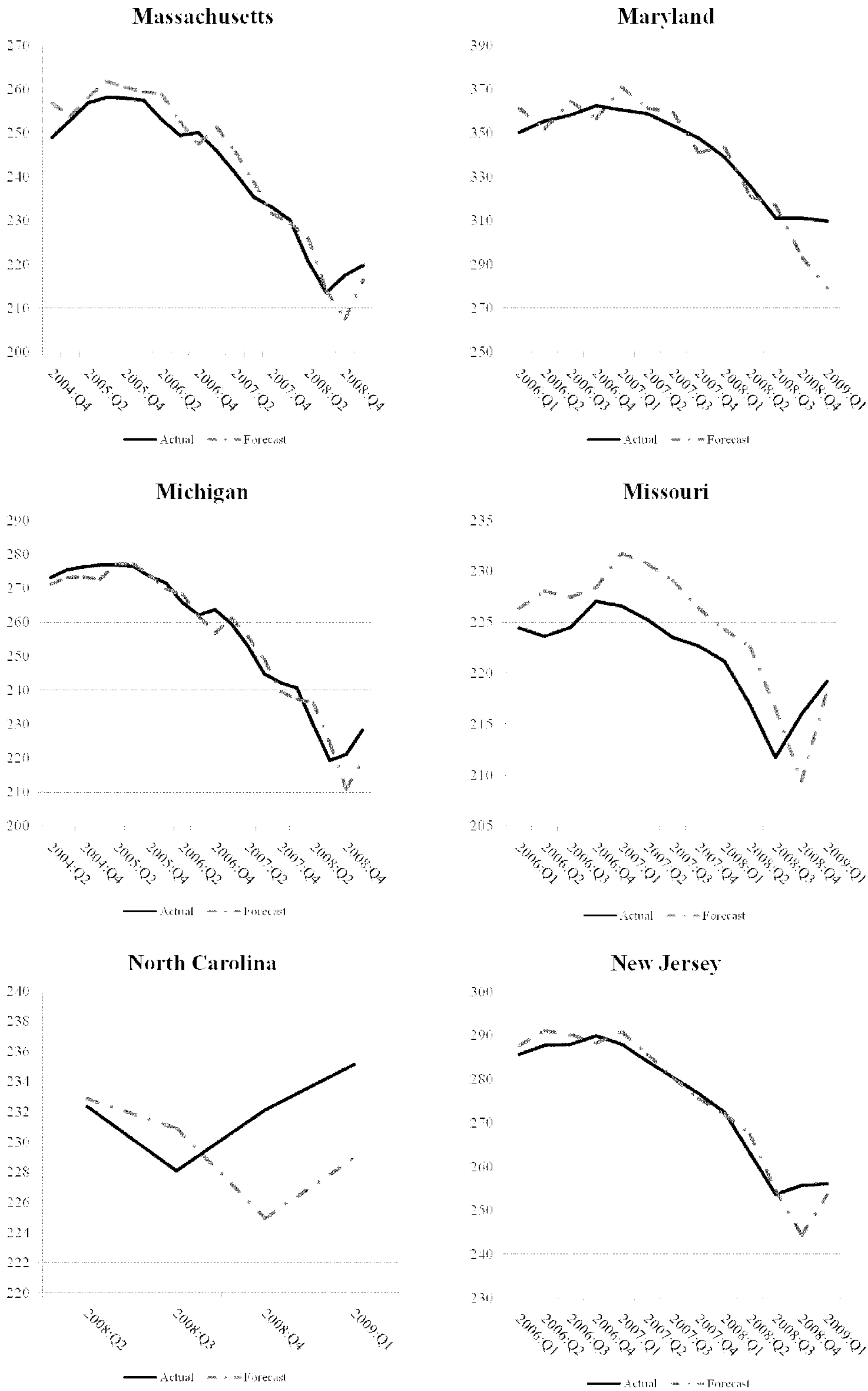


**Exhibit 4. Recursive Forecasts (continued)**

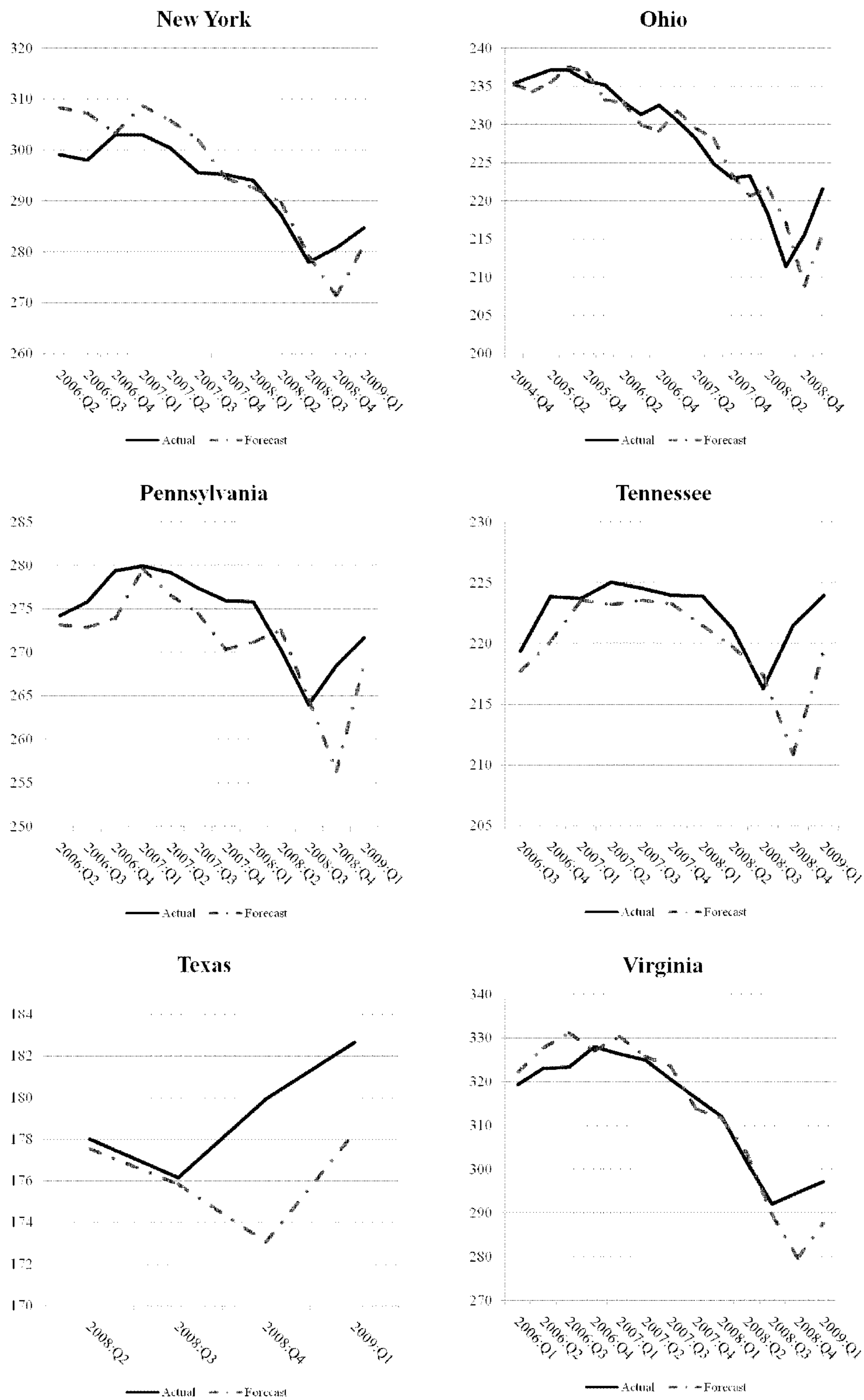


**Exhibit 4. Recursive Forecasts (continued)**


The recursive forecasts track the movements in the real house price indexes rather closely. Sometimes the forecast series leads the turning points in the actual series. But more frequently the forecast series turns at or later than the actual series.

## Conclusion

House prices in 20 U.S. states are forecasted here using the VAR and BVAR models, both with and without the information content of 151 additional quarterly national and regional economic 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) or factor-augmented Bayesian vector autoregressive (FABVAR) models or Bayesian shrinkage in a large-scale Bayesian vector autoregressive (LBVAR) models. In addition, spatial or causality priors are introduced to augment the forecasting models.

Using the period of 1976:Q1 to 1994:Q4 as the in-sample period and 1995:Q1 to 2009:Q1 as the out-of-sample horizon, the forecast performance of the alternative models is compared for one- to four-quarters ahead forecasts. There are mixed results based on the average root mean squared error (RMSE) for the one-, two-, three-, and four–quarter-ahead forecasts. The spatial factor-augmented models outperform the other models in 10 of the 20 states examined. In three states, the spatial large-scale BVAR models provide the best forecasts. The spatial BVAR models that do not include the information for the 151-variable data set of national and regional variables perform the best in seven states.

Averaging across the 20 states, however, suggests that the spatial BVAR models perform the best in terms of average RMSE, as well as exhibiting the second lowest variability of those RMSEs across states. That is, the spatial BVAR models prove the most-steady in their overall performance. The factor-augmented VAR model achieves the lowest variability across states, but it does not outperform the VAR model in forecast ability, although it is a close call. That is, if a researcher wants to use a common methodology to forecast, then either the VAR, the factor-augmented VAR, or the spatial BVAR ($w = 0.3$, $d = 0.5$) are reasonable choices.

The findings provide mixed evidence on the role of macroeconomic fundamentals in improving the forecasting performance of time-series models. For 13 states, models that include the information of macroeconomic fundamentals improve the forecasting performance, but for seven states they do not.

## Appendix

### Table A1. Variables

| Data Code | Variable Name | Format |
|---|---|---|
| a0m052 | PERSONAL INCOME (AR, BILL. CHAIN 2000 $) | 5 |
| A0M051 | PERSONAL INCOME LESS TRANSFER PAYMENTS (AR, BILL. CHAIN 2000 $) | 5 |
| A0M224_R | REAL CONSUMPTION (AC) A0M224/GMDC | 5 |
| A0M057 | MANUFACTURING AND TRADE SALES (MIL. CHAIN 1996 $) | 5 |
| A0M059 | SALES OF RETAIL STORES (MIL. CHAIN 2000 $) | 5 |
| IPS10 | INDUSTRIAL PRODUCTION INDEX – TOTAL INDEX | 5 |
| IPS11 | INDUSTRIAL PRODUCTION INDEX – PRODUCTS, TOTAL | 5 |
| IPS299 | INDUSTRIAL PRODUCTION INDEX – FINAL PRODUCTS | 5 |
| IPS12 | INDUSTRIAL PRODUCTION INDEX – CONSUMER GOODS | 5 |
| IPS13 | INDUSTRIAL PRODUCTION INDEX – DURABLE CONSUMER GOODS | 5 |
| IPS18 | INDUSTRIAL PRODUCTION INDEX – NONDURABLE CONSUMER GOODS | 5 |
| IPS25 | INDUSTRIAL PRODUCTION INDEX – BUSINESS EQUIPMENT | 5 |
| IPS32 | INDUSTRIAL PRODUCTION INDEX – MATERIALS | 5 |
| IPS34 | INDUSTRIAL PRODUCTION INDEX – DURABLE GOODS MATERIALS | 5 |
| IPS38 | INDUSTRIAL PRODUCTION INDEX – NONDURABLE GOODS MATERIALS | 5 |
| IPS43 | INDUSTRIAL PRODUCTION INDEX – MANUFACTURING (SIC) | 5 |
| IPS307 | INDUSTRIAL PRODUCTION INDEX – RESIDENTIAL UTILITIES | 5 |
| IPS306 | INDUSTRIAL PRODUCTION INDEX – FUELS | 5 |
| IPDM | INDUSTRIAL PRODUCTION: DURABLE MANUFACTURING (NAICS) | 5 |
| IPNDM | INDUSTRIAL PRODUCTION: NONDURABLE MANUFACTURING (NAICS) | 5 |
| IPM | INDUSTRIAL PRODUCTION: MINING | 5 |
| IPGEU | INDUSTRIAL PRODUCTION: ELECTRIC AND GAS UTILITIES | 5 |
| PMP | NAPM PRODUCTION INDEX (PERCENT) | 1 |
| A0m082 | CAPACITY UTILIZATION (MFG) | 2 |
| LHEL | INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS (1967 = 100; SA) | 2 |
| LHELX | EMPLOYMENT: RATIO; HELP-WANTED ADS: NO. UNEMPLOYED CLF | 2 |
| LHEM | CIVILIAN LABOR FORCE: EMPLOYED, TOTAL (THOUS., SA) | 5 |
| LHNAG | CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC. INDUSTRIES (THOUS., SA) | 5 |
| LHUR | UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%, SA) | 2 |
| LHU680 | UNEMPLOY. BY DURATION: AVERAGE (MEAN) DURATION IN WEEKS (SA) | 2 |

**Table A1. Variables (continued)**

| Data Code | Variable Name | Format |
|---|---|---|
| LHU5 | UNEMPLOY. BY DURATION: PERSONS UNEMPL. LESS THAN 5 WKS (THOUS., SA) | 5 |
| LHU14 | UNEMPLOY. BY DURATION: PERSONS UNEMPL. 5 TO 14 WKS (THOUS., SA) | 5 |
| LHU15 | UNEMPLOY. BY DURATION: PERSONS UNEMPL. 15 WKS + (THOUS., SA) | 5 |
| LHU26 | UNEMPLOY. BY DURATION: PERSONS UNEMPL. 15 TO 26 WKS (THOUS., SA) | 5 |
| LHU27 | UNEMPLOY. BY DURATION: PERSONS UNEMPL. 27 WKS + (THOUS, SA) | 5 |
| A0M005 | AVERAGE WEEKLY INITIAL CLAIMS, UNEMPLOYMENT INSURANCE (THOUS.) | 5 |
| CES002 | EMPLOYEES ON NONFARM PAYROLLS – TOTAL PRIVATE | 5 |
| CES003 | EMPLOYEES ON NONFARM PAYROLLS – GOODS-PRODUCING | 5 |
| CES006 | EMPLOYEES ON NONFARM PAYROLLS – MINING | 5 |
| CES017 | EMPLOYEES ON NONFARM PAYROLLS – DURABLE GOODS | 5 |
| CES033 | EMPLOYEES ON NONFARM PAYROLLS – NONDURABLE GOODS | 5 |
| CES046 | EMPLOYEES ON NONFARM PAYROLLS – SERVICE-PROVIDING | 5 |
| CES049 | EMPLOYEES ON NONFARM PAYROLLS – WHOLESALE TRADE | 5 |
| CES053 | EMPLOYEES ON NONFARM PAYROLLS – RETAIL TRADE | 5 |
| CES140 | EMPLOYEES ON NONFARM PAYROLLS – GOVERNMENT | 5 |
| CESNRM | ALL EMPLOYEES: NATURAL RESOURCES & MINING | 5 |
| CEML | MINING & LOGGING EMPLOYMENT | 5 |
| CEC | CONSTRUCTION EMPLOYMENT | 5 |
| CEM | MANUFACTURING EMPLOYMENT | 5 |
| CETTU | TRADE, TRANS. & UTIL. EMPLOYMENT | 5 |
| CEFA | FINANCIAL ACTIVITIES EMPLOYMENT | 5 |
| CEPBS | PROF & BUS. SERV. EMPLOYMENT | 5 |
| CELH | LEISURE & HOSPITALITY EMPLOYMENT | 5 |
| CEOS | OTHER SERVICES EMPLOYMENT | 5 |
| CES151 | AVERAGE WEEKLY HOURS: MANUFACTURING | 1 |
| CES155 | AVERAGE WEEKLY HOURS: OVERTIME: MANUFACTURING | 2 |
| PMEMP | NAPM EMPLOYMENT INDEX (PERCENT) | 1 |
| HSFR | HOUSING STARTS: TOTAL (THOUS. U.S.A.) | 4 |
| HSNE | HOUSING STARTS: NORTHEAST (THOUS. U.S.A.) | 4 |
| HSMW | HOUSING STARTS: MIDWEST (THOUS. U.S.A.) | 4 |
| HSSOU | HOUSING STARTS: SOUTH (THOUS. U.S.A.) | 4 |
| HSWST | HOUSING STARTS: WEST (THOUS. U.S.A.) | 4 |
| HSBR | HOUSING AUTHORIZED: TOTAL NEW PRIV HOUSING UNITS (THOUS., SAAR) | 4 |
| HSBNE | HOUSES AUTHORIZED BY BUILD. PERMITS: NORTHEAST (THOU. U.S.A.) | 4 |
| HSBMW | HOUSES AUTHORIZED BY BUILD. PERMITS: MIDWEST (THOU. U.S.A.) | 4 |
| HSBSOU | HOUSES AUTHORIZED BY BUILD. PERMITS: SOUTH (THOU. U.S.A.) | 4 |
| HSBWST | HOUSES AUTHORIZED BY BUILD. PERMITS: WEST (THOU. U.S.A.) | 4 |
| HPNE | REAL HOUSE PRICE NORTHEAST | 6 |
| HPMW | REAL HOUSE PRICE MIDWEST | 6 |
| HPS | REAL HOUSE PRICE SOUTH | 6 |

**Table A1. Variables (continued)**

| Data Code | Variable Name | Format |
|---|---|---|
| HPW | REAL HOUSE PRICE WEST | 6 |
| HPUS | REAL HOUSE PRICE US | 6 |
| SNE | HOME SALES NORTHEAST | 6 |
| SMW | HOME SALES MIDWEST | 6 |
| SS | HOME SALES SOUTH | 6 |
| SW | HOME SALES WEST | 6 |
| SUS | HOME SALES US | 6 |
| HMOB | MOBILE HOMES: MANUFACTURERS' SHIPMENTS (THOUS. OF UNITS, SAAR) | 4 |
| PMI | PURCHASING MANAGERS' INDEX (SA) | 1 |
| PMNO | NAPM NEW ORDERS INDEX (PERCENT) | 1 |
| PMDEL | NAPM VENDOR DELIVERIES INDEX (PERCENT) | 1 |
| PMNV | NAPM INVENTORIES INDEX (PERCENT) | 1 |
| A0M008 | MFRS' NEW ORDERS, CONSUMER GOODS AND MATERIALS (BILL. CHAIN 1982 $) | 5 |
| A0M007 | MFRS' NEW ORDERS, DURABLE GOODS INDUSTRIES (BILL. CHAIN 2000 $) | 5 |
| A0M027 | MFRS' NEW ORDERS, NONDEFENSE CAPITAL GOODS (MIL. CHAIN 1982 $) | 5 |
| A1M092 | MFRS' UNFILLED ORDERS, DURABLE GOODS INDUS. (BILL. CHAIN 2000 $) | 5 |
| A0M070 | MANUFACTURING AND TRADE INVENTORIES (BILL. CHAIN 2000 $) | 5 |
| A0M077 | RATIO, MFG. AND TRADE INVENTORIES TO SALES (BASED ON CHAIN 2000 $) | 2 |
| FM1 | MONEY STOCK: M1 (CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP) (BIL$, SA) | 6 |
| FM2 | MONEY STOCK: M2 (M1 + O'NITE RPS, EURO$, G/P&B/D MMMFS&SAV&SM TIME DEP (BIL$, | 6 |
| FM3 | MONEY STOCK: MZM (BIL$, SA) | 6 |
| FM2DQ | MONEY SUPPLY − M2 IN 2005 DOLLARS (BCI) | 5 |
| FMFBA | MONETARY BASE, ADJ FOR RESERVE REQUIREMENT CHANGES (MIL$, SA) | 6 |
| FMRRA | DEPOSITORY INST RESERVES: TOTAL, ADJ FOR RESERVE REQ CHGS (MIL$, SA) | 6 |
| FMRNBA | DEPOSITORY INST RESERVES: NONBORROWED, ADJ RES REQ CHGS (MIL$, SA) | 6 |
| FCLNQ | COMMERCIAL & INDUSTRIAL LOANS OUSTANDING IN 1996 DOLLARS (BCI) | 6 |
| FCLBMC | NET CHANGE IN BUSINESS LOANS | 1 |
| CCINRV | CONSUMER CREDIT OUTSTANDING − NONREVOLVING (G19) | 6 |
| A0M095 | RATIO, CONSUMER INSTALLMENT CREDIT TO PERSONAL INCOME (PCT.) | 2 |
| FSPCOM | S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941–43 = 10) | 5 |
| FSPIN | S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941–43 = 10) | 5 |
| FSDXP | S&P'S COMPOSITE COMMON STOCK: PRICE-DIVIDEND RATIO (%NSA) | 5 |
| FSPXE | S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%NSA) | 5 |
| FYFF | INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM, NSA) | 2 |
| CP90 | COMMERCIAL PAPER RATE (AC) | 2 |
| FYGM3 | INTEREST RATE: U.S. TREASURY BILLS, SEC MKT, 3-MO. (% PER ANN, NSA) | 2 |

**Table A1. Variables (continued)**

| Data Code | Variable Name | Format |
|---|---|---|
| FYGM6 | INTEREST RATE: U.S. TREASURY BILLS, SEC MKT, 6-MO. (% PER ANN, NSA) | 2 |
| FYGT1 | INTEREST RATE: U.S. TREASURY CONST MATURITIES, 1-YR. (% PER ANN, NSA) | 2 |
| FYGT5 | INTEREST RATE: U.S. TREASURY CONST MATURITIES, 5-YR. (% PER ANN, NSA) | 2 |
| FYGT10 | INTEREST RATE: U.S. TREASURY CONST MATURITIES, 10-YR. (% PER ANN, NSA) | 2 |
| FYAAAC | BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM) | 2 |
| FYBAAC | BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM) | 2 |
| scp90 | CP90-FYFF | 1 |
| sfygm3 | FYGM3-FYFF | 1 |
| sFYGM6 | FYGM6-FYFF | 1 |
| sFYGT1 | FYGT1-FYFF | 1 |
| sFYGT5 | FYGT5-FYFF | 1 |
| sFYGT10 | FYGT10-FYFF | 1 |
| sFYAAAC | FYAAAC-FYFF | 1 |
| sFYBAAC | FYBAAC-FYFF | 1 |
| EXRUS | UNITED STATES; EFFECTIVE EXCHANGE RATE (MERM) (INDEX NO.) | 5 |
| EXRSW | FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$) | 5 |
| EXRJAN | FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$) | 5 |
| EXRUK | FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND) | 5 |
| EXRCAN | FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$) | 5 |
| PWFSA | PRODUCER PRICE INDEX: FINISHED GOODS (82 = 100, SA) | 6 |
| PWFCSA | PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS (82 = 100, SA) | 6 |
| PWIMSA | PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS (82 = 100, SA) | 6 |
| PWCMSA | PRODUCER PRICE INDEX:CRUDE MATERIALS (82 = 100, SA) | 6 |
| PSCCOM | SPOT MARKET PRICE INDEX:BLS & CRB: ALL COMMODITIES (1967 = 100) | 6 |
| NFS | NON-FERROUS SCRAP (1982 = 100) | 6 |
| PMCP | NAPM COMMODITY PRICES INDEX (PERCENT) | 1 |
| PUNEW | CPI-U: ALL ITEMS (82–84 = 100, SA) | 6 |
| PU83 | CPI-U: APPAREL & UPKEEP (82–84 = 100, SA) | 6 |
| PU84 | CPI-U: TRANSPORTATION (82–84 = 100, SA) | 6 |
| PU85 | CPI-U: MEDICAL CARE (82–84 = 100, SA) | 6 |
| PUC | CPI-U: COMMODITIES (82–84 = 100, SA) | 6 |
| PUCD | CPI-U: DURABLES (82–84 = 100, SA) | 6 |
| PUS | CPI-U: SERVICES (82–84 = 100, SA) | 6 |
| PUXF | CPI-U: ALL ITEMS LESS FOOD (82–84 = 100, SA) | 6 |
| PUXHS | CPI-U: ALL ITEMS LESS SHELTER (82–84 = 100, SA) | 6 |
| PUXM | CPI-U: ALL ITEMS LESS MIDICAL CARE (82–84 = 100, SA) | 6 |
| PUE | CPI-U: ALL ITEMS LESS ENERGY (82–84 = 100, SA) | 6 |
| GMDC | PCE, IMPL PR DEFL:PCE (1987 = 100) | 6 |
| GMDCD | PCE, IMPL PR DEFL:PCE; DURABLES (1987 = 100) | 6 |
| GMDCN | PCE, IMPL PR DEFL:PCE; NONDURABLES (1996 = 100) | 6 |

### Table A1. Variables (continued)

| Data Code | Variable Name | Format |
|---|---|---|
| GMDCS | PCE, IMPL PR DEFL:PCE; SERVICES (1987 = 100) | 6 |
| CES275 | AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NO | 6 |
| CES277 | AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NO | 6 |
| CES278 | AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NO | 6 |
| HHSNTN | U. OF MICH. INDEX OF CONSUMER EXPECTATIONS (BCD-83) | 2 |

Notes: For BVAR models: 1, 2 = No transformation; 4, 5 and 6 = Log(data) × 100; For FAVAR models: 1 = No transformation; 2 = First-difference of data; 4 = Log(data) × 100; 5. 6: Growth rate of data in percentage. We collected the data as monthly series and converted to quarterly data through temporal aggregation (flow variables) or systematic sampling of the third month (stock variables).

### Endnotes

1 The results for all 50 states are available on request from the authors. Where relevant, the findings for all 50 states are reported as a counterpoint to the results reported in this paper for the 20 largest states.

2 Housing experts in the United Kingdom found a ''ripple'' effect of house prices that begins in the Southeast U.K. and proceeds toward the Northwest. Meen (1999) outlines four different theories to justify the ripple effect: migration, equity conversion, spatial arbitrage, and exogenous shocks with different timing of spatial effects. The migration explanation requires that households move from one metropolitan area to another to take advantage of regional house price differences. The equity conversion explanation requires that residents of one region sell their home and move to a lower cost region where they can buy a similar quality home for a lower price and pocket the residual equity. The spatial arbitrage explanation means that investors acquire properties in lower priced regions, where higher anticipated return on housing investment exists. The exogenous shocks explanation implies that if the determinants of house prices in different regions experience a correlated movement, then house prices will also exhibit the same correlated movement. The ripple effect receives little support in the U.S. For example, most analyses relate to a given geographic housing market, such as a metropolitan area (Tirtiroglu, 1992; Clapp and Tirtiroglu, 1994; and Gupta and Miller, forthcoming b). More recent evidence across census regions also exists, which may reflect the fourth of Meen's explanations (Pollakowski and Ray, 1997; Meen, 2002). Gupta and Miller (forthcoming a) find evidence of a ripple effect from Los Angeles to Las Vegas and from Las Vegas to Phoenix, which they attribute to the first three of Meen's (1999) rationalizations.

3 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 better forecasts.

[4] Note that Dua and Smyth (1995), Dua and Miller (1996), and Dua, Miller, and Smyth (1999) used coincident and leading indexes in BVAR models to forecast home sales for the Connecticut and the overall U.S. economy, respectively. Coincident and leading indexes incorporate information from component series, using the procedures established by the Department of Commerce and described in U.S. Department of Commerce (1977, 1984) and in Niemira and Klein (1994).

[5] The discussion in this section relies heavily on LeSage (1999), Gupta and Sichei (2006), Gupta (2006), Gupta and Miller (forthcoming a; forthcoming b), and Das, Gupta, R. and Kabundi (2010).

[6] That is, $A(L) = A_1L + A_2L^2 + \ldots + A_pL^p$.

[7] The Minnesota prior assumes that variables approximate a unit-root process and sets the expected value of the first own lag equal to one. Alternatively, for data that exhibit mean reversion, assume that the expected value of the first own lag equals zero (Banbura, Giannone, and Reichlin, 2010).

[8] For an illustration, see Dua and Ray (1995).

[9] The analysis of the 50 states uses 201 quarterly series, house prices in the 50 states, as well as 151 macroeconomic variables.

[10] Higher and lower interaction values were also examined, in comparison to those specified above, using the star variables in both the star and circle equations. The rank ordering of the alternative forecasts remained the same.

[11] An earlier version of this paper used 308 quarterly macroeconomic variables to forecast real house prices of the 20 states. The data, however, only ran until 2003:Q4, and hence did not include the recent crisis. Thus, one referee suggested that the sample include the crisis (i.e., through 2009:Q1). The number of variables in the data set was also reduced. Interestingly, for the forecasting exercise, the results based on the larger data set proved similar to those in the current paper. These results are available from the authors.

[12] The data were collected as monthly series and converted to quarterly data through temporal aggregation (flow variables) or systematic sampling, where the third month value is used as the corresponding quarterly data (stock variables).

[13] For this, the algorithm in the Econometric Toolbox of MATLAB, version R2009a, was used.

[14] Note that if $A_{t+n}$ denotes the actual value of a specific variable in period $t + n$ and ${}_tF_{t+n}$ equals the forecast made in period $t$ for $t + n$, the RMSE statistic equals the following: $\sqrt{[\sum_1^N({}_tF_{t+n} - A_{t+n})^2/N]}$, where $N$ equals the number of forecasts.

[15] The story changes slightly the results for the 50-state analysis are examined. Now, the spatial factor-augmented BVAR models prove the steadiest with the lowest average and standard deviation across all 50 states. None of the models, however, outperforms the VAR benchmark model on average across the 50 states. The spatial large-scale BVAR model still proves the worst performing model with much higher averages and standard deviations across the 50 states. The FAVAR and spatial BVAR models perform a little worse than the spatial factor-augmented BVAR models.

[16] The findings for the 50-state analysis are as follows. For six states—Alabama, Kansas, North Carolina, North Dakota, Oklahoma, and Wyoming—the VAR model does that best in forecasting. Excluding these six states, the spatial factor-augmented BVAR models perform the best in 18 states. Then the spatial BVAR model performs the best in 12 states. The spatial large-scale model performs the best in eight states. Finally, the FAVAR model performs the best in six states. Compared to the findings for the 20-state analysis, the ranking of the models in terms of best performance does not change. The FAVAR models, however, do on average perform better in the 50-state analysis.

[17] Note that the model selection relies on the forecasting performance of the various models in the out-of-sample forecasts over the 1995:Q1 to 2009:Q1 period based on in-sample estimates for 1976:Q1 to 1994:Q4.

[18] One referee asked whether the data appear in a timely fashion so that the information and forecasts can be updated before the forecast period arrives. Two points need to be considered on this issue. First, Freddie Mac releases the house price index data at the end of the second month into the next quarter. For example, the data for the fourth quarter of 2010 were released on February 28, 2011. Thus, a two-month delay exists in the release of the house price index data. Second, all 151 data series on national and regional macroeconomic variables appear monthly, where we convert the data to quarterly frequency. Most monthly data appear with a two-month lag. In sum, the data needed to carry out the forecast exercise should appear with a three month, one quarter lead on the house price index that the model forecasts. Here, a pseudo out-of-sample forecasting exercise is discussed that assumes that all data are available at the end of every in-sample, as is done in the forecasting literature. The recent research, however, now incorporates actual real-time forecasting by accounting for dates of data releases. This literature, called ''nowcasting,'' is gaining prominence (see Giannone, Reichlin, and Small, 2008).

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