Using Large Data Sets to Forecast Sectoral Employment

Rangan Gupta*
Department of Economics
University of Pretoria
Pretoria, 0002, SOUTH AFRICA

Alain Kabundi
Department of Economics and Econometrics
University of Johannesburg
Johannesburg, 2006, SOUTH AFRICA

Stephen M. Miller
Department of Economics,
University of Nevada, Las Vegas
Las Vegas, Nevada, 89154-6005 USA

Josine Uwilingiye
Department of Economics and Econometrics
University of Johannesburg
Johannesburg, 2006, SOUTH AFRICA

Abstract

We use several models using classical and Bayesian methods to forecast employment for eight sectors of the US economy. In addition to using standard vector-autoregressive and Bayesian vector autoregressive models, we also augment these models to include the information content of 143 additional monthly series in some models. Several approaches exist for incorporating information from a large number of series. We consider two multivariate approaches – extracting common factors (principal components) and Bayesian shrinkage. After extracting the common factors, we use Bayesian factor-augmented vector autoregressive and vector error-correction models, as well as Bayesian shrinkage in a large-scale Bayesian vector autoregressive models. For an in-sample period of January 1972 to December 1989 and an out-of-sample period of January 1990 to March 2010, we compare the forecast performance of the alternative models. More specifically, we perform *ex-post* and *ex-ante* out-of-sample forecasts from January 1990 through March 2009 and from April 2009 through March 2010, respectively. We find that factor augmented models, especially error-correction versions, generally prove the best in out-of-sample forecast performance, implying that in addition to macroeconomic variables, incorporating long-run relationships along with short-run dynamics play an important role in forecasting employment. Forecast combination models, however, based on the simple average forecasts of the various models used, outperform the best performing individual models for six of the eight sectoral employment series.

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* *Corresponding author*

1. Introduction

Unlike the standard post-WWII recession, analysts called the recoveries from recession in the early 1990s and 2000s "jobless" recoveries. Most analysts also predict a jobless recovery from the recent Great Recession. Pundits argue that the midterm election results of 2010 depended in great measure on the state of the national and local economies, the lack of employment growth, and the stubbornly high unemployment rate. Macroeconomists debate whether the Great Recession largely reflects insufficient aggregate demand or structural issues. Simplifying, we can argue that if the problem largely reflects insufficient aggregate demand, then different sectors of the economy will experience similar difficulties. But, if the problem contains important structural problems, then different sectors will experience different difficulties.

The most recent Great Recession did affect employment in sectors differently. More specifically, the largest percentage employment loss from peak to trough occurred in the construction sector with a loss of 27.7 percent or 2.14 million jobs and the smallest percentage loss occurred in the leisure and hospitality sector with a loss of 4.1 percent or 551 thousand jobs. Thus, monitoring employment movements across sectors provides an important way to measure differences in macroeconomic effects across these sectors. Rapach and Strauss (2008) note "forecasting employment growth has received little attention ... relative to such macroeconomic stalwarts as inflation, GDP growth, and the unemployment rate." (p. 75). But, forecasting total employment, which Rapach and Strauss (2008, 2010) do, may hide potentially important differences as some sectors expand and others contract in response to technological change, shifts in demand, and so on. We go one step further and argue that forecasting employment at the sectoral level needs more attention.

When forecasting macroeconomic variables such as employment, researchers may improve their forecasts by using other macroeconomic variables such as industrial production, personal income, manufacturers' orders, initial claims for unemployment insurance, building starts, and so on as they may provide leading information about the future movements in the macroeconomy. Several approaches to variable selection exist. One approach uses economic theory and the intuitive, subjective judgment of the researcher to select the variables used in the forecasting exercise. A second approach, an agnostic view, collects a large set of variables that can potentially improve the forecasting performance and lets the data speak for themselves. We adopt this second approach and gather a large dataset of 143 variables plus the eight sectoral employment series.[1]

In sum, this paper considers the ability of different time-series models to forecast sectoral employment. Our main focus considers how the researcher can use large datasets to forecast, using factor analysis or Bayesian shrinkage of the parameter estimates in large-scale vector autoregressive (VAR) models. We consider employment from eight sectors -- mining and logging; construction; manufacturing; trade, transportation, and utilities; financial activities; professional and business services; leisure and hospitality; and other services.

More specifically, we compare the out-of-sample forecasting performance of various time-series models – autoregressive (AR), vector AR (VAR), Bayesian AR (BAR), Bayesian VAR (BVAR), vector error-correction (VEC), Bayesian VEC (BVEC), Bayesian factor-augmented AR (BFAAR), Bayesian factor augmented VAR (BFAVAR), Bayesian factor augmented VEC (BFAVEC), and medium-scale and large-scale BVAR (MBVAR and LBVAR) models, as well as combination forecasts of the simple average across all the individual forecasting models. Ignoring the combination forecasts, a factor-augmented model performs the

[1] One referee suggests a third approach to select variables -- a statistical procedure using general-to-specific modeling. That is, one includes variables and their lags generally based on their in-sample significance or out-of-sample performance. Since we use as many as 143 predictors, this approach is difficult to implement in practice.

best in six of the eight employment series, using the average root-mean-squared-error (RMSE) criterion. The LBVAR models outperform the factor-augmented models for two employment series – construction, and professional and business services. Finally, the models that exclude the information from the large set of data generally come in a distant third in forecast performance and only prove the best forecasting models on a few occasions, implying that the macroeconomic fundamentals partly drive employment. Finally, the combination forecasts perform the best for six of the eight employment series. The exceptions include the BFAAR and BFAVEC models that provide the best forecasts for trade, transportation, and utilities, and other services employment, respectively.

We organize the rest of the paper as follows. Section 2 provides a brief review of the literature on using large datasets in forecasting models. Section 3 discusses the literature on forecasting employment. Section 4 specifies the various time-series models estimated and used for forecasting. Section 5 discusses the data and the results. Section 6 concludes.

2. Forecasting with Large Datasets

We consider a set of reduced-form multivariate time-series models in the forecasting exercise. Reduced-form models typically forecast better than structural models.[2] An important issue involves documenting whether additional information improves the forecasting performance over a simple univariate autoregressive or autoregressive-moving-average representation.

One approach uses an autoregressive distributed lag (ARDL) model (Stock and Watson 1999, 2003, 2004), also called a transfer-function model (Enders 2004, Ch. 5). That is, the researcher runs a transfer-function model, where the variable to forecast enters as an autoregressive process and one driver variable enters as a distributed lag. The researcher

[2] Some recent work suggests that a few DSGE models can out-perform reduced-form time-series models in out-of-sample forecasting. See Christofffel *et al.* (2010) and Gupta *et al.* (2011).

compares the baseline model, the pure autoregressive specification forecasts with the forecasts for the transfer-function (ARDL) specification. Researchers extend this further and repeat the process for a whole set of potential driver variables. Now, one can aggregate across the individual forecasts to generate a combined forecast. Combination forecasts range from simple means or medians to more complicated principal-components- or mean-square-forecast-error-weighted forecasts.

The VAR or VEC models do not impose exogeneity assumptions on the included predictor variables. Unlike the single-equation bivariate ARDL or transfer-function model, the VAR or VEC approaches assume that lagged values of each variable may provide valuable information in forecasting each endogenous variable. VAR and VEC models, however, come with their own issues such as over-parameterization, since the estimated number of parameters increases dramatically with additional variables or additional lags in the system. One solution to the over-parameterization problem extracts common factors from a large dataset, which then get added to much smaller VAR or VEC specifications (Bernanke, Boivin, and Eliazs 2005, Stock and Watson 2002a, 2005). Adding a few common factors from the large dataset to smaller VAR and VEC systems economizes on the number of new parameters to estimate.

Bayesian VAR (BVAR) or VEC (BVEC) models may overcome the over-parameterization problem by limiting the uncertainty in the prior distributions of all parameters in the system. Since the Bayesian approach can address the over-parameterization problem through Bayesian shrinkage, researchers can estimate BVAR or BVEC systems that include a large number of additional explanatory variables, obviating the need to extract common factors. Nothing prevents, however, the extraction of common factors (principal components) from the large set of macroeconomic variables to include in factor-augmented VAR (FAVAR) or VEC

(FAVEC) systems and imposing Bayesian priors, which we also do.

In this paper, we consider the multivariate reduced-form time-series models that incorporate the information from a large dataset using factor analysis and Bayesian shrinkage. These methods provide the natural extension of the VAR, VEC, BVAR, and BVEC models.

3. Forecasting Employment

As noted in the introduction, little work exists on forecasting national employment trends. Much forecasting of employment does exist, however, at the regional level. Regional economists use employment, since other macroeconomic indicators such as GDP or industrial production either do not exist at the regional level, do not provide sufficient disaggregation, or appear too infrequently. As a result, regional economists use employment trends by sector to help understand the growth of the regional economy.

Regional economists developed the ideas of economic base and shift-share analysis to track and predict regional growth, using employment data. The popularity of these analyses comes from the simplicity of execution and the easily accessible data to execute the analysis. Lane (1966) and Williamson (1975) provide some history and background on economic base analysis, whereas Stevens and Moore (1980) provide a critical review of shift-share analysis as a forecasting tool. Since these analyses do not consider structural issues, but instead rely on simple constructs from the employment data itself, we can consider the approaches as a rudimentary time-series forecasting technique.

In another related line of research, regional economists consider the relative advantages and disadvantages of forecasting regional economic activity, including employment, using time-series and structural models. Early efforts compare the forecasting performance of structural and autoregressive integrated moving average (ARIMA) models (Taylor 1982, Glennon, Lane, and

Johnson 1987).

More recently, a few economists consider the performance of different models in forecasting employment at the national level. For example, Stock and Watson (2002b) forecast eight monthly macroeconomic time-series variables, including nonagricultural employment, from 1970 through 1998. They use a larger dataset of 215 additional potential predictors, extracting principal components, to see if forecasting accuracy improves over simpler time-series models. They conclude that these new forecasts outperform univariate ARs, small VARs, and leading indicator models.

Rapach and Strauss (2008) forecast employment growth, using monthly seasonally adjusted civilian employment from the Conference Board dataset and an autoregressive distributed lag (ARDL) model framework, containing 30 determinants, to forecast national employment growth. Given the difficulty in determining *a priori* the particular variables that prove the most important in forecasting employment growth, the authors also use various methods to combine the individual ARDL model forecasts, which result in better forecasts of employment growth. The combining method based on principal components does the best, while those methods that rely on simple averaging, clusters, and discounted mean square forecast error also produce forecasts better than the individual ARDL without combining. In an earlier paper, Rapach and Strauss (2005) obtain similar results when forecasting the employment growth in Missouri, using an ARDL approach based on 22 regional and national predictors. They observe that combining methods based on Bayesian shrinkage techniques produce substantially more accurate out-of-sample forecasts than those from a benchmark AR model.

Rapach and Strauss (2010) forecast national employment growth, using the same dataset as in Rapach and Strauss (2008), by applying bootstrap aggregating (bagging) to a general-to-specific procedure based on a general dynamic linear regression model. When they compared bagging to the forecast combination approaches, the authors find bagging forecasts often deliver the lowest forecast errors. Further, the authors note that incorporating information from both bagging and combination forecasts (based on principal components) often leads to further gains in forecast accuracy.

More recently, Rapach and Strauss (2012) forecast state employment growth using several distinct econometric approaches, such as combinations of individual ARDL models, general-to-specific modeling coupled with bagging, and factor models. As in their earlier studies, the results show that these forecasting approaches consistently deliver sizable reductions in forecast errors relative to the benchmark AR model across states. Further, they observe forecasting improvements on amalgamating these approaches, especially during national business-cycle recessions.

Banbura *et al.*, (2010) show that a VAR model with Bayesian shrinkage, incorporating a large number of explanatory variables, often produces better forecasts for non-farm employment than those from small-scale VAR and FAVAR models.

Against this backdrop, our paper extends the above mentioned studies, in the sense that we use a variety of large-scale models that allow a wider possible set of fundamentals to affect the dynamic movement of employment. Note that the motivation to use a large dataset (143 explanatory variables), rather than 20 to 30 variables used as predictors in the ARDL model, received support since the models based on the large dataset almost always outperform medium-scale models that used 20 variables in forecasting employment.[3]

[3] See Subsection 5.2 for further details.

4. VAR, VEC, BVAR, BVEC, FAVAR, FAVEC, BFAVAR, BFAVEC, and LBVAR Specifications and Estimation[4]

4.1 VAR, VEC, BVAR, BVEC, and LBVAR:

Following Sims (1980), we can write an unrestricted VAR model 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*,[5] and ε equals an $(n \times 1)$ vector of error terms. In our case, we assume that ε is an *n*-dimensional Gaussian white-noise process with covariance matrix Ψ .

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 results in 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.

If non-stationary variables in a standard VAR model are cointegrated, then this generates a VEC model that incorporates the long-run information. While including short-run dynamic adjustment, the VEC model also incorporates the cointegration relationship so that it restricts the movement of endogenous variables to converge to their long-run relationships. The error correction term, gradually corrects through a series of partial short-run adjustments.

More explicitly, assume that Y_t includes *n* time-series variables integrated of order one,

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[4] The discussion in this section relies heavily on LeSage (1999), Gupta and Miller (2012a, 2012b), and Das *et al*., (2009).

[5] That is, *A(L)* = $A_1 L + A_2 L^2 + ... + A_p L^p$;

(i.e., *I(1)*).[6] The error-correction counterpart of the VAR model in equation (1) converts into a VEC model as follows:[7]

$$\Delta Y_t = \pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t, \quad (2)$$

where $\pi = -[I - \sum_{i=1}^{p} A_i]$ and $\Gamma_i = -\sum_{j=i+1}^{p} A_j$.

Litterman (1981), Doan *et al.*, (1984), Todd (1984), Litterman (1986), and Spencer (1993) use the Bayesian shrinkage for a VAR model to overcome the over-parameterization problem. Rather than eliminating lags or variables, the Bayesian shrinkage is tantamount to imposing inexact restrictions on the coefficients across different lag lengths, assuming that the coefficients of longer lags may more likely equal 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 proves the exception with a unitary mean. Finally, Litterman (1981) and the other authors impose 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:

$$\beta_i \sim N(1, \sigma_{\beta_i}^2) \text{ and } \beta_j \sim N(0, \sigma_{\beta_j}^2), \quad (3)$$

where β_i denotes 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 denotes any other

[6] See Lesage (1999) and references cited therein for further details regarding the non-stationary of most macroeconomic time series.

[7] See, Dickey *et al.* (1991) and Johansen (1995) for further technical details.

coefficient. In sum, the prior specification reduces to a random-walk with drift model for each variable, if we set all prior variances to zero. The prior variances, $\sigma^2_{\beta_i}$ and $\sigma^2_{\beta_j}$, specify uncertainty about the prior means, $\bar{\beta}_i$ = 1, and $\bar{\beta}_j$ = 0.

Doan *et al.*, (1984) propose a formula to generate prior 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 prior distribution imposed on variable *j* in equation *i* at lag *m*, for all *i*, *j* and *m*, equals $S_1(i, j, m)$, defined as follows:

$$S_1(i, j, m) = [w \times g(m) \times f(i, j)] \frac{\hat{\sigma}_i}{\hat{\sigma}_j}, \qquad (4)$$

where *f*(*i*, *j*) = *1*, if *i* = *j* and k_{ij} otherwise, with ($0 \le k_{ij} \le 1$), and $g(m) = m^{-d}$, with $d > 0$. $\hat{\sigma}_i$ equals the estimated standard error of the univariate autoregression for variable *i*. The ratio $\hat{\sigma}_i / \hat{\sigma}_j$ accounts for the different scale and variability of the data. 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 is a harmonic function (i.e., m^{-d}) with decay factor *d*, which tightens the prior at longer lags. The parameter *f*(*i*, *j*) governs the tightness of variable *j* in equation *i* relative to variable *i*.[8] Note that, following LeSage (1990), in the Bayesian versions of the VEC models, we impose no priors on the error-correction terms.

We also follow Banbura, Giannone, and Reichlin (2010) and set the value of the overall tightness parameter to obtain a desired average fit for the eight employment variables of interest

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[8] For an illustration, see Dua and Ray (1995). We use k_{ij} = 0.5.

in the in-sample period (1972:1 to 1989:12). We then retain the optimal value of *w(Fit)* (= 0.0230), with d =2.0, for the LBVAR model with 151 variables obtained in this fashion for the entire evaluation period. The values of w for the eight variable BVAR and one variable Bayesian Autoregressive (BAR) models, given d = 2, equal 0.2366 and 1.8250, respectively. While, the corresponding value of w for the BVEC with eight employment series equals 0.2419. In addition to these models, we also consider a medium-scale BVAR (MBVAR) model based on 20 macroeconomic variables, besides the 8 employment series. Note that the 20 variables chosen match those used by Banbura *et al.*, (2010) in their medium-scale BVAR, and are a subset of the 143 variables used in our large-scale models. The optimal value of *w(Fit)* equals 0.0681 for the MBVAR model. Specifically, for a desired *Fit* of 0.50, we choose w as follows:

$$w(Fit) = \arg\min_{w} \left| Fit - \frac{1}{8}\sum_{i=1}^{8} \frac{MSE_i^w}{MSE_i^0} \right|, \tag{5}$$

where $MSE_i^w = \sqrt{\frac{1}{T_0 - p - 1}\sum_{t=p}^{T_0-2}(y_{i,t+1|t}^w - y_{i,t+1})^2}$. That is, we evaluate the one-step-ahead mean squared error (MSE) using the training sample $t = 1, ..., T_0 -1$, where T_0 is the beginning of the *ex-post* out-of-sample period and p is the order of the VAR. The value MSE_i^0 is the MSE of variable i with the prior restriction imposed exactly (w=0).[9]

We estimate the BVAR models using Theil's (1971) mixed estimation technique. 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-

[9] In addition to using a *Fit* of 0.50, we also experiment with a *Fit* as the average relative MSE from an OLS-estimated VAR containing the eight sectoral employment variables, i.e., $Fit = \frac{1}{8}\sum_{i=1}^{8}\frac{MSE_i^{\infty}}{MSE_i^0}$, as well as a *Fit* value of 0.25. In both cases, the forecasting performances of the alternative Bayesian models deteriorate. These results are available upon request from the authors.

parameterization in the classical VAR models does not emerge as a concern in BVAR specifications, which compensates through the tightness of the prior.

4.2 FAVAR and BFAVAR:

We assume that our data conform to a factor structure and adopt a factor model. The factor model 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. Using the factor model, we extract a few factors from the large data set of national and regional variables of the US economy. These factors summarize information from the large dataset.

Suppose that Z_t equals a $n \times 1$ covariance stationary vector standardized to possess a mean zero and a variance equal to one, obtained from the original $n \times 1$ vector of *I(1)* variables Y_t. Under factor models, we write Z_t as the sum of two orthogonal components as follows:

$$Z_t = \Lambda f_t + \xi_t , \tag{6}$$

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 factor model, f_t and ξ_t are mutually orthogonal stationary processes, while, $\chi_t = \Lambda f_t$ is the common component.

Since common factors are latent, we must estimate them. This paper adopts the Stock and Watson (2002b) method, which employs the static principal component (PC) approach on Z_t [10].

The factor estimates, therefore, equal the first principal components of Z_t, (i.e., $\hat{f}_t = \hat{\Lambda}' Z_t$, where $\hat{\Lambda}$ equals the $n \times r$ matrix of the eigenvectors corresponding to the r largest eigenvalues

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[10] We can estimate factors using the generalized principal component approach as in Forni, Hallin, Lippi, and Reichlin (2005) or static factor based on principal component as in Stock and Watson (2002b). See Stock and Watson (2005) for a review literature on factor analysis.

of the sample covariance matrix $\hat{\Sigma}$).

We use Bai and Ng (2002) criterion to determine the number of stationary static factors. We, then, add three extracted factors to the 8-variable VAR model to create a factor-augmented VAR (FAVAR) model in the process. We choose the three common factors (principal components) from the dataset of 143 variables, since the fourth factor explains less that 5-percent of the total variation. We also choose three common factors from the medium-scale dataset of 20 predictors as well, since it covers all the sectors of the economy as the large data set does. Furthermore, we estimate idiosyncratic component (see below) with AR(*p*) processes as suggested by Boivin and Ng (2005).

For forecasting purposes, we use an 8-variable VAR augmented by extracted common factors using the Stock and Watson (2002a) approach. 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

$$\hat{Y}_{t+h} = \hat{\Phi}(L)Y_t + \hat{\Gamma}(L) f_t, \tag{7}$$

where h equals the forecasting horizon, $\hat{\Phi}(L)$ and $\hat{\Gamma}(L)$ equal lag polynomials, which we estimate with and without shrinkage. As Boivin and Ng (2005) clearly note, VAR models are special cases of equation (7). With known factors and the parameters, the FAVAR approach should produce smaller mean squared errors relative to VAR models. In practice, however, one does not observe the factors and we must estimate them. Moreover, the forecasting equation should reflect a correct specification. We consider the following specifications:

- MBFA(V)AR: Bayesian restrictions on lags of the employment in 1 (8) sector(s) and the three common factors (principal components) extracted from the medium-scale model of 20 predictors, based on the priors outlined above. The values of *w* obtained for the MBFAAR and MBFAVAR, given *d*=2, were 0.5710 and 0.2015, respectively; and

- BFA(V)AR: the FA(V)AR specification with Bayesian restrictions on lags of the employment in 1 (8) sector(s) and the three common factors (principal components) extracted from the large dataset of 143 variables, based on the priors outlined above. The values of *w* obtained for the BFAAR and BFAVAR, given *d*=2, were 0.4672 and 0.1699, respectively.

4.3 FAVEC and BFAVEC:

For the FAVEC models, we follow the procedure proposed by Banerjee and Marcellino (2009) and Banerjee, Marcellino, and Masten (2010).[11] We begin with a set of *n* $I(1)$ variables (Y_t). The unrestricted VAR model appears in equation (1) above. We can rewrite this equation in its error-correction and common-trend specifications, respectively, as follows::[12]

$$\Delta Y_t = \alpha\beta' Y_{t-1} + v_t \tag{8}$$

and

$$Y_t = \Psi F_t + u_t ,^{13} \tag{9}$$

where $A = \sum_{s=1}^{p} A_s - I_n = \underset{n\times n-r}{\alpha}\ \underset{n-r\times n}{\beta'}$,

$$v_t = \Gamma_1 \Delta Y_{t-1} + \ldots + \Gamma_{p-1}\Delta Y_{t-p+1} + \varepsilon_t ,\ \ \Gamma_i = -\sum_{s=i+1}^{p} A_s ,\ \ \Gamma = I - \sum_{i=1}^{p-1}\Gamma_i ,$$

[11] See these papers for more details on the model and the estimation.

[12] When we extract the common factors (principal components) for the MBFAVAR and BFAVAR models, we transform all variables to induce stationarity. Now, we transform all variables to induce non-stationarity. That is, for stationary variables, we accumulate to make them I(1). We also extract three common factors from the non-stationary variables, excluding the stationary variables. The findings prove similar to the three factors extracted when we accumulate the I(0) variables to make them I(1).

[13] Banerjee, Marcellino, and Masten (2010) note that to extract common factors F_t, one must standardized variables Y_t (mean zero, variance one).

$$\underset{n\times r}{\Psi} = \beta \perp (\alpha' \perp \Gamma\beta \perp)^{-1},\ \underset{r\times 1}{F_t} = \alpha' \perp \sum_{s=1}^{t} \varepsilon_s,\ \text{and}\ u_t = C(L)\varepsilon_t.$$

In these two specifications, β' denotes the $(n-r)\times n$ matrix of cointegrating vectors with rank $n-r$, where $n-r$ is the number of cointegrating vectors. Thus, r equals the number of $I(1)$ common stochastic trends or factors, $0 < r \le n$, contained in the $r\times 1$ vector F_t and the matrix $\alpha' \perp \Gamma\beta \perp$ is invertible, since each variable is $I(1)$. α denotes the loading matrix, which also exhibits reduced rank $n-r$ and determines how the cointegrating vectors enter into each individual element $Y_{i,t}$ of the $n\times 1$ vector Y_t[14]. u_t denotes an n-dimensional vector of stationary and, in general, moving average errors.

We can rewrite equation (9) in first differences as:

$$\Delta Y_t = \Psi \Delta F_t + \Delta u_t .\text{[15]} \tag{10}$$

Here, Δu_t and v_t can correlate over time and across variables.

The literature on cointegration focuses mainly on equation (8), also known as the VEC model, while Banerjee and Marcellino (2009) reconcile the factor analysis in equation (10) and the cointegration concept in equation (8). In other words, the error-correction model experiences practical difficulties (i.e., the curse of dimensionality) when faced with so many cointegrating vectors. Hence, if important information does not enter the VEC model, then the model results in biased coefficients caused by omitted variables. In this case, the FAVEC model improves on the standard VEC model. Banerjee, Marcellino, and Masten (2010) demonstrate that the information set in the FAVEC model improves the forecasting performance of models, especially at the longer horizon.

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[14] Note that as $n \to \infty$, and the number of factors r remains fixed, the number of cointegrating relations $n-r \to \infty$.

[15] Bai and Ng (2004) and Bai (2004) allow for the possibility that u_t or some elements of u_t are $I(1)$.

By including the error-correction terms in the FAVAR model, the FAVEC model enhances the former model, especially in the presence of cointegration. The FAVEC model naturally generalizes the FAVAR model developed by Bernanke, Boivin, and Eliazs (2005) and Stock and Watson (2005).

Assume that we only want to forecast a few variables in the entire economy. We, therefore, divide our panel into two parts, n^A including the variables of interest, Y_t^A and $n^B = n - n^A$ containing the remaining variables, Y_t^B. Equation (8) becomes:

$$\begin{pmatrix} Y_t^A \\ Y_t^B \end{pmatrix} = \begin{pmatrix} \Lambda^A \\ \Lambda^B \end{pmatrix} F_t + \begin{pmatrix} \xi_t^A \\ \xi_t^B \end{pmatrix} \tag{11}$$

where Λ^A is $n^A \times r$ matrix and Λ^B is $n^B \times r$. The dimension of Λ^A does not change as n increases while the dimension of Λ^B increases with n. Banerjee and Marcellino (2009) argue that to preserve a factor structure asymptotically, driven by r common factors, it is necessary that the rank of Λ^B, $r^B = r$, whereas the rank of Λ^A, $r^A \leq r$. That is, a smaller or equal number of trends drive Y_t^A. Assume from equation (11) that F_t are uncorrelated random walks and Y_t^A and F_t are cointegrated.

From the Granger representation theorem, there exists an error correction specification as follows:

$$\begin{pmatrix} \Delta Y_t^A \\ \Delta F_t \end{pmatrix} = \begin{pmatrix} \gamma^A \\ \gamma^B \end{pmatrix} \delta' \begin{pmatrix} Y_{t-1}^A \\ F_{t-1} \end{pmatrix} + \begin{pmatrix} \nu_t^A \\ \nu_t \end{pmatrix} \tag{12}$$

We can extend equation (12) by adding additional lags to account for correlation in the errors as follows:

$$\begin{pmatrix} \Delta Y_{t\ At}^A \\ \Delta F_t \end{pmatrix} = \begin{pmatrix} \gamma^A \\ \gamma^B \end{pmatrix} \delta' \begin{pmatrix} Y_{t-1}^A \\ F_{t-1} \end{pmatrix} + A_1 \begin{pmatrix} \Delta Y_{t-1}^A \\ \Delta F_{t-1} \end{pmatrix} + \cdots + A_q \begin{pmatrix} \Delta Y_{t-q}^A \\ \Delta F_{t-q} \end{pmatrix} + \begin{pmatrix} u_t^A \\ u_t \end{pmatrix} \tag{13}$$

where the errors $\left(u_t^{A}{}', u_t'\right)'$ are *i.i.d.* Equation (13) is a FAVEC model.

Banerjee and Marcellino (2009) show that n^A cointegrating relationships must exist in equation (13), given that equation (13) includes $n^A + r$ dependent variables and that Y_t^A is driven by F_t or a subset of F_t, and that elements of F_t are uncorrelated random walks.

Since Λ^A is $n^A \times r$, but can have a reduced rank of r^A, $n^A - r^A$ cointegrating relationships exist, including Y_t^A variables only. Banerjee and Marcellino (2009) demonstrate that this emerges from a standard VEC model. The remaining r^A cointegrating relationships involve Y_t^A and F_t.

Equation (13) improves on the factor and FAVAR models, if the data generating process displays a common trend, given that the error-correction terms do not appear in equation (7). That is, the FAVAR does not account for the long-run information and, hence, $\gamma^A = \gamma^B = 0$. The FAVAR model does not account for cointegration and, therefore, it is misspecified in the presence of long-run relationships. It follows that the FAVEC model nests the VEC, FAVAR, and VAR models and, hence, it more likely outperforms these other models in forecasting, since the trend and the information content in the data set matter.

- MBFAVEC: includes the employment in 8 sectors, three common static factor (principal component) extracted from 20 predictors, and the error-correction terms, with Bayesian restrictions on lags of the model based on the priors outlined above. The value of *w* for the MBFAVEC model, given *d*=2, equals 0.2138 ; and
- BFAVEC: Bayesian restrictions on lags of the model based on the priors outlined above, with the model including the employment in 8 sectors, three

common static factors (principal components) extracted from 143 predictors, and the error-correction terms. The value of *w* for the BFAVEC model, given *d*=2, equals 0.1782.

Note that even though the Bai (2004) approach suggests 4 static common factors for the large dataset, we use 3 factors, as for the FAVAR models. Using the cumulative variance share of common component, we find that that the fourth factor explains only 3 percent of the variation, which is less than our pre-specified cut-off limit of 5 percent.

5. Data Description, Model Estimation, and Results

5.1 Data

While the small-scale VARs, both the classical and Bayesian variants, only include employment data for the eight sectors, the large-scale BVAR and factor models also include the 143 monthly national and regional series. Besides, the large-scale BVAR and factor models, we also estimate medium-scale BVAR and factor models based on 20 variables, which is a subset of the variables included in the large dataset. Seasonally adjusted employment data come from the Bureau of Labor Statistics. For the remaining 143 seasonally adjusted national and regional variables, we collected the data from various sources such as the Conference Board, the Global Insight database, the FREDII database of the St. Louis Federal Reserve Bank, the US Census Bureau, and the National Association of Realtors.

We transformed all data to induce stationarity for the FAVAR-type models before extracting the three factors. We can use non-stationary data, however, with the BVAR. Sims *et al.* (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 exhibit mean-reversion, however, we set a white-noise prior (i.e., $\bar{\beta}_i$ = 0); otherwise, we impose the random walk prior (i.e., $\bar{\beta}_i$ = 1). Note that when considering the medium-scale or the large-scale BVAR models based on 28 or 151 variables, given that the system defined by equation (1) contains both *I(1)* and *I(0)* variables, we use the random-walk prior or white-noise prior accordingly. As for the BFAVEC (MBFAVEC) model based on 151 (28) variables, we begin with 115 (15) I(1) variables, not counting the eight employment series, and we then cumulate the remaining 28 (5) I(0) variables to transform them into non-stationary variables, before extracting the three (one) common factor(s). Appendix A lists these variables as well as the transformations used prior to analyzing the data. The italicized variables in Appendix A correspond to the ones used in the medium-scale BVAR and factor models.

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.

5.2 Estimation and Results

In this section, we first select the best model for forecasting each sector's employment, using the minimum average root mean squared error (RMSE) across the one-, two-, … , and twelve-month-ahead *ex-post* out-of-sample forecasts. Then, second, we consider *ex-ante* out-of-sample forecasts based on the best performing individual model and a forecast combination model.[16] Note that we consider 13 types of individual forecasting models. The *ex-post* forecasting exercise allows us to choose the best individual model to use for the *ex-ante* forecasting exercise. This particular individual model, in turn, also serves as a competing model to the forecast combination model when comparing *ex-ante* forecasts to the actual data. Forecasting, *ex-post* or *ex-ante*, without competing models is less informative.

The data sample for all eight employment series runs from January 1972 (1972:1) through March 2009 (2009:3). First, the cointegration tests amongst the eight employment series for the (B)VEC models as well as amongst the eight employment series and the one and three common static factors for the MBFAVEC and BFAVEC models, use data from 1972:1 through 1989:12. Further, this sample provides the base for estimating all of the various specifications considered for possible out-of-sample forecasting experiments. Second, the *ex-post* out-of-sample forecasting experiments cover 1990:1 through 2009:3. Third, we keep the number of factors extracted for the FAVAR and FAVEC models fixed over the forecasting period, but recursively update their estimates. Fourth, as each forecasting recursion also includes model selection, we choose the number of cointegrating vectors for the BVEC, MBFAVEC, and BFAVEC models by using the trace test proposed by Johansen (1991). Fifth, we base the lag-length for the various models at each recursive estimation on the unanimity of at least two of the following five lag length selection criteria: the sequential modified likelihood ratio (LR) test statistic (each test at the 5-percent level), the final prediction error (FPE), the Akaike information criterion (AIC), the Schwarz information criterion (SIC), and the Hannan-Quinn information

[16] *Ex-post* forecasts use actual values of the variables used in the forecasting equation to generate the forecasts whereas the *ex-ante* forecasts use forecasted values. The *ex-ante* forecasts give an objective statistical method (approach) to choose the best performing models, which, in turn, we use to predict the turning points.

criterion (HQIC).[17] Finally, for the large-scale BVAR, we use the lag-length chosen for the eight variable small-scale VAR containing only the eight sectoral employment series.

5.2.1 One- to Twelve-Month-Ahead Ex-Post Forecast Accuracy

Given the different forecasting models specified in Section 4, we estimate these alternative small- and large-scale models for the eight employment series in our sample over the period 1972:1 to 1989:12 using monthly data. We then compute *ex-post* out-of-sample one-, two-, …, and twelve-month-ahead forecasts for the period of 1990:1 to 2009:3, and compare the forecast accuracy relative to the forecasts generated by the benchmark random-walk (RW) with drift and estimated in levels. Note that the choice of the in-sample period, especially the starting date, depends on data availability. The starting point of this out-of-sample period precedes by a few months the recession in the 1990 and the jobless recovery that followed that recession as well as the recession in the 2001.

We estimate the RW and classical VAR models, the small-scale BAR, BVAR, and BVEC models, the medium-scale and large-scale BVAR models, and the Bayesian FA(V)AR and FAVEC models over the period 1972:1 to 1989:12, and then forecast from 1990:1 through 2009:3.[18] Depending on the number of lags selected, specific initial months feed the lags. We re-estimate the models each month over the *ex-post* out-of-sample forecast horizon in order to update the estimate of the coefficients, before producing the one-, two-, …, and twelve-month-

[17] After determining the in-sample lag length for the VEC- and FAVEC-type models, we apply the trace test of cointegration to the eight employment series, and the eight employment series and the three factors for the medium and large FAVEC models. The tests suggest 5, 8, and 8 cointegrating vectors, respectively, implying 3 common trends in all the cases. Note that, at each recursion, we choose the number of cointegrating vectors for the BVEC, MBFAVEC, and BFAVEC models by using the trace test. Hence, we update the number of cointegrating relations over the *ex-post* out-of-sample period. Interestingly, at the end of the out-of-sample period, we find that the number of cointegrating vectors falls to 3 in the BVEC model, while the number stays at 8 and 8, respectively, for the MBFAVEC and BFAVEC models. Note that the results for the MBFAVEC and BFAVEC are consistent with theory, since the number of factors (3) equals the number of common trends (= number of variables in the (M)BFAVEC less the number of cointegrating vectors). These results are available upon request from the authors.

[18] We also estimated in prior versions of this paper AR, VEC, FAAR, FAVAR, and FAVEC models. These models exhibited much worse performance than those reported it the text. Results are available from the authors.

ahead forecasts. We implement this iterative estimation and the forecast procedure for 219 months, with the first forecast beginning in 1990:1. This produced a total of 219 one-, 219 two-, …, and 219 twelve-month-ahead forecasts. We calculate the root mean squared errors (RMSE)[19] for the 219 one-, two-, …, and twelve-month-ahead forecasts for the eight employment series across all of the different specifications. We then examine the average of the RMSE statistic for one-, two-, …, and twelve-month-ahead forecasts over 1990:1 to 2009:3. We select the model that produces the lowest average RMSE values as the 'best' specification for a specific employment sector.

Tables 1 to 8 report the ratio of the one-, two-, …, and twelve-month-ahead RMSEs as well as the average across the 12 monthly RMSEs relative to the RMSE of the benchmark random-walk (RW) with drift model across the eight employment series, respectively. Thus, the 0.2250 average entry for the BFAVEC model in Table 1 means that the BFAVEC model experiences an average forecast RMSE across the 12-month horizon of only 22.50 percent of the forecast RMSE for the RW model (i.e., the average RMSE of the RW model equals 1.2287). First, we consider the best performing model, ignoring the combination forecast, based on the average RMSE across the one-, two-, …, and twelve-month-ahead forecasts. Three different specifications prove the best of our models across the eight employment series. One, the BFAVEC models with w=0.1782 and d=2 prove best for mining and logging; manufacturing; financial activities; leisure and hospitality; and other service employment. Two, the LBVAR models with w=0.0230 and d=2 prove best for construction; and professional and business services, and come in a close second to the BFAAR models with w= 0.4672 and d=2, which

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

proves best for forecasting trade, transportation, and utilities employment. Also, note that in general, large-scale models outperform the medium-scale models, thus vindicating our decision to use 143 predictors in forecasting sectoral employment. These results appear as the bold numbers in the Average column in Tables 1 to 8.

The forecasting results for the one-, two-, …, and twelve-month-ahead forecasts generally follow a similar pattern. The best performing individual models in forecasting the average across the 12-month horizon also produces the best performance for each individual month's forecast for five employment series – mining and logging; manufacturing; professional and business services; leisure and hospitality; and other services. For the remaining employment series, construction sees one additional individual model and in trade, transportation and utilities and financial activities see two additional individual models show the best performance on a month-by-month basis along with the model that proves best at forecasting the average across the entire 12-month forecasting horizon.[20]

Tables 1 to 8 report in their last row the findings for the combination forecasts. The average forecast performs the best for five employment sectors – mining and logging, manufacturing, financial activities, professional and business services, and leisure and

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[20] As a robustness check, we estimate the BFAAR, BFAVAR, and LBVAR models using the first-differenced employment series (which, in our case, amounts to forecasting growth rates of employment, since the employment series are in logarithms). We then recover the (log-)level forecasts of the data using the actual observation of the period before the starting point of the recursive out-of-sample forecast period. We observe that the forecast performance of the BFAAR model (for the log-level of employment) improves in seven out of the eight cases (the manufacturing forecasts worsen). For the BFAVAR model, forecast performances improve for construction; trade, transportation, and utilities; and professional and business services. For the LBVAR model, the improvements only occur for professional and business services; and leisure and hospitality. As with the Bayesian models for forecasting the levels of employment, we forecast the first-differences (growth rates) of employment with the tightness of the prior based on an in-sample fit of 50 percent. Importantly, however, our general conclusions do not change. In other words, the improved performances of these models do not make them the preferred models for cases where they were non-optimal. One exception does occur. To wit, now the BFAAR model does the best at the margin for construction employment instead of the LBVAR model. This result highlights the importance of modeling the long-run relationships over and above differencing the data (which is also done for the BFAVECM before recovering the log-level forecasts) to provide more robust results in the presence of structural breaks (Carriero *et al.*, 2011). The details of these results are available upon request from the authors.

hospitality. When the combination forecast performs the best in forecasting the average across the 12-monthly forecasting horizons, it also performs the best in every month, except for manufacturing employment.

Table 9 also tests whether the difference in forecasting performance proves significant relative to the RW forecasts, using the Giacomini and White (2006) statistic. As indicated by Carriero et al., (2009), this test of equal forecasting accuracy can handle forecasts based on both nested and non-nested models, and also irrespective of the estimation procedures (classical or Bayesian) used for the derivation of the forecasts. The combination forecasts provide significantly better forecasts at the 1-percent level at all monthly horizon as well as the average for five employment series – mining and logging; construction; financial activities; professional and business services; and leisure and hospitality. The BFAAR and BFAVEC models provide significantly better forecasts than the combination forecasts for trade, transportation, and utilities; and other services employment. Finally, the combination forecast provides better forecasts than the BFAVEC for manufacturing employment except at months 9 and 10 where there is no significant difference.

In sum, a few different specifications yield the best forecast performance based on RMSEs for different employment series and at different forecast horizons. One common pattern does emerge, nevertheless. No matter the forecast horizon, models that include additional information, generally the set of 143 additional variables, perform the best.

5.2.2 Comparing One- to Twelve-Month-Ahead Ex-Ante Forecasts with the Actual Series

Figure 1 plots the *ex-ante* out-of-sample forecasts and actual values from April 2009 through March 2010, using the best forecasting model for each employment series (see Table 9 for models). We used the average RMSEs reported in Tables 1 to 8 to select the best models.[21] Note that since the BFAVEC performs the best in five of the eight employment series, we plot the *ex-ante* forecasts from this model, even for the cases where the LBVAR and BFAAR models prove best. In addition, we also plot the combination forecasts obtained based on the average forecasts from the 14 different (including the RW) models estimated.

The forecast period captures the preliminary turn around in employment for all series except financial activities in our sample. The worst forecast performance occurs in mining and logging employment, where the actual employment series bottomed in October 2009 while the forecast series (BFAVEC and Combination) continue on a downward trends throughout the forecast period. Note that the Combination forecast lies everywhere above the BFAVEC forecast series and the Combination forecast tracks the actual series well until the actual series begins its recovery.

The best forecast performance occurs for construction and professional and business services employment, where the actual and forecast series (BFAVEC and Combination) track each other closely. Note that the BVAR forecasts for construction and professional and business services employment perform poorly, where the forecast errors increase at an increasing rate as time goes forward. The forecast series for manufacturing, financial activities, and leisure and hospitality employment each show a turnaround in employment or slowdown in its decline over this period. But the forecast values for the BFAVEC models recover too rapidly as compared to the actual series. The Combination forecasts do a much better job of tracking the actual series. The forecasts for trade, transportation, and utilities show a good performance for the BFAVEC

[21] In addition to the *ex-ante* out-of-sample forecasting exercise over 2009:4 to 2010:3, we also analyze the in-sample (1972:1-1989:12) and *ex-post* out-of-sample (1990:1-2009:3) forecasts obtained from the best models for each of the eight employment series. The differences between the actual data and the predicted data for the in-sample are virtually inseparable, while the *ex-post* out-of-sample forecasts from the best models tend to predict the turning points quite well. We suppress these results to save space, but are available upon request from the authors.

model, while the combination forecast does poorly, trending down and away from the actual series. The BFAAR forecasts perform better than the combination forecasts. For the remaining series – other services employment, the actual series show a more rapid turnaround over this period than the forecast values. Note that the Combination forecast series performs the worst in this case when compared across all eight employment categories.

6. Conclusion

We forecast employment in eight sectors, using the AR, VAR, VEC, and their Bayesian counterparts, both with and without the information content of 20 or 143 additional monthly economic series. We examine two approaches for incorporating information from a large number of data series – extracting common factors (principal components) in a FAVAR, FAVEC, and their Bayesian counterparts or Bayesian shrinkage in MBVAR and LBVAR models. Finally, we consider combination forecasts that take the simple average of the forecasts from the individual models.

Using the period of 1972:1 to 1989:12 as the in-sample period and 1990:1 to 2009:3 as the *ex-post* out-of-sample horizon, we first compare the forecast performance of the alternative individual models and second combination forecasts for one- to twelve-month-ahead forecasts. Based on the average root mean squared error (RMSE) for the one-, two-, …, and twelve–month-ahead forecasts, we find that the factor-augmented models generally outperform the small- and large-scale VAR models for the eight employment series examined. LBVAR models only provide the best forecasting performance for two employment series – construction employment and professional and business services employment. In addition, amongst the factor augmented models, the BFAVEC models generally perform the best, highlighting the importance of modeling the long-run equilibrium relationship over and above the short-run dynamics. We note, however, the well-known sensitivity of the results of Bayesian models to the choice of the hyperparameters of the priors. Thus, we need to devise an “optimal” way of choosing the values of the hyperparameters to obtain appropriate shrinkage. Given this, we follow Banbura, Giannone, and Reichlin (2010) and set the hyperparameter that defines overall shrinkage to obtain a desired average fit for the eight employment variables of interest in the in-sample period for the models that incorporate more than just the employment series. Finally, when we compare the combination forecasts with the individual forecasts, the combination forecasts perform the best, except for manufacturing; trade, transportation, and utilities; and other services employment.

We also compare the *ex-ante* out-of-sample forecast and actual values of the employment series over April 2009 through March 2010 when all employment series, save one, show preliminary evidence of bottoming and starting to increase. The Combination forecasts generally perform the best. The LBVAR forecasts perform the worst. The BFAVEC models perform well in some cases and poorly in others. The worst performing model forecasts mining and logging employment while the best performing model forecasts construction; trade, transportation, and utilities; and professional and business services employment.

In sum, the utilization of a large dataset of economic variables, as well as long-run relationship with the short-run dynamics, improve the forecasting performance over models that do not use this data. In other words, macroeconomic fundamentals do matter when forecasting the eight employment series.

References:

Bai, J., (2004). Estimating Cross-Section Common Stochastic Trends in Nonstationary Panel Data, *Journal of Econometrics* 122, 137-183.

Bai, J., and Ng, S., (2002). Determining the Number of Factors in Approximate Factor Models. *Econometrica* 70, 191–221.

Bai, J., and Ng, S., (2004). A PANIC Attack on Unit Roots and Cointegration. *Econometrica* 72, 1127-1177.

Bańbura, M., Giannone, D., and Reichlin, L., (2010). Large Bayesian Vector Auto Regressions. *Journal of Applied Econometrics* 25, 71–92.

Banerjee, A., and Marcellino, M. G., (2009). Factor-Augmented Error Correction Models. In Castle , J. L., and Shephard, N. (eds.), *The Methodology and Practice of Econometrics - A Festschrift for David Hendry*. Oxford: Oxford University Press, 227-254.

Banerjee, A., Marcellino, M. G., and Maston, I., (2010). Forecasting with Factor-Augmented Error Correction Models. CEPR Discussion Paper No. DP7677.

Bhardwaj, G., and Swanson, N. R., (2006). An Empirical Investigation of the Usefulness of ARFIMA Models for Predicting Macroeconomic and Financial Time Series. *Journal of Econometrics* 131, 539-578.

Bernanke, B. S., Boivin, J., and Eliazs, P., (2005). Measuring the Effects of Monetary Policy: A Factor-Augmented Vector autoregressive (FAVAR) Approach, *The Quarterly Journal of Economics* 120, 387–422.

Boivin, J., and Ng, S., (2005). Understanding and comparing factor based forecasts. *International Journal of Central Banking* 1, 117-152.

Carriero, A., Kapetanios, G., and Marcellino, M. (2009). Forecasting exchange rates with a large Bayesian VAR. *International Journal of Forecasting 25*, 400-417.

Carriero, A., Kapetanios, G., and Marcellino, M., (2011). Forecasting large datasets with Bayesian reduced rank multivariate models. *Journal of Applied Econometrics 26*, 735–761.

Clark, T. E., and McCracken, M. W., (2001). Tests of Equal Forecast Accuracy and Encompassing for Nested Models. *Journal of Econometrics* 105, 85–110.

Das, S., Gupta, R., and Kabundi, A. (2009). Could We Have Forecasted the Recent Downturn in the South African Housing Market? *Journal of Housing Economics* 18, 325-335..

Christoffel, K., Coenen, G., and Warne, A., (2010). Forecasting with DSGE Models. European Central Bank, Working Paper No. 1185.

Doan, T. A., Litterman, R. B., and Sims, C. A., (1984). Forecasting and Conditional Projections Using Realistic Prior Distributions. *Econometric Reviews* 3, 1-100.

Dua, P., and Ray, S. C., (1995). A BVAR Model for the Connecticut Economy. *Journal of Forecasting* 14, 167-180.

Enders, W., (2004). *Applied Econometric Time Series*, 2nd Ed. John Wiley & Sons.

Forni, M., Hallin, M., Lippi, M., and Reichlin, L., (2005). The Generalized Dynamic Factor Model, One Sided Estimation and Forecasting. *Journal of the American Statistical Association* 100, 830–840.

Forni, M., Giannone, D., Lippi, M., and Reichlin, L., (2009). Opening the Black Box: Structural Factor Models versus Structural VARs. Econometric Theory 25, 1319-1347.

Giacomini, R., and White, H., (2006). Tests of conditional predictive ability. *Econometrica* 74, 1545–1578.

Glennon, D., Lane, J., and Johnson, S., (1987). Regional Econometric Models that Reflect Labor Market Relations. *International Journal of Forecasting* 3, 299-312.

Gupta, R., Kabundi, A., and Miller, S. M., (2011). Forecasting the US Real House Price Index: Structural and Non-Structural Models with and without Fundamentals. *Economic Modelling* 26, 2013-2021.

Gupta, R., and Miller, S. M., (2012a). 'Ripple Effects" and Forecasting Home Prices in Los Angeles, Las Vegas, and Phoenix. *Annals of Regional Science* 48, 763-782.

Gupta, R., and Miller, S. M., (2012b). The Time-Series Properties on Housing Prices: A Case Study of the Southern California Market. *Journal of Real Estate Finance and Economics* 44, 339-361.

Johansen, S., (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica* 59, 1551-1580.

Lane, T., (1966). The Urban Base Multiplier: An Evaluation of the State of the Art. *Land Economics* 42, 339-347.

LeSage, J. P., (1990). A Comparison of the Forecasting Ability of ECM and VAR Models, *Review of Economics and Statistics* 72, 664-671.

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, 25-38.

Newey, W. K., and West, K. D., (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55, 703-708.

Rapach, D. E., and Strauss, J. K., (2005). Forecasting Employment Growth in Missouri with Many Potentially Relevant Predictors: An Analysis of Forecast Combining Methods. Federal Reserve Bank of Saint Louis *Regional Economic Development* 1, 97-112.

Rapach, D. E., and Strauss, J. K., (2008). Forecasting US Employment Growth using Forecast Combining Methods. *Journal of Forecasting* 27, 75–93.

Rapach, D. E., and Strauss, J. K., (2010). Bagging or Combining (or Both)? An Analysis Based on Forecasting U.S. Employment Growth. *Econometric Reviews* 29, 511–533.

Rapach, D. E., and Strauss, J. K., (2012). Forecasting U.S. State-Level Employment Growth: An Amalgamation Approach. *International Journal of Forecasting* 28, 315-327.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica* 48, 1-48.

Sims, C. A., Stock, J. H., and Watson, M. W., (1990). Inference in Linear Time Series Models with Some Unit Roots. *Econometrica* 58, 113–144.

Spencer, D. E., (1993). Developing a Bayesian Vector Autoregression Model. *International Journal of Forecasting* 9, 407-421.

Stevens, B. H., and Moore, C. L., (1980). A Critical Review of the Literature on Shift-Share as a Forecasting Technique. *Journal of Regional Science* 20, 419–437.

Stock, J. H., and Watson, M. W., (1999). Forecasting Inflation. *Journal of Monetary Economics* 44, 293-335.

Stock, J. H., and Watson, M. W., (2002a). Forecasting Using Principal Components from a Large Number of Predictors. *Journal of the American Statistical Association* 97, 147–162.

Stock, J. H., and Watson, M. W., (2002b). Macroeconomics forecasting using diffusion indexes, *Journal of Business and Economic Statistics* 20, 147–162.

Stock, J. H., and Watson, M. W., (2003). Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature* 41, 788-829.

Stock, J. H., and Watson, M. W., (2004). Combination Forecasts of Output Growth in a Seven-Country Data Set. *Journal of Forecasting* 23, 405-430.

Stock, J. H., and Watson, M. W., (2005). Implications of dynamic factor models for VAR analysis. NBER Working Paper No. 11467.

Taylor, C. A., (1982). Econometric Modeling of Urban and Other Substate Areas: An Analysis of Alternative Methodologies. *Regional Science and Urban Economics* 12, 425-448.

Theil, H., (1971). *Principles of Econometrics*. New York: John Wiley.

Todd, R. M., (1984). Improving Economic Forecasting with Bayesian Vector Autoregression. *Quarterly Review*, Federal Reserve Bank of Minneapolis, Fall, 18-29.

Williamson, R. B., (2006). Predictive Power of the Export Base Theory. *Growth and Change* 6, 3–10.

Table 1: One- to twelve-months-ahead forecast for Mining & Logging Employment (1990:1-2009:3)

	Models	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
	RW	0.2637	0.4537	0.6375	0.8158	0.9890	1.1574	1.3211	1.4846	1.6516	1.8209	1.9892	2.1596	1.2287
	VAR	3.7004	4.0382	3.9870	4.1106	4.1408	4.2559	4.3870	4.5101	4.6408	4.8198	4.9835	5.1304	4.3920
w=0.5710, d=2	**MBFAAR**	2.1718	2.1865	2.1941	2.2017	2.1829	2.1850	2.1908	2.2054	2.2189	2.2340	2.2464	2.2567	2.2062
w=0.2015, d=2	**MBFAVAR**	4.1099	4.5596	4.6427	4.7188	4.7073	4.7703	4.8822	4.9955	5.1010	5.2089	5.2952	5.3789	4.8642
w=0.2138, d=2	**MBFAVEC**	2.9057	2.7896	2.7131	2.6514	2.5932	2.5464	2.5050	2.4731	2.4492	2.4309	2.4130	2.3971	2.5723
w=0.0681, d=2	**MBVAR**	1.0768	1.2034	1.2622	1.4904	1.8771	2.0345	2.6463	3.5414	4.8303	6.7084	9.4408	13.2408	4.1127
w=1.8250, d=2	**BAR**	0.9732	0.9879	0.9902	0.9883	0.9726	0.9692	0.9723	0.9806	0.9892	0.9979	1.0038	1.0071	0.9860
w=0.2336, d=2	**BVAR**	1.3440	1.4630	1.5297	1.5742	1.6090	1.6385	1.6677	1.6931	1.7141	1.7350	1.7550	1.7744	1.6248
w=0.4672, d=2	**BFAAR**	0.9722	0.9378	0.9110	0.8708	0.8534	0.8448	0.8360	0.8273	0.8188	0.8106	0.8045	0.8017	0.8574
w=0.1699, d=2	**BFAVAR**	1.3228	1.4151	1.4749	1.5265	1.5713	1.6022	1.6336	1.6593	1.6795	1.6996	1.7192	1.7390	1.5869
w=0.4755, d=2	**BVEC**	1.5758	1.7180	1.7898	1.8152	1.8213	1.8214	1.8169	1.8099	1.8003	1.7910	1.7831	1.7753	1.7765
w=0.1782, d=2	**BFAVEC**	**0.1852**	**0.1865**	**0.1921**	**0.2034**	**0.2193**	**0.2360**	**0.2523**	**0.2699**	**0.2538**	**0.2417**	**0.2330**	**0.2272**	**0.2250**
w=0.0230, d=2	**LBVAR**	0.8531	0.8323	0.8547	0.8804	0.9249	0.9852	1.0304	1.0720	1.1013	1.1197	1.1232	1.1314	0.9924
	Combination	***0.1606***	***0.1610***	***0.1626***	***0.1661***	***0.1716***	***0.1772***	***0.1836***	***0.1913***	***0.1873***	***0.1858***	***0.1861***	***0.1890***	***0.1769***

Note: RW, AR, VAR, FAAR, FAVAR, VEC, and FAVEC refer to random walk, autoregressive, vector autoregressive, factor-augmented vector autoregressive, factor-augmented vector autoregressive, vector error-correction, and factor-augmented error-correction models. BAR, BVAR, BFAAR, BFAVAR, BVEC, and BFAVEC refer to Bayesian AR, VAR, FAAR, FAVAR, VEC, and FAVEC models. MBFAAR, MBFAVAR, MBFAVEC, and MBVAR refer to medium-scale BFAAR, BFAVAR, BFAVEC, and BVAR models. Finally, LBVAR refers to a large-scale VAR model. The text identifies various priors and parameterizations. RMSE means root mean square error, which is reported in the RW row. For the other rows, the entries measure the average RMSE across all forecasts at each horizon – one-, two-, …, and twelve-month-ahead forecasts as well as the average RMSE across the individual forecasts relative to the RMSE of the benchmark RW model. Bold numbers represent the minimum value in each column for the individual models only. The bold and italic numbers refer to the minimum value in each column, including the combination forecast.

Table 2: One-to Twelve-months-ahead forecast for Construction Employment (1990:1-2009:3)

	Models	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
	RW	0.2806	0.4826	0.6856	0.8811	1.0762	1.2610	1.4420	1.6193	1.7944	1.9654	2.1309	2.2935	1.3260
	VAR	1.2265	1.1850	1.2043	1.2825	1.3994	1.5316	1.6489	1.7582	1.8682	1.9590	2.0251	2.0771	1.5972
w=0.5710, d=2	**MBFAAR**	1.9245	1.8388	1.8234	1.8307	1.8559	1.8758	1.8955	1.9151	1.9369	1.9568	1.9748	1.9942	1.9018
w=0.2015, d=2	**MBFAVAR**	2.2845	2.2715	2.2821	2.3426	2.4349	2.5420	2.6366	2.7277	2.8265	2.9132	2.9780	3.0336	2.6061
w=0.2138, d=2	**MBFAVEC**	2.1310	2.1783	2.2359	2.2293	2.2142	2.2000	2.1829	2.1641	2.1495	2.1364	2.1188	2.1027	2.1702
w=0.0681, d=2	**MBVAR**	0.7559	0.7274	0.7852	0.9051	1.1437	0.8409	0.9101	1.0298	1.1997	1.4500	1.7925	1.7035	1.1037
w=1.8250, d=2	**BAR**	0.7533	0.6596	0.6389	0.6409	0.6600	0.6766	0.6947	0.7130	0.7331	0.7523	0.7708	0.7901	0.7069
w=0.2336, d=2	**BVAR**	0.7461	0.6591	0.6420	0.6506	0.6773	0.7056	0.7349	0.7622	0.7891	0.8182	0.8442	0.8669	0.7413
w=0.4672, d=2	**BFAAR**	0.7320	0.6352	0.6115	0.6139	0.6312	0.6458	0.6696	0.6903	0.7134	0.7353	0.7536	0.7688	0.6834
w=0.1699, d=2	**BFAVAR**	0.7333	0.6427	0.6223	0.6328	0.6624	0.6912	0.7225	0.7498	0.7767	0.8054	0.8313	0.8541	0.7270
w=0.4755, d=2	**BVEC**	0.9354	0.9406	1.0019	1.0487	1.0871	1.1045	1.1099	1.1063	1.1039	1.0996	1.0894	1.0817	1.0591
w=0.1782, d=2	**BFAVEC**	**0.5821**	0.6190	0.6034	0.5818	0.6056	0.6289	0.6501	0.6689	0.6874	**0.7026**	**0.7145**	**0.7227**	0.6473
w=0.0230, d=2	**LBVAR**	0.6843	**0.5665**	**0.5361**	**0.5375**	**0.5630**	**0.5933**	**0.6214**	**0.6531**	**0.6841**	0.7116	0.7328	0.7610	**0.6371**
	Combination	***0.1119***	***0.1070***	***0.1056***	***0.1057***	***0.1068***	***0.1081***	***0.1094***	***0.1109***	***0.1129***	***0.1148***	***0.1174***	***0.1234***	***0.1111***

Note: See Table 1. RMSE means root mean square error, which is reported in the RW row. For the other rows, the entries measure the average RMSE across all forecasts at each horizon – one-, two-, …, and twelve-month-ahead forecasts as well as the average RMSE across the individual forecasts relative to the RMSE of the benchmark RW model.. Bold numbers represent the minimum value in each column for the individual models only. The bold and italic numbers refer to the minimum value in each column, including the combination forecast.

Table 3: One-to Twelve-months-ahead forecast for Manufacturing Employment (1990:1-2009:3)

	Models	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
	RW	0.1451	0.2680	0.3906	0.5027	0.6091	0.7116	0.8084	0.9028	0.9942	1.0831	1.1714	1.2590	0.7372
	VAR	1.0242	1.1526	1.3530	1.5924	1.8180	2.0323	2.2204	2.3976	2.5559	2.6869	2.7974	2.8891	2.0433
w=0.5710, d=2	**MBFAAR**	1.7659	1.7286	1.7644	1.8185	1.8749	1.9317	1.9761	2.0185	2.0548	2.0845	2.1144	2.1465	1.9399
w=0.2015, d=2	**MBFAVAR**	1.9282	1.9997	2.1225	2.2754	2.4242	2.5571	2.6700	2.7708	2.8565	2.9294	3.0009	3.0734	2.5506
w=0.2138, d=2	**MBFAVEC**	1.8267	1.8965	1.9899	2.0335	2.0542	2.0635	2.0631	2.0609	2.0584	2.0562	2.0515	2.0477	2.0168
w=0.0681, d=2	**MBVAR**	0.5956	0.5445	0.5902	0.7251	0.9624	0.6842	0.7444	0.8145	0.8965	1.0294	1.2555	1.5189	0.8634
w=1.8250, d=2	**BAR**	0.6859	0.6579	0.7035	0.7706	0.8381	0.9048	0.9583	1.0087	1.0519	1.0872	1.1207	1.1555	0.9119
w=0.2336, d=2	**BVAR**	0.6164	0.5616	0.5815	0.6259	0.6764	0.7223	0.7587	0.7932	0.8226	0.8481	0.8717	0.8941	0.7310
w=0.4672, d=2	**BFAAR**	0.6373	0.5791	0.5942	0.6274	0.6564	0.6947	0.7386	0.7803	0.8194	0.8527	0.8774	0.8991	0.7297
w=0.1699, d=2	**BFAVAR**	0.5984	0.5417	0.5613	0.6026	0.6489	0.6891	0.7298	0.7652	0.7958	0.8218	0.8458	0.8680	0.7057
w=0.4755, d=2	**BVEC**	0.7173	0.7894	0.8829	0.9230	0.9477	0.9595	0.9591	0.9603	0.9581	0.9525	0.9445	0.9383	0.9110
w=0.1782, d=2	**BFAVEC**	**0.3033**	**0.3070**	**0.2788**	**0.2662**	**0.2581**	**0.2505**	**0.2463**	***0.2437***	***0.2420***	***0.2404***	***0.2415***	***0.2427***	***0.2600***
w=0.0230, d=2	**LBVAR**	0.4883	0.4076	0.4000	0.4396	0.4903	0.5372	0.5711	0.5957	0.6171	0.6204	0.6137	0.6187	0.5333
	Combination	***0.2428***	***0.2447***	***0.2300***	***0.2251***	***0.2264***	***0.2313***	***0.2424***	0.2640	0.2980	0.3584	0.4423	0.5588	0.2970

Note: See Table 1. RMSE means root mean square error, which is reported in the RW row. For the other rows, the entries measure the average RMSE across all forecasts at each horizon – one-, two-, …, and twelve-month-ahead forecasts as well as the average RMSE across the individual forecasts relative to the RMSE of the benchmark RW model.. Bold numbers represent the minimum value in each column for the individual models only. The bold and italic numbers refer to the minimum value in each column, including the combination forecast.

Table 4: One-to Twelve-months-ahead forecast for Trade, Transport. & Utilities Employment (1990:1-2009:3)

	Models	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
	RW	0.0964	0.1720	0.2488	0.3248	0.3983	0.4683	0.5368	0.6029	0.6682	0.7324	0.7954	0.8566	0.4917
	VAR	1.0339	0.9817	0.9906	1.0421	1.1235	1.2288	1.3329	1.4258	1.5168	1.5983	1.6587	1.7066	1.3033
w=0.5710, d=2	**MBFAAR**	1.8586	1.7689	1.7612	1.7775	1.8005	1.8172	1.8346	1.8475	1.8645	1.8815	1.8990	1.9158	1.8355
w=0.2015, d=2	**MBFAVAR**	2.0514	1.9921	1.9925	2.0244	2.0775	2.1461	2.2179	2.2775	2.3382	2.3929	2.4396	2.4825	2.2027
w=0.2138, d=2	**MBFAVEC**	1.9979	2.0404	2.1019	2.1462	2.1737	2.1933	2.2090	2.2212	2.2306	2.2369	2.2406	2.2417	2.1694
w=0.0681, d=2	**MBVAR**	0.6998	0.6776	0.7218	0.8273	0.9922	0.8105	0.8530	0.9616	1.1170	1.3431	1.6079	1.2205	0.9860
w=1.8250, d=2	**BAR**	0.7119	0.6198	0.6109	0.6268	0.6487	0.6655	0.6834	0.6967	0.7139	0.7313	0.7489	0.7650	0.6852
w=0.2336, d=2	**BVAR**	0.7010	0.6212	0.6158	0.6334	0.6562	0.6791	0.7033	0.7239	0.7468	0.7699	0.7908	0.8090	0.7042
w=0.4672, d=2	**BFAAR**	0.6598	0.5545	0.5386	0.5566	0.5739	0.5889	0.6161	***0.6373***	***0.6624***	0.6849	0.7034	0.7197	***0.6247***
w=0.1699, d=2	**BFAVAR**	0.6840	0.5950	0.5809	0.5995	0.6248	0.6476	0.6763	0.7003	0.7274	0.7542	0.7781	0.7992	0.6806
w=0.4755, d=2	**BVEC**	0.8110	0.8225	0.8948	0.9458	0.9761	1.0011	1.0205	1.0324	1.0425	1.0485	1.0494	1.0473	0.9743
w=0.1782, d=2	**BFAVEC**	0.6755	0.7334	0.7304	0.7222	0.7080	0.6945	0.6849	0.6791	0.6716	***0.6651***	***0.6610***	***0.6590***	0.6904
w=0.0230, d=2	**LBVAR**	***0.6522***	***0.5533***	***0.5343***	***0.5397***	***0.5633***	***0.5884***	***0.6153***	0.6386	0.6690	0.6957	0.7175	0.7427	0.6258
	Combination	1.4551	1.2362	1.2045	1.2474	1.2873	1.3296	1.3978	1.4458	1.5116	1.5695	1.6287	1.6705	1.4153

Note: See Table 1. RMSE means root mean square error, which is reported in the RW row. For the other rows, the entries measure the average RMSE across all forecasts at each horizon – one-, two-, …, and twelve-month-ahead forecasts as well as the average RMSE across the individual forecasts relative to the RMSE of the benchmark RW model.. Bold numbers represent the minimum value in each column for the individual models only. The bold and italic numbers refer to the minimum value in each column, including the combination forecast.

Table 5: One- to Twelve-months-ahead forecast for Financial Activities Employment (1990:1-2009:3)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
	RW	0.0863	0.1625	0.2367	0.3086	0.3795	0.4483	0.5148	0.5793	0.6428	0.7047	0.7651	0.8241	0.4711
	VAR	0.7615	0.7362	0.7624	0.8210	0.8830	0.9627	1.0351	1.1120	1.1940	1.2782	1.3578	1.4410	1.0288
w=0.5710, d=2	**MBFAAR**	1.7268	1.6912	1.6976	1.7278	1.7604	1.7980	1.8314	1.8609	1.8886	1.9151	1.9377	1.9583	1.8162
w=0.2015, d=2	**MBFAVAR**	1.8452	1.8279	1.8584	1.9144	1.9704	2.0392	2.1042	2.1764	2.2550	2.3372	2.4171	2.5001	2.1038
w=0.2138, d=2	**MBFAVEC**	1.8229	1.8773	1.9488	1.9857	2.0014	2.0085	2.0077	2.0048	2.0017	1.9981	1.9945	1.9910	1.9702
w=0.0681, d=2	**MBVAR**	0.6762	0.6783	0.7182	0.7746	0.8586	0.9092	1.0146	1.1552	1.3627	1.6765	2.1426	2.8492	1.2347
w=1.8250, d=2	**BAR**	**0.5950**	**0.5560**	**0.5609**	**0.5862**	0.6162	0.6492	0.6777	0.7017	0.7247	0.7449	0.7612	0.7752	0.6624
w=0.2336, d=2	**BVAR**	0.6352	0.6169	0.6429	0.6905	0.7430	0.7989	0.8533	0.9056	0.9587	1.0106	1.0598	1.1064	0.8351
w=0.4672, d=2	**BFAAR**	0.6025	0.5636	0.5679	0.5892	**0.6153**	0.6460	0.6737	0.6960	0.7199	0.7423	0.7610	0.7761	0.6628
w=0.1699, d=2	**BFAVAR**	0.6353	0.6161	0.6416	0.6880	0.7394	0.7945	0.8486	0.9001	0.9527	1.0043	1.0532	1.0995	0.8311
w=0.4755, d=2	**BVEC**	0.6633	0.7249	0.8144	0.8583	0.8820	0.8946	0.8997	0.9009	0.9018	0.9015	0.9003	0.8995	0.8534
w=0.1782, d=2	**BFAVEC**	0.6495	0.6197	0.6245	0.6214	0.6291	**0.6353**	**0.6332**	**0.6312**	**0.6322**	**0.6317**	**0.6300**	**0.6270**	**0.6304**
w=0.0230, d=2	**LBVAR**	0.6424	0.6308	0.6515	0.6821	0.7218	0.7682	0.8146	0.8534	0.8871	0.9193	0.9517	0.9889	0.7927
	Combination	***0.1502***	***0.1465***	***0.1455***	***0.1417***	***0.1392***	***0.1357***	***0.1345***	***0.1329***	***0.1366***	***0.1419***	***0.1494***	***0.1650***	***0.1433***

Note: See Table 1. RMSE means root mean square error, which is reported in the RW row. For the other rows, the entries measure the average RMSE across all forecasts at each horizon – one-, two-, …, and twelve-month-ahead forecasts as well as the average RMSE across the individual forecasts relative to the RMSE of the benchmark RW model.. Bold numbers represent the minimum value in each column for the individual models only. The bold and italic numbers refer to the minimum value in each column, including the combination forecast.

Table 6: One-to Twelve-months-ahead forecast for Profession & Business Services Employment (1990:1-2009:3)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
	RW	0.1505	0.2769	0.4011	0.5244	0.6458	0.7657	0.8844	1.0012	1.1167	1.2313	1.3439	1.4554	0.8164
	VAR	0.7868	0.7398	0.7656	0.8175	0.8657	0.9266	0.9902	1.0477	1.0982	1.1398	1.1696	1.1877	0.9613
w=0.5710, d=2	**MBFAAR**	1.7274	1.6638	1.6548	1.6631	1.6742	1.6936	1.7150	1.7317	1.7486	1.7658	1.7800	1.7937	1.7176
w=0.2015, d=2	**MBFAVAR**	1.8122	1.7570	1.7622	1.7902	1.8190	1.8568	1.8975	1.9357	1.9705	1.9989	2.0200	2.0355	1.8880
w=0.2138, d=2	**MBFAVEC**	1.9212	1.9257	1.9662	1.9904	2.0029	2.0103	2.0148	2.0159	2.0179	2.0184	2.0175	2.0151	1.9930
w=0.0681, d=2	**MBVAR**	0.6046	0.5853	0.6130	0.6641	0.7556	0.6667	0.7200	0.8205	0.9702	1.1928	1.4964	1.7014	0.8992
w=1.8250, d=2	**BAR**	0.6503	0.5886	0.5811	0.5924	0.6071	0.6308	0.6560	0.6758	0.6957	0.7156	0.7324	0.7482	0.6562
w=0.2336, d=2	**BVAR**	0.6613	0.6104	0.6100	0.6280	0.6490	0.6757	0.7023	0.7246	0.7468	0.7685	0.7883	0.8060	0.6976
w=0.4672, d=2	**BFAAR**	0.6413	0.5739	0.5652	0.5784	0.5913	0.6111	0.6355	0.6556	0.6771	0.6974	0.7129	0.7264	0.6388
w=0.1699, d=2	**BFAVAR**	0.6586	0.6038	0.6020	0.6208	0.6422	0.6686	0.6964	0.7191	0.7419	0.7640	0.7840	0.8022	0.6920
w=0.4755, d=2	**BVEC**	0.7551	0.7579	0.8014	0.8313	0.8525	0.8705	0.8840	0.8922	0.8974	0.9007	0.9011	0.9000	0.8537
w=0.1782, d=2	**BFAVEC**	0.6755	0.7334	0.7304	0.7222	0.7080	0.6945	0.6849	0.6791	0.6715	0.6651	0.6610	0.6590	0.6904
w=0.0230, d=2	**LBVAR**	**0.5409**	**0.4670**	**0.4528**	**0.4544**	**0.4665**	**0.4919**	**0.5178**	**0.5389**	**0.5634**	**0.5850**	**0.6072**	**0.6306**	**0.5264**
	Combination	***0.1766***	***0.1638***	***0.1614***	***0.1617***	***0.1639***	***0.1684***	***0.173***	***0.1767***	***0.18***	***0.1823***	***0.1842***	***0.1845***	***0.1730***

Note: See Table 1. RMSE means root mean square error, which is reported in the RW row. For the other rows, the entries measure the average RMSE across all forecasts at each horizon – one-, two-, …, and twelve-month-ahead forecasts as well as the average RMSE across the individual forecasts relative to the RMSE of the benchmark RW model.. Bold numbers represent the minimum value in each column for the individual models only. The bold and italic numbers refer to the minimum value in each column, including the combination forecast.

Table 7: One- to Twelve-months-ahead forecast for Leisure & Hospitality Employment (1990;1-2009:3)

	Models	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
	RW	0.1115	0.1763	0.2357	0.2954	0.3535	0.4048	0.4531	0.4994	0.5450	0.5892	0.6295	0.6698	0.4136
	VAR	1.5839	1.7317	1.7335	1.6661	1.6182	1.6311	1.6621	1.7261	1.7963	1.8488	1.8845	1.9015	1.7320
w=0.5710, d=2	**MBFAAR**	2.1043	2.0302	1.9789	1.9556	1.9335	1.9073	1.8726	1.8383	1.8099	1.7910	1.7762	1.7627	1.8967
w=0.2015, d=2	**MBFAVAR**	2.4146	2.4549	2.4028	2.3121	2.2369	2.1922	2.1541	2.1349	2.1240	2.1158	2.1102	2.1073	2.2300
w=0.2138, d=2	**MBFAVEC**	2.2764	2.1699	2.1689	2.1735	2.1805	2.1904	2.2024	2.2086	2.2146	2.2166	2.2237	2.2233	2.2041
w=0.0681, d=2	**MBVAR**	0.8287	0.7995	0.8180	0.8601	0.9592	0.7645	0.8000	0.9404	1.1668	1.5000	1.9407	2.1555	1.1278
w=1.8250, d=2	**BAR**	0.9499	0.9237	0.9086	0.9162	0.9329	0.9429	0.9457	0.9448	0.9447	0.9453	0.9464	0.9478	0.9374
w=0.2336, d=2	**BVAR**	0.9331	0.8938	0.8681	0.8508	0.8408	0.8388	0.8423	0.8447	0.8586	0.8704	0.8881	0.9020	0.8693
w=0.4672, d=2	**BFAAR**	0.9163	0.8665	0.8310	0.8178	0.8156	0.8107	0.8140	0.8137	0.8225	0.8350	0.8426	0.8471	0.8361
w=0.1699, d=2	**BFAVAR**	0.9381	0.8988	0.8704	0.8516	0.8411	0.8356	0.8378	0.8383	0.8515	0.8638	0.8814	0.8950	0.8669
w=0.4755, d=2	**BVEC**	1.1082	1.0674	1.0986	1.0925	1.1020	1.1235	1.1408	1.1479	1.1551	1.1590	1.1675	1.1671	1.1275
w=0.1782, d=2	**BFAVEC**	**0.1827**	**0.1950**	**0.2052**	**0.2244**	**0.2094**	**0.2013**	**0.1982**	**0.1982**	**0.2017**	**0.2074**	**0.2141**	**0.2180**	**0.2046**
w=0.0230, d=2	**LBVAR**	0.8288	0.7583	0.7171	0.7036	0.7027	0.6904	0.6847	0.6839	0.6891	0.6987	0.7036	0.7119	0.7144
	Combination	***0.1510***	***0.1556***	***0.1593***	***0.1666***	***0.1611***	***0.1587***	***0.1574***	***0.1598***	***0.1651***	***0.1760***	***0.1906***	***0.2066***	***0.1673***

Note: See Table 1. RMSE means root mean square error, which is reported in the RW row. For the other rows, the entries measure the average RMSE across all forecasts at each horizon – one-, two-, …, and twelve-month-ahead forecasts as well as the average RMSE across the individual forecasts relative to the RMSE of the benchmark RW model.. Bold numbers represent the minimum value in each column for the individual models only. The bold and italic numbers refer to the minimum value in each column, including the combination forecast.

Table 8: One-to Twelve-months-ahead forecast for Other Services Employment (1990:1-2009:3)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
	RW	0.0869	0.1561	0.2236	0.2907	0.3544	0.4150	0.4761	0.5364	0.5956	0.6544	0.7115	0.7671	0.4390
	VAR	1.1039	1.0204	1.0366	1.1111	1.1882	1.2731	1.3637	1.4380	1.5027	1.5643	1.6178	1.6517	1.3226
w=0.5710, d=2	**MBFAAR**	1.8733	1.8294	1.8298	1.8535	1.8729	1.8876	1.9064	1.9216	1.9359	1.9530	1.9676	1.9783	1.9008
w=0.2015, d=2	**MBFAVAR**	2.0686	2.0196	2.0250	2.0788	2.1306	2.1840	2.2432	2.2899	2.3325	2.3760	2.4153	2.4435	2.2173
w=0.2138, d=2	**MBFAVEC**	2.1388	2.1711	2.2227	2.2646	2.2956	2.3205	2.3428	2.3629	2.3833	2.4031	2.4195	2.4335	2.3132
w=0.0681, d=2	**MBVAR**	0.8042	0.8313	0.8547	0.9135	1.0111	1.0305	1.1945	1.4416	1.8039	2.3444	3.1238	4.1857	1.6283
w=1.8250, d=2	**BAR**	0.7704	0.7310	0.7296	0.7502	0.7680	0.7793	0.7961	0.8113	0.8257	0.8425	0.8558	0.8653	0.7938
w=0.2336, d=2	**BVAR**	0.7803	0.7484	0.7508	0.7673	0.7851	0.7996	0.8175	0.8321	0.8446	0.8582	0.8706	0.8796	0.8112
w=0.4672, d=2	**BFAAR**	0.7897	0.7533	0.7527	0.7682	0.7765	0.7779	0.7945	0.8096	0.8258	0.8428	0.8554	0.8636	0.8008
w=0.1699, d=2	**BFAVAR**	0.7841	0.7500	0.7510	0.7668	0.7828	0.7938	0.8114	0.8253	0.8379	0.8513	0.8631	0.8714	0.8074
w=0.4755, d=2	**BVEC**	0.9262	0.9530	1.0124	1.0653	1.1114	1.1572	1.2000	1.2370	1.2711	1.3008	1.3244	1.3425	1.1584
w=0.1782, d=2	**BFAVEC**	***0.3675***	***0.3531***	***0.3390***	***0.3298***	***0.3226***	***0.3306***	***0.3382***	***0.3451***	***0.3523***	***0.3587***	***0.3649***	***0.3698***	***0.3476***
w=0.0230, d=2	**LBVAR**	0.7414	0.7237	0.7380	0.7541	0.7877	0.8130	0.8480	0.8822	0.9176	0.9533	0.9824	1.0070	0.8457
	Combination	0.7871	0.7758	0.7647	0.7737	0.7909	0.8445	0.9011	0.9374	0.9728	0.9982	1.0419	1.0387	0.8856

Note: See Table 1. RMSE means root mean square error, which is reported in the RW row. For the other rows, the entries measure the average RMSE across all forecasts at each horizon – one-, two-, …, and twelve-month-ahead forecasts as well as the average RMSE across the individual forecasts relative to the RMSE of the benchmark RW model.. Bold numbers represent the minimum value in each column for the individual models only. The bold and italic numbers refer to the minimum value in each column, including the combination forecast.

Table 9: Giacomini and White (2006) Test of Differences between Best, Combination, and Random-Walk Models

	Models	1	2	3	4	5	6	7	8	9	10	11	12
Mining & Logging	BFAVEC vs RW	-81.48*	-81.35*	-80.79*	-79.66*	-78.07*	-76.40*	-74.77*	-73.01*	-74.62*	-75.83*	-76.70*	-77.28*
	Combination vs RW	-92.25*	-92.21*	-92.05*	-91.70*	-91.15*	-90.59*	-89.95*	-89.18*	-89.58*	-89.73*	-89.70*	-89.41*
	Combination vs BFAVEC	-58.16*	-58.21*	-58.59*	-59.22*	-59.66*	-60.11*	-60.15*	-59.90*	-58.95*	-57.52*	-55.80*	-53.37*
Construction	LBVAR vs RW	-31.57^{+}	-43.35**	-46.39**	-46.25**	-43.70**	-40.67**	-37.86**	-34.69^{+}	-31.59^{+}	-28.84^{+}	-26.72^{+}	-23.90^{+}
	Combination vs RW	-97.12*	-97.61*	-97.75*	-97.74*	-97.63*	-97.50*	-97.37*	-97.22*	-97.02*	-96.83*	-96.57*	-95.97*
	Combination vs LBVAR	-95.79*	-95.79*	-95.80*	-95.80*	-95.79*	-95.78*	-95.78*	-95.74*	-95.65*	-95.54*	-95.31*	-94.71*
Manufact-uring	BFAVEC vs RW	-69.67*	-69.30*	-72.12*	-73.38*	-74.19*	-74.95*	-75.37*	-75.63*	-75.80*	-75.96*	-75.85*	-75.73*
	Combination vs RW	-84.03*	-83.84*	-85.31*	-85.80*	-85.67*	-85.18*	-84.07*	-81.91*	-78.51*	-72.47*	-64.08*	-52.43*
	Combination vs BFAVEC	-47.35**	-47.34**	-47.30**	-46.64**	-44.48**	-40.83**	-35.34**	-25.76^{+}	-11.16	14.53	48.76**	96.04*
Trade, Transport. & Utilities	BFAAR vs RW	-34.02^{+}	-44.55**	-46.14**	-44.34**	-42.61**	-41.11**	-38.39**	-36.27**	-33.76^{+}	-31.51^{+}	-29.66^{+}	-28.03^{+}
	Combination vs RW	37.20**	15.31	12.14	16.43	20.42^{+}	24.65^{+}	31.47^{+}	36.27**	42.85**	48.64**	54.56*	58.74*
	Combination vs BFAAR	107.94*	107.94*	108.20*	109.18*	109.83*	111.68*	113.40*	113.84*	115.66*	117.02*	119.72*	120.56*
Financial Activities	BFAVEC vs RW	-35.05**	-38.03**	-37.55**	-37.86**	-37.09**	-36.47**	-36.68**	-36.88**	-36.78**	-36.83**	-37.00**	-37.30**
	Combination vs RW	-93.29*	-93.66*	-93.76*	-94.14*	-94.39*	-94.74*	-94.86*	-95.02*	-94.65*	-94.12*	-93.37*	-91.81*
	Combination vs BFAVEC	-89.67*	-89.77*	-90.01*	-90.58*	-91.08*	-91.72*	-91.88*	-92.11*	-91.53*	-90.70*	-89.47*	-86.93*
Professional & Business Services	LBVAR vs RW	-45.91**	-53.30*	-54.72*	-54.56*	-53.35*	-50.81*	-48.22**	-46.12**	-43.66**	-41.50**	-39.28**	-36.94**
	Combination vs RW	-90.65*	-91.93*	-92.17*	-92.14*	-91.92*	-91.47*	-91.01*	-90.64*	-90.31*	-90.08*	-89.89*	-89.86*
	Combination vs LBVAR	-82.71*	-82.72*	-82.71*	-82.71*	-82.69*	-82.67*	-82.64*	-82.63*	-82.81*	-83.05*	-83.35*	-83.91*
Leisure & Hospitality	BFAVEC vs RW	-81.73*	-80.50*	-79.48*	-77.56*	-79.06*	-79.87*	-80.18*	-80.18*	-79.83*	-79.26*	-78.59*	-78.20*
	Combination vs RW	-93.21*	-92.75*	-92.38*	-91.65*	-92.20*	-92.44*	-92.57*	-92.33*	-91.80*	-90.71*	-89.25*	-87.65*
	Combination vs BFAVEC	-62.85*	-62.83*	-62.87*	-62.82*	-62.75*	-62.42*	-62.50*	-61.33*	-59.31*	-55.22*	-49.80*	-43.35**
Other Services	BFAVEC vs RW	-63.25*	-64.69*	-66.10*	-67.02*	-67.74*	-66.94*	-66.18*	-65.49*	-64.77*	-64.13*	-63.51*	-63.02*
	Combination vs RW	-29.60^{+}	-30.73^{+}	-31.84^{+}	-30.94^{+}	-29.22^{+}	-23.86^{+}	-18.20	-14.57	-11.03	-8.49	-4.12	-4.44
	Combination vs BFAVEC	91.58*	96.21*	101.05*	109.37*	119.43*	130.29*	141.84*	147.57*	152.52**	155.08*	162.75*	158.39*

Note: The Giacomini and White (2006) statistic tests the difference in RMSEs between the best model relative to the random-walk model, the forecast combination method relative to the random-walk model, and the forecast combination model relative to the best model. Negative signs mean that the best model or the forecast combination method forecasts better than the random-walk model, as well as that the forecast combination method outperforms the best model.

* means significant at the 1-percent level.

** means significant at the 5-percent level.

† means significant at the 10-percent level.

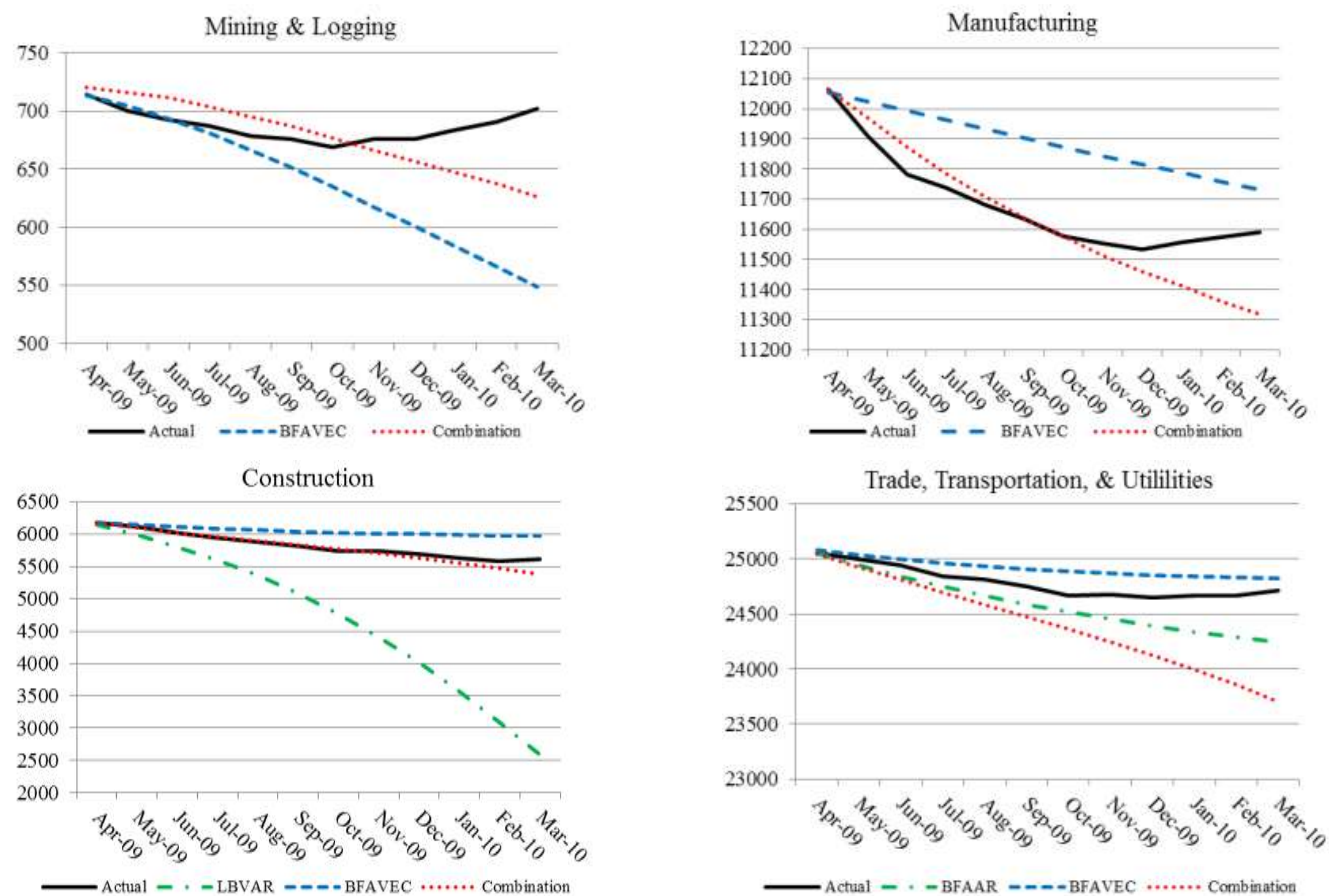

Figure 1: Actual and *Ex-Ante* Forecast Values of Eight Employment Series

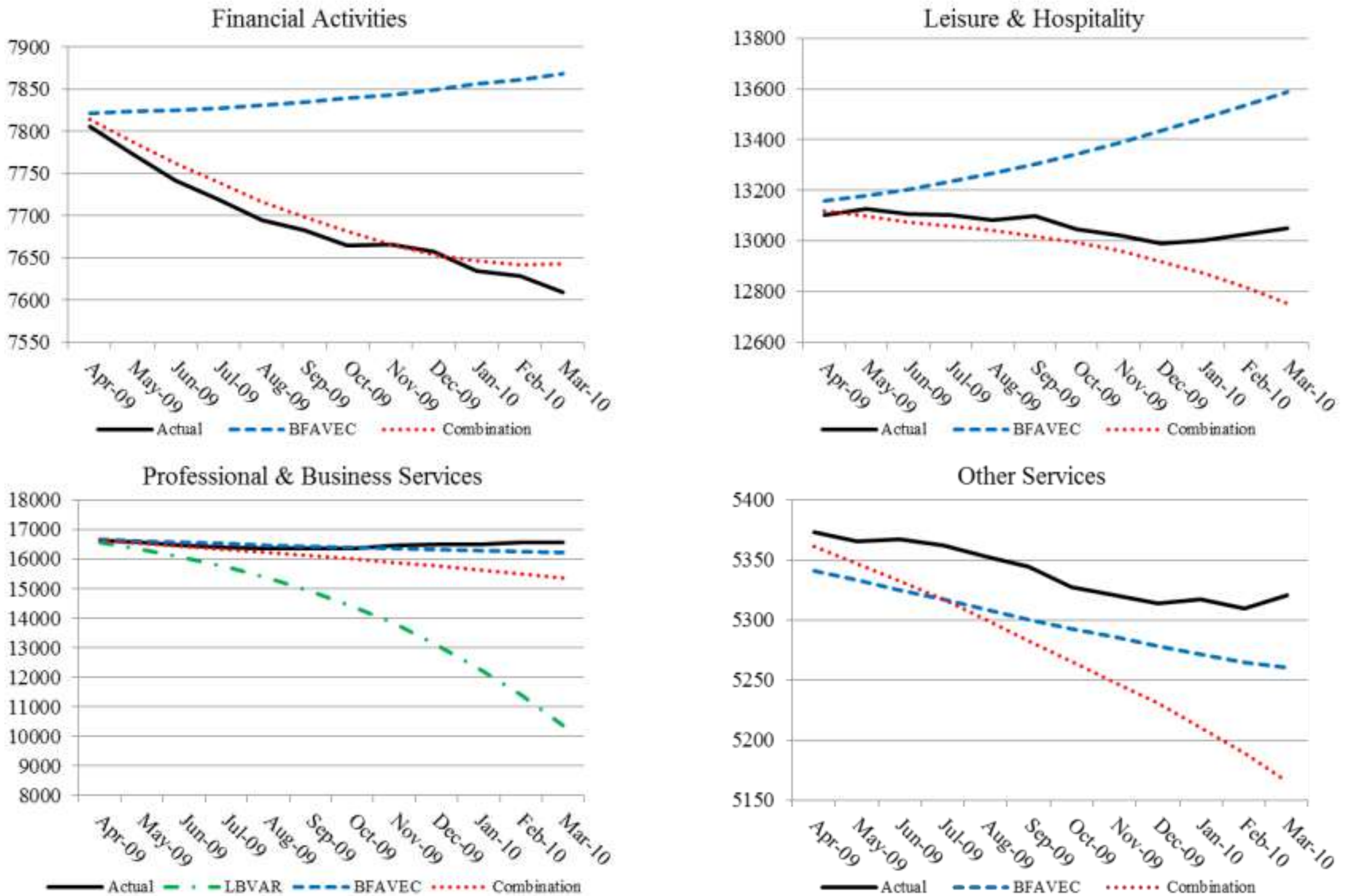

Figure 1: Actual and *Ex-Ante* Forecast Values of Eight Employment Series (continued)

Appendix A:

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
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

Data Code	*Variable Name*	Format
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
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
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

Data Code	Variable Name	Format
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
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

Note: 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. Variables in italics correspond to those included in the medium-scale models.