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Using Large Data Sets to Forecast Sectoral Employment

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Abstract

We implement several Bayesian and classical models to forecast employment for eight sectors of the US economy. In addition to standard vector-autoregressive and Bayesian vector autoregressive models, we also 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 approaches – extracting common factors (principle components) in a factor-augmented vector autoregressive or vector error-correction, Bayesian factor-augmented vector autoregressive or vector error-correction models, or Bayesian shrinkage in a large-scale Bayesian vector autoregressive models. Using the period of January 1972 to December 1999 as the in-sample period and January 2000 to March 2009 as the out-of-sample horizon, we compare the forecast performance of the alternative models. Finally, we forecast out-of sample from April 2009 through March 2010, using the best forecasting model for each employment series. 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.

Journal of Economic Literature Classification: C32, R31

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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. As such, forecasting employment should receive more attention in the literature. Rapach and Strauss (2008) state "forecasting employment growth has received little attention ... relative to such macroeconomic stalwarts as inflation, GDP growth, and the unemployment rate." (p. 75).

This paper considers the dynamics of employment and the ability of different pure time-series models to forecast sectoral employment.[1] The main focus considers how the researcher can incorporate large data sets into forecasting equations, using dynamic factor analysis or shrinking large-scale BVAR models. We illustrate the process using employment from 8 subsectors -- 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 – vector autoregressive (VAR) vector error-correction (VEC), factor augmented VAR (FAVAR), factor augmented VEC (FAVEC), and various Bayesian time-series models. For the Bayesian models, we estimate Bayesian VAR (BVAR), Bayesian VEC (BVEC), Bayesian factor augmented (BFAVAR), Bayesian factor augmented VEC (BFAVEC), and large-

[1] Focusing on the employment numbers, however, obscures a large part of employment dynamics. That is, much job churning occurs in the labor markets. New businesses open and hire thousands of workers each month, while other businesses close and thousands of other workers find themselves without employment.

scale BVAR (LBVAR) models. A factor-augmented model generally performs the best across the 8 employment series, using the average root-mean-squared-error (RMSE) criteria. The LBVAR models come in a close second to the factor-augmented models on several occasions, and actually outperform the factor-augmented models for an extremely small number of forecast horizons. 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.

We organize the rest of the paper as follows. Section 2 provides a brief review of the literature on using large data sets in forecasting models. Section 3 discusses the literature on forecasting 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 Data Sets

Zellner and Palm (1974) theoretically rationalize why time-series models generally perform as well as or better than dynamic structural econometric specifications.[2] An important issue involves determining how additional information can or cannot improve the forecasting performance over a simple univariate autoregressive or autoregressive-moving-average representation.

A simple approach uses an autoregressive distributed lag (ARDL) model (Stock and Watson 1999, 2003, 2004), 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

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

autoregressive process and one driver variable enters as a distributed lag. The researcher compares the baseline model, the pure autoregressive specification forecasts with the forecasts for the transfer function or ARDL specification. Researchers extend this further and repeat the process for a whole series 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.

Another method adopts "atheoretical" VAR or VEC models to generate forecasts. These models do not impose exogeneity assumptions on the included variables. Unlike the single-equation 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 data set, which then get added to the VAR or VEC specifications (Bernanke, Boivin, and Eliazs 2005, Stock and Watson 2002a, 2005). Adding a few common factors from the large dataset to VAR and VEC systems economizes on the number of new parameters to estimate.

Bayesian VAR (BVAR) or VEC (BVEC) models overcome the over-parameterization problem by estimating a small number of hyper-parameters in the specification that defines all parameters in the system. Since the Bayesian approach already addresses 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 from the large set of macroeconomic variables to include in factor-augmented VAR (FAVAR) or VEC (FAVEC) systems, which we also do.

The ADRL method, in contrast to the VAR, BVAR, VEC, or BVEC modeling approaches, uses information from a large dataset one variable at a time and then aggregates across all forecasts. As a result, this approach does not differentiate between common factors and non-common factors in the large dataset. Each exhibits the same effect on the forecast, over and above the autoregressive part of the model. In the factor-augmented approach, the researcher potentially leaves information on the table by only extracting the common factor information and leaving the remaining information out of the analysis. On the other hand, the Bayesian approach, includes all the information from the large set of data, but restricts the estimation by imposing conditions on the parameters of the estimating equation. In sum, all methods introduce restrictions on the way information from the large dataset affects the estimation process. Thus, any of the individual approaches may lead to better forecasts *a priori*.

In this paper, we consider the factor-augmented and large-scale Bayesian methods for incorporating the information from a large dataset. These methods provide the natural extension of the VAR, VEC, BVAR, and BVEC models. The ARDL model involves a single-equation, whereas the VAR, VEC, BVAR, and BVEC models involve multiple equations. Thus, we exclude the ARDL approach from our analysis.

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 data set of 215 additional potential predictors, extracting principle components using dynamic factor modeling, 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 a large data set of economic variables. They use the monthly seasonally adjusted civilian employment from the Conference Board data set and employ 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 principle 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 (2010a) forecast national employment growth, using the same data set 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 (2010b) 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 facilitate the role of a wider possible set of fundamentals to affect the dynamic movement of employment.

4. VAR, VEC, BVAR, BVEC, FAVAR, FAVEC, BFAVAR, BFAVEC, and LBVAR Specifications and Estimation[3]

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

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

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

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,*[4] and ε equals an ($n \times 1$) vector of error terms. In our case, we assume that $\varepsilon \sim N(0, \sigma^2 I_n)$, where I_n equals an ($n \times n$) identity matrix.

The VAR method typically use equal lag lengths for all variables, which implies that the

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

[4] That is, $A(L) = A_1L + A_2L^2 + ... + A_pL^p$;

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

Imposing additional restrictions on a standard VAR model generates a VEC model that uses cointegrated non-stationary series. 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 cointegration term, called 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, (i.e., *I(1)*).[5] The error-correction counterpart of the VAR model in equation (1) converts into a VEC model as follows:[6]

$$\Delta y_t = \pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + \varepsilon_t \tag{2}$$

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 BVAR model to overcome the over-parameterization problem. Rather than eliminating lags, the Bayesian method imposes restrictions on the coefficients across different lag lengths, assuming that the coefficients of longer lags may more closely approach zero than

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

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

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) imposes a diffuse prior for the constant. We employ this "Minnesota prior" in our analysis, where we implement Bayesian variants of the classical VAR models.

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

$$\beta_i \sim N(1, \sigma^2_{\beta_i}) \text{ and } \beta_j \sim N(0, \sigma^2_{\beta_j}) \tag{3}$$

where β_i equals the coefficients associated with the lagged dependent variables in each equation of the VAR model (i.e., the first own-lag coefficient), while β_j equals any other coefficient. In sum, the prior specification reduces to a random-walk with drift model for each variable, if we set all variances to zero. The prior variances, $\sigma^2_{\beta_i}$ 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 standard deviations that depend on a small numbers of hyper-parameters: *w, d*, and a weighting matrix *f*(*i, j*) to reduce the over-parameterization in the VAR models. This approach specifies individual prior variances for a large number of coefficients, using only a few hyper-parameters. The specification of the standard deviation of the distribution of the prior imposed on variable *j* in equation *i* at lag *m*, for all *i, j* and *m*, equals $S_1(i, j, m)$, defined as follows:

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

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 $d > 0$. The estimated standard error of the univariate autoregression for variable i equals $\hat{\sigma}_i$. The ratio $\hat{\sigma}_i / \hat{\sigma}_j$ scales the variables to account for differences in the units of measurement and, hence, causes the specification of the prior without consideration of the magnitudes of the variables. The term w indicates the overall tightness, with the prior getting tighter as the value falls. The parameter $g(m)$ measures the tightness on lag m with respect to lag 1, and equals a harmonic shape with decay factor d, which tightens the prior at longer lags. The parameter $f(i, j)$ equals the tightness of variable j in equation i relative to variable i, and by increasing the interaction (i.e., the value of k_{ij}), we loosen the prior.[7] The overall tightness (w) and the lag decay (d) hyper-parameters equal 0.1 and 1.0, respectively, in the standard Minnesota prior, while k_{ij} = 0.5.

Since researchers believe that the lagged dependant variable in each equation proves most important, F imposes $\bar{\beta}_i = 1$ loosely. The β_j coefficients, however, that associate with less-important variables receive a coefficient in the weighting matrix (F) that imposes the prior means of zero more tightly. Since the Minnesota prior treats all variables in the VAR, except for the first own-lag of the dependent variable, in an identical manner, several researchers attempt to alter this fact. Usually, this means increasing the value for the overall tightness (w) hyper-parameter from 0.10 to 0.20, so that more influence comes from other variables in the model. In addition, Dua and Ray (1995) introduce a prior that imposes fewer restrictions on the other variables in the VAR model (i.e., w = 0.30 and d = 0.50).

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

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

variables of interest in the in-sample period (1972:1 to 1989:12). The optimal value of *w(Fit)* (= 0.0627), with d =2.0, obtained in this fashion is then retained for the entire evaluation period. Specifically, for a desired *Fit*, 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 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), while we define the baseline *Fit* as the average relative MSE from an OLS-estimated VAR containing the eight sectoral employment variables. That is,

$$Fit = \frac{1}{8}\sum_{i=1}^{8}\frac{MSE_i^\infty}{MSE_i^0} . \tag{6}$$

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

4.2 FAVAR and BFAVAR:

We use the dynamic factor (DF) model to extract common components between macroeconomic series and then use these common components to forecast employment, adding three extracted factors to the 8-variable VAR model to create a factor-augmented VAR (FAVAR) model in the process.[8] We choose the three factors by the cumulative variance share, under which, the fourth eigenvalue fell below the threshold of 5 percent. Furthermore, we estimate idiosyncratic component (see below) with AR(p) processes as suggested by Boivin and Ng (2005).

The DF 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. The DF model extracts the few factors that explain the co-movement of the US economy. Forni *et al.* (2005) demonstrate that for a small number of factors relative to the number of variables and a heterogeneous panel, we can recover the factors from present and past observations.

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

$$X_t = \lambda F_t + \xi_t \tag{7}$$

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 DF model, F_t and ξ_t are mutually orthogonal stationary process, while, $\chi_t = \lambda F_t$ equals the common component.

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

[8] We first transform all data to induce stationarity. Then, using the transformed data, we extract the common components.

the $n \times r$ matrix of the eigenvectors corresponding to the r largest eigenvalues of the sample covariance matrix $\hat{\Sigma}$).

For forecasting purposes, we use 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

$$\begin{bmatrix} \hat{Y}_{t+h} \\ \hat{F}_{t+h} \end{bmatrix} = \hat{\Phi}(L) \begin{bmatrix} Y_t \\ F_t \end{bmatrix} \tag{8}$$

where h equals the forecasting horizon, $\hat{\Phi}(L)$ equal lag polynomials, which we estimate with and without restrictions. As Boivin and Ng (2005) clearly note, VAR models are special cases of equation (8). With known factors and the parameters, the FAVAR approach should produce smaller mean squared errors. 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 DF model specifications:

- FAVAR: includes the employment in 8 sectors and the three common static factors; and
- BFAVAR: the FAVAR specification with Bayesian restrictions on lags of the employment in 8 sectors and the three factors, based on the priors outlined above.

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).[9] We begin with a common trend representation for a set of N $I(1)$ cointegrated variables X_t as shown in equation (7) above. Rewriting equation (7) in first differences gives the following:[10]

$$\Delta X_t = \lambda \Delta F_t + \Delta \xi_t . \qquad (9)$$

Equation (9) represents the well-known DF models proposed by Stock and Watson (2002a, b) and Forni, Hallin, Lippi, and Reichlin (2005), but in first-differenced form. Bai and Ng (2004) and Bai (2004), however, allow for the possibility that ξ_t or some elements of ξ_t do not converge or are $I(1)$.

We can rewrite equation (8) as follows:

$$\Delta X_t = \alpha \beta' \Delta F_t + \varepsilon_t \qquad (10)$$

where $\beta' = \Lambda'_{\perp}$ and hence $\beta' x_t$ is $I(0)$ and an over-time correlation can exist between the errors $\Delta \xi_t$ and ε_t.

The literature on cointegration focuses mainly on equation (10), also known as the VEC model, while Banerjee and Marcellino (2009) reconcile the factor analysis in equation (9) and the cointegration concept in equation (10). The new hybrid model addresses, on the one hand, the problem associated with large number of data sets that the simple VEC model (equation 2) does not consider. 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

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

[10] When we extracted the common factors for the FAVAR and BFAVAR models, we transformed all variables to induce stationarity. Now, we transform all variables to induce non-stationarity. That is, for stationary variables, we accumulated to make them I(1). The two approaches produce different numbers of common factors – three versus four, respectively. We also extracted four common factors from the non-stationary variables, excluding the stationary variables. The findings proved similar to the four factors extracted when we accumulated the I(0) variables to make them I(1).

the information set in the FAVEC model improves the forecasting performance of models, especially at the longer horizon. On the other hand, the FAVEC model studies the relationship between the common-trend representation for x_t and DF model for Δx_t.

By including the error-correction terms in the DF model, the FAVEC model enhances the former model, especially in presence of cointegration. Thus, the factors extracted from a large panel of economic variables in levels jointly associate with the limited set of economic variables of main interest while allowing for cointegration. The FAVEC model naturally generalizes the FAVAR model developed by Bernanke, Boivin, and Eliaz (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, X_t^A and $N^B = N - N^A$ containing the remaining variables, X_t^B. Equation (7) becomes:

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

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. The theory requires that the rank of Λ^B, $r^B = r$, whereas the rank of Λ^A, $r^A \leq r$. That is, a smaller number of trends drives X_t^A. From equation (11), we see that X_t^A and F_t are cointegrated, while F_t are uncorrelated random walks.

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

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

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

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

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

Banerjee and Marcellino (2009) show that there must be N^A cointegrating relationships in equation (13), given that equation (13) includes $N^A + r$ dependent variables and that X_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 X_t^A variables only. Banerjee and Marcellino (2009) demonstrate that this emerges from a standard VEC model. The remaining r^A cointegrating relationships involve X_t^A and F_t. Therefore, potentially $N - N^A$ omitted cointegrating relationships exist in the standard VEC model.

Similarly, equation (13) improves on DF model and FAVAR models, given that the error-correction terms do not appear. That is, the FAVAR does not account for the long-run information and, hence, $\gamma^A = \gamma^B = 0$. Like the DF model, 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 should outperform these models in forecasting.

- FAVEC: includes the employment in 8 sectors, the four common static factors, extracted based on the Bai (2004) approach, and the error-correction terms; and
- BFAVEC: the FAVEC specification with Bayesian restrictions on lags of the FAVEC model based on the priors outlined above.

4.4 Comparing Forecasts:

For each of one- to twelve-months-ahead forecasts, we test whether the gain (loss) in the RMSE from the alternative "optimal" models relative to the random walk model is significant. The optimal models minimize the average RMSE across all twelve forecast horizons. We use the *ENC-T* test of Clark and McCracken (2001). This test applies to nested models, given that the "optimal" models nest the random-walk model.

The test statistic is defined as follows:

$$ENC-T=(P-1)^{1/2}\frac{\bar{c}}{(P^{-1}\sum_{t=R}^{T-1}(c_{t+h}-\bar{c}))^{1/2}}, \tag{14}$$

where, $c_{t+h}=\hat{v}_{0,t+h}(\hat{v}_{0,t+h}-\hat{v}_{1,t+h})$ and $\bar{c}=\sum_{t=R}^{T-1}c_{t+1}$, R denotes the estimation period, P is the prediction period, f is some generic loss function ($f(v_{0,t+h})=v_{0,t+h}^{2}$, in our case), $h\geq 1$ is the forecast horizon, $\hat{\upsilon}_{0,t+h}$ and $\hat{\upsilon}_{1,t+h}$ are h-step ahead prediction errors for models 0 and 1 (where model 0 is the "optimal" model), constructed using Newey and West (1987) type consistent estimators.

The hypotheses of interest are:

$$H_0: E\left(f\left(\upsilon_{0,t+h}\right)-f\left(\upsilon_{1,t+h}\right)\right)=0\text{, and} \tag{15}$$

$$H_A: E\left(f\left(\upsilon_{0,t+h}\right)-f\left(\upsilon_{1,t+h}\right)\right)>0\,. \tag{16}$$

The limiting distribution is $N(0, 1)$ for $h = 1$. The limiting distribution for $h > 1$ is non-standard, as discussed in Clark and McCraken (2001). As long as a Newey and West (1987) type estimator is used when $h > 1$, however, then the tabulated critical values closely approximate the $N(0, 1)$ values (Bhardwaj and Swanson, 2006).

5. Data Description, Model Estimation, and Results

5.1 Data

While the small-scale VARs, both the classical and Bayesian variants, include data of only the employment in 8 sectors, the large-scale BVARs and the DF model also include the 143 monthly national and regional series. 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 series 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 are characterized by mean-reversion, however, we set a white-noise prior (i.e., $\overline{\beta}_i = 0$); otherwise, we impose the random walk prior (i.e., $\overline{\beta}_i = 1$). As for the FAEC models, we begin with 115 I(1) variables and we then cumulate the remaining 35 I(0) variables to transform them into non-stationary variables, before extracting the four factors. Appendix A lists these variables as well as the transformations used prior to analyzing the data.

The real activity group consists of variables such as industrial production, capacity utilization, retail sales, real personal consumption, real personal income, new orders, inventories, new housing starts (national and regional), housing sales (national and regional), employment, average working hours, and so on. The price and inflation group consists of variables such as the consumer price index, the producer price index, real housing prices (national and regional), the personal consumption expenditure deflator, average hourly earnings, exchange rates, and so on. The monetary sector group consists of variables such as monetary aggregates, various interest rates, credit outstanding, and so on.

5.2 Estimation and Results

In this section, we first, , select the optimal model for forecasting each sector's employment, using the minimum average root mean squared error (RMSE) across the one-, two-, … , and twelve-month-ahead out-of-sample forecasts. Then second, we consider ex ante out-of-sample forecasts.

The data sample for all 8 employment series runs from January 1972 (1972:1) through March 2009 (2009:3). First, the cointegration tests amongst the eight employment series and the eight employment series and the four common static factors, extracted based on the Bai (2004) approach, for the (B)FAVEC 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 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 (B)VEC and (B)FAVEC models by using the trace test proposed by Johansen (1991). Fifth, we base the leg-length for the various models at each recursive estimation on the unanimity of at least two of the following five lag length selection criteria, namely, 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 criterion (HQIC).[11] 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 Forecast Accuracy

Given the different forecasting models specified in Section 4, we estimate these alternative small- and large-scale models for the 8 employment series in our sample over the period 1972:1 to 1989:12 using monthly data. We then compute 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 random-walk (RW) benchmark. Note that the choice of the in-sample period, especially the starting date, depends on data availability. The starting point of the out-of-sample period precedes 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 multivariate versions of the classical AR, VAR, and VEC, the small-scale BVARs and BVECs, the large-scale BVARs, and the classical and Bayesian FAVARs and FAVECs over the period 1972:1 to 1989:12, and then forecast from 1990:1 through 2009:3. Depending on the number of lags selected, specific initial months feed the lags. We re-estimate the models each month over the out-of-sample forecast horizon in order to update the estimate of the coefficients, before producing the on-, two-, …, and twelve-month-ahead forecasts. We implemented 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-

[11] 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 four factors for the FAVEC models, The tests suggest 5 and 11 cointegrating vectors, respectively, implying that the system contains 3 and 1 common trends, respectively. These results are available upon request rom the authors.

month-ahead forecasts. We calculate the root mean squared errors (RMSE)[12] for the 219 one-, two-, …, and twelve-month-ahead forecasts for the 8 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 'optimal' specification for a specific state.

Tables 1 to 8 report the average of the one-, two-, …, and twelve-month-ahead RMSEs across the 8 employment series, respectively. The benchmark for all forecast evaluations is the random-walk (RW) model forecast RMSEs. Thus, the 0.307 entry for the BFAVEC model in Table 1 means that the BFAVEC model experienced a forecast RMSE of only 30.7 percent of the forecast RMSE for the RW model. First, we consider the best performing model based on the average RMSE across the one-, two-, …, and twelve-month-ahead forecasts. Two different specifications prove optimal across the 8 employment series. One, the BFAVEC models with different value for *w* and *d* prove optimal for mining and logging; manufacturing; financial activities; leisure and hospitality; and other service employment. Two, the BFAAR models with different values for *w* and *d* prove optimal for construction; trade, transportation, and utilities; and professional and business services. These results appear as the bold numbers in the Average column in Tables 1 to 8.

Table 9 also tests whether the difference in forecasting performance proves significant relative to the RW forecasts, using the ENC-t test statistic. The BFAVEC models all provide significantly better forecasts at the 1-percent level. The BFAAR models provide significantly better forecasts at only the 10-percent level.

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[12] 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: $\sqrt{\left[\sum_1^N \left({}_tF_{t+n} - A_{t+n}\right)^2 / N\right]}$ where N equals the number of forecasts.

The forecasting results for the one-, two-, …, and twelve-month-ahead forecasts generally follow a similar pattern. In most cases, a VEC (i.e., VEC, BVEC, FAVEC, or BFAVEC) model provides the best forecasting performance. This conclusion holds no matter whether the optimal model based on the Average of the one-, two-, ..., and twelve-month-ahead forecasts yields a BFAVEC or a BFAAR model. That is, even when the optimal models for the Average across all forecast horizons is a BFAAR model, the VEC (i.e., VEC, BVEWC, FAVEC, and BFAVEC) models frequently still provide the best forecasts in many instances. But in this latter case, the BFAAR sometimes provides the best forecast performance.

In sum, 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, the VEC (i.e., VEC, BVEC, FAVEC, and BFAVEC) models generally provide the best forecast performance, albeit for differing values for *w* and *d*.

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

Figures 1 to 8 plot the 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.

The forecast period captures the preliminary turn around in employment for all series except financial activities. Of course, whether the employment series actually bottom during this period or continue to fall with future releases remains an unanswered question. The worst forecast performance occurs in mining and logging employment, where the actual employment series bottomed in October 2009 while the forecast series continues on a downward trend throughout the forecast period.

The best forecast performance occurs for construction employment, where the actual and forecast series track each other closely. But, construction employment appears to bottom only in February 2010. The forecast series for manufacturing, financial activities,, and leisure and hospitality employment each show a turnaround in employment over this period. But the forecast values recover too rapidly as compared to the actual series. For the remaining series – trade, transportation, and utilities; business services; and other services employment, the actual series show a more rapid turnaround over this period than the forecast values.

6. Conclusion

We forecast employment in 8 sectors, using the AR, VAR, VEC, and their Bayesian counterparts, both with and without the information content of 143 additional monthly economic series. Two approaches exist for incorporating information from a large number of data series – extracting common factors (principle components) in a FAVAR, FAVEC, and their Bayesian counterparts or Bayesian shrinkage in a LBVAR models.

Using the period of 1972:1 to 1989:12 as the in-sample period and 1990:1 to 2009:3 as the out-of-sample horizon, we compare the forecast performance of the alternative models 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, albeit with different values for *w* and *d*, generally outperform the large-scale models for the 8 employment series examined. A LBVAR model only provides the best forecasting performance for two employment series – construction employment at one-step ahead forecast horizon and professional and business services employment at one-, two-, and three-step ahead forecast horizons. In addition, amongst the factor augmented models, generally the VEC (i.e., FAVEC and BFAVEC) generally perform the best, highlighting the importance of modeling the long-run equilibrium relationship over and above the short-run dynamics.

We also compare the 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 worst performing model forecasts mining and logging employment while the best performing model forecasts construction 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 8 employment series.

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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

Data Code	Variable Name	Format
CES049	EMPLOYEES ON NONFARM PAYROLLS - WHOLESALE TRADE	5
CES053	EMPLOYEES ON NONFARM PAYROLLS - RETAIL TRADE	5
CES140	EMPLOYEES ON NONFARM PAYROLLS - GOVERNMENT	5
CESNRM	All Employees: Natural Resources & Mining	5
CEML	Mining & Logging Employment	5
CEC	Construction Employment	5
CEM	Manufacturing Employment	5
CETTU	Trade, Trans. & Util. Employment	5
CEFA	Financial Activities Employment	5
CEPBS	Prof & Bus. Serv. Employment	5
CELH	Leisure & Hospitality Employment	5
CEOS	Other Services Employment	5
CES151	Average Weekly Hours: Manufacturing	1
CES155	Average Weekly Hours: Overtime: Manufacturing	2
PMEMP	NAPM EMPLOYMENT INDEX (PERCENT)	1
HSFR	HOUSING STARTS:TOTAL (THOUS.U)S.A.	4
HSNE	HOUSING STARTS: NORTHEAST (THOUS.U.)S.A.	4
HSMW	HOUSING STARTS: MIDWEST (THOUS.U.)S.A.	4
HSSOU	HOUSING STARTS: SOUTH (THOUS.U.)S.A.	4
HSWST	HOUSING STARTS: WEST (THOUS.U.)S.A.	4
HSBR	HOUSING AUTHORIZED: TOTAL NEW PRIV HOUSING UNITS (THOUS.,SAAR)	4
HSBNE	HOUSES AUTHORIZED BY BUILD. PERMITS: NORTHEAST (THOU.U.)S.A	4
HSBMW	HOUSES AUTHORIZED BY BUILD. PERMITS: MIDWEST (THOU.U.)S.A.	4
HSBSOU	HOUSES AUTHORIZED BY BUILD. PERMITS: SOUTH (THOU.U.)S.A.	4
HSBWST	HOUSES AUTHORIZED BY BUILD. PERMITS: WEST (THOU.U.)S.A.	4
HPNE	Real House Price Northeast	6
HPMW	Real House Price Midwest	6
HPS	Real House Price South	6
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

Data Code	Variable Name	Format
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
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

Data Code	Variable Name	Format
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.

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
	AR	0.985	1.009	1.014	1.012	1.001	0.997	0.998	1.002	1.007	1.012	1.016	1.019	1.006
	VAR	3.700	4.038	3.987	4.111	4.141	4.256	4.387	4.510	4.641	4.820	4.983	5.130	4.392
	FAAR	4.275	4.255	4.204	4.272	4.206	4.166	4.115	4.081	4.017	4.064	4.056	4.040	4.146
	FAVAR	1.442	1.354	1.205	1.111	1.010	0.950	0.892	0.861	0.830	0.794	0.768	0.745	0.997
	VEC	2.757	**0.184**	**0.263**	3.676	3.761	1.832	1.959	0.614	5.315	9.559	21.455	22.825	6.183
	FAVEC	0.404	1.719	1.595	2.253	2.268	2.375	2.365	2.544	2.252	2.107	1.847	1.634	1.947
	BAR	0.973	0.988	0.990	0.988	0.973	0.969	0.972	0.981	0.989	0.998	1.004	1.007	0.986
	BVAR	1.833	2.150	2.292	2.377	2.395	2.432	2.481	2.531	2.571	2.607	2.640	2.672	2.415
	BFAAR	1.251	1.240	1.180	1.097	1.010	0.965	0.934	0.919	0.904	0.885	0.868	0.853	1.009
w=0.3, d=0.5	**BFAVAR**	1.598	1.794	1.888	1.946	1.967	2.000	2.033	2.063	2.079	2.094	2.112	2.138	1.976
	BVEC	2.904	4.217	4.877	2.291	1.534	3.057	3.551	3.596	5.612	7.135	13.173	11.971	5.326
	BFAVEC	0.348	1.498	1.389	2.098	2.159	2.262	2.263	2.445	2.202	2.116	1.917	1.723	1.868
	LBVAR	2.525	2.773	2.742	2.436	2.820	3.207	3.719	4.246	4.875	5.474	6.092	6.742	3.971
	BAR	0.971	0.984	0.989	0.990	0.987	0.988	0.992	0.997	1.002	1.007	1.010	1.013	0.994
	BVAR	1.512	1.710	1.803	1.846	1.860	1.870	1.884	1.900	1.912	1.924	1.937	1.951	1.843
	BFAAR	1.022	1.005	0.978	0.919	0.881	0.864	0.853	0.843	0.833	0.823	0.815	0.810	0.888
w=0.2,d=1	**BFAVAR**	1.403	1.545	1.626	1.679	1.715	1.737	1.761	1.781	1.793	1.807	1.822	1.840	1.709
	BVEC	2.213	7.371	7.182	5.774	4.864	6.175	7.999	9.625	10.223	12.217	13.744	12.149	8.295
	BFAVEC	**0.035**	0.693	0.780	1.434	1.485	1.540	1.543	1.641	1.584	1.667	1.658	1.605	1.305
	LBVAR	1.911	2.154	2.204	2.100	2.520	2.816	3.225	3.638	4.162	4.672	5.173	5.694	3.356
	BAR	0.992	1.005	1.013	1.018	1.021	1.026	1.031	1.036	1.039	1.043	1.045	1.046	1.026
	BVAR	1.364	1.507	1.584	1.628	1.655	1.675	1.694	1.709	1.720	1.730	1.739	1.749	1.646
	BFAAR	0.972	0.938	0.911	0.871	0.853	0.845	0.836	0.827	0.819	0.811	0.804	0.802	0.857
w=0.1,d=1	**BFAVAR**	1.316	1.433	1.506	1.562	1.603	1.629	1.654	1.673	1.685	1.697	1.709	1.722	1.599
	BVEC	1.648	6.532	6.614	5.483	4.560	5.070	6.144	7.358	7.607	8.691	9.204	8.155	6.422
	BFAVEC	0.317	0.479	0.525	0.916	0.939	0.923	0.853	0.800	0.778	0.727	0.652	0.657	0.714
	LBVAR	1.392	1.576	1.658	1.660	2.053	2.384	2.761	3.142	3.611	4.058	4.482	4.918	2.808

Table 1: One- to Twelve-Months-Ahead Forecast for Mining & Logging Employment: 1990:1-2009:3 (continued)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
	BAR	1.009	1.029	1.041	1.048	1.053	1.058	1.061	1.063	1.062	1.061	1.058	1.055	1.050
	BVAR	1.461	1.612	1.685	1.726	1.753	1.774	1.795	1.813	1.826	1.839	1.853	1.866	1.750
	BFAAR	1.028	0.985	0.951	0.918	0.911	0.913	0.912	0.910	0.908	0.906	0.905	0.906	0.929
w=0.2, d=2	**BFAVAR**	1.439	1.543	1.601	1.650	1.695	1.722	1.751	1.774	1.791	1.807	1.825	1.844	1.704
	BVEC	0.648	3.581	3.802	3.128	2.580	2.452	2.429	2.431	2.190	2.103	1.911	1.573	2.402
	BFAVEC	0.309	0.273	0.340	0.505	0.588	0.570	0.510	0.420	0.416	0.312	0.227	0.271	0.395
	LBVAR	1.823	1.935	1.938	1.938	2.380	2.681	3.104	3.549	4.063	4.540	4.969	5.434	3.196
	BAR	1.029	1.046	1.054	1.059	1.063	1.066	1.069	1.071	1.070	1.069	1.067	1.065	1.061
	BVAR	1.344	1.463	1.530	1.574	1.609	1.639	1.668	1.693	1.714	1.735	1.755	1.774	1.625
	BFAAR	1.033	0.983	0.948	0.925	1.122	1.316	1.500	1.681	1.865	2.049	2.235	2.429	1.507
w=0.1,d=2	**BFAVAR**	1.323	1.415	1.475	1.527	1.571	1.602	1.634	1.659	1.679	1.700	1.719	1.739	1.587
	BVEC	1.209	3.236	3.233	2.603	2.090	1.886	1.742	1.601	1.359	1.162	0.920	0.708	1.812
	BFAVEC	0.509	0.333	0.340	**0.444**	**0.518**	**0.480**	**0.397**	**0.270**	**0.248**	**0.098**	**0.029**	**0.015**	**0.307**
	LBVAR	1.349	1.446	1.495	1.535	1.928	2.247	2.634	3.036	3.484	3.899	4.266	4.656	2.665
w=0.0627,d=2	**LBVAR(FIT)**	1.109	1.171	1.223	1.272	1.611	1.912	2.260	2.620	3.015	3.381	3.699	4.032	2.275

Note: AR, VAR, FAAR, FAVAR, VEC, and FAVEC refer to 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, BFAVEC, and LBVAR refer to Bayesian AR, VAR, FAAR, FAVAR, VEC, and FAVEC models. The text identifies various priors and parameterizations. RMSE means root mean square error. 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. Bold numbers represent the minimum value in each column.

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
	AR	0.766	0.677	0.662	0.669	0.693	0.713	0.733	0.754	0.775	0.796	0.815	0.834	0.741
	VAR	1.226	1.185	1.204	1.282	1.399	1.532	1.649	1.758	1.868	1.959	2.025	2.077	1.597
	FAAR	1.379	1.409	1.425	1.506	1.591	1.683	1.757	1.835	1.915	1.987	2.028	2.062	1.715
	FAVAR	0.827	0.722	0.668	0.664	0.682	0.703	0.730	0.750	0.775	0.798	0.813	0.828	0.747
	VEC	2.494	3.957	6.568	46.533	3.734	2.280	2.307	0.957	1.035	0.486	0.805	0.903	6.005
	FAVEC	1.052	1.583	2.819	19.200	1.396	0.583	0.401	0.039	0.102	0.230	0.290	0.319	2.335
	BAR	0.756	0.661	0.641	0.645	0.666	0.685	0.704	0.723	0.744	0.764	0.783	0.803	0.715
	BVAR	0.827	0.775	0.775	0.805	0.850	0.900	0.945	0.981	1.015	1.047	1.069	1.090	0.923
	BFAAR	0.762	0.664	0.633	0.634	0.650	0.667	0.690	0.713	0.738	0.762	0.780	0.796	0.707
w=0.3, d=0.5	**BFAVAR**	0.806	0.729	0.692	0.703	0.741	0.793	0.845	0.887	0.927	0.961	0.986	1.005	0.840
	BVEC	2.430	3.669	5.942	20.933	1.235	**0.055**	0.546	0.155	0.080	0.271	0.139	0.234	2.974
	BFAVEC	1.056	1.576	2.802	19.100	1.392	0.600	0.404	0.048	0.094	0.225	0.283	0.314	2.325
	LBVAR	1.180	1.129	1.068	1.038	1.085	1.130	1.106	1.125	1.169	1.222	1.255	1.294	1.150
	BAR	0.753	0.660	0.639	0.641	0.660	0.677	0.695	0.713	0.733	0.752	0.771	0.790	0.707
	BVAR	0.768	0.694	0.685	0.701	0.733	0.767	0.801	0.831	0.859	0.891	0.917	0.940	0.799
	BFAAR	0.732	**0.635**	**0.611**	**0.614**	0.631	0.646	0.670	0.690	0.713	0.735	0.754	0.769	**0.683**
w=0.2,d=1	**BFAVAR**	0.744	0.660	0.639	0.654	0.689	0.726	0.764	0.796	0.825	0.856	0.882	0.906	0.762
	BVEC	1.959	3.052	4.531	14.567	**0.024**	0.665	0.449	0.585	0.453	0.566	0.435	0.418	2.309
	BFAVEC	1.076	1.510	2.654	18.067	1.372	0.697	0.404	0.094	0.051	0.196	0.248	0.292	2.222
	LBVAR	0.980	0.980	0.972	0.926	0.956	1.003	0.998	1.033	1.086	1.139	1.176	1.213	1.038
	BAR	0.765	0.681	0.665	0.669	0.688	0.704	0.722	0.739	0.759	0.777	0.794	0.813	0.731
	BVAR	0.746	0.659	0.642	0.651	0.677	0.706	0.735	0.762	0.789	0.818	0.844	0.867	0.741
	BFAAR	0.731	0.636	0.615	0.620	0.637	0.649	0.673	0.691	0.713	0.733	0.751	0.766	0.685
w=0.1,d=1	**BFAVAR**	0.733	0.643	0.622	0.633	0.662	0.691	0.722	0.750	0.777	0.805	0.831	0.854	0.727
	BVEC	1.643	2.580	3.914	18.767	0.853	0.124	**0.061**	0.243	0.235	0.331	0.312	0.335	2.450
	BFAVEC	1.098	1.456	2.498	16.700	1.239	0.653	0.333	0.065	0.071	0.215	0.261	0.310	2.075
	LBVAR	0.827	0.795	0.804	0.772	0.802	0.848	0.868	0.905	0.956	1.006	1.043	1.075	0.892

Table 2: One- to Twelve-Months-Ahead Forecast for Construction Employment: 1990:1-2009:3 (continued)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
w=0.2, d=2	**BAR**	0.838	0.800	0.807	0.821	0.840	0.853	0.865	0.875	0.885	0.893	0.900	0.907	0.857
	BVAR	0.776	0.713	0.711	0.728	0.760	0.792	0.824	0.854	0.884	0.916	0.948	0.976	0.824
	BFAAR	0.740	0.659	0.649	0.664	0.687	0.702	0.728	0.746	0.765	0.783	0.798	0.811	0.728
	BFAVAR	0.743	0.667	0.655	0.676	0.715	0.752	0.790	0.823	0.854	0.887	0.922	0.954	0.787
	BVEC	1.374	2.168	3.654	23.167	1.710	0.855	0.376	0.086	**0.044**	0.192	0.230	0.270	2.844
	BFAVEC	1.161	1.458	2.366	14.600	1.044	0.549	0.221	**0.007**	0.120	0.259	0.300	0.345	1.869
	LBVAR	0.933	0.921	0.926	0.845	0.867	0.900	0.947	0.997	1.055	1.112	1.155	1.194	0.988
w=0.1,d=2	**BAR**	0.921	0.913	0.922	0.932	0.941	0.948	0.953	0.957	0.961	0.965	0.967	0.970	0.946
	BVAR	0.828	0.804	0.823	0.853	0.890	0.926	0.960	0.991	1.022	1.052	1.083	1.112	0.945
	BFAAR	0.761	0.693	0.688	0.709	0.736	0.749	0.776	0.792	0.807	0.822	0.835	0.846	0.768
	BFAVAR	0.778	0.732	0.745	0.781	0.826	0.865	0.906	0.941	0.974	1.007	1.040	1.072	0.889
	BVEC	1.289	2.000	3.519	23.900	1.993	1.149	0.638	0.312	0.159	**0.021**	**0.071**	**0.125**	2.931
	BFAVEC	1.176	1.506	2.469	15.467	1.154	0.625	0.271	0.028	0.092	0.238	0.283	0.331	1.970
	LBVAR	0.800	0.754	0.757	0.724	0.754	0.791	0.836	0.886	0.939	0.991	1.031	1.067	0.861
w=0.0627,d=2	**LBVAR(FIT)**	**0.730**	0.650	0.643	0.635	0.668	0.709	0.751	0.798	0.847	0.892	0.925	0.960	0.767

Note: See Table 4. Bold numbers represent the minimum value in each column.

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
	AR	0.695	0.666	0.711	0.777	0.842	0.908	0.961	1.012	1.056	1.092	1.125	1.158	0.917
	VAR	1.024	1.153	1.353	1.592	1.818	2.032	2.220	2.398	2.556	2.687	2.797	2.889	2.043
	FAAR	1.158	1.312	1.567	1.882	2.166	2.423	2.631	2.804	2.932	3.027	3.107	3.177	2.349
	FAVAR	0.703	0.630	0.630	0.648	0.660	0.691	0.730	0.767	0.800	0.826	0.843	0.856	0.732
	VEC	0.680	2.106	1.936	1.439	1.472	0.968	0.460	0.781	1.597	1.980	1.878	1.749	1.420
	FAVEC	0.840	0.697	0.269	0.074	**0.069**	**0.006**	0.155	**0.198**	**0.221**	0.238	0.346	0.342	0.288
	BAR	0.686	0.658	0.704	0.771	0.838	0.905	0.958	1.009	1.052	1.087	1.121	1.156	0.912
	BVAR	0.689	0.685	0.744	0.838	0.936	1.023	1.092	1.154	1.205	1.246	1.285	1.322	1.018
	BFAAR	0.637	0.579	0.594	0.627	0.656	0.695	0.739	0.780	0.819	0.853	0.877	0.899	0.730
w=0.3, d=0.5	**BFAVAR**	0.658	0.638	0.693	0.783	0.879	0.970	1.051	1.122	1.183	1.232	1.276	1.318	0.983
	BVEC	0.674	2.682	1.891	1.238	1.150	0.582	**0.009**	0.218	0.785	1.053	0.970	0.849	1.009
	BFAVEC	0.840	0.652	0.231	0.082	0.084	0.011	0.168	0.207	0.228	0.240	0.347	0.343	**0.286**
	LBVAR	0.854	0.778	0.839	0.954	1.074	1.155	1.170	1.203	1.288	1.368	1.434	1.507	1.135
	BAR	0.687	0.667	0.717	0.786	0.854	0.922	0.978	1.032	1.078	1.118	1.154	1.189	0.932
	BVAR	0.631	0.580	0.601	0.651	0.710	0.763	0.803	0.841	0.874	0.901	0.926	0.950	0.769
	BFAAR	0.619	0.570	0.590	0.628	0.667	0.706	0.751	0.791	0.829	0.861	0.888	0.911	0.734
w=0.2,d=1	**BFAVAR**	0.604	0.545	0.561	0.606	0.661	0.710	0.759	0.802	0.838	0.868	0.896	0.921	0.731
	BVEC	0.400	4.394	2.513	1.963	1.456	1.141	0.705	0.649	0.785	0.839	0.608	0.552	1.334
	BFAVEC	0.794	0.652	0.154	**0.025**	0.135	0.104	0.228	0.264	0.277	0.279	0.377	0.369	0.305
	LBVAR	0.683	0.632	0.694	0.802	0.912	0.993	1.048	1.108	1.195	1.270	1.330	1.393	1.005
	BAR	0.706	0.698	0.753	0.819	0.883	0.947	1.001	1.052	1.097	1.136	1.172	1.206	0.956
	BVAR	0.616	0.562	0.582	0.626	0.676	0.722	0.759	0.793	0.823	0.848	0.872	0.894	0.731
	BFAAR	0.628	0.590	0.617	0.662	0.708	0.749	0.796	0.834	0.868	0.898	0.923	0.945	0.768
w=0.1,d=1	**BFAVAR**	0.598	0.542	0.561	0.603	0.649	0.689	0.730	0.765	0.796	0.822	0.846	0.868	0.706
	BVEC	**0.109**	4.000	2.083	1.570	1.050	0.891	0.585	0.499	0.514	0.510	0.289	0.271	1.031
	BFAVEC	0.771	0.606	0.083	0.066	0.203	0.192	0.298	0.334	0.341	0.341	0.430	0.422	0.341
	LBVAR	0.609	0.540	0.572	0.660	0.758	0.841	0.910	0.971	1.051	1.112	1.160	1.208	0.866

Table 3: One- to Twelve-Months-Ahead Forecast for Manufacturing Employment: 1990:1-2009:3 (continued)

	Models	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
	BAR	0.717	0.716	0.773	0.833	0.888	0.939	0.980	1.017	1.049	1.075	1.098	1.120	0.934
	BVAR	0.628	0.586	0.617	0.667	0.721	0.772	0.815	0.854	0.890	0.923	0.953	0.983	0.784
	BFAAR	0.650	0.620	0.643	0.682	0.720	0.751	0.790	0.819	0.845	0.868	0.887	0.905	0.765
w=0.2, d=2	**BFAVAR**	0.597	0.538	0.559	0.607	0.666	0.716	0.769	0.813	0.851	0.886	0.921	0.956	0.740
	BVEC	0.251	2.879	1.474	1.139	0.736	0.689	0.439	0.336	0.298	0.272	0.079	0.075	0.722
	BFAVEC	0.754	0.545	**0.026**	0.090	0.248	0.249	0.346	0.380	0.387	0.387	0.470	0.462	0.362
	LBVAR	0.662	0.617	0.659	0.747	0.844	0.892	0.976	1.051	1.138	1.204	1.256	1.310	0.946
	BAR	0.783	0.799	0.846	0.886	0.918	0.946	0.967	0.984	0.997	1.007	1.015	1.022	0.931
	BVAR	0.698	0.695	0.743	0.792	0.840	0.884	0.920	0.953	0.981	1.006	1.030	1.053	0.883
	BFAAR	0.663	0.637	0.661	0.700	0.743	0.775	0.814	0.841	0.862	0.881	0.897	0.912	0.782
w=0.1,d=2	**BFAVAR**	0.633	0.603	0.644	0.699	0.755	0.801	0.849	0.887	0.920	0.949	0.978	1.006	0.810
	BVEC	0.343	2.636	1.372	1.053	0.668	0.625	0.385	0.285	0.249	**0.226**	**0.041**	**0.039**	0.660
	BFAVEC	0.777	**0.394**	0.058	0.164	0.303	0.305	0.393	0.423	0.427	0.426	0.502	0.494	0.389
	LBVAR	0.592	0.523	0.543	0.617	0.700	0.757	0.828	0.886	0.954	1.000	1.034	1.071	0.792
w=0.0627,d=2	**LBVAR(FIT)**	0.569	0.488	0.496	0.560	0.633	0.691	0.750	0.796	0.847	0.876	0.892	0.915	0.709

Note: See Table 4. Bold numbers represent the minimum value in each column.

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
	AR	0.712	0.615	0.603	0.617	0.636	0.651	0.667	0.678	0.694	0.710	0.726	0.740	0.671
	VAR	1.034	0.982	0.991	1.042	1.123	1.229	1.333	1.426	1.517	1.598	1.659	1.707	1.303
	FAAR	1.184	1.096	1.090	1.136	1.216	1.303	1.375	1.435	1.498	1.540	1.555	1.561	1.332
	FAVAR	0.713	0.582	0.551	0.560	0.572	0.587	0.610	0.629	0.656	0.678	0.695	0.711	0.629
	VEC	2.541	8.974	12.692	5.818	4.616	4.009	3.118	2.452	2.343	2.092	1.849	1.774	4.357
	FAVEC	1.399	4.256	3.821	1.509	0.612	0.313	0.175	0.021	0.085	0.158	0.190	0.229	1.064
	BAR	0.712	0.620	0.611	0.627	0.649	0.666	0.683	0.697	0.714	0.731	0.749	0.765	0.685
	BVAR	0.743	0.670	0.671	0.699	0.735	0.774	0.810	0.840	0.872	0.902	0.930	0.955	0.800
	BFAAR	0.672	0.561	0.542	0.559	0.574	0.591	0.618	0.640	0.668	0.692	0.711	0.727	0.630
w=0.3, d=0.5	**BFAVAR**	0.727	0.635	0.623	0.647	0.680	0.717	0.755	0.787	0.821	0.852	0.877	0.900	0.752
	BVEC	2.426	7.667	9.821	3.836	3.073	2.453	1.635	1.170	1.131	1.018	0.884	0.842	2.996
	BFAVEC	1.399	4.231	3.769	1.491	0.589	0.297	0.164	0.027	0.093	0.163	0.196	0.233	1.054
	LBVAR	0.916	0.873	0.908	0.793	0.847	0.908	0.924	0.964	1.032	1.101	1.154	1.207	0.969
	BAR	0.711	0.621	0.612	0.628	0.649	0.666	0.684	0.698	0.716	0.734	0.752	0.768	0.687
	BVAR	0.703	0.625	0.620	0.639	0.663	0.687	0.711	0.733	0.757	0.782	0.806	0.827	0.713
	BFAAR	**0.660**	**0.555**	**0.539**	**0.557**	0.574	0.589	0.616	0.637	0.662	0.685	0.703	0.720	**0.625**
w=0.2,d=1	**BFAVAR**	0.684	0.595	0.581	0.600	0.625	0.648	0.676	0.700	0.727	0.754	0.778	0.799	0.681
	BVEC	2.007	6.872	9.077	3.773	2.342	1.575	0.986	0.648	0.601	0.544	0.509	0.449	2.449
	BFAVEC	1.466	4.359	3.846	1.473	0.539	0.256	0.123	0.038	0.110	0.171	0.212	0.236	1.069
	LBVAR	0.777	0.742	0.798	0.721	0.774	0.833	0.863	0.918	0.985	1.053	1.206	1.365	0.920
	BAR	0.714	0.630	0.623	0.638	0.658	0.675	0.693	0.707	0.725	0.742	0.758	0.773	0.695
	BVAR	0.701	0.621	0.616	0.633	0.656	0.679	0.703	0.724	0.747	0.770	0.791	0.809	0.704
	BFAAR	0.667	0.568	0.554	0.572	0.590	0.603	0.629	0.647	0.669	0.689	0.705	0.720	0.635
w=0.1,d=1	**BFAVAR**	0.687	0.602	0.592	0.611	0.635	0.656	0.682	0.703	0.727	0.751	0.772	0.790	0.684
	BVEC	1.811	5.718	6.821	2.727	1.507	0.938	0.573	0.336	0.275	0.211	0.167	0.131	1.768
	BFAVEC	1.480	4.410	3.923	1.445	0.525	0.244	0.107	0.048	0.115	0.171	0.211	0.231	1.076
	LBVAR	0.707	0.648	0.687	0.644	0.687	0.740	0.782	0.832	0.894	0.954	1.092	1.231	0.825

Table 4: One- to Twelve-Months-Ahead Forecast for Trade, Transport, & Utilities Employment: 1990:1-2009:3 (continued)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
	BAR	0.752	0.695	0.704	0.729	0.754	0.773	0.791	0.805	0.818	0.831	0.843	0.853	0.779
	BVAR	0.736	0.687	0.700	0.730	0.762	0.793	0.824	0.851	0.879	0.906	0.934	0.960	0.813
	BFAAR	0.680	0.600	0.599	0.628	0.656	0.675	0.704	0.722	0.742	0.760	0.774	0.787	0.694
w=0.2, d=2	**BFAVAR**	0.700	0.636	0.641	0.674	0.712	0.745	0.784	0.814	0.846	0.878	0.909	0.941	0.773
	BVEC	1.534	3.923	3.667	1.382	0.589	0.338	0.206	0.055	**0.004**	0.046	0.083	0.096	0.994
	BFAVEC	1.419	2.949	2.615	1.036	0.429	0.266	0.190	0.073	0.051	**0.025**	**0.008**	**0.016**	0.756
	LBVAR	0.752	0.694	0.725	0.688	0.724	0.776	0.825	0.887	0.950	1.017	1.170	1.326	0.878
	BAR	0.841	0.828	0.847	0.868	0.886	0.898	0.907	0.914	0.920	0.924	0.928	0.931	0.891
	BVAR	0.784	0.767	0.793	0.828	0.863	0.896	0.927	0.953	0.978	1.003	1.028	1.052	0.906
	BFAAR	0.703	0.642	0.647	0.677	0.708	0.727	0.753	0.768	0.783	0.795	0.806	0.815	0.735
w=0.1,d=2	**BFAVAR**	0.731	0.694	0.715	0.756	0.798	0.834	0.872	0.903	0.932	0.961	0.990	1.018	0.850
	BVEC	1.405	3.615	3.256	1.182	0.466	0.253	0.142	**0.007**	0.036	0.078	0.112	0.120	0.889
	BFAVEC	1.257	2.564	1.872	0.582	**0.100**	**0.034**	**0.100**	0.193	0.215	0.237	0.252	0.250	0.638
	LBVAR	0.692	0.613	0.626	0.617	0.649	0.691	0.733	0.781	0.835	0.888	1.014	1.141	0.773
w=0.0627,d=2	**LBVAR(FIT)**	0.671	0.575	0.574	0.575	0.604	0.641	0.678	0.716	0.762	0.804	0.910	1.018	0.711

Note: See Table 4. Bold numbers represent the minimum value in each column.

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
	AR	0.594	**0.556**	0.560	0.588	0.620	0.655	0.686	0.713	0.740	0.764	0.785	0.802	0.672
	VAR	0.762	0.736	0.762	0.821	0.883	0.963	1.035	1.112	1.194	1.278	1.358	1.441	1.029
	FAAR	0.814	0.767	0.801	0.862	0.915	0.986	1.047	1.109	1.169	1.233	1.295	1.360	1.030
	FAVAR	0.627	0.577	0.578	0.606	0.640	0.687	0.729	0.769	0.809	0.851	0.888	0.922	0.724
	VEC	0.870	3.762	2.714	3.649	2.746	5.781	6.923	4.840	2.247	1.187	0.951	1.275	3.079
	FAVEC	0.826	1.238	**0.214**	1.108	0.763	0.969	0.923	0.651	0.169	0.044	0.212	0.345	0.622
	BAR	0.595	0.557	0.561	0.588	0.618	0.651	0.680	0.704	0.726	0.746	0.762	0.775	0.664
	BVAR	0.655	0.641	0.671	0.725	0.782	0.848	0.914	0.980	1.048	1.116	1.183	1.250	0.901
	BFAAR	0.607	0.564	0.564	0.587	0.614	0.649	0.679	0.705	0.732	0.759	0.781	0.798	0.670
w=0.3, d=0.5	**BFAVAR**	0.649	0.629	0.653	0.704	0.760	0.828	0.894	0.959	1.027	1.096	1.162	1.228	0.882
	BVEC	0.957	3.571	2.595	3.595	2.458	4.953	6.179	4.755	2.675	1.716	1.443	1.591	3.041
	BFAVEC	0.783	1.238	0.262	1.162	0.797	1.000	0.949	0.689	0.193	**0.022**	0.192	0.328	0.634
	LBVAR	0.776	0.764	0.775	0.815	0.882	0.940	1.024	1.109	1.194	1.276	1.339	1.398	1.024
	BAR	0.595	0.556	0.561	**0.586**	0.616	0.649	0.678	0.702	0.725	0.745	0.761	0.775	0.662
	BVAR	0.634	0.616	0.643	0.694	0.751	0.812	0.873	0.933	0.993	1.053	1.109	1.164	0.856
	BFAAR	0.602	0.564	0.568	0.589	0.615	0.646	0.674	0.696	0.720	0.742	0.761	0.776	0.663
w=0.2,d=1	**BFAVAR**	0.633	0.611	0.636	0.684	0.739	0.801	0.861	0.920	0.980	1.039	1.095	1.149	0.846
	BVEC	1.217	2.571	2.143	2.676	1.898	2.750	3.205	2.858	2.175	1.844	1.717	1.655	2.226
	BFAVEC	**0.391**	1.333	0.452	1.378	0.915	1.172	1.103	0.811	0.301	0.076	0.124	0.268	0.694
	LBVAR	0.684	0.684	0.724	0.734	0.804	0.844	0.916	0.991	1.060	1.123	1.178	1.231	0.914
	BAR	0.606	0.571	0.578	0.603	0.633	0.664	0.691	0.714	0.736	0.756	0.773	0.789	0.676
	BVAR	0.635	0.617	0.643	0.690	0.743	0.799	0.853	0.906	0.959	1.011	1.060	1.106	0.835
	BFAAR	0.612	0.576	0.584	0.605	0.629	0.656	0.681	0.700	0.721	0.741	0.759	0.774	0.670
w=0.1,d=1	**BFAVAR**	0.635	0.616	0.642	0.688	0.739	0.794	0.849	0.900	0.953	1.004	1.053	1.100	0.831
	BVEC	1.261	2.190	1.762	2.135	1.576	1.844	1.923	1.764	1.512	1.391	1.316	1.263	1.661
	BFAVEC	1.130	1.952	1.524	1.324	0.780	0.281	0.115	0.274	0.151	0.120	**0.039**	**0.032**	0.644
	LBVAR	0.642	0.642	0.688	0.682	0.744	0.799	0.870	0.937	0.998	1.052	1.104	1.152	0.859

Table 5: One- to Twelve-Months-Ahead Forecast for Financial Activities Employment: 1990:1-2009:3 (continued)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
w=0.2, d=2	**BAR**	0.610	0.584	0.597	0.623	0.652	0.681	0.705	0.723	0.741	0.757	0.770	0.782	0.686
	BVAR	0.661	0.665	0.707	0.767	0.828	0.891	0.949	1.004	1.057	1.107	1.155	1.199	0.916
	BFAAR	0.609	0.581	0.594	0.616	0.639	0.664	0.687	0.703	0.720	0.735	0.749	0.760	0.672
	BFAVAR	0.663	0.666	0.708	0.767	0.828	0.890	0.950	1.004	1.058	1.109	1.158	1.203	0.917
	BVEC	1.348	1.762	1.286	1.162	0.915	0.797	0.731	0.717	0.771	0.800	0.827	0.851	0.997
	BFAVEC	1.261	1.429	1.071	0.703	**0.475**	**0.109**	**0.103**	0.132	**0.042**	0.120	0.215	0.288	**0.496**
	LBVAR	0.680	0.682	0.728	0.705	0.768	0.820	0.894	0.962	1.018	1.060	1.101	1.136	0.879
w=0.1,d=2	**BAR**	0.679	0.680	0.705	0.733	0.760	0.784	0.803	0.816	0.828	0.838	0.845	0.851	0.777
	BVAR	0.745	0.778	0.833	0.895	0.955	1.012	1.066	1.117	1.164	1.209	1.252	1.292	1.026
	BFAAR	0.664	0.656	0.679	0.706	0.729	0.750	0.771	0.783	0.795	0.805	0.813	0.820	0.747
	BFAVAR	0.738	0.767	0.823	0.885	0.945	1.003	1.059	1.110	1.158	1.204	1.248	1.289	1.019
	BVEC	1.217	1.476	1.095	0.865	0.695	0.516	0.449	0.472	0.578	0.636	0.691	0.730	0.785
	BFAVEC	1.435	1.476	1.071	0.757	0.559	0.281	0.103	**0.094**	0.247	0.316	0.394	0.457	0.599
	LBVAR	0.659	0.664	0.707	0.696	0.753	0.812	0.883	0.946	0.996	1.037	1.075	1.114	0.862
w=0.0627,d=2	**LBVAR(FIT)**	0.656	0.656	0.690	0.701	0.755	0.816	0.883	0.940	0.987	1.026	1.064	1.108	0.857

Note: See Table 4. Bold numbers represent the minimum value in each column.

Table 6: One- to Twelve-Months-Ahead Forecast for Professional & Business Services Employment: 1990:1-2009:3

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
	AR	0.650	0.588	0.582	0.595	0.610	0.634	0.658	0.678	0.699	0.719	0.737	0.754	0.659
	VAR	0.787	0.740	0.766	0.818	0.866	0.927	0.990	1.048	1.098	1.140	1.170	1.188	0.961
	FAAR	0.832	0.766	0.779	0.830	0.873	0.929	0.982	1.028	1.062	1.087	1.103	1.111	0.949
	FAVAR	0.673	0.599	0.585	0.599	0.613	0.641	0.672	0.699	0.728	0.756	0.778	0.798	0.679
	VEC	6.235	1.926	3.642	14.939	3.601	1.381	0.611	0.321	0.786	0.765	0.902	0.593	2.975
	FAVEC	3.529	1.895	2.074	3.788	**0.143**	**0.004**	0.047	0.308	0.384	0.476	0.495	0.529	1.139
	BAR	0.650	0.589	0.581	0.592	0.607	0.631	0.656	0.676	0.696	0.716	0.732	0.748	0.656
	BVAR	0.678	0.632	0.639	0.666	0.695	0.734	0.773	0.807	0.841	0.873	0.902	0.926	0.764
	BFAAR	0.649	0.578	0.567	0.580	0.593	0.615	0.642	0.664	0.688	0.710	0.727	0.742	0.646
w=0.3, d=0.5	**BFAVAR**	0.672	0.615	0.613	0.637	0.665	0.706	0.749	0.786	0.825	0.861	0.892	0.920	0.745
	BVEC	6.353	1.905	3.484	11.788	2.780	0.812	**0.003**	0.289	**0.043**	**0.058**	**0.188**	**0.048**	2.313
	BFAVEC	3.588	1.916	2.116	3.909	0.173	0.021	0.030	0.294	0.372	0.467	0.488	0.523	1.158
	LBVAR	0.772	0.690	0.683	0.715	0.757	0.815	0.871	0.910	0.969	1.026	1.078	1.136	0.869
	BAR	0.648	0.587	0.581	0.595	0.611	0.634	0.658	0.678	0.698	0.717	0.733	0.748	0.657
	BVAR	0.660	0.609	0.611	0.631	0.653	0.683	0.713	0.738	0.765	0.792	0.817	0.840	0.709
	BFAAR	0.641	0.574	0.565	0.578	0.591	0.611	0.636	0.656	0.677	0.697	0.713	0.726	**0.639**
w=0.2,d=1	**BFAVAR**	0.655	0.596	0.593	0.613	0.636	0.666	0.699	0.726	0.755	0.783	0.809	0.834	0.697
	BVEC	5.118	1.853	2.842	7.152	1.298	0.611	0.116	0.201	0.176	0.269	0.270	0.395	1.692
	BFAVEC	3.941	1.958	2.263	4.273	0.298	0.126	0.015	0.249	0.331	0.437	0.462	0.502	1.238
	LBVAR	0.681	0.615	0.621	0.645	0.691	0.744	0.801	0.851	0.912	0.966	1.016	1.070	0.801
	BAR	0.654	0.595	0.589	0.604	0.621	0.643	0.667	0.686	0.705	0.723	0.739	0.754	0.665
	BVAR	0.661	0.610	0.610	0.628	0.649	0.676	0.702	0.725	0.747	0.768	0.788	0.806	0.698
	BFAAR	0.649	0.585	0.579	0.593	0.607	0.625	0.649	0.667	0.687	0.706	0.720	0.733	0.650
w=0.1,d=1	**BFAVAR**	0.659	0.604	0.602	0.621	0.642	0.669	0.696	0.719	0.742	0.764	0.784	0.802	0.692
	BVEC	4.000	1.779	2.411	4.818	0.548	0.243	0.027	0.273	0.315	0.416	0.436	0.498	1.314
	BFAVEC	3.235	1.158	1.505	2.576	0.190	0.192	0.122	**0.080**	0.126	0.229	0.228	0.264	0.825
	LBVAR	0.647	0.578	0.581	0.595	0.630	0.674	0.725	0.770	0.822	0.868	0.914	0.959	0.730

Table 6: One- to Twelve-Months-Ahead Forecast for Professional & Business Services Employment: 1990:1-2009:3 (continued)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
	BAR	0.678	0.635	0.641	0.664	0.686	0.710	0.734	0.752	0.769	0.785	0.798	0.809	0.722
	BVAR	0.690	0.659	0.672	0.698	0.724	0.753	0.780	0.802	0.823	0.843	0.862	0.878	0.765
	BFAAR	0.678	0.633	0.641	0.666	0.687	0.709	0.735	0.753	0.772	0.789	0.803	0.814	0.723
w=0.2, d=2	**BFAVAR**	0.683	0.643	0.652	0.680	0.709	0.739	0.769	0.793	0.815	0.836	0.856	0.874	0.754
	BVEC	2.588	1.621	2.147	4.061	0.363	0.226	0.059	0.193	0.276	0.393	0.419	0.465	1.068
	BFAVEC	1.294	0.916	1.095	**0.182**	0.554	0.515	0.525	0.602	0.614	0.654	0.648	0.659	0.688
	LBVAR	0.676	0.611	0.624	0.632	0.667	0.695	0.746	0.794	0.849	0.894	0.934	0.978	0.758
	BAR	0.756	0.747	0.767	0.792	0.815	0.835	0.852	0.866	0.876	0.885	0.892	0.898	0.832
	BVAR	0.739	0.728	0.748	0.777	0.805	0.833	0.858	0.880	0.899	0.917	0.934	0.950	0.839
	BFAAR	0.726	0.700	0.717	0.746	0.771	0.791	0.814	0.829	0.842	0.854	0.863	0.871	0.794
w=0.1,d=2	**BFAVAR**	0.719	0.698	0.717	0.750	0.781	0.810	0.839	0.861	0.882	0.901	0.919	0.937	0.818
	BVEC	2.353	1.674	2.232	4.333	0.423	0.268	0.092	0.170	0.258	0.380	0.407	0.455	1.087
	BFAVEC	0.765	0.989	1.168	0.182	0.607	0.607	0.632	0.700	0.715	0.749	0.748	0.758	0.718
	LBVAR	0.643	0.567	0.565	0.571	0.595	0.627	0.671	0.710	0.756	0.794	0.830	0.868	0.683
w=0.0627,d=2	**LBVAR(FIT)**	**0.630**	**0.550**	**0.542**	0.545	0.564	0.597	0.638	0.672	0.712	0.745	0.778	0.813	0.649

Note: See Table 4. Bold numbers represent the minimum value in each column.

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
	AR	0.953	0.924	0.902	0.908	0.927	0.939	0.942	0.942	0.943	0.946	0.948	0.951	0.936
	VAR	1.584	1.732	1.734	1.666	1.618	1.631	1.662	1.726	1.796	1.849	1.885	1.901	1.732
	FAAR	1.826	2.012	1.989	1.860	1.781	1.755	1.696	1.644	1.587	1.539	1.506	1.469	1.722
	FAVAR	1.183	1.180	1.148	1.108	1.056	1.023	0.983	0.945	0.923	0.921	0.926	0.925	1.027
	VEC	**0.114**	4.202	4.643	2.758	1.264	1.138	1.193	1.186	1.109	1.320	1.057	1.137	1.760
	FAVEC	2.343	0.769	1.944	0.802	**0.117**	0.084	0.402	0.521	0.390	0.442	0.163	0.106	0.674
	BAR	0.998	0.992	0.982	0.988	0.995	0.997	0.984	0.968	0.956	0.949	0.947	0.945	0.975
	BVAR	1.083	1.111	1.116	1.091	1.057	1.030	1.000	0.968	0.953	0.947	0.954	0.958	1.022
	BFAAR	1.013	0.997	0.974	0.956	0.925	0.906	0.885	0.868	0.865	0.867	0.868	0.866	0.916
w=0.3, d=0.5	**BFAVAR**	1.099	1.128	1.130	1.105	1.071	1.042	1.008	0.972	0.950	0.937	0.939	0.942	1.027
	BVEC	0.200	3.780	4.141	2.344	2.750	0.568	0.505	0.585	0.552	0.856	0.632	0.702	1.468
	BFAVEC	2.314	0.769	1.958	0.798	0.988	0.084	0.394	0.511	0.383	0.437	0.164	0.105	0.742
	LBVAR	1.458	1.599	1.690	1.764	1.784	1.742	1.734	1.715	1.737	1.766	1.801	1.836	1.719
	BAR	0.950	0.924	0.909	0.916	0.933	0.943	0.946	0.945	0.945	0.945	0.946	0.948	0.937
	BVAR	0.965	0.941	0.924	0.904	0.881	0.864	0.852	0.837	0.841	0.846	0.860	0.872	0.882
	BFAAR	0.923	0.879	0.851	0.843	0.838	0.836	0.836	0.834	0.839	0.848	0.854	0.858	0.853
w=0.2,d=1	**BFAVAR**	0.973	0.949	0.928	0.907	0.885	0.863	0.848	0.830	0.831	0.835	0.849	0.859	0.880
	BVEC	0.843	2.543	3.005	1.547	0.348	0.113	0.152	0.233	0.201	0.316	0.290	0.285	0.823
	BFAVEC	1.986	0.757	1.906	0.671	0.740	0.121	0.348	0.450	0.330	0.386	0.161	0.105	0.663
	LBVAR	1.221	1.321	1.381	1.431	1.461	1.442	1.455	1.486	1.536	1.596	1.658	1.707	1.474
	BAR	0.951	0.929	0.921	0.929	0.943	0.951	0.955	0.957	0.960	0.962	0.964	0.966	0.949
	BVAR	0.933	0.894	0.868	0.851	0.841	0.839	0.842	0.845	0.859	0.870	0.888	0.902	0.869
	BFAAR	0.915	0.868	0.839	0.829	0.828	0.825	0.829	0.828	0.835	0.846	0.852	0.855	0.846
w=0.1,d=1	**BFAVAR**	0.938	0.899	0.870	0.852	0.841	0.836	0.838	0.838	0.852	0.864	0.881	0.895	0.867
	BVEC	0.629	1.838	2.272	1.018	0.296	**0.005**	0.075	0.116	0.094	0.085	**0.127**	0.107	0.555
	BFAVEC	1.571	0.711	1.681	0.493	0.494	0.164	0.298	0.382	0.285	0.336	0.163	0.129	0.559
	LBVAR	1.081	1.144	1.176	1.208	1.241	1.245	1.271	1.305	1.354	1.412	1.471	1.515	1.285

Table 7: One- to Twelve-Months-Ahead Forecast for Leisure & Hospitality Employment: 1990:1-2009:3 (continued)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
	BAR	0.964	0.953	0.950	0.957	0.967	0.973	0.976	0.978	0.980	0.983	0.984	0.985	0.971
	BVAR	0.993	1.007	1.021	1.033	1.042	1.057	1.078	1.095	1.118	1.137	1.163	1.184	1.077
	BFAAR	0.916	0.866	0.831	0.818	0.816	0.811	0.814	0.814	0.823	0.835	0.843	0.847	0.836
w=0.2, d=2	**BFAVAR**	1.000	1.008	1.010	1.014	1.021	1.032	1.054	1.071	1.096	1.120	1.152	1.178	1.063
	BVEC	0.800	1.139	1.540	0.516	1.305	0.187	0.281	0.226	0.200	0.057	0.134	0.111	0.541
	BFAVEC	0.171	0.734	1.117	0.224	0.506	0.082	**0.024**	**0.072**	**0.091**	0.196	0.128	0.135	**0.290**
	LBVAR	1.179	1.243	1.257	1.264	1.284	1.295	1.324	1.372	1.430	1.503	1.578	1.636	1.364
	BAR	0.982	0.980	0.981	0.986	0.991	0.993	0.995	0.996	0.997	0.998	0.998	0.999	0.991
	BVAR	0.967	0.970	0.985	1.010	1.035	1.062	1.093	1.123	1.155	1.183	1.214	1.243	1.087
	BFAAR	0.921	0.877	0.845	0.831	0.828	0.821	0.825	0.822	0.828	0.838	0.844	0.847	0.844
w=0.1,d=2	**BFAVAR**	0.962	0.951	0.953	0.969	0.991	1.014	1.046	1.076	1.109	1.141	1.176	1.207	1.050
	BVEC	1.514	1.179	1.554	0.540	1.325	0.219	0.304	0.237	0.203	**0.054**	0.128	**0.103**	0.613
	BFAVEC	0.157	**0.272**	**0.540**	**0.067**	1.143	0.226	0.148	0.168	0.165	0.249	0.174	0.172	0.290
	LBVAR	1.065	1.100	1.106	1.112	1.134	1.148	1.176	1.217	1.268	1.330	1.390	1.436	1.207
w=0.0627,d=2	**LBVAR(FIT)**	1.007	1.016	1.013	1.018	1.041	1.053	1.078	1.112	1.156	1.207	1.256	1.295	1.104

Note: See Table 4. Bold numbers represent the minimum value in each column.

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
	AR	**0.767**	**0.728**	**0.725**	**0.744**	0.760	0.770	0.786	0.802	0.818	0.836	0.850	0.860	0.787
	VAR	1.104	1.020	1.037	1.111	1.188	1.273	1.364	1.438	1.503	1.564	1.618	1.652	1.323
	FAAR	1.298	1.170	1.170	1.241	1.301	1.356	1.414	1.456	1.489	1.526	1.554	1.564	1.378
	FAVAR	0.816	0.757	0.748	0.765	0.781	0.803	0.830	0.851	0.876	0.903	0.927	0.947	0.834
	VEC	2.205	2.519	6.855	18.286	7.355	1.320	0.549	0.508	1.149	1.409	1.535	1.127	3.735
	FAVEC	1.542	1.662	2.217	2.400	0.785	**0.037**	0.281	0.405	0.458	0.440	0.474	0.467	0.931
	BAR	0.770	0.731	0.730	0.750	0.768	0.779	0.796	0.811	0.826	0.842	0.856	0.865	0.794
	BVAR	0.809	0.788	0.802	0.837	0.873	0.905	0.942	0.970	0.996	1.023	1.044	1.059	0.921
	BFAAR	0.803	0.764	0.763	0.783	0.796	0.805	0.825	0.841	0.859	0.878	0.892	0.902	0.826
w=0.3, d=0.5	**BFAVAR**	0.828	0.806	0.818	0.849	0.886	0.919	0.955	0.982	1.008	1.034	1.055	1.069	0.934
	BVEC	2.217	2.623	6.797	15.314	6.054	0.758	**0.084**	0.289	0.209	0.376	0.529	**0.167**	2.951
	BFAVEC	1.578	1.714	2.261	2.543	0.860	0.068	0.259	0.386	0.443	0.427	0.463	0.459	0.955
	LBVAR	1.068	1.116	1.163	1.181	1.209	1.209	1.224	1.259	1.305	1.358	1.405	1.450	1.246
	BAR	0.774	0.738	0.737	0.755	0.770	0.779	0.794	0.810	0.824	0.840	0.852	0.861	0.795
	BVAR	0.783	0.753	0.758	0.778	0.798	0.813	0.831	0.845	0.857	0.869	0.879	0.885	0.821
	BFAAR	0.790	0.753	0.753	0.768	0.777	0.778	0.795	0.810	0.826	0.843	0.855	0.864	0.801
w=0.2,d=1	**BFAVAR**	0.789	0.756	0.758	0.776	0.795	0.807	0.826	0.840	0.852	0.865	0.876	0.882	0.818
	BVEC	1.916	2.636	5.246	10.057	3.882	0.858	0.084	**0.165**	**0.081**	**0.097**	**0.143**	0.313	2.123
	BFAVEC	1.771	2.013	2.507	3.143	1.140	0.151	0.178	0.314	0.388	0.387	0.424	0.428	1.070
	LBVAR	0.928	0.996	1.075	1.050	1.079	1.092	1.104	1.147	1.202	1.261	1.314	1.367	1.135
	BAR	0.786	0.754	0.753	0.769	0.784	0.793	0.808	0.822	0.836	0.851	0.861	0.868	0.807
	BVAR	0.780	0.748	0.751	0.767	0.785	0.800	0.817	0.832	0.845	0.858	0.871	0.880	0.811
	BFAAR	0.793	0.759	0.760	0.775	0.784	0.785	0.801	0.816	0.831	0.846	0.857	0.865	0.806
w=0.1,d=1	**BFAVAR**	0.784	0.750	0.751	0.767	0.783	0.794	0.811	0.825	0.838	0.851	0.863	0.871	0.807
	BVEC	1.747	2.442	3.986	6.171	2.108	0.342	0.136	0.287	0.312	0.343	0.397	0.461	1.561
	BFAVEC	1.530	1.442	1.580	1.057	**0.323**	0.155	0.287	0.293	0.300	0.264	0.261	0.239	**0.644**
	LBVAR	0.847	0.886	0.944	0.897	0.917	0.935	0.966	1.009	1.060	1.115	1.170	1.222	0.997

Table 8: One- to Twelve-Months-Ahead Forecast for Other Services Employment: 1990:1-2009:3 (continued)

	Models	1	2	3	4	5	6	7	8	9	10	11	12	Average
	BAR	0.840	0.837	0.854	0.879	0.899	0.911	0.926	0.939	0.950	0.961	0.969	0.975	0.912
	BVAR	0.807	0.790	0.799	0.816	0.833	0.846	0.860	0.870	0.878	0.887	0.897	0.905	0.849
	BFAAR	0.845	0.835	0.851	0.875	0.891	0.898	0.916	0.929	0.943	0.955	0.965	0.973	0.906
w=0.2, d=2	**BFAVAR**	0.815	0.791	0.797	0.813	0.827	0.834	0.847	0.856	0.864	0.872	0.881	0.888	0.840
	BVEC	1.398	2.065	2.913	4.171	1.473	0.265	0.097	0.211	0.297	0.323	0.369	0.390	1.164
	BFAVEC	1.072	0.922	0.826	1.229	0.957	0.895	0.872	0.842	0.823	0.794	0.778	0.757	0.897
	LBVAR	0.902	0.929	0.982	0.951	0.973	1.001	1.035	1.081	1.134	1.190	1.240	1.296	1.059
	BAR	0.935	0.948	0.965	0.983	0.995	1.002	1.010	1.016	1.022	1.026	1.030	1.032	0.997
	BVAR	0.839	0.827	0.837	0.852	0.867	0.880	0.892	0.902	0.909	0.916	0.924	0.931	0.881
	BFAAR	0.905	0.904	0.922	0.945	0.961	0.968	0.982	0.991	1.000	1.008	1.015	1.020	0.968
w=0.1,d=2	**BFAVAR**	0.836	0.817	0.825	0.840	0.855	0.865	0.879	0.888	0.896	0.904	0.912	0.920	0.870
	BVEC	1.386	2.013	2.797	3.857	1.323	0.196	0.139	0.247	0.327	0.349	0.389	0.408	1.119
	BFAVEC	0.940	0.935	0.899	1.143	1.000	0.959	0.944	0.926	0.914	0.897	0.886	0.873	0.943
	LBVAR	0.838	0.842	0.874	0.845	0.868	0.892	0.927	0.968	1.016	1.066	1.112	1.159	0.951
w=0.0627,d=2	**LBVAR(FIT)**	0.811	0.805	0.826	0.800	0.827	0.849	0.885	0.924	0.969	1.015	1.055	1.094	0.905

Note: See Table 4. Bold numbers represent the minimum value in each column.

Table 9: ENC-T Test of Differences between Optimal and Random-Wlak Models

		QA											
Employment Series	**Optimal Model**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Mining & Logging	**BFAECM (w=0.1,d=2)**	-49.13*	-66.67*	-65.95*	-55.56*	-48.22*	-51.98*	-60.33*	-73.01*	-75.17*	-90.19*	-97.12*	-98.54*
Construction	**BFAAR (w=0.2,d=1)**	-26.80†	-36.48**	-38.85**	-38.61**	-36.88**	-35.42**	-33.04†	-30.97†	-28.66†	-26.47†	-24.64†	-23.12†
Manufacturing	**BFAECM (w=0.3,d=0.5)**	-16.00	-34.85†	-76.92*	-91.80*	-91.56*	-98.93*	-83.23*	-79.35*	-77.23*	-75.96*	-65.28*	-65.72*
Trade, Transport. & Utilities	**BFAAR (w=0.2,d=1)**	-34.02†	-44.55**	-46.14*	-44.34**	-42.61**	-41.11**	-38.39**	-36.27**	-33.76†	-31.51†	-29.66†	-28.03†
Financial Activities	**BFAECM (w=0.2,d=2)**	26.09†	42.86**	7.14	-29.73†	-52.54*	-89.06*	-89.74*	-86.79*	-95.78*	-88.00*	-78.50*	-71.22*
Profession & Business Services	**BFAAR (w=0.2,d=1)**	-35.87**	-42.61**	-43.48**	-42.16**	-40.87**	-38.89**	-36.45**	-34.44†	-32.29†	-30.26†	-28.71†	-27.36†
Leisure & Hospitality	**BFAECM (w=0.2,d=2)**	-82.86*	-26.59†	11.74	-77.56*	-49.43*	-91.82*	-97.57*	-92.82*	-90.94*	-80.45*	-87.22*	-86.54*
Other Services	**BFAECM (w=0.1,d=1)**	53.01*	44.16**	57.97*	5.71	-67.74*	-84.47*	-71.31*	-70.68*	-69.98*	-73.57*	-73.92*	-76.06*

Note: The ENC-T statistics test the difference in RMSEs betweenthe optimal model relative to the random-walk model. Negative signs mean that the optimal model forecasts better than the random-walk model.

* means significant at the 1-percent level.

** means significant at the 5-percent level.

† means significant at the 10-percent level.

Figure 1: **Mining and Logging Employment: Ex Ante Forecasts, 2009:3 to 2010:3 (SA, thousands)**

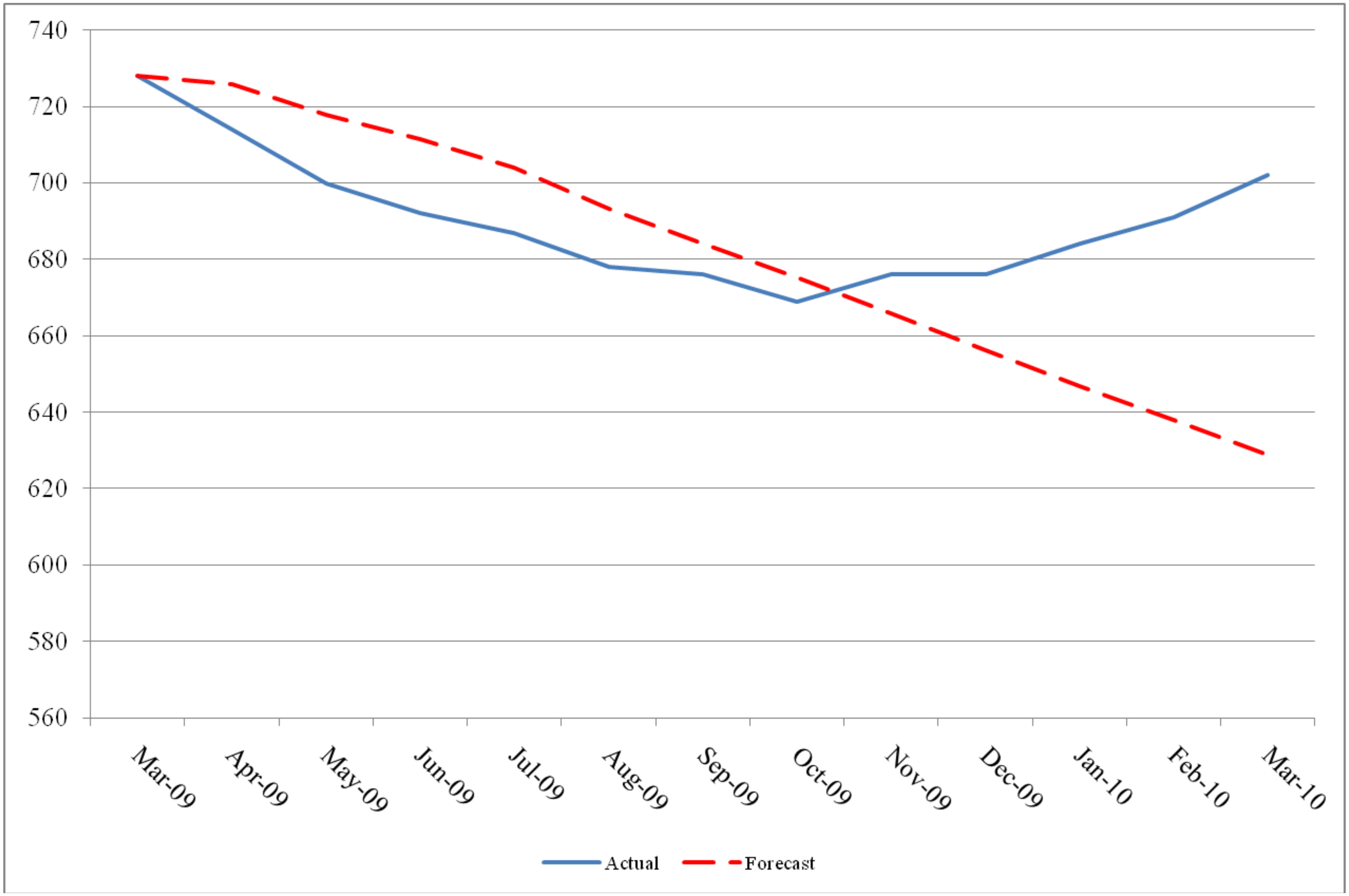

Figure 2: **Construction Employment: Ex Ante Forecasts, 2009:3 to 2010:3 (SA, thousands)**

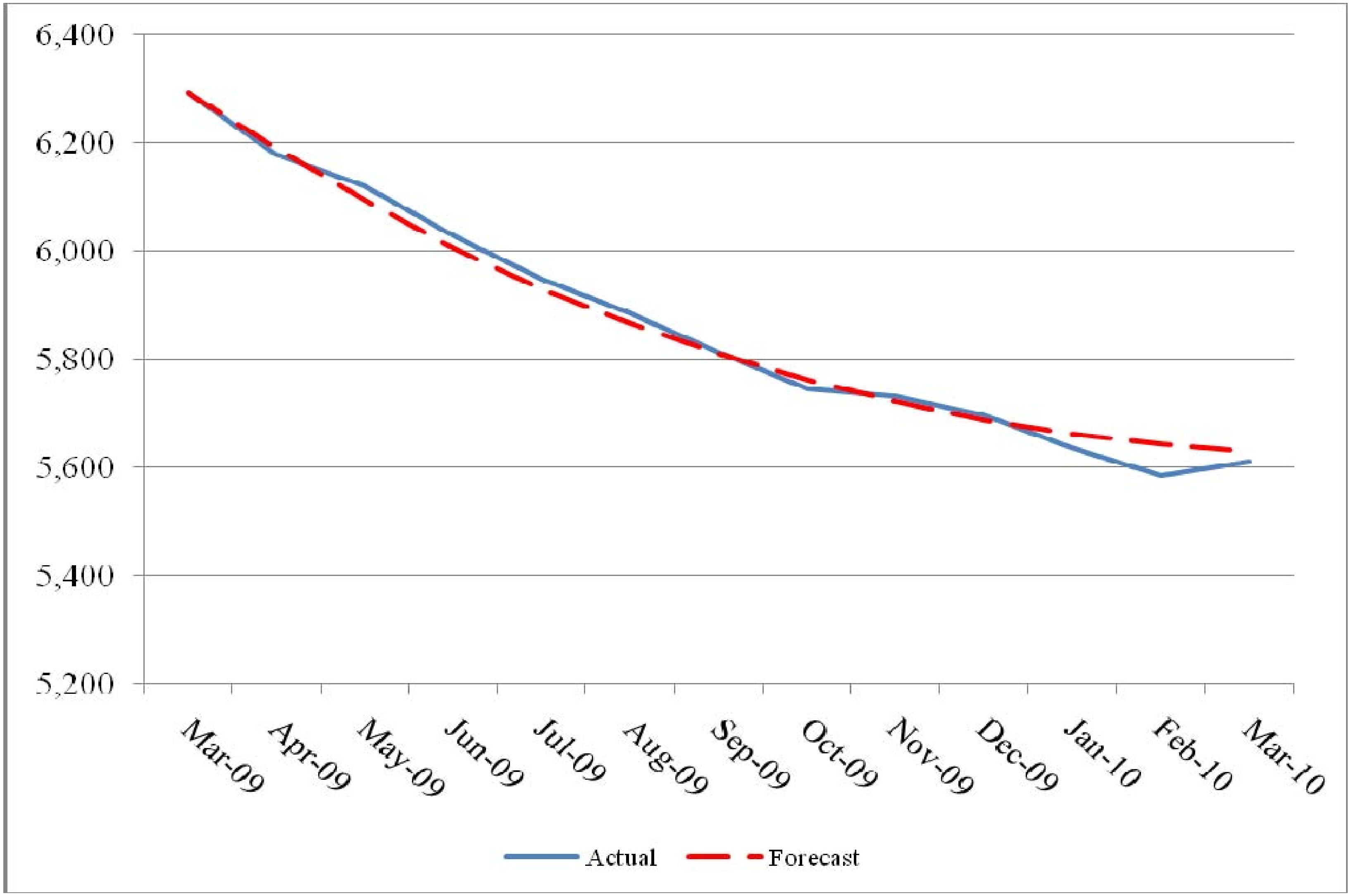

Figure 3: Manufacturing Employment: Ex Ante Forecasts, 2009:3 to 2010:3 (SA, thousands)

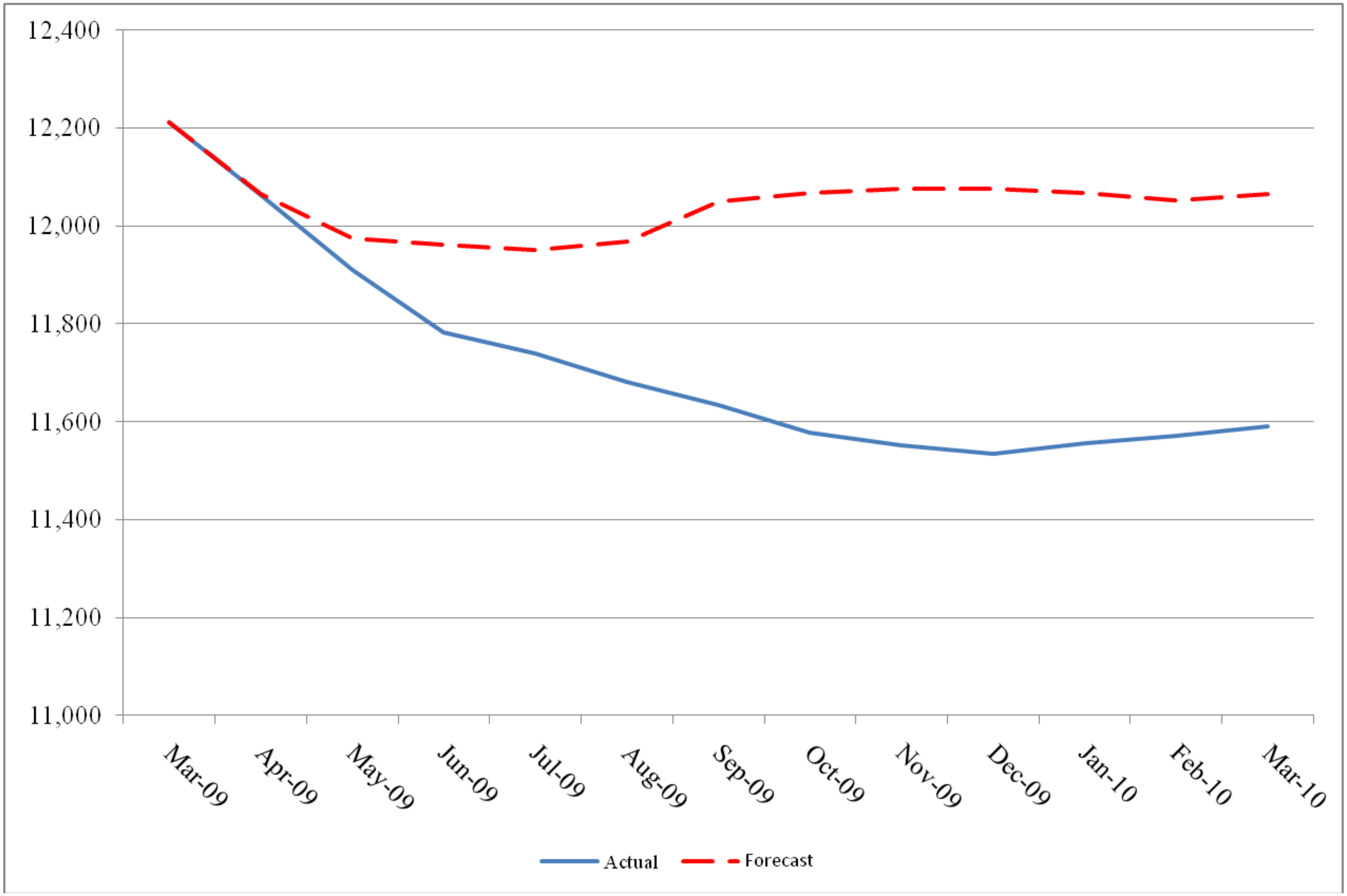

Figure 4: Trade, Transportation, and Utilities Employment: Ex Ante Forecasts, 2009:3 to 2010:3 (SA, thousands)

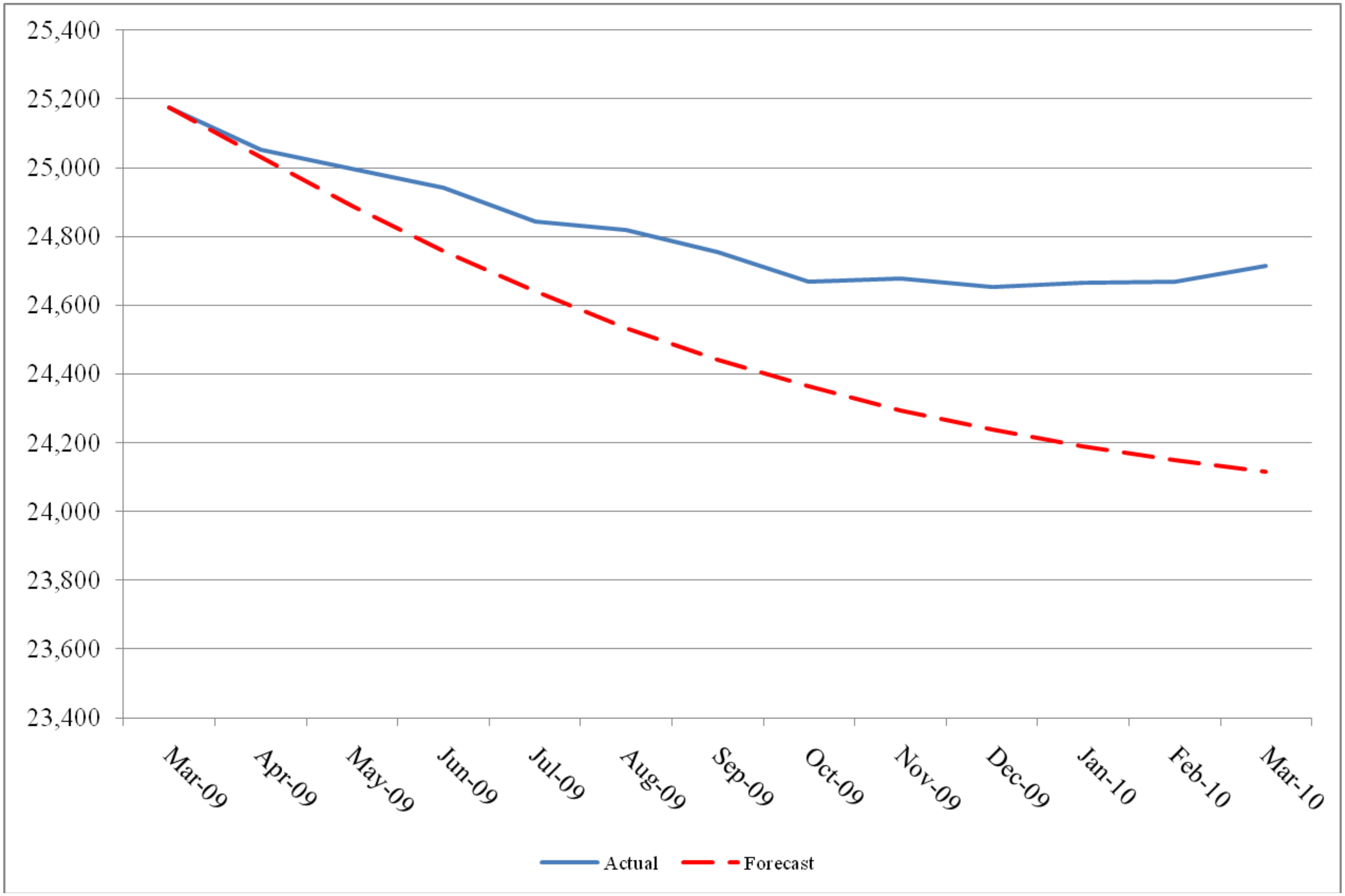

Figure 5: Financial Activities Employment: Ex Ante Forecasts, 2009:3 to 2010:3 (SA, thousands)

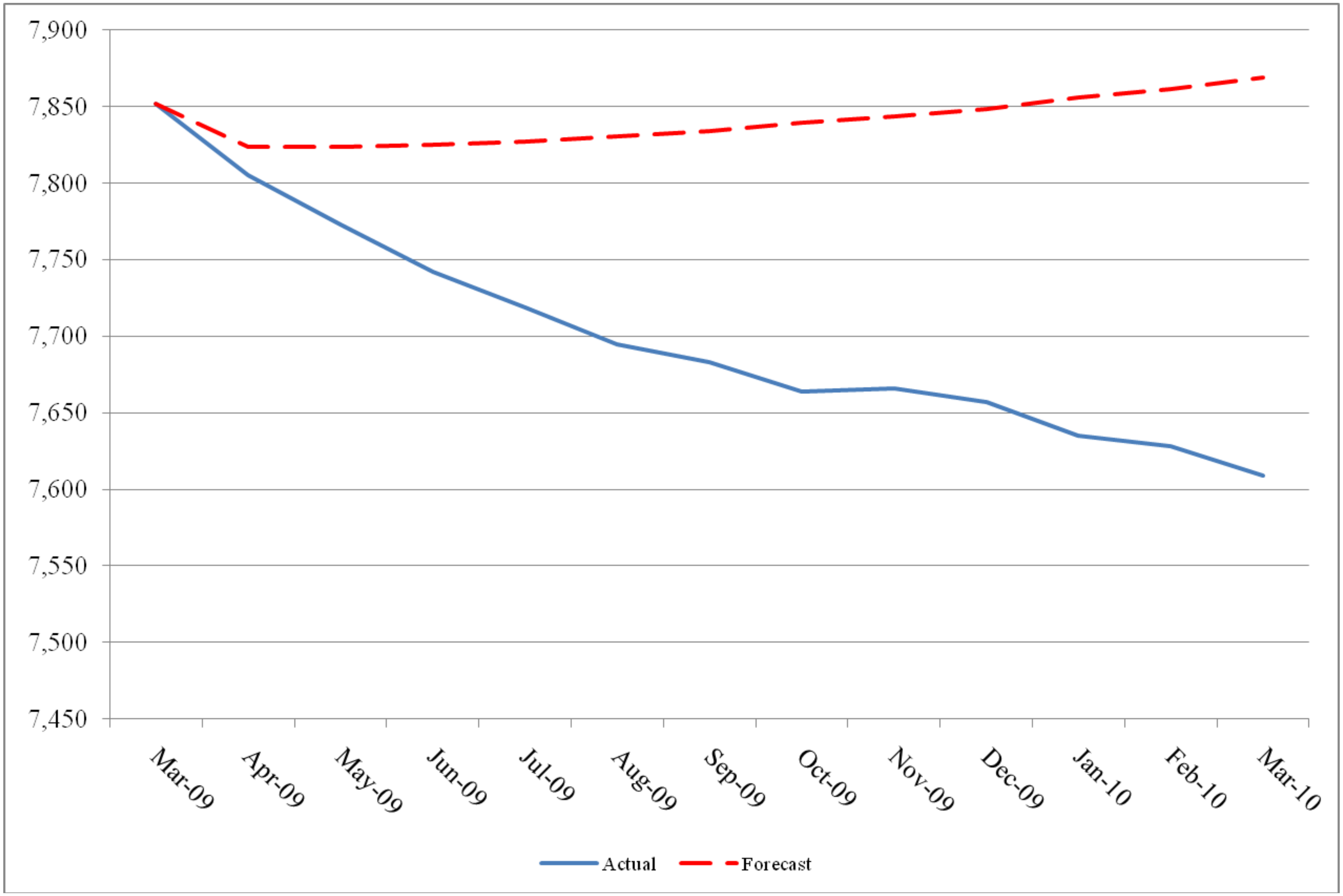

Figure 6: Professional and Business Services Employment: Ex Ante Forecasts, 2009:3 to 2010:3 (SA, thousands)

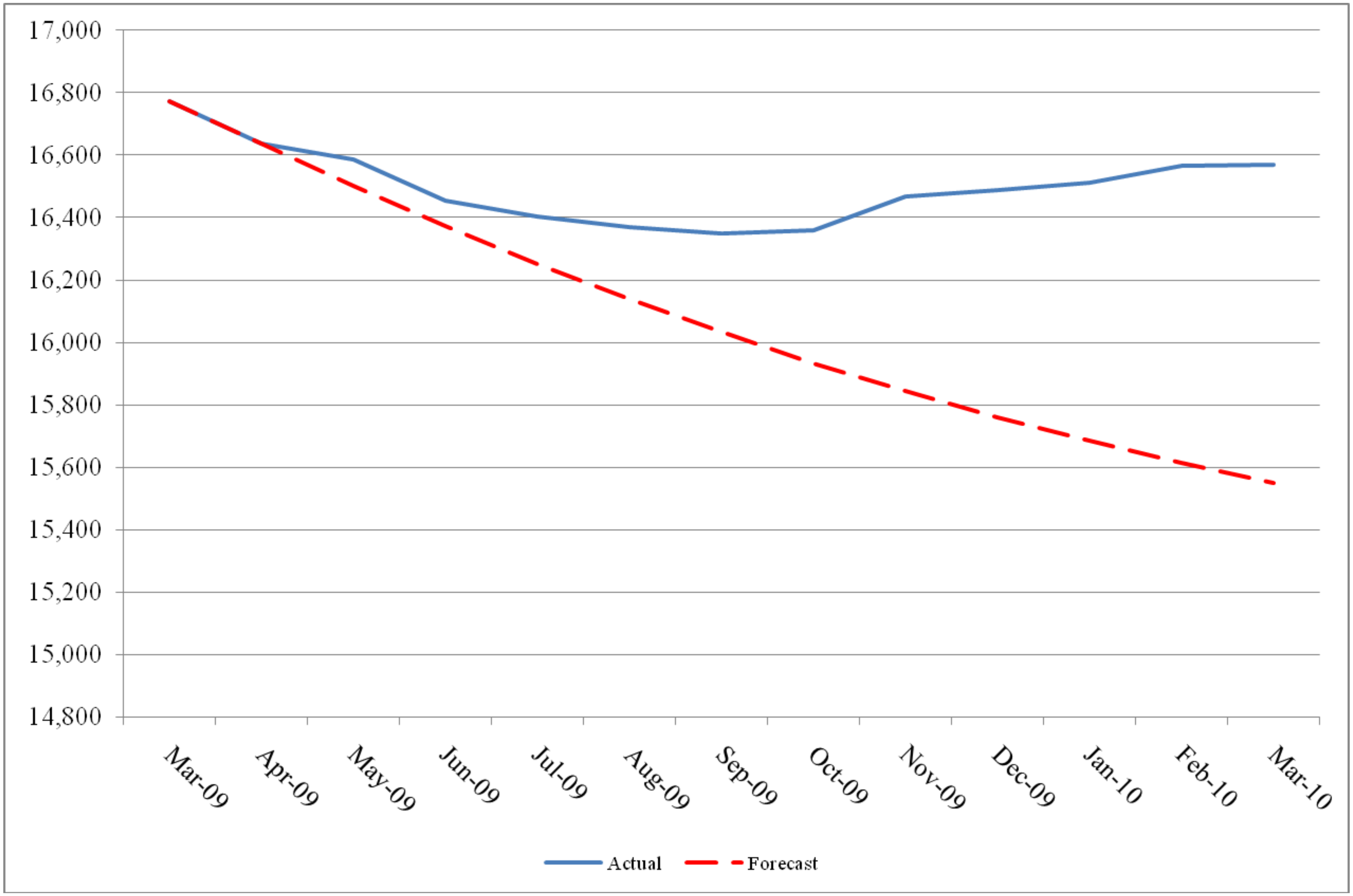

Figure 7: Leisure and Hospitality Employment: Ex Ante Forecasts, 2009:3 to 2010:3 (SA, thousands)

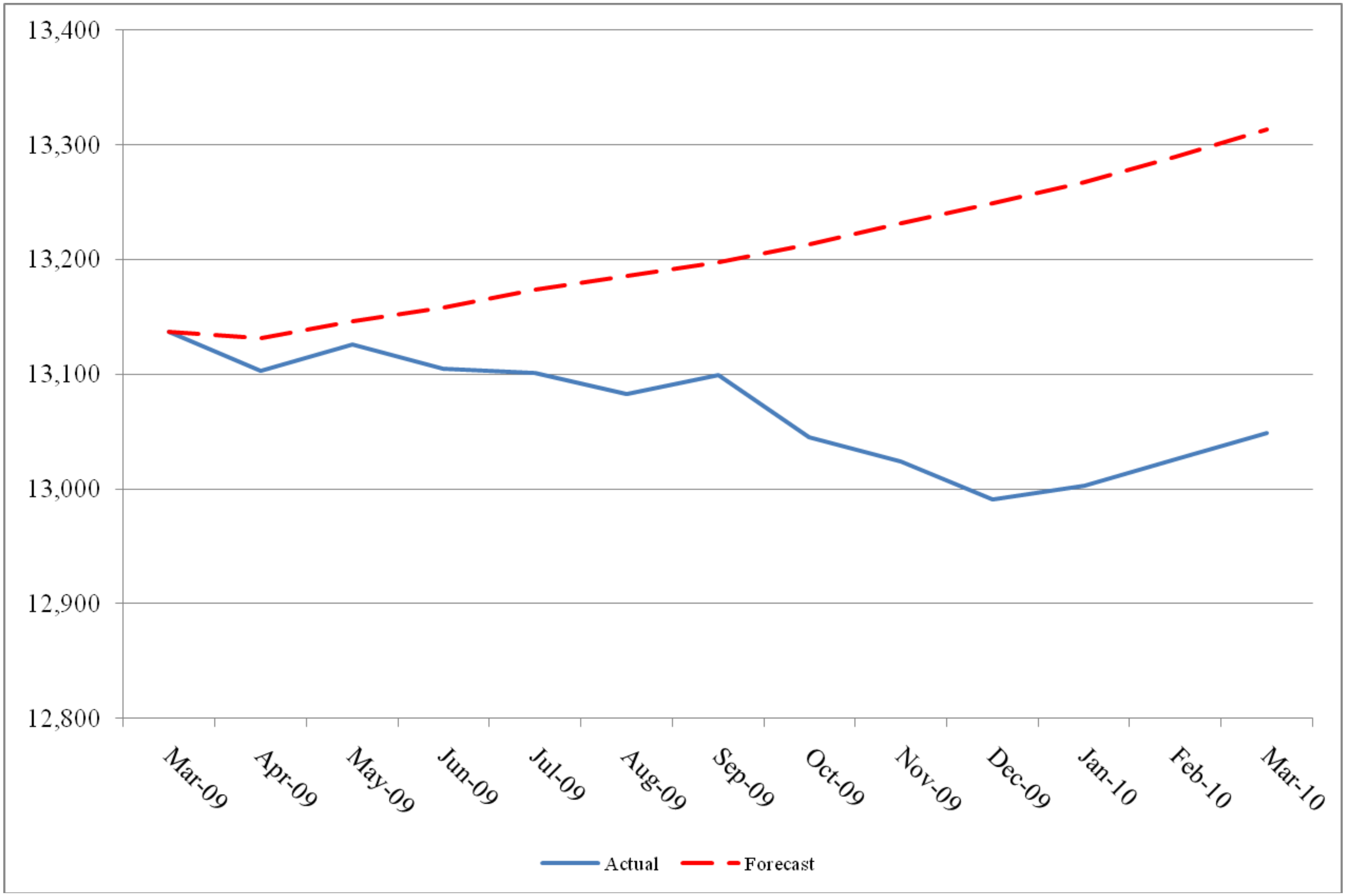

Figure 8: Other Services Employment: Ex Ante Forecasts, 2009:3 to 2010:3 (SA, thousands)