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Financial Nowcasts and Their Usefulness in Macroeconomic Forecasting

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Financial data often contain information that is helpful for macroeconomic forecasting, while multistep forecast accuracy also benefits by incorporating good nowcasts of macroeconomic variables. This paper considers the role of nowcasts of financial variables in making conditional forecasts of real and nominal macroeconomic variables using standard quarterly Bayesian vector autoregressions (BVARs). For nowcasting the quarterly value of a variety of financial variables, we document that the average of the available daily data and a daily random walk forecast to fill in the missing days in the quarter typically outperforms other nowcasting approaches. Using real-time data and out-of-sample forecasting exercises, we find that the inclusion of financial variable nowcasts by themselves generally improves forecast accuracy for macroeconomic variables relative to unconditional forecasts, although we document several exceptions in which current-quarter forecast accuracy worsens with the inclusion of the financial nowcasts. Incorporating financial nowcasts and nowcasts of macroeconomic variables generally improves the forecast accuracy for all the macroeconomic indicators of interest, beyond including the nowcasts of the macroeconomic variables alone. Conditional forecasts generated from quarterly BVARs augmented with nowcasts of key financial variables rival the forecast accuracy of mixed-frequency dynamic factor models (MF-DFMs) and mixed-data sampling (MIDAS) models that explicitly link the quarterly data and forecasts to high-frequency financial data.

Keywords: conditional forecasting, nowcasting, vector autoregressions, mixed-frequency models, Bayesian methods.

JEL classifications: C53, C11, C32, G17.

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1. Introduction

Forecasters routinely employ a rich set of empirical macroeconomic models for forecasting and policy analysis. These models take a variety of forms, but among the most popular are vector autoregressions (VARs) and Bayesian VARs (BVARs), factor augmented vector autoregressions (FAVARs), dynamic stochastic general equilibrium (DSGE) models, and dynamic factor models (DFMs). In many cases, both for real-world forecasting and for forecast evaluation exercises, these models are estimated entirely with quarterly data to match the frequency of key macroeconomic data series in the U.S. such as GDP. However, forecasts themselves are often generated more frequently than once per quarter to update the outlook based on new information, including revisions to past data and developments in the intraquarterly data. Nowcasting approaches take advantage of the intraquarterly data by explicitly modeling the relationship between quarterly variables and the high frequency indicators. Giannone et al. (2008) provide a seminal contribution to the GDP nowcasting literature; Modugno (2013) and Knotek and Zaman (2015, forthcoming) contribute to nowcasting U.S. inflation.

For forecasters interested in forecasting the medium- to longer-term evolution of the economy using a single multivariate model, the outputs (i.e., the nowcasts) from external nowcasting models can provide useful inputs as “jumping-off points.” Faust and Wright (2013) and Del Negro and Schorfheide (2013) document gains in the forecast accuracy of quarterly models augmented with good quarterly nowcasts of macroeconomic variables obtained from other sources, such as surveys. Krüger et al. (2015, forthcoming) use entropic tilting to combine external nowcasts with medium-term forecasts from BVARs. Alternatively, one can use mixed-frequency models to do both nowcasting and forecasting within the context of a single model, as in, e.g., mixed-frequency VARs (Schorfheide and Song 2015; Brave et al. 2016), mixed data sampling (MIDAS) regression models (Ghysels et al. 2005 and 2006), and mixed-frequency dynamic factor models (MF-DFMs) (e.g., Giannone et al. 2008 and Modugno 2013).

The need to track the economy at a high frequency naturally gives rise to the question of which data may be helpful in nowcasting and forecasting macroeconomic variables. At the daily frequency, financial data provide an obvious choice due to their timeliness. Stock and Watson (2003) provide a comprehensive survey of the predictive content of a variety of financial variables—such as credit spreads, term spreads, interest rates of various maturities, foreign exchange rates, oil prices, commodity prices, stock market indices, etc.—for economic activity. Following financial variables becomes even more obvious given that quarterly macroeconomic models sometimes include financial variables that are aggregated at the quarterly frequency.

The estimation of empirical macroeconomic models at a quarterly frequency with financial variables has a long tradition going back at least to Mitchell and Burns (1938), and the 2008 financial crisis has rekindled interest in the topic. In particular, Alessi et al. (2014) emphasize that the failure of forecasters to predict the financial crisis and their subsequent poor forecasting record was due in large part to inadequate modeling of the relationship between quarterly macroeconomic variables and daily financial variables, given that the latter are inherently forward-looking. They show that, by using a MIDAS framework that links quarterly real GDP to timely intra-quarterly daily financial data as inspired by Andreou et al. (2013), one could improve upon the accuracy of real GDP growth forecasts and importantly could have seen the recession coming, albeit with limited advance warning. A similar theme comes from Del Negro and Schorfheide (2013). By incorporating more timely information on the federal funds rate and the Baa/10-year Treasury spread than what was available for quarterly GDP data in real time, they show that their DSGE model would have been successful in accurately forecasting the contraction in economic activity experienced at the depths of the Great Recession. Faust et al. (2013) document forecasting gains from financial indicators, particularly related to credit spreads, while Adrian et al. (2016) find that broad financial conditions affect the lower quantiles of the distribution of GDP growth forecasts—thus reducing the mean—whereas broad economic conditions only affect the median of the distribution.

In one paper that considers how intraquarterly financial data impact longer-term forecasts, Espinoza et al. (2012) use quarterly BVARs with U.S. real GDP growth, euro area GDP growth, and a select combination of financial variables to investigate whether monthly financial information helps predict U.S. and euro area GDP growth relative to a model that ignores the high-frequency financial information.[1] They find that, in the near term, conditioning on monthly financial information worsens the forecast accuracy of GDP growth (for both the U.S. and the euro area), but monthly financial information helps in the medium term for forecasting U.S. GDP growth.

This paper builds on these literatures to consider how to take advantage of high-frequency financial data in the context of quarterly forecasting models, making both methodological and empirical contributions. Our main findings are as follows.

First, we contribute to the area of financial nowcasting by providing and comparing the range of approaches that can be used to generate quarterly nowcasts of financial variables based on higher-frequency data. Across a variety of financial variables, we show that a daily random walk—that is, taking the average of the available daily data up to some date and assuming a daily random walk forecast for the variable to fill in the missing days in the quarter—typically

[1] Ghysels and Wright (2009) use high-frequency financial data to predict the forecasts of professional forecasters using MIDAS regressions.

outperforms other forecasting or nowcasting approaches including MIDAS and MF-DFMs for nowcasting the quarterly value of the financial variable. We use this daily random walk to generate nowcasts of financial variables that are used as conditions in our quarterly models.

Second, using real-time data in out-of-sample forecasting exercises, we investigate the forecasting accuracy of quarterly models for key macroeconomic indicators in unconditional exercises, in exercises conditional on only financial nowcasts, in exercises conditional on only nowcasts of macroeconomic variables, and finally in exercises where we condition on both financial nowcasts and macroeconomic nowcasts. We find that incorporating daily financial information in the form of financial nowcasts along with nowcasts of macroeconomic variables of interest in multivariate quarterly BVAR models leads to improved forecast accuracy for real GDP, core and headline inflation, the unemployment rate, and the federal funds rate compared with using just the macroeconomic nowcasts or just the nowcasts of financial variables.[2] This finding is consistent with Andreou et al. (2013), who use MIDAS regressions to show that using both intraquarterly daily financial data and monthly macroeconomic factors leads to gains in forecasting real GDP beyond only using either monthly macroeconomic indicators or daily financial data. Similar to Bańbura et al. (2013) and Espinoza et al. (2012), only conditioning on financial information within the quarter worsens the one-step-ahead forecast (i.e., nowcast) accuracy of real GDP and CPI inflation, but in subsequent quarters the financial information improves forecasting accuracy relative to unconditional forecasts; by contrast, Andreou et al. (2013) do not find a deterioration in near-term forecast accuracy from financial variables. These somewhat counterintuitive findings come from the choice of financial variables: a small number

[2] It is worth noting that previous studies investigating the usefulness of monthly or daily financial information in the context of macroeconomic forecasting have exclusively focused on real GDP, whereas our study looks at a variety of variables of interest for forecasters and policymakers.

of financial indicators may capture idiosyncratic financial market fluctuations that are unrelated to contemporaneous economic conditions and thus can generate a deterioration in forecasting accuracy, while a large number of financial indicators reduces this risk.

Third, we run a novel forecasting horserace that compares the forecast accuracy of quarterly BVAR models augmented with conditions from financial variable nowcasts with more sophisticated mixed-frequency models. We find that the forecasting accuracy of the quarterly BVAR models augmented with external nowcasts is essentially equivalent to that of mixed-frequency models such as MIDAS models and MF-DFMs for our variables of interest—real GDP, the unemployment rate, inflation, and the federal funds rate. Given the simplicity and low computational costs of nowcasting the financial variables and running the quarterly multivariate BVAR, we view this outcome as an important practical result.

Section 2 discusses our real-time data and the quarterly models. Section 3 considers nowcasting financial variables. Section 4 conducts unconditional and conditional forecasting exercises using our quarterly models, and section 5 conducts horseraces between quarterly BVAR models augmented with financial nowcasts as conditions and alternative mixed-frequency approaches. Section 6 concludes.

2. Data and Quarterly Models

2.1. Data

The goal of this paper is to generate and evaluate real-time out-of-sample forecasts for U.S. macroeconomic and financial variables. To do so, we construct a real-time dataset consisting of daily, monthly, and quarterly data. Financial data are real-time by construction. Monthly financial data are the average of the daily readings over the month, and quarterly financial data are the average of the three monthly readings in the quarter; both are assumed to be available as soon as the month or quarter is complete, respectively.[3] The other real-time data come from the St. Louis Fed's ALFRED database and from the Philadelphia Fed's real-time dataset for macroeconomists. Each vintage of real-time quarterly data corresponds to the survey date for the Survey of Professional Forecasters (SPF); the SPF is a quarterly survey, released approximately in the middle of the middle month of each quarter, with the survey date occurring several days earlier. Our real-time vintages begin in 1994:Q1 and end in 2015:Q4; for a small number of vintages, we use pseudo real-time data as necessary. In our forecast evaluation exercises, we treat the "truth" for purposes of forecast evaluation as the latest available (i.e., most revised) data, so we also collect the most revised quarterly data.[4]

The quarterly dataset used for estimation begins in 1959:Q4 and ends in 2015:Q4. The monthly dataset begins in October 1959 and ends in December 2015. For the monthly variables, we also collect the corresponding daily data that begin on January 3, 1984, and end December 31, 2015. In addition, we collect a larger dataset of daily (financial) data, which is a subset of Andreou et al. (2013) and which begins January 2, 1985, and ends December 31, 2015.[5]

We also collect quarterly nowcasts (i.e., current quarter forecasts) available from the Survey of Professional Forecasters (SPF) starting in 1994:Q1 and ending in 2015:Q4. We have

[3] For quarterly financial variables, taking the average of the three monthly readings in the quarter is consistent with how we construct quarterly labor market variables and quarterly inflation variables from monthly data. In some cases, long histories of daily observations on financial variables are less readily available than monthly observations. For cases in which we have daily data, the differences between the average of the three monthly averages and the average of the daily readings within a quarter have historically been quite small.

[4] The latest available data (vintage) comes from the third week of February 2016.

[5] In the Appendix, Table A.1 provides a list of transformations performed on the data. Table A.2, Table A.3, and Table A.4 list the quarterly, monthly, and daily variables in the dataset.

nowcasts for the following macroeconomic variables from SPF: real GDP, CPI inflation, core CPI inflation (which excludes food and energy prices), and the unemployment rate. We have SPF nowcasts for the following financial variables: the yield on 10-year Treasury bonds, the yield on 3-month Treasury bills, and Aaa corporate bond yields. To supplement the financial nowcasts from SPF, we collect financial nowcasts from Blue Chip Financial Forecasts for the period 2001:Q1 to 2015:Q4 for the yield on 10-year Treasury bonds, the yield on 3-month Treasury bills, Aaa corporate bond yields, Baa corporate bond yields, and the nominal trade-weighted exchange rate (against major currencies).

2.2. Quarterly Models: Bayesian VAR and Bayesian Factor Augmented VAR Models

Our benchmark quarterly empirical models are VARs given their general popularity as forecasting tools, which reflects both their simplicity to use and the accurate forecasts they produce (see Bańbura et al. 2010 and Carriero et al. 2015). A general representation of a VAR(p) model can be written as:

$$Y_t = A_c + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + \varepsilon_t \quad (1)$$

where t=1,…,T, $Y_t = [y_{1,t}, y_{2,t}, ..., y_{n,t}]$ is an n×1 data vector of n random variables, $A_c = [c_1, c_2, ..., c_n]$ is an n×1 vector of constants, $A_1, ..., A_p$ are n×n matrices of VAR coefficients, and ε_t is an n×1 vector of normally distributed error terms with zero mean and covariance matrix, $\Sigma = E\varepsilon_t\varepsilon_t'$. In this n dimensional VAR, each equation has k=np+1 regressors, and with n equations, there are n×k parameters to be estimated. In our exercises, n will range from 5 to 14, and we set the number of lags, p, to 4.

High-dimensional VARs are susceptible to overfitting, and so to deal with this curse of dimensionality we estimate them using Bayesian methods as discussed in Bańbura et al. (2010), Beauchemin and Zaman (2011), Koop (2013), and Carriero et al. (2015). Specifically, coefficient estimates in $A_1, ..., A_p$ and Σ are shrunk to their prior means. The prior beliefs for the mean and variances of the coefficient matrices are:

$$E[A_k^{(i,j)}] = \begin{cases} \delta_i & \text{if } i = j, k = 1 \\ 0 & \text{otherwise} \end{cases}$$
$$Var[A_k^{(i,j)}] = \lambda^2 \frac{1}{l^2} \frac{\sigma_i^2}{\sigma_j^2}, l = 1, ..., p \quad (2)$$

For variables that enter in natural-log-levels in our BVARs, we set δ_i =1; for the remaining variables other than inflation, we set δ_i =0.8, reflecting the persistent nature of those variables (the unemployment rate, the federal funds rate, and financial variables). We follow Kozicki and Tinsley (2001), Clark and McCracken (2015), Faust and Wright (2013), Zaman (2013), and Clark and Doh (2014), which document improvements in forecasting inflation by modeling it as a deviation from its long-run trend, and hence we model inflation in gap form.[6] For the inflation gaps, we set δ_i =0. As such, our VAR system can be described a priori as a mixture of random walk and stationary processes. The scale factor $1/l^2$ helps impose the prior belief that recent lags play a more influential role compared with more distant lags by proportionally shrinking the variances on the more distant lags (centered on a prior mean of zero). The prior parameter σ_i is set equal to the standard deviation of the residuals obtained from regressing the variable y_i on its own *p* lags and a constant over the sample period up to any point in time *t*. The hyperparameter

[6] As in Knotek et al. (2015), the long-run trend for inflation comes from splicing the long-term inflation expectations series from the Federal Reserve Board of Governor's FRB/US econometric model, denoted PTR, with the long-run inflation expectations series from the Survey of Professional Forecasters.

λ governs the tightness of our priors. As $\lambda \to 0$, the prior dominates and so the posterior equals the prior, i.e., the data have no say. On the other hand, as $\lambda \to \infty$, the prior has no influence and so posterior estimates converge to OLS estimates.

The above-mentioned BVAR studies document further gains in forecast accuracy by imposing a "sum of coefficients" (SOC) prior on the equations of the VAR. This prior imposes the belief that coefficients on own lags sum to one, which we make operational on variables that enter the model in log-levels. The parameter μ governs the tightness of this prior. We set the values of the hyperparameters λ and μ based on optimizing the marginal log likelihood along a two-dimensional grid at every point in time *t* that we make a forecast.[7] Note that prior specification for each equation is symmetric in its treatment of own lags of the dependent variable and lags of other variables. As such, we have a prior that is natural conjugate (Normal-inverted Wishart prior) which is convenient when solving for the model as these priors can be implemented easily by augmenting the data matrices with dummy variables. We estimate the model equation by equation using OLS (see Bańbura et al. 2010 and Carriero et al. 2015).

2.3. Model Specifications

We consider a number of variants of VAR models. All the VAR models are estimated using quarterly data with four lags and have four primary variables of interest: real GDP (in natural log levels), CPI inflation, the unemployment rate, and the effective federal funds rate.[8] In half of the variants, we also treat core CPI inflation as a variable of interest. We estimate the

[7] Our results are qualitatively similar if we instead fix the hyperparameters λ=0.2 and μ=0.2 (for models estimated with data going back to 1959) and λ=0.1 and μ=0.1 (i.e., with tighter priors, for models estimated with data going back to 1985) throughout the forecasting exercise.

[8] We treat the federal funds rate as a variable to be forecasted rather than a financial variable to be nowcasted.

models with Bayesian methods and equip the models with Minnesota and sum of coefficient priors; Bańbura et al. (2010), Beauchemin and Zaman (2011), and Koop (2013), among others, document substantial gains in forecasting accuracy from equipping these types of models with these priors. We allow the model specifications to differ along the following dimensions: in the number of financial variables included; in whether financial variables are included in the regressions in levels or transformed into spreads (e.g., we construct the risk spread as the Baa corporate bond yield less the 10-year Treasury yield); and in the estimation period (i.e., we begin the estimation in either 1985 or 1959). We also estimate a Bayesian Factor Augmented Vector Auto Regression (BFAVAR), where we extract the factor from a large database of high-frequency financial data (consisting of 58 financial variables).[9]

In all, we estimate 10 specifications of BVAR and BFAVAR models which we detail below, and for each specification we generate forecast evaluation results for the full sample for which we have real-time data vintages (1994:Q1-2015:Q4) and for a pre-crisis sample (1994:Q1-2006:Q4), giving us a total of 20 sets of results for each forecasting exercise.[10]

Model 1. The BVAR consists of four macro variables of interest—real GDP, CPI inflation, the unemployment rate, and the federal funds rate—and three financial variables—the risk spread between the Baa corporate bond yield and the 10-year Treasury note yield, the term spread between the 10-year Treasury note yield and the 3-month Treasury bill yield, and the S&P 500 index. The estimation period is 1959:Q4 onward.

[9] The financial variable dataset is approximately the same as the smaller of the two datasets in Andreou et al. (2013).

[10] When estimating VARs with Bayesian methods, in order to operationalize the prior, an important setting is that of the hyperparameters—in our case, the Minnesota and sum of coefficient priors—that govern the tightness of the prior. We follow Carriero et al. (2012), Carriero et al. (2015), and Giannone et al. (2015) and set the prior values at each forecast origin to maximize the log marginal data density of the model. As in Carriero et al. (2015), for each model specification we optimize over a discrete grid: we choose the Minnesota prior from the set {0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.5}, and we choose the sum of coefficient prior from the set {0.25, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0}. Figure A.1 and Figure A.2 plot the optimized values of these hyperparameters over our forecast evaluation sample.

Model 2. The model's variables match those in Model 1, but estimation begins 1985:Q4.

Model 3. The BVAR consists of four macro variables of interest—real GDP, CPI inflation, the unemployment rate, and the federal funds rate—and five financial variables—the Baa corporate bond yield, the 10-year Treasury note yield, the 3-month Treasury bill yield, the S&P 500 index, and the nominal exchange rate. The estimation period is 1959:Q4 onward.

Model 4. The model's variables match those in Model 3, but estimation begins 1985:Q4.

Model 5. The BVAR consists of nine macro variables—real GDP, real personal consumption expenditures, CPI inflation, core CPI inflation, productivity, the employment cost index, nonfarm payroll employment, the unemployment rate, and the federal funds rate—and three financial variables—the risk spread between the Baa corporate bond yield and the 10-year Treasury note yield, the term spread between the 10-year Treasury note yield and the 3-month Treasury bill yield, and the S&P 500 index. The estimation period is 1959:Q4 onward.

Model 6. The model's variables match those in Model 5, but estimation begins 1985:Q4.

Model 7. The BVAR consists of nine macro variables—real GDP, real personal consumption expenditures, CPI inflation, core CPI inflation, productivity, the employment cost index, nonfarm payroll employment, the unemployment rate, and the federal funds rate—and five financial variables—the Baa corporate bond yield, the 10-year Treasury note yield, the 3-month Treasury bill yield, the S&P 500 index, and the nominal exchange rate. The estimation period is 1959:Q4 onward.

Model 8. The model's variables match those in Model 7, but estimation begins 1985:Q4.

Model 9. The model is a BVAR augmented with a factor, producing a Bayesian Factor Augmented Vector Auto Regression (BFAVAR) model. In practice, many financial variables may improve our ability to forecast our macro variables of interest. Because adding a very large number of financial variables to a VAR may not be the best approach, we instead extract a common factor from a large balanced set of financial variables, and we treat this financial factor as an additional variable in a BVAR that also contains our variables of interest. The financial dataset consists of 58 financial variables and similar to the dataset used by Andreou et al. (2013). The estimation of this BFAVAR model closely follows Bernanke et al. (2005), Bańbura et al. (2010), and Berg and Henzel (2015). Specifically, parameters are estimated using a two-step approach. In the first step, we ensure stationarity for all the financial variables of our financial dataset, and then center (i.e., demean) and standardize the entire dataset. Once the dataset is centered and standardized, we extract the first principal component (common factor). In the second step, we estimate a BVAR model consisting of nine macro variables—real GDP, real personal consumption expenditures, CPI inflation, core CPI inflation, productivity, the employment cost index, nonfarm payroll employment, the unemployment rate, and the federal funds rate—and this financial factor. The estimation period is 1985:Q4 onward.[11]

Model 10. We estimate a BFAVAR model with four macro variables—real GDP, CPI inflation, the unemployment rate, and the federal funds rate—along with the financial factor described above. The estimation period is 1985:Q1 onward.

3. Nowcasting Financial Variables: Which Approach Works Best?

Before constructing forecasts that take advantage of nowcasts of current-quarter financial conditions, we first consider the question of how to nowcast financial variables. Looking across

[11] We plot the financial factor alongside GDP growth in Figure A.3. The financial factor looks reasonable as has been moderately (negatively) correlated with the evolution of the economy as measured by real GDP growth: the correlation is −0.41.

econometric models and across financial variables, we document that, at any point within a quarter, the average of the available daily data and a daily random walk forecast to complete the quarter typically outperforms other nowcasting approaches. We show that such an approach has also historically been competitive with—if not superior to—the nowcasts for financial variables coming from surveys of professional forecasters.

3.1. Comparing Econometric Models

We consider the following econometric models to nowcast financial variables.

Random walk (RW). In this model, the previous quarter's average value for the financial variable is the forecast for the current quarter—i.e., the quarter to be nowcasted.

Average available + RW (monthly). We assume the financial variable follows a random walk at a monthly frequency, and the quarterly value is the average of the three monthly readings within the quarter. For example, if we only have financial data for the first month of the quarter, then the quarterly nowcast is equal to that value. If we have financial data for the first two months of the quarter, then the quarterly nowcast is equal to one-third of the sum of the first monthly value and twice the second monthly value. If we have partial-month financial data, then the monthly value is the average over the available daily data from that month.

Average available + RW (daily). We assume the financial variable follows a random walk at a daily frequency, thus we forecast the last observed daily reading to persist for the remaining missing trading days within the quarter. We aggregate to the monthly frequency by taking averages of the daily observations and/or forecasts, and then take quarterly averages of the monthly values to generate the quarterly nowcast.

Average of the available monthly. The quarterly nowcast is the average of the available monthly values, where the available monthly values are the average of the available daily data within the corresponding month. No forecasts are used; if, e.g., the third month of the quarter does not have any available daily financial data, it is omitted when calculating the quarterly average. For example, if we have only 10 business days of financial data available, the monthly value is the average of those 10 trading days of financial data.

MIDAS (mixed data sampling) models. As in Andreou et al. (2011), a general representation of an ADL-MIDAS with leads model for generating *h*-step-ahead forecasts using high-frequency (i.e., intra-quarterly daily or monthly) data is:

$$Y_{t+h}^{Q} = \mu^{(h)} + \sum_{j=0}^{P_Y^Q - 1} \mu_{j+1}^{(h)} Y_{t-j}^{Q} + \beta^{(h)} \left[\sum_{i=0}^{J_X^D - 1} \omega_i(\theta_{(h)}^{D}) X_{J_X^D - i, t+h}^{D} + \sum_{j=0}^{P_X^D - 1} \sum_{i=0}^{N_D - 1} \omega_{i+j*N_D}(\theta_{(h)}^{D}) X_{N_D - i, t-j}^{D} \right] + u_{t+h}, \quad (3)$$

where Y^Q is a dependent variable sampled at a quarterly frequency, P_Y^Q is the number of lags of the dependent variable, X^D is a high-frequency indicator (e.g., with a daily or monthly frequency), N_D is the number of high-frequency lags in a quarter, J_X^D is the number of high-frequency leads, and P_X^D is the number of quarterly lags of the high-frequency indicator.[12] In MIDAS models, the functions $\omega(\theta^D)$ are polynomials that parsimoniously rely on few parameters; Ghysels et al. (2007) and Ghysels (2016) discuss a variety of polynomial specifications. For the purpose of nowcasting the quarterly values of financial variables in the presence of high-frequency data, we also choose between using high-frequency daily financial data or high-frequency monthly financial data as regressors in equation (3). Our MIDAS nowcasts are derived from the following combinations of polynomial specifications and high-

[12] Clements and Galvão (2008) introduced the autoregressive terms of the dependent variable into MIDAS regressions.

frequency financial data: (1) monthly data and U-MIDAS—i.e., an unrestricted set of MIDAS coefficients that are estimated via OLS; (2) monthly data and a normalized beta density polynomial with a non-zero last lag (BetaNN); (3) monthly data and a normalized exponential Almon lag polynomial (ExpAlmon); (4) daily data and a normalized beta density polynomial with a zero last lag; (5) daily data and the BetaNN polynomial specification; and (6) daily data and the ExpAlmon polynomial specification.[13]

Mixed-frequency dynamic factor models (MF-DFMs). Building on the factor model approach to nowcasting of Giannone et al. (2008), Modugno (2013) considers a MF-DFM to nowcast and forecast U.S. CPI inflation by extracting a common factor at a daily frequency, and we follow a similar framework for nowcasting quarterly financial variables. Our model combines data at the quarterly, monthly, and daily frequencies into a trading-day-frequency factor model with missing observations that are cast in a state space representation. In our specification, the same seven financial variables appear at the quarterly, monthly, and daily frequencies in stationary terms—(natural log) first differences.[14] The dynamic factor model takes the general form:

$$y_t = Cf_t + \varepsilon_t,\ \ \varepsilon_t \sim N(0,\Sigma) \tag{4}$$

with t referring to the trading-day frequency, y_t a vector of observations, C a block diagonal matrix of factor loadings, ε_t a vector of idiosyncratic components, and f_t a vector of latent common factors following VAR dynamics:

$$Bf_t = A(L)\, f_{t-1} + u_t,\ \ u_t \sim N(0,Q)\,, \tag{5}$$

[13] The Appendix provides further details on the MIDAS models and MF-DFMs.
[14] The seven financial variables are the S&P 500, the 10-year Treasury yield, the 3-month Treasury yield, the Baa yield, the exchange rate, the risk spread, and the term spread; the S&P 500 and exchange rate are included as natural log growth rates while the other variables are included as first differences. The inclusion of only financial variables in this model is in keeping with the spirit of the other nowcasting exercises.

where B and $A(L)$ are matrices governing factor dynamics, some of which may be time-varying. The model is estimated with the Expectation Maximization (EM) algorithm as described in Bańbura and Modugno (2012). Assuming that the quarterly variables and monthly variables in our system at any time t represent a stock (i.e., a snapshot), accordingly the quarterly first difference (or growth rate) and monthly first difference (or growth rate) of those variables can be formed by summing up their respective daily first differences (or growth rates). Ultimately, the daily factors are forecasted via the transition equation (5) and are translated to daily nowcasts and aggregated to monthly and quarterly nowcasts via equation (4). Finally, as noted in Modugno (2013), when forecasting with factor models there is no consensus a priori in selecting the number of factors in equation (4) and the number of lags governing the factor VAR dynamics in equation (5). As a result, we follow Modugno (2013) and generate a nowcast based on an arithmetic average of 24 factor models that reflect all possible combinations of 1 or 2 factors and 1 through 12 lags. We also report results from the model that produces the most accurate nowcast from each of the 24 models ex post (i.e., the combination of factors and lags that produces the lowest root mean squared errors over the evaluation period).[15] Of course, an inherent limitation of using the best combination of factors and lags ex post is that this knowledge would not have been available to forecasters for use in real-time nowcasting.

3.2. Comparison across Nowcasting Models

Table 1 reports the root mean squared errors (RMSEs) from nowcasting financial variables using the econometric models described above. Our recursive out-of-sample forecast

[15] The ex post best performing model potentially varies based on the target variable—that is, the ex post best model parameterization for the S&P 500 is potentially different than the ex post best model for the exchange rate.

evaluation period spans 1994:Q1 to 2015:Q4.[16] We conduct the nowcasting exercises at three points in time within each quarter, reflecting different nowcast origins with different sets of available financial information. The "+0 months" case is conducted on the first day of the quarter, when all financial data through the last day of the previous quarter is assumed to be available but no daily or monthly data from the current quarter to be nowcasted is available. Thus, these nowcasts are effectively one-step-ahead forecasts for the quarterly values of the financial variables. The "+1 month" case corresponds to making the nowcast at the end of the first month of the quarter to be nowcasted; at that point, one has complete daily data for the first of the three months of the quarter. The "+2 months" case similarly corresponds to making the nowcast at the end of the second month of the quarter to be nowcasted.[17] The bold numbers in the table correspond to the methodology with the lowest RMSE for the particular financial variable based on a particular information set.

As documented elsewhere in the nowcasting literature (e.g., Bańbura et al. 2013), nowcasting performance improves as more data become available within the quarter. This finding holds for all of the nowcasting model specifications we consider. For a given specification, nowcast RMSEs are smaller with 1 month of data than with 0 months of data, and those with 2 months of data are smaller than with only 1 month of data.

Across model specifications, one of the simplest approaches to nowcasting quarterly financial variables—using a random walk forecast for the financial variable at a daily frequency to fill in the missing observations for the quarter and then taking averages of the available daily data and daily forecasts—produces the smallest RMSEs for 14 of the 21 cases we consider. If

[16] The MIDAS models are estimated beginning July 1, 1984, and the MF-DFMs are estimated beginning March 1, 1985.
[17] At the "+3 months" case, all financial data for the quarter being nowcasted would be known and RMSEs would be zero.

we include comparisons with the MF-DFM model that uses the best combination of factors and lags on an ex post basis, then the daily random walk model produces the lowest RMSEs in 10 of the 21 cases, while the best MF-DFM produces the lowest RMSEs in 9 cases. While taking the average of the available daily data and a daily random walk often produces the lowest RMSEs, in most cases the gains in nowcast accuracy are modest compared with MIDAS models using daily regressors and MF-DFM approaches—often on the order of 1 to 2 basis points for bond yields and spreads. On the basis of parsimony, ease of use, and relative historical nowcasting accuracy, in the exercises below we construct our quarterly nowcasts of financial market variables by using the model that takes the average of the available daily data and a daily random walk forecast.

3.3. Comparison with Professional Forecasters: SPF and Blue Chip

As a test of our preferred approach, we examine how its quarterly financial nowcasts compare with those of professional forecasters in the Survey of Professional Forecasters (SPF) and Blue Chip Financial Forecasts (BCFF). The SPF is a quarterly survey published in the middle of the middle month of the quarter.[18] Along with the projections of macroeconomic variables, the SPF reports the forecasts of select financial variables, all of which are quarterly averages: the 10-year Treasury bond rate, the 3-month Treasury bill rate, and the Aaa corporate bond yield.[19] Given nowcasts for the 10-year and 3-month rates, we compute the term spread as the 10-year rate minus the 3-month rate. The nowcast horserace sample begins in 1994:Q1 and

[18] For the forecast comparison exercises, we match information sets that would have been available in real time; hence, we only use financial variable information (and, in some cases below, other information) that would have been available up through the day before the SPF survey deadline.

[19] More recently—since 2010:Q1—the SPF began reporting nowcasts for the Baa corporate bond yield. Given the short history of such nowcasts, we omit them from our horserace.

ends in 2015:Q4. To match information sets that would have been available in real time, we only use financial information that would have been available up through the day prior to the SPF survey deadline in generating model-based nowcasts.[20] The SPF reports the mean and median forecasts for each of the variables they survey; we use the median forecast.

Table 2 reports the nowcast RMSEs from our preferred nowcasting model and those from the SPF. Across financial measures, the nowcasting accuracy of the model that averages the available daily data and a daily random walk forecast has historically been comparable to the SPF median; in fact, the model has outperformed the SPF on average by 3 to 7 basis points.[21] The Diebold and Mariano (DM, 1995) test with the Harvey et al. (1997) adjustment for small samples rejects the null of equal predictive accuracy between the nowcasts from the model and the nowcasts from SPF at the 1% level for all four financial variables.

The BCFF is a monthly survey with a release date of the first of the month (e.g., January 1, 1995), with survey dates that are roughly one week prior to its release.[22] Given it is released monthly, we can evaluate three sets of financial nowcasts for each reference quarter that differ based on the available daily financial information. For example, the BCFF with a release date of

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[20] When working with the SPF survey in subsequent sections, we also use other, nonfinancial information that would have been available in real time as of the SPF survey dates.

[21] While we do not use Aaa corporate bond yields in our conditional forecasting exercises, we include it here for the sake of comparing our preferred approach to nowcasting financial variables with SPF nowcasts. While we omit results for Aaa corporate bond yields from Table 1 when comparing various econometric approaches, the model that uses the average of the available daily data and a daily random walk forecast tends to outperform the alternative model-based approaches.

[22] The BCFF has not always released survey dates. In cases where we do not have the exact release date, we set the release date based on the following algorithm. During the last complete (Sunday through Saturday) week of each month, we set the survey end date to the Thursday of that week if there are at least 3 business days in the month after that Thursday; if there are not 3 business days in the month after that Thursday, we set the survey end date to the Tuesday of that week. Given that the survey is normally conducted over two days, we require that neither of those days can be a holiday. If the survey close date or the preceding day is a holiday, the survey end date is assumed to be the previous Thursday or Tuesday, whichever comes first. For months in which we have the actual (true) survey date, this algorithm exactly matches the BCFF survey dates 66% of the time and is earlier than the BCFF survey dates 20% of the time. Provided that the non-reported survey dates followed a similar pattern to the reported survey dates, our algorithm would be expected to produce an accurate or conservative survey date 86% of the time; the remaining 14% of the time, our proposed survey date could give us an informational advantage.

January 1 provides financial variable forecasts for the first quarter that are one-step-ahead forecasts—similar to our "+0 months" case from above. The subsequent BCFF released on February 1 has nowcasts for the first quarter that presumably take into account the available high-frequency daily readings for January, along with other data releases. Similarly, the BCFF with a release date of March 1 will have updated nowcasts for Q1 that take into account the available high-frequency data for both January and February up through the survey date. BCFF reports forecasts for the yield on 10-year Treasury notes, the yield on 3-month Treasury bills, Aaa corporate bond yields, Baa corporate bond yields, and the nominal trade-weighted exchange rate (versus major currencies). Based on these nowcasts, we compute the implied risk spread (BAA yield minus 10-year Treasury yield) and the implied term spread (10-year Treasury yield minus 3-month Treasury yield). Our nowcast evaluation sample spans 2001:Q1 through 2015:Q4. We use the Blue Chip consensus for each financial variable, which reports the average across forecasters.

Table 3 reports the nowcast RMSEs from our preferred nowcasting model and those from the BCFF. As with the SPF, on average our preferred nowcasting model has historically outperformed the BCFF for all the financial variables shown; this same finding holds at different points within the quarter, accounting for differences in information sets. In most cases, the DM test rejects the null of equal predictive accuracy between the nowcasts from the model and the nowcasts from BCFF, especially later in the quarter as more information becomes available. These comparisons provide some external validity that the nowcasting model we implement to construct our nowcasts of financial variables for inclusion in our conditional forecasting exercises is reasonable and also fairly accurate.

4. Forecasting Results

This paper makes extensive use of conditional forecasts. To define terminology, assume that we have data for all variables through time *T*. An "unconditional" forecast is simply the path that the model would predict using estimation based on data through time *T*; forecasts can recursively depend on future forecasts, but all forecasts are made on the basis of data through time *T*. A "conditional" forecast is the path that the model would predict based on estimation through time *T*, but where forecasts are influenced by knowledge of the future values (e.g., from time *T*+1) of one or more variables. We generate conditional forecasts following the approach developed by Doan et al. (1984) and Waggoner and Zha (1999), where we impose our financial nowcasts as "hard conditions."[23]

To further fix ideas, suppose we have a stylized bivariate VAR(1) model:

$$\mathbf{y}_t = B\mathbf{y}_{t-1} + \mathbf{u}_t = B\mathbf{y}_{t-1} + C\boldsymbol{\varepsilon}_t \qquad (6)$$

with $\mathbf{y}_t = [y_{1,t}, y_{2,t}]'$, reduced form errors $\mathbf{u}_t = [u_{1,t}, u_{2,t}]'$, and structural errors $\boldsymbol{\varepsilon}_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]'$ which are i.i.d. N(0,1). Using data available through time *T*, one could estimate the parameters in equation (6) and generate an unconditional forecast, $\mathbf{y}_{T+1}^U = [y_{1,T+1}^U, y_{2,T+1}^U]'$. Suppose, however, that we have information for the value of $y_{1,T+1}$—e.g., we have a nowcast or condition, $y_{1,T+1}^C$, that we wish to impose—and that the matrix *C* is lower triangular with $\hat{C} = [[1, \hat{\rho}]', [0,1]']$. By taking advantage of the condition for $y_{1,T+1}^C$, we can generate a conditional forecast for $y_{2,T+1}$ that is:

[23] This contrasts with the imposition of "soft conditions" (Waggoner and Zha 1999) or other methods for imposing nowcasts as conditions, such as entropic tilting (e.g., Robertson et al. 2005 or Krüger et al. 2015, forthcoming). Robertson and Tallman (1999) provide an accessible introduction to conditional and unconditional forecasting. Bańbura et al. (2015) depart from the Waggoner and Zha (1999) approach and use Kalman filtering to compute the distribution of conditional forecasts.

$$y_{2,T+1}^{C} = y_{2,T+1}^{U} + \hat{\rho}(y_{1,T+1}^{C} - y_{1,T+1}^{U}), \qquad (7)$$

as in Clark and McCracken (2015).[24]

To investigate the usefulness of financial variables in forecasting our variables of interest—e.g., real GDP, inflation, the unemployment rate, and the federal funds rate—we compare the performance of unconditional and conditional forecasts from our quarterly BVAR models. As set out in section 2.2, we consider 10 models over two forecast evaluation periods—one that excludes the Great Recession and one that includes the Great Recession—for a total of 20 exercises. To summarize our results, we construct diffusion indexes in four steps. First, for each model, we recursively generate unconditional forecasts of our variables of interest starting in 1994:Q1 and ending in either 2006:Q4 (for the evaluation period that excludes the Great Recession) or 2015:Q4 (for the evaluation period that includes the Great Recession).[25] Second, we use the same model and parameter estimates to generate conditional forecasts of our variables of interest, where the conditions are nowcasts of the financial variables that are included in the VAR using intraquarterly information up to time τ within the quarter. For example, if τ is one month, then the financial nowcasts are made using high-frequency financial information through the end of the first month of the quarter. As described above, financial nowcasts are made using the average of the available daily data and a daily random walk forecast. Third, for each model specification i, each variable of interest v, and each forecast horizon h, we compute the mean squared forecast error (MSE) for the unconditional forecast, $MSE_{i,v,h}^{U}$, and for the conditional forecast, $MSE_{i,v,h}^{C}$, where we use the most revised vintage data as the "truth" for each variable of

[24] Note that ordering does not matter in conditional forecasting; see Clark and McCracken (2015).
[25] The first out-of-sample unconditional forecasts are made using the real-time data that would have been available in 1994:Q1—i.e., the quarterly data run through 1993:Q4, and the forecasts are for 1994:Q1 (one-step) through 1995:Q4 (eight-step-ahead forecast).

interest. We define the relative MSE $\mu_{i,v,h} = MSE^{C}_{i,v,h} / MSE^{U}_{i,v,h}$, so that ratios less than one suggest that for variable *v* and forecast horizon *h* in model specification *i*, the forecast conditional on nowcasts of financial variables is on average more accurate than the unconditional forecast—i.e., intraquarterly financial information is helpful in improving the forecast for the variable of interest. Fourth, we summarize our 20 sets of results—corresponding to 10 models and 2 forecast evaluation samples—by constructing diffusion indexes.[26] For each variable *v* and forecast horizon *h*, we set

$$f_{i,v,h} = \begin{cases} 1 & \text{if} \quad \mu_{i,v,h} \geq 1.1 \\ -1 & \text{if} \quad \mu_{i,v,h} \leq 0.9 \end{cases} \tag{8}$$

which allows us to ignore trivial improvements or deteriorations in MSE, and the diffusion index at forecast horizon *h* is then

$$(\text{Diffusion index})_{v,h} = \sum_{i=1}^{20} f_{i,v,h} \,. \tag{9}$$

The value of diffusion index ranges from +20 to −20. A value of −20 suggests that the accuracy of the conditional forecast of the particular variable is substantially better than its unconditional forecast in all 20 combinations of model specifications and forecast evaluation samples; a value of +20 suggests the opposite. Small negative (positive) numbers indicate some net improvements (deterioration) in forecast accuracy from the conditional forecasts compared with the unconditional forecasts.

[26] While we rely on these diffusion indexes in the body of the paper, the detailed results and tables underlying the creation of the diffusion indexes are available in Table B in the Appendix.

4.1. Conditional Forecasting with Financial Nowcasts

We conduct an initial set of conditional forecasting exercises using intraquarterly financial information through the end of the first month (+1 month) of the first quarter of the forecast horizon—i.e., we are in 1994:Q1 and using quarterly data through 1993:Q4 to make forecasts for 1994:Q1 (1-step-ahead) through 1995:Q4 (8-steps-ahead) by taking advantage of the financial data available through the end of January 1994.[27] Figure 1 displays the diffusion indexes by forecast horizon for real GDP, CPI inflation, the unemployment rate, and the federal funds rate. The diffusion indexes show that conditioning on only this limited near-term information coming from the financial variables in the models typically improves the forecast accuracy for the unemployment rate and the federal funds rate for many quarters into the future. For the unemployment rate, the additional financial information does not seem to matter for the first two forecast quarters but thereafter it appears to help; for forecasting the federal funds rate, the additional financial information is useful immediately. At the other extreme, information on financial variables does not have a large effect—positive or negative—on CPI inflation forecast accuracy; the diffusion index is near zero, suggesting that the conditional forecasts' accuracy is little different from the unconditional forecasts' accuracy. For real GDP, conditioning on financial information from the first month of the quarter on average hurts forecast performance in the conditioning quarter, as the diffusion index is +7, but it subsequently helps in the next two

[27] To simplify this subsection, for nonfinancial variables we use the real-time data that were available at each SPF survey date within a quarter when making both the conditional and unconditional forecasts, regardless of whether we use only the first month's financial data, the financial data available up through the SPF survey date, or all three months' financial data.

quarters. After that point, the financial conditions have little net impact on real GDP forecast accuracy, as the real GDP process reverts to its unconditional mean very quickly.[28]

Figures 2 and 3 display the diffusion index by forecast horizon for the same variables as we take into account more financial information. Figure 2 is computed based on financial information available through approximately the first month and a half of the quarter (+1.5 months).[29] Figure 3 uses all three months' financial data (+3 months) in generating the conditional forecasts.[30] As documented earlier, the accuracy of our financial variable nowcasts improves as we have more available daily information. This improved accuracy of our financial conditions improves the accuracy of the conditional forecasts for our variables of interest, with more of the diffusion indexes' mass residing below zero. For example, with +3 months of financial data, the conditional forecasts for the unemployment rate regularly outperform the unconditional forecasts starting at the 2-step forecast horizon. The diffusion indexes for the federal funds rate register −20 at the 2- and 3-step forecast horizons, indicating that all of our models find gains in forecasting the federal funds rate from the financial variable conditioning. The additional financial information appears to provide some slight assistance in near-term GDP forecasting: on net, fewer of the conditional GDP forecasts are worse than the unconditional GDP forecasts at the 1-step horizon, and more of the conditional GDP forecasts outperform the unconditional GDP forecasts at the 2- and 3-step horizons.

Our finding that near-term financial conditions can worsen 1-step-ahead forecast accuracy is consistent with Bańbura et al. (2013), who show in the context of nowcasting real

[28] Chauvet and Potter (2013) survey the literature that has found it difficult to accurately forecast output beyond the near term regardless of model, with naïve or constant-growth models often outperforming sophisticated competitors.
[29] Technically, we use the SPF survey date in each quarter as the cutoff, which is usually before the 1.5 month point.
[30] That is, in the "+3 months" case, we know with certainty the value of the financial variables for the quarter, but because of data release lags we would not yet have that quarter's other variables of interest and would still be trying to forecast them along with the next 7 quarters.

GDP that within-quarter financial information worsens the nowcast accuracy of real GDP. In our case, this finding appears to be sensitive to the forecast evaluation period and to the financial nowcasts being used as conditions.[31] In particular, the models that feature a smaller number of financial variables and an evaluation period that ends in 2006:Q4 show deterioration in 1-step-ahead GDP forecast accuracy when conditioning on financial nowcasts compared with the unconditional forecasts; we do not see the same deterioration when the forecast evaluation period ends in 2015:Q4. Furthermore, the conditional forecasts from the BFAVAR models, which take into account a large number of financial indicators via the financial factors, do not show deterioration in 1-step-ahead GDP forecast accuracy. Together, these results suggest that using a small number of financial indicators raises the potential for idiosyncratic financial market fluctuations to erroneously influence the 1-step GDP forecast, while a large number of financial indicators reduces this risk.

4.2. Conditional Forecasting with Financial Nowcasts and Other Nowcasts

Figure 1 through Figure 3 show that while conditioning on nowcasts of the financial variables within the quarter generally improves forecast accuracy over a multi-step horizon, this is not universally true: in some cases, forecasting performance at the 1-step horizon deteriorates, even when the financial variables values are known with certainty, as in the +3 months case. In practice, of course, one could condition on nowcasts of other model variables from surveys or alternative nowcasting models in addition to the financial variable nowcasts. Faust and Wright (2013) and Del Negro and Schorfheide (2013) illustrate the potential gains in forecast accuracy

[31] For further details, see Table B in the Appendix.

by augmenting quarterly models with nowcasts from external sources. The nowcasting literature provides evidence that nowcasts using intraquarterly data often outperform 1-step-ahead forecasts from quarterly models; among others, see Giannone et al. (2008) and Bańbura et al. (2013) for GDP, and Modugno (2013) and Knotek and Zaman (2015, forthcoming) for inflation.

Thus, conditional forecasts made with a combination of financial variable nowcasts and nowcasts for key macroeconomic variables of interest have the potential to improve both multi-step and near-term forecasting accuracy. To illustrate the power of such an approach in the context of our BVAR models, we impose conditions on a number of real and nominal variables using real-time nowcasts from the SPF for real GDP, the unemployment rate, nonfarm payroll employment, headline CPI inflation, and core CPI inflation.[32] In doing so, we are mindful of the SPF survey deadline dates and thus generate nowcasts for our financial variables as we did above using the daily available data up through that time within each quarter, which is approximately +1.5 months of financial data from the first quarter to be forecasted.

Figure 4 displays the results of this exercise across our 20 models in a diffusion index.[33] Conditioning on both nowcasts of financial variables and nowcasts of macroeconomic variables of interest generally leads to improvements across the board, as the diffusion index values are all non-positive. The improved accuracy of the conditional forecasts over the unconditional forecasts for the unemployment rate and the federal funds rate persists throughout the forecast horizon. For real GDP and inflation, the gains persist up to four quarters into the future.

[32] The SPF history of nowcasts and forecasts for core CPI inflation only goes back to 2007:Q1; prior to that time, for models that have core CPI inflation, we omit the condition. Note that we do not impose a nowcast condition from the SPF on the federal funds rate, because imposing nowcasts for the financial variables as conditions in the model dramatically improves the forecasts of the federal funds rate.

[33] Detailed results of this exercise are reported in the center set of columns in Table B in the Appendix.

Importantly, improvements in forecast accuracy when we condition on both financial nowcasts and other nowcasts of macroeconomic variables are not entirely driven by the latter. Table 4 documents this finding by showing the percentage of forecast RMSEs across our model specifications, for a given variable and forecast horizon, that are smaller when we condition on both financial nowcasts and other nowcasts than when we condition on only the other nowcasts. The top panel considers results including both evaluation periods (1994:Q1 through 2006:Q4, and 1994:Q1 through 2015:Q4), while the bottom panel considers only the evaluation period that includes the Great Recession (1994:Q1 through 2015:Q4). In the majority of cases, forecast RMSEs are smaller when conditioning on both financial nowcasts and other nowcasts of macroeconomic variables than when we condition on only the other nowcasts. The percentages are higher—i.e., results are stronger—for the evaluation period including the Great Recession.

5. Comparing Forecasts from Quarterly BVARs and Mixed-Frequency Models

5.1. Horserace between Quarterly BVAR Augmented with Financial Nowcasts and MIDAS

MIDAS regressions have gained widespread adaptability in nowcasting and forecasting macroeconomic variables, as they are able to handle data with different frequencies (e.g., Clements and Galvão 2008; Armesto et al. 2010; Kuzin et al. 2011; Andreou et al. 2013). Therefore, a natural experiment is to compare the forecasting performance of the MIDAS technique with the conditional BVAR methodology. For example, when nowcasting or forecasting real GDP (a variable that is sampled at a quarterly frequency) using a high-frequency variable such as the S&P 500, a MIDAS model would regress quarterly real GDP at time t on its own lags and the available daily observations corresponding to the S&P 500 within quarter *t*; the regression may also include daily observations corresponding to the lagged quarter(s). There is no restriction on the number of right hand side variables in the MIDAS regression, but a large number of variables can complicate parameter estimation and reduce forecast accuracy, as emphasized in Schorfheide and Song (2015). Hence, adding to the MIDAS regressions all the variables that we have been estimating in our BVARs is not a feasible route. Instead, to construct a fair comparison between MIDAS models and quarterly BVARs, we follow an approach similar to Schorfheide and Song (2015) in their comparison of mixed frequency VARs and MIDAS models by looking at forecasts coming from bivariate models.

In this approach, we construct forecasts using quarterly bivariate BVARs in which we separately consider each macroeconomic variable of interest and pair it with a particular financial variable. The quarterly macroeconomic variables of interest are: real GDP, headline CPI inflation, core CPI inflation, the unemployment rate, and the federal funds rate. The financial variables that we use for this exercise are: the risk spread (the Baa yield less the 10-year Treasury yield), the S&P 500, and the term spread (the 10-year Treasury yield less the 3-month Treasury yield). As above, we nowcast the financial variable in the current quarter and impose that value as a hard condition in the bivariate BVAR when forecasting. For each macroeconomic variable, we estimate three bivariate BVARs—one for each of the financial variables—and generate three sets of (conditional) forecasts, and we then take a simple average of these three forecasts to generate a composite forecast for the relevant macroeconomic variable.[34]

[34] The bivariate BVARs are estimated with Minnesota and sum of coefficient (SOC) priors. The value of the hyperparameter governing the Minnesota prior is set to 0.2, and the SOC prior is set to 1; these values are fairly loose and are standard in the VAR literature, see Carriero et al. (2015). For assessing the sensitivity of the results to prior values, we also ran the exercise with tighter priors, which generated slightly greater outperformance of the BVARs relative to the MIDAS models.

Next, for each of our five macroeconomic variables of interest, we run MIDAS regressions for each of the three financial variables and generate forecasts. We average these three forecasts for each macroeconomic variable to generate a composite forecast.[35] The MIDAS with leads model takes the form of equation (3), where we include four quarterly lags $(P_Y^Q = P_X^D = 4)$, 60 lags of the high-frequency financial variable in a quarter $(N_D = 60)$, and the number of high-frequency leads (J_X^D) ranges from 0 to 60 depending on the amount of available financial data at any point within a quarter. The polynomial specification is the normalized beta density polynomial with a zero last lag.

The forecast evaluation sample spans 1994:Q1 to 2015:Q4. The bivariate BVAR and the MIDAS model are both estimated with expanding windows of data starting in 1985:Q4. For each quarter in the evaluation sample (e.g., 1994:Q1), the quarterly data end in the previous quarter (e.g., 1993:Q4) and we examine the forecasting accuracy of the two approaches at four points in time within the quarter: (1) on the first day of the quarter (+0 months), when no financial data is available from the current quarter; (2) at the end of the first month of the quarter, once the first month's financial data are available (+1 month of financial data); (3) at the end of the second month of the quarter (+2 months); (4) at the end of the third month of the quarter (+3 months).[36] At each forecast origin, we iteratively generate 1- through 8-step-ahead forecasts for

[35] When averaging across forecasts in the MIDAS case, the combination weights are determined by the discounted mean square forecast error (MSFE) method, as in Andreou et al. (2013). We also ran our MIDAS exercises using forecast combination weights determined by a simple arithmetic average (as in Alessi et al. 2014), BIC criteria, and AIC criteria; all three yielded slightly worse forecast accuracy compared with the MSFE method.

[36] For comparability, both the bivariate BVAR model and the MIDAS model use matched real-time information sets; however, for simplicity within a given quarter, we use the real-time macroeconomic data that would have been available at the time of the SPF survey for that quarter, although the financial data differ depending on the case. Thus, e.g., when making forecasts during 1994:Q1, the 1993:Q4 data are assumed to be available and unchanged from the +0 months of financial data case through the +3 months of financial data case.

the bivariate BVAR models and directly generate 1- through 8-step-ahead forecasts for the MIDAS models, where the latter approach requires a different regression for each horizon.[37]

Table 5 reports the relative RMSEs for the quarterly bivariate BVARs with financial nowcasts as conditions relative to the MIDAS models based on different amounts of intraquarterly financial data. For the unemployment rate, the federal funds rate, and real GDP, the forecast accuracy of the two approaches has been quite comparable. For headline CPI inflation and core CPI inflation, the quarterly bivariate BVAR model with conditioning has historically generated somewhat smaller forecast errors than the MIDAS models. Overall, these results suggest that the historical forecasting performance of a quarterly BVAR that takes advantage of high-frequency financial data by imposing a nowcast of financial variables has been competitive with the forecasts coming from MIDAS with leads models that incorporate the high-frequency financial data in a more direct fashion.

5.2. Horserace between Quarterly BVAR Augmented with Nowcasts and MF-DFMs

Mixed-frequency dynamic factor models (MF-DFMs) offer an alternative approach to MIDAS models to combine data at different frequencies, and these models have become popular in macroeconomic nowcasting and forecasting following the studies of, e.g., Giannone et al. (2008), Modugno (2013), and Bańbura et al. (2013), to name a few. In the exercises in section 3, the nowcast accuracy of MF-DFMs for financial variables was competitive with that of other

[37] The MIDAS model results are relatively computationally intensive: given 86 recursive forecast evaluation runs, 5 macroeconomic variables of interest, 3 financial variables as predictors for each macroeconomic variable, and 1- through 8-step-ahead forecasts, we have approximately 10,320 MIDAS model runs. We evaluate the model at four points within each quarter to simulate different intraquarterly financial variable information sets (+0 months, +1 month, +2 months, and +3 months), leading to a total of 41,280 MIDAS model runs.

approaches. In this section, we compare the performance of a MF-DFM for forecasting our macroeconomic variables of interest with the conditional forecasts formed from a quarterly BVAR augmented with external nowcasts. Our forecast evaluation period is 1994:Q1 through 2015:Q4. In each quarter, we use the real-time data that would have been available as of the SPF survey date to generate out-of-sample forecasts for the two models.

To put the models on a level footing, we use the same real-time datasets and variables in the two models, although the models will treat the data in different ways. The variables we include match those from model 6 in section 2.3: real GDP, real personal consumption expenditures, CPI inflation, core CPI inflation, productivity, the employment cost index, nonfarm payroll employment, the unemployment rate, the federal funds rate, the risk spread between the Baa corporate bond yield and the 10-year Treasury note yield, the term spread between the 10-year Treasury note yield and the 3-month Treasury bill yield, and the S&P 500 index. The expanding window used for estimation begins in 1985:Q4. The difference between the two models is the way information enters. In the MF-DFM, the following variables enter at the quarterly frequency: real GDP, productivity, the employment cost index, real personal consumption expenditures, and the federal funds rate.[38] The following variables enter at a monthly frequency in the MF-DFM: core CPI inflation, headline CPI inflation, nonfarm payroll employment, and the unemployment rate. Finally, the MF-DFM uses daily information for variables sampled at a daily frequency, which is the three financial variables: the risk spread, the term spread, and the S&P 500. As in section 3.1 (and as detailed in the Appendix), the MF-DFM has data at the quarterly, monthly, and daily frequencies that are combined into a business day

[38] Real personal consumption expenditures are available at a monthly frequency, but for the sake of our exercise we treat them as a quarterly release. Similarly, data for the federal funds rate is available at a daily frequency, but because we treat this variable as a policy variable to be forecasted rather than a high-frequency financial indicator, we assume it is a quarterly variable.

frequency factor model with missing observations that are cast in a state space representation.[39] By contrast, all data in the BVAR enter at a quarterly frequency; information at a higher-than-quarterly frequency only enters the model via nowcasts that are imposed as conditions when doing conditional forecasting.

To compare the forecasting performance of the MF-DFM with the quarterly BVAR augmented with nowcasts, we perform two exercises that differ based on how the nowcasts of the macroeconomic variables that go into the quarterly BVAR are formed. In both exercises, we condition on nowcasts of financial variables in the quarterly BVAR by taking the average of the available daily data and a daily random walk to forecast the missing observations for the quarter. We also impose conditions on some of the macroeconomic variables of interest, to allow for the inclusion of some higher-than-quarterly frequency information.

In the first exercise, we use the monthly data that would have been available in real-time to generate nowcasts for four macroeconomic variables: the unemployment rate, nonfarm payroll employment, CPI inflation, and core CPI inflation. By the time of the SPF survey date within a quarter (e.g., 1994:Q1), the first monthly reading (e.g., January) on the unemployment rate and nonfarm payroll employment would have been available for the current quarter. For the unemployment rate, the nowcast for the current quarter is simply the monthly unemployment rate for the first month of the quarter. To produce a nowcast for nonfarm payroll employment in the current quarter, we assume the monthly growth rate between the last month of the previous quarter and the first month of the current quarter persists over the following two months; the nowcast is the implied (natural log) level of nonfarm payroll employment. For CPI inflation and

[39] As noted in section 3.1, there is no a priori consensus on how to select the number of factors in equation (4) and number of lags for the factor VAR dynamics in equation (5), hence our MF-DFM forecasts are based on arithmetic averages of 24 factor models—all possible combinations of 1 or 2 factors and 1 to 12 lags.

core CPI inflation, we use a simplification of Knotek and Zaman (2015, forthcoming) and use a 12-month moving average of monthly growth rates to forecast the missing monthly readings for the current quarter; the nowcast is then the quarterly annualized growth in the index. These four nowcasts are simplistic but allow the quarterly model to take into account the monthly information that is entering the MF-DFM; the financial nowcasts that are also included as conditions account for the daily information that is entering the MF-DFM.

In the second exercise, we use nowcasts from the SPF as conditions for the macroeconomic variables in the quarterly BVAR: we impose the current quarter SPF median nowcasts for real GDP, the unemployment rate, CPI inflation, and core CPI inflation as quarterly conditions. This exercise is broadly representative of the use of external nowcasts as conditions in quarterly models.

Table 6 reports relative RMSEs for the conditional forecasts coming from the quarterly BVAR relative to the forecasts coming from the MF-DFM. The top half of the table reports results from the first exercise, in which the quarterly BVAR forecasts are conditional on financial nowcasts and we use the available monthly data to nowcast macroeconomic variables. The conditional forecasts from the quarterly BVAR augmented with nowcasts have historically outperformed the forecasts from the MF-DFM for CPI inflation, the unemployment rate, and the federal funds rate; the reverse is true for real GDP. However, based on conventional statistical tests for equal predictive accuracy, forecast accuracy across the approaches has been comparable.

The bottom half of the table reports results from the second exercise, in which the quarterly BVAR forecasts are conditional on financial nowcasts and SPF nowcasts. At the one-step horizon, the quarterly BVAR with the SPF conditions has historically outperformed the MF-DFM across all variables by a statistically significant margin. However, this outperformance for real GDP, CPI inflation, and the unemployment rate reflects the superior accuracy of the SPF nowcasts used as conditions.[40] Beyond the one-step horizon, the quarterly BVAR forecasts have outperformed the MF-DFM forecasts for CPI inflation, the unemployment rate, and the federal funds rate and have underperformed for real GDP, but the differences have not been statistically significant for most variables and forecast horizons. As with the MIDAS exercise above, this horserace with a MF-DFM suggests that the forecasts coming from a quarterly BVAR model augmented with nowcasts have been competitive with those from models that directly incorporate mixed frequency data.

6. Conclusion

Quarterly BVARs are a popular tool for macroeconomic forecasting, and the financial crisis has rekindled interest in the inclusion of financial variables to assist in forecasting. However, quarterly models with financial variables face the perpetual problem of omitting information coming from high-frequency financial information as forecasters wait for the release of lower-frequency macroeconomic indicators. Mixed-frequency models present one natural solution to this problem, as they allow for the inclusion of high-frequency financial information and low-frequency macroeconomic variables.

In this paper, we investigate an alternative approach by generating conditional forecasts from quarterly BVARs augmented with nowcasts of financial information, where the latter take into account the high-frequency daily data. To nowcast financial variables, we first show that taking the average of the available daily data up to some date in a quarter and assuming a daily

[40] Recall that the federal funds rate is not being conditioned. As discussed earlier, imposing financial nowcasts as conditions dramatically improves our quarterly BVAR's ability to forecast the federal funds rate.

random walk for the financial variable over the remaining days of the quarter typically outperforms other forecasting or nowcasting approaches for nowcasting the quarterly value of the financial variable. Second, we assess the conditional forecasting performance of these quarterly BVARs augmented with nowcasts of financial variables. We find that conditioning on financial nowcasts improves historical forecast accuracy compared with unconditional forecasts, and that conditioning on both financial nowcasts and other nowcasts of macroeconomic variables improves forecast accuracy compared with the case in which the financial nowcasts are omitted.

Finally, we compare our quarterly BVAR models augmented with financial nowcasts with mixed-frequency models that can directly incorporate data with high and low frequencies—MIDAS regressions and MF-DFMs. We show that the historical forecast accuracy of the conditional forecasts from the quarterly BVAR augmented with nowcasts is highly comparable to the forecast accuracy of the mixed-frequency models. Given the simplicity and low computational costs of nowcasting the financial variables and running the quarterly multivariate BVAR, we view this outcome as an important practical result for forecasters who wish to incorporate high-frequency data into otherwise quarterly models.

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Table 1: RMSEs for 1-Step-Ahead Forecasts/Nowcasts of Financial Variables, 1994:Q1-2015:Q4

Methodology	S&P 500	10-yr. Treas.	3-mo. Treas.	Baa Yield	Exch. Rate	Risk Spread	Term Spread
+0 months of data							
Random walk (daily)	7.813	**0.297**	**0.270**	**0.238**	3.492	**0.268**	0.338
Random walk (monthly)	7.791	0.304	0.294	0.296	3.477	0.303	0.346
Random walk (quarterly)	6.948	0.380	0.414	0.366	3.459	0.379	0.438
MIDAS (monthly data)							
+0 months: U-MIDAS	5.968	0.322	0.293	0.300	2.449	0.312	0.350
+0 months: BetaNN	5.874	0.321	0.289	0.299	2.393	0.306	0.346
+0 months: ExpAlmon	5.754	0.321	0.305	0.303	2.455	0.314	0.349
MIDAS (daily data)							
+0 months (0 days): Beta	5.520	0.315	0.278	0.258	2.293	0.287	0.339
+0 months (0 days): BetaNN	5.488	0.316	0.276	0.257	2.303	0.289	**0.335**
+0 months (0 days): ExpAlmon	5.353	0.316	0.281	0.257	2.305	0.289	0.338
MF-DFM (average of 24 models)	**5.326**	0.319	0.278	0.245	**2.232**	0.269	0.349
MF-DFM (best model ex post)	*5.263*	0.308	0.274	0.244	*2.208*	*0.264*	0.341
+1 month of data							
Average of the available monthly	3.178	0.200	0.176	0.150	1.407	0.158	0.210
Average available + RW (monthly)	3.178	0.200	0.176	0.150	1.407	0.158	0.210
Average available + RW (daily)	2.510	**0.179**	**0.126**	**0.127**	**1.090**	0.117	**0.169**
MIDAS (monthly data)							
+1 month: U-MIDAS	3.145	0.209	0.179	0.152	1.425	0.164	0.208
+1 month: BetaNN	3.145	0.209	0.179	0.152	1.425	0.164	0.208
+1 month: ExpAlmon	3.145	0.209	0.179	0.152	1.425	0.164	0.208
MIDAS (daily data)							
+1 month (19 days): Beta	2.972	0.185	0.135	0.144	1.216	0.128	0.177
+1 month (19 days): BetaNN	2.765	0.182	0.135	0.149	1.241	0.126	0.182
+1 month (19 days): ExpAlmon	2.820	0.185	0.139	0.142	1.216	0.128	0.181
MF-DFM (average of 24 models)	**2.473**	0.194	0.128	0.152	1.169	**0.114**	0.173
MF-DFM (best model ex post)	*2.458*	*0.175*	*0.123*	0.143	1.154	0.115	*0.163*
+2 months of data							
Average of the available monthly	1.442	0.107	0.087	0.077	0.662	0.082	0.105
Average available + RW (monthly)	1.076	0.086	0.065	0.067	0.520	0.063	0.083
Average available + RW (daily)	**0.886**	**0.056**	0.048	**0.049**	**0.393**	0.039	**0.066**
MIDAS (monthly data)							
+2 months: U-MIDAS	1.050	0.079	0.054	0.067	0.515	0.058	0.077
+2 months: BetaNN	1.050	0.079	0.054	0.067	0.515	0.058	0.077
+2 months: ExpAlmon	1.050	0.079	0.054	0.067	0.515	0.058	0.077
MIDAS (daily data)							
+2 months (39 days): Beta	1.158	0.067	0.049	0.061	0.473	0.050	**0.066**
+2 months (39 days): BetaNN	1.127	0.068	0.048	0.061	0.471	0.051	0.067
+2 months (39 days): ExpAlmon	1.160	0.069	0.059	0.062	0.489	0.056	0.074
MF-DFM (average of 24 models)	0.983	0.066	**0.047**	0.057	0.430	**0.038**	0.074
MF-DFM (best model ex post)	0.972	0.059	*0.046*	0.054	0.419	*0.037*	0.069

Notes: Forecasts or nowcasts are made conditional on having no data (+0 months) from the quarter, one month (+1 month) of data from the quarter, and two months (+2 months) of data from the quarter. Entries in **bold** denote the lowest RMSE for a given financial variable across models for a given information set; entries in *italics* denote the lowest RMSE is produced from the ex post best MF-DFM, which would not have been known in real time.

Table 2: RMSEs from Financial Variable Nowcasts at SPF Survey Dates, 1994:Q1-2015:Q4

Forecast source	10-yr. Yield	3-mo. Yield	Aaa Yield	Term Spread
Model: average available + RW (daily)	0.14	0.10	0.10	0.13
Survey of Professional Forecasters (SPF)	0.18	0.13	0.17	0.17
Relative RMSE: SPF/model	1.33***	1.39***	1.64***	1.28***

Notes: The cutoff date for constructing each model-based quarterly nowcast is one day before the SPF survey date for the quarter. RMSEs from the SPF are based on median forecasts for the financial variables. *** denotes a rejection of the null of equal predictive accuracy at the 1% level based on the Diebold-Mariano test.

Table 3: RMSEs from Financial Variable Nowcasts at Blue Chip Financial Forecast Survey Dates, 2001:Q1-2015:Q4

Forecast source	10-yr. Treas.	3-mo. Treas.	Aaa Yield	Baa Yield	Exch. Rate	Risk Spread	Term Spread
Release date: first day of first month of the quarter							
Model: average available + RW (daily)	0.27	0.25	0.23	0.24	1.70	0.22	0.31
BCFF consensus	0.34	0.31	0.30	0.39	3.23	0.40	0.36
Relative RMSE: BCFF/model	1.27*	1.26	1.28	1.64**	1.90***	1.79	1.16
Release date: first day of second month of the quarter							
Model: average available + RW (daily)	0.19	0.18	0.16	0.16	1.43	0.16	0.19
BCFF consensus	0.24	0.19	0.22	0.24	2.23	0.23	0.24
Relative RMSE: BCFF/model	1.26***	1.07	1.37***	1.47***	1.56***	1.47*	1.27***
Release date: first day of third month of the quarter							
Model: average available + RW (daily)	0.08	0.07	0.07	0.07	0.52	0.06	0.09
BCFF consensus	0.12	0.11	0.11	0.11	1.69	0.13	0.12
Relative RMSE: BCFF/model	1.40***	1.52***	1.63***	1.74***	3.25***	2.07***	1.32**

Notes: The BCFF consensus provides an average across forecasters. Model nowcasts are generated using information up through the day before the Blue Chip Financial Forecasts survey date. *** (or ** or *) denotes a rejection of the null of equal predictive accuracy at the 1% (or 5% or 10%) level based on the Diebold-Mariano test.

Table 4: Reductions in Forecast RMSE from Conditioning on Financial and Other Nowcasts Compared with Conditioning on Other Nowcasts Alone

Forecast horizon (quarters)	Real GDP	Core CPI inflation	CPI inflation	Unemployment rate	Federal funds rate
Evaluation periods include and exclude Great Recession					
2	95	40	50	30	100
3	100	40	45	60	100
4	95	50	65	80	100
5	60	60	75	80	85
6	25	80	40	80	90
7	75	70	70	75	85
8	55	70	80	80	90
Evaluation period includes Great Recession					
2	100	60	80	60	100
3	100	40	80	70	100
4	90	80	100	80	100
5	50	60	80	70	100
6	20	100	80	70	90
7	90	100	80	60	80
8	80	100	90	70	80

Notes: Numbers report the percentage of model forecasts for which the forecast RMSE is smaller for a given variable and forecast horizon when conditioning on both financial nowcasts and other nowcasts than the forecast RMSE when conditioning on only the other nowcasts. The evaluation periods are 1994:Q1 through 2006:Q4 (excluding the Great Recession) and 1994:Q1 through 2015:Q4 (including the Great Recession). The table omits the 1-step forecast horizon because the same nowcasts are used for real GDP, CPI inflation, and the unemployment rate.

Table 5: Relative RMSEs from Quarterly BVAR with Conditions v. MIDAS Horserace, 1994:Q1-2015:Q4

Forecast horizon (quarters)	Real GDP	Core CPI inflation	CPI inflation	Unemployment rate	Federal funds rate
+0 months of financial data					
1	1.03	0.97	0.98	1.07	1.16*
2	0.97	0.95	0.89*	1.05	1.04
3	0.99	0.87**	0.92*	1.03	1.04
4	0.97	0.88*	0.88*	1.05	1.04
5	0.93***	0.80***	0.91	1.08	1.05
6	0.94	0.80**	0.96	1.09	1.06
7	0.97	0.83**	0.90	1.09	1.07
8	0.95	0.88*	0.89	1.08	1.08
+1 month of financial data					
1	1.00	0.98	0.99	1.06	1.10
2	0.94**	0.95	0.88	1.02	0.95
3	0.96	0.87***	0.92*	1.00	0.98
4	0.96	0.90	0.88*	1.02	1.00
5	0.92**	0.82***	0.91*	1.06	1.02
6	0.94	0.79***	0.95	1.08	1.04
7	0.97	0.80***	0.91	1.08	1.06
8	0.95	0.87*	0.88	1.08	1.07
+2 months of financial data					
1	1.04	0.96	0.99	1.09	1.14
2	0.93*	0.96	0.88*	1.03	0.97
3	0.94	0.89**	0.92*	1.00	0.97
4	0.95	0.89	0.87**	1.02	1.00
5	0.93*	0.84***	0.91	1.05	1.02
6	0.96	0.79***	0.94	1.07	1.04
7	0.95	0.81**	0.91	1.08	1.06
8	0.95	0.86*	0.88	1.08	1.07
+3 months of financial data					
1	1.03	0.96	0.99	1.09	1.03
2	0.93*	0.95	0.88*	1.02	1.00
3	0.93*	0.90	0.93*	1.00	0.98
4	0.95	0.89	0.87**	1.02	0.99
5	0.93	0.84***	0.91*	1.05	1.02
6	0.93*	0.80***	0.95	1.07	1.04
7	0.95	0.81**	0.91	1.08	1.06
8	0.96	0.84**	0.88	1.08	1.07

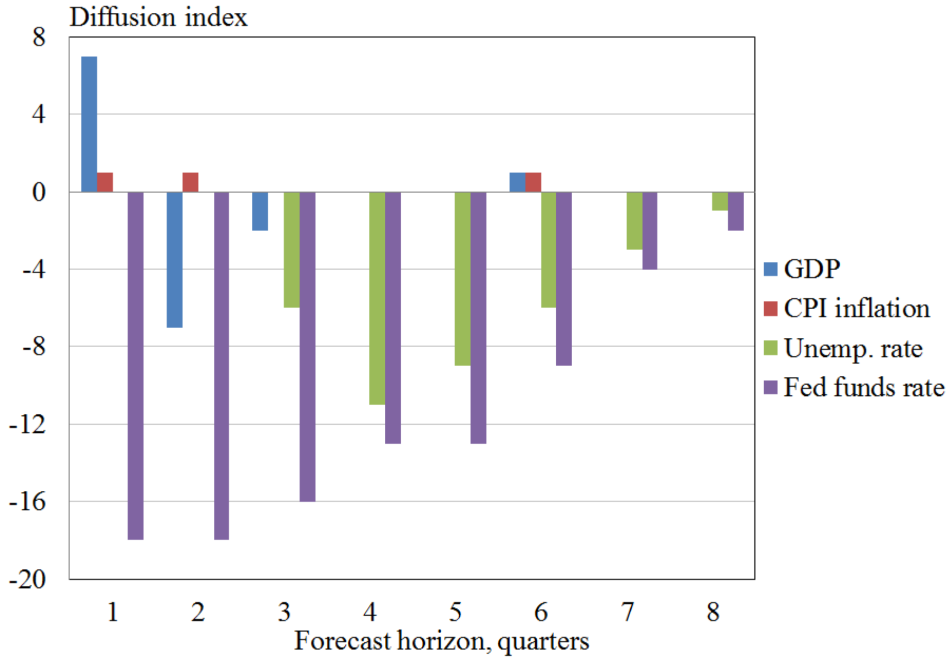
Notes: Relative RMSEs show quarterly BVAR RMSEs divided by MIDAS RMSEs; numbers less than 1.0 indicate smaller historical RMSEs from forecasts produced with the quarterly BVAR model than from forecasts produced with the MIDAS model. *** (or ** or *) denotes a rejection of the null of equal predictive accuracy at the 1% (or 5% or 10%) level based on the Diebold-Mariano test. The models are estimated using data from 1985:Q4 onward.

Table 6: Relative RMSEs from Quarterly BVAR with Conditions v. MF-DFM Horserace, 1994:Q1-2015:Q4

Forecast horizon (quarters)	Real GDP	CPI inflation	Unemployment rate	Federal funds rate
BVAR conditions: financial nowcasts + monthly data nowcasts				
1	0.98	1.11	0.97	0.66***
2	0.97	0.92	0.79	0.79
3	1.03	0.98	0.77	0.87
4	1.06	0.93	0.78	0.90
5	1.05	0.96	0.80	0.91
6	1.05	0.95	0.82	0.90
7	1.06	0.93	0.83	0.88
8	1.10	0.95	0.85	0.86
BVAR conditions: financial nowcasts + SPF nowcasts				
1	0.74**	0.61**	0.80**	0.65***
2	0.96	0.92	0.72*	0.82
3	1.03	0.99	0.73	0.89
4	1.09	0.94	0.75	0.92
5	1.06	0.96	0.79	0.92
6	1.06	0.95	0.81	0.91
7	1.06	0.93	0.83	0.89
8	1.10	0.96	0.85	0.86

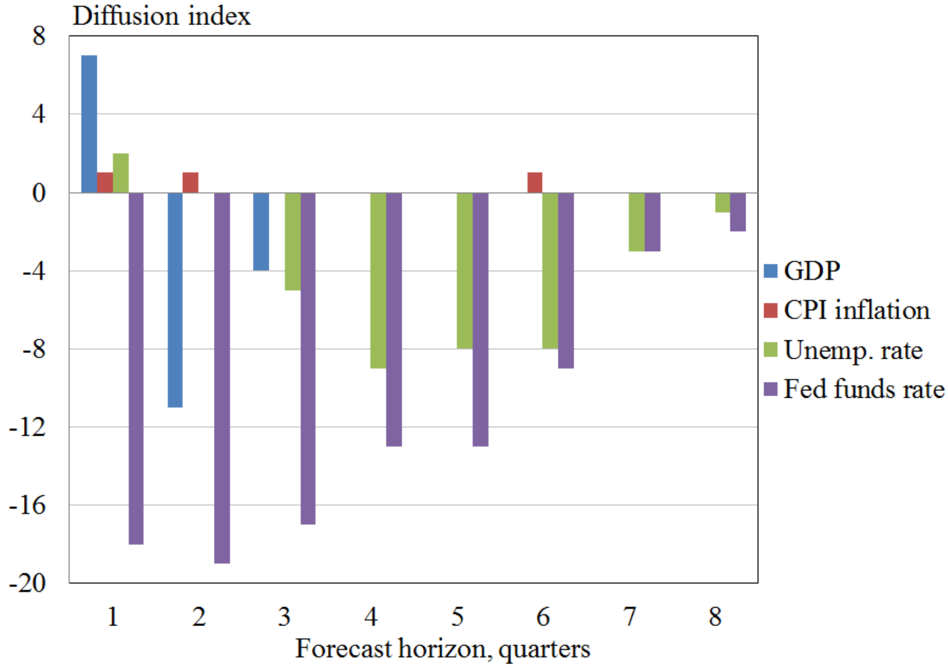
Notes: Relative RMSEs show quarterly BVAR RMSEs divided by MF-DFM RMSEs; numbers less than 1.0 indicate smaller historical RMSEs from forecasts produced with the quarterly BVAR model than from forecasts produced with the MF-DFM. *** (or ** or *) denotes a rejection of the null of equal predictive accuracy at the 1% (or 5% or 10%) level based on the Diebold-Mariano test. Forecasts are made using the real-time data available at the SPF survey date in each quarter in the evaluation period. The models are estimated using an expanding window of data from 1985:Q4 onward. Conditions used in the quarterly BVAR include nowcasts of financial variables and nowcasts generated based on (a) the available monthly frequency indicators that are shared with the MF-DFM, or (b) SPF survey nowcasts.

Figure 1: Diffusion Index of Results Using +1 Month of Financial Data for Nowcasts



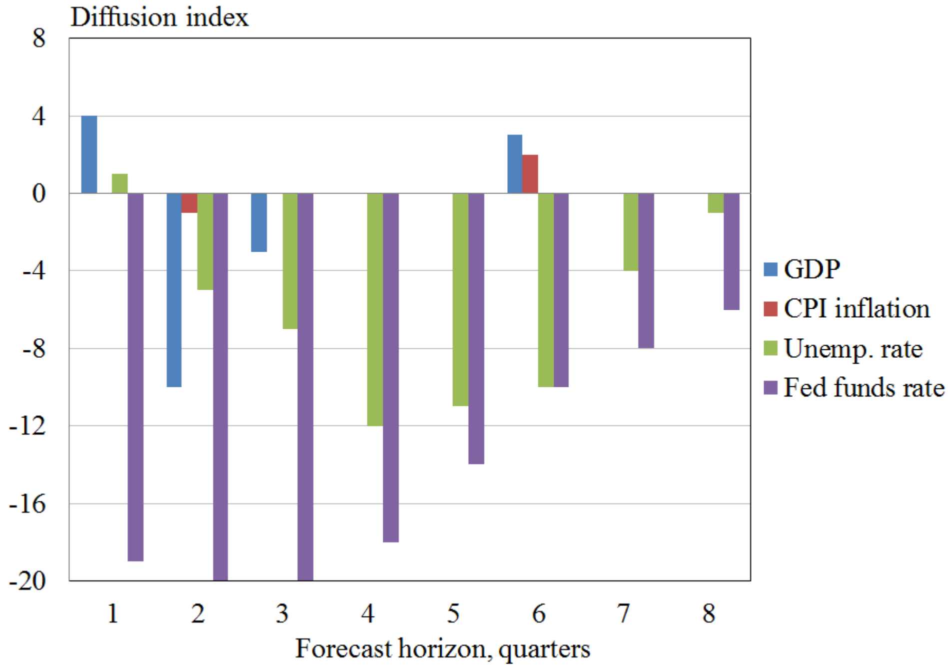
Note: For each of the 20 models, we compute the forecast MSE using financial nowcasts as a condition relative to the forecast MSE without the financial nowcasts as a condition. At each forecast horizon and for each variable, the diffusion index shows the number of models that produce a relative MSE≥1.1 minus the number of models that produce a relative MSE≤0.9.

Figure 2: Diffusion Index of Results Using +1.5 Months of Financial Data for Nowcasts



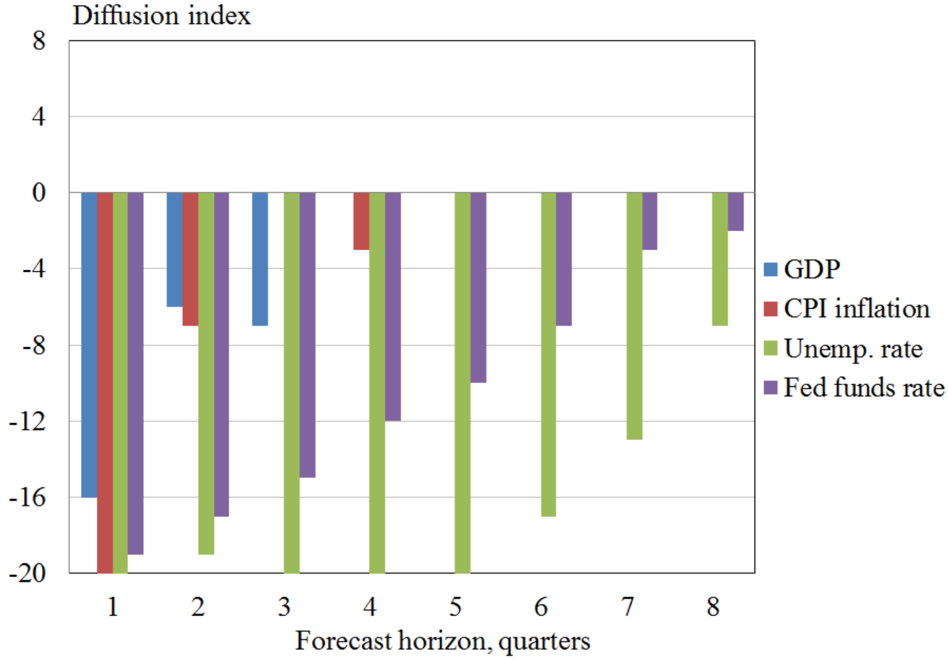
Note: For each of the 20 models, we compute the forecast MSE using financial nowcasts as a condition relative to the forecast MSE without the financial nowcasts as a condition. At each forecast horizon and for each variable, the diffusion index shows the number of models that produce a relative MSE≥1.1 minus the number of models that produce a relative MSE≤0.9.

Figure 3: Diffusion Index of Results Using +3 Months of Financial Data for Nowcasts



Note: For each of the 20 models, we compute the forecast MSE using financial nowcasts as a condition relative to the forecast MSE without the financial nowcasts as a condition. At each forecast horizon and for each variable, the diffusion index shows the number of models that produce a relative MSE≥1.1 minus the number of models that produce a relative MSE≤0.9.

Figure 4: Diffusion Index of Results Using +1.5 Months of Financial Data for Nowcasts and Nowcasts for Other Variables



Note: For each of the 20 models, we compute the forecast MSE using both financial nowcasts and other nowcasts as conditions relative to the forecast MSE without the financial and other nowcasts as conditions. At each forecast horizon and for each variable, the diffusion index shows the number of models that produce a relative MSE≥1.1 minus the number of models that produce a relative MSE≤0.9.

Appendix

A.1. Description of MIDAS Models

As in Andreou et al. (2011), a general representation of an ADL-MIDAS model is:

$$Y_{t+h}^{Q}=\mu^{(h)}+\sum_{j=0}^{P_{Y}^{Q}-1}\mu_{j+1}^{(h)}Y_{t-j}^{Q}+\beta^{(h)}\sum_{j=0}^{P_{X}^{D}-1}\sum_{i=0}^{N_{D}-1}\omega_{i+j*N_{D}}(\theta_{(h)}^{D})X_{N_{D}-i,t-j}^{D}+u_{t+h}, \tag{10}$$

where Y^{Q} is a dependent variable sampled at quarterly frequency, P_{Y}^{Q} is the number of lags of the dependent variable, N_{D} refers to the number of high-frequency lags (e.g., daily or monthly) in a quarter, and P_{X}^{D} refers to the number of quarterly lags of the high-frequency indicator X^{D}. The product of P_{X}^{D} and N_{D} gives the total number of high-frequency lags to use. All the parameters are indexed by *h* to indicate that they may change as the model is estimated for each forecast horizon *h*. To identify the slope coefficient $\beta^{(h)}$, assume $\sum_{j=0}^{P_{X}^{D}-1}\sum_{i=0}^{N_{D}-1}\omega_{i+j*N_{D}}(\theta_{(h)}^{D})=1$, and the parameters μ, β, and θ^{D} can then be estimated using nonlinear least squares (NLS). The above representation can be expanded to incorporate the leads of the high-frequency predictor (e.g., intra-quarterly daily or monthly data) in a MIDAS with leads specification of the form:

$$Y_{t+h}^{Q}=\mu^{(h)}+\sum_{j=0}^{P_{Y}^{Q}-1}\mu_{j+1}^{(h)}Y_{t-j}^{Q}+\beta^{(h)}\left[\sum_{i=0}^{J_{X}^{D}-1}\omega_{i}(\theta_{(h)}^{D})X_{J_{X}^{D}-i,t+h}^{D}+\sum_{j=0}^{P_{X}^{D}-1}\sum_{i=0}^{N_{D}-1}\omega_{i+j*N_{D}}(\theta_{(h)}^{D})X_{N_{D}-i,t-j}^{D}\right]+u_{t+h}, \tag{11}$$

where J_{X}^{D} is the number of high-frequency leads.

For nowcasting the financial variables in section 3.2, we set the number of quarterly lags of the dependent variable (P_{Y}^{Q}) to zero; the number of high-frequency leads and lags varies depending on the available information. For the horserace in section 5.1, we set both $P_Y^Q = P_X^D = 4$.

Ghysels et al. (2007) and Ghysels (2016) discuss a variety of polynomial specifications for the lag structure in equations (11). For nowcasting the financial variables in section 3.2, the MIDAS models differ in the combinations of polynomial specifications and whether the intra-quarterly predictors are monthly or daily.

(1) Monthly data and U-MIDAS. This combination uses available high-frequency monthly values $(N_D = 3)$ within the quarter to generate the quarterly financial variable nowcasts. Specifically, the quarterly values of the financial variable are regressed on the most recently available monthly values within the quarter using the unrestricted MIDAS (U-MIDAS) functional form for the polynomial specification—i.e., the estimated coefficients are unconstrained and OLS regressions suffice; see Foroni et al. (2015). This polynomial specification is feasible only when the number of high-frequency regressors is small. When no monthly data from the *t*+1 quarter to be nowcasted are available, then we set $J_X^D = 0$ and $P_X^D = 1$, and the U-MIDAS regressions take the form:

$$Y_{t+h}^Q = \mu^{(h)} + \sum_{i=0}^{N_D-1} \beta_i^{(h)} X_{N_D-i,t}^D + u_{t+h}; \tag{12}$$

By contrast, with one ($J_X^D = 1$) or two ($J_X^D = 2$) monthly data readings from the *t*+1 quarter to be nowcasted are available, we set $P_X^D = 0$ and the U-MIDAS regressions take the form:

$$Y_{t+h}^Q = \mu^{(h)} + \sum_{i=0}^{J_X^D-1} \beta_i^{(h)} X_{J_X^D-i,t+h}^D + u_{t+h}. \tag{13}$$

(2) Monthly data and BetaNN. This combination uses the high-frequency monthly data $(N_D = 3)$ available within the quarter to generate quarterly financial variable nowcasts. As above, when $J_X^D = 0$—i.e., we have no monthly data from the quarter to be nowcasted—then we set $P_X^D = 1$; with one ($J_X^D = 1$) or two ($J_X^D = 2$) monthly data readings from the *t*+1 quarter to be nowcasted are available, we set $P_X^D = 0$. The polynomial specification takes the form of a normalized beta probability density function with non-zero last lag ("BetaNN" in Ghysels 2016), due to the small number of lags. The weights are given by:

$$\omega_i(\theta_{(h)}^D) = \omega_i(\theta_1, \theta_2, \theta_3) = \frac{x_i^{\theta_1 - 1}(1 - x_i)^{\theta_2 - 1}}{\sum_{i=1}^{N} x_i^{\theta_1 - 1}(1 - x_i)^{\theta_2 - 1}} + \theta_3, \tag{14}$$

with $x_i = i/(N+1)$.

(3) Monthly data and ExpAlmon. This combination uses the high-frequency monthly data $(N_D = 3)$ available within the quarter to generate quarterly financial variable nowcasts. As above, when $J_X^D = 0$—i.e., we have no monthly data from the quarter to be nowcasted—then we set $P_X^D = 1$; with one ($J_X^D = 1$) or two ($J_X^D = 2$) monthly data readings from the *t*+1 quarter to be nowcasted are available, we set $P_X^D = 0$. The polynomial specification takes the form of a normalized exponential Almon lag polynomial:

$$\omega_i(\theta_{(h)}^D) = \omega_i(\theta_1, \theta_2) = \frac{e^{\theta_1 i + \theta_2 i^2}}{\sum_{i=1}^{N} e^{\theta_1 i + \theta_2 i^2}} \tag{15}$$

(4) Daily data and Beta. This combination uses the high-frequency daily data available within the quarter to generate financial variable nowcasts. We use $N_D = 64$ trading days in a quarter. Without any daily data from the quarter *t*+1 to be nowcasted (i.e., the +0 months case),

$J_X^D = 0$ and we set $P_X^D = 1$. With one month of data ($J_X^D = 19$ trading days) or two months of data ($J_X^D = 39$ trading days) from the quarter to be nowcasted, we set $P_X^D = 0$.[41] The polynomial specification takes the form of a normalized beta probability density function with a zero last lag:

$$\omega_i(\theta_{(h)}^D) = \omega_i(\theta_1, \theta_2) = \frac{x_i^{\theta_1 - 1}(1 - x_i)^{\theta_2 - 1}}{\sum_{i=1}^{N} x_i^{\theta_1 - 1}(1 - x_i)^{\theta_2 - 1}}, \tag{16}$$

with $x_i = i/(N+1)$.

(5) Daily data and BetaNN. This combination uses the high-frequency daily data available within the quarter to generate financial variable nowcasts, as in combination (4). The polynomial specification takes the form of a normalized beta probability density function with non-zero last lag, as in equation (14).

(6) Daily data and ExpAlmon. This combination uses the high-frequency daily data available within the quarter to generate financial variable nowcasts, as in combination (4). The polynomial specification takes the form of a normalized exponential Almon lag polynomial, as in equation (15).

A.2. Description of MF-DFM Models

The mixed-frequency dynamic factor model (MF-DFM) we implement follows closely from Modugno (2013). Modugno (2013) uses monthly, weekly, and daily data to estimate a MF-DFM at a trading-day frequency and uses the model to nowcast and forecast U.S. CPI inflation.

[41] While most months or quarters have more trading days than the numbers we use, we take a conservative approach to minimize the number of occurrences in which the window extends into the prior month or quarter.

In that framework, the nowcasts for monthly CPI inflation and its monthly components are based on the daily factor extracted from variables that are sampled at a daily frequency (e.g., oil prices, financial asset prices, and commodity prices). We modify this methodology to incorporate quarterly, monthly, and daily frequency data and estimate the MF-DFM at a trading-day frequency.

Specifically, in section 3.2 we nowcast quarterly financial variables using a daily factor that is extracted from a set of daily variables. In this exercise, we have the same number of quarterly, monthly, and daily variables: the quarterly data for each variable are the averages of the monthly readings on the seven financial variables of interest, and the monthly data are the averages of the daily readings on the seven financial variables of interest.

Let Y_t^Q be the (natural log) level of the quarterly series Y in quarter Q and trading day t; similarly, Y_t^M is the (natural log) level of the monthly series Y in month M and trading day t, and Y_t^D is the (natural log) level of the daily series Y on trading day t. To work with stationary variables, let y_t^Q, y_t^M, and y_t^D be the first differences (or growth rates) of the quarterly, monthly, and data variables on trading day t, respectively.

The dynamic factor model takes the general form:

$$y_t = Cf_t + \varepsilon_t,\ \ \varepsilon_t \sim N(0,\Sigma) \tag{17}$$

with t referring to the trading-day frequency, y_t is an n×1 vector of observations $y_t = [y_t{}^Q, y_t{}^M, y_t{}^D]'$, C is an n×r block diagonal matrix of factor loadings, ε_t is an n×1 vector of idiosyncratic components, and f_t is an r×1 vector of latent common factors following VAR dynamics:

$$Bf_t = A(L)f_{t-1} + u_t,\ \ u_t \sim N(0,Q), \tag{18}$$

where B and $A(L)$ are $r\times r$ matrices governing factor dynamics, some of which may be time-varying, and u_t is $r\times 1$.

With quarterly, monthly, and daily data, we have r=3 factors, one for each data frequency: $f_t = [f_t^Q, f_t^M, f_t^D]'$. Thus equations (17) and (18) can be written as:

$$\begin{bmatrix} y_t^Q \\ y_t^M \\ y_t^D \end{bmatrix} = \begin{bmatrix} C_Q & 0 & 0 \\ 0 & C_M & 0 \\ 0 & 0 & C_D \end{bmatrix} \begin{bmatrix} f_t^Q \\ f_t^M \\ f_t^D \end{bmatrix} + \begin{bmatrix} \varepsilon_t^Q \\ \varepsilon_t^M \\ \varepsilon_t^D \end{bmatrix} \tag{19}$$

and

$$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f_t^Q \\ f_t^M \\ f_t^D \end{bmatrix} = \begin{bmatrix} \Theta_t^Q & 0 & 0 \\ 0 & \Theta_t^M & 0 \\ 0 & 0 & A \end{bmatrix} \begin{bmatrix} f_{t-1}^Q \\ f_{t-1}^M \\ f_{t-1}^D \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ u_t^D \end{bmatrix} \tag{20}$$

The matrices C_Q, C_M, and C_D are the loadings for the quarterly, monthly, and daily variables. Θ_t^Q and Θ_t^M are time varying coefficients: Θ_t^Q is equal to zero the day after the release of the quarterly data (i.e., the first business day of the start of the quarter—because we are working with financial variables, they are assumed to be available on the last business day of the quarter) and is equal to one elsewhere; similarly, Θ_t^M is equal to zero the day after the release of the monthly data (i.e., the first business day of the start of the month) and is equal to one elsewhere.

Assuming that the quarterly variables and monthly variables in our system at any time t represent a stock (i.e., a snapshot), accordingly the quarterly first difference (or growth rate) and monthly first difference (or growth rate) of those variables can be formed by summing up their respective daily first differences (or growth rates). Equivalently, if one does not have the daily first differences, Modugno (2013) shows that the quarterly and monthly variables are functions of the quarterly and monthly factors via equation (19), and the latter factors are both functions of the daily factors via equation (20). Thus, the daily factors play a key role in the MF-DFM. In section 3.2, we generate the quarterly financial variable nowcasts based on a combination of the available daily data and forecasts for the daily factors within a quarter.[42] In section 5.2, our variables are as follows: y_t^Q contains real GDP, real consumption, productivity, the ECI, and the federal funds rate; y_t^M contains CPI inflation, core CPI inflation, payroll employment, and the unemployment rate; and y_t^D contains the three financial variables—the risk spread, the S&P 500, and the term spread. Thus, for inflation and labor market variables, the daily factors are used to forecast the monthly factors, which in turn inform the missing monthly observations within a quarter; for quarterly variables, the daily factors forecast the quarterly factors, and the quarterly factors are then used to forecast the quarterly variables.

[42] In this exercise, we can choose among three alternatives: (1) to directly use the nowcasts or forecasts of the quarterly values, y^Q; (2) to combine the monthly data and forecasted monthly factors; or (3) to combine the daily data and forecasted daily factors. We opt for the third approach, as it generated the most accurate results.

Table A.1: Series Transformations

Transformation code	Transformation
1	$Y_t = X_t$
2	$Y_t = \ln X_t$
3	$Y_t = 400 * \Delta \ln(X_t) - LongRun_t$

Table A.2: Quarterly Dataset

Variable	Transformation code
Real Gross Domestic Product (SAAR, Bil. Chn. 2009 $)	2
Real Personal Consumption Expenditures (SAAR, Bil. Chn. 2009 $)	2
CPI-U: All Items (SA, 1982-84=100)	3
CPI-U: All Items Less Food and Energy (SA, 1982-84=100)	3
Nonfarm Business Sector: Real Output Per Hour of All Persons (Productivity)	2
ECI: Compensation: Private Industry Workers	2
All Employees: Total Nonfarm	2
Unemployment Rate	1
Federal Funds Rate	1
Standard & Poor’s 500 Stock Price Index (1941-43=100)	2
Nominal Trade-Weighted Exchange Value of US $ vs. Major Currencies	2
Moody’s Seasoned Baa Corporate Bond Yield	1
10-Year Treasury Note Yield, Constant Maturity	1
3-Month Treasury Bill Yield, Constant Maturity	1
Risk Spread: Baa Bond Yield Minus 10-Yr. Treasury Note Yield	1
Term Spread: 10-Year Treasury Note Yield Minus 3-Mo. Treasury Bill Yield	1

Sources: Bureau of Economic Analysis, Bureau of Labor Statistics, Board of Governors of the Federal Reserve System, Standard & Poor’s, Moody’s, Federal Reserve Bank of Philadelphia, Federal Reserve Bank of St. Louis, Haver Analytics.

Table A.3: Monthly Dataset

Variable	Transformation code
CPI-U: All Items (SA, 1982-84=100)	3
CPI-U: All Items Less Food and Energy (SA, 1982-84=100)	3
All Employees: Total Nonfarm	2
Unemployment Rate	1
Federal Funds Rate	1
Standard & Poor's 500 Stock Price Index (1941-43=100)	2
Nominal Trade-Weighted Exchange Value of US $ vs. Major Currencies	2
Moody's Seasoned Baa Corporate Bond Yield	1
10-Year Treasury Note Yield, Constant Maturity	1
3-Month Treasury Bill Yield, Constant Maturity	1
Risk Spread: Baa Bond Yield Minus 10-Yr. Treasury Note Yield	1
Term Spread: 10-Year Treasury Note Yield Minus 3-Mo. Treasury Bill Yield	1

Sources: Bureau of Labor Statistics, Board of Governors of the Federal Reserve System, Standard & Poor's, Moody's, Federal Reserve Bank of Philadelphia, Federal Reserve Bank of St. Louis, Haver Analytics.

Table A.4: Daily Dataset

Variable	Transformation code
Light Sweet Crude Oil Futures Price: 1st Expiring Contract Settlement ($/Bbl)	2
Corn Futures Price: 1st Expiring Contract Settlement (cents/Bu)	2
Soybeans Futures Price: 1st Expiring Contract Settlement (Cents/Bu)	2
Wheat Futures Price: 1st Expiring Contract Settlement (Cents/Bu)	2
World Sugar Futures Price: 1st Expiring Contract Settlement (Cents/Lb)	2
Cotton Futures Price: 1st Expiring Contract Settlement (Cents/Lb)	2
Commodity Prices: Crude Oil, West Texas Intermediate ($/Barrel)	2
Commodity Prices: Crude Oil, Brent ($/Barrel)	2
Reuters/Jefferies CRB Futures Price Index: All Commodities (1967=100)	2
S&P GSCI Gold Index	2
S&P GSCI Silver Index (Dec 29-72=100)	2
S&P GSCI Wheat Index (Dec-31-69=100)	2
S&P GSCI Soybeans Index (Dec-31-69=100)	2
S&P GSCI Cotton Index	2
S&P GSCI Sugar Index (Dec-29-72=100)	2
S&P GSCI Cocoa Index (Dec-30-83=100)	2
S&P GSCI Live Cattle Index (Dec-31-69=100)	2
S&P GSCI Lean Hogs Index (Dec-31-75=100)	2
Live Cattle Futures	2
COMEX Gold Futures Prices	2
Oat Futures Price	2
Soybean Oil Futures Price (Cents/Pound)	2
Corn Spot Price (US$/Bushel)	2
Oat Spot Price (US$/Bushel)	2
Platinum Cash Price (US$/Ounce)	2
Soybean Oil Cash Price (Cents/Pound)	2
1-Month London Interbank Offered Rate (%)	1
3-Month London Interbank Offered Rate (%)	1
6-Month London Interbank Offered Rate (%)	1
1-Year London Interbank Offered Rate (%)	1
Moody’s Seasoned Aaa Corporate Bond Yield (%PA) minus 10-yr. Treas. Yield	1
Moody’s Seasoned Baa Corporate Bond Yield (%PA) minus 10-yr. Treas. Yield	1
1-Month Eurodollar Deposits (London Bid) (%PA) minus Federal Funds Rate	1
3-Month Eurodollar Deposits (London Bid) (%PA) minus Federal Funds Rate	1
6-Month Eurodollar Deposits (London Bid) (%PA) minus Federal Funds Rate	1
Ted 3-Month T-bill minus 3-Month LIBOR (%) minus Federal Funds Rate	1
Dow Jones 30 Industrials, NYSE (close)	2
Standard & Poor’s 500 Stock Price Index (1941-43=100)	2
Standard &Poor’s 500 Industrial Stock Index (1941-43=100)	2
NASDAQ Composite (2/5/71=100)	2
CBOE Market Volatility Index, VIX	1
S&P 500 Futures Price: 1st Expiring Contract Settlement (Index)	2
S&P 500/VIX	2
Canada: Spot Exchange Middle Rate, NY Close (Canadian$/US$)	2
Japan: Spot Exchange Middle Rate, NY Close (Yen/US$)	2
Switzerland: Spot Exchange Middle Rate, NY Close (Francs/US$)	2
United Kingdom: Spot Exchange Middle Rate, NY Close (Pounds/US$)	2
Nominal Trade-Weighted Exchange Value of US $ vs. Major Currencies	2
3-Month Treasury Bill Yield, Secondary Market (%PA)	1
6-Month Treasury Bill Yield, Secondary Market (%PA)	1
1-Year Treasury Bill Yield, Constant Maturity (%PA)	1

10-Year Treasury Bond Yield, Constant Maturity (%PA)	1
6-Mo. Treas. Bill Yield, Constant Maturity (%PA), minus 3-Mo. Treas. Bill Yield	1
1-Yr. Treas. Bill Yield, Constant Maturity (%PA), minus 3-Mo. Treas. Bill Yield	1
10-Yr. Treas. Bond Yield, Constant Maturity (%PA), minus 3-Mo. Treas. Bill Yield	1
6-Mo. Treas. Bill Yield, Constant Maturity (%PA), minus Federal Funds Rate	1
1-Yr. Treasury Bill Yield, Constant Maturity (%PA), minus Federal Funds Rate	1
10-Yr. Treas. Bond Yield, Constant Maturity (%PA), minus Federal Funds Rate	1

Sources: Board of Governors of the Federal Reserve System, Standard & Poor’s, Moody’s, Dow Jones, NASDAQ, CBOE, Haver Analytics.

Table B.1(a): Relative MSEs for Model 1, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	0.99	1.01	1.03	0.63										
2	0.89	0.95	0.89	0.83										
3	0.94	0.96	0.82	0.92										
4	1.01	0.99	0.83	0.94										
5	1.01	0.97	0.86	0.96										
6	1.05	0.99	0.90	0.98										
7	0.96	0.97	0.94	1.00										
8	0.99	0.98	0.96	1.00										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	0.98	1.05	0.99	0.53	1	0.61	0.32	0.33	0.52	1	0.61	0.32	0.33	1.10
2	0.87	0.97	0.87	0.78	2	0.83	0.86	0.49	0.85	2	0.95	0.89	0.57	1.14
3	0.92	0.97	0.81	0.90	3	0.90	0.97	0.58	0.97	3	0.98	1.02	0.70	1.09
4	1.01	1.00	0.82	0.93	4	1.03	0.97	0.67	1.00	4	1.03	1.00	0.80	1.05
5	1.01	0.98	0.85	0.95	5	1.04	1.00	0.75	0.99	5	1.04	1.02	0.86	1.03
6	1.03	0.99	0.89	0.98	6	1.09	0.99	0.83	1.00	6	1.07	1.00	0.91	1.01
7	0.96	0.98	0.93	1.00	7	1.00	0.99	0.88	1.00	7	1.03	1.00	0.94	1.00
8	0.99	1.00	0.94	1.00	8	1.01	1.00	0.91	0.99	8	1.03	1.00	0.96	0.98
+3 months of financial conditions					+3 months of financial and other conditions									
1	0.96	1.01	1.05	0.56	1	0.61	0.32	0.33	0.56					
2	0.88	0.93	0.88	0.70	2	0.84	0.85	0.48	0.78					
3	0.94	0.96	0.81	0.81	3	0.91	0.98	0.57	0.91					
4	1.02	0.98	0.80	0.84	4	1.04	0.97	0.66	0.95					
5	1.04	0.95	0.84	0.86	5	1.07	1.00	0.75	0.95					
6	1.07	0.97	0.89	0.91	6	1.12	0.98	0.83	0.96					
7	0.99	0.95	0.93	0.94	7	1.03	0.98	0.89	0.97					
8	0.99	0.97	0.96	0.95	8	1.02	0.99	0.93	0.96					

Notes: The estimation period is 1959:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.1(b): Relative MSEs for Model 1, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	1.28	1.02	1.00	1.08										
2	0.96	1.13	1.13	1.01										
3	0.96	1.02	1.01	1.01										
4	0.98	1.07	0.87	1.03										
5	0.99	1.03	0.87	1.05										
6	1.10	1.12	0.88	1.06										
7	1.03	1.00	0.92	1.06										
8	1.06	1.03	0.95	1.04										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	1.24	1.03	0.98	0.92	1	0.73	0.51	0.36	0.77	1	0.73	0.51	0.36	0.95
2	0.92	1.11	1.08	0.99	2	0.94	0.92	0.66	0.96	2	1.01	0.86	0.61	1.00
3	0.94	1.03	0.95	1.00	3	0.94	0.97	0.62	0.96	3	0.98	0.94	0.66	0.99
4	0.98	1.06	0.82	1.02	4	0.98	0.89	0.63	0.98	4	0.99	0.89	0.75	0.99
5	0.99	1.02	0.84	1.04	5	1.01	0.95	0.69	1.01	5	1.01	0.94	0.82	0.99
6	1.09	1.10	0.87	1.05	6	1.07	1.06	0.78	1.01	6	0.99	1.01	0.87	1.00
7	1.02	1.00	0.92	1.05	7	1.05	0.97	0.86	1.01	7	1.01	0.96	0.92	1.01
8	1.06	1.03	0.95	1.03	8	1.02	0.98	0.91	0.99	8	0.95	0.98	0.95	1.00
+3 months of financial conditions					+3 months of financial and other conditions									
1	1.18	0.99	0.93	0.98	1	0.73	0.51	0.36	0.83					
2	0.93	1.10	1.02	0.83	2	0.94	0.92	0.62	0.82					
3	0.94	1.02	0.92	0.86	3	0.93	0.97	0.59	0.85					
4	0.97	1.07	0.77	0.91	4	0.98	0.91	0.59	0.89					
5	1.00	1.03	0.80	0.96	5	1.03	0.97	0.66	0.95					
6	1.11	1.12	0.84	0.99	6	1.10	1.09	0.75	0.97					
7	1.08	1.01	0.90	1.00	7	1.10	0.98	0.85	0.98					
8	1.08	1.03	0.94	0.99	8	1.05	0.99	0.91	0.96					

Notes: The estimation period is 1959:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.2(a): Relative MSEs for Model 2, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	1.06	1.00	1.01	0.70										
2	0.88	1.00	0.93	0.93										
3	0.94	0.99	0.91	1.01										
4	0.99	1.00	0.92	1.02										
5	0.99	1.00	0.93	1.04										
6	1.02	1.01	0.96	1.05										
7	0.98	0.99	0.97	1.04										
8	1.00	1.00	0.98	1.03										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	1.07	1.03	0.99	0.67	1	0.64	0.31	0.30	0.68	1	0.64	0.31	0.30	1.06
2	0.87	1.01	0.93	0.89	2	0.87	0.99	0.53	0.95	2	0.98	0.97	0.54	1.12
3	0.94	1.00	0.91	0.97	3	0.92	1.02	0.63	1.00	3	0.98	1.03	0.65	1.08
4	0.99	1.00	0.92	1.00	4	0.97	1.02	0.71	1.00	4	0.98	1.02	0.73	1.03
5	0.99	1.00	0.94	1.02	5	1.00	1.00	0.77	0.98	5	1.00	1.00	0.79	0.99
6	1.01	1.01	0.96	1.03	6	1.02	1.02	0.83	0.96	6	1.01	1.02	0.84	0.95
7	0.98	0.99	0.98	1.03	7	0.99	1.00	0.87	0.95	7	1.01	1.01	0.87	0.93
8	1.00	1.00	0.98	1.02	8	1.01	1.01	0.90	0.92	8	1.01	1.02	0.90	0.91
+3 months of financial conditions					+3 months of financial and other conditions									
1	1.02	0.99	1.01	0.58	1	0.64	0.31	0.30	0.63					
2	0.86	0.99	0.93	0.78	2	0.85	0.98	0.52	0.86					
3	0.93	0.99	0.91	0.90	3	0.90	1.02	0.62	0.94					
4	0.98	1.01	0.91	0.94	4	0.96	1.01	0.71	0.95					
5	1.00	0.99	0.92	0.98	5	1.00	1.00	0.76	0.95					
6	1.02	1.00	0.94	1.00	6	1.03	1.01	0.82	0.95					
7	0.99	0.98	0.96	1.02	7	1.00	0.99	0.86	0.94					
8	0.99	0.99	0.97	1.02	8	1.01	1.00	0.90	0.93					

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.2(b): Relative MSEs for Model 2, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	1.32	1.01	1.02	0.65										
2	0.95	1.02	1.03	0.80										
3	0.97	0.98	0.96	0.87										
4	0.98	1.00	0.93	0.92										
5	0.98	0.99	0.95	0.95										
6	1.03	1.05	0.96	0.97										
7	0.98	1.00	0.97	0.97										
8	1.01	1.03	0.97	0.98										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	1.30	1.01	1.02	0.65	1	0.82	0.51	0.33	0.51	1	0.82	0.51	0.33	0.72
2	0.92	1.02	1.02	0.79	2	0.88	0.98	0.67	0.71	2	0.95	0.95	0.65	0.81
3	0.96	0.99	0.96	0.86	3	0.93	1.00	0.71	0.81	3	0.96	1.00	0.70	0.85
4	0.98	1.01	0.93	0.91	4	0.97	1.00	0.76	0.86	4	0.98	0.99	0.78	0.87
5	0.99	0.99	0.95	0.94	5	0.99	1.00	0.79	0.90	5	1.00	1.01	0.82	0.90
6	1.03	1.05	0.96	0.96	6	1.03	1.08	0.83	0.91	6	1.01	1.06	0.86	0.91
7	0.98	1.00	0.97	0.97	7	0.99	1.01	0.87	0.93	7	1.02	1.00	0.89	0.93
8	1.01	1.03	0.98	0.98	8	1.01	1.06	0.89	0.92	8	1.00	1.05	0.92	0.93
+3 months of financial conditions					+3 months of financial and other conditions									
1	1.26	0.98	0.95	0.55	1	0.82	0.51	0.33	0.44					
2	0.90	1.00	0.96	0.69	2	0.87	0.97	0.66	0.63					
3	0.95	0.97	0.92	0.80	3	0.92	0.99	0.69	0.76					
4	0.97	1.01	0.90	0.87	4	0.95	1.00	0.75	0.83					
5	1.00	0.99	0.93	0.92	5	0.99	1.00	0.78	0.89					
6	1.02	1.04	0.95	0.94	6	1.03	1.08	0.83	0.91					
7	0.98	1.00	0.97	0.96	7	0.99	1.01	0.87	0.93					
8	1.00	1.02	0.97	0.97	8	1.00	1.06	0.89	0.93					

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.3(a): Relative MSEs for Model 3, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	0.96	1.10	1.04	0.18										
2	0.90	0.92	0.93	0.35										
3	0.90	0.91	0.87	0.57										
4	0.97	0.92	0.86	0.63										
5	0.99	0.93	0.87	0.68										
6	1.01	0.97	0.90	0.75										
7	0.95	0.94	0.93	0.80										
8	0.94	0.96	0.95	0.84										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	0.96	1.10	1.03	0.21	1	0.60	0.33	0.33	0.21	1	0.60	0.33	0.33	1.17
2	0.88	0.92	0.93	0.38	2	0.87	0.83	0.51	0.46	2	0.97	0.88	0.57	1.15
3	0.89	0.91	0.86	0.58	3	0.88	0.93	0.58	0.71	3	0.99	0.99	0.71	1.08
4	0.96	0.93	0.85	0.65	4	0.99	0.95	0.68	0.78	4	1.03	0.98	0.81	1.05
5	0.98	0.94	0.87	0.70	5	1.04	0.99	0.75	0.80	5	1.03	1.02	0.88	1.03
6	1.00	0.97	0.90	0.76	6	1.07	0.99	0.83	0.84	6	1.06	1.00	0.93	1.01
7	0.95	0.95	0.92	0.82	7	1.00	0.96	0.88	0.87	7	1.02	1.00	0.95	1.01
8	0.94	0.96	0.94	0.86	8	0.97	0.98	0.91	0.89	8	1.02	1.00	0.98	1.00
+3 months of financial conditions					+3 months of financial and other conditions									
1	0.93	1.05	1.05	0.20	1	0.60	0.33	0.33	0.21					
2	0.89	0.88	0.93	0.29	2	0.87	0.82	0.51	0.40					
3	0.90	0.90	0.86	0.51	3	0.89	0.93	0.58	0.66					
4	0.97	0.92	0.84	0.57	4	1.00	0.95	0.67	0.74					
5	1.02	0.92	0.85	0.61	5	1.07	0.99	0.75	0.75					
6	1.04	0.94	0.89	0.68	6	1.11	0.98	0.83	0.78					
7	0.98	0.92	0.92	0.74	7	1.03	0.95	0.89	0.82					
8	0.95	0.94	0.95	0.79	8	0.99	0.97	0.93	0.84					

Notes: The estimation period is 1959:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.3(b): Relative MSEs for Model 3, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	1.13	0.93	0.89	0.29										
2	0.93	0.93	0.99	0.44										
3	0.89	0.97	0.96	0.69										
4	0.93	1.01	0.88	0.77										
5	0.97	0.98	0.89	0.83										
6	1.05	1.09	0.88	0.89										
7	1.01	0.97	0.89	0.93										
8	1.00	1.00	0.91	0.93										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	1.12	0.95	0.92	0.34	1	0.71	0.52	0.34	0.38	1	0.71	0.52	0.34	1.00
2	0.89	0.92	1.00	0.49	2	0.93	0.84	0.69	0.56	2	1.02	0.86	0.63	1.01
3	0.88	0.98	0.92	0.70	3	0.88	0.97	0.65	0.77	3	0.97	0.95	0.67	0.99
4	0.93	1.00	0.83	0.78	4	0.94	0.89	0.66	0.85	4	0.97	0.87	0.77	0.99
5	0.97	0.97	0.86	0.83	5	1.01	0.93	0.71	0.89	5	0.99	0.94	0.83	1.01
6	1.03	1.07	0.86	0.90	6	1.03	1.08	0.77	0.94	6	0.97	1.01	0.88	1.02
7	1.01	0.96	0.88	0.93	7	1.04	0.93	0.83	0.97	7	1.00	0.95	0.92	1.04
8	0.99	0.99	0.91	0.94	8	0.97	0.96	0.87	0.96	8	0.95	0.98	0.93	1.04
+3 months of financial conditions					+3 months of financial and other conditions									
1	1.04	0.91	0.87	0.28	1	0.71	0.52	0.34	0.31					
2	0.89	0.91	0.93	0.32	2	0.92	0.84	0.69	0.41					
3	0.86	0.97	0.91	0.56	3	0.87	0.99	0.66	0.66					
4	0.92	0.99	0.80	0.64	4	0.94	0.90	0.65	0.74					
5	0.99	0.98	0.83	0.70	5	1.04	0.94	0.70	0.80					
6	1.06	1.09	0.84	0.78	6	1.07	1.11	0.76	0.85					
7	1.06	0.96	0.87	0.83	7	1.09	0.93	0.82	0.89					
8	1.01	0.99	0.91	0.84	8	0.99	0.96	0.88	0.89					

Notes: The estimation period is 1959:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.4(a): Relative MSEs for Model 4, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	1.05	1.00	1.11	0.34										
2	0.88	0.96	1.08	0.45										
3	0.93	1.00	1.03	0.59										
4	0.99	0.99	1.00	0.67										
5	0.99	0.99	0.98	0.75										
6	1.00	1.00	0.98	0.82										
7	0.99	0.98	0.98	0.88										
8	1.00	0.99	0.98	0.92										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	1.03	1.01	1.11	0.48	1	0.62	0.32	0.32	0.46	1	0.62	0.32	0.32	1.02
2	0.87	0.96	1.08	0.54	2	0.90	0.97	0.59	0.57	2	1.00	0.98	0.56	1.14
3	0.93	1.01	1.04	0.65	3	0.92	1.04	0.70	0.69	3	0.98	1.03	0.67	1.12
4	0.98	1.00	1.01	0.72	4	0.97	1.01	0.77	0.75	4	1.00	1.02	0.75	1.06
5	0.99	0.99	0.99	0.78	5	0.99	0.99	0.81	0.80	5	1.01	1.01	0.81	1.01
6	0.99	1.00	0.99	0.85	6	1.00	1.01	0.86	0.85	6	1.01	1.02	0.85	0.98
7	0.99	0.98	0.99	0.90	7	0.99	0.99	0.88	0.88	7	1.01	1.01	0.88	0.96
8	0.99	0.99	0.98	0.94	8	1.00	1.00	0.90	0.89	8	1.01	1.02	0.91	0.93
+3 months of financial conditions					+3 months of financial and other conditions									
1	1.01	0.95	1.11	0.33	1	0.62	0.32	0.32	0.33					
2	0.88	0.93	1.05	0.29	2	0.89	0.95	0.58	0.35					
3	0.92	1.00	1.00	0.45	3	0.91	1.04	0.68	0.52					
4	0.98	1.00	0.97	0.56	4	0.97	1.00	0.75	0.61					
5	1.00	0.98	0.95	0.65	5	1.00	0.99	0.80	0.68					
6	1.01	1.00	0.95	0.74	6	1.01	1.01	0.84	0.75					
7	1.00	0.98	0.96	0.81	7	1.00	0.98	0.87	0.80					
8	1.00	0.99	0.97	0.87	8	1.00	0.99	0.90	0.84					

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.4(b): Relative MSEs for Model 4, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	1.07	1.02	1.01	0.39										
2	0.92	0.98	1.00	0.50										
3	0.97	1.00	0.93	0.62										
4	0.97	1.01	0.89	0.71										
5	0.96	0.99	0.92	0.78										
6	0.99	1.04	0.94	0.85										
7	0.97	0.98	0.95	0.89										
8	0.99	1.02	0.95	0.92										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	1.09	1.03	1.08	0.51	1	0.89	0.53	0.35	0.47	1	0.89	0.53	0.35	0.78
2	0.89	0.98	1.08	0.59	2	0.91	0.96	0.76	0.61	2	0.97	0.96	0.70	0.88
3	0.97	1.01	0.99	0.68	3	0.95	1.01	0.78	0.72	3	0.97	1.01	0.75	0.93
4	0.97	1.00	0.93	0.75	4	0.95	1.00	0.82	0.78	4	0.98	1.00	0.82	0.93
5	0.96	0.99	0.95	0.81	5	0.95	0.99	0.83	0.85	5	1.00	1.01	0.84	0.96
6	0.98	1.03	0.96	0.86	6	0.99	1.05	0.85	0.89	6	1.00	1.05	0.88	0.97
7	0.97	0.98	0.97	0.91	7	0.98	0.99	0.88	0.92	7	1.01	1.00	0.91	0.99
8	0.98	1.02	0.96	0.93	8	0.99	1.04	0.89	0.93	8	0.99	1.05	0.93	0.98
+3 months of financial conditions					+3 months of financial and other conditions									
1	1.06	1.00	0.99	0.32	1	0.89	0.53	0.35	0.31					
2	0.90	0.96	0.88	0.32	2	0.91	0.95	0.72	0.36					
3	0.96	0.99	0.84	0.46	3	0.94	1.00	0.74	0.52					
4	0.96	1.01	0.81	0.58	4	0.94	1.01	0.78	0.64					
5	0.96	0.98	0.87	0.67	5	0.95	0.99	0.80	0.73					
6	0.98	1.04	0.91	0.76	6	0.99	1.06	0.84	0.80					
7	0.98	0.99	0.94	0.82	7	0.99	0.99	0.87	0.86					
8	0.98	1.02	0.94	0.87	8	0.98	1.04	0.89	0.88					

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.5(a): Relative MSEs for Model 5, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
	+1 month of financial conditions																
1	0.96	1.07	1.01	1.00	0.51												
2	0.86	0.86	0.93	0.85	0.73												
3	0.92	0.98	0.96	0.79	0.82												
4	1.02	0.97	0.97	0.81	0.86												
5	1.00	0.95	0.96	0.85	0.89												
6	1.04	0.89	0.98	0.90	0.93												
7	0.96	0.90	0.96	0.93	0.95												
8	0.99	0.94	0.98	0.95	0.96												
	+1.5 months of financial conditions						+1.5 months of financial and other conditions						+1.5 months other conditions only				
1	0.95	1.14	1.05	0.97	0.44	1	0.67	0.46	0.32	0.36	0.37	1	0.67	0.45	0.32	0.36	0.90
2	0.85	0.88	0.95	0.84	0.69	2	0.89	0.71	0.86	0.55	0.75	2	1.02	0.79	0.90	0.62	1.11
3	0.91	0.99	0.96	0.79	0.80	3	0.90	0.88	0.97	0.67	0.88	3	0.96	0.88	1.02	0.78	1.08
4	1.00	0.98	0.98	0.80	0.86	4	1.04	0.85	0.96	0.75	0.93	4	1.04	0.87	0.99	0.87	1.05
5	0.99	0.95	0.97	0.84	0.89	5	1.00	0.91	0.98	0.81	0.95	5	1.00	0.94	1.00	0.91	1.05
6	1.03	0.90	0.98	0.88	0.93	6	1.05	0.82	0.97	0.88	0.97	6	1.03	0.90	0.98	0.95	1.03
7	0.96	0.91	0.97	0.92	0.95	7	0.98	0.83	0.97	0.91	0.99	7	1.00	0.90	0.99	0.97	1.03
8	0.99	0.95	0.99	0.94	0.96	8	1.02	0.89	0.95	0.93	0.99	8	1.03	0.93	0.96	0.98	1.01
	+3 months of financial conditions						+3 months of financial and other conditions										
1	0.91	1.07	1.00	1.01	0.44	1	0.67	0.44	0.32	0.36	0.41						
2	0.85	0.81	0.90	0.83	0.60	2	0.88	0.69	0.84	0.54	0.67						
3	0.92	0.95	0.95	0.77	0.71	3	0.91	0.88	0.97	0.66	0.81						
4	1.03	0.97	0.97	0.78	0.77	4	1.05	0.88	0.96	0.74	0.87						
5	1.02	0.93	0.95	0.82	0.81	5	1.02	0.93	0.97	0.81	0.89						
6	1.07	0.88	0.96	0.88	0.86	6	1.08	0.82	0.96	0.88	0.93						
7	0.99	0.88	0.95	0.92	0.90	7	1.00	0.83	0.97	0.93	0.95						
8	0.99	0.91	0.97	0.95	0.91	8	1.02	0.88	0.94	0.95	0.96						

Notes: The estimation period is 1959:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.5(b): Relative MSEs for Model 5, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
+1 month of financial conditions																	
1	1.33	0.84	1.00	1.00	0.87												
2	0.94	1.04	1.05	1.14	0.89												
3	0.93	1.03	1.01	1.00	0.96												
4	0.97	1.10	1.02	0.82	1.00												
5	0.98	1.03	1.00	0.83	1.02												
6	1.09	1.06	1.08	0.84	1.02												
7	1.03	1.04	1.00	0.89	1.01												
8	1.06	1.04	1.01	0.92	0.99												
+1.5 months of financial conditions						+1.5 months of financial and other conditions						+1.5 months other conditions only					
1	1.29	0.90	1.01	1.00	0.75	1	0.90	0.60	0.48	0.44	0.64	1	0.90	0.60	0.48	0.44	0.83
2	0.90	1.00	1.03	1.12	0.89	2	0.93	0.78	0.89	0.86	0.90	2	1.00	0.74	0.84	0.80	0.98
3	0.91	1.00	1.01	0.96	0.96	3	0.89	0.79	0.97	0.82	0.96	3	0.95	0.76	0.95	0.87	1.00
4	0.97	1.06	1.02	0.78	0.99	4	0.95	0.88	0.89	0.73	1.01	4	0.96	0.81	0.90	0.89	1.02
5	0.98	1.00	0.99	0.80	1.01	5	0.97	0.88	0.94	0.76	1.06	5	0.97	0.84	0.95	0.91	1.05
6	1.08	1.02	1.07	0.83	1.01	6	1.06	0.91	1.03	0.80	1.06	6	0.98	0.89	0.99	0.91	1.06
7	1.02	1.00	1.00	0.88	1.01	7	1.03	0.89	0.97	0.86	1.05	7	0.99	0.88	0.97	0.93	1.06
8	1.05	1.02	1.01	0.92	0.99	8	1.01	0.93	0.96	0.90	1.02	8	0.96	0.91	0.97	0.94	1.05
+3 months of financial conditions						+3 months of financial and other conditions											
1	1.21	0.82	0.97	0.94	0.79	1	0.90	0.55	0.48	0.44	0.68						
2	0.90	0.99	1.02	1.04	0.75	2	0.92	0.80	0.88	0.80	0.78						
3	0.90	1.04	1.00	0.92	0.84	3	0.89	0.84	0.97	0.77	0.86						
4	0.96	1.14	1.03	0.71	0.90	4	0.95	0.96	0.91	0.67	0.93						
5	1.00	1.08	1.00	0.73	0.95	5	1.00	0.96	0.95	0.70	1.00						
6	1.11	1.11	1.09	0.79	0.97	6	1.09	1.00	1.06	0.77	1.02						
7	1.08	1.07	1.01	0.86	0.97	7	1.08	0.95	0.99	0.85	1.02						
8	1.08	1.05	1.02	0.91	0.96	8	1.04	0.96	0.97	0.90	1.00						

Notes: The estimation period is 1959:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.6(a): Relative MSEs for Model 6, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
	+1 month of financial conditions																
1	1.04	1.06	0.99	1.01	0.58												
2	0.90	0.99	1.00	0.92	0.79												
3	0.94	1.01	0.99	0.88	0.89												
4	0.98	1.01	0.99	0.88	0.93												
5	0.98	1.00	0.99	0.89	0.96												
6	1.01	0.95	0.99	0.92	0.98												
7	0.98	0.94	0.98	0.94	0.98												
8	1.01	0.97	0.98	0.95	0.98												
	+1.5 months of financial conditions						+1.5 months of financial and other conditions						+1.5 months other conditions only				
1	1.05	1.12	1.02	1.00	0.57	1	0.66	0.79	0.31	0.33	0.59	1	0.66	0.83	0.31	0.33	1.02
2	0.89	1.02	1.00	0.93	0.78	2	0.92	1.05	1.00	0.61	0.83	2	1.03	1.01	0.98	0.63	1.09
3	0.95	1.04	0.99	0.89	0.87	3	0.96	0.98	1.02	0.72	0.91	3	1.01	0.95	1.03	0.76	1.07
4	0.98	1.02	0.99	0.89	0.93	4	1.01	1.04	1.01	0.80	0.96	4	1.03	1.05	1.02	0.85	1.05
5	0.99	1.01	0.99	0.91	0.96	5	1.01	1.02	1.00	0.85	0.97	5	1.02	1.03	1.01	0.89	1.03
6	1.01	0.97	1.00	0.93	0.98	6	1.03	0.97	1.00	0.90	0.97	6	1.03	1.03	1.01	0.94	1.01
7	0.98	0.96	0.98	0.95	0.99	7	0.99	0.96	0.99	0.92	0.98	7	1.01	1.01	1.01	0.95	1.00
8	1.00	0.99	0.99	0.96	0.99	8	1.01	1.00	0.99	0.94	0.96	8	1.01	1.02	1.00	0.96	0.98
	+3 months of financial conditions						+3 months of financial and other conditions										
1	1.00	1.04	0.98	1.02	0.49	1	0.66	0.82	0.31	0.33	0.52						
2	0.87	0.98	0.99	0.92	0.66	2	0.88	1.02	1.00	0.60	0.73						
3	0.93	0.98	0.98	0.87	0.79	3	0.94	0.95	1.02	0.70	0.83						
4	0.98	1.02	0.99	0.86	0.86	4	1.00	1.03	1.00	0.78	0.90						
5	1.00	0.97	0.99	0.87	0.90	5	1.02	1.00	0.99	0.83	0.92						
6	1.01	0.93	0.99	0.90	0.93	6	1.04	0.94	1.00	0.88	0.93						
7	0.99	0.91	0.97	0.92	0.95	7	1.00	0.92	0.98	0.91	0.94						
8	1.00	0.94	0.97	0.94	0.97	8	1.01	0.96	0.97	0.93	0.94						

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.6(b): Relative MSEs for Model 6, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
+1 month of financial conditions																	
1	1.33	0.90	0.97	1.04	0.59												
2	1.00	1.08	1.02	1.06	0.74												
3	0.99	0.94	0.98	0.98	0.84												
4	0.97	1.00	1.00	0.95	0.91												
5	0.97	0.94	0.99	0.96	0.95												
6	1.03	1.02	1.05	0.96	0.96												
7	0.98	1.01	1.02	0.97	0.97												
8	1.01	1.03	1.03	0.97	0.98												
+1.5 months of financial conditions						+1.5 months of financial and other conditions						+1.5 months other conditions only					
1	1.30	0.92	0.99	1.05	0.61	1	0.93	0.86	0.48	0.34	0.54	1	0.93	0.95	0.48	0.34	0.85
2	0.98	1.09	1.01	1.05	0.74	2	0.92	1.12	1.00	0.74	0.72	2	0.96	0.97	0.97	0.72	0.92
3	0.99	0.96	0.99	0.98	0.83	3	1.00	0.91	1.00	0.79	0.85	3	1.00	0.94	1.00	0.80	0.95
4	0.98	1.00	1.00	0.95	0.90	4	0.99	1.01	0.98	0.83	0.92	4	1.00	1.01	0.99	0.87	0.96
5	0.99	0.95	0.99	0.96	0.94	5	0.99	0.95	0.99	0.86	0.97	5	1.00	1.01	1.01	0.91	0.98
6	1.03	1.01	1.04	0.97	0.95	6	1.03	1.00	1.06	0.87	0.96	6	1.02	1.01	1.04	0.92	0.97
7	0.98	1.00	1.02	0.98	0.97	7	0.99	0.98	1.02	0.89	0.96	7	1.01	0.98	1.00	0.93	0.98
8	1.01	1.02	1.02	0.98	0.98	8	1.00	1.01	1.03	0.90	0.95	8	0.99	1.00	1.02	0.94	0.96
+3 months of financial conditions						+3 months of financial and other conditions											
1	1.27	0.94	0.97	0.99	0.50	1	0.93	0.92	0.48	0.34	0.46						
2	0.96	1.06	1.00	1.00	0.63	2	0.91	1.09	0.98	0.71	0.63						
3	0.98	0.94	0.97	0.95	0.77	3	0.99	0.89	0.99	0.77	0.79						
4	0.96	1.01	1.00	0.92	0.86	4	0.96	1.03	0.99	0.81	0.89						
5	0.99	0.93	1.00	0.93	0.92	5	1.01	0.94	1.00	0.84	0.96						
6	1.02	1.01	1.04	0.94	0.94	6	1.03	1.00	1.06	0.86	0.95						
7	0.99	0.99	1.02	0.96	0.96	7	1.00	0.98	1.02	0.88	0.96						
8	1.00	1.01	1.02	0.96	0.97	8	0.99	1.01	1.03	0.89	0.94						

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.7(a): Relative MSEs for Model 7, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
+1 month of financial conditions					
1	0.93	1.63	1.12	1.05	0.20
2	0.88	0.78	0.91	0.91	0.36
3	0.91	0.91	0.93	0.83	0.59
4	0.99	0.90	0.95	0.83	0.66
5	1.00	0.88	0.96	0.86	0.72
6	1.03	0.84	0.98	0.90	0.79
7	0.97	0.87	0.95	0.92	0.84
8	0.97	0.92	0.97	0.94	0.87
+1.5 months of financial conditions					
1	0.92	1.51	1.12	1.04	0.21
2	0.86	0.79	0.92	0.91	0.38
3	0.90	0.92	0.93	0.83	0.60
4	0.98	0.90	0.95	0.83	0.67
5	0.99	0.88	0.96	0.85	0.72
6	1.02	0.84	0.98	0.88	0.80
7	0.97	0.87	0.96	0.91	0.84
8	0.97	0.92	0.98	0.93	0.88
+3 months of financial conditions					
1	0.88	1.64	1.08	1.05	0.20
2	0.87	0.75	0.88	0.89	0.29
3	0.90	0.89	0.92	0.81	0.52
4	0.99	0.90	0.94	0.81	0.59
5	1.02	0.86	0.94	0.83	0.65
6	1.06	0.83	0.96	0.88	0.72
7	0.99	0.84	0.93	0.92	0.78
8	0.97	0.88	0.96	0.94	0.83

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
+1.5 months of financial and other conditions					
1	0.66	0.59	0.33	0.37	0.18
2	0.92	0.65	0.85	0.60	0.49
3	0.90	0.87	0.95	0.68	0.73
4	1.02	0.88	0.97	0.76	0.80
5	1.02	0.92	0.99	0.81	0.83
6	1.06	0.81	0.98	0.87	0.88
7	0.99	0.83	0.96	0.91	0.92
8	1.00	0.88	0.95	0.93	0.93
+3 months of financial and other conditions					
1	0.66	0.60	0.33	0.37	0.17
2	0.92	0.64	0.84	0.59	0.41
3	0.90	0.88	0.95	0.68	0.67
4	1.03	0.92	0.97	0.75	0.75
5	1.05	0.94	0.99	0.81	0.78
6	1.10	0.83	0.97	0.88	0.83
7	1.01	0.83	0.94	0.92	0.87
8	1.01	0.87	0.93	0.95	0.90

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
+1.5 months other conditions only					
1	0.66	0.49	0.33	0.37	1.01
2	1.03	0.81	0.91	0.65	1.18
3	0.98	0.88	1.01	0.80	1.12
4	1.05	0.89	0.99	0.89	1.09
5	1.01	0.96	1.00	0.93	1.07
6	1.04	0.92	0.98	0.97	1.05
7	1.01	0.92	0.99	0.98	1.04
8	1.03	0.94	0.96	0.99	1.03

Notes: The estimation period is 1959:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.7(b): Relative MSEs for Model 7, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
	+1 month of financial conditions																
1	1.14	1.05	0.94	0.94	0.23												
2	0.91	0.91	0.96	1.08	0.46												
3	0.90	1.01	1.02	1.02	0.73												
4	0.96	1.09	1.03	0.84	0.83												
5	1.00	1.03	1.00	0.85	0.88												
6	1.09	1.06	1.09	0.84	0.94												
7	1.04	1.07	1.00	0.87	0.96												
8	1.03	1.04	1.01	0.90	0.95												
	+1.5 months of financial conditions						+1.5 months of financial and other conditions						+1.5 months other conditions only				
1	1.13	1.08	0.96	0.98	0.23	1	0.88	0.86	0.49	0.45	0.25	1	0.88	0.63	0.49	0.45	0.99
2	0.88	0.88	0.95	1.10	0.49	2	0.90	0.73	0.87	0.94	0.59	2	1.00	0.75	0.87	0.83	1.09
3	0.89	0.99	1.02	0.98	0.73	3	0.88	0.83	1.01	0.88	0.86	3	0.95	0.78	0.97	0.88	1.08
4	0.95	1.06	1.02	0.79	0.82	4	0.95	0.93	0.94	0.74	0.95	4	0.96	0.81	0.91	0.88	1.09
5	1.00	1.00	0.99	0.81	0.88	5	1.01	0.90	0.96	0.75	1.01	5	0.98	0.84	0.96	0.90	1.10
6	1.08	1.01	1.08	0.82	0.93	6	1.07	0.92	1.07	0.77	1.04	6	0.98	0.90	0.99	0.91	1.10
7	1.03	1.02	0.99	0.86	0.95	7	1.04	0.91	0.97	0.83	1.05	7	0.99	0.89	0.98	0.93	1.10
8	1.03	1.02	1.00	0.89	0.95	8	0.99	0.92	0.97	0.87	1.02	8	0.96	0.92	0.98	0.94	1.09
	+3 months of financial conditions						+3 months of financial and other conditions										
1	1.04	1.11	0.92	0.94	0.22	1	0.88	0.88	0.49	0.45	0.23						
2	0.87	0.88	0.94	1.01	0.34	2	0.90	0.74	0.87	0.93	0.44						
3	0.87	1.03	1.03	0.96	0.60	3	0.86	0.90	1.04	0.89	0.74						
4	0.95	1.14	1.03	0.74	0.69	4	0.94	1.04	0.96	0.72	0.85						
5	1.02	1.09	1.00	0.76	0.76	5	1.04	1.00	0.98	0.72	0.91						
6	1.10	1.11	1.11	0.79	0.84	6	1.10	1.04	1.10	0.76	0.96						
7	1.09	1.09	1.00	0.84	0.88	7	1.09	0.99	0.97	0.82	0.99						
8	1.05	1.07	1.01	0.89	0.88	8	1.02	0.97	0.97	0.87	0.97						

Notes: The estimation period is 1959:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.8(a): Relative MSEs for Model 8, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
+1 month of financial conditions																	
1	1.09	1.15	1.02	1.09	0.23												
2	0.88	0.99	0.97	1.04	0.44												
3	0.94	1.03	1.00	0.99	0.63												
4	0.99	1.03	1.00	0.96	0.72												
5	0.99	1.02	0.99	0.95	0.80												
6	1.01	0.98	1.00	0.96	0.87												
7	1.00	0.95	0.98	0.96	0.91												
8	1.00	0.98	0.99	0.97	0.95												
+1.5 months of financial conditions						+1.5 months of financial and other conditions						+1.5 months other conditions only					
1	1.07	1.17	1.02	1.10	0.35	1	0.64	0.93	0.32	0.33	0.35	1	0.64	0.91	0.32	0.33	1.03
2	0.87	1.00	0.97	1.05	0.51	2	0.93	1.02	0.99	0.63	0.55	2	1.04	1.00	0.99	0.62	1.14
3	0.94	1.04	1.00	1.00	0.67	3	0.96	0.99	1.04	0.74	0.71	3	1.01	0.95	1.04	0.75	1.11
4	0.98	1.04	1.00	0.98	0.77	4	1.00	1.04	1.02	0.82	0.80	4	1.02	1.04	1.03	0.84	1.06
5	0.99	1.03	0.99	0.97	0.83	5	1.01	1.03	1.00	0.86	0.85	5	1.01	1.01	1.01	0.89	1.02
6	1.00	0.99	1.00	0.97	0.89	6	1.03	0.98	1.00	0.91	0.89	6	1.03	1.00	1.01	0.93	1.00
7	0.99	0.96	0.99	0.97	0.93	7	1.00	0.96	0.99	0.93	0.92	7	1.01	0.99	1.01	0.95	0.99
8	1.00	0.98	0.99	0.97	0.96	8	1.00	0.99	0.99	0.94	0.93	8	1.01	1.01	1.01	0.97	0.97
+3 months of financial conditions						+3 months of financial and other conditions											
1	1.05	1.16	0.97	1.09	0.21	1	0.64	0.96	0.32	0.33	0.23						
2	0.87	0.97	0.95	1.01	0.28	2	0.91	1.02	0.97	0.62	0.33						
3	0.93	1.02	1.00	0.96	0.50	3	0.95	0.98	1.05	0.72	0.55						
4	0.98	1.03	1.00	0.94	0.63	4	0.99	1.04	1.02	0.80	0.67						
5	1.00	1.00	0.99	0.93	0.73	5	1.02	1.01	0.99	0.85	0.75						
6	1.01	0.97	0.99	0.94	0.81	6	1.03	0.97	1.00	0.90	0.82						
7	1.00	0.93	0.98	0.95	0.87	7	1.01	0.93	0.99	0.92	0.87						
8	1.00	0.95	0.98	0.96	0.92	8	1.00	0.96	0.98	0.94	0.90						

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.8(b): Relative MSEs for Model 8, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
+1 month of financial conditions																	
1	1.15	1.03	0.98	0.96	0.22												
2	0.96	1.04	0.98	0.95	0.47												
3	0.98	1.02	1.01	0.89	0.66												
4	0.96	1.03	1.03	0.87	0.77												
5	0.96	0.99	1.01	0.91	0.85												
6	1.02	1.01	1.05	0.93	0.92												
7	0.99	0.97	1.01	0.95	0.96												
8	1.01	1.01	1.03	0.95	0.98												
+1.5 months of financial conditions						+1.5 months of financial and other conditions						+1.5 months other conditions only					
1	1.17	1.03	1.00	1.03	0.30	1	0.97	1.01	0.49	0.35	0.29	1	0.97	0.97	0.49	0.35	0.88
2	0.94	1.04	0.98	1.02	0.54	2	0.93	1.07	0.98	0.75	0.56	2	0.97	1.00	0.98	0.72	0.97
3	0.98	1.03	1.02	0.95	0.69	3	1.00	0.99	1.03	0.77	0.72	3	1.01	0.94	1.01	0.79	0.99
4	0.96	1.04	1.03	0.92	0.80	4	0.97	1.06	1.02	0.80	0.82	4	1.00	1.01	1.00	0.85	0.98
5	0.97	1.00	1.00	0.94	0.87	5	0.97	1.00	1.00	0.84	0.89	5	1.00	1.00	1.00	0.89	1.00
6	1.02	1.01	1.04	0.94	0.92	6	1.02	1.00	1.05	0.85	0.92	6	1.01	1.00	1.03	0.90	0.98
7	0.99	0.97	1.01	0.96	0.96	7	0.99	0.96	1.01	0.87	0.94	7	1.01	0.97	1.01	0.91	0.98
8	1.01	1.00	1.02	0.96	0.98	8	1.00	0.99	1.02	0.88	0.94	8	0.99	1.00	1.03	0.93	0.97
+3 months of financial conditions						+3 months of financial and other conditions											
1	1.15	1.06	0.98	0.93	0.17	1	0.97	1.07	0.49	0.35	0.18						
2	0.95	1.02	0.97	0.83	0.30	2	0.93	1.09	0.97	0.69	0.33						
3	0.98	1.02	1.01	0.80	0.51	3	1.00	0.99	1.04	0.72	0.56						
4	0.95	1.04	1.03	0.80	0.66	4	0.95	1.07	1.03	0.75	0.70						
5	0.96	0.97	1.00	0.86	0.77	5	0.98	0.98	1.00	0.81	0.81						
6	1.01	1.01	1.05	0.90	0.85	6	1.01	1.00	1.06	0.83	0.86						
7	0.99	0.96	1.01	0.93	0.92	7	1.00	0.95	1.02	0.86	0.90						
8	1.00	1.00	1.03	0.94	0.95	8	1.00	0.99	1.03	0.88	0.91						

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.9(a): Relative MSEs for Model 9, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
+1 month of financial conditions																	
1	1.01	1.03	1.03	1.09	0.53												
2	0.96	1.01	0.99	1.07	0.62												
3	1.00	1.02	1.00	1.03	0.72												
4	1.00	1.00	0.99	1.02	0.79												
5	1.00	1.01	1.00	1.01	0.85												
6	1.00	0.99	1.00	1.01	0.89												
7	1.00	0.99	1.00	1.01	0.93												
8	1.00	0.99	1.00	1.01	0.96												
+1.5 months of financial conditions						+1.5 months of financial and other conditions						+1.5 months other conditions only					
1	1.01	1.03	1.03	1.08	0.55	1	0.65	0.92	0.38	0.21	0.68	1	0.65	0.91	0.38	0.21	1.24
2	0.96	1.02	1.00	1.07	0.63	2	0.94	1.04	1.00	0.48	0.72	2	0.97	1.04	1.02	0.47	1.15
3	0.99	1.02	1.00	1.03	0.72	3	0.98	1.01	1.01	0.66	0.80	3	0.99	1.00	1.02	0.65	1.10
4	1.00	1.01	0.99	1.02	0.79	4	0.99	1.01	1.00	0.77	0.85	4	0.99	1.02	1.01	0.77	1.06
5	1.00	1.01	1.00	1.01	0.84	5	1.01	1.00	0.99	0.84	0.87	5	1.01	1.00	0.99	0.84	1.03
6	1.00	1.00	1.00	1.01	0.89	6	1.01	0.99	1.00	0.90	0.90	6	1.01	1.00	1.00	0.90	1.00
7	1.00	0.99	1.00	1.01	0.93	7	1.01	0.98	1.00	0.94	0.93	7	1.01	0.99	1.00	0.93	0.99
8	1.00	0.99	1.00	1.01	0.95	8	1.00	0.98	1.00	0.96	0.94	8	1.00	0.99	1.00	0.96	0.98
+3 months of financial conditions						+3 months of financial and other conditions											
1	1.01	0.98	1.08	1.10	0.62	1	0.65	0.92	0.38	0.21	0.83						
2	0.97	1.03	1.01	1.08	0.70	2	0.94	1.02	1.00	0.47	0.81						
3	1.02	1.04	1.02	1.04	0.76	3	0.99	1.01	1.01	0.64	0.84						
4	0.99	0.99	1.01	1.03	0.81	4	1.00	0.99	1.00	0.76	0.87						
5	0.99	1.02	1.02	1.03	0.86	5	1.01	1.00	0.99	0.84	0.88						
6	1.02	1.00	1.03	1.03	0.91	6	1.01	0.98	1.00	0.90	0.90						
7	1.02	0.99	1.02	1.03	0.95	7	1.01	0.97	1.00	0.94	0.92						
8	1.00	1.00	1.02	1.03	0.97	8	1.00	0.98	1.00	0.96	0.94						

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.9(b): Relative MSEs for Model 9, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate	Horizon	GDP	Core CPI inf.	CPI inf.	Unemp. rate	Fed funds rate
+1 month of financial conditions																	
1	1.02	1.03	1.01	1.03	0.91												
2	1.02	1.00	1.01	1.02	0.85												
3	1.01	0.99	1.02	1.01	0.85												
4	1.00	0.98	1.00	1.00	0.87												
5	1.01	1.00	1.00	1.00	0.89												
6	1.01	0.99	1.00	1.00	0.92												
7	1.00	0.99	1.00	1.00	0.95												
8	1.00	1.00	1.00	1.00	0.97												
+1.5 months of financial conditions						+1.5 months of financial and other conditions						+1.5 months other conditions only					
1	1.00	1.02	1.01	1.04	0.91	1	0.90	0.96	0.55	0.21	0.96	1	0.90	0.95	0.55	0.21	1.29
2	1.01	1.00	1.02	1.02	0.85	2	1.03	1.05	1.01	0.54	0.86	2	1.02	1.04	0.98	0.53	1.15
3	1.01	0.99	1.01	1.01	0.85	3	1.00	1.01	1.01	0.67	0.87	3	1.00	1.02	0.99	0.66	1.11
4	1.00	0.98	1.00	1.01	0.88	4	1.00	0.99	1.00	0.77	0.89	4	1.01	1.02	1.00	0.76	1.08
5	1.00	1.00	1.00	1.00	0.90	5	1.00	1.01	1.00	0.84	0.91	5	1.01	1.02	1.00	0.84	1.06
6	1.00	0.99	1.00	1.00	0.92	6	1.01	1.00	1.00	0.89	0.93	6	1.01	1.02	1.00	0.90	1.04
7	1.00	0.99	1.00	1.00	0.95	7	1.00	0.99	1.00	0.92	0.95	7	1.01	1.01	1.00	0.93	1.02
8	1.00	1.00	1.00	1.00	0.97	8	1.00	1.00	1.00	0.95	0.96	8	1.00	1.01	1.00	0.96	1.01
+3 months of financial conditions						+3 months of financial and other conditions											
1	1.01	1.01	1.02	1.03	0.83	1	0.90	0.96	0.55	0.21	0.91						
2	1.05	1.04	1.05	1.05	0.83	2	1.03	1.05	1.00	0.54	0.83						
3	1.05	1.02	1.04	1.04	0.85	3	1.00	1.00	1.00	0.67	0.85						
4	0.94	0.98	1.03	1.03	0.89	4	1.00	0.99	1.00	0.77	0.89						
5	0.94	1.00	1.04	1.02	0.92	5	1.00	1.01	1.00	0.84	0.91						
6	1.03	1.01	1.04	1.02	0.96	6	1.01	1.01	1.00	0.89	0.93						
7	1.03	0.99	1.04	1.02	0.99	7	1.00	0.99	1.00	0.92	0.95						
8	0.98	1.00	1.00	1.01	1.01	8	1.00	1.00	1.00	0.95	0.96						

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

Table B.10(a): Relative MSEs for Model 10, Evaluation Period 1994:Q1-2015:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	1.00	1.03	1.04	0.47										
2	0.94	0.99	1.01	0.57										
3	0.98	1.00	0.98	0.68										
4	0.99	0.99	0.97	0.76										
5	1.00	1.00	0.97	0.83										
6	1.00	1.00	0.98	0.88										
7	1.00	1.00	0.99	0.92										
8	1.00	1.00	0.99	0.95										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	1.00	1.03	1.04	0.49	1	0.63	0.39	0.17	0.52	1	0.63	0.39	0.17	1.08
2	0.94	1.00	1.01	0.57	2	0.92	1.00	0.40	0.55	2	0.96	1.00	0.38	0.96
3	0.98	1.00	0.98	0.68	3	0.96	1.00	0.55	0.63	3	0.97	1.01	0.54	0.91
4	0.98	0.99	0.97	0.76	4	0.97	0.99	0.67	0.70	4	0.97	1.00	0.66	0.89
5	1.00	1.00	0.97	0.83	5	0.99	0.99	0.76	0.76	5	0.99	0.99	0.76	0.89
6	1.00	1.00	0.98	0.88	6	1.01	1.00	0.84	0.83	6	1.00	1.00	0.84	0.91
7	1.00	1.00	0.98	0.92	7	1.02	1.00	0.89	0.89	7	1.02	1.00	0.89	0.94
8	1.01	1.00	0.99	0.95	8	1.02	1.01	0.94	0.94	8	1.02	1.01	0.94	0.96
+3 months of financial conditions					+3 months of financial and other conditions									
1	0.99	1.08	1.03	0.58	1	0.63	0.39	0.17	0.73					
2	0.94	1.01	1.01	0.64	2	0.90	0.99	0.38	0.67					
3	1.00	1.02	0.97	0.72	3	0.96	1.01	0.53	0.69					
4	0.97	1.01	0.97	0.78	4	0.97	0.99	0.65	0.72					
5	0.99	1.02	0.98	0.84	5	0.99	0.99	0.75	0.77					
6	1.02	1.02	0.99	0.89	6	1.01	1.00	0.83	0.82					
7	1.02	1.03	1.00	0.94	7	1.02	1.00	0.89	0.88					
8	1.01	1.02	1.01	0.97	8	1.03	1.01	0.94	0.93					

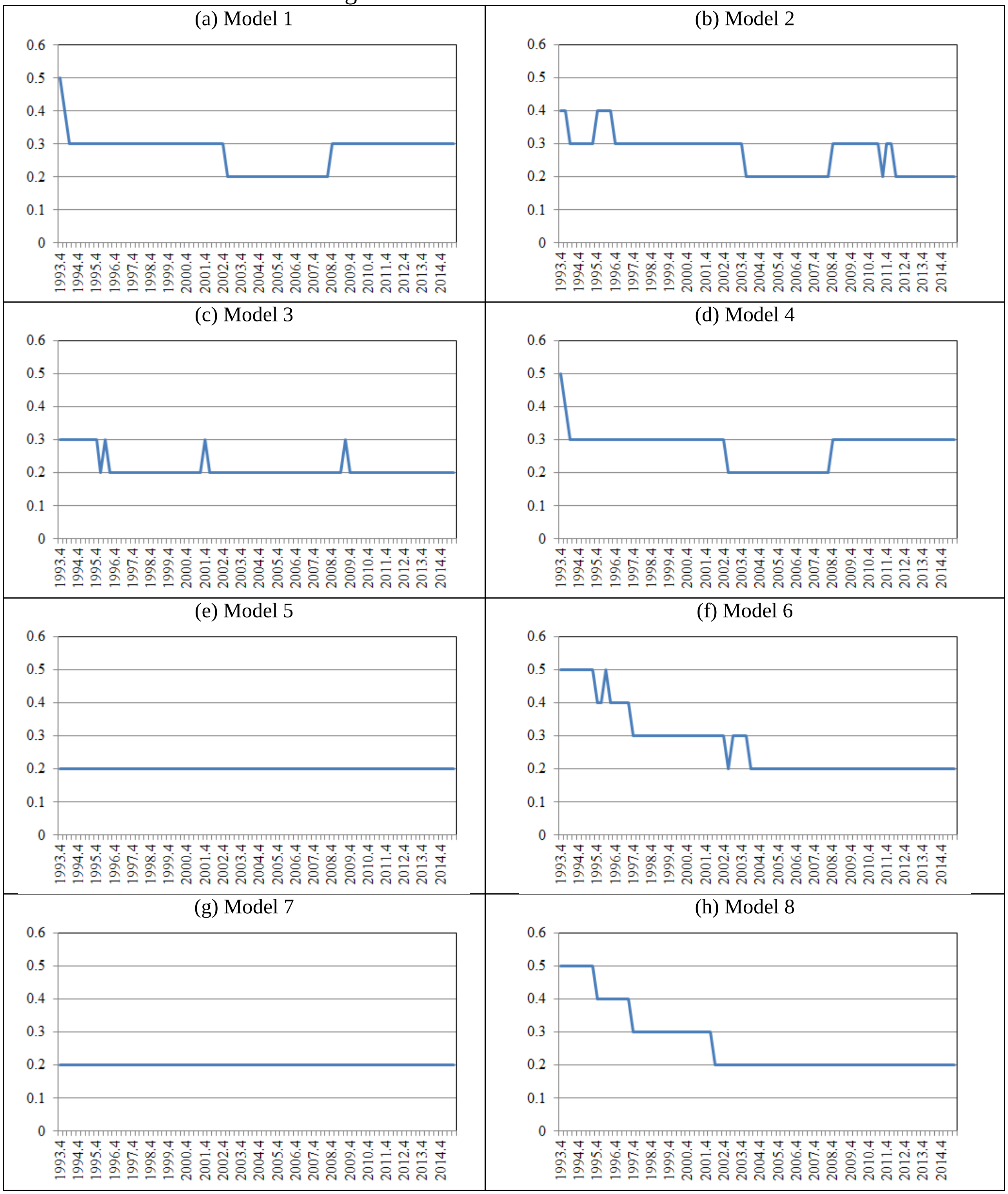
Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

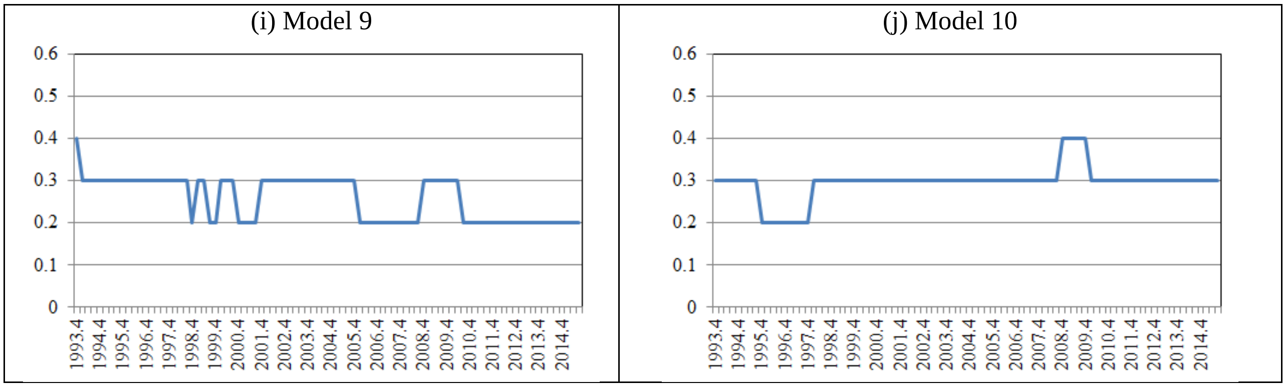
Table B.10(b): Relative MSEs for Model 10, Evaluation Period 1994:Q1-2006:Q4

Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate	Horizon	GDP	CPI inflation	Unemp. rate	Fed funds rate
+1 month of financial conditions														
1	1.01	1.03	1.04	0.78										
2	1.00	1.02	1.04	0.71										
3	1.00	1.02	1.02	0.73										
4	1.00	1.00	1.01	0.78										
5	1.00	1.00	1.00	0.82										
6	1.00	1.00	1.00	0.87										
7	1.00	1.00	1.00	0.91										
8	1.00	0.99	1.00	0.95										
+1.5 months of financial conditions					+1.5 months of financial and other conditions					+1.5 months other conditions only				
1	1.00	1.03	1.06	0.78	1	0.84	0.55	0.20	0.78	1	0.84	0.55	0.20	1.27
2	1.00	1.02	1.05	0.71	2	1.00	1.02	0.50	0.69	2	1.01	0.99	0.46	1.11
3	1.00	1.02	1.03	0.73	3	0.98	1.01	0.63	0.71	3	0.99	1.00	0.60	1.05
4	1.00	1.00	1.02	0.79	4	1.00	1.00	0.74	0.76	4	1.00	1.00	0.71	1.03
5	1.00	1.00	1.01	0.83	5	1.00	1.00	0.82	0.81	5	1.01	1.00	0.80	1.02
6	1.00	1.00	1.01	0.87	6	1.00	1.00	0.89	0.86	6	1.01	1.00	0.87	1.01
7	1.00	1.00	1.01	0.91	7	1.00	1.00	0.93	0.90	7	1.01	1.00	0.93	1.01
8	1.00	0.99	1.00	0.95	8	0.99	0.99	0.96	0.94	8	0.99	1.00	0.96	1.00
+3 months of financial conditions					+3 months of financial and other conditions									
1	1.01	1.04	1.05	0.71	1	0.84	0.55	0.20	0.73					
2	1.04	1.05	1.07	0.69	2	1.01	1.02	0.49	0.66					
3	1.04	1.05	1.06	0.74	3	0.98	1.01	0.63	0.70					
4	0.94	1.04	1.04	0.80	4	1.00	1.00	0.74	0.76					
5	0.93	1.04	1.03	0.86	5	1.00	1.00	0.82	0.81					
6	1.02	1.04	1.03	0.91	6	1.00	1.00	0.89	0.86					
7	1.03	1.04	1.02	0.96	7	1.00	1.00	0.93	0.91					
8	0.98	1.00	1.01	0.99	8	0.99	0.99	0.96	0.94					

Notes: The estimation period is 1985:Q4 onward. Relative MSEs are the mean-squared errors for forecasts from the model with financial and/or other conditions divided by the mean-squared errors for forecasts from the model without any conditions.

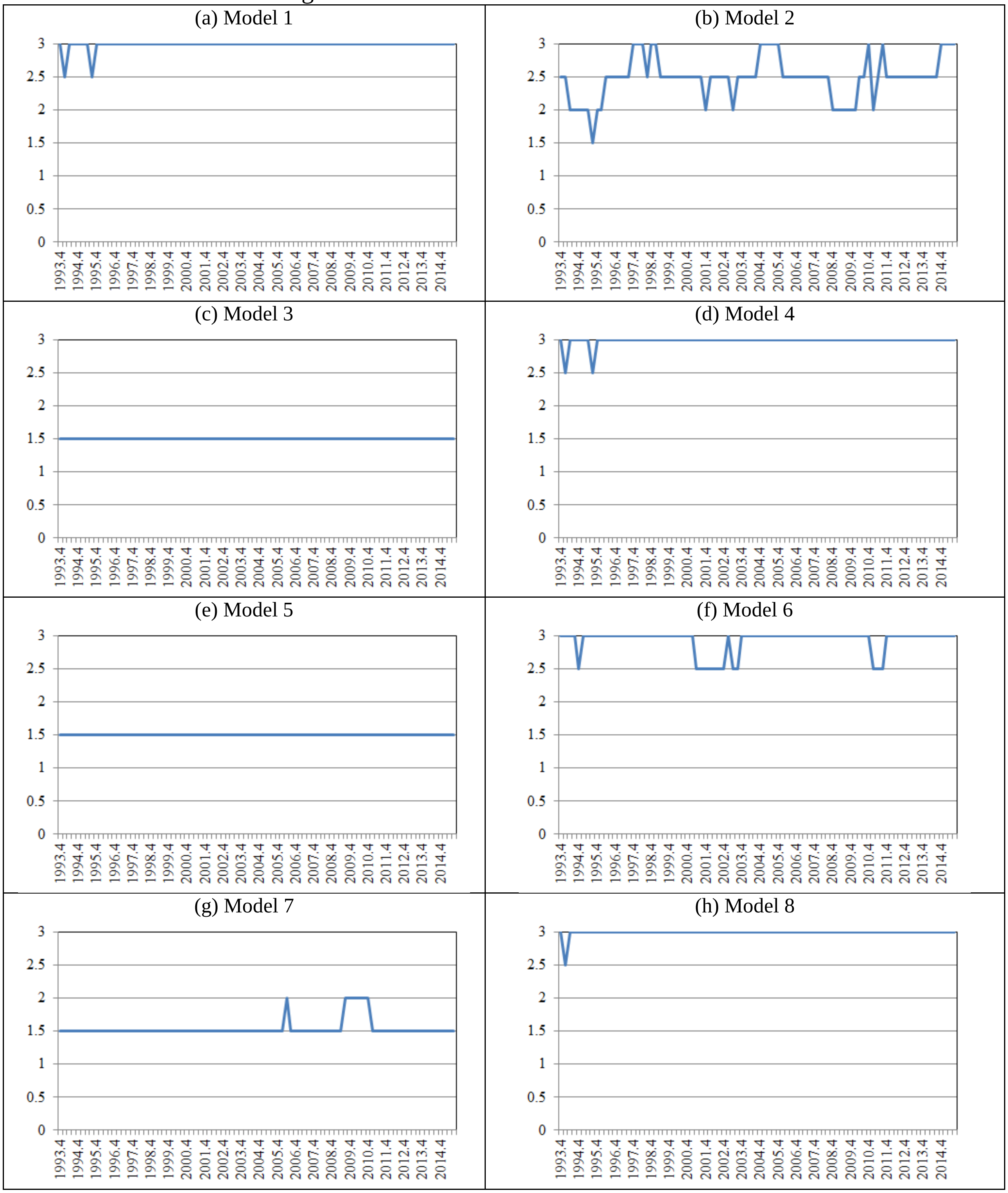
Figure A.1: Minnesota Prior Values

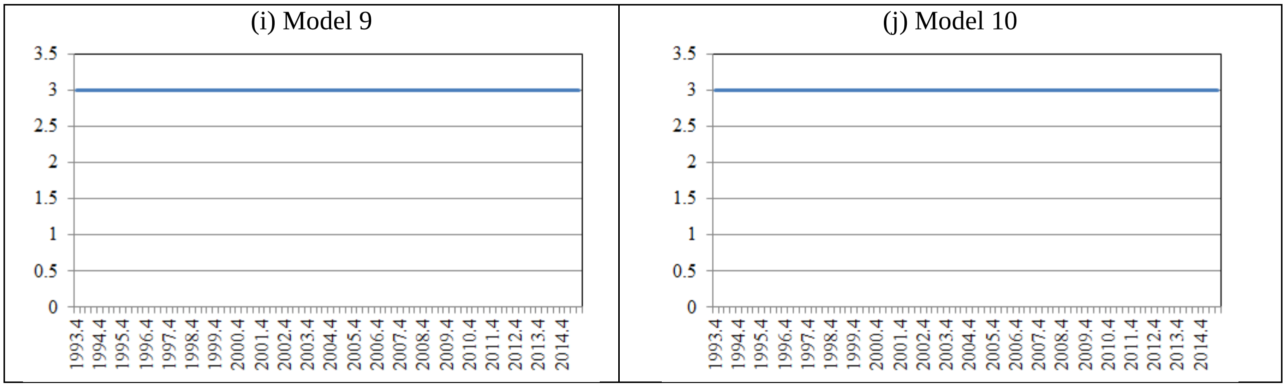




Notes: For each model specification as defined in section 2.3, we show the optimized Minnesota prior value at each point in time that is used for forecasting.

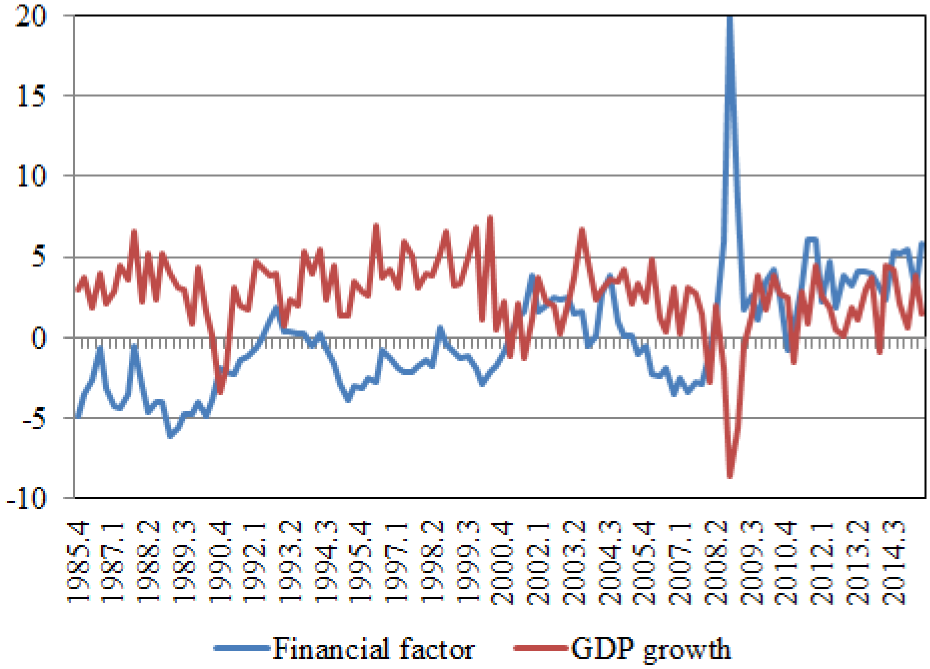
Figure A.2: Sum of Coefficient Prior Values





Notes: For each model specification as defined in section 2.3, we show the optimized sum of coefficient prior value at each point in time that is used for forecasting.

Figure A.3: GDP Growth and the Financial Factor



Notes: GDP growth is shown at quarterly annualized rates. The financial factor is described in section 2.3.