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Nowcasting Tail Risks to Economic Activity with Many Indicators

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This paper focuses on tail risk nowcasts of economic activity, measured by GDP growth, with a potentially wide array of monthly and weekly information. We consider different models (Bayesian mixed frequency regressions with stochastic volatility, classical and Bayesian quantile regressions, quantile MIDAS regressions) and also different methods for data reduction (either the combination of forecasts from smaller models or forecasts from models that incorporate data reduction). The results show that classical and MIDAS quantile regressions perform very well in-sample but not out-of-sample, where the Bayesian mixed frequency and quantile regressions are generally clearly superior. Such a ranking of methods appears to be driven by substantial variability over time in the recursively estimated parameters in classical quantile regressions, while the use of priors in the Bayesian approaches reduces sampling variability and its effects on forecast accuracy. From an economic point of view, we find that the weekly information flow is quite useful in improving tail nowcasts of economic activity, with initial claims for unemployment insurance, stock prices, a term spread, a credit spread, and the Chicago Fed's index of financial conditions emerging as particularly relevant indicators. Additional weekly indicators of economic activity do not improve historical forecast accuracy but do not harm it much, either.

Keywords: forecasting, downside risk, pandemics, big data, mixed frequency, quantile regression.
JEL classification codes: C53, E17, E37, F47.

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1 Introduction

Nowcasting is commonly viewed as an important and unique forecasting problem; see, e.g., Banbura, Giannone, and Reichlin (2011), Banbura, et al. (2013), and Giannone, Reichlin, and Small (2008). It is important because current-quarter forecasts of GDP growth and inflation provide useful summaries of recent news on the economy and because these forecasts are commonly used as inputs to forecasting models, such as some of the DSGE models in use at central banks, that are effective in medium-term forecasting but not necessarily short-term forecasting. As studies such as Faust and Wright (2009, 2013) have emphasized, initial-quarter forecasts often play a key role in the accuracy of forecasts at subsequent horizons. Nowcasting is unique in that, to some degree, it involves "simply" adding up information in data releases for the current quarter. A key challenge is dealing with the differences in data release dates that cause the available information set to differ over points in time within the quarter — what Wallis (1986) refers to as the "ragged edge" of data.

Much (although not all) of the nowcasting literature has focused on data available at a monthly and quarterly frequency. In part, this may reflect data availability: the histories of weekly indicators of economic activity are in many cases not all that long, constraining formal evaluation of forecasts obtained from estimated models. The literature's limited treatment of weekly data may also in part reflect the finding by Banbura, et al. (2013) that higher frequency information does not seem to be especially useful for nowcasting US GDP growth (except perhaps in a continuous monitoring context). That said, higher frequencies have not been entirely ignored; for example, since 2008, the Federal Reserve Bank of Philadelphia has published a weekly index of economic activity that makes use of weekly data on initial claims for unemployment insurance, as developed by Aruoba, Diebold, and Scotti (2009).

In 2020, the shutdown of significant portions of the economy to restrain the outbreak of the coronavirus has raised practical interest in high-frequency indicators of economic activity in the US and other economies. For example, in the US, it was clear by mid-March that much of consumer spending would be shutting down and would lead to large drops in employment and GDP in at least the first and second quarters of the year. Yet, in the second half of March, the usual monthly indicators of economic activity were only available for the month of February. Weekly indicators, including — among others — initial claims for unemployment insurance, weekly retail sales from Redbook, raw steel production, and output of electric utilities, began to draw attention for the light they could more quickly shed on the emerging downturn. Lewis, Mertens, and Stock (2020) developed and began to publish regular updates of a weekly economic index formed as a principal component of 10 underlying series.

Apart from nowcasting considerations, a rapidly growing body of research has examined tail risks in macroeconomic outcomes, typically at a horizon of one quarter or one year ahead. Most of this work has focused on the risks of significant declines in GDP, and has relied on quantile regression methods to estimate tail risks, as developed in Adrian, Boyarchenko, and Giannone (2019), Adrian, et al. (2018), and Giglio, Kelly, and Pruitt (2016) and extended to vector autoregressive models in Chavleishvili and Manganelli (2019). This work has emphasized the link of tail risks to output stemming from poor financial conditions. Other work has considered tail risks to other variables, such as unemployment (e.g., Galbraith and van Norden (2019) and Kiley (2018)), or used other methods. Reichlin, Ricco, and Hasenzagl (2020) propose using leverage indicators to obtain earlier signals of economic vulnerabilities. Earlier work of Manzan (2015) used quantile regression to assess the value of a large number of macroeconomic indicators in forecasting the complete distribution of some key variables.[1] Cook and Doh (2019) apply quantile regression methods with a large set of predictors of growth, unemployment, and inflation, considering various approaches to dimension reduction and forecast combination.

In this context, this paper assesses the ability of models to produce accurate point and tail risk nowcasts of economic activity with a potentially wide array of information. We consider not only different models but also different methods for data reduction, either the combination of forecasts from smaller models or forecasts from models that incorporate data reduction. Our starting point is the mixed frequency regression setup of Carriero, Clark, and Marcellino (2015) (henceforth, CCM). In this CCM setup, for nowcasting GDP growth within a quarter, each time series of monthly indicators is transformed into three quarterly time series, each containing observations for, respectively, the first, second, or third month of the quarter. At the moment in time that the forecast is formed, the model includes only the quarterly series without missing observations, which addresses the ragged edge of the data. Bayesian methods are used to estimate the model, which facilitates providing shrinkage on estimates of a model that can be quite large, conveniently generates predictive densities, and readily allows for stochastic volatility. One of this paper's contributions consists of extending the CCM forecast calendar setup: to use 15 different weeks as forecast origins for a quarter's nowcast rather than four months. This setup permits an assessment of the evolution of point forecasts and tail risks with the week by week flow of information in the quarter, along with which indicators are most informative in that information flow. A second

[1] Other examples of studies of quantile forecasts in macroeconomics include Gaglianone and Lima (2012), Korobilis (2017), and Manzan and Zerom (2013, 2015).

contribution is to consider higher frequency data — in this paper a number of indicators at a weekly frequency and not just monthly indicators as in CCM. We extend CCM by including in the quarterly regression weekly indicators available at the time of the forecast origin. Our third and key contribution is that we examine nowcasts of tail risks to economic activity. Following precedents such as Adrian, Boyarchenko, and Giannone (2019) and Adrian, et al. (2018), we use the 5 percent quantile forecast as the measure of tail risk, which we evaluate with the quantile score (tick loss function). We consider tail risk nowcasts from not only Bayesian regressions but also several other quantile regression-based approaches making use of mixed frequency data: simple quantile regression, Bayesian quantile regression, and quantile regression with mixed-data sampling (MIDAS).

Our results show that, within some limits, more information helps, for both point and tail risk forecasts. Forecast accuracy typically improves as time moves forward from week to week within a quarter, making additional data available. In a given week, models with a wider array of indicators often forecast — in point forecasts and tail risk forecasts — as well as or better than small models. In our real-time out-of-sample results, there is a clear benefit to adding a base set of financial indicators to the base set of macro indicators; in this variable set, the weekly information available comes from initial claims for unemployment insurance, stock prices, a term spread, a credit spread, and the Chicago Fed's index of financial conditions. On an out-of-sample basis, adding other weekly indicators of economic activity doesn't have much effect on forecast accuracy, either to help or harm. Admittedly, it is possible that, over time, as the time series samples of these indicators grow and permit more precise model estimation, these indicators could become more helpful to forecast accuracy. Among the models or estimation approaches we consider, our regression with stochastic volatility and our Bayesian quantile regression perform consistently, offering solid gains in forecast accuracy (both point and tail risk) when financial indicators are included in the model. With some other methods, particularly simple quantile regression and quantile regression making use of MIDAS, performance looks much better in in-sample forecasts (which we consider in part due to limited overall samples, particularly with downturns) than in out-of-sample forecasts. On an out-of-sample basis, these two methods fare poorly, evidently reflecting the high variability in their point and tail risk forecasts. That said, even on this basis, quantile regression with MIDAS often does quite well in recessions.

We conclude the paper with a report on current (2020:Q1) nowcasts from this set of specifications. It turns out that the arrival of weekly information within the quarter systematically lowers the point and tail nowcasts, though they remain more optimistic than the realization that recently became available with the first estimate from the Bureau of Economic Analysis. The quantile MIDAS produces more negative forecasts, but too much so, likely due to the above-mentioned parameter instability that can affect this type of method.

In light of practical interest in the topics indicated above, this paper serves as a progress report on our analysis to date. Over time, we will build on the results of this draft to consider a wider array of methods, as well as additional questions raised by the results in hand. As we produce these results, we will periodically update the working paper to reflect them. For example, in upcoming drafts, we plan to add forecasts from models that include Bayesian quantile regression with a LASSO penalty, forecasts that combine predictions from smaller individual models, and forecasts based on factor-reduction of available predictors.

The paper proceeds as follows. The remainder of this section summarizes some other related nowcasting work. Sections 2 through 4 detail the data (including the release calendar setup), models, and forecast metrics, respectively. Section 5 provides our empirical results. Section 6 concludes.

1.1 Relationship to other nowcasting work

To place our proposed approach within the broader nowcasting literature, it is helpful to use the "partial model" (or single equation) methods and "full system" methods classification used by Banbura, et al. (2013). The former type of approach involves specifications focused on the low frequency variable, in which the high frequency explanatory variables are not modeled. In the latter approach, the low and high frequency variables are jointly modeled. Our proposed modeling approach falls in the partial models class.

Among partial model methods, bridge and MIDAS models are most commonly used. Bridge models, considered in such studies as Baffigi, Golinelli, and Parigi (2004), Diron (2008), and Bencivelli, Marcellino, and Moretti (2017), relate the period t value of the quarterly variable of interest, such as GDP growth, to the period t quarterly average of key monthly indicators. The period t average of each monthly indicator is obtained with data available within the quarter and forecasts for other months of the quarter (obtained typically from an autoregressive model for the monthly indicator). MIDAS-based models, developed in Ghysels, Santa-Clara, and Valkanov (2004) for financial applications and applied to macroeconomic forecasting by, e.g., Clements and Galvao (2008) and Guerin and Marcellino (2013), relate the period t value of the quarterly variable of interest to a constrained distributed lag of monthly or weekly or even daily data on the predictors of interest.

The resulting model is then estimated by non-linear least squares and used to forecast the variable of interest from constrained distributed lags of the available data. Foroni, Marcellino and Schumacher (2015) propose the use of unconstrained distributed lags of the high frequency indicators, a specification labeled unrestricted MIDAS, or U-MIDAS.

Full system methods for nowcasting include factor models and mixed frequency VARs. We refer to the surveys in Banbura et al. (2013) and Foroni, Ghysels, and Marcellino (2013) for details and references. Here we only mention a few studies closely related to our proposal. These include Aastveit, et al. (2014), which, in contrast to most of the nowcasting literature, focuses on density forecasts; Eraker, et al. (2015); Ghysels (2016); Schorfheide and Song (2015) and McCracken, Owyang, and Sekhposyan (2020), both of which develop mixed frequency Bayesian VARs; and Marcellino, Porqueddu, and Venditti (2016), which introduces a small scale factor model that allows for stochastic volatility in the common and idiosyncratic components and provides density forecasts.[2]

In other related quantile forecasting work, Lima, Meng, and Godeiro (2019) develop an approach for combining quantile forecasts to obtain point forecasts, in a setting with some mixed frequency data. Ferrara, Mogliani, and Sahuc (2019) use the quantile regression setup of Adrian, Boyarchenko, and Giannone (2019) to nowcast Euro area GDP growth with an indicator of financial conditions updated on a daily basis, making use of quantile regression and Bayesian quantile regression with MIDAS. By comparison, our paper deploys a much richer set of economic and financial variables and model specifications, along with an alternative approach to accommodating mixed frequency data. Mazzi and Mitchell (2019) use quantile regression methods to form density nowcasts of Euro area GDP growth. We build on their work by focusing on point and tail risk forecasts, a wider information set, and methods other than quantile regression and quantile regression with LASSO (both estimated by Bayesian methods in their analysis).

2 Data

This section first explains the general design of the forecast calendar used in our analysis and then details the data used.

[2]Koop, Gefang, and Poon (2020) develop variational Bayes methods to estimate large Bayesian mixed frequency VARs with much greater computational efficiency.

2.1 General design of the forecast calendar and data set

In this draft, we focus on current-quarter forecasting of real GDP (or GNP for some of the sample) in real time. (In subsequent drafts, we will add results for nowcasting the unemployment rate.)

Whereas most of the nowcasting literature (including CCM) focuses on a monthly calendar of data releases and forecast origins for nowcasting, we depart from and extend much of this literature by considering a weekly calendar of data releases and forecast origins.[3] With this weekly calendar, we consider monthly data as well as weekly data. Our forecast calendar includes 15 weeks for each quarter, reflecting four weeks per month of the quarter and the first three weeks of the following quarter. We begin with the first full week of the quarter and end with the third week of the following quarter (the last week before GDP for the prior quarter is typically released). For each indicator we consider, we assign it a typical release or availability week based on its usual publication schedule. As examples, at the end of week 1 of a quarter, a forecaster has available data on employment, unemployment claims, interest rates, stock prices, and the NFCI for the prior month, as well as interest rates and stock prices for the first week of the quarter. At the end of week 2, a forecaster also has available (in addition to the data of week 1) retail sales for the prior month, the NFCI for week 1 of the quarter, and interest rates and stock prices for week 2 of the quarter.

Our starting point variable set largely corresponds to the small-model specification of CCM (in their results, the small model performed as well as models with additional leading indicators of the business cycle). In particular, we consider 5 monthly indicators broadly informative about economic conditions, selected with some eye to timeliness: payroll employment, industrial production, real retail sales (nominal deflated by the CPI), housing starts, and the manufacturing index from purchasing managers published by the Institute for Supply Management (ISM). In our baseline macro set, we add initial claims for unemployment insurance, using both monthly and weekly observations as available. Initial claims are commonly considered to be a leading indicator of the business cycle and have the advantage of being available weekly with a fairly short lag (one week). We also consider financial indicators with an eye toward those that have been found in the literature to have some predictive content for output: the Chicago Fed's national financial conditions index (NFCI), stock prices as measured by the S&P 500 index, the term spread between the 10-year and 1-year Treasury yields (constant maturity), and the credit spread between Moody's Baa corporate yield and the 10-year Treasury yield. Finally, in some additional specifications, we add to models

[3]Some studies consider a higher frequency calendar of nowcast updates. For example, Aastveit, et al. (2014) consider 15 dates for data releases — most monthly or quarterly — in the three months of the quarter and the first month of the following quarter.

some indicators of economic activity available at ta weekly frequency and over time samples going back into at least the 1990s. For the most part, these series are those used in the weekly economic activity index of Lewis, Mertens, and Stock (2020). Our set of additional weekly indicators consists of consumer comfort from Bloomberg, raw steel production, electric utility output, loadings of railroad cars, total fuel sales, and Redbook same-store retail sales. Table 1 lists the variables and our calendar assumptions.

Our model specifications reflect additional choices regarding transformations and treatment of data frequency. As Table 1 indicates, with variables subject to trends, such as GDP, employment, or stock prices, we use growth rates. For variables available at a daily frequency (interest rates and stock prices), we use monthly averages and weekly averages as our monthly and weekly observations. At a monthly frequency, the growth rate of the S&P 500 is the percent change in the month-average index values. At a weekly frequency, to smooth out some of the higher frequency noise in stock prices, we use the percent change in the average weekly value of the index in one week compared to the average in the same week one quarter ago. In the case of the weekly indicators of steel production, utility output, car loadings, fuel sales, and Redbook retail sales, in light of the noisiness of the data and strong seasonality, we follow Lewis, Mertens, and Stock (2020) and rely on year-over-year (52-week) growth rates. We smooth the consumer comfort measure by using a four-week moving average of the weekly data. The next section will provide additional detail on the treatment of monthly and weekly data in our nowcasting models.

2.2 Details of data used

Quarterly real-time data on GDP or GNP are taken from the Federal Reserve Bank of Philadelphia's Real-Time Data Set for Macroeconomists (RTDSM), in monthly vintages. For simplicity, hereafter "GDP" refers to the output series, even though the measures are based on GNP and a fixed weight deflator for much of the sample.

For the variables we use to nowcast GDP growth, for those subject to significant revisions — payroll employment, industrial production, retail sales, and housing starts — we use real-time data, obtained from the RTDSM (employment, industrial production, and housing starts) or the Federal Reserve Bank of St. Louis' ALFRED database (retail sales). For the CPI used to deflate retail sales, we use the 1967-base-year CPI available from the BLS rather than a real-time series; Kozicki and Hoffman (2004) show that the 1967-base-year series is very similar to real-time CPI inflation. For the other variables, subject to either small revisions or no revision, we simply use the currently available time series, obtained from sources including the Federal Reserve Board's FAME database, the Federal Reserve Bank of St. Louis' FRED database, or Haver Analytics. Appendix Table A1 gives the source from which we obtained each series.

The full forecast evaluation period runs from 1985:Q1 through 2019:Q3 (using period t to refer to a forecast for period t), which involves real-time data vintages from January 1985 through February 2020. For each forecast origin t starting in the first week of 1985:Q1, we use the real-time data vintage t to estimate the forecast models and construct forecasts of GDP growth in the quarter. In forming the data set used to estimate the forecasting models at each point in time, we use the monthly vintages of (quarterly) GDP available from the RTDSM, taking care to make sure the GDP time series used in the regression is the one available at the time the forecast is being formed. The starting point of the model estimation sample varies across some of our specifications due to differences in data availability. With our baseline macro models, estimation starts with 1970:Q2, the soonest possible given data availability and lags allowed in models. Adding financial indicators makes the estimation starting point 1971:Q2, due to the availability of the NFCI. Adding more weekly indicators pulls the estimation sample start up to 1987:Q1. In this case, we shorten the evaluation sample to run from 2000:Q1 through 2019:Q3.

As discussed in such sources as Croushore (2006), Romer and Romer (2000), and Sims (2002), evaluating the accuracy of real-time forecasts requires a difficult decision on what to take as the actual data in calculating forecast errors. The GDP data available today for, say, 1985, represent the best available estimates of output in 1985. However, output as defined and measured today is quite different from output as defined and measured in 1970. For example, today we have available chain-weighted GDP; in the 1980s, output was measured with fixed-weight GNP. Forecasters in 1985 could not have foreseen such changes and the potential impact on measured output. Accordingly, we follow studies such as Clark (2011), Faust and Wright (2009), and Romer and Romer (2000) and use the second available estimates in the quarterly vintages of the RTDSM of GDP/GNP as actuals in evaluating forecast accuracy.

3 Models

This section details our proposed nowcasting models. To help the discussion flow, we first specify the general model forms in sections 3.1 through 3.4, and then in section 3.5 we detail the sets of indicators in the model. We conclude by presenting in sections 3.6 and 3.7 the priors and algorithms used in Bayesian estimation.

3.1 General model forms: The Bayesian mixed frequency (BMF) model with stochastic volatility (SV)

We use as a starting point the Bayesian mixed frequency (BMF) model of CCM. Starting with our specification that treats the error variance of the model as constant over time, we consider nowcasting the quarterly growth rate of GDP in week w of the current quarter based on the regression:

$$y_t = X'_{w,t}\beta_w + v_{w,t}, \;\; v_{w,t} \sim i.i.d.N(0, \sigma^2_w), \tag{1}$$

where the vector $X_{w,t}$ contains the available predictors at the time the forecast is formed, t is measured in quarters, and w indicates a week within the quarter. As detailed below, given a set of indicators to be used, there is a different regressor set $X_{w,t}$ (and therefore model) for each week $w = 1, \ldots, 15$ within the quarter, reflecting data availability.

In the stochastic volatility case, our proposed forecasting model for week w within the quarter takes the form:

$$\begin{aligned} y_t &= X'_{w,t}\beta_w + v_{w,t} \\ v_{w,t} &= \lambda^{0.5}_{w,t}\epsilon_{w,t}, \; \epsilon_{w,t} \sim i.i.d.N(0,1) \\ \log(\lambda_{w,t}) &= \log(\lambda_{w,t-1}) + \nu_{w,t}, \; \nu_{w,t} \sim \; i.i.d.N(0, \phi_w). \end{aligned} \tag{2}$$

Following the approach pioneered in Cogley and Sargent (2005) and Primiceri (2005), the log of the conditional variance of the error term in equation (2) follows a random walk process. In a vector autoregressive context, studies such as Clark (2011), D'Agostino, Gambetti, and Giannone (2013), and Clark and Ravazzolo (2015) have found that this type of stochastic volatility formulation improves the accuracy of both point and density forecasts.

The specification of the regressor vector $X_{w,t}$ in the BMF and BMF-SV models is partly a function of the way we sample the monthly and weekly variables. For each monthly variable, we first transform it at a monthly frequency as necessary to achieve stationarity. At a quarterly frequency, for each monthly variable, we then define three different variables, by sampling the monthly series separately for each month of the quarter. The availability of these variables for forecasting GDP in period t as of week w of the quarter drives whether they appear in the forecasting model for that forecast origin.

Exactly which variables are included in $X_{w,t}$ depends on when in the quarter the forecast is formed. As noted in section 2, we consider forecasts formed at 15 weeks associated with each quarter. At each of the 15 forecast origins we consider for each quarter t, the regressor set $X_{w,t}$

is specified to include the subset of variables available for t as of that week (details are given below in subsection 3.5). At these points in time, the availability of other indicators also varies. As a consequence, the model specification changes in each week of the quarter, reflecting and accommodating the ragged edge of the data, in line with a direct approach to forecasting. Subsection 3.5 provides additional details.

We should stress that this approach does not involve bridge methods. Bridge methods require forecasting monthly or weekly observations of monthly or weekly variables for any months or weeks of quarter t for which data are not yet available. We do not use such forecasts. Rather, we only put on the right hand side of the regression model the actual monthly and weekly observations that are available for the quarter, in the form of different quarterly variables associated with the different months and weeks of the quarter.

3.2 Quantile regression (QR)

Particularly for the purpose of evaluating tail forecasts of output growth, we include quantile regression specifications patterned after the forecasting formulation developed in, among others, Adrian, Boyarchenko, and Giannone (2019). For a given quantile τ we estimate a regression model of the form

$$y_t = X'_{w,t}\beta_{\tau,w} + \epsilon_{\tau,w,t}, \tag{3}$$

in which the coefficient vector and innovation term are specific to quantile τ. The vector of predictors is the same as that included in the BMF and BMF-SV specifications. The parameter vector $\beta_{\tau,w}$ is obtained with quantile regression:

$$\hat{\beta}_{\tau,w} = \underset{\beta_{\tau,w}}{\operatorname{argmin}} \sum_{t=1}^{T} \left(\tau \cdot \mathbf{1}_{(y_t \geq X'_{w,t}\beta_{\tau,w})} |y_t - X'_{w,t}\beta_{\tau,w}| + (1-\tau) \cdot \mathbf{1}_{(y_t < X'_{w,t}\beta_{\tau,w})} |y_t - X'_{w,t}\beta_{\tau,w}| \right). \tag{4}$$

We estimate the model for quantiles of $\tau = 0.05$, 0.10, and 0.95, as well as $\tau = 0.5$. Note that the quantile forecast is the predicted component $X'_{w,t}\hat{\beta}_{\tau,w}$.

3.3 Bayesian quantile regression (BQR)

Particularly with the large number of indicators included in the regression under our mixed frequency approach, estimate imprecision may harm the forecast performance of simple quantile regression. Bayesian shrinkage may mitigate such imprecision and help the forecast performance of quantile models. Accordingly, we also consider models estimated with Bayesian quantile regression methods. Yu and Moyeed (2001) established that quantile regression has a convenient mixture representation that enables Bayesian estimation. We use the Gibbs sampler of Khare and Hobert (2012), along with their mixture representation.

In our BQR formulation, for GDP growth in quarter t to be forecast as of week k of the quarter, we begin with a model

$$y_t = X'_{w,t}\beta_{\tau,w} + \sigma_{\tau,w}\epsilon_{\tau,w,t}, \tag{5}$$

where $\epsilon_{\tau,w,t}$ has a mixture representation. For each model at quantile τ and week w, the representation includes $z_{\tau,w,t}$, which is exponentially distributed with scale parameter $\sigma_{\tau,w}$. The mixture representation of the quantile regression model can be written as

$$y_t = X'_{w,t}\beta_{\tau,w} + \theta z_{\tau,w,t} + \kappa\sqrt{\sigma_{\tau,w}z_{\tau,w,t}}u_{\tau,w,t}, \tag{6}$$

where θ and κ are fixed parameters as functions of the quantile κ and $u_{\tau,w,t}$ is i.i.d. standard normal. The quantile forecast is the predicted component $X'_{w,t}\hat{\beta}_{\tau,w}$. For simplicity, we will compute the forecast at the single point of the posterior mean of the coefficient vector $\beta_{\tau,w}$. We estimate the model and form its forecast for the same quantile set indicated above: $\tau = 0.05$, 0.10, and 0.95, as well as $\tau = 0.5$.

3.4 QR-MIDAS

MIDAS approaches could provide another effective way to avoid undue estimator imprecision in quantile regression featuring a large number of indicators representing different periods of time. In our setup to be detailed in subsection 3.5, due to the approach we take with weekly data, this proliferation of parameters matter is likely most important with the monthly indicators, for which we have available different variables for each month of the quarter. Accordingly we consider a MIDAS version of quantile regression. For computational simplicity, instead of estimating a non-linear quantile model to jointly estimate the quantile parameters and the lag polynomial coefficients with the MIDAS averaging of data, we follow a basic profile approach and search across a grid of polynomial parameters to pick the best-fitting quantile regression using weighted averages of monthly data in the regression.

With the QR-MIDAS approach, the underlying regression takes the form of a simple quantile regression

$$y_t = \tilde{X}_{w,t}(\theta)'\beta_{\tau,w} + \epsilon_{\tau,w,t}, \tag{7}$$

in which the regressor vector $X_{w,t}(\theta)$ includes some MIDAS-weighted averages of monthly data, with weights that depend on a parameter θ. Our MIDAS implementation uses the single-parameter beta polynomial of Ghysels and Qian (2019).[4] In a given quarter t, for a given monthly variable x, as of forecast origin week w, let x_s denote the most recently available month's reading of x, where s refers to a month. We form a polynomial lag-weighted sum of x_s and its preceding months of data (in monthly sequence) from $s-J+1$ through $s-1$, as $\tilde{x}_t = \sum_{j=0}^{J} c_j(\theta) x_{s-j}$, where $\Gamma(\cdot)$ denotes the usual Gamma function and

$$c_j(\theta) = \frac{f(j/J, \theta)}{\sum_{j=1}^{J} f(j/J, \theta)}, \quad f(j/J, \theta) = \frac{(1-j)^{\theta-1}\Gamma(1+\theta)}{\Gamma(1)\Gamma(\theta)}. \tag{8}$$

With the monthly data and nowcasting objective, we set the upper limit J to 5, so as to use 6 monthly observations in the MIDAS-averaged variables. As an example of the polynomial-driven weights of the moving average, with a setting of $\theta = 4$, the c_j coefficients are $c_0 = 0.490$, $c_1 = 0.283$, $c_2 = 0.14$, ..., $c_5 = 0.002$. At lower values of θ, the polynomial coefficients are relatively more equal across months, whereas at higher values, the coefficients put more weight on more recent months compared to months further in the past.

At each forecast horizon and quantile, we consider a grid of QR-MIDAS regressions, each using a regressor vector $X_{w,t}(\theta)$ that relies on a different θ setting to obtain the polynomial-weighted averages of the available monthly observations. Our grid of θ values includes 1 through 10, 12, 15, 20, 25. For each different theta, we form $\tilde{X}_{w,t}(\theta)$ and estimate the quantile regression with the standard method indicated above. We then select as the QR-MIDAS forecasting model for that forecast origin and quantile the regression yielding the best fit as defined by the minimal value of the QR loss function indicated above. As with the QR and BQR formulations, we form estimates and forecasts for quantiles of $\tau = 0.05$, 0.10, 0.95, and 0.5.

3.5 Indicators used

We report below results for a total of six different variable combinations, each applied with the BMF, BMF-SV, QR, BQR, and QR-MIDAS models or methods (henceforth, for simplicity, we just refer to them as models).

- Our starting point is the *base macro* set of six macroeconomic activity indicators consisting of the small variable set of CCM plus initial claims for unemployment insurance. In this case, we have six monthly variables (payroll employment, ISM manufacturing index, industrial production, real retail sales, housing starts, and claims) and one weekly variable (claims).

[4] As they suggest, we make the polynomial dependent on a single parameter by restricting the first parameter θ_1 of a two-parameter polynomial to equal 1. Our notation here drops out this second parameter that appears in the notation of Ghysels and Qian (2019), and our θ corresponds to their θ_2.

- To help shed some light on the value of weekly data in nowcasting, we use a small variant of the base macro variable set in the benchmark forecast from a BMF-SV model to which all other forecasts are compared. In this variant, we omit initial claims for unemployment insurance, so that the model includes just the five monthly indicators (payroll employment, ISM manufacturing index, industrial production, real retail sales, and housing starts) used in the small BMF and BMF-SV models of CCM. In their results on point and density accuracy, larger models had no consistent advantage over the small model.

- We also consider a *base macro plus NFCI* set that adds to the base macro variable set a single summary indicator of financial conditions, the NFCI, available both monthly and weekly.

- Our third variable set — *base macro and finance* — adds to the base macro variable set a set of financial indicators (monthly and weekly) consisting of the NFCI, S&P 500 stock returns, the Treasury term spread, and the Baa-Treasury credit spread.

- The variable set *base macro and small weekly* adds to the base macro variable set a small set of weekly indicators of economic activity with historical data back to the mid-1980s: consumer comfort, steel production, and electric utility output.

- The variable set *base macro-finance and small weekly* adds to the base macro and finance variable set the small set of weekly indicators (consumer comfort, steel production, and electric utility output).

- The variable set *base macro and large weekly* adds to the base macro and small weekly variable set a few more weekly activity indicators with historical data that only date back to the 1990s: loadings of railroad cars, fuel sales, and Redbook retail sales. Note that, with this data set, the sample is short enough that we only report in-sample results and current nowcast results and omit an out-of-sample forecast evaluation.

- The variable set *base macro-finance and large weekly* adds to the base macro and finance variable set the large set of weekly indicators (consumer comfort, steel production, electric utility output, car loadings, fuel sales, and Redbook sales). Again, with a short sample available, we only report in-sample results and current nowcast results and omit an out-of-sample forecast evaluation.

In the results reported in this paper, for the most part we only include in the model values of these variables for the current quarter t, the quarter for which GDP growth is being forecast (although our MIDAS implementation does allow the use of monthly observations from the previous quarter or two). Our rationale is primarily that, in the simpler monthly setup of CCM, we didn't find any payoff to longer lags. However, in most of our variable-model combinations, our general approach easily allows the use of values from previous quarters (while this makes the models even larger, Bayesian shrinkage helps limit the effects of parameter estimation error on forecast accuracy).

All model specifications include in the regressor set $X_{w,t}$ a constant and one lag of GDP growth. In most cases, this means the models include GDP growth in period $t-1$. However, in the case of models used to forecast in the first few weeks of the quarter, because the value of GDP growth in period $t-1$ is not actually available in real time, we include in the models GDP growth in period $t-2$. (This is consistent with our general direct multi-step treatment of the forecasting models.)

As noted above, depending on the week of the quarter the forecast is being formed, exactly which variables are in the forecasting models (that is, in $X_{w,t}$) varies, reflecting real-time data availability and the usual publication schedules of the indicators. Table 2 details the model specifications (and variable timing) we use, covering, for simplicity, just a few of our variable sets. For each week indicated in the first column, the table has three rows of entries, with the first listing the relevant base macro indicators, the second row covering the base finance indicators, and the third listing the small weekly indicators included in the given week's models (in the week 1 case, the row is blank because no weekly variables for the quarter are available or included). The variable sets *base macro*, *base macro and finance*, *base macro and small weekly*, and *base macro-finance and small weekly* combine these predictors as indicated. Of the other variable sets, models for the *base macro plus NFCI* set include the first row indicators plus the NFCI indicators shown in the second row (for a given week). Models for the *base macro and large weekly* variable set include the first and third row indicators plus three additional weekly indicators with the same specification shown for the variables in the third row. Models for the *base macro-finance and large weekly* variable set include the first, second, and third row indicators plus the same three additional weekly indicators.

We now offer some additional explanations of model details:

- The dependent variable of the model is GDP growth in quarter t. Subscripts of $t+1$, t, $t-1$, and $t-2$ refer to the next, current, once lagged, and twice lagged quarters, respectively.

- Months and weeks within the quarter are indicated by superscripts containing $m1$, $m2$, $m3$ for the first to third weeks of the month and containing $w1$, $w2$, $\ldots$, $w12$ for weeks 1 through 12 of the quarter and $w13$ through $w15$ for the first few weeks of the next quarter. For a given variable in a given week, the table shows in the superscripted notation which months or weeks of the variable in question are available and included in the model. For example, in week 9 of the quarter, we have available and included in the model employment data for the first two months of the quarter and retail sales for just the first month of the quarter. The table indicates this aspect of the specification with the week 9, row 1 entries of $\text{emp}_t^{(m1,m2)}$ and $\text{retail}_t^{(m1)}$.

- With the weekly indicators of unemployment claims and financial conditions, in light of their overlap with monthly data, our models reflect some specific choices on the timing or selection of which readings are included. For these variables, once a full month is available, we include the full month average in the model and not weekly observations from that month. With weekly observations that are included, we take an average across the weeks available for the month and put that average in the model and not each week's reading. For example, with stock prices and spreads, at the end of the third week of a month, we have available readings for weeks 1 through 3, and we enter the three-week average in the model. In the table, this is denoted with a superscript showing $w1+w2+w3$. For instance, in the specification for week 10 using the base macro and finance variable set, the BMF, QR, and BQR specifications include variables for each of the month 1, month 2, and week 9 readings of the NFCI (indicated by the row 2 entry $\text{NFCI}_t^{(m1,m2,w9)}$) and variables for each of the month 1, month 2, and weeks 9-10 average reading of the term spread (indicated by $\text{SP}_t^{(m1,m2,w9+w10)}$).

- With other weekly indicators of economic activity, in light of the underlying transformations used to reduce their noise (52-week percent changes in most cases), we only include in the model a single weekly reading that is the most recent available for the quarter. For example, in the specification for week 10 including the small set of weekly economic activity indicators, the predictors include the week 9 readings on consumer sentiment (the 4-week average), steel production (52-week percent change), and electric utility output (52-week percent change), indicated by the table entries $\text{sment}_t^{(w9)}$, $\text{steel}_t^{(w9)}$, and $\text{util}_t^{(w9)}$.

- Finally, in the case of monthly variables, the details of Table 2 apply to the BMF, BMF-SV, QR, and BQR specifications. In the case of the QR-MIDAS approach, the structure of monthly variables simplifies so that, for each monthly variable, it enters the predictive model used for each week, with the monthly indicator transformed as a 6-month weighted moving average using MIDAS weights chosen to maximize model fit (note that the polynomial coefficient is restricted to be the same for each variable). For example, each week's predictive model includes employment, the ISM, industrial production, retail sales, housing starts, and claims, using a 6-month weighted average of the observations most recently available as of that week. (The individual months of observations indicated in the table are not included as regressors in the QR-MIDAS specification.)

Across variable sets and forecast origins, our forecasting models vary widely in size. In some cases (base macro, week 5), the model is relatively small, with six predictors. In many other cases, the models have a healthy number of regressors without necessarily being large (e.g., the week 7, base macro-finance model has 17 predictors). In some settings, the model becomes quite large, peaking at 43 regressors (base macro-finance and large weekly, week 15). With models of these medium to large sizes, under simple OLS or QR estimation, parameter estimation error may be expected to have large adverse effects on forecast accuracy (and our results for QR will bear that out; we abstract from OLS estimation of other models, in light of the evidence in CCM in support of Bayesian shrinkage for point and density nowcasting). Our Bayesian approaches to estimation incorporate shrinkage to help limit the effects of parameter estimation error on forecast accuracy.

3.6 Priors for models estimated with Bayesian methods

In the case of the BMF, BMF-SV, and BQR models, Bayesian estimation methods necessitate priors. In the case of the BMF models with constant volatility, we use a normal-diffuse prior. As detailed in sources such as Kadiyala and Karlsson (1997), this prior combines a normal distribution for the prior on the regression coefficients with a diffuse prior on the error variance of the regression. For the BMF-SV models with stochastic volatility, we use independent priors for the coefficients (normal distribution) and volatility components (details below). Since the form of the prior is not dependent on m, in spelling out the prior we drop the index m from the model parameters for notational simplicity. Finally, for the BQR specifications, we use an independent Normal-Gamma prior, with a normal distribution for the regression coefficients and a Gamma distribution for the scale parameter (following Khare and Hobert (2012)).

The normal priors on the coefficient vector β have mean 0 (for all coefficients) and variance that takes a diagonal, Minnesota-style form. The prior variance is Minnesota style in the sense that shrinkage increases with the lag (with the quarter, not with the month within the quarter), and in the sense that we take account of the relative scales of variables. The shrinkage is controlled by three hyperparameters (in all cases, a smaller number means more shrinkage): λ_1, which controls the overall rate of shrinkage; λ_2, which controls the rate of shrinkage on variables other than lags of the dependent variable; and λ_3, which determines the rate of shrinkage associated with longer lags of GDP growth (it is not applied with monthly variables).

At each forecast origin, the prior standard deviation associated with the coefficient on variable $x_{i,t}$ of $X_{w,t}$, where i denotes one of the elements of the vector of indicators $X_{w,t}$ — excluding the constant and lagged GDP growth, which are treated differently — is specified as follows:

$$\text{sd}_{i,t} = \lambda_1 \lambda_2 \frac{\sigma_{GDP}}{\sigma_i}. \tag{9}$$

For coefficients on lag l of GDP, the prior standard deviation is

$$\text{sd}_l = \frac{\lambda_1}{l^{\lambda_3}}. \tag{10}$$

Finally, for the intercept, the prior is uninformative:

$$\text{sd}_{int} = 1000\sigma_{GDP}. \tag{11}$$

In setting these components of the prior, for σ_{GDP} and σ_i we use standard deviations from AR(4) models for GDP growth and $x_{i,t}$ estimated with the available sample of data as of the forecast origin. In all of our results, we follow CCM and fix the hyperparameters at values that may be considered very common in Minnesota-type priors and forecasting: $\lambda_1 = 0.2$, $\lambda_2 = 0.2$, and $\lambda_3 = 1$.

In the prior for the volatility-related components of the model, our approach is similar to that used in such studies as Clark (2011), Cogley and Sargent (2005), and Primiceri (2005). For the prior on ϕ, we use a mean of 0.035 and 5 degrees of freedom. For the period 0 value of volatility of each equation i, we use a prior of

$$\underline{\mu}_\lambda = \log \hat{\lambda}_{0,OLS}, \ \underline{\Omega}_\lambda = 4. \tag{12}$$

To obtain $\log \hat{\lambda}_{0,OLS}$, we use a training sample of 40 observations preceding the estimation sample to fit an AR(4) model to GDP growth. Finally, for the scale parameter $\sigma_{\tau,w}$ of the Bayesian quantile regression, we use an inverse Gamma prior with 5 degrees of freedom and for simplicity the mean set at the standard deviation of the residuals from regressing GDP growth on the variables of the model over the sample.

3.7 Estimation algorithms

The model with constant volatility is estimated with a Gibbs sampler, using the approach for the Normal-diffuse prior and posterior detailed in such studies as Kadiyala and Karlsson (1997). At any given forecast origin, estimation is quite fast, because the forecasting model is a single equation.

The model with stochastic volatility is estimated with a Metropolis-within-Gibbs algorithm, used in such studies as Clark (2011) and CCM. The posterior mean and variance of the coefficient vector are given by

$$\bar{\mu}_\beta = \bar{\Omega}_\beta \left\{ \sum_{t=1}^{T} \lambda_t^{-1} X_{w,t} y_t + \underline{\Omega}_\beta^{-1} \underline{\mu}_\beta \right\} \tag{13}$$

$$\bar{\Omega}_\beta^{-1} = \underline{\Omega}_\beta^{-1} + \sum_{t=1}^{T} \lambda_t^{-1} X_{w,t} X'_{w,t}, \tag{14}$$

where we again omit the w index from the parameters for notational simplicity. For the BMF-SV model and its constant volatility version BMF, we obtain forecasts from the posterior predictive distribution. The point forecast is the posterior mean forecast, and we compute the quantiles of interest from the quantiles of forecast draws.

Finally, we estimate the Bayesian quantile regression with the three-step Gibbs sampling approach of Khare and Hobert (2012). The first step samples the mixture state time series z from an inverse Gaussian distribution. The second draws the scale parameter $\sigma_{\tau,w}$ from its inverse Gamma conditional posterior. In the third step, the regression parameter vector $\beta_{\tau,w}$ is drawn from its Normal conditional posterior, with posterior mean and variance that can be expressed in the same basic form indicated above for the BMF-SV case.

The last aspect of estimation to mention is that our forecasts are produced by estimating the forecasting models with a recursive scheme: the estimation sample expands as forecasting moves forward in time. A rolling scheme, under which the size of the estimation sample remains fixed over time but the first observation moves forward in time, is in general less efficient but can be more robust in the presence of changes in regression parameters and (for density forecasts) error variances. However, in the nowcast (point and density) comparisons of CCM, recursive scheme forecasts were more accurate than rolling scheme forecasts.

4 Forecast Metrics

In assessing the efficacy of the models described in the previous section, we consider a range of forecast metrics. In the paper, we provide results using lower and upper quantiles of 5 and 95 percent, respectively. We have verified that our main results on lower tail forecasts (QS and coverage) are robust to using the 10 percent quantile; the appendix provides 10 percent quantile results.

In the assessment of point forecasts, we define them as the mean of the predictive distributions for the BMF and BMF-SV models and the prediction obtained from the quantile regression at the quantile $\tau = 0.5$ for the quantile-based models. We evaluate the point forecasts with the root mean squared error (RMSE). Although the quantile methods advocated in Adrian, Boyarchenko, and Giannone (2019) are not intended to produce good point forecasts, the point forecasts provide a basic check of the model; at a minimum, in practice it is useful to know if a model that might be useful for assessing downside risks is also successful at capturing the center of the distribution.

To assess the efficacy of the models in quantifying tail risks, we consider two basic measures of the accuracy of the lower tail quantile estimate. Again, we focus on the 5 percent quantile in the paper and provide 10 percent quantile results in the appendix. For the BMF and BMF-SV models, the quantile is simply estimated as the associated percentile of the simulated predictive distribution. For the quantile regression, we use the prediction obtained from the quantile regression at the quantiles $\tau = 0.05$ and 0.10. Applied to these quantile estimates, the first accuracy measure is the quantile score, commonly associated with the tick loss function (see, e.g., Giacomini and Komunjer (2005)). The quantile score is computed as

$$\mathrm{QS}_t = (y_t - Q_{\tau,t})(\tau - \mathbf{1}_{(y_t <= Q_{\tau,t})}), \tag{15}$$

where y_t is the actual outcome for GDP growth, $Q_{\tau,t}$ is the forecast quantile at quantile $\tau = 0.05$ or 0.10, and the indicator function $\mathbf{1}_{(y_t <= Q_{\tau,t})}$ has a value of 1 if the outcome is at or below the forecast quantile and 0 otherwise. Although much of the recent literature has not included formal statistical evaluations of quantile accuracy, Manzan (2015) relied on the quantile score. The second accuracy measure is a simple coverage measure for the interval forecast: the percentage of outcomes falling below the 5 and 10 percent quantiles of the forecast distribution.

To gauge statistical significance, we estimate Diebold and Mariano (1995)–West (1996) t-tests for equality of the average loss (with loss defined as squared error or quantile score). We also compute t-tests for the empirical coverage rate equaling the nominal rate of 5 or 10 percent. In the tables, differences in accuracy or departures from nominal coverage that are statistically different from zero are denoted by one, two, or three asterisks, corresponding to significance levels of 10 percent, 5 percent, and 1 percent, respectively. The underlying p-values are based on t-statistics computed with a serial correlation-robust variance, using the pre-whitened quadratic spectral estimator of Andrews and Monahan (1992). For the equal MSE and QS tests, we conduct them on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark.

The remaining sections of the paper present results using these forecast metrics. Although our focus is on conventional out-of-sample forecasts, we also provide some results on in-sample forecasts.

We do so in part because, due to some of the weekly data having data starting only in the 1990s, the overall sample is too short to allow out-of-sample evaluation over a period of meaningful length. In addition, for assessing tail risks, the most relevant periods are probably recessions, and these only occur periodically (roughly once every 10 years since the early 1980s). We compute in-sample forecast results just as we do for the out-of-sample case, with the differences that the parameter estimates used are obtained for the full sample rather than a recursive window, and we abstract from real-time data in the in-sample results. In addition, in light of the interest in tail risks and recent events, we also report some forecast accuracy results for just the periods of NBER-dated recessions (using their quarterly dating, in line with with our forecasting of quarterly GDP growth). These results address forecast accuracy conditional on being in a state of recession (taking as given the ex post dating by NBER). In these results, though, in light of the small samples of observations occurring in recessions, we abstract from tests of statistical significance.

5 Empirical Results

This section begins with results on in-sample accuracy and then proceeds with out-of-sample forecasts. Again, with the tail risk results presented herein, we focus on the 5 percent quantile; our general results also apply to the 10 percent quantile, and the appendix reports these estimates. The third subsection presents a recent example of nowcasts, using 2020:Q1.

5.1 In-sample evidence

To begin with a general sense of how additional data affect model fit, for the BMF-SV specification we estimate and compare log marginal likelihoods (although not shown, fit is substantially better with stochastic volatility than without, across all variable sets and samples considered). In particular, we compare log marginal likelihoods (MLs) for models estimated with the base macro variable set to models estimated with larger variable sets, for each forecast origin of 1 week through 15 weeks. The top panel 1 of Figure 1 reports the MLs for specifications fit with the three variable sets for which the available sample is 1971:Q2 through 2019:Q4. With the base macro variable set, model fit is essentially flat over the first several weeks of the quarter before beginning to improve as monthly data on the quarter become available starting in week 5. From weeks 5 through 15, the baseline model fit increases substantially, by about 30. Adding the NFCI to the model only modestly improves model fit; adding the broader set of financial indicators to the model yields a more notable improvement in fit. The middle and bottom panels of the figure indicate that, when the BMF-SV model is estimated with the shorter samples of data over which the small and large sets of weekly economic activity indicators are available, the same basic patterns apply. It remains the case that, across weeks, model fit does not begin to improve until about week 5 of the quarter, and that adding variables improves model fit. Adding the small set of weekly activity indicators to the model improves on the fit of the base macro and finance specification, and adding the large set of weekly activity indicators offers further improvement. Of course, model fit need not necessarily translate to accuracy of point or tail risk forecasts, but at least model fit suggests gains might be achieved by increasing the set of indicators and including weekly activity measures.

Turning to the accuracy of in-sample forecasts, Figures 2 through 4 and Table 3 provide RMSE, QS (5 percent), and coverage results, using the variable sets available for the long sample of 1971:Q2 through 2019:Q4. Consistent with the evidence on in-sample fit, for the benchmark forecasts from the BMF-SV specification estimated with the base macro variable set excluding initial unemployment claims, the top rows of the RMSE and QS panels of Table 3 show that forecast accuracy improves as more information on the quarter becomes available across weeks, with most of the gain coming from week 5 through 15. The RMSE ratios provided in the top panel of Figure 2 show that, with the base macro variable set, the accuracy of point forecasts is quite similar for the BMF, BMF-SV, and BQR models. The QR and QR-MIDAS models offer some gain in point forecast accuracy, peaking at about 20 percent in the middle weeks of the quarter with QR-MIDAS. The same pattern applies with the NFCI added to the models (middle panel). Adding other financial indicators to the model offers some additional gains in forecast accuracy, for all models (bottom panel). According to the Diebold-Mariano-West tests, these gains are statistically significant (Table 3) — with the qualifier that these tests as developed are not intended for in-sample projections. The QS ratios in Figure 3 yield results qualitatively similar in two respects. First, forecast accuracy (in this case, tail risk forecast rather than point forecast) improves with the addition of more variables. For a given model, the score ratios across weeks fall moving from (1) the base macro variable set in the top panel to (2) the variable set adding the NFCI in the middle to (3) the base macro and finance variable set of the third panel. Second, for a given data set, of the models considered, the most accurate forecasts come from the QR and QR-MIDAS models. For example, the QR-MIDAS forecast using the base macro and finance variable set improves on the quantile score of the benchmark model by as much as 45 percent. Of the other models, BQR is not quite as good as simple QR and is often comparable to the BMF-SV model, which consistently improves on the (conditionally homoskedastic) BMF specification. Finally, regarding the empirical coverage rate of the 5 percent quantile forecast (in-sample), the results of Figure 4 and Table 3 (middle panel) indicate that empirical coverage is generally close to 5 percent for the BMF, BMF-SV, and BQR specifications, for all variable sets of the 1971-2019 sample. The QR and QR-MIDAS coverage rates show more departures from nominal coverage, along with more variability across weeks of the quarter — with variability that increases as the variable set increases.

In broad terms, we obtain qualitatively similar results for the sample of 1996:Q3 through 2019:Q4 that covers the small and large sets of weekly economic activity indicators, as indicated in Figures 5 and 6 and Tables 4 and 5. (Note that, in these and other charts comparing relative accuracy, on a given page scales are held the same to facilitate comparisons across variable sets.) In the interest of brevity, we focus here on RMSE and QS accuracy; the appendix includes coverage rate results. In RMSE accuracy, the BMF, BMF-SV, and BQR models are most similar, showing some gains in accuracy over the benchmark as financial indicators and weekly activity indicators are added to the models. The most accurate models for point forecasts are the QR and QR-MIDAS specifications. Adding weekly activity indicators has a bigger effect on the forecast accuracy of these models than the others — for example, for QR-MIDAS yielding as much as a roughly 25 percent reduction in RMSE compared to the benchmark — without sizable differences between the small and large sets of indicators. In tail risk forecast accuracy as measured by the 5 percent QS, it is again the case that accuracy improves with the addition of more variables. For a given model, the score ratios across weeks fall, moving from the base macro variable set to models including financial indicators and again with the addition of the small or large sets of weekly activity indicators. In addition, the most accurate forecasts come from the QR and QR-MIDAS models. For example, the QR-MIDAS forecast using the base macro-finance plus large weekly variable set improves on the quantile score of the benchmark model by as much as 64 percent. That said, as indicated in the coverage rates in the appendix, the QR and QR-MIDAS models yield considerable variability in empirical coverage rates. This may be one indication that, with relatively few observations in the tail, these models are overfitting. The out-of-sample analysis in the next subsection will provide a check on that.

In light of the interest in downside tail risks and the interest in quickly detecting the extent of the downturn following the recent outbreak of the pandemic, we now consider the accuracy of point and tail risk forecasts during past NBER recessions.[5] Table 6 provides RMSE and QS (5 percent) results for 1971:Q2-2019:Q4, the longest sample available among our variable sets. In general, the patterns on point forecast accuracy in recessions (upper panel of the table) mirror those for the

[5]We define the periods of recessions using the NBER's quarterly dating of business cycle peaks and troughs.

full sample covering expansions and recessions, with the difference that the advantages of larger variable sets and different models over the benchmark are larger in the recession subsample. Among variable set choices, including the NFCI improves on the base macro variable set, and including the larger set of financial indicators helps even more. The most accurate predictions come from the QR and QR-MIDAS specifications, particularly with larger variable sets. In tail risk forecasting, the patterns are similar but more extreme. For example, with the base macro and finance variable set, the QR-MIDAS model improves the baseline point forecast accuracy by as much as (roughly) 50 percent and the QS accuracy by as much as 80 percent. At least on this in-sample basis, for forecasts of GDP growth in recessions, there can be tremendous gains in accuracy to using a large information set featuring some weekly data, particularly with the QR-MIDAS model specification. Yet, particularly with the large sizes of some of the models and relatively few observations in the tails, the in-sample performance could reflect some overfitting. The next section's analysis of real-time, out-of-sample forecasts will shed light on that.

5.2 Out-of-sample evidence

As a starting point, we assess how increasing the basic information set over the weeks of the quarter affects forecast accuracy. Figure 7 reports RMSEs and 5 percent quantile scores from the benchmark BMF-SV model estimated with the base macro variable set excluding unemployment claims (so that, as noted above, the variable set consists entirely of monthly indicators, which become increasingly available across weeks of the quarter). For the 1985:Q1-2019:Q3 sample, both RMSE and 5 percent QS fairly steadily improve by the week; additional information on the quarter materially improves the accuracy of both point and tail risk forecasts. That said, even at week 15, shortly before the initial estimate of GDP is released, the forecast uncertainty is considerable, with the RMSE at about 1.45. For the shorter sample of 2000:Q1-2019:Q3, the patterns are generally similar, although with more unevenness in the path of QS across the early weeks of the quarter.

Comparing real-time accuracy across models and variable sets yields a picture fairly different from that of the in-sample results. Figures 8 through 10 and Table 7 provide RMSE, QS (5 percent), and coverage results using the variable sets available for the forecast evaluation sample of 1985:Q1 through 2019:Q3. In RMSE accuracy, the benchmark model is much harder to beat than in the in-sample results. For each of the base-macro, base macro plus NFCI, and base macro and finance variable sets, the BMF, BMF-SV, and BQR models produce point forecasts that match but do not improve the accuracy of the benchmark; the RMSE ratios are very close to 1 across all weeks. The QR and QR-MIDAS specifications that fared very well in-sample fare poorly out-of-sample, with

RMSE ratios as much as 56 percent higher than the benchmark. In tail risk forecasting for the 1985:Q1-2019:Q3 sample, the QR and QR-MIDAS specifications also perform poorly (in some cases, performance is worse than the chart suggests, because for scale reasons the maximum of the chart is set at 2, even though the QS ratio goes above 2, as shown in the table). These forecast accuracy problems of the QR and QR-MIDAS appear to stem from imprecision in the coefficient estimates in the recursive setting. As an example (see Appendix Figure A11), with the base macro and finance variable set, the QR model's coefficient estimates vary substantially over time, more so with the tail quantiles than the median. Applying Bayesian shrinkage with the BQR specification greatly reduces the variability of coefficient estimates over the forecast origins of the sample. Estimation details omitted in the interest of brevity show that, in the QR-MIDAS specification, the variability of coefficients over time tends to increase as the size of the model grows, either across the weeks of the quarter or across variable sets.[6]

In these real-time accuracy results, the cases in which the benchmark is beaten are those using the BMF-SV and BQR specifications with the NFCI or the larger set of financial indicators added to the base macro variable set. In these cases, the benchmark QS is lowered as much as 10 to 16 percent, although only with statistical significance in a few cases, all with the BMF-SV specification and not BQR. Note that, in general, on an out-of-sample basis, Bayesian shrinkage consistently improves the performance of quantile regression (i.e., BQR beats simple QR in forecast accuracy), likely helped by the reductions in sampling variability noted above. Finally, regarding the empirical coverage of the 5 percent quantile forecast, the BMF-SV specifications typically yield correct coverage. Other models are less successful in achieving accurate coverage. Empirical coverage rates for the BMF and BQR specifications are commonly below 5 percent, often significantly so (implying the quantile estimates are too low). Coverage rates for the QR and QR-MIDAS models are much more variable and often far too high (implying the quantile estimates are too high), more so with the larger models than the smaller ones.

Figures 11 and 12 and Table 8 provide RMSE and QS (5 percent) results using the variable sets available for the forecast evaluation sample of 2000:Q1 through 2019:Q3 (for brevity, corresponding coverage rates appear in the appendix). The shorter sample means significant gains are harder to achieve, particularly with only two recessions in the sample and the evaluation of lower tail risks. But the shorter sample is necessary to be able to evaluate forecasts from models including the small set of weekly economic activity indicators. In these results on RMSE accuracy, as in those for the

[6]We observe this pattern looking at medians and interquartile ranges (across coefficients) of relative standard deviation estimates for the forecast sample.

1985-2019 sample, there is little to distinguish the accuracy of forecasts from the BMF, BMF-SV, and BQR specifications, whereas the QR and QR-MIDAS approaches perform relatively poorly in the larger variable sets (macro-finance and those adding the small set of weekly indicators). In tail risk forecasting, forecast accuracy of the BMF and QR models improves with including additional indicators in the model, but that is more so the case with finance indicators than with the weekly economic activity indicators. For example, with the base macro and finance variable set, the BMF-SV and BQR specifications improve the quantile score by as much as 27 percent, whereas with the base macro and small weekly variable set, their QR ratios are in some cases slightly above 1 and in others slightly below. All this said, likely due to small sample considerations, even when the QS gains are numerically sizable, they are not typically statistically significant. The tail risk forecast performance of the QR and QR-MIDAS specifications is much more uneven across variable sets and weeks of the quarter. In some cases, typically in smaller models, these models improve on the accuracy of the benchmark model, whereas in the larger models, these models are consistently worse than the benchmark. As in the larger evaluation sample, Bayesian shrinkage typically improves the accuracy of tail risk forecasts from quantile regression, with the advantage increasing with the dimension of the variable set.

When we limit the evaluation sample to the periods of recessions, forecast accuracy gains are more difficult to achieve out-of-sample than in-sample. Again, predictions during recessions may be particularly relevant in light of the general interest in assessing downside tail risks and quickly detecting the extent of the downturn following the recent outbreak of the pandemic. Table 9 provides RMSE and QS (5 percent) results for 1985:Q1-2019:Q3, the longest out-of-sample evaluation period available among our variable sets. In point forecast accuracy, the different variable sets and models or methods we consider are somewhat challenged to materially improve on the benchmark. Including financial indicators in the models is generally helpful to RMSE accuracy. For example, with the BMF-SV model, RMSEs for the base macro and finance variable set can be as much as (roughly) 25 percent better than the benchmark RMSEs (although this does not apply in the early weeks of the quarter). For a given variable set, the lowest RMSE is typically achieved with the QR-MIDAS specification, except that with the base macro and finance variable set, the BMF-SV and BQR specifications are about as good up until about the middle of the quarter and then dominate, as the QR-MIDAS performance deteriorates sharply. Quantile score accuracy displays patterns similar to those of RMSE accuracy. QR-MIDAS often performs relatively well but its accuracy can deteriorate sharply as the model's size increases. Simple quantile regression is also uneven across models and weeks of the quarter, more noticeably so than in RMSE performance. With the base macro and finance variable set, the BMF-SV and BQR specifications perform relatively well, yielding gains similar to those that are achieved by QR-MIDAS but without the unevenness across forecast origins.

To help shed some light on the patterns documented above, we conclude our evidence with a few examples of the historical time series of forecasts (although not presented in the prior subsection, the patterns we are about to summarize are very similar in in-sample forecasts for the 1971-2019 period). We first show in Figures 13 and 14 forecasts from the BMF-SV and QR-MIDAS specifications estimated with the base macro and finance variable set. These charts include the point, 5 percent quantile, and 95 percent quantile forecasts produced at a set of selected forecast origins within the quarter, along with the actual GDP growth outcome. Figure 15 shows just the point and 5 percent quantile forecasts obtained with the same variable set, at weeks 5 and 11, for a wider array of models.

As indicated in Figure 13, with the BMF-SV model and the base macro and finance variable set, the 5 percent and 9 percent forecast quantiles tend to move together. In nowcasting, with conditioning on some information for the quarter being forecast, we don't seem to obtain the asymmetric moves in quantiles (with the downside moving down more than the upside does, around the times of recessions) evident in the 1-quarter-ahead and 4-quarter-ahead results of Carriero, Clark, and Marcellino (2020). Consistent with the results already documented, the visual evidence on the forecasts suggests that the point forecast gets a little more accurate as more data become available across the weeks of the quarter, especially during recessions. In addition, during recessions, the 5 percent forecast quantile declines with more weeks of data becoming available in the quarter, as does the 95 percent quantile. In weeks of the first half of the quarter, the tail forecast ends up being close to actual GDP growth in downturns, but in later weeks, the outcome is not as bad as the 5 percent quantile forecast. As evident from Figure 14, the forecast quantiles of the QR-MIDAS model are much more variable. They are clearly too wide from a coverage perspective; in recessions, the 5 percent quantile is well below the GDP growth outcome (except at the 3-week origin). On the other hand, the point forecast from the model is often quite accurate in recessions (for most of these weeks shown, but less so at later weeks of the quarter, as noted above). With the QR-MIDAS model, as with the BMF-SV model, with some conditioning on information within the quarter for nowcasting, there doesn't appear to be much asymmetry in downside tail risks as compared to upside risks. From Figure 15's selected comparison to other forecasts, the recession-period advantage that the QR-MIDAS model has in point forecast accuracy at a number of forecast origins is quite clear. But those successes are part of a general pattern of more variability compared to the other forecasts; over the full sample that is dominated by periods of expansion, the QR-MIDAS specification's forecasts are less accurate than those of the benchmark and other models. The BQR forecast is typically quite similar to the BMF-SV projection. In the QS results in the lower panels, the picture is qualitatively similar. The QR-MIDAS quantile forecast is the most variable; its 5 percent quantile forecasts were persistently around -2 or -3 in much of the 2011-2016 period, despite the ongoing expansion of the economy. The other methods yield fairly similar 5 percent quantile forecasts.

5.3 Current example: Forecasts for 2020:Q1 produced with data through mid-April 2020

We conclude our analysis with a real-time example of nowcasting GDP growth in the early stages of what most observers believe to be a pandemic-driven recession in the US. In particular, with selected variable sets and models, we report forecasts for growth in 2020:Q1 produced across the weeks of the quarter using data available in mid-April 2020, which is weeks 1 through 14 in our setup.[7] Partly to limit the volume of results, we use just a few variable sets and models, selected on the basis of our assessment of the more successful historical approaches. In particular, we report results for the BMF-SV, BQR, and QR-MIDAS models estimated with the base macro and finance, base macro-finance plus small weekly, and base macro-finance plus large weekly variable sets.[8] Note that, shortly after these forecasts were produced, the Bureau of Economic Analysis published the first estimate of GDP in 2020:Q1, and that outcome (as an annualized log growth rate) was -4.9 percent.

As indicated in the forecasts in Figure 16, early in 2020:Q1, before the pandemic spread and shutdowns began (in mid- to late March in most of the US), the BMF-SV and BQR point forecasts were around 3 percent, with little difference across the variable sets used. Around week 8, by which time stock prices had started to register a falloff in response to global news on the pandemic's outbreak, the forecasts began to gradually decline, with the pace of decline steepening from weeks

[7] In this exercise, for simplicity we use the third estimate of GDP growth in 2019:Q4 and the current vintage time series of monthly and weekly indicators available in mid-April and abstract from updates of preliminary data that occurred over the course of 2020:Q1.

[8] However, relative to our results in the paper, we adjust the macro variable set to omit initial claims for unemployment insurance. In the estimated models, claims typically have small and imprecise coefficients, although positive rather than negative in some cases. With these estimates, the recent unprecedented spike in claims in some cases leads recent GDP growth forecasts to rise significantly rather than fall. For simplicity, in this initial version of the paper, we address the counter-intuitive pattern by removing claims from the models.

12 to 14 as more post-shutdown data became available. Still, the point forecasts from these models were around 0 or slightly positive, far more optimistic than the outcome turned out to be. The models including the small set of weekly activity indicators showed more of a falloff in growth than did the model without them, but the models with the large set of weekly activity indicators instead yielded forecasts more optimistic than the base macro and finance specification. As indicated in the right column of the figure, the tail risk forecasts from the BMF-SV and BQR follow paths generally similar to those of the point forecasts, at lower levels. The specifications with the base macro and finance variable set or the variable set adding in the small set of weekly indicators put the 5 percent tail around -1.5 or -2 percent. Finally, the behavior of forecasts from the QR-MIDAS specification is quite different. Their behavior is not so easily explained except as part of their general volatility noted in our historical evaluation above. In most cases, the point and tail risk forecasts from this model are extremely negative, but in some cases (depending on the week or whether the variable set includes the large collection of weekly activity indicators) positive.

What should one make of this example exercise? In our reading, it confirms the value of being able to update model forecasts on a weekly basis, particularly in a rapidly changing situation like that following the outbreak of the pandemic and the economic shutdown that ensued. But it also shows that, in unprecedented circumstances, models have their limits.

6 Conclusions

This paper focuses on point and tail risk nowcasts of economic activity, measured by GDP growth, with a potentially wide array of monthly and weekly information. We consider different models (Bayesian mixed frequency regressions with stochastic volatility, classical and Bayesian quantile regressions, quantile MIDAS regressions) and also different methods for data reduction (either the combination of forecasts from smaller models or forecasts from models that incorporate data reduction).

The results show that classical and MIDAS quantile regressions perform very well in-sample but not out-of-sample, where the Bayesian mixed frequency and quantile regressions are generally clearly superior, though the MIDAS quantile regression works well also out-of-sample during recessionary periods. Such a ranking of methods appears to be driven by substantial variability over time in the recursively estimated parameters in classical quantile regressions, while the use of priors in the Bayesian approaches reduces sampling variability and its effects on forecast accuracy.

From an economic point of view, we find that the weekly information flow is quite useful in improving tail nowcasts of economic activity, with initial claims for unemployment insurance, stock prices, a term spread, a credit spread, and the Chicago Fed's index of financial conditions emerging as particularly relevant indicators. Additional weekly indicators of economic activity do not improve historical forecast accuracy but do not harm it much, either.

We should mention that we plan to include in subsequent drafts a wider array of methods, including Bayesian quantile regression with a LASSO penalty, forecasts that combine predictions from smaller individual models, and forecasts based on factor-reduction of available predictors.

To conclude, based on the many results already presented, what would we recommend for point and tail risk nowcasts? Our starting points would be the mixed frequency regression with stochastic volatility and Bayesian quantile regression, applied to our baseline set of macroeconomic and financial indicators. As a practical matter, we would also consider forecasts from these same specifications but adding our small and large sets of weekly economic indicators. In circumstances in which the economy is feared to be nearing or in a recession, we would also consider quantile regression with MIDAS, applied to our baseline set of macroeconomic and financial indicators.

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Table 1: **Variables used**

indicator	*mnemonic (transformation)*	*frequency*	*release week*
real GDP	GDP ($400\Delta \ln$)	quarterly	4
payroll employment	emp ($\Delta \ln$)	monthly	1
ISM purchasing managers index, manufacturing	ISM	monthly	1
retail sales (nominal/CPI)	retail ($\Delta \ln$)	monthly	2
industrial production	IP ($\Delta \ln$)	monthly	3
housing starts	starts (ln)	monthly	3
initial claims for unemployment insurance	claims	weekly, monthly	2
Chicago Fed index of financial conditions	NFCI	weekly, monthly	2
S&P index of stock prices	SP ($\Delta \ln$)	weekly, monthly	1
term spread: 10-year less 1-year Treasury rates	TS	weekly, monthly	1
credit spread: Moody's Baa yield less 10-year Treasury	CS	weekly, monthly	1
Bloomberg index of consumer comfort	sment	weekly	2
raw steel production	steel ($\Delta \ln$, 52 week)	weekly	2
electric utility output	util ($\Delta \ln$, 52 week)	weekly	2
loadings of railroad cars	loads ($\Delta \ln$, 52 week)	weekly	2
fuel sales	fuel ($\Delta \ln$, 52 week)	weekly	2
Redbook same-store retail sales	rbook ($\%\Delta$, 52 week)	weekly	2

Notes: The first column lists the variables included in our models. The second column gives the indicator names used, along with any transformations made of the data. Note that because Redbook sales are reported as a 52-week percent change, for this indicator we used the simple percent change rather than the log growth rate applied to other trending variables. The third column indicates the frequency of the underlying data available and used. The final column gives the week in which each indicator is commonly reported and which determines which variables enter our models at each forecast origin (our dating is based on end-of-week availability). As examples, GDP for quarter $t-1$ is typically reported in the last (fourth) week of month 1 of quarter t, employment for month $t-1$ is normally published in week 1 of month t, the NFCI for week $t-1$ is reported in week t, and Treasury yields and stock prices for week t are published in (at the end of) week t.

Table 2: **Specifications of BMF models of GDP growth**

week	*variables (in addition to constant)*
1 (qrtr. t)	GDP_{t-2}, $\text{emp}_{t-1}^{(m1,m2,m3)}$, $\text{ISM}_{t-1}^{(m1,m2,m3)}$, $\text{retail}_{t-1}^{(m1,m2)}$, $\text{IP}_{t-1}^{(m1,m2)}$, $\text{starts}_{t-1}^{(m1,m2)}$, $\text{claims}_{t-1}^{(m1,m2,m3)}$ $\text{NFCI}_{t-1}^{(m1,m2,m3)}$, $\text{SP}_{t-1}^{(m1,m2,m3)}$, $\text{TS}_{t-1}^{(m1,m2,m3)}$, $\text{CS}_{t-1}^{(m1,m2,m3)}$, $\text{SP}_{t}^{(w1)}$, $\text{TS}_{t}^{(w1)}$, $\text{CS}_{t}^{(w1)}$
2 (qrtr. t)	GDP_{t-2}, $\text{emp}_{t-1}^{(m1,m2,m3)}$, $\text{ISM}_{t-1}^{(m1,m2,m3)}$, $\text{retail}_{t-1}^{(m1,m2,m3)}$, $\text{IP}_{t-1}^{(m1,m2)}$, $\text{starts}_{t-1}^{(m1,m2)}$, $\text{claims}_{t-1}^{(m1,m2,m3)}$, $\text{claims}_{t}^{(w1)}$ $\text{NFCI}_{t-1}^{(m1,m2,m3)}$, $\text{SP}_{t-1}^{(m1,m2,m3)}$, $\text{TS}_{t-1}^{(m1,m2,m3)}$, $\text{CS}_{t-1}^{(m1,m2,m3)}$, $\text{NFCI}_{t}^{(w1)}$, $\text{SP}_{t}^{(w1+w2)}$, $\text{TS}_{t}^{(w1+w2)}$, $\text{CS}_{t}^{(w1+w2)}$ $\text{sment}_{t}^{(w1)}$, $\text{steel}_{t}^{(w1)}$, $\text{util}_{t}^{(w1)}$
3 (qrtr. t)	GDP_{t-2}, $\text{emp}_{t-1}^{(m1,m2,m3)}$, $\text{ISM}_{t-1}^{(m1,m2,m3)}$, $\text{retail}_{t-1}^{(m1,m2,m3)}$, $\text{IP}_{t-1}^{(m1,m2,m3)}$, $\text{starts}_{t-1}^{(m1,m2,m3)}$, $\text{claims}_{t}^{(w1+w2)}$ $\text{NFCI}_{t}^{(w1+w2)}$, $\text{SP}_{t}^{(w1+w2+w3)}$, $\text{TS}_{t}^{(w1+w2+w3)}$, $\text{CS}_{t}^{(w1+w2+w3)}$ $\text{sment}_{t}^{(w2)}$, $\text{steel}_{t}^{(w2)}$, $\text{util}_{t}^{(w2)}$
4 (qrtr. t)	GDP_{t-1}, $\text{emp}_{t-1}^{(m1,m2,m3)}$, $\text{ISM}_{t-1}^{(m1,m2,m3)}$, $\text{retail}_{t-1}^{(m1,m2,m3)}$, $\text{IP}_{t-1}^{(m1,m2,m3)}$, $\text{starts}_{t-1}^{(m1,m2,m3)}$, $\text{claims}_{t}^{(w1+w2+w3)}$ $\text{NFCI}_{t}^{(w1+w2+w3)}$, $\text{SP}_{t}^{(w1+w2+w3+w4)}$, $\text{TS}_{t}^{(w1+w2+w3+w4)}$, $\text{CS}_{t}^{(w1+w2+w3+w4)}$ $\text{sment}_{t}^{(w3)}$, $\text{steel}_{t}^{(w3)}$, $\text{util}_{t}^{(w3)}$
5 (qrtr. t)	GDP_{t-1}, $\text{emp}_{t}^{(m1)}$, $\text{ISM}_{t}^{(m1)}$, $\text{claims}_{t}^{(m1)}$ $\text{NFCI}_{t}^{(m1)}$, $\text{SP}_{t}^{(m1,w5)}$, $\text{TS}_{t}^{(m1,w5)}$, $\text{CS}_{t}^{(m1,w5)}$ $\text{sment}_{t}^{(w4)}$, $\text{steel}_{t}^{(w4)}$, $\text{util}_{t}^{(w4)}$
6 (qrtr. t)	GDP_{t-1}, $\text{emp}_{t}^{(m1)}$, $\text{ISM}_{t}^{(m1)}$, $\text{retail}_{t}^{(m1)}$, $\text{claims}_{t}^{(m1,w5)}$ $\text{NFCI}_{t}^{(m1,w5)}$, $\text{SP}_{t}^{(m1,w5+w6)}$, $\text{TS}_{t}^{(m1,w5+w6)}$, $\text{CS}_{t}^{(m1,w5+w6)}$ $\text{sment}_{t}^{(w5)}$, $\text{steel}_{t}^{(w5)}$, $\text{util}_{t}^{(w5)}$
7 (qrtr. t)	GDP_{t-1}, $\text{emp}_{t}^{(m1)}$, $\text{ISM}_{t}^{(m1)}$, $\text{retail}_{t}^{(m1)}$, $\text{IP}_{t}^{(m1)}$, $\text{starts}_{t}^{(m1)}$, $\text{claims}_{t}^{(m1,w5+w6)}$ $\text{NFCI}_{t}^{(m1,w5+w6)}$, $\text{SP}_{t}^{(m1,w5+w6+w7)}$, $\text{TS}_{t}^{(m1,w5+w6+w7)}$, $\text{CS}_{t}^{(m1,w5+w6+w7)}$ $\text{sment}_{t}^{(w6)}$, $\text{steel}_{t}^{(w6)}$, $\text{util}_{t}^{(w6)}$
8 (qrtr. t)	GDP_{t-1}, $\text{emp}_{t}^{(m1)}$, $\text{ISM}_{t}^{(m1)}$, $\text{retail}_{t}^{(m1)}$, $\text{IP}_{t}^{(m1)}$, $\text{starts}_{t}^{(m1)}$, $\text{claims}_{t}^{(m1,w5+w6+w7)}$ $\text{NFCI}_{t}^{(m1,w5+w6+w7)}$, $\text{SP}_{t}^{(m1,w5+w6+w7+w8)}$, $\text{TS}_{t}^{(m1,w5+w6+w7+w8)}$, $\text{CS}_{t}^{(m1,w5+w6+w7+w8)}$ $\text{sment}_{t}^{(w7)}$, $\text{steel}_{t}^{(w7)}$, $\text{util}_{t}^{(w7)}$
9 (qrtr. t)	GDP_{t-1}, $\text{emp}_{t}^{(m1,m2)}$, $\text{ISM}_{t}^{(m1,m2)}$, $\text{retail}_{t}^{(m1)}$, $\text{IP}_{t}^{(m1)}$, $\text{starts}_{t}^{(m1)}$, $\text{claims}_{t}^{(m1,m2)}$ $\text{NFCI}_{t}^{(m1,m2)}$, $\text{SP}_{t}^{(m1,m2,w9)}$, $\text{TS}_{t}^{(m1,m2,w9)}$, $\text{CS}_{t}^{(m1,m2,w9)}$ $\text{sment}_{t}^{(w8)}$, $\text{steel}_{t}^{(w8)}$, $\text{util}_{t}^{(w8)}$
10 (qrtr. t)	GDP_{t-1}, $\text{emp}_{t}^{(m1,m2)}$, $\text{ISM}_{t}^{(m1,m2)}$, $\text{retail}_{t}^{(m1,m2)}$, $\text{IP}_{t}^{(m1)}$, $\text{starts}_{t}^{(m1)}$, $\text{claims}_{t}^{(m1,m2,w9)}$ $\text{NFCI}_{t}^{(m1,m2,w9)}$, $\text{SP}_{t}^{(m1,m2,w9+w10)}$, $\text{TS}_{t}^{(m1,m2,w9+w10)}$, $\text{CS}_{t}^{(m1,m2,w9+w10)}$ $\text{sment}_{t}^{(w9)}$, $\text{steel}_{t}^{(w9)}$, $\text{util}_{t}^{(w9)}$
11 (qrtr. t)	GDP_{t-1}, $\text{emp}_{t}^{(m1,m2)}$, $\text{ISM}_{t}^{(m1,m2)}$, $\text{retail}_{t}^{(m1,m2)}$, $\text{IP}_{t}^{(m1,m2)}$, $\text{starts}_{t}^{(m1,m2)}$, $\text{claims}_{t}^{(m1,m2,w9+w10)}$ $\text{NFCI}_{t}^{(m1,m2,w9+w10)}$, $\text{SP}_{t}^{(m1,m2,w9+w10+w11)}$, $\text{TS}_{t}^{(m1,m2,w9+w10+w11)}$, $\text{CS}_{t}^{(m1,m2,w9+w10+w11)}$ $\text{sment}_{t}^{(w10)}$, $\text{steel}_{t}^{(w10)}$, $\text{util}_{t}^{(w10)}$
12 (qrtr. t)	GDP_{t-1}, $\text{emp}_{t}^{(m1,m2)}$, $\text{ISM}_{t}^{(m1,m2)}$, $\text{retail}_{t}^{(m1,m2)}$, $\text{IP}_{t}^{(m1,m2)}$, $\text{starts}_{t}^{(m1,m2)}$, $\text{claims}_{t}^{(m1,m2,w9+w10+w11)}$ $\text{NFCI}_{t}^{(m1,m2,w9+w10+w11)}$, $\text{SP}_{t}^{(m1,m2,w9+w10+w11+w12)}$, $\text{TS}_{t}^{(m1,m2,w9+w10+w11+w12)}$, $\text{CS}_{t}^{(m1,m2,w9+w10+w11+w12)}$ $\text{sment}_{t}^{(w11)}$, $\text{steel}_{t}^{(w11)}$, $\text{util}_{t}^{(w11)}$
13 (qrtr. $t+1$)	GDP_{t-1}, $\text{emp}_{t}^{(m1,m2,m3)}$, $\text{ISM}_{t}^{(m1,m2,m3)}$, $\text{retail}_{t}^{(m1,m2)}$, $\text{IP}_{t}^{(m1,m2)}$, $\text{starts}_{t}^{(m1,m2)}$, $\text{claims}_{t}^{(m1,m2,m3)}$ $\text{NFCI}_{t}^{(m1,m2,m3)}$, $\text{SP}_{t}^{(m1,m2,m3,w13)}$, $\text{TS}_{t}^{(m1,m2,m3,w13)}$, $\text{CS}_{t}^{(m1,m2,m3,w13)}$ $\text{sment}_{t}^{(w12)}$, $\text{steel}_{t}^{(w12)}$, $\text{util}_{t}^{(w12)}$
14 (qrtr. $t+1$)	GDP_{t-1}, $\text{emp}_{t}^{(m1,m2,m3)}$, $\text{ISM}_{t}^{(m1,m2,m3)}$, $\text{retail}_{t}^{(m1,m2,m3)}$, $\text{IP}_{t}^{(m1,m2)}$, $\text{starts}_{t}^{(m1,m2)}$, $\text{claims}_{t}^{(m1,m2,m3,w13)}$ $\text{NFCI}_{t}^{(m1,m2,m3,w13)}$, $\text{SP}_{t}^{(m1,m2,m3,w13+w14)}$, $\text{TS}_{t}^{(m1,m2,m3,w13+w14)}$, $\text{CS}_{t}^{(m1,m2,m3,w13+w14)}$ $\text{sment}_{t}^{(w13)}$, $\text{steel}_{t}^{(w13)}$, $\text{util}_{t}^{(w13)}$
15 (qrtr. $t+1$)	GDP_{t-1}, $\text{emp}_{t}^{(m1,m2,m3)}$, $\text{ISM}_{t}^{(m1,m2,m3)}$, $\text{retail}_{t}^{(m1,m2,m3)}$, $\text{IP}_{t}^{(m1,m2,m3)}$, $\text{starts}_{t}^{(m1,m2,m3)}$, $\text{claims}_{t}^{(m1,m2,m3,w13+w14)}$ $\text{NFCI}_{t}^{(m1,m2,m3,w13+w14)}$, $\text{SP}_{t}^{(m1,m2,m3,w13+w14+w15)}$, $\text{TS}_{t}^{(m1,m2,m3,w13+w14+w15)}$, $\text{CS}_{t}^{(m1,m2,m3,w13+w14+w15)}$ $\text{sment}_{t}^{(w14)}$, $\text{steel}_{t}^{(w14)}$, $\text{util}_{t}^{(w14)}$

Notes: For each week indicated in the first column, the table has three rows of entries, with the first listing the relevant base macro indicators, the second row covering the base finance indicators, and the third listing the small weekly indicators included in the given week's models (in the week 1 case, the row is blank because no weekly variables for the quarter are available or included). The variable sets *base macro*, *base macro and finance*, *base macro and small weekly*, and *base macro-finance and small weekly* combine these predictors as indicated.

Table 3: **In-sample forecast accuracy, 1971:Q2-2019:Q4**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	RMSE							
base macro ex claims: BMF-SV	2.55	2.39	2.45	2.19	2.12	2.05	2.00	1.99
base macro: BMF	0.97	1.01	1.01	1.00	0.99	0.99	0.99	0.99
base macro: BMF-SV	0.97 ***	1.00	1.00 *	0.99 *	0.98 **	0.99 **	0.99 *	0.99 *
base macro: QR	0.90 ***	0.92 ***	0.90 **	0.90 **	0.92 **	0.92 **	0.94 *	0.93 **
base macro: BQR	0.99	1.00	1.01	1.00	1.00	1.01	1.02	1.02
base macro: QR-MIDAS	0.97 **	0.91 ***	0.84 ***	0.81 ***	0.84 ***	0.89 **	0.93 *	0.97
base macro + NFCI: BMF	0.91 ***	0.96 **	0.97 *	0.95 *	0.95 **	0.96 *	0.97	0.97
base macro + NFCI: BMF-SV	0.91 ***	0.96 **	0.96 **	0.95 **	0.95 **	0.96 *	0.97	0.97 *
base macro + NFCI: QR	0.86 ***	0.93 **	0.87 ***	0.87 **	0.89 **	0.90 **	0.92 **	0.91 **
base macro + NFCI: BQR	0.94 **	0.99	0.99	0.97	0.97	0.98	0.99	0.98
base macro + NFCI: QR-MIDAS	0.90 **	0.88 **	0.82 ***	0.78 ***	0.81 ***	0.89 **	0.93 *	0.97
base macro-finance: BMF	0.87 ***	0.93 ***	0.93 **	0.91 **	0.91 ***	0.93 **	0.95 **	0.95 **
base macro-finance: BMF-SV	0.87 ***	0.93 ***	0.92 **	0.90 **	0.91 ***	0.92 **	0.94 **	0.94 ***
base macro-finance: QR	0.83 ***	0.90 ***	0.83 ***	0.84 ***	0.84 ***	0.89 **	0.89 *	0.93
base macro-finance: BQR	0.90 ***	0.96 *	0.96	0.93 *	0.93 **	0.95 *	0.96	0.96
base macro-finance: QR-MIDAS	0.86 **	0.87 ***	0.80 ***	0.78 ***	0.77 ***	0.89 ***	0.92 **	0.94 *
	5% quantile score							
base macro ex claims: BMF-SV	0.27	0.25	0.25	0.23	0.22	0.21	0.20	0.20
base macro: BMF	1.19	1.19	1.20	1.18	1.21	1.19	1.20	1.23
base macro: BMF-SV	0.99	1.01	1.01	1.01	1.01	1.01	0.99	1.02
base macro: QR	0.66 ***	0.70 ***	0.80 **	0.78 ***	0.82 **	0.78 **	0.75 ***	0.73 ***
base macro: BQR	0.86 **	0.79 ***	0.88 **	0.89 *	0.93	0.90 *	0.88 **	0.88 **
base macro: QR-MIDAS	0.94	0.88	0.79 **	0.76 **	0.82 **	0.84 **	0.89	0.96
base macro + NFCI: BMF	0.95	1.01	1.03	0.99	1.02	1.00	1.05	1.07
base macro + NFCI: BMF-SV	0.86 ***	0.91 ***	0.94 **	0.89 ***	0.91 **	0.90 **	0.93 **	0.94 **
base macro + NFCI: QR	0.63 ***	0.70 ***	0.79 **	0.77 ***	0.80 **	0.77 ***	0.75 ***	0.71 ***
base macro + NFCI: BQR	0.85 ***	0.80 ***	0.89 *	0.89 *	0.93	0.90 *	0.88 **	0.88 **
base macro + NFCI: QR-MIDAS	0.73 ***	0.74 ***	1.12	0.66 ***	0.73 ***	0.76 ***	0.80 **	0.83 **
base macro-finance: BMF	0.89 **	0.93	0.94	0.90	0.93	0.93	0.98	1.02
base macro-finance: BMF-SV	0.82 ***	0.86 ***	0.86 **	0.81 ***	0.86 **	0.85 **	0.89 **	0.91 **
base macro-finance: QR	0.52 ***	0.64 ***	0.67 ***	0.61 ***	0.62 ***	0.60 ***	0.59 ***	0.59 ***
base macro-finance: BQR	0.74 ***	0.76 ***	0.78 **	0.77 **	0.86 **	0.84 **	0.84 ***	0.85 ***
base macro-finance: QR-MIDAS	0.64 ***	0.68 ***	0.61 ***	0.56 ***	0.61 ***	0.75 ***	0.75 ***	0.77 ***
	5% coverage							
base macro ex claims: BMF-SV	0.05	0.05	0.06	0.06	0.06	0.07	0.06	0.06
base macro: BMF	0.06	0.05	0.05	0.05	0.04	0.04	0.05	0.05
base macro: BMF-SV	0.06	0.06	0.07	0.06	0.06	0.06	0.05	0.05
base macro: QR	0.02 ***	0.03 **	0.07	0.04	0.09 *	0.02 ***	0.10 **	0.12 ***
base macro: BQR	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.05
base macro: QR-MIDAS	0.05	0.03	0.08	0.08 *	0.03	0.04	0.07	0.07
base macro + NFCI: BMF	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04
base macro + NFCI: BMF-SV	0.05	0.04	0.05	0.05	0.06	0.04	0.04	0.05
base macro + NFCI: QR	0.12 ***	0.12 ***	0.04	0.09 **	0.09 *	0.01 ***	0.10 **	0.14 ***
base macro + NFCI: BQR	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.04
base macro + NFCI: QR-MIDAS	0.03 **	0.08	0.03 *	0.09 **	0.03	0.09 **	0.03 **	0.02 ***
base macro-finance: BMF	0.05	0.04	0.05	0.05	0.05	0.04	0.04	0.04
base macro-finance: BMF-SV	0.06	0.05	0.05	0.05	0.05	0.05	0.04	0.05
base macro-finance: QR	-0.00 ***	0.13 ***	0.05	0.10 ***	0.13 ***	0.04	0.18 ***	0.19 ***
base macro-finance: BQR	0.05	0.05	0.05	0.04	0.05	0.04	0.05	0.04
base macro-finance: QR-MIDAS	0.02 ***	0.03 **	0.01 ***	0.01 ***	0.11 **	0.02 ***	0.11 ***	0.02 ***

Notes: The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). In the top panel, the first top row gives the RMSEs of nowcasts from the benchmark model and variable set. Other rows report the ratio of RMSEs for the indicated variable set and model to the benchmark. In the middle panel, the top row gives the 5% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). The bottom panel reports empirical coverage rates for 5% quantile forecasts (percentage of outcomes at or below the quantile). Statistical significance of differences in MSEs and quantile scores is indicated by *** (1%), ** (5%), or * (10%), obtained with the Diebold and Mariano–West t-test, conducted on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark. Statistical significance of departures of empirical coverage from the nominal 5% is also indicated by *** (1%), ** (5%), or * (10%), obtained with two-sided t-tests.

Table 4: **In-sample forecast accuracy: RMSE, 1996:Q3-2019:Q4**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
base macro ex claims: BMF-SV	1.91	1.76	1.95	1.80	1.70	1.66	1.63	1.61
base macro: BMF	0.99	1.01	1.00	0.99	0.99	1.00	0.99	0.99
base macro: BMF-SV	0.97 **	1.00	1.00	0.99 *	0.98 **	0.98 **	0.99 *	0.98 **
base macro: QR	0.92	0.97	0.98	1.01	1.00	1.02	1.06	1.05
base macro: BQR	1.02	1.03	1.01	1.01	1.02	1.02	1.03	1.03
base macro: QR-MIDAS	0.98	0.99	0.88	0.86 *	0.90	0.90 *	0.93	0.93 *
base macro + NFCI: BMF	0.99	1.01	0.99	0.98	0.98	0.99	0.99	1.00
base macro + NFCI: BMF-SV	0.97	1.00	0.98	0.98	0.98	0.98	0.99	0.98
base macro + NFCI: QR	0.91	0.99	0.97	0.96	0.94 *	0.98	1.02	1.03
base macro + NFCI: BQR	1.00	1.02	1.01	0.99	0.99	1.00	1.00	1.00
base macro + NFCI: QR-MIDAS	0.98	0.98	0.91	0.86 *	0.89 *	0.92	0.93	0.95
base macro-finance: BMF	0.95	0.99	0.90	0.88 *	0.90 *	0.92 *	0.94 *	0.95 *
base macro-finance: BMF-SV	0.92	0.98	0.88	0.88 *	0.89 *	0.90 **	0.93 **	0.94 **
base macro-finance: QR	0.89	1.01	0.89	0.86	0.89 *	0.92 *	0.93	0.94
base macro-finance: BQR	0.96	1.00	0.91	0.90 *	0.90 *	0.91 *	0.93 **	0.94 **
base macro-finance: QR-MIDAS	1.01	1.00	0.85	0.84 *	0.86 *	0.91	0.91 **	0.93 *
base macro + small weekly: BMF	1.01	1.06	1.00	1.03	1.02	1.01	0.99	0.98
base macro + small weekly: BMF-SV	1.01	1.05	0.99	1.02	1.00	1.00	0.98	0.97 *
base macro + small weekly: QR	0.95	1.00	0.86 **	0.91 **	0.93 *	0.91	0.93	0.94
base macro + small weekly: BQR	1.05	1.11	1.04	1.07	1.05	1.05	1.02	1.01
base macro + small weekly: QR-MIDAS	0.93 *	0.95 *	0.89 **	0.82 **	0.87 *	0.89 *	0.87 **	0.91 *
base macro + large weekly: BMF	1.02	1.06	1.00	1.03	1.02	1.02	1.01	1.01
base macro + large weekly: BMF-SV	1.01	1.02	0.99	1.01	0.97	0.99	0.99	0.99
base macro + large weekly: QR	0.89	0.87 **	0.86 **	0.90	0.83 **	0.90	0.92 *	0.92
base macro + large weekly: BQR	1.06	1.10	1.03	1.06	1.07	1.08	1.06	1.06
base macro + large weekly: QR-MIDAS	0.96	0.94	0.78 **	0.80 **	0.82 **	0.87 *	0.87 **	0.90 **
base macro-finance + small weekly: BMF	0.95	1.02	0.88 *	0.91	0.93	0.92 *	0.92 **	0.94 **
base macro-finance + small weekly: BMF-SV	0.94 *	1.00	0.86 *	0.90 *	0.90 *	0.90 **	0.90 **	0.90 ***
base macro-finance + small weekly: QR	0.87	1.00	0.81 *	0.86	0.87	0.90	0.91	0.87 *
base macro-finance + small weekly: BQR	0.99	1.05	0.90 *	0.94	0.94	0.94	0.93 **	0.94 **
base macro-finance + small weekly: QR-MIDAS	0.92	1.00	0.81	0.75 **	0.86 **	0.81 **	0.83 **	0.84 ***
base macro-finance + large weekly: BMF	0.96 *	1.01	0.89	0.92	0.92	0.92 *	0.92 **	0.94 **
base macro-finance + large weekly: BMF-SV	0.93 **	0.97 *	0.87 *	0.89	0.88 *	0.89 **	0.90 **	0.90 **
base macro-finance + large weekly: QR	0.75 **	0.91	0.79 *	0.79 *	0.79 **	0.86 *	0.91	0.81 **
base macro-finance + large weekly: BQR	1.00	1.05	0.92 *	0.95	0.96	0.96	0.95	0.96
base macro-finance + large weekly: QR-MIDAS	0.93	0.91	0.72 **	0.72 **	0.74 **	0.78 ***	0.81 **	0.80 ***

Notes: The top row gives the RMSEs of nowcasts from the benchmark model and variable set. Other rows report the ratio of RMSEs for the indicated variable set and model to the benchmark. The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). Statistical significance of differences in MSEs is indicated by *** (1%), ** (5%), or * (10%), obtained with the Diebold and Mariano–West t-test, conducted on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark.

Table 5: **In-sample forecast accuracy: 5% QS, 1996:Q3-2019:Q4**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
base macro ex claims: BMF-SV	0.22	0.19	0.22	0.19	0.17	0.17	0.16	0.16
base macro: BMF	1.20	1.20	1.13	1.19	1.23	1.19	1.20	1.22
base macro: BMF-SV	1.00	1.01	1.02	0.99	0.98	0.99	0.99	1.00
base macro: QR	0.65 *	0.81	0.84	0.88 ***	0.82 *	0.79 *	0.89	0.90
base macro: BQR	0.96	0.87	0.92	0.91	0.93	0.89	0.89	0.91
base macro: QR-MIDAS	1.12	1.02	0.78 *	0.74 *	0.85	0.92	0.98	1.21
base macro + NFCI: BMF	1.08	1.08	1.04	1.07	1.10	1.08	1.10	1.14
base macro + NFCI: BMF-SV	0.96	0.96 **	0.97 *	0.92 **	0.95 *	0.93 **	0.98	0.99
base macro + NFCI: QR	0.64 *	0.81	0.83	0.88 ***	0.80	0.92	0.93	0.88
base macro + NFCI: BQR	0.96	0.86	0.90 *	0.91	0.92	0.89	0.88	0.90
base macro + NFCI: QR-MIDAS	0.82	0.94	0.72 *	0.69 *	0.76 *	0.87	0.91	0.94
base macro-finance: BMF	1.02	1.05	0.91	0.90	0.96	0.96	1.02	1.07
base macro-finance: BMF-SV	0.95	0.96	0.85	0.79 *	0.86	0.83	0.89	0.94
base macro-finance: QR	0.56 **	0.77	0.72 *	0.62 **	0.74 *	0.69 **	0.77 **	0.74 ***
base macro-finance: BQR	0.86	0.90	0.74 *	0.72 *	0.82	0.81	0.86	0.88 *
base macro-finance: QR-MIDAS	0.82	0.82	0.61 ***	0.64 **	0.75 *	0.80 *	0.77 **	0.87
base macro + small weekly: BMF	1.10	1.18	1.08	1.16	1.13	1.08	1.06	1.06
base macro + small weekly: BMF-SV	1.02	1.09	1.01	1.08	1.10	1.04	1.02	0.99
base macro + small weekly: QR	0.74	0.75 *	0.73 ***	0.71 *	0.69 **	0.64 ***	0.59 ***	0.56 ***
base macro + small weekly: BQR	1.03	1.10	0.98	0.99	0.93	0.89	0.89	0.89 *
base macro + small weekly: QR-MIDAS	0.79	0.82	0.63 **	0.60 **	0.69 **	0.70 **	0.71 ***	0.76 ***
base macro + large weekly: BMF	1.11	1.19	1.08	1.17	1.15	1.11	1.09	1.12
base macro + large weekly: BMF-SV	1.02	1.12	1.03	1.10	1.10	1.08	1.06	1.07
base macro + large weekly: QR	0.62 **	0.54 ***	0.57 ***	0.64 **	0.55 ***	0.55 ***	0.53 ***	0.49 ***
base macro + large weekly: BQR	1.06	1.13	1.01	1.04	0.97	0.92	0.93	0.92
base macro + large weekly: QR-MIDAS	0.81	0.65 **	0.44 ***	0.55 ***	0.55 ***	0.63 ***	0.64 ***	0.65 ***
base macro-finance + small weekly: BMF	1.04	1.06	0.89	0.88	0.97	0.93	1.00	0.99
base macro-finance + small weekly: BMF-SV	0.98	1.03	0.84 *	0.88	0.90	0.85	0.87	0.92
base macro-finance + small weekly: QR	0.46 ***	0.58 ***	0.52 ***	0.55 **	0.55 ***	0.58 ***	0.52 ***	0.47 ***
base macro-finance + small weekly: BQR	0.85	0.86	0.69 **	0.72 *	0.79	0.78 *	0.79 **	0.82 **
base macro-finance + small weekly: QR-MIDAS	0.60 **	0.65 **	0.49 ***	0.43 ***	0.62 **	0.71 *	0.69 ***	0.72 ***
base macro-finance + large weekly: BMF	1.06	1.10	0.88	0.93	0.96	0.94	0.97	1.02
base macro-finance + large weekly: BMF-SV	0.98	1.06	0.84 *	0.90	0.87	0.85	0.91	0.96
base macro-finance + large weekly: QR	0.38 ***	0.44 ***	0.45 ***	0.46 ***	0.43 ***	0.40 ***	0.36 ***	0.36 ***
base macro-finance + large weekly: BQR	0.90	0.89	0.69 **	0.75	0.81	0.77 *	0.81 **	0.83 **
base macro-finance + large weekly: QR-MIDAS	0.58 **	0.51 ***	0.38 ***	0.36 ***	0.43 ***	0.46 ***	0.52 ***	0.56 ***

Notes: The top row gives the 5% quantile scores (QS) from the benchmark model and variable set. Other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). Statistical significance of differences in quantile scores is indicated by *** (1%), ** (5%), or * (10%), obtained with the Diebold and Mariano–West t-test, conducted on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark.

Table 6: **In-sample forecast accuracy during recessions: RMSE and 5% QS, 1971:Q2-2019:Q4**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	RMSE							
base macro ex claims: BMF-SV	4.42	3.86	4.19	3.69	3.34	3.17	3.00	2.95
base macro: BMF	0.99	1.00	1.00	1.00	1.00	1.00	1.01	1.01
base macro: BMF-SV	0.99	1.01	1.00	1.01	1.01	1.01	1.01	1.01
base macro: QR	0.76	0.83	0.76	0.78	0.78	0.81	0.88	0.80
base macro: BQR	0.91	0.93	0.95	0.90	0.92	0.94	0.97	0.97
base macro: QR-MIDAS	0.94	0.82	0.77	0.68	0.75	0.86	0.94	0.92
base macro + NFCI: BMF	0.81	0.87	0.87	0.84	0.86	0.88	0.90	0.92
base macro + NFCI: BMF-SV	0.81	0.87	0.88	0.84	0.86	0.87	0.91	0.91
base macro + NFCI: QR	0.69	0.83	0.69	0.68	0.73	0.79	0.86	0.78
base macro + NFCI: BQR	0.87	0.93	0.93	0.88	0.89	0.92	0.93	0.94
base macro + NFCI: QR-MIDAS	0.74	0.66	0.57	0.59	0.63	0.84	0.90	0.93
base macro-finance: BMF	0.73	0.79	0.75	0.72	0.76	0.78	0.83	0.84
base macro-finance: BMF-SV	0.72	0.78	0.73	0.72	0.75	0.78	0.83	0.84
base macro-finance: QR	0.52	0.74	0.52	0.57	0.54	0.63	0.63	0.89
base macro-finance: BQR	0.78	0.83	0.81	0.76	0.79	0.81	0.87	0.88
base macro-finance: QR-MIDAS	0.51	0.57	0.46	0.53	0.49	0.71	0.83	0.90
	5% quantile score							
base macro ex claims: BMF-SV	0.72	0.58	0.62	0.55	0.45	0.45	0.39	0.33
base macro: BMF	1.17	1.19	1.25	1.14	1.25	1.19	1.23	1.33
base macro: BMF-SV	1.06	1.05	1.03	1.08	1.08	1.04	1.02	1.11
base macro: QR	0.32	0.42	0.46	0.66	0.69	0.39	0.47	0.42
base macro: BQR	0.72	0.45	0.65	0.65	0.72	0.64	0.67	0.67
base macro: QR-MIDAS	0.54	0.55	0.47	0.43	0.49	0.64	0.82	0.78
base macro + NFCI: BMF	0.80	0.85	0.91	0.77	0.81	0.76	0.89	0.99
base macro + NFCI: BMF-SV	0.77	0.79	0.87	0.79	0.79	0.74	0.83	0.88
base macro + NFCI: QR	0.32	0.43	0.41	0.50	0.50	0.42	0.42	0.38
base macro + NFCI: BQR	0.72	0.44	0.65	0.65	0.71	0.63	0.65	0.65
base macro + NFCI: QR-MIDAS	0.41	0.28	0.26	0.28	0.37	0.44	0.50	0.56
base macro-finance: BMF	0.64	0.66	0.60	0.53	0.55	0.54	0.64	0.73
base macro-finance: BMF-SV	0.66	0.61	0.57	0.53	0.59	0.54	0.65	0.73
base macro-finance: QR	0.16	0.32	0.28	0.22	0.16	0.23	0.23	0.26
base macro-finance: BQR	0.41	0.34	0.35	0.34	0.53	0.50	0.53	0.57
base macro-finance: QR-MIDAS	0.25	0.28	0.20	0.20	0.22	0.35	0.38	0.44

Notes: In the upper panel, the top row gives the RMSEs of nowcasts from the benchmark model and variable set for periods of NBER-dated recessions (on a quarterly basis), and other rows report the ratio of RMSEs for the indicated variable set and model to the benchmark. In the lower panel, the first row gives the 5% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table).

Table 7: **Out-of-sample forecast accuracy, 1985:Q1-2019:Q3**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	RMSE							
base macro ex claims: BMF-SV	1.90	1.83	1.78	1.67	1.59	1.54	1.48	1.45
base macro: BMF	0.99	0.99	1.00	1.00	0.99	1.01	1.01	1.01
base macro: BMF-SV	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
base macro: QR	1.11	1.23	1.13	1.08	1.10	1.12	1.16	1.21
base macro: BQR	0.97	0.98	1.04	1.01	1.01	1.00	1.01	1.02
base macro: QR-MIDAS	1.17	1.18	1.19	1.06	1.15	1.01	1.07	1.14
base macro + NFCI: BMF	0.97	0.97 *	1.00	1.00	1.00	1.01	1.01	1.02
base macro + NFCI: BMF-SV	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.02
base macro + NFCI: QR	1.23	1.31	1.13	1.08	1.14	1.21	1.19	1.35
base macro + NFCI: BQR	0.98	0.98	1.04	1.01	1.01	1.01	1.01	1.03
base macro + NFCI: QR-MIDAS	1.18	1.04	1.14	1.02	1.11	1.05	1.09	1.17
base macro-finance: BMF	1.02	0.97	0.99	0.97	0.97	0.98	1.00	1.01
base macro-finance: BMF-SV	1.04	1.02	0.99	0.98	0.98	0.98	1.00	1.02
base macro-finance: QR	1.36	1.46	1.21	1.08	1.19	1.29	1.38	1.56
base macro-finance: BQR	1.01	0.97	1.00	0.98	0.98	0.98	1.00	1.01
base macro-finance: QR-MIDAS	1.32	1.26	1.21	1.12	1.10	1.24	1.34	1.41
	5% quantile score							
base macro ex claims: BMF-SV	0.25	0.22	0.22	0.20	0.18	0.18	0.18	0.17
base macro: BMF	1.23	1.27	1.25	1.27	1.27	1.25	1.27	1.33
base macro: BMF-SV	0.97 *	0.99	0.95 **	0.98 ***	1.00	1.00	0.99	1.01
base macro: QR	1.19	1.42	1.22	1.21	1.13	1.18	1.58	1.88
base macro: BQR	1.24	1.26	1.22	1.21	1.24	1.21	1.25	1.30
base macro: QR-MIDAS	1.21	1.37	1.40	1.06	1.32	1.09	1.35	1.35
base macro + NFCI: BMF	1.04	1.15	1.12	1.09	1.13	1.11	1.15	1.19
base macro + NFCI: BMF-SV	0.86 **	0.93 ***	0.88 **	0.91 **	0.97	0.99	0.98	1.00
base macro + NFCI: QR	1.50	1.79	0.92	1.21	1.32	1.61	1.76	1.96
base macro + NFCI: BQR	0.91	1.01	0.93	0.98	1.02	0.99	0.97	0.98
base macro + NFCI: QR-MIDAS	1.11	1.22	0.97	0.96	1.12	1.00	1.01	1.04
base macro-finance: BMF	0.97	1.11	1.02	1.01	1.07	1.08	1.14	1.19
base macro-finance: BMF-SV	0.88	0.92 **	0.85	0.86	0.95	0.99	1.03	1.12
base macro-finance: QR	2.90	2.52	1.01	1.26	1.44	1.76	2.00	2.70
base macro-finance: BQR	0.91	0.92	0.84	0.86	0.96	0.93	0.95	1.03
base macro-finance: QR-MIDAS	1.85	1.87	1.28	1.39	1.20	1.46	1.18	1.35
	5% coverage							
base macro ex claims: BMF-SV	0.04	0.04	0.04	0.03 *	0.04	0.04	0.04	0.03 *
base macro: BMF	0.01 **	0.01 ***	0.02 *	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***
base macro: BMF-SV	0.04	0.04	0.04	0.03 *	0.04	0.04	0.04	0.03 *
base macro: QR	0.04	0.06	0.03 *	0.06	0.02 ***	0.08	0.08	0.12 ***
base macro: BQR	0.01 ***	0.01 ***	0.02 *	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***
base macro: QR-MIDAS	0.04	0.04	0.04	0.05	0.01 ***	0.03	0.04	0.04
base macro + NFCI: BMF	0.02 *	0.01 ***	0.02 *	0.02 **	0.01 ***	0.01 ***	0.01 ***	0.01 ***
base macro + NFCI: BMF-SV	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
base macro + NFCI: QR	0.14 **	0.16 ***	0.05	0.06	0.07	0.07	0.07	0.14 ***
base macro + NFCI: BQR	0.03	0.01 ***	0.02 *	0.02 **	0.02 **	0.03	0.03	0.04
base macro + NFCI: QR-MIDAS	0.10 *	0.11 **	0.04	0.05	0.04	0.06	0.01 ***	0.05
base macro-finance: BMF	0.02 *	0.01 ***	0.02 *	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***
base macro-finance: BMF-SV	0.09	0.05	0.06	0.06	0.04	0.04	0.04	0.04
base macro-finance: QR	0.25 ***	0.21 ***	0.11 *	0.09 *	0.09 *	0.09 *	0.13 ***	0.17 ***
base macro-finance: BQR	0.05	0.01 ***	0.04	0.03	0.04	0.03	0.03	0.04
base macro-finance: QR-MIDAS	0.13 ***	0.15 ***	0.17 ***	0.12 ***	0.10 **	0.12 ***	0.08	0.07

Notes: The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). In the top panel, the first top row gives the RMSEs of nowcasts from the benchmark model and variable set. Other rows report the ratio of RMSEs for the indicated variable set and model to the benchmark. In the middle panel, the top row gives the 5% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). The bottom panel reports empirical coverage rates for 5% quantile forecasts (percentage of outcomes at or below the quantile). Statistical significance of differences in MSEs and quantile scores is indicated by *** (1%), ** (5%), or * (10%), obtained with the Diebold and Mariano–West t-test, conducted on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark. Statistical significance of departures of empirical coverage from the nominal 5% is also indicated by *** (1%), ** (5%), or * (10%), obtained with two-sided t-tests.

Table 8: **Out-of-sample forecast accuracy: RMSE, 2000:Q1-2019:Q3**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	RMSE							
base macro ex claims: BMF-SV	2.04	1.91	1.92	1.81	1.71	1.69	1.61	1.56
base macro: BMF	0.97	0.99	1.01	1.00	0.99	1.00	1.01	1.01
base macro: BMF-SV	0.97 *	1.00	1.00	1.00	1.00	0.99 *	0.99 **	0.99
base macro: QR	0.99	1.13	1.03	1.00	1.03	1.05	1.10	1.13
base macro: BQR	0.94	0.98	1.04	1.00	1.00	0.99	1.01	1.02
base macro: QR-MIDAS	1.11	0.99	1.02	0.94	1.00	0.91	0.97	0.96
base macro + NFCI: BMF	0.95	0.98	1.00	0.99	0.98	0.99	1.00	1.01
base macro + NFCI: BMF-SV	0.95	0.99	0.99	0.98	0.98	0.99	0.98	1.00
base macro + NFCI: QR	1.03	1.12	1.01	1.02	1.10	1.14	1.12	1.26
base macro + NFCI: BQR	0.94	0.98	1.02	0.99	0.98	0.99	1.00	1.02
base macro + NFCI: QR-MIDAS	1.06	0.94	0.97	0.93	0.99	0.98	0.99	1.03
base macro-finance: BMF	0.94	0.96	0.93	0.91	0.91	0.93	0.96	0.98
base macro-finance: BMF-SV	0.93	0.97	0.91	0.91	0.92	0.93	0.95	0.97
base macro-finance: QR	0.93	1.07	1.03	0.98	1.07	1.07	1.21	1.32
base macro-finance: BQR	0.91	0.94	0.93	0.91	0.91	0.93	0.95	0.97
base macro-finance: QR-MIDAS	1.11	1.04	1.02	0.95	0.93	1.05	1.14	1.21
base macro + small weekly: BMF	1.04	1.10	1.04	1.08	1.07	1.07	1.07	1.06
base macro + small weekly: BMF-SV	1.03	1.09	1.02	1.05	1.05	1.04	1.03	1.02
base macro + small weekly: QR	1.16	1.28	1.10	1.30	1.17	1.32	1.30	1.31
base macro + small weekly: BQR	1.05	1.10	1.06	1.09	1.10	1.09	1.09	1.07
base macro + small weekly: QR-MIDAS	1.18	1.23	1.13	1.00	1.04	1.06	1.13	1.09
base macro-finance + small weekly: BMF	1.00	1.05	0.96	1.00	1.00	1.01	1.02	1.02
base macro-finance + small weekly: BMF-SV	1.01	1.05	0.95	0.99	0.99	0.99	1.00	1.00
base macro-finance + small weekly: QR	1.49	1.35	1.06	1.36	1.42	1.84	1.65	1.95
base macro-finance + small weekly: BQR	0.97	1.04	0.93	0.98	0.99	0.99	1.00	1.00
base macro-finance + small weekly: QR-MIDAS	1.08	1.57	1.32	1.31	1.11	1.55	1.13	1.30
	5% quantile score							
base macro ex claims: BMF-SV	0.28	0.23	0.25	0.22	0.20	0.20	0.19	0.18
base macro: BMF	1.05	1.10	1.03	1.08	1.08	1.07	1.10	1.14
base macro: BMF-SV	0.96 **	1.00	0.95 *	0.97 ***	0.99	1.00	0.98	1.00
base macro: QR	1.00	1.22	1.01	1.19	1.08	1.24	1.24	1.49
base macro: BQR	1.08	1.12	0.95	1.01	1.03	1.03	1.08	1.12
base macro: QR-MIDAS	0.96	1.02	0.92	0.92	1.29	1.15	1.25	1.45
base macro + NFCI: BMF	0.95	1.03	0.94	0.97	1.00	0.98	1.03	1.05
base macro + NFCI: BMF-SV	0.89 *	0.98	0.88 *	0.92	0.95	0.96	0.98	0.98
base macro + NFCI: QR	1.03	1.25	0.71	1.17	1.35	1.54	1.50	1.58
base macro + NFCI: BQR	0.88	0.93	0.75	0.93	0.96	0.96	0.95	0.96
base macro + NFCI: QR-MIDAS	1.02	1.10	0.81	0.86	1.06	1.03	0.89	1.01
base macro-finance: BMF	0.90	1.01	0.84	0.86	0.92	0.95	1.01	1.05
base macro-finance: BMF-SV	0.86	0.95	0.78	0.78	0.83	0.85	0.90	0.93
base macro-finance: QR	1.68	1.30	0.80	0.94	1.20	1.39	1.88	1.94
base macro-finance: BQR	0.90	0.94	0.73	0.79	0.89	0.87	0.92	1.02
base macro-finance: QR-MIDAS	1.18	1.18	0.98	1.00	1.01	1.27	1.07	1.20
base macro + small weekly: BMF	1.07	1.21	1.02	1.08	1.02	1.00	0.98	0.94 *
base macro + small weekly: BMF-SV	1.08	1.14	0.96	0.98	0.95	0.97	0.96	0.94
base macro + small weekly: QR	1.61	2.27	1.34	1.86	2.10	2.37	1.95	2.82
base macro + small weekly: BQR	1.03	1.27	1.01	1.10	1.04	1.04	1.02	0.97
base macro + small weekly: QR-MIDAS	1.12	1.47	1.30	1.24	1.29	1.75	1.61	1.29
base macro-finance + small weekly: BMF	0.89	1.04	0.79	0.90	0.86	0.85	0.89	0.89 *
base macro-finance + small weekly: BMF-SV	0.89	0.96	0.80	0.90	0.88	0.91	0.95	1.00
base macro-finance + small weekly: QR	2.51	3.72	1.54	2.52	2.16	2.51	2.84	4.91
base macro-finance + small weekly: BQR	0.86	1.03	0.76	0.84	0.86	0.86	0.92	0.97
base macro-finance + small weekly: QR-MIDAS	1.49	3.47	2.10	2.17	1.85	1.78	1.35	1.88

Notes: The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). In the top panel, the first top row gives the RMSEs of nowcasts from the benchmark model and variable set. Other rows report the ratio of RMSEs for the indicated variable set and model to the benchmark. In the bottom panel, the top row gives the 5% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). Statistical significance of differences in MSEs and quantile scores is indicated by *** (1%), ** (5%), or * (10%), obtained with the Diebold and Mariano–West t-test, conducted on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark.

Table 9: **Out-of-sample forecast accuracy during recessions: RMSE and 5% QS, 1985:Q1-2019:Q3**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	RMSE							
base macro ex claims: BMF-SV	3.52	2.98	3.43	2.82	2.49	2.34	2.09	1.94
base macro: BMF	0.98	0.97	1.00	1.01	1.00	1.00	1.02	1.04
base macro: BMF-SV	0.98	1.00	0.97	0.99	0.99	0.99	0.99	0.99
base macro: QR	0.90	1.02	0.85	1.01	1.03	1.20	1.28	1.40
base macro: BQR	1.03	1.06	1.10	1.08	1.08	1.05	1.09	1.14
base macro: QR-MIDAS	0.91	0.95	0.72	0.75	0.78	0.71	0.82	0.80
base macro + NFCI: BMF	1.01	0.99	0.97	1.02	1.00	1.00	1.04	1.08
base macro + NFCI: BMF-SV	0.98	1.01	0.91	0.96	0.96	0.97	0.99	1.03
base macro + NFCI: QR	0.80	1.17	0.73	0.96	1.12	1.35	1.33	1.74
base macro + NFCI: BQR	1.06	1.06	1.04	1.03	1.02	1.02	1.05	1.12
base macro + NFCI: QR-MIDAS	0.94	0.84	0.63	0.81	0.77	0.85	0.86	0.89
base macro-finance: BMF	0.98	0.98	0.86	0.86	0.82	0.82	0.89	0.95
base macro-finance: BMF-SV	0.92	0.97	0.79	0.81	0.76	0.77	0.84	0.89
base macro-finance: QR	0.73	0.84	0.78	0.76	0.96	1.16	1.49	1.72
base macro-finance: BQR	0.98	0.96	0.88	0.86	0.81	0.81	0.89	0.97
base macro-finance: QR-MIDAS	0.93	0.96	0.84	0.70	0.75	1.06	1.18	1.37
	5% quantile score							
base macro ex claims: BMF-SV	0.71	0.39	0.65	0.52	0.44	0.37	0.29	0.23
base macro: BMF	0.64	0.62	0.72	0.75	0.73	0.80	0.90	0.98
base macro: BMF-SV	0.97	1.01	0.89	0.96	0.95	0.98	0.95	0.94
base macro: QR	0.28	0.52	0.52	1.36	1.05	1.46	1.36	2.75
base macro: BQR	0.41	0.51	0.52	0.76	0.77	0.75	0.88	0.92
base macro: QR-MIDAS	0.37	0.59	0.56	0.50	0.62	0.79	1.13	0.95
base macro + NFCI: BMF	0.62	0.59	0.64	0.66	0.65	0.66	0.73	0.82
base macro + NFCI: BMF-SV	0.93	1.06	0.80	0.82	0.85	0.89	0.89	0.91
base macro + NFCI: QR	0.66	1.61	0.33	1.33	1.54	2.43	2.85	2.99
base macro + NFCI: BQR	0.74	0.61	0.39	0.76	0.82	0.94	0.97	0.98
base macro + NFCI: QR-MIDAS	0.80	1.37	0.25	0.50	0.84	0.53	0.79	0.79
base macro-finance: BMF	0.49	0.54	0.30	0.28	0.34	0.43	0.58	0.72
base macro-finance: BMF-SV	0.78	0.92	0.58	0.45	0.40	0.45	0.57	0.67
base macro-finance: QR	2.08	1.36	0.61	0.65	0.84	1.14	3.43	3.28
base macro-finance: BQR	0.80	0.67	0.30	0.43	0.58	0.56	0.83	0.98
base macro-finance: QR-MIDAS	0.99	1.81	0.44	0.52	0.81	0.54	0.74	1.09

Notes: In the upper panel, the top row gives the RMSEs of nowcasts from the benchmark model and variable set for periods of NBER-dated recessions (on a quarterly basis), and other rows report the ratio of RMSEs for the indicated variable set and model to the benchmark. In the lower panel, the first row gives the 5% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table).

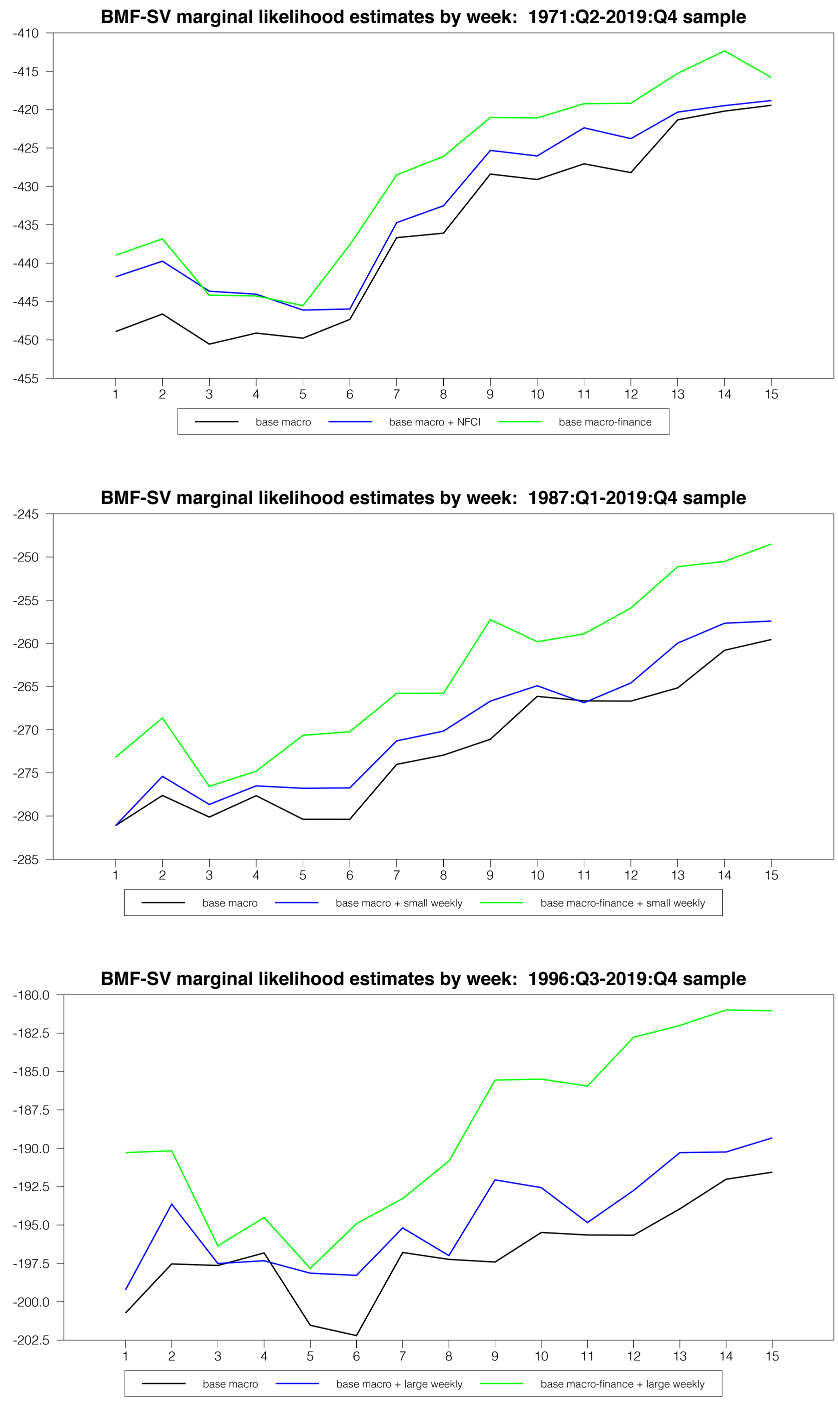


Figure 1: Marginal likelihoods, BMF-SV models fit over different time samples and variable sets. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

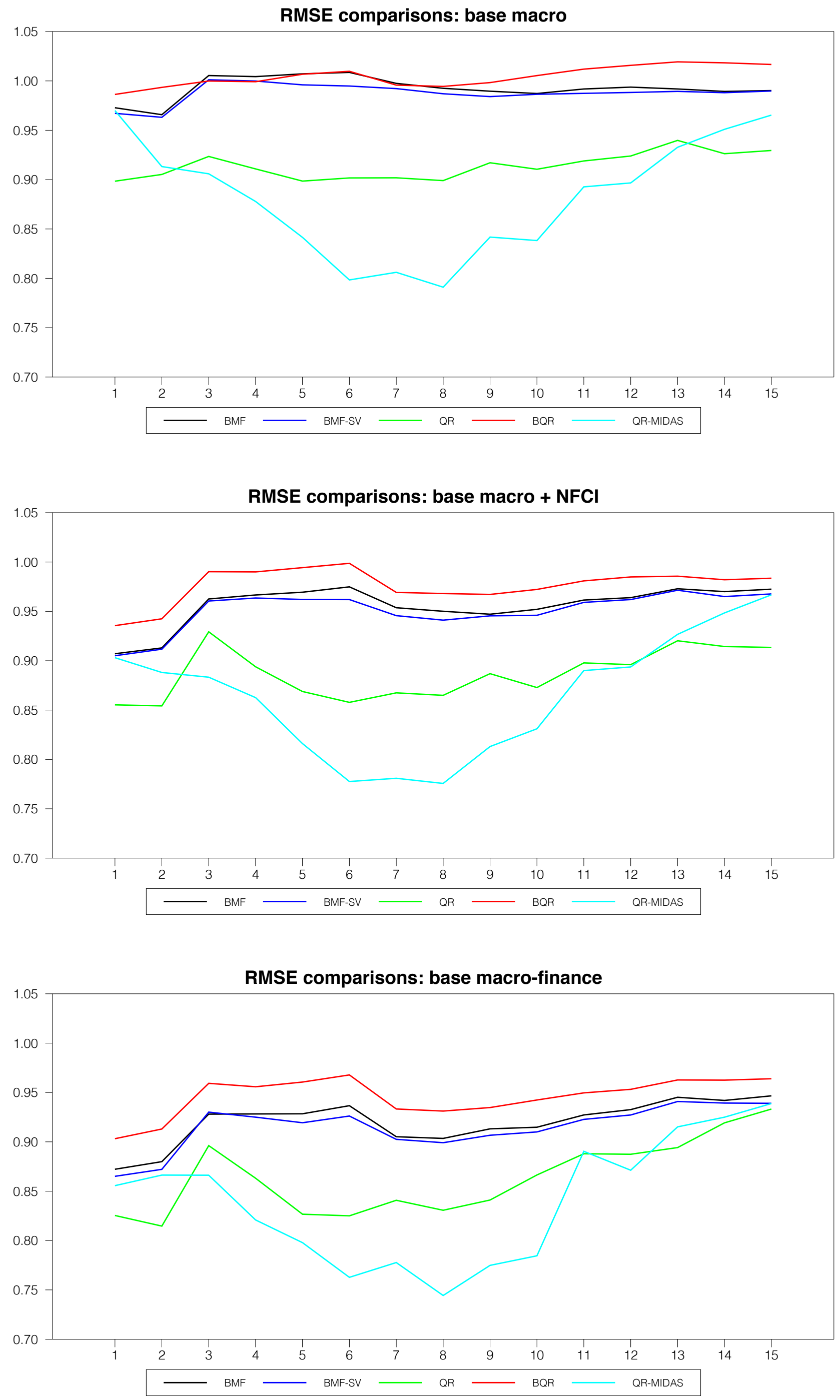


Figure 2: In-sample forecast accuracy, 1971:Q2-2019:Q4: comparisons of RMSE across variable sets (indicated in panel header) and models (indicated in key label). RMSEs are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

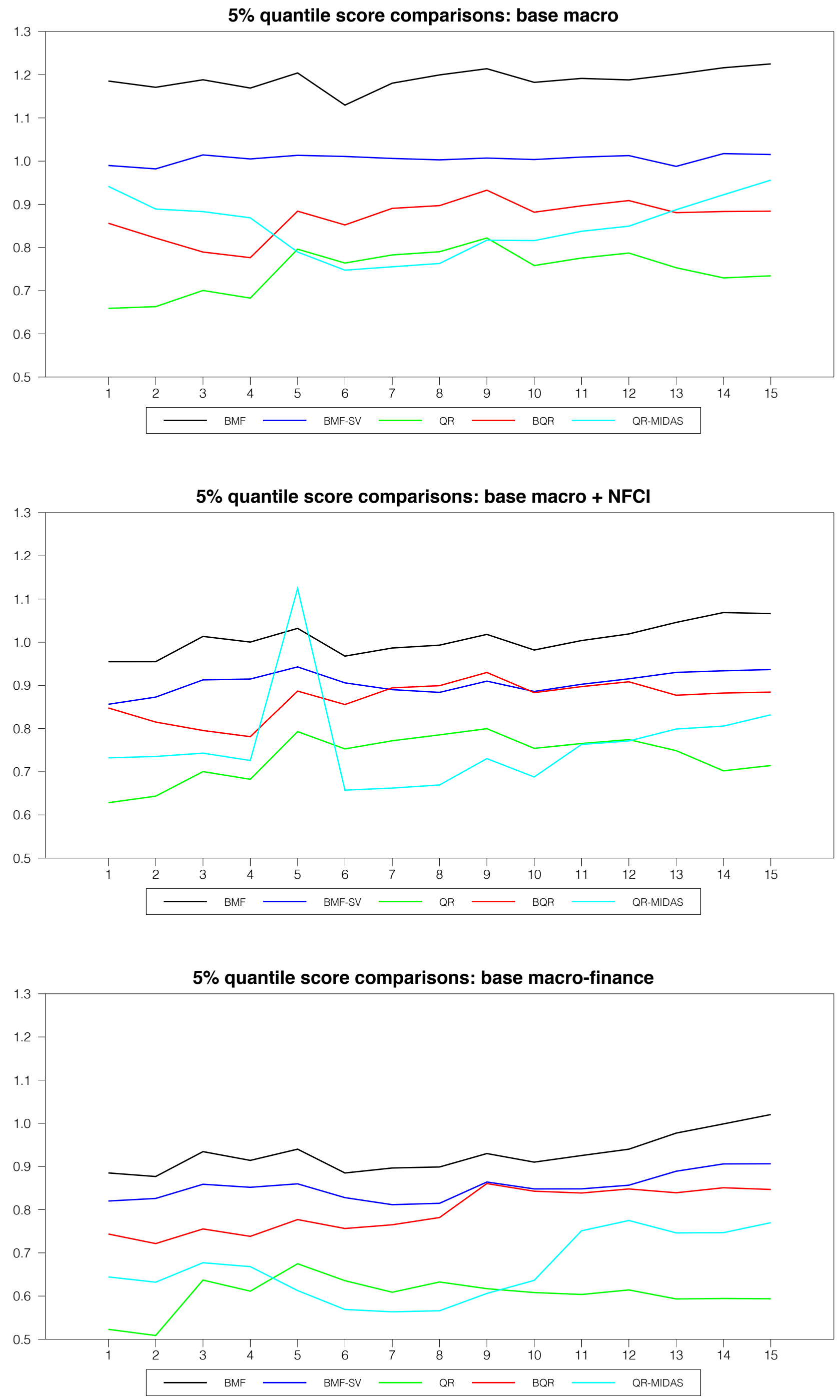


Figure 3: In-sample forecast accuracy, 1971:Q2-2019:Q4: comparisons of 5% QS across variable sets (indicated in panel header) and models (indicated in key label). Scores are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

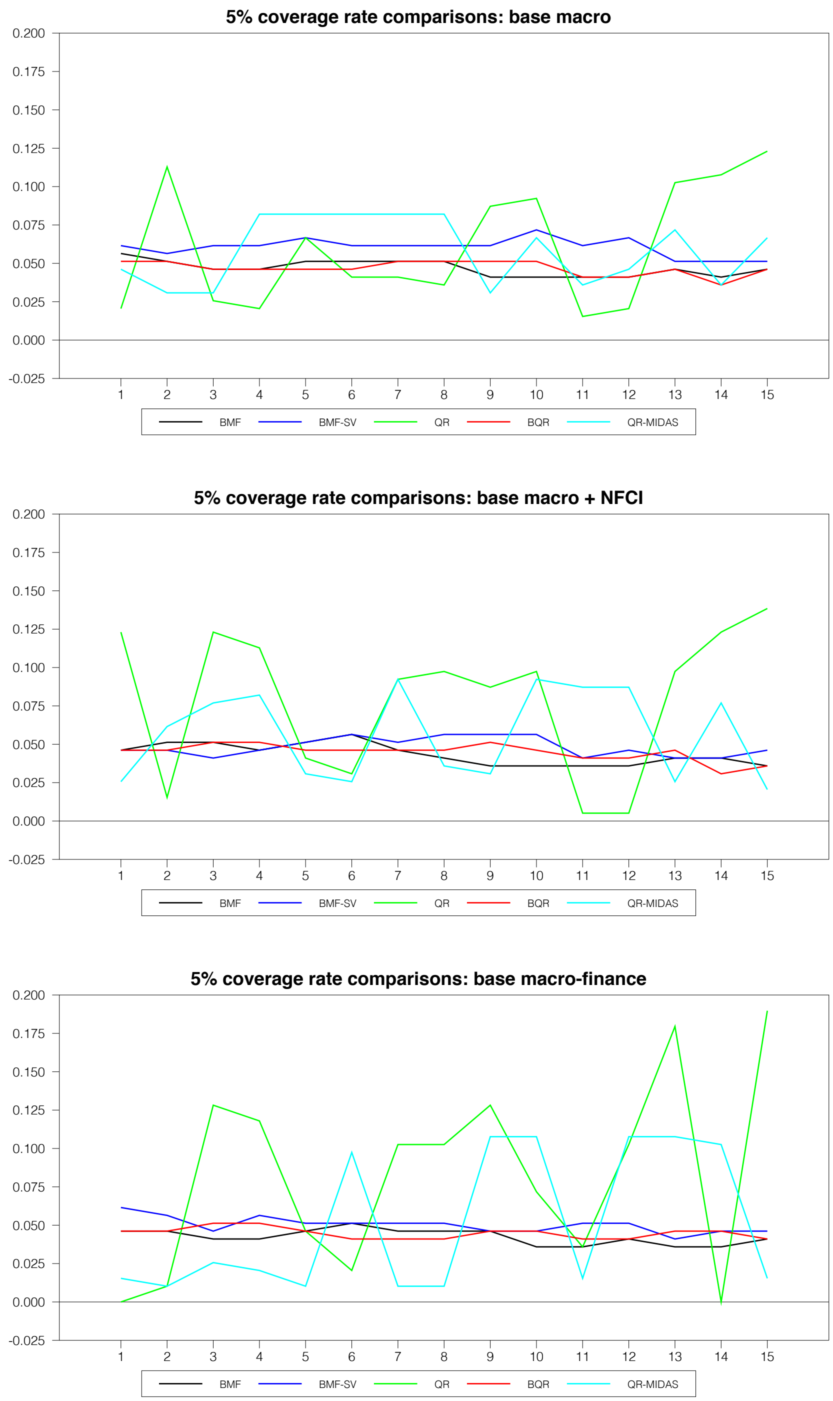


Figure 4: In-sample forecast accuracy, 1971:Q2-2019:Q4: comparisons of 5% coverage rates across variable sets (indicated in panel header) and models (indicated in key label). The black horizontal line at 0.05 denotes the nominal coverage rate. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure 5: In-sample forecast accuracy, 1996:Q3-2019:Q4: comparisons of RMSE across variable sets (indicated in panel header) and models (indicated in key label). RMSEs are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure 6: In-sample forecast accuracy, 1996:Q3-2019:Q4: comparisons of 5% QS across variable sets (indicated in panel header) and models (indicated in key label). Scores are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

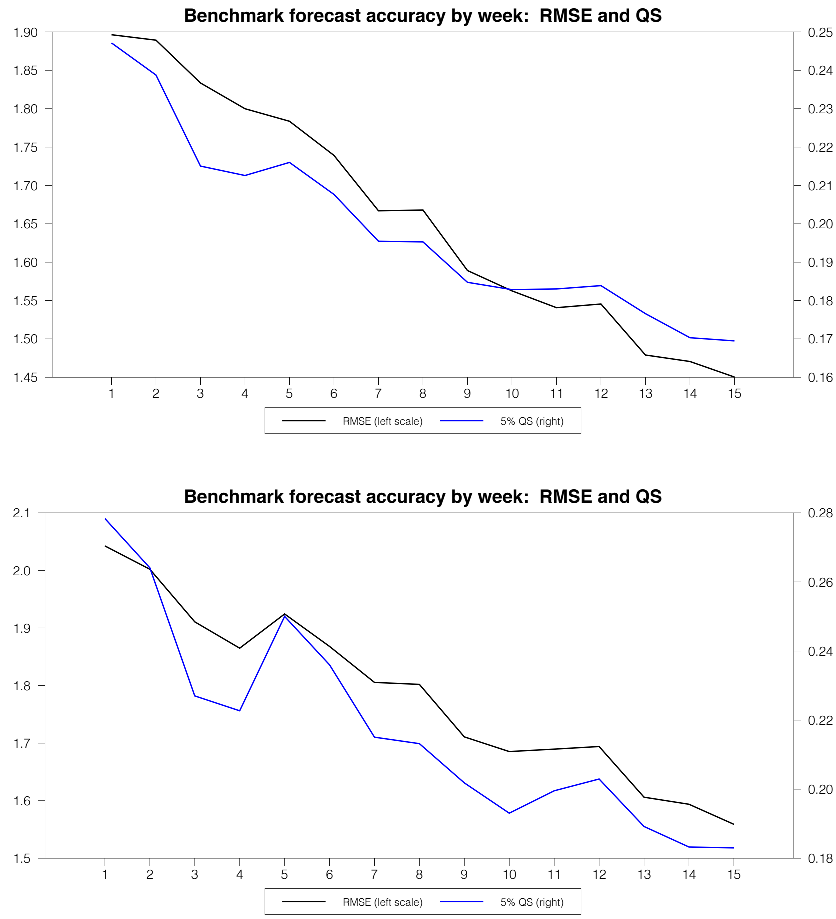


Figure 7: Out-of-sample forecast accuracy of benchmark forecasts: levels of RMSE and 5% QS across weeks 1 through 15 of forecast origins are indicated on the horizontal axis. The benchmark forecasts come from the BMF-SV model estimated with the base macro variable set excluding initial claims. The top and bottom panels provide results for the 1985:Q1-2019:Q3 and 2000:Q1-2019:Q3 samples, respectively.

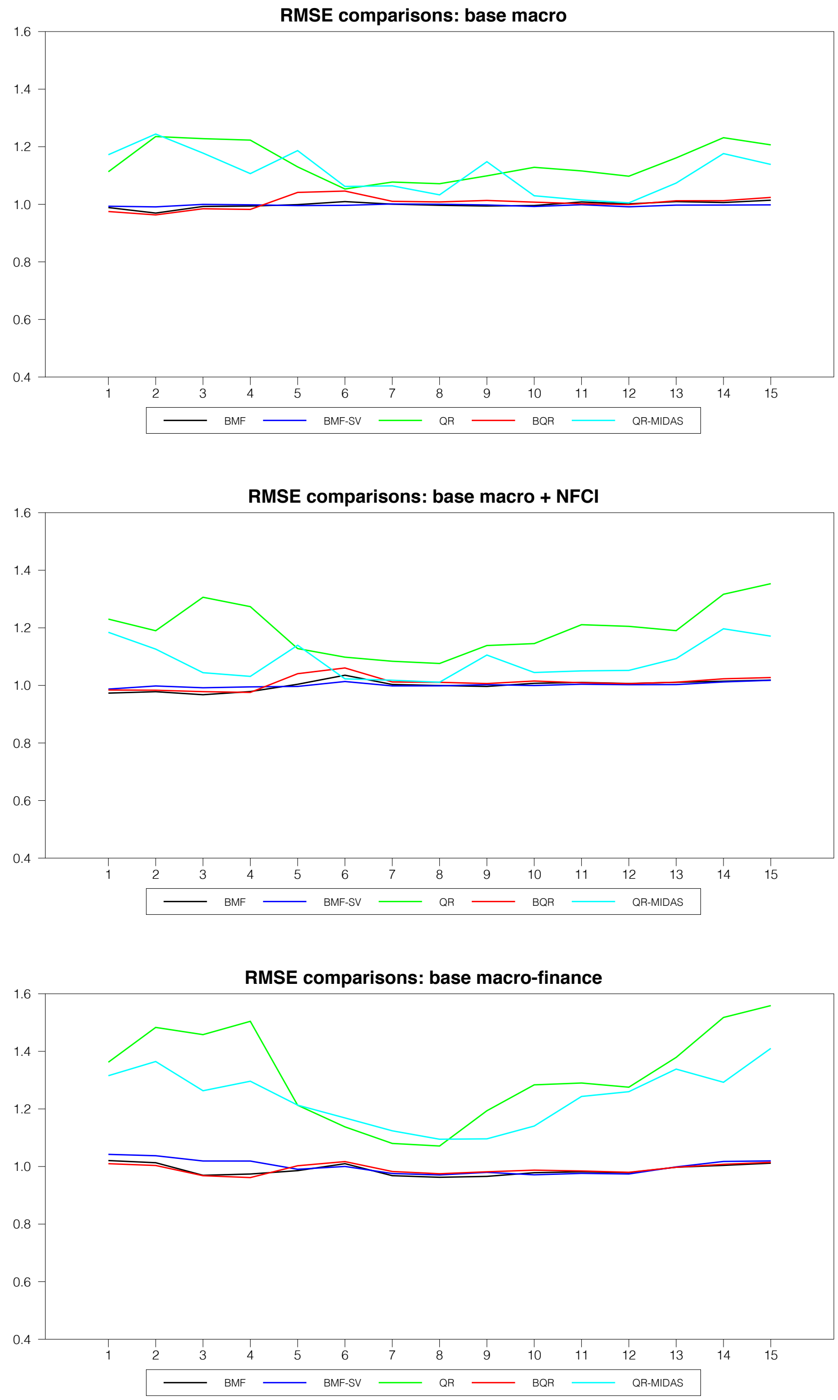


Figure 8: Out-of-sample forecast accuracy, 1985:Q1-2019:Q3: comparisons of RMSE across variable sets (indicated in panel header) and models (indicated in key label). RMSEs are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure 9: Out-of-sample forecast accuracy, 1985:Q1-2019:Q3: comparisons of 5% QS across variable sets (indicated in panel header) and models (indicated in key label). Scores are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

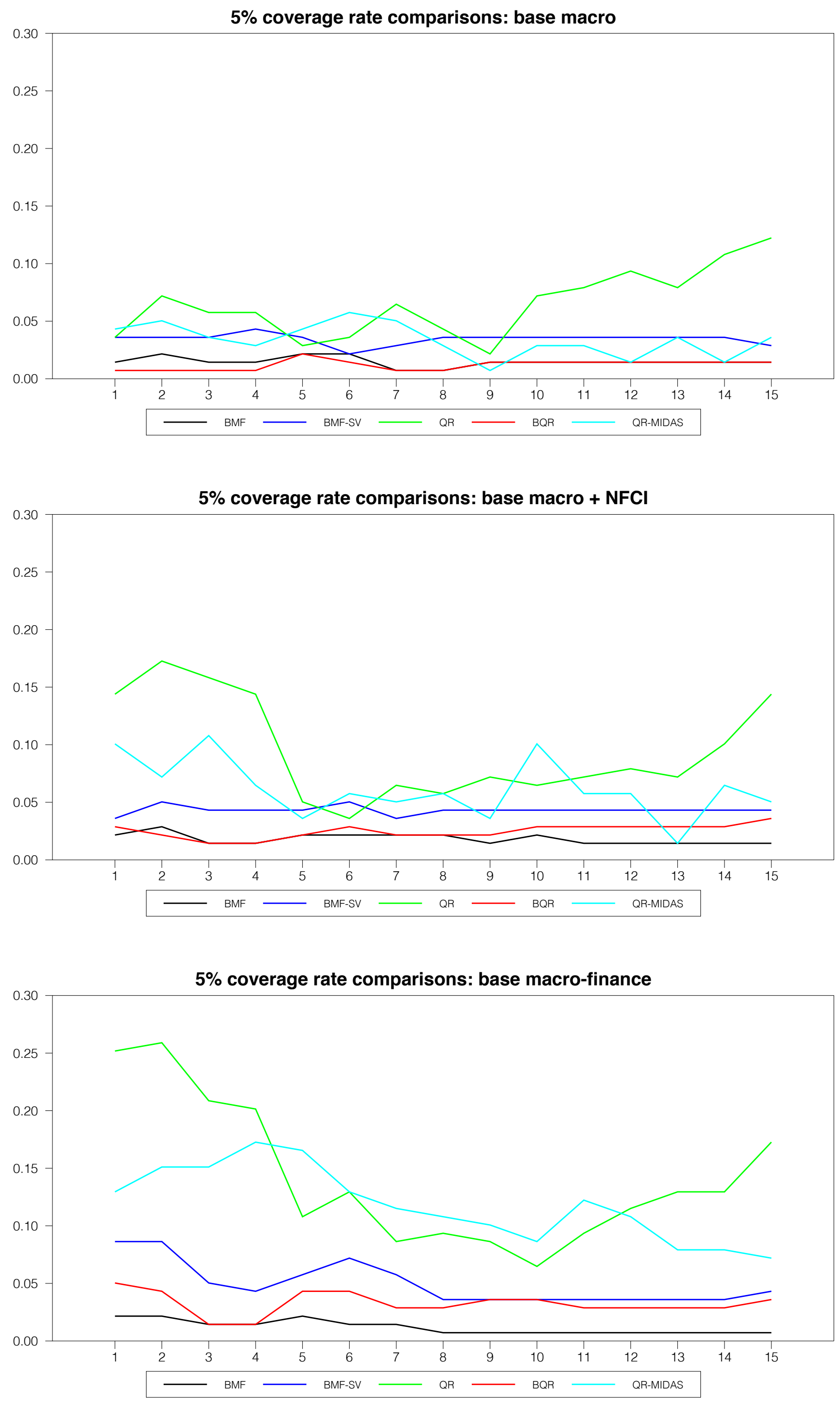


Figure 10: Out-of-sample forecast accuracy, 1985:Q1-2019:Q3: comparisons of 5% coverage rates across variable sets (indicated in panel header) and models (indicated in key label). The black horizontal line at 0.05 denotes the nominal coverage rate. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure 11: Out-of-sample forecast accuracy, 2000:Q1-2019:Q3: comparisons of RMSE across variable sets (indicated in panel header) and models (indicated in key label). RMSEs are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure 12: Out-of-sample forecast accuracy, 2000:Q1-2019:Q3: comparisons of 5% QS across variable sets (indicated in panel header) and models (indicated in key label). Scores are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

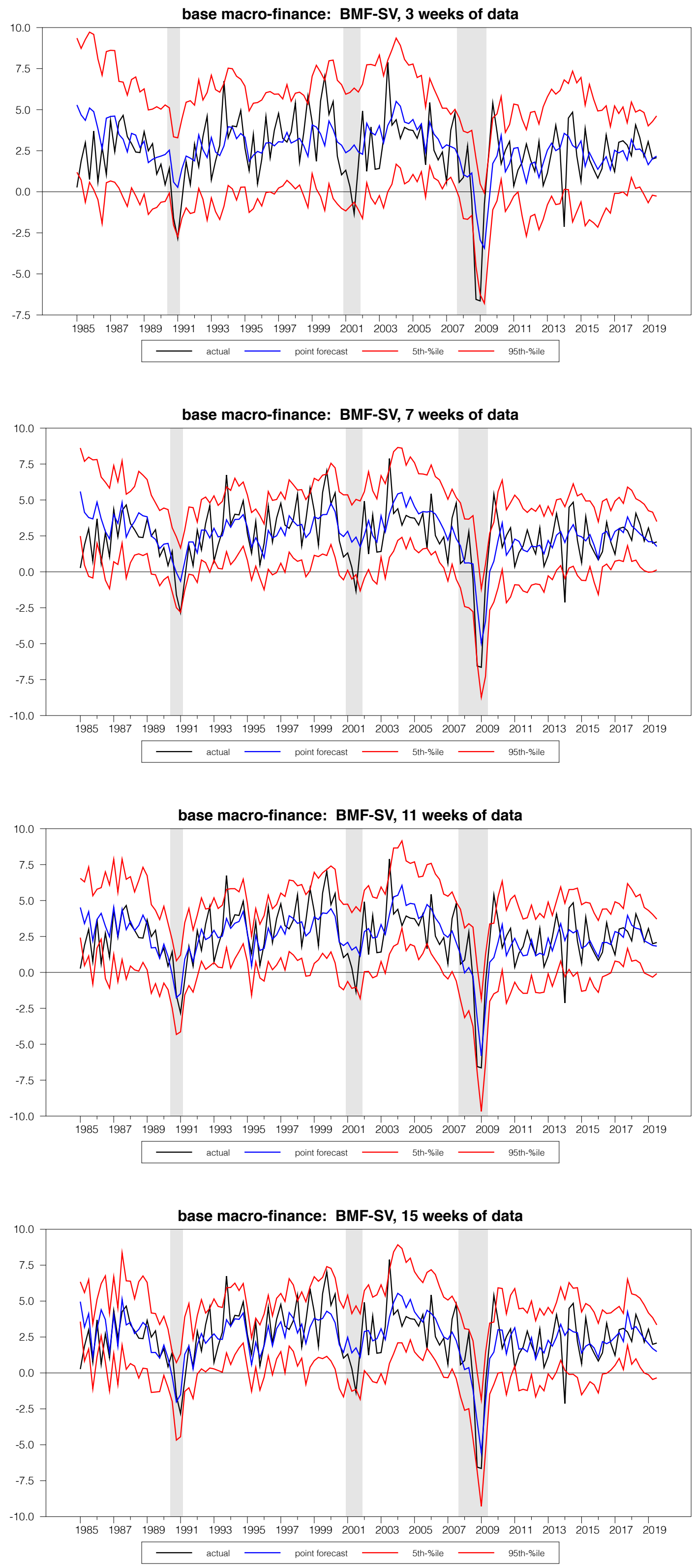


Figure 13: Out-of-sample forecasts from the base macro and finance variable set and BMF-SV model, selected weeks indicated in panel headers. Each panel reports actual GDP growth (black line), the point forecast (blue line), and 5%-95% forecast quantiles (red lines). Shaded regions denote NBER recessions.

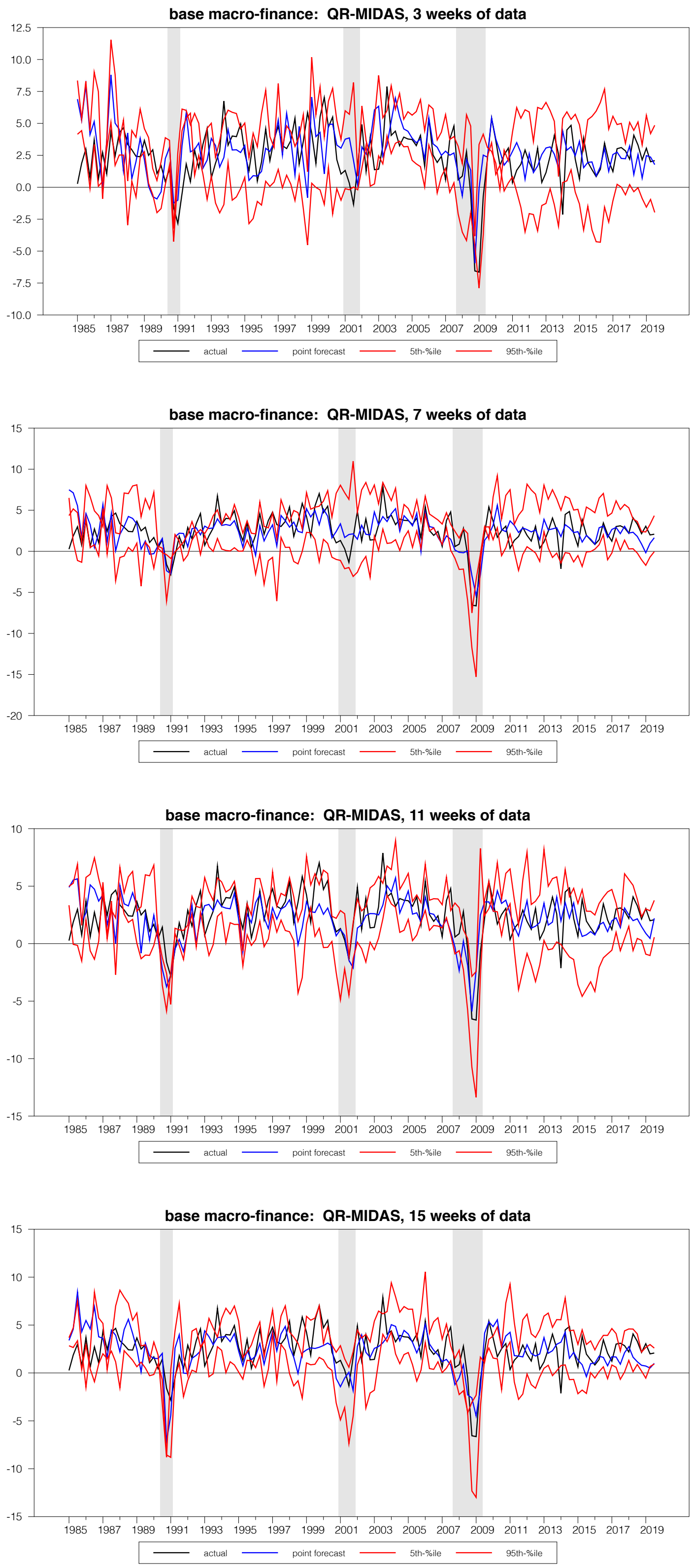


Figure 14: Out-of-sample forecasts from the base macro and finance variable set and QR-MIDAS model, selected weeks indicated in panel headers. Each panel reports actual GDP growth (black line), the point forecast (blue line), and 5%-95% forecast quantiles (red lines). Shaded regions denote NBER recessions.

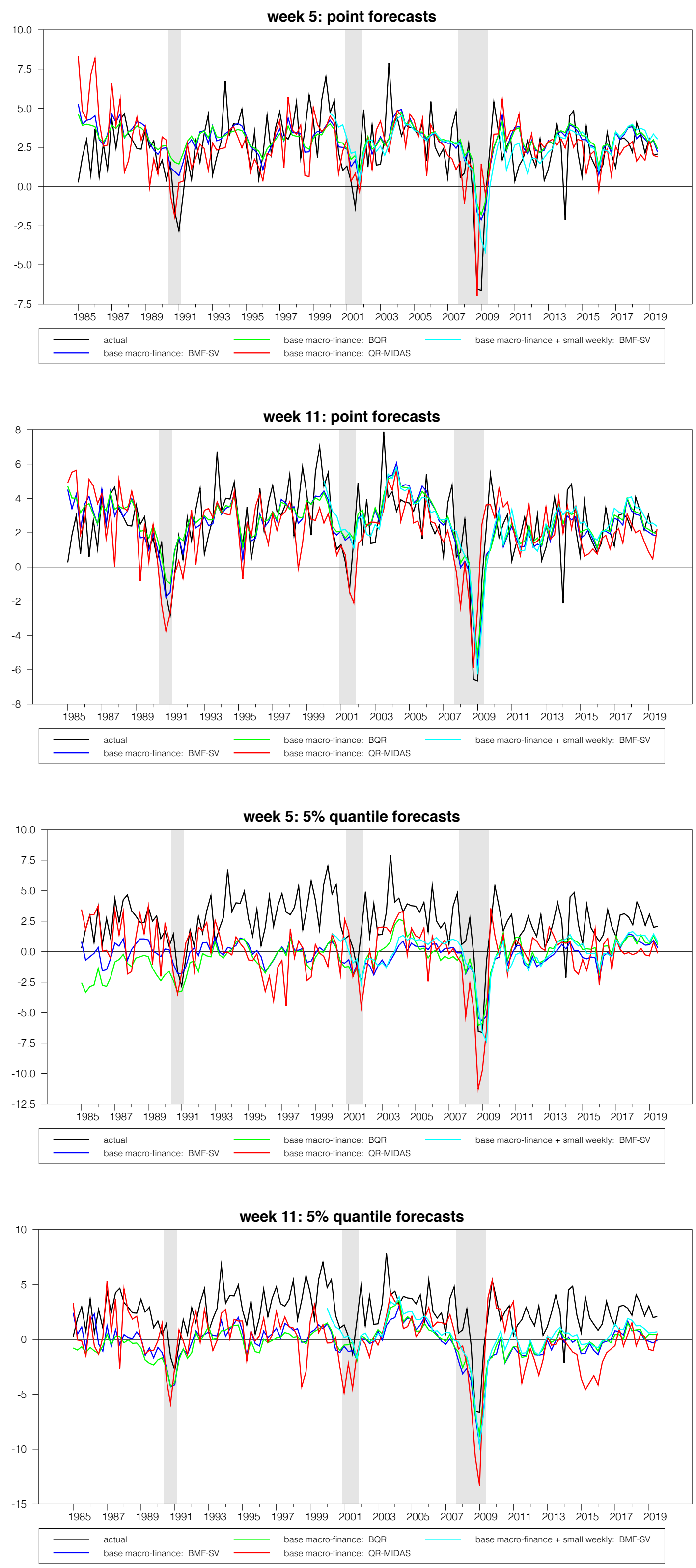


Figure 15: Comparisons of in-sample forecasts (point and 5 percent quantile) across selected variable-model combinations (indicated in key labels for each chart), for selected weeks of the quarter, indicated in panel headers. Shaded regions denote NBER recessions.

Figure 16: Forecasts of GDP growth in 2020:Q1 from selected variable sets and models, for weeks in which data were available up through mid-April 2020. Weeks of forecast origin are indicated on the horizontal axis. The left column of figures provides point forecasts, and the right column provides 5 percent quantile forecasts.

A Appendix

Table A1: Data sources

indicator	*data source*
real GDP	RTDSM
payroll employment	RTDSM
ISM purchasing managers index, manufacturing	FAME
retail sales (nominal/CPI)	ALFRED for retail sales, BLS website for CPI
industrial production	RTDSM
housing starts	RTDSM
initial claims for unemployment insurance	FAME (monthly), FRED (weekly)
Chicago Fed index of financial conditions	FRED
S&P index of stock prices	FAME
term spread: 10-year less 1-year Treasury rates	FAME
credit spread: Moody's Baa yield less 10-year Treasury	FAME
Bloomberg index of consumer comfort	Bloomberg
raw steel production	Haver Analytics
electric utility output	Haver Analytics
loadings of railroad cars	Haver Analytics
fuel sales	Energy Information Agency website
Redbook same-store retail sales	Haver Analytics

Notes: RTDSM refers to the Federal Reserve Bank of Philadelphia's Real-Time Data Set for Macroeconomists. FAME refers to the FAME database of the Federal Reserve Board of Governors. FRED is the Federal Reserve Bank of St. Louis' public database; ALFRED, also maintained by the St. Louis Fed, is an archive of FRED containing real-time data.

Table A2: **In-sample forecast accuracy: 5% coverage rates, 1996:Q3-2019:Q4**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
base macro ex claims: BMF-SV	0.04	0.03	0.05	0.04	0.03	0.04	0.03	0.03
base macro: BMF	0.02 *	0.01 ***	0.02 *	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***
base macro: BMF-SV	0.04	0.04	0.06	0.03	0.03	0.03	0.02 **	0.02 **
base macro: QR	0.02 **	0.03	0.06	0.02 **	0.06	0.00 ***	0.07	0.10 *
base macro: BQR	0.05	0.04	0.04	0.05	0.05	0.04	0.04	0.05
base macro: QR-MIDAS	0.03	0.02 **	0.05	0.04	0.02 **	0.02 **	0.04	0.04
base macro + NFCI: BMF	0.03	0.02 **	0.03	0.02 *	0.01 ***	0.01 ***	0.02 **	0.01 ***
base macro + NFCI: BMF-SV	0.05	0.03	0.06	0.04	0.05	0.02 **	0.02 **	0.03
base macro + NFCI: QR	0.11 *	0.10 *	0.03	0.06	0.06	0.00 ***	0.05	0.11 *
base macro + NFCI: BQR	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.04
base macro + NFCI: QR-MIDAS	0.03	0.07	0.02 **	0.05	0.01 ***	0.07	0.03	0.02 **
base macro-finance: BMF	0.03	0.02 **	0.03	0.01 ***	0.02 **	0.01 ***	0.01 ***	0.02 **
base macro-finance: BMF-SV	0.06	0.04	0.05	0.04	0.03	0.03	0.02 **	0.02 **
base macro-finance: QR	0.00 ***	0.14 ***	0.04	0.06	0.10	0.04	0.12 **	0.15 ***
base macro-finance: BQR	0.04	0.04	0.03	0.03	0.04	0.03	0.04	0.04
base macro-finance: QR-MIDAS	0.03	0.03	0.01 ***	0.01 ***	0.09	0.01 ***	0.11 *	0.03
base macro + small weekly: BMF	0.04	0.06	0.05	0.04	0.05	0.04	0.05	0.04
base macro + small weekly: BMF-SV	0.05	0.07	0.07	0.05	0.07	0.06	0.06	0.05
base macro + small weekly: QR	0.01 ***	0.00 ***	0.11 *	0.11 **	0.01 ***	0.14 ***	0.19 ***	0.20 ***
base macro + small weekly: BQR	0.05	0.05	0.05	0.03	0.06	0.06	0.06	0.05
base macro + small weekly: QR-MIDAS	0.03	0.11 **	0.07	0.00 ***	0.03	0.13 ***	0.03	0.11 *
base macro + large weekly: BMF	0.03	0.05	0.03	0.03	0.04	0.04	0.03	0.04
base macro + large weekly: BMF-SV	0.06	0.07	0.07	0.06	0.06	0.06	0.06	0.05
base macro + large weekly: QR	0.00 ***	0.00 ***	0.13 ***	0.10	0.00 ***	0.22 ***	0.23 ***	0.29 ***
base macro + large weekly: BQR	0.04	0.04	0.04	0.04	0.03	0.04	0.05	0.04
base macro + large weekly: QR-MIDAS	0.01 ***	0.02 **	0.01 ***	0.16 ***	0.00 ***	0.16 **	0.00 ***	0.00 ***
base macro-finance + small weekly: BMF	0.05	0.06	0.05	0.05	0.05	0.04	0.03	0.03
base macro-finance + small weekly: BMF-SV	0.05	0.05	0.06	0.06	0.06	0.06	0.03	0.05
base macro-finance + small weekly: QR	0.13 *	0.00 ***	0.15 ***	0.09	0.22 ***	0.14 ***	0.00 ***	0.30 ***
base macro-finance + small weekly: BQR	0.04	0.04	0.03	0.04	0.04	0.04	0.03	0.04
base macro-finance + small weekly: QR-MIDAS	0.02 **	0.17 ***	0.16 ***	0.18 ***	0.17 ***	0.11 **	0.01 ***	0.01 ***
base macro-finance + large weekly: BMF	0.04	0.05	0.04	0.05	0.04	0.04	0.03	0.03
base macro-finance + large weekly: BMF-SV	0.07	0.07	0.05	0.06	0.09	0.05	0.04	0.05
base macro-finance + large weekly: QR	0.34 ***	0.00 ***	0.00 ***	0.03	0.00 ***	0.33 ***	0.43 ***	0.46 ***
base macro-finance + large weekly: BQR	0.03	0.03	0.04	0.04	0.04	0.02 **	0.02 **	0.02 **
base macro-finance + large weekly: QR-MIDAS	0.16 ***	0.24 ***	0.00 ***	0.14 ***	0.24 ***	0.23 ***	0.26 ***	0.00 ***

Notes: The table reports empirical coverage rates for 5% quantile forecasts (percentage of outcomes at or below the quantile). The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). Statistical significance of departures of empirical coverage from the nominal 5% is indicated by *** (1%), ** (5%), or * (10%), obtained with two-sided t-tests.

Table A3: **In-sample forecast accuracy: 10% QS and coverage rates, 1971:Q2-2019:Q4**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	10% quantile score							
base macro ex claims: BMF-SV	0.45	0.42	0.42	0.39	0.36	0.35	0.34	0.33
base macro: BMF	1.13	1.13	1.13	1.11	1.12	1.11	1.13	1.14
base macro: BMF-SV	0.98 *	1.01	1.01	0.99	0.99	1.00	0.99	1.00
base macro: QR	0.74 ***	0.76 ***	0.83 **	0.81 ***	0.82 ***	0.81 ***	0.82 **	0.81 ***
base macro: BQR	0.90 **	0.89 ***	0.92 **	0.91 **	0.93 *	0.93 *	0.93 *	0.94 *
base macro: QR-MIDAS	1.03	0.92	0.83 **	0.77 ***	0.82 **	0.87 *	0.91	0.96
base macro + NFCI: BMF	0.96	1.01	1.02	0.97	1.00	1.00	1.01	1.03
base macro + NFCI: BMF-SV	0.87 ***	0.92 ***	0.94 ***	0.90 ***	0.92 **	0.93 **	0.94 **	0.94 **
base macro + NFCI: QR	0.70 ***	0.75 ***	0.82 **	0.79 ***	0.81 ***	0.80 ***	0.81 ***	0.80 ***
base macro + NFCI: BQR	0.88 ***	0.89 **	0.92 *	0.91 *	0.93 *	0.93 *	0.93 **	0.94 *
base macro + NFCI: QR-MIDAS	0.82 **	0.81 **	0.93	0.69 ***	0.75 ***	0.83 **	0.86 **	0.89 *
base macro-finance: BMF	0.91 **	0.94 *	0.94	0.90 **	0.93	0.94	0.98	0.99
base macro-finance: BMF-SV	0.84 ***	0.87 ***	0.88 **	0.84 ***	0.87 **	0.87 ***	0.89 ***	0.91 ***
base macro-finance: QR	0.63 ***	0.71 ***	0.73 ***	0.69 ***	0.68 ***	0.70 ***	0.68 ***	0.67 ***
base macro-finance: BQR	0.82 ***	0.81 ***	0.82 **	0.82 **	0.87 **	0.86 **	0.88 **	0.89 **
base macro-finance: QR-MIDAS	0.75 ***	0.76 ***	0.68 ***	0.63 ***	0.68 ***	0.79 ***	0.81 **	0.83 **
	10% coverage							
base macro ex claims: BMF-SV	0.09	0.10	0.09	0.09	0.10	0.08	0.09	0.09
base macro: BMF	0.08	0.09	0.07	0.07	0.07	0.07 **	0.06 **	0.07 **
base macro: BMF-SV	0.09	0.10	0.09	0.11	0.09	0.09	0.11	0.10
base macro: QR	0.06 **	0.06 **	0.12	0.08	0.08	0.07 **	0.15 **	0.15 **
base macro: BQR	0.09	0.10	0.10	0.10	0.10	0.09	0.10	0.10
base macro: QR-MIDAS	0.08	0.07	0.13	0.13	0.12	0.13	0.13	0.09
base macro + NFCI: BMF	0.08	0.09	0.08	0.09	0.08	0.07 *	0.08	0.08
base macro + NFCI: BMF-SV	0.11	0.13	0.09	0.11	0.11	0.11	0.09	0.11
base macro + NFCI: QR	0.15 **	0.05 ***	0.08	0.13	0.14	0.06 ***	0.16 **	0.18 ***
base macro + NFCI: BQR	0.09	0.10	0.10	0.10	0.10	0.09	0.10	0.10
base macro + NFCI: QR-MIDAS	0.07	0.13	0.09	0.13	0.08	0.06 **	0.06 **	0.07 *
base macro-finance: BMF	0.08	0.09	0.08	0.09	0.08	0.08	0.07	0.08
base macro-finance: BMF-SV	0.10	0.10	0.11	0.10	0.11	0.10	0.08	0.10
base macro-finance: QR	0.03 ***	0.16 **	0.08	0.15 **	0.16 **	0.06 **	0.18 ***	0.23 ***
base macro-finance: BQR	0.09	0.09	0.10	0.09	0.09	0.08	0.08	0.08
base macro-finance: QR-MIDAS	0.07 **	0.11	0.07	0.07 **	0.15 **	0.14 *	0.14 **	0.15 **

Notes: The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). In the upper panel, the first row gives the 10% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). Statistical significance of differences in quantile scores is indicated by *** (1%), ** (5%), or * (10%), obtained with the Diebold and Mariano–West t-test, conducted on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark. The lower panel of the table reports empirical coverage rates for 10% quantile forecasts (percentage of outcomes at or below the quantile). Statistical significance of departures of empirical coverage from the nominal 10% is indicated by *** (1%), ** (5%), or * (10%), obtained with two-sided t-tests.

Table A4: **In-sample forecast accuracy: 10% QS, 1996:Q3-2019:Q4**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
base macro ex claims: BMF-SV	0.35	0.32	0.35	0.31	0.29	0.28	0.27	0.26
base macro: BMF	1.19	1.16	1.11	1.13	1.15	1.14	1.17	1.17
base macro: BMF-SV	0.99	1.01	1.02	0.97 **	0.99	1.00	1.01	1.00
base macro: QR	0.72 *	0.82	0.88	0.84 ***	0.93 *	0.88 *	1.01	0.96
base macro: BQR	1.00	0.98	0.94 *	0.98	0.99	0.97	0.98	0.98
base macro: QR-MIDAS	1.18	1.04	0.88	0.76 **	0.81 **	0.87	0.92	1.04
base macro + NFCI: BMF	1.09	1.08	1.03	1.03	1.07	1.05	1.09	1.12
base macro + NFCI: BMF-SV	0.97	0.98	0.98 *	0.94 **	0.98	0.98	1.01	1.00
base macro + NFCI: QR	0.76 *	0.84	0.87	0.87 **	0.94 *	0.93	0.98	0.96
base macro + NFCI: BQR	0.99	0.97	0.95 *	0.97	0.98	0.97	0.97	0.97
base macro + NFCI: QR-MIDAS	0.95	0.97	0.82	0.76 **	0.83 *	0.88	0.93	0.95
base macro-finance: BMF	1.07	1.05	0.93	0.92	0.97	0.98	1.05	1.07
base macro-finance: BMF-SV	0.95	0.95	0.87	0.85 *	0.88	0.87 *	0.92	0.95
base macro-finance: QR	0.68 **	0.84	0.77 *	0.75 **	0.88	0.89	0.92	0.91
base macro-finance: BQR	0.96	0.95	0.80 *	0.83	0.88	0.86	0.90	0.92
base macro-finance: QR-MIDAS	0.89	0.96	0.69 **	0.69 **	0.85	0.84 *	0.80 **	0.92
base macro + small weekly: BMF	1.11	1.14	1.09	1.12	1.11	1.08	1.07	1.08
base macro + small weekly: BMF-SV	1.03	1.07	1.02	1.06	1.06	1.03	1.04	1.01
base macro + small weekly: QR	0.88	0.84	0.78 ***	0.83 ***	0.78 *	0.77 **	0.71 ***	0.67 ***
base macro + small weekly: BQR	1.05	1.10	1.04	1.08	1.04	1.02	1.01	1.00
base macro + small weekly: QR-MIDAS	0.94	0.91	0.74 *	0.71 **	0.73 **	0.85	0.86 *	0.83 **
base macro + large weekly: BMF	1.13	1.14	1.11	1.15	1.15	1.12	1.13	1.12
base macro + large weekly: BMF-SV	1.04	1.08	1.06	1.07	1.05	1.06	1.06	1.05
base macro + large weekly: QR	0.75 *	0.65 ***	0.70 ***	0.77 **	0.66 ***	0.66 ***	0.65 ***	0.58 ***
base macro + large weekly: BQR	1.06	1.12	1.05	1.08	1.05	1.03	1.05	1.02
base macro + large weekly: QR-MIDAS	0.92	0.75 **	0.53 ***	0.67 ***	0.65 ***	0.73 **	0.77 **	0.75 **
base macro-finance + small weekly: BMF	1.03	1.05	0.90	0.95	0.98	0.94	0.99	0.99
base macro-finance + small weekly: BMF-SV	0.97	0.99	0.87 **	0.91	0.92	0.91	0.90 *	0.92
base macro-finance + small weekly: QR	0.59 ***	0.71 **	0.61 ***	0.63 **	0.66 ***	0.65 ***	0.62 ***	0.56 ***
base macro-finance + small weekly: BQR	0.93	0.98	0.80 *	0.86	0.88	0.86	0.84 *	0.86 **
base macro-finance + small weekly: QR-MIDAS	0.76 *	0.73 **	0.57 ***	0.52 ***	0.66 ***	0.78 **	0.76 ***	0.77 **
base macro-finance + large weekly: BMF	1.05	1.08	0.91	0.97	0.98	0.96	0.98	1.01
base macro-finance + large weekly: BMF-SV	0.98	1.03	0.87 *	0.93	0.89	0.90	0.89	0.91
base macro-finance + large weekly: QR	0.49 ***	0.53 ***	0.56 ***	0.55 ***	0.51 ***	0.48 ***	0.44 ***	0.43 ***
base macro-finance + large weekly: BQR	0.96	1.00	0.82 *	0.88	0.89	0.87	0.85 *	0.86 **
base macro-finance + large weekly: QR-MIDAS	0.70 **	0.62 ***	0.46 ***	0.45 ***	0.52 ***	0.55 ***	0.60 ***	0.66 ***

Notes: The top row gives the 10% quantile scores (QS) from the benchmark model and variable set. Other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). Statistical significance of differences in quantile scores is indicated by *** (1%), ** (5%), or * (10%), obtained with the Diebold and Mariano–West t-test, conducted on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark.

Table A5: **In-sample forecast accuracy: 10% coverage rates, 1996:Q3-2019:Q4**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
base macro ex claims: BMF-SV	0.11	0.12	0.07	0.09	0.11	0.07	0.07	0.07
base macro: BMF	0.04 ***	0.05 *	0.05 *	0.03 ***	0.03 ***	0.04 ***	0.03 ***	0.04 ***
base macro: BMF-SV	0.09	0.11	0.07	0.10	0.07	0.09	0.10	0.09
base macro: QR	0.07	0.07	0.11	0.06	0.07	0.06	0.15	0.15
base macro: BQR	0.11	0.12	0.11	0.12	0.12	0.12	0.14	0.13
base macro: QR-MIDAS	0.03 ***	0.06	0.09	0.12	0.07	0.11	0.11	0.07
base macro + NFCI: BMF	0.05 **	0.06	0.06	0.07	0.06	0.05 **	0.06	0.05 **
base macro + NFCI: BMF-SV	0.13	0.15	0.09	0.12	0.12	0.12	0.09	0.12
base macro + NFCI: QR	0.14	0.05 **	0.07	0.11	0.11	0.03 ***	0.12	0.16 *
base macro + NFCI: BQR	0.11	0.12	0.12	0.12	0.13	0.12	0.13	0.12
base macro + NFCI: QR-MIDAS	0.10	0.15	0.07	0.10	0.06	0.05 **	0.06	0.09
base macro-finance: BMF	0.06	0.07	0.04 ***	0.07	0.04 ***	0.05 **	0.04 ***	0.04 ***
base macro-finance: BMF-SV	0.10	0.11	0.09	0.10	0.09	0.09	0.05 **	0.07
base macro-finance: QR	0.05 **	0.16 *	0.09	0.11	0.12	0.02 ***	0.15	0.20 ***
base macro-finance: BQR	0.11	0.11	0.10	0.10	0.10	0.09	0.09	0.07
base macro-finance: QR-MIDAS	0.07	0.11	0.06	0.06	0.13	0.10	0.14	0.14
base macro + small weekly: BMF	0.09	0.09	0.10	0.10	0.10	0.11	0.10	0.09
base macro + small weekly: BMF-SV	0.11	0.13	0.12	0.12	0.11	0.11	0.10	0.12
base macro + small weekly: QR	0.04 ***	0.04 ***	0.15	0.15	0.05 **	0.18 **	0.21 ***	0.23 ***
base macro + small weekly: BQR	0.10	0.11	0.11	0.14	0.12	0.10	0.11	0.11
base macro + small weekly: QR-MIDAS	0.06	0.04 ***	0.07	0.07	0.05 **	0.15	0.06	0.17 **
base macro + large weekly: BMF	0.09	0.07	0.10	0.09	0.09	0.07	0.10	0.09
base macro + large weekly: BMF-SV	0.14	0.15	0.12	0.12	0.10	0.10	0.10	0.10
base macro + large weekly: QR	0.04 ***	0.00 ***	0.19 ***	0.03 ***	0.06	0.24 ***	0.04 ***	0.29 ***
base macro + large weekly: BQR	0.11	0.10	0.11	0.11	0.11	0.10	0.10	0.09
base macro + large weekly: QR-MIDAS	0.14	0.04 ***	0.20 ***	0.18 **	0.19 **	0.18 **	0.03 ***	0.19 **
base macro-finance + small weekly: BMF	0.07	0.09	0.10	0.10	0.07	0.10	0.06	0.07
base macro-finance + small weekly: BMF-SV	0.12	0.11	0.11	0.12	0.10	0.10	0.10	0.10
base macro-finance + small weekly: QR	0.16	0.22 ***	0.18 **	0.09	0.22 ***	0.15	0.02 ***	0.30 ***
base macro-finance + small weekly: BQR	0.10	0.11	0.11	0.11	0.10	0.10	0.09	0.09
base macro-finance + small weekly: QR-MIDAS	0.19 **	0.19 **	0.04 ***	0.04 ***	0.05 **	0.06	0.03 ***	0.07
base macro-finance + large weekly: BMF	0.07	0.07	0.07	0.06	0.07	0.07	0.06	0.06
base macro-finance + large weekly: BMF-SV	0.15	0.13	0.11	0.12	0.12	0.12	0.07	0.10
base macro-finance + large weekly: QR	0.34 ***	0.01 ***	0.03 ***	0.05 **	0.01 ***	0.24 ***	0.43 ***	0.46 ***
base macro-finance + large weekly: BQR	0.11	0.10	0.11	0.10	0.10	0.09	0.09	0.06
base macro-finance + large weekly: QR-MIDAS	0.20 ***	0.26 ***	0.02 ***	0.18 ***	0.26 ***	0.24 ***	0.27 ***	0.03 ***

Notes: The table reports empirical coverage rates for 10% quantile forecasts (percentage of outcomes at or below the quantile). The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). Statistical significance of departures of empirical coverage from the nominal 10% is indicated by *** (1%), ** (5%), or * (10%), obtained with two-sided t-tests.

Table A6: **Out-of-sample forecast accuracy: 5% coverage rates, 2000:Q1-2019:Q3**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
base macro ex claims: BMF-SV	0.06	0.06	0.05	0.04	0.05	0.05	0.05	0.04
base macro: BMF	0.03	0.03	0.04	0.01 ***	0.03	0.03	0.03	0.03
base macro: BMF-SV	0.05	0.06	0.05	0.04	0.05	0.05	0.05	0.04
base macro: QR	0.03	0.05	0.03	0.05	0.03	0.09	0.06	0.10
base macro: BQR	0.01 ***	0.01 ***	0.04	0.01 ***	0.03	0.03	0.03	0.03
base macro: QR-MIDAS	0.04	0.01 ***	0.03	0.04	0.01 ***	0.04	0.03	0.05
base macro + NFCI: BMF	0.04	0.03	0.04	0.04	0.03	0.03	0.03	0.03
base macro + NFCI: BMF-SV	0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.05
base macro + NFCI: QR	0.05	0.08	0.06	0.05	0.08	0.06	0.06	0.10 *
base macro + NFCI: BQR	0.05	0.03	0.04	0.04	0.04	0.05	0.05	0.06
base macro + NFCI: QR-MIDAS	0.10	0.11	0.04	0.05	0.03	0.06	0.01 ***	0.05
base macro-finance: BMF	0.04	0.03	0.04	0.03	0.01 ***	0.01 ***	0.01 ***	0.01 ***
base macro-finance: BMF-SV	0.09	0.06	0.06	0.05	0.03	0.04	0.04	0.05
base macro-finance: QR	0.16 **	0.13 *	0.11	0.08	0.08	0.11 *	0.11 **	0.14 *
base macro-finance: BQR	0.06	0.03	0.06	0.04	0.05	0.04	0.04	0.04
base macro-finance: QR-MIDAS	0.11	0.13 **	0.14 **	0.10 *	0.09	0.10	0.09	0.04
base macro + small weekly: BMF	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04
base macro + small weekly: BMF-SV	0.09	0.10	0.09	0.05	0.05	0.05	0.06	0.09
base macro + small weekly: QR	0.11	0.18 ***	0.15 **	0.13	0.14 **	0.18 **	0.18 ***	0.28 ***
base macro + small weekly: BQR	0.05	0.06	0.06	0.05	0.05	0.06	0.08	0.05
base macro + small weekly: QR-MIDAS	0.05	0.16 **	0.15 *	0.09	0.13 **	0.15 **	0.13 **	0.10
base macro-finance + small weekly: BMF	0.04	0.05	0.05	0.04	0.04	0.04	0.01 ***	0.01 ***
base macro-finance + small weekly: BMF-SV	0.09	0.09	0.09	0.06	0.09	0.11 *	0.09	0.14 **
base macro-finance + small weekly: QR	0.23 ***	0.28 ***	0.14 **	0.25 ***	0.24 ***	0.24 ***	0.23 ***	0.33 ***
base macro-finance + small weekly: BQR	0.04	0.06	0.06	0.05	0.05	0.06	0.06	0.06
base macro-finance + small weekly: QR-MIDAS	0.14 **	0.22 **	0.18 ***	0.20 ***	0.14 *	0.13 **	0.10	0.15 **

Notes: The table reports empirical coverage rates for 5% quantile forecasts (percentage of outcomes at or below the quantile). The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). Statistical significance of departures of empirical coverage from the nominal 5% is indicated by *** (1%), ** (5%), or * (10%), obtained with two-sided t-tests.

Table A7: **Out-of-sample forecast accuracy: 10% QS and coverage rates, 1985:Q1-2019:Q3**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	10% quantile score							
base macro ex claims: BMF-SV	0.37	0.34	0.33	0.30	0.29	0.28	0.27	0.26
base macro: BMF	1.31	1.30	1.28	1.28	1.29	1.29	1.31	1.36
base macro: BMF-SV	0.98	1.00	0.97 **	0.98 ***	1.00	1.00	1.01	1.01
base macro: QR	1.25	1.39	1.29	1.21	1.25	1.22	1.45	1.52
base macro: BQR	1.26	1.29	1.16	1.20	1.21	1.22	1.23	1.26
base macro: QR-MIDAS	1.36	1.22	1.39	1.06	1.19	1.06	1.13	1.30
base macro + NFCI: BMF	1.07	1.16	1.13	1.11	1.14	1.15	1.19	1.22
base macro + NFCI: BMF-SV	0.91 **	0.95 **	0.91 **	0.92 ***	0.95 **	0.98	0.98	1.00
base macro + NFCI: QR	1.29	1.43	0.93	1.25	1.38	1.44	1.47	1.70
base macro + NFCI: BQR	0.90 *	1.03	0.96	0.94 *	0.96	0.96	0.98	1.00
base macro + NFCI: QR-MIDAS	1.15	1.15	1.05	1.17	1.09	1.06	1.08	1.08
base macro-finance: BMF	1.02	1.11	1.05	1.06	1.09	1.10	1.16	1.20
base macro-finance: BMF-SV	0.98	0.95 *	0.94	0.89 *	0.95	0.99	1.03	1.08
base macro-finance: QR	2.16	1.88	1.16	1.27	1.37	1.56	1.56	2.17
base macro-finance: BQR	0.93	0.94	0.92	0.91	0.94	0.93	0.99	1.02
base macro-finance: QR-MIDAS	1.46	1.56	1.22	1.23	1.15	1.30	1.11	1.29
	10% coverage							
base macro ex claims: BMF-SV	0.06	0.05 **	0.06	0.05 ***	0.04 ***	0.06 **	0.05 ***	0.04 ***
base macro: BMF	0.02 ***	0.02 ***	0.02 ***	0.02 ***	0.02 ***	0.03 ***	0.01 ***	0.01 ***
base macro: BMF-SV	0.05 **	0.06	0.09	0.05 ***	0.04 ***	0.06 **	0.05 ***	0.05 ***
base macro: QR	0.07	0.08	0.06 **	0.05 ***	0.06 **	0.09	0.09	0.15
base macro: BQR	0.03 ***	0.03 ***	0.03 ***	0.03 ***	0.03 ***	0.03 ***	0.03 ***	0.02 ***
base macro: QR-MIDAS	0.06 *	0.05 ***	0.06 **	0.04 ***	0.04 ***	0.06 **	0.06 *	0.06
base macro + NFCI: BMF	0.03 ***	0.03 ***	0.03 ***	0.02 ***	0.02 ***	0.03 ***	0.03 ***	0.03 ***
base macro + NFCI: BMF-SV	0.09	0.09	0.11	0.05 ***	0.05 ***	0.05 ***	0.04 ***	0.05 ***
base macro + NFCI: QR	0.19 **	0.18 **	0.06 *	0.12	0.08	0.10	0.06 *	0.14
base macro + NFCI: BQR	0.06 *	0.04 ***	0.06 **	0.04 ***	0.04 ***	0.05 ***	0.04 ***	0.04 ***
base macro + NFCI: QR-MIDAS	0.12	0.11	0.10	0.08	0.05 ***	0.09	0.06 *	0.09
base macro-finance: BMF	0.05 ***	0.03 ***	0.04 ***	0.03 ***	0.03 ***	0.04 ***	0.03 ***	0.03 ***
base macro-finance: BMF-SV	0.13	0.09	0.12	0.07	0.07	0.06 **	0.06 *	0.06 **
base macro-finance: QR	0.26 ***	0.22 ***	0.18 **	0.13	0.11	0.09	0.14	0.22 ***
base macro-finance: BQR	0.07	0.04 ***	0.08	0.07	0.06 *	0.06 **	0.06 **	0.06 **
base macro-finance: QR-MIDAS	0.14	0.15	0.14	0.11	0.13	0.14	0.07	0.13

Notes: The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). In the upper panel, the first row gives the 10% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). Statistical significance of differences in quantile scores is indicated by *** (1%), ** (5%), or * (10%), obtained with the Diebold and Mariano–West t-test, conducted on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark. The lower panel of the table reports empirical coverage rates for 10% quantile forecasts (percentage of outcomes at or below the quantile). Statistical significance of departures of empirical coverage from the nominal 10% is indicated by *** (1%), ** (5%), or * (10%), obtained with two-sided t-tests.

Table A8: **Out-of-sample forecast accuracy: 10% QS and coverage rates, 2000:Q1-2019:Q3**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	10% quantile score							
base macro ex claims: BMF-SV	0.41	0.35	0.36	0.32	0.30	0.30	0.29	0.28
base macro: BMF	1.16	1.16	1.08	1.13	1.14	1.14	1.15	1.19
base macro: BMF-SV	0.97 *	1.01	0.98	0.97 ***	1.00	1.00	1.01	1.01
base macro: QR	1.06	1.26	1.06	1.21	1.26	1.15	1.17	1.15
base macro: BQR	1.11	1.17	0.94	1.05	1.07	1.07	1.05	1.07
base macro: QR-MIDAS	1.18	1.05	1.03	0.94	1.11	1.06	0.97	1.20
base macro + NFCI: BMF	1.03	1.07	0.98	1.04	1.07	1.08	1.09	1.12
base macro + NFCI: BMF-SV	0.91 **	0.97 *	0.90 *	0.95 *	0.96	1.00	0.99	1.00
base macro + NFCI: QR	1.03	1.13	0.81	1.25	1.40	1.39	1.32	1.44
base macro + NFCI: BQR	0.90	0.98	0.83 *	0.92	0.94	0.95	0.96	0.99
base macro + NFCI: QR-MIDAS	0.99	1.13	0.88	1.01	1.00	1.05	0.97	0.99
base macro-finance: BMF	1.00	1.05	0.91	0.96	0.99	1.00	1.04	1.07
base macro-finance: BMF-SV	0.93	0.96	0.87	0.85 *	0.89	0.91	0.95	0.98
base macro-finance: QR	1.45	1.14	0.95	1.03	1.27	1.28	1.28	1.73
base macro-finance: BQR	0.93	0.95	0.85	0.85	0.90	0.89	0.93	0.97
base macro-finance: QR-MIDAS	1.03	1.14	0.96	0.98	0.98	1.09	0.99	1.21
base macro + small weekly: BMF	1.04	1.14	1.03	1.09	1.02	1.01	0.99	0.98
base macro + small weekly: BMF-SV	1.05	1.11	1.02	1.02	0.98	0.95 *	0.96	0.96
base macro + small weekly: QR	1.33	1.80	1.18	1.44	1.62	1.76	1.56	1.92
base macro + small weekly: BQR	0.99	1.15	1.01	1.09	1.06	1.07	1.05	1.01
base macro + small weekly: QR-MIDAS	1.08	1.45	1.39	1.07	1.20	1.41	1.14	1.43
base macro-finance + small weekly: BMF	0.90	1.02	0.87	0.93	0.93	0.91	0.94	0.91
base macro-finance + small weekly: BMF-SV	0.90	1.00	0.88	0.95	0.98	0.99	0.99	1.03
base macro-finance + small weekly: QR	1.95	2.63	1.12	1.58	1.75	2.00	1.95	3.34
base macro-finance + small weekly: BQR	0.87	1.04	0.91	0.95	0.98	0.95	0.95	0.96
base macro-finance + small weekly: QR-MIDAS	1.34	2.55	1.54	1.80	1.54	1.51	1.24	1.57
	10% coverage							
base macro ex claims: BMF-SV	0.09	0.06	0.09	0.06	0.05 **	0.06	0.05 **	0.05 **
base macro: BMF	0.04 **	0.04 **	0.04 **	0.04 ***	0.04 ***	0.05 **	0.03 ***	0.03 ***
base macro: BMF-SV	0.08	0.08	0.11	0.06	0.05 **	0.06	0.05 **	0.06
base macro: QR	0.06	0.06	0.05 **	0.06	0.06	0.09	0.08	0.13
base macro: BQR	0.05	0.05	0.05	0.05 **	0.05 **	0.05 **	0.05 **	0.04 ***
base macro: QR-MIDAS	0.05 **	0.04 ***	0.05 **	0.05 **	0.04 ***	0.05 **	0.06	0.05 **
base macro + NFCI: BMF	0.05	0.05	0.05	0.04 ***	0.04 ***	0.05 **	0.05 **	0.05 **
base macro + NFCI: BMF-SV	0.08	0.10	0.10	0.06	0.05 **	0.06	0.05 **	0.06
base macro + NFCI: QR	0.15	0.11	0.08	0.13	0.10	0.10	0.08	0.11
base macro + NFCI: BQR	0.08	0.06	0.10	0.06	0.06	0.08	0.06	0.08
base macro + NFCI: QR-MIDAS	0.11	0.10	0.06	0.08	0.05 **	0.09	0.06	0.08
base macro-finance: BMF	0.06	0.05	0.05	0.04 ***	0.04 ***	0.05 **	0.04 ***	0.04 ***
base macro-finance: BMF-SV	0.11	0.09	0.11	0.08	0.08	0.06	0.08	0.06
base macro-finance: QR	0.18 *	0.11	0.18 *	0.13	0.11	0.09	0.13	0.22 **
base macro-finance: BQR	0.08	0.06	0.11	0.09	0.09	0.08	0.08	0.06
base macro-finance: QR-MIDAS	0.13	0.11	0.10	0.11	0.10	0.13	0.09	0.10
base macro + small weekly: BMF	0.06	0.08	0.10	0.06	0.09	0.08	0.06	0.08
base macro + small weekly: BMF-SV	0.13	0.13	0.14	0.14	0.13	0.10	0.11	0.10
base macro + small weekly: QR	0.09	0.20 *	0.14	0.16	0.16	0.16	0.18	0.30 ***
base macro + small weekly: BQR	0.06	0.09	0.14	0.11	0.10	0.10	0.10	0.10
base macro + small weekly: QR-MIDAS	0.06	0.16	0.18	0.13	0.16 **	0.15	0.13	0.10
base macro-finance + small weekly: BMF	0.08	0.08	0.09	0.08	0.09	0.09	0.09	0.09
base macro-finance + small weekly: BMF-SV	0.13	0.15	0.14	0.15	0.15	0.14	0.15	0.19 **
base macro-finance + small weekly: QR	0.24 ***	0.27 ***	0.14	0.20 **	0.25 ***	0.24 ***	0.20 **	0.33 ***
base macro-finance + small weekly: BQR	0.09	0.09	0.11	0.11	0.10	0.10	0.10	0.08
base macro-finance + small weekly: QR-MIDAS	0.15	0.24 **	0.14	0.25 ***	0.25 ***	0.13	0.09	0.18 *

Notes: The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table). In the upper panel, the first row gives the 10% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). Statistical significance of differences in quantile scores is indicated by *** (1%), ** (5%), or * (10%), obtained with the Diebold and Mariano–West t-test, conducted on a one-sided basis, such that the alternative hypothesis is that the indicated forecast is more accurate than the benchmark. The lower panel of the table reports empirical coverage rates for 10% quantile forecasts (percentage of outcomes at or below the quantile). Statistical significance of departures of empirical coverage from the nominal 10% is indicated by *** (1%), ** (5%), or * (10%), obtained with two-sided t-tests.

Table A9: **10% QS accuracy accuracy during recessions, in-sample and out-of-sample**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	In-sample, 1971:Q2-2019:Q4							
base macro ex claims: BMF-SV	1.13	0.97	1.01	0.89	0.75	0.74	0.67	0.62
base macro: BMF	1.02	1.03	1.09	1.04	1.06	1.01	1.03	1.06
base macro: BMF-SV	1.01	1.04	1.03	1.03	1.02	1.01	1.00	1.03
base macro: QR	0.44	0.44	0.52	0.54	0.62	0.58	0.56	0.46
base macro: BQR	0.77	0.68	0.75	0.69	0.73	0.72	0.72	0.69
base macro: QR-MIDAS	0.69	0.56	0.46	0.45	0.58	0.80	0.92	0.69
base macro + NFCI: BMF	0.78	0.84	0.89	0.79	0.82	0.80	0.84	0.89
base macro + NFCI: BMF-SV	0.77	0.82	0.86	0.77	0.83	0.79	0.85	0.88
base macro + NFCI: QR	0.36	0.45	0.53	0.48	0.56	0.57	0.53	0.42
base macro + NFCI: BQR	0.76	0.67	0.72	0.69	0.73	0.71	0.71	0.69
base macro + NFCI: QR-MIDAS	0.52	0.45	0.28	0.29	0.34	0.57	0.65	0.60
base macro-finance: BMF	0.66	0.71	0.66	0.58	0.60	0.59	0.67	0.68
base macro-finance: BMF-SV	0.68	0.69	0.65	0.57	0.61	0.61	0.65	0.71
base macro-finance: QR	0.25	0.34	0.32	0.22	0.15	0.22	0.27	0.27
base macro-finance: BQR	0.59	0.49	0.41	0.44	0.53	0.52	0.56	0.57
base macro-finance: QR-MIDAS	0.34	0.31	0.22	0.20	0.24	0.51	0.53	0.54
	Out-of-sample, 1985:Q1-2019:Q3							
base macro ex claims: BMF-SV	0.97	0.69	0.98	0.65	0.59	0.55	0.47	0.42
base macro: BMF	0.70	0.58	0.68	0.83	0.80	0.85	0.88	0.96
base macro: BMF-SV	0.97	1.01	0.93	0.97	0.99	1.00	1.01	0.97
base macro: QR	0.41	0.59	0.60	1.23	1.18	1.11	1.19	1.11
base macro: BQR	0.73	0.70	0.65	0.85	0.87	0.89	0.93	1.04
base macro: QR-MIDAS	0.60	0.58	0.48	0.57	0.60	0.72	0.75	0.86
base macro + NFCI: BMF	0.72	0.60	0.62	0.82	0.81	0.82	0.87	0.93
base macro + NFCI: BMF-SV	1.00	1.08	0.85	0.89	0.91	0.94	0.94	0.97
base macro + NFCI: QR	0.62	1.02	0.37	1.35	1.81	1.89	1.53	1.76
base macro + NFCI: BQR	0.80	0.72	0.55	0.80	0.82	0.82	0.86	0.88
base macro + NFCI: QR-MIDAS	0.88	0.89	0.40	0.57	0.54	0.68	0.71	0.70
base macro-finance: BMF	0.70	0.59	0.42	0.53	0.49	0.50	0.61	0.66
base macro-finance: BMF-SV	0.86	0.94	0.70	0.69	0.57	0.62	0.71	0.78
base macro-finance: QR	1.35	0.88	0.52	0.45	0.73	0.68	0.59	1.91
base macro-finance: BQR	0.79	0.62	0.45	0.59	0.53	0.53	0.70	0.76
base macro-finance: QR-MIDAS	0.62	1.13	0.39	0.47	0.50	0.57	0.78	1.02

Notes: The table reports 10% quantile scores for periods of NBER-dated recessions (on a quarterly basis), using in-sample forecasts in the upper panel and out-of-sample forecasts in the lower panel. In each panel, the first row gives the 10% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table).

Table A10: **In-sample forecast accuracy during recessions: RMSE and 5% QS, 1987:Q1-2019:Q4**

variable and model	week 1	week 3	week 5	week 7	week 9	week 11	week 13	week 15
	RMSE							
base macro ex claims: BMF-SV	3.81	3.20	3.71	3.29	2.89	2.63	2.40	2.25
base macro: BMF	0.98	1.00	1.00	0.99	1.00	1.01	1.01	1.02
base macro: BMF-SV	0.98	1.01	1.00	1.00	0.99	0.99	0.99	0.99
base macro: QR	0.79	0.87	0.83	0.94	0.93	0.92	1.01	0.97
base macro: BQR	1.04	1.05	1.03	0.99	1.00	1.04	1.07	1.09
base macro: QR-MIDAS	0.92	0.86	0.69	0.74	0.80	0.68	0.67	0.75
base macro + NFCI: BMF	0.97	0.99	0.95	0.94	0.95	0.97	0.99	1.02
base macro + NFCI: BMF-SV	0.96	0.99	0.94	0.94	0.94	0.95	0.98	0.97
base macro + NFCI: QR	0.77	0.91	0.78	0.86	0.86	0.90	1.01	1.00
base macro + NFCI: BQR	1.04	1.05	1.02	0.99	0.99	1.03	1.03	1.07
base macro + NFCI: QR-MIDAS	0.95	0.78	0.70	0.77	0.80	0.74	0.76	0.79
base macro-finance: BMF	0.88	0.90	0.73	0.72	0.73	0.74	0.80	0.83
base macro-finance: BMF-SV	0.83	0.88	0.69	0.69	0.69	0.70	0.76	0.79
base macro-finance: QR	0.53	0.67	0.47	0.54	0.61	0.74	0.67	0.69
base macro-finance: BQR	0.92	0.95	0.81	0.77	0.75	0.77	0.83	0.88
base macro-finance: QR-MIDAS	0.54	0.59	0.46	0.55	0.57	0.47	0.75	0.89
base macro + small weekly: BMF	1.03	1.13	1.03	1.09	1.06	1.06	1.03	1.01
base macro + small weekly: BMF-SV	1.04	1.14	1.02	1.10	1.06	1.05	1.01	0.98
base macro + small weekly: QR	0.90	1.02	0.77	0.85	0.88	0.78	0.77	0.95
base macro + small weekly: BQR	1.13	1.28	1.15	1.23	1.19	1.23	1.19	1.17
base macro + small weekly: QR-MIDAS	0.86	0.81	0.86	0.72	0.68	0.71	0.66	0.72
base macro-finance + small weekly: BMF	0.92	0.99	0.75	0.82	0.81	0.82	0.85	0.91
base macro-finance + small weekly: BMF-SV	0.90	0.98	0.72	0.80	0.78	0.81	0.81	0.84
base macro-finance + small weekly: QR	0.58	1.03	0.46	0.50	0.56	0.69	0.54	0.57
base macro-finance + small weekly: BQR	1.04	1.12	0.86	0.95	0.91	0.94	0.96	1.01
base macro-finance + small weekly: QR-MIDAS	0.65	0.56	0.43	0.59	0.68	0.70	0.63	0.86
	5% quantile score							
base macro ex claims: BMF-SV	0.72	0.56	0.64	0.57	0.43	0.40	0.33	0.27
base macro: BMF	0.74	0.69	0.83	0.82	0.94	0.85	0.90	0.97
base macro: BMF-SV	1.03	1.01	1.00	1.02	1.05	0.97	1.00	0.97
base macro: QR	0.38	0.60	0.41	0.75	0.47	0.44	0.58	0.57
base macro: BQR	1.02	0.53	0.71	0.69	0.66	0.52	0.52	0.51
base macro: QR-MIDAS	0.43	0.43	0.45	0.41	0.54	0.56	0.66	1.00
base macro + NFCI: BMF	0.84	0.67	0.81	0.77	0.81	0.74	0.81	0.93
base macro + NFCI: BMF-SV	1.00	0.91	0.95	0.89	0.94	0.86	0.94	0.98
base macro + NFCI: QR	0.41	0.61	0.38	0.71	0.33	0.55	0.56	0.52
base macro + NFCI: BQR	1.01	0.51	0.73	0.69	0.65	0.50	0.49	0.48
base macro + NFCI: QR-MIDAS	0.45	0.28	0.38	0.37	0.54	0.47	0.52	0.71
base macro-finance: BMF	0.58	0.50	0.37	0.35	0.32	0.32	0.40	0.50
base macro-finance: BMF-SV	0.83	0.72	0.50	0.49	0.49	0.41	0.52	0.65
base macro-finance: QR	0.16	0.42	0.26	0.21	0.21	0.27	0.41	0.41
base macro-finance: BQR	0.51	0.39	0.26	0.22	0.32	0.30	0.38	0.43
base macro-finance: QR-MIDAS	0.31	0.27	0.22	0.21	0.24	0.38	0.29	0.45
base macro + small weekly: BMF	1.19	1.33	1.28	1.36	1.40	1.32	1.20	1.30
base macro + small weekly: BMF-SV	1.12	1.34	1.23	1.36	1.52	1.41	1.32	1.35
base macro + small weekly: QR	0.46	0.21	0.51	0.21	0.36	0.30	0.28	0.32
base macro + small weekly: BQR	1.11	1.08	0.99	0.92	0.71	0.52	0.58	0.58
base macro + small weekly: QR-MIDAS	0.30	0.26	0.17	0.24	0.28	0.23	0.21	0.39
base macro-finance + small weekly: BMF	0.98	1.04	0.75	0.70	0.70	0.66	0.74	0.81
base macro-finance + small weekly: BMF-SV	1.10	1.07	0.71	0.77	0.77	0.72	0.73	0.98
base macro-finance + small weekly: QR	0.10	0.25	0.21	0.08	0.11	0.10	0.20	0.05
base macro-finance + small weekly: BQR	0.56	0.39	0.27	0.27	0.33	0.35	0.37	0.48
base macro-finance + small weekly: QR-MIDAS	0.16	0.15	0.16	0.06	0.12	0.14	0.25	0.42

Notes: In the upper panel, the top row gives the RMSEs of nowcasts from the benchmark model and variable set for periods of NBER-dated recessions (on a quarterly basis), and other rows report the ratio of RMSEs for the indicated variable set and model to the benchmark. In the lower panel, the first row gives the 5% quantile scores (QS) from the benchmark model and variable set, and other rows report the ratio of QS for the indicated variable set and model to the benchmark (lower is better). The weeks indicated in the columns refer to the weeks of forecast origins for the quarter (omitting even-numbered weeks to reduce the size of the table).

Figure A1: In-sample forecast accuracy, 1996:Q3-2019:Q4: comparisons of 5% coverage rates across variable sets (indicated in panel header) and models (indicated in key label). The black horizontal line at 0.05 denotes the nominal coverage rate. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

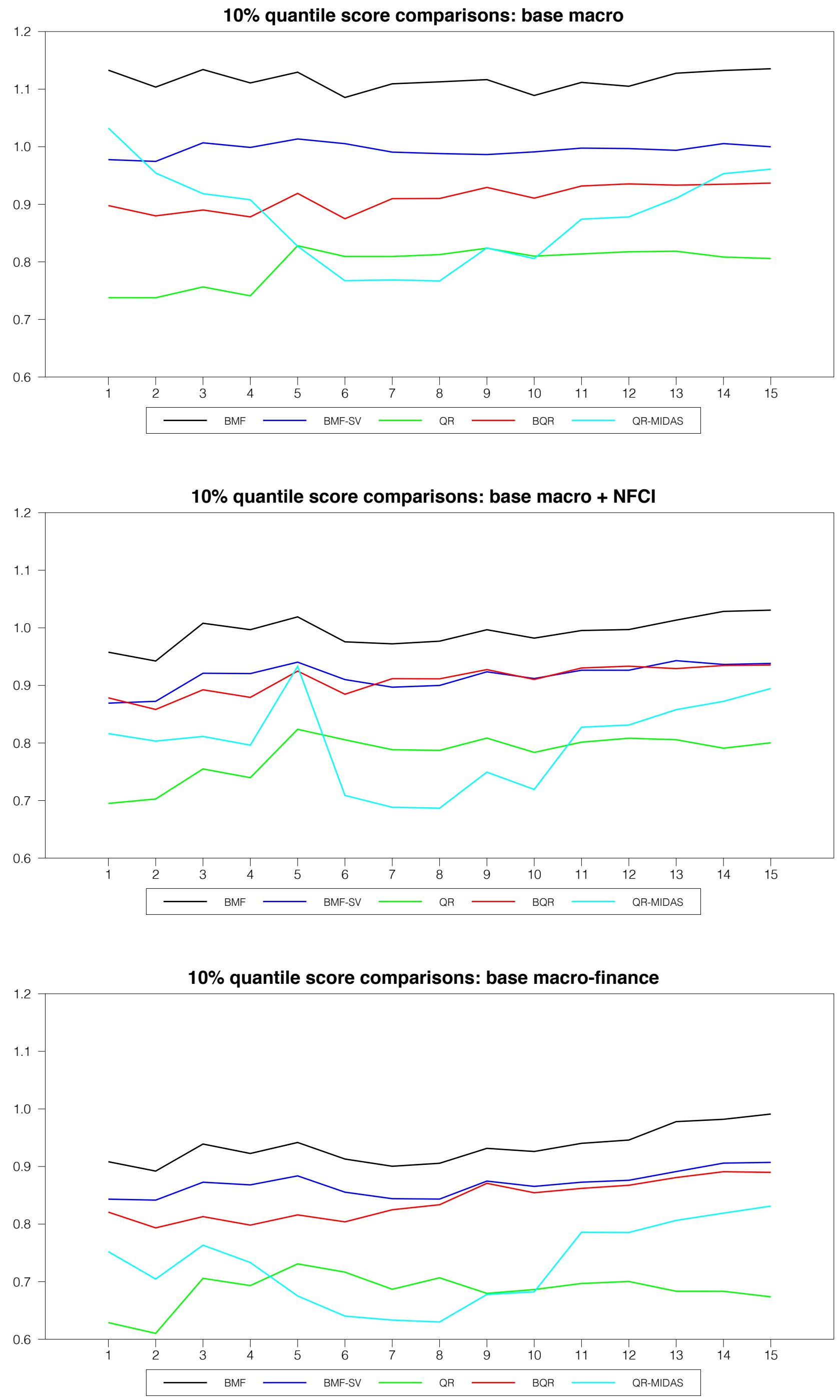


Figure A2: In-sample forecast accuracy, 1971:Q2-2019:Q4: comparisons of 10% QS across variable sets (indicated in panel header) and models (indicated in key label). Scores are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

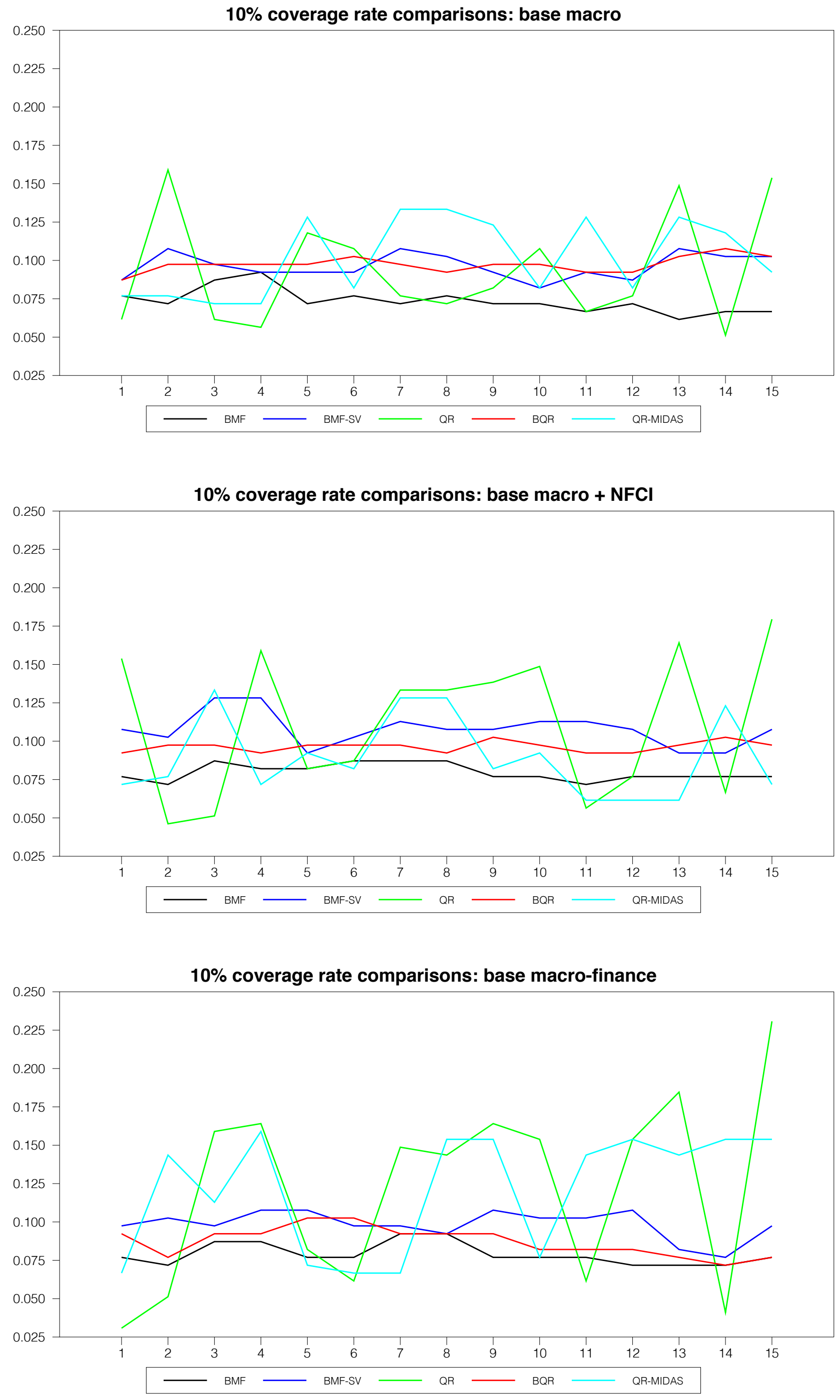
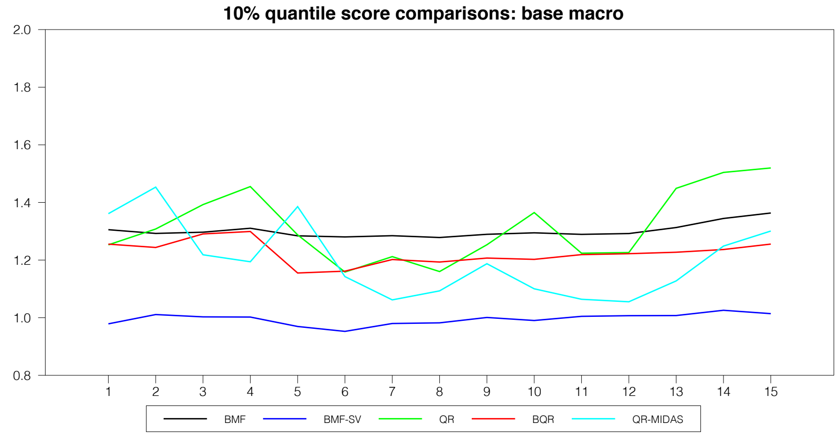


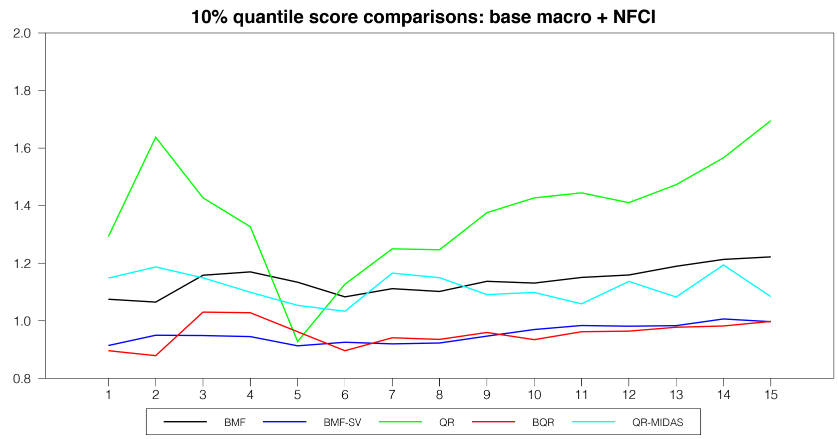
Figure A3: In-sample forecast accuracy, 1971:Q2-2019:Q4: comparisons of 10% coverage rates across variable sets (indicated in panel header) and models (indicated in key label). The black horizontal line at 0.05 denotes the nominal coverage rate. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure A4: In-sample forecast accuracy, 1996:Q3-2019:Q4: comparisons of 10% QS across variable sets (indicated in panel header) and models (indicated in key label). Scores are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure A5: In-sample forecast accuracy, 1996:Q3-2019:Q4: comparisons of 10% coverage rates across variable sets (indicated in panel header) and models (indicated in key label). The black horizontal line at 0.05 denotes the nominal coverage rate. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure A6: Out-of-sample forecast accuracy, 2000:Q1-2019:Q3: comparisons of 5% coverage rates across variable sets (indicated in panel header) and models (indicated in key label). The black horizontal line at 0.05 denotes the nominal coverage rate. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.





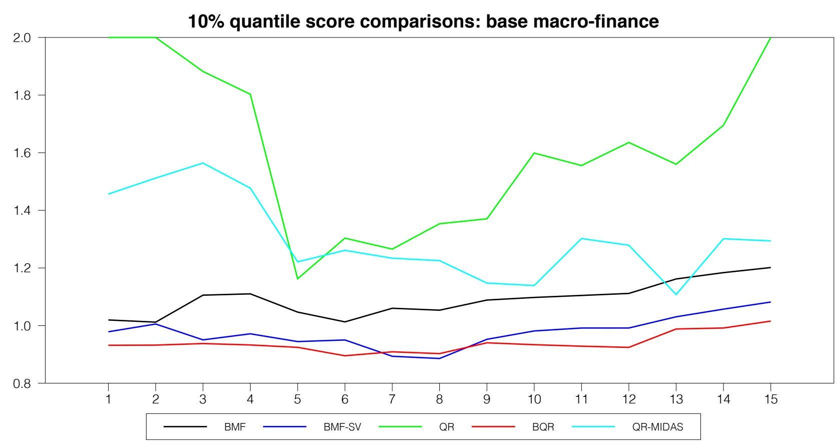


Figure A7: Out-of-sample forecast accuracy, 1985:Q1-2019:Q3: comparisons of 10% QS across variable sets (indicated in panel header) and models (indicated in key label). Scores are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

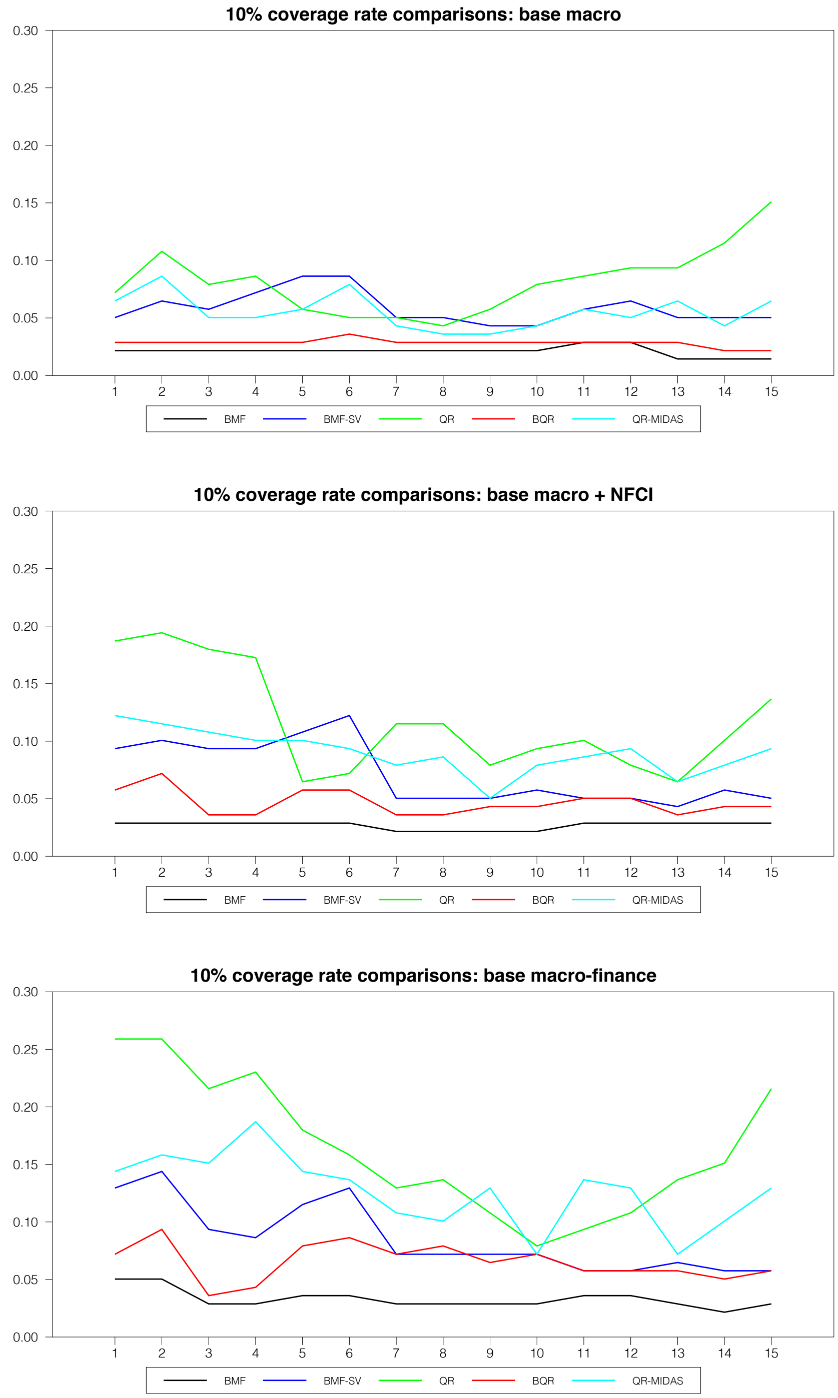


Figure A8: Out-of-sample forecast accuracy, 1985:Q1-2019:Q3: comparisons of 10% coverage rates across variable sets (indicated in panel header) and models (indicated in key label). The black horizontal line at 0.05 denotes the nominal coverage rate. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure A9: Out-of-sample forecast accuracy, 2000:Q1-2019:Q3: comparisons of 10% QS across variable sets (indicated in panel header) and models (indicated in key label). Scores are reported as relative to the benchmark BMF-SV model with monthly macroeconomic indicators, so lower numbers represent more accurate forecasts. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

Figure A10: Out-of-sample forecast accuracy, 2000:Q1-2019:Q3: comparisons of 10% coverage rates across variable sets (indicated in panel header) and models (indicated in key label). The black horizontal line at 0.05 denotes the nominal coverage rate. The weeks 1 through 15 of forecast origins are indicated on the horizontal axis.

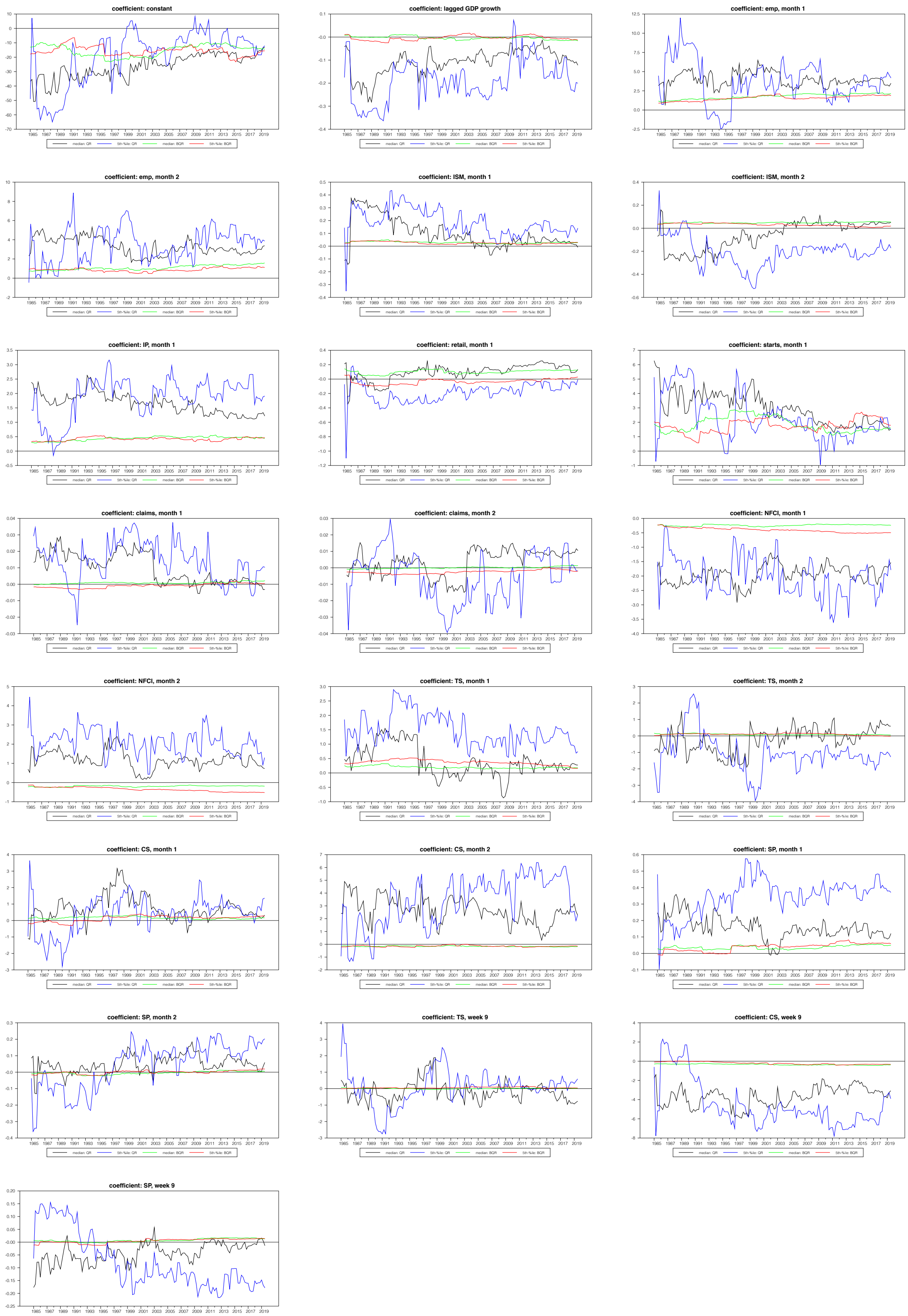


Figure A11: Recursively estimated coefficients from QR and BQR specifications, 50% (median) and 5% quantiles, base macro-finance variable set.