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Forecasting Tail Risks

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Abstract

Reliable early warning signals are essential for timely implementation of macroeconomic and macro-prudential policies. This paper presents an early warning system as a set of multi-period forecasts of indicators of tail real and financial (systemic) risks. Forecasts are obtained from: (a) autoregressive and factor-augmented VARs with linear GARCH volatility (FAVARs), and (b) auto-regressive and factor-augmented Quantile Projections (QPs). We use a large database of monthly U.S. data for the period 1972:1-2014:12 to forecasts our tail risk indicators with each model in pseudo-real time. Our key finding is that forecasts obtained with autoregressive and FAVAR models significantly underestimate tail risks, while forecasts obtained with autoregressive and factor-augmented QPs deliver superior and fairly reliable early warning signals for tail real and financial risks up to a one-year horizon.

JEL-Code: C500, E300, G200.

Keywords: tail risks, density forecasts, factor models, quantile projections.

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I. INTRODUCTION

The 2007-2009 financial crisis and its adverse impact on real activity has spurred renewed efforts in modeling adverse "tail" events in both the financial and real sectors. Bisias et al. (2012) provide an extensive survey of the models currently available to measure and track indicators of tail (systemic) financial risk. Yet, most of these models focus exclusively on vulnerabilities in the financial system or some of its components, with no assessment of either their impact on real activity, or on how vulnerabilities in the real sector may affect the financial sector. Most importantly, the out-of-sample forecasting power of many of the proposed measures is seldom assessed, making it difficult to gauge their usefulness as early warning signals. Tail real risks are also the focus of an important theoretical literature—briefly reviewed by Acemoglu et al. (2015)—which aims at explaining how aggregate tail real risks can arise from a variety of shock configurations at disaggregated levels of an economy. To the best of our knowledge, however, this literature has not tackled the issue of forecasting tail risks. Operationally, reliable early warning signals for tail real and financial risks—where reliability is defined as the ability of a model to issue signals with relatively small percentages of missed realizations of future adverse extreme events—are essential for timely implementation of macroeconomic and macroprudential policies.

Building on our previous work (De Nicolò and Lucchetta, 2012, 2013), this paper develops an *early warning system (EWS)* as a set of multi-period forecasts of indicators of *tail real and financial risks*. Our analysis introduces three novel features. First, we compare *multi-period* forecasts of indicators of tail real and financial risks obtained using two types of forecasting models: autoregressions (AR) and factor-augmented VARs, with the volatility of each indicator following a linear GARCH process (FAVARs), and autoregressive and factor-augmented Quantile Projections (sometimes referred to as QPs), which we already partially used in our previous work and here extend in terms of model specification and data quality. As pointed out in Komunjer (2013), a potential advantage of these models is that they do not require assumptions about the underlying distribution of a variable to be forecast, and in principle they can capture any type of asymmetry. Therefore, one key objective of this study is to assess the comparative forecasting performance for tail risks of workhorse forecasting models, such as AR and FAVAR models, and Quantile Projection models. Second, we assess the forecasting performance of Equally Weighted Pools of forecasts obtained under FAVARs and QPs to gauge whether the superiority of simple pooled forecasts documented in Amisano and Geweke (2011, 2013) extends to the tails of a predicted distribution. Lastly, the out-of sample forecasting accuracy of the tail risk indicators under each model is assessed by comparing their multi-period tail forecasts using a scoring rule which places heavier weight on the tails of interest. In essence, our aim is to identify the specification or combination of models among those considered that can deliver reliable early warning signals of tail real and financial risks.

Our measures of tail risks are constructed following a standard risk management approach. Tail *real* risks are measured by the Value at-Risk (*VaR)* of two standard aggregate macroeconomic variables, industrial production growth and employment growth. Tail *financial* risk in the *corporate* and *banking* sectors are measured by the *VaR* of a “portfolio” version of the *distance to insolvency* measure introduced by Atkenson et al (2013), which is based on a large class of theoretical structural models, and is germane to other theory-based indicators of tail financial risk used in recent studies (see e.g. Acharya et al., 2010 or Brownlee and Engle, 2010). Tail risks in *financial markets* are measured by the *VaR* of changes in a Financial Condition Index.

We implement our *EWS* using a large set of monthly U.S. data for the period 1973:2-2014:12. Estimation and forecasting is conducted using both a moving and an expanding window of data: the moving window estimation is used to account for time variation in parameters and possible structural breaks, while the estimation based on the longer expanding window provides us a forecasting "hedge" against possible imprecision of parameter estimation under the shorter moving window. For each variable underlying our tail risk measures, we compute multi-period density and *VaR* forecasts at a three month, six months and 12 month horizons, and compare their accuracy using the Quantile Weighted Probability Score (QWPS) introduced by Gneiting and Ranjan (2011).

Our analysis delivers three main results. First, factor models deliver density and *VaR* forecasts significantly more accurate, or at least as accurate, than those of autoregressions and quantile autoregressions for all variables and forecasting horizons. This result extends the finding of superior predictive ability of factor models with many predictors (see e.g. Stock and Watson, 2006) to density and *VaR* forecasts at multiple forecasting horizons. Second, density and *VaR* forecasts of the Equally Weighted Pool of both types of models turn out to be significantly more accurate, or at least as accurate, than those obtained from each model in the pool. This result extends the finding of superior predictive ability of Equally Weighted Pool forecasts (see e.g. Amisano and Geweke, 2011 and 2012) to density and quantile forecasts at multiple forecasting horizons as well.

Our third result is the most important operationally, since it involves an assessment of the ability of our tail risk forecasts to serve as reliable early warning signals. In this regard, we have bad news and good news for risk-averse policy makers. The bad news is that the AR and FAVAR models deliver *VaR* forecasts that *significantly underestimate tail risks* for each tail risk indicator and forecast horizon. Furthermore, their accuracy decreases substantially for the subsample that includes the recent financial crisis, this implying that their reliability falls when it is needed most. The failure of this class of models to issue reliable early warning signals is due to their inability to capture asymmetric and time varying changes in the shapes of the tails of distributions owing to their underlying Gaussian assumption. Policy makers may be particularly concerned about this result, since forecasts of this class of models (as well as their DSGE versions) are often used in central banks and international organizations as inputs for stress testing purposes. The good news is that factor-augmented Quantile Projections are far superior to AR and FAVAR forecasts, delivering tail forecasts that are reliable early warning signals for horizons up to one year. Importantly, their reliability is broadly preserved for the subsample that includes the recent financial crisis. In sum, these models seem to anticipate those asymmetric changes in the shape of the distribution that may result in significant changes in its tails.

The remainder of the paper is composed of five sections and two Appendixes. Section II defines our tail risk measures. Section III details the data used to extract factors as predictors and the choice of factors. Section IV describes the forecasting models, their estimation and the evaluation of their forecasting accuracy. Section V details the results, and Section VI concludes. The Data Appendix details data and their sources, while the Tables Appendix contains some auxiliary tables.

II. TAIL RISK MEASURES

Our tail risk measures are VaR_{α} s of indicators of real activity and financial stress, with the probability level α set equal to 10% (i.e. $\alpha = 0.10$). The tail *real* risks measures are: the $VaR_{0.10}$ of the (log) change in the industrial production index IPG, denoted by

$VaR_{\alpha}(IPG)$ (also called *Industrial Production-at-Risk)*, and the $VaR_{0.10}$ of the (log) change in total employment EMG, denoted by $VaR_{\alpha}(EMG)$ (also called *Employment-at-Risk)*.

Tail *financial* risks in the corporate and banking sectors are measured by the $VaR_{0.10}$ of a portfolio version of the Distance-to-Insolvency (DI) introduced by Atkeson et al. (2013), who show that: (i) DI is a measure of the adequacy of a firm's equity cushion relative to its riskiness based on Leland's (1994) structural model of credit risk; (ii) it is satisfactorily proxied by the reciprocal of its estimated instantaneous equity volatility; and (iii) it tracks closely other measures of risk derived from structural models of firm valuation, such as the distance-to-default. In our implementation, we compute the DI of returns of value weighted portfolios including all firms in the DataStream equity indexes of non-financial firms and banks, denoted by *CDI* and *BDI* respectively. These portfolios represents large portions of the corporate and banking sectors, the latter including all banks considered "systemically important". Thus, a "portfolio" DI is a lower bound of the probability of insolvency of these two sectors, as profits and losses of each firm in the portfolio are evened out. As in Atkenson et al (2013), a proxy measure of the instantaneous equity return volatility is obtained by monthly averaging daily squared returns. Thus, tail risk in the corporate sector is measured by the $VaR_{0.10}$ of the DI of the portfolio of non-financial firms, denoted by $VaR_{\alpha}(CDI)$ (also called *Corporate Sector-at-Risk)*, and in the banking sector by the $VaR_{0.10}$ of the DI of the portfolio of banks, denoted by $VaR_{\alpha}(BDI)$ (also called *Banking Sector-at-Risk.*).

Our measure of tail risks in *financial markets* is based on the National Financial Condition Index (NFCI) produced by the Federal Reserve Bank of Chicago. Brave and Butters (2011) document the FCI's construction, obtained as a weighted average of more than 100 standardized indicators of risk, credit, and leverage in the financial system, and show that this FCI captures well-known periods of financial stress. Financial Conditions Indexes (FCIs)—initially studied by Hatzius et al.(2010) in the aftermath of the 2007-2009 financial crisis, and later produced in several central banks and international organizations—have been typically designed either to measure whether broad financial conditions are loose or tight by historical standards, thus serving as coincident indicators, or to assess whether the financial system experiences historically unusual stress, therefore serving as early warning indicators. As documented in Aramonte et al. (2013), however, the existing evidence on whether FCIs are useful as coincident indicators or as early warning indicators is mixed. In our study, we measure tail risk in financial markets by the $VaR_{0.10}$ of the negative first differences in the NFCI[1] (DNFCI), denoted by $VaR_{\alpha}(DNFCI)$ (also called *Financial Markets-at-Risk*).

Table 1 reports descriptive statistics of the series underlying our tail risk indicators and their correlation matrix. As it may be expected, there is a negative and significant contemporaneous correlation between financial risk and real activity.

[Insert Table 1 around here]

III. Choice of Factors

As in Stock and Watson, 2002, Pesaran et al., 2011, Stock and Watson, 2012), among others, we estimate factors by principal components—called PCA factors—obtained as the solution of a maximization problem subject to a factor loading constraint, as detailed in Stock

[1] Positive (negative) values of the NFCI indicate financial conditions that are tighter (looser), We take the negative of NFCI first difference to preserve the negative orientation of all our other tail risk measures.

and Watson (2011). The dataset to estimate PCA factors includes 164 monthly time series of the U.S. economy for the period 1973:1-2014:12 taken from the FRED-MD database constructed by McCracken and Ng (2014) and from DataStream.[2] As shown in Table 2, the distribution of the series by group is fairly comprehensive and relatively balanced. A description of the series and the relevant transformations used to ensure their stationarity are detailed in the Data Appendix.

[Insert Table 2 about here]

In forecasting exercises of the type we consider, two issues are addressed at the outset: what is the maximum number of PCA factors to use as predictors, and which factors among those selected are specified in a forecasting model.

On the first issue, information criteria are typically used to determine the number of PCA factors. In large datasets—such as that used in Stock and Watson (2002), as well as in similarly sized datasets— the widely used Bai and Ng (2002) criteria (BN henceforth) typically select between 7 and 9 factors. In the FRED-MD dataset—which is a subset of our dataset for our selected data range—McCracken and Ng (2014) find 8 factors selected according to the BN PCP2 criterion. However, they further observe that the incremental explanatory power of PCA factors declines significantly moving from 5 to 8 factors, and that the existence of several series which are not significantly explained by PCA factors may introduce estimation errors of the type pointed out by Boivin and Ng (2006) that may, in turn, affect the determination of the number of factors.

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[2] We are grateful to Michael McCracken for having allowed us access to the FRED-MD database prior to its public release. The counting of series in our dataset includes the NFCI series taken from the Federal Reserve Bank of Chicago website.

In this study we use two selection criteria recently proposed by Ahn and Horenstein (2013) (AH henceforth) that perform similarly to, or even better than, competing criteria under a variety of simulations. The first criterion, called ER (from “eigenvalue ratio”), selects the number of factors that maximize the ratio of two adjacent eigenvalues arranged in descending order; the second one, called GR, selects the number of factors that maximizes the rate of growth of adjacent eigenvalues arranged in descending order. Figure 2 shows that for the entire time range of our dataset, both AH criteria deliver three factors which explain 0.34 percent of the total variation in the data.

[Insert Figure 1 about here]

On the issue of which factors are specified in a forecasting model, Bai and Ng (2008, 2009) have shown that the ranking of factors by information criteria might not be the best one for inclusion of factors in predictive regressions, and have proposed selection methods aimed at improving forecasting performance whose application is outside the scope of this paper. In our study, we consider models with the factors selected according to the AH criteria and, in addition, models with five factors. This last choice is motivated by McCracken and Ng (2014) evidence on the decreases of explanatory power of factors after the estimated fifth, and on judgment by Stock and Watson (2012) that the use of five factors can be a useful benchmark in evaluating forecasting models. For the entire time range of our dataset, five factors explain 0.43 percent of the total variation in the data.

As shown in Table 3, the explanatory power of factors in contemporaneous regressions of the variables underlying our measures of tail risk on factors and AR terms is anything but trivial: *R2s* with five factors ranges from 0.28 to 0.76, and the addiction of five AR terms in each equation yields *R2s* ranging from 0.56 to 0.76.

[Insert Table 3 about here]

IV. FORECASTING MODELS

A. AR and FAVAR models

Denote with $Y_t \equiv \{IPG_t, EMG_t, CDI_t, BDI_t, DNFCI_t\}$ the set of variables we wish to forecast, with y_t an element of Y_t , and with F_t a vector of PCA factors. For each $y_t \in Y_t$, the FAVAR specification we use is given by the following equations:

$$\begin{bmatrix} F_t \\ y_t \end{bmatrix} = \begin{pmatrix} A(L) & B(L) \\ a(L) & b(L) \end{pmatrix} \begin{bmatrix} F_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ u_{yt} \end{bmatrix} \qquad (1)$$

$$\begin{aligned} u_{yt} &= \sigma_{yt}\varepsilon_{yt} \\ \sigma_{yt} &= a + b\sigma_{yt-1} + c\,|\,u_{yt-1}\,| \end{aligned} \qquad (2),$$

Note that in (1) we do not impose $B(L) = 0$, which is a restriction that has been applied in many forecasting exercises in the literature (see e.g. Stock and Watson, 2006, or Pesaran at al., 2011). Stock and Watson (2005) found that this restriction was rejected in their FAVAR version of an approximate dynamic factor model, but its impact was not quantitatively significant. However, this is not the case for our dataset and the variables underlying our tail risk measures.

Table 4 reports the results of exclusion tests similar to those carried out by Stock and Watson (2005): it shows the percentiles of the distribution of p-values of chi-square tests of including a lag of the 5 variables in Y_t in each equation of a VAR(4) with 5 factors, and the associated increase in *R2*. Estimations were carried out using an expanding data window starting from an initial estimation period of 120 month (370 regressions for each factor and each variable), resulting in a total of 1850 tests. It can be seen that that for the entire set of tests, 25% of the *p*-values are less than .002 and 50% are less than .09. These rejections are associated with economically significant improvements in the ability to predict the PCA factors, since about 25% of the total number of the regressions is associated with improvements in the *R*2 greater than or equal to 0.09, with the financial variables *CDI, BDI* and *DNFCI* yielding improvements in the *R2* greater than or equal to 0.26.

[Insert Table 4 about here]

Equation (2) describes a linear GARCH(1,1) process for y_t , where ε_{yt} are assumed to be i.i.d. 0-mean random variables distributed with a Gaussian cdf, and σ_{yt} is the conditional standard deviation. This specification is supported by standard ARCH tests, which reveal that the null of absence of time variation in second moments is rejected for all variables except *EMG*. This specification is also helpful in assessing whether a simple GARCH specification can improve tail forecasts over the standard constant volatility assumption.

To account for time variation in parameters and possible structural breaks, we used two window-based forecasting schemes. The first window is a rolling window of 120 months, while the second one is an expanding window starting with the first estimation period of 120 month (1973:2-1984:1), and adding one observation sequentially at each forecasting date. For each $y_t \in Y_t$ and the two estimation windows, we estimated density forecasts and $VaR_{0.10}$ obtained with two FAVAR models, an AR model, and an Equally Weighted Pool of all forecasts. FAVAR(*x*) is a factor model where the optimal number of factors *x*, is selected according to the AH criteria, while FAVAR(5) is a factor model with five factors. In order to assess the incremental forecasting power of PCA factors, we estimated an AR model where the conditional variance of $y_t \in Y_t$ follows a linear GARCH(1,1) process. Finally, we constructed the EWP forecast based on evidence of the superior forecasting power of combinations of density forecasts over component density forecasts documented by Amisano and Geweke (2011, 2012 and 2013).

Let the mean and volatility forecasts of y at horizon $h \geq 1$ be $\hat{y}_{t+h}$ and $\hat{\sigma}_{t+h}$ respectively. Since *IPG* and *EMG* are expressed in percentage changes, and *DNFCI* is expressed in first differences, their multi-period mean forecasts at horizon h are given by $\hat{y}_{t+h} = \sum_{i=1}^{h} \hat{y}_{t+i}$. Following Ghysels et al (2009) and Andersen et al (2010), the multi-period volatility forecasts at horizon h are proxied by the expected quadratic variation, given by $\hat{\sigma}_{t+h} = \sum_{i=1}^{h} \hat{\sigma}_{t+i}$ where each term of this sum is the forward iteration of the linear GARCH equation. Since the variables *CDI* and *BDI* are in levels, the relevant forecasts are just the iterated forecast values h periods ahead. Therefore, the *VaR* of y_{t+h} at probability level $\alpha \in (0,1)$ is given by:

$$VaR_{\alpha}(y_{t+h}) = Q_{\alpha}(y_{t+h}) = \hat{y}_{t+h} + \hat{\sigma}_{t+h} F^{-1}(\alpha) \qquad (3),$$

where $F^{-1}(\alpha)$ is the inverse Gaussian cdf.

Summing up, the structure of our forecasting set-up with AR and FAVAR models is similar to set-ups of individual forecasts of several macroeconomic variables, such as that considered by Stock and Watson (2002). However, this study extends this type of forecasting set-up in two important dimensions. First, we use FAVARs with time varying volatility of the predicted variable: While the GARCH specification is standard for the financial variables, its adoption for the real variables is also instrumental in assessing whether a fairly general time varying variance specification can account for the differential behavior in the tails of real variables, such as GDP, noted by Acemoglu et al (2015). Second, we use forward iterations of the FAVAR and the linear GARCH process for each y_t and its variance to obtain multi-period density forecasts. This is in contrast to direct forecasts obtained as projections of the forecast variable at different horizons, based on current information. This choice is motivated by the empirical findings of Marcellino and Watson (2006) and Pesaran et al. (2011) on the superiority of iterated forecasts over direct forecasts for first moments, and the superiority of iterated forecasts over direct forecasts for second moments documented in Ghysels et al (2009).

B. AR and Factor-Augmented Quantile Projections

For each $y_t \in Y_t$ we estimate quantile projections (QPs) of the following form:

$$y_{t+h}(\alpha) = A(\alpha) + B(\alpha)F_t + C(L)y_t + \varepsilon_{t+h} \qquad (4)$$

In Equation (4), estimated factors F_t and lagged values of y_t are the predictors of $y_{t+h}(\alpha)$ at each forecasting horizon (h=3, 6, and 12). The VaR_α of y_{t+h} is the quantile forecast:

$$VaR_\alpha(y_{t+h}) = \hat{A}(\alpha) + \hat{B}(\alpha)F_t + \hat{C}(L)y_t \qquad (5),$$

where the "hat" denotes the estimated parameters of the quantile projections (4).

In this case—differing form the AR and FAVAR estimations—forecasts are direct rather than iterated. We chose to use direct QPs for two reasons. First, to the best of our knowledge, this study and our previous contributions are the first to consider factor-augmented quantile predictions in the mold of the literature of forecasting with many predictors. This literature has proceeded first with direct forecasts, and then has progressed comparing direct with iterated forecasts. As we do not have previous evidence on direct forecasts with quantile projections, we wished to provide such evidence first. Second, to the best of our knowledge, we are unaware of studies examining the statistical properties of iterated quantile forecasts, especially in the context of choices of factors and autoregressive lags, which in the standard linear regression framework are determined by well-known information criteria. A systematic comparison of direct and iterated quantile predictions in the context of forecasting with factors as predictors may be a worthwhile effort deserving a specific detailed study of its own.

However, to maintain broad comparability of QP specifications with the AR and FAVAR models, for each $y_t \in Y_t$ and estimation window, we estimate the following three QP specifications similar to those of the AR and FAVAR models: quantile projections as autoregressions with five lags (QAR); two factor-augmented quantile autoregressions with two lags, where we introduce three factors (model QARF(3)) and five factors (model QARF(5)) respectively. In addition, as in the case of AR and FAVAR models, we computed Equally Weighted Pool of quantile projections (EWPQ) of the six quantile forecasts (three for each estimation window), averaging them at each forecasting date as in Giacomini and Kumanjer (2005).

C. Forecast evaluation

As is common in the density forecast literature (see, e.g. Corradi and Swanson, 2006, and Gneiting et al. ,2007), we compared the accuracy of density and *VaR* forecasts generated by different models using a scoring rule, consistently with our objective of assessing the ability of different models to deliver forecasts of tail risk indicators useful as early warning signals. The scoring rule we use is the Quantile-Weighted Probability Score (QWPS) proposed by Gneiting and Ranjan (2011), which allows us to compare the accuracy of density forecasts with reference to particular regions of a distribution, such as its tails, as well as the predictive accuracy of specific quantiles (or *VaRs*).

Following Gneiting and Ranjan (2011), the QWPS can be briefly described as follows. Denote with f a density forecast, with y a realization of the forecast variable, with F the cdf corresponding to the density f, and with $F^{-1}(\alpha)$ the *predicted* quantile at level $\alpha \in (0,1)$. The (continuous) quantile-weighted probability score $QWPS(f, y)$ is defined by:

$$QWPS(f, y) = \int_0^1 QS(F^{-1}(\alpha), y, \alpha) w(\alpha) d\alpha \quad (6),$$

where

$$QS(F^{-1}(\alpha), y, \alpha) \equiv 2(I\{y \leq F^{-1}(\alpha)\} - \alpha)(F^{-1}(\alpha) - y) \quad (7)$$

is the *score* of quantile α, $I\{.\}$ is an indicator function, and $w(\alpha)$ is a non-negative weighting function on the unit interval. This score has negative orientation, with lower values indicating better performance. The quantile prediction $F^{-1}(\alpha)$ is optimal when the ex-post loss is $L(x, y, \alpha) = 2(1-\alpha)|y - x|$ in case of an over-prediction ($x \geq y$), and $L(x, y, \alpha) = 2\alpha|y - x|$ in case of an under-prediction ($x \leq y$). If $w(\alpha) = 1$ for all $\alpha \in (0,1)$, each quantile is assigned equal weight, resulting in an unweighted or uniform QWPS. To evaluate the performance of density forecasts over the left tail, we constructed a left tail QWPS. setting $w(\alpha) = (1-\alpha)^2$, as suggested by Gneiting and Ranjan (2011).[3] If $w(\alpha) = 1$

[3] In the empirical implementation of the AR and FAVAR models, we compute a discretized version of the QWPS using a grid of 100 quantiles.

for a specific $\alpha \in (0,1)$ and is 0 otherwise, the QWPS collapses to the quantile score (7), which we use to compare the predictive ability of $VaR_{0.10}$ forecasts of different models.

Following Amisano and Giannini (2007) and Gneiting and Ranjan (2011), comparisons of the predictive power of density and $VaR_{0.10}$ forecasts are carried out applying Diebold and Mariano (1995) tests (DM henceforth) of equal forecasting performance of two different density or quantile scores. Under standard regularity conditions, the t-statistics of the differences between the scores of two density or $VaR_{0.10}$ forecasts is asymptotically standard normal under the null hypothesis of equality of scores. Given the negative orientation of QWPS and quantile scores, a forecast with score m is superior (inferior) to a forecast with score h if the t-stat is significantly negative (positive).[4]

To evaluate our tail risk forecasts as early warning signals, we also compare $VaR_{0.10}$ forecasts using standard measures of coverage ratios or *VaR* violations, defined as the percentage of cases where the realized value of a variable is *lower* than the predicted *VaR* for a given target probability level (in our case, $\alpha = 0.10$). The finding of a coverage ratio *higher* than the target probability level would indicate that the relevant forecast *underestimates* tail risk, since it does not capture all adverse risk realizations at that given target probability level (a Type I error). Conversely, the finding of a *VaR* forecast whose coverage ratio is lower than the target probability level would indicate it *overestimates* tail risk, since it would issue a percentage of signals that are "false alarms" relative to the target

[4] Diks et al. (2011) implement Montecarlo experiments testing the power of DM tests for comparisons of scoring rules: they find their power adequate when the number of occurrences in the rejection region is greater than 40, which is a threshold satisfied by most of our forecasts using the expanding window.

probability level (a Type II error). A risk-averse policy maker would likely consider as more reliable a forecast that potentially overestimates rather than underestimates tail risks, as the consequences of missing adverse tail realizations may entail significantly larger costs than those associated with false alarms.

V. RESULTS

Estimation and forecasting was conducted in pseudo-real time. Factors and parameters of all models were re-estimated for each estimation window. At each forecasting date, the lags of the AR and FAVAR models are selected according to the SBIC criterion allowing a maximum of six lags. As shown in Figure 3, the AH criteria selected two factors until 1992:7, and three factors thereafter. By contrast, under the rolling window the AH selected factors range from one to three, suggesting time variations likely related to the changing sources of common shocks across variables.

[Insert Figure 3 about here]

In sum, the total number of forecasts was 369 at a 3-months horizon, 366 at a 6-months horizon, and 362 at a 12-month horizon.

A. Results of AR and FAVAR models

Table 5 reports the matrix of DM tests of left tail QWPSs for each variable, estimation window and forecast horizon. Each cell of the matrix contains the t-stat of the difference test between the left tail QWPS of the row model and the column model. A negative (positive) and significant t-stat indicates that the left tail QWPS of the model row is superior (inferior) to that of the column model. The suffixes attached to models' names denotes estimation with a rolling window (-R) or an expanding window (-E).

[Insert Table 5 about here]

The DM tests for the real variables *IPG* and *EMG* (Panels A and B) show that at least one factor model delivers significantly better left tail forecasts than AR models, and that the EWP forecasts are are significantly superior to, or not significantly different from, the AR and FAVAR forecasts at any forecasting horizon. A more muted differential forecasting power of FAVARs relative to the AR models is found for the financial variables *CDI*, *BDI* and *DNFCI* (Panels C-E) . The relevant DM tests show that for some of these variables and forecasting horizon, at least one AR model produces better left tail forecasts than some FAVARs. Yet, for all variables and forecasting horizons, no AR or FAVAR model produces left tail forecasts superior to those of the EWP. This result indicates the usefulness of including FAVARs in the forecast pool.[5]

All the foregoing results hold when we consider the full matrix of DM tests of equal predictive ability of $VaR_{0.10}$ forecasts, which we do not report in full for brevity. The (weak) dominance of the $VaR_{0.10}$ forecasts of the EWP model is illustrated in Table 6, which reports DM tests of the $VaR_{0.10}$ scores of the EWP against scores of all other six models. The EWP indeed delivers strictly better $VaR_{0.10}$ forecasts in 68 tests out of the total of 90, with 22 DM tests indicating no significant difference in forecasting performance.

[Insert Table 6 about here]

In sum, two key results stand out. First, FAVAR models exhibit tail risk forecasts significantly better than, or not significantly different from, those obtained with AR models

[5] Tables A.1 and A.2 in the Table Appendix report results for the uniform QWPS and the right tail QWPS as well, the latter defined symmetrically to the left tail by setting $w(\alpha) = \alpha^2$, as suggested by Gneiting and Ranjan (2011). An interesting result common to all models is that density forecasts at all horizons for all variables except *CDI* are better in predicting the right tail (i.e. good tail outcomes) rather than the left tail (i.e. bad tail outcomes), since the left tail QWPS is uniformly lower than the right tail QWPS. This suggests the presence of asymmetries that are not adequately captured by a specification based on the symmetric Gaussian assumption, even allowing for GARCH effects.

for most variables and forecasting horizons, although there are few cases where they are significantly worse than those of some AR models for some financial variables. Yet, FAVAR forecasts are useful components of the EWP, since the EWP exhibits $VaR_{0.10}$ forecasts significantly better or at least as good as those obtained from the majority of all other models for any variable and all horizons. This result complements the evidence reported in Geweke and Amisano (2012, 2013) about EWPs as enhancers of forecasting performance of overall density forecasts, since our results indicate that factors also enhance density forecasts of the left tail.

B. Results of Quantile Projections

Table 7 reports the matrix of DM tests of $VaR_{0.10}$ scores of the forecasts associated with all Quantile Projection models for each variable, estimation window and forecast horizon in the same format of Table 5.

[Insert Table 7 about here]

The DM tests for the real variables *IPG* and *EMG* (Panels A and B) are similar to those obtained previously: at least one factor-augmented quantile projection delivers significantly better $VaR_{0.10}$ forecasts than QAR projections, and the EWPQ delivers $VaR_{0.10}$ forecasts significantly better or at least as good than those of factor-augmented quantile projections at any forecasting horizon. Differing from previous results, however, the results of the DM tests for the financial variables *CDI*, *BDI* and *DNFCI* (Panels C-E) indicate that the forecasts of either the factor-augmented QPs or the EWPQ are superior to, or at least as good than, those of the QAR projections for most variables and horizons. The only exception are the DM tests for the *DNFCI* variable, for which the $VaR_{0.10}$ forecasts of the QARF(3)-R and QARF(5)-R projections are significantly superior to those of the EWPQ.

Summing up, factors in QPs improve the accuracy of forecasts of tail risks more markedly than in the case of AR and FAVAR models, since for all variables and forecasting horizons, factor -augmented QPs exhibit significantly better or at least as good $VaR_{0.10}$ forecasts than those obtained with QAR projections. In addition, and similarly to the results of the AR and FAVAR models, $VaR_{0.10}$ forecasts of the EWPQ are significantly superior or at least as good as those of factor-augmented QPs for most variables and forecasting horizons.

C. Comparing $VaR_{0.10}$ forecasts of the EWP and EWPQ

The finding of the (weak) dominance of EWP and EWPQ $VaR_{0.10}$ forecasts over all component models for most variables and time horizons allows us to compare the forecasting power of AR and FAVAR models relative to QPs by just focusing on comparisons of EWP and EWPQ forecasts. Table 8 reports the ratio of the EWPQ $VaR_{0.10}$ score over the EWP $VaR_{0.10}$ score for each variable and forecasting horizon, with marks of significance associated with the relevant DM tests.

[Insert Table 8 about here]

It is apparent that the $VaR_{0.10}$ forecasts of the EWPQ are significantly more accurate than those of the EWP for all variables and horizons, with the only exception being the $VaR_{0.10}$ forecast of *DNFCI* at the three months horizon, where EWPQ and EWP forecasts do not differ significantly.

The dominance of the $VaR_{0.10}$ forecasts of the EWPQ over those of the EWP is further illustrated in Table 9, which reports coverage ratios of $VaR_{0.10}$ forecasts obtained with the EWP and the EWPQ for all variables and forecasting horizons, further broken down in statistics for the whole sample and the sample starting in 2007, which includes all observations related to the 2007-2009 financial crisis.

[Insert Table 9 about here]

With the exception of $VaR_{0.10}$ forecast for *IPG* at the three month horizon, all other EWP $VaR_{0.10}$ coverage ratios significantly exceed the target coverage of 10%, and often by a large magnitude. In addition, EWP $VaR_{0.10}$ forecasts become significantly worse during the sample period that includes the 2007-2009 financial crisis, indicating that the accuracy of these tail risk predictions becomes poorer when accuracy is needed most. Thus, the tail forecasts of the AR and FAVAR models do not issue reliable early warning signals, that is, signals associated with a moderate percentage of missed realizations of adverse tail events.

A different picture emerges from the forecasting results of the EWPQ. As shown in Table 9, the improvement in the precision of EWPQ $VaR_{0.10}$ forecasts relative to the EWP forecasts is fairly dramatic. Specifically, note that the coverage ratios of the EWPQ $VaR_{0.10}$ forecasts are *not higher* than the target coverage for about half of the predictions for both the full sample and the sub-sample including the 2007-2009 financial crisis, and that the coverage ratios of the EWPQ $VaR_{0.10}$ forecasts is higher in about half of all cases by a much smaller magnitude than that associated with the EWP $VaR_{0.10}$ forecasts in such cases. All in all, the $VaR_{0.10}$ forecasts issued by the EWPQ are significantly more reliable early warning signals than those associated with the EWP.

The usefulness of the EWPQ $VaR_{0.10}$ forecasts as early warning signals is also visually illustrated in the Figures in Set 1, which depict actual and $VaR_{0.10}$ 12 month forecasts for each variable. In most instances, the decline in $VaR_{0.10}$ forecasts predicts subsequent declines in each of the indicators considered fairly accurately, even though the accuracy of EWPQ $VaR_{0.10}$ forecasts at the exact forecasting date may occur with a lag.

Thus, factor-augmented QPs deliver forecasts that appear to be fairly reliable early warning signals for tail real and financial risks. Their superiority over forecasts obtained with AR and FAVAR models is due to their ability to capture and anticipate asymmetric changes in the distribution of a variable that may shift the probability mass to the left tail.

VI. Conclusions

In this paper we developed a novel early warning system for tail real and financial risks. Using new measures of tail risks, we (i) assessed the predictive role of PCA factors in improving tail forecasts obtained with workhorse forecasting models such as AR and FAVAR models and factor-augmented Quantile Projections; (ii) gauged the additional predictive power of Equally Weighted Pools of forecasts for both modeling frameworks; and (iii) compared the accuracy of tail forecasts in terms of their ability to issue reliable early warning signals.

Our results regarding the significant improvement in the accuracy of tail forecasts arising from the use of PCA factors as predictors, and the overall dominance of Equally Weighted Pools of forecasts over single model forecasts complement the results of a large portion of the existing literature that has not specifically focused on tail forecasts. Our positive result concerning the ability of factor-augmented Quantile Projections to deliver relatively reliable early warning signals for different measures of tail real and financial risks is encouraging, and motivates several potentially useful extensions of our EWS. These extensions include tailoring our modeling framework to different countries or sets of country in a region and identifying the economic drivers of shifts in the probability distribution of tail risks based on stress-test type exercises: these extensions are already part of our research agenda.

TABLES AND FIGURES

Table 1
Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
IPG	503	0.176	0.731	-4.299	2.068
EMG	503	0.114	0.276	-0.852	1.502
CDI	504	0.083	0.032	0.014	0.241
BDI	504	0.082	0.044	0.008	0.316
DNFCI	504	0.025	1.000	-4.515	1.053

Correlations

(Significance at 5% confidence level=*)

	IPG	EMG	CDI	BDI	DNFCI
IPG	1				
EMG	0.3823*	1			
CDI	0.1798*	0.1287*	1		
BDI	0.1390*	0.2230*	0.5916*	1	
DNFCI	-0.2351*	-0.1572*	0.0323	0.046	1

Table 2. Dataset series by group

Group	Summary description	# of series
1	Real output and income	17
2	Employment and hours	30
3	Housing starts and permits	10
4	Consumption expeditures, retail sales, ISM and consumer confidence indexes	13
5	Money and credit quantities	14
6	Interest rates, spreads and exchange rates	22
7	Goods and commodity prices	21
8	Equity market (stock prices, dividend yields, price-earnings ratios)	27
9	Risks in the financial and corporate sectors (Distance to Insolvency, NFCI)	10
	Total number of series	164

Figure 1. AH factor selection criteria ER and GR as a function of the number of PCA factors *k*

(Sample range: 1973:2-2014:12)

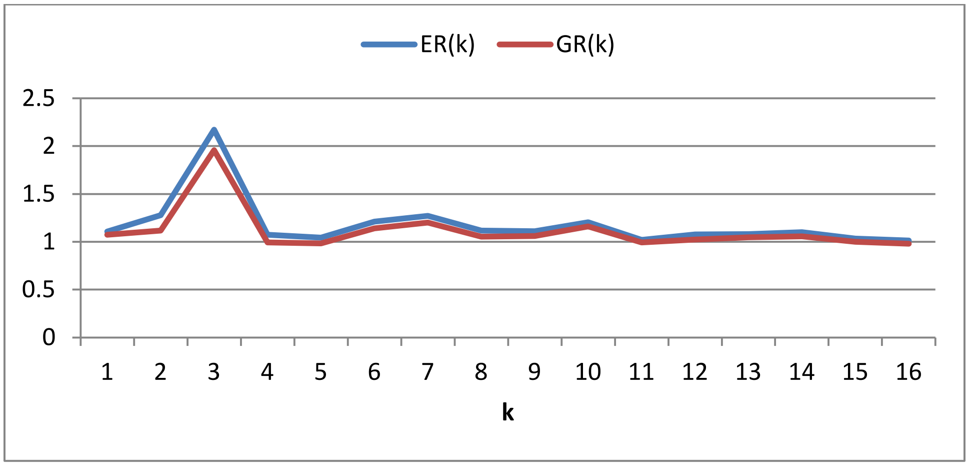

Table 3. R2 of regressions of variables on each factor, factor combination, and factor combinations with AR(5) terms

	f1	f2	f3	f4	f5	f1-f3	f1-f5	f1-f3+AR(5)	f1-f5+AR(5)
IPG	0.48	0.16	0.07	0.01	0.03	0.71	0.76	0.73	0.76
EMG	0.28	0.04	0.00	0.01	0.01	0.32	0.33	0.33	0.35
CDI	0.06	0.12	0.01	0.00	0.16	0.20	0.36	0.46	0.51
BDI	0.13	0.01	0.10	0.01	0.15	0.24	0.40	0.57	0.61
DNFCI	0.13	0.02	0.01	0.12	0.00	0.16	0.28	0.51	0.56

Table 4. Tests of FAVAR exclusion restrictions

	percentiles	0.01	0.05	0.1	0.25	0.5	0.75	0.9	0.95	0.99
All series	p-values	**0.00**	**0.00**	**0.00**	**0.01**	**0.09**	0.41	0.70	0.80	0.93
	marginal R2	0.00	0.00	0.00	0.01	**0.02**	**0.09**	**0.52**	**0.70**	**0.89**
IPG	p-values	**0.00**	**0.00**	**0.00**	**0.00**	**0.02**	**0.10**	0.24	0.39	0.61
	marginal R2	0.00	0.00	0.00	0.00	0.01	**0.02**	**0.04**	**0.10**	**0.16**
EMG	p-values	**0.02**	**0.02**	**0.04**	**0.10**	0.32	0.66	0.82	0.89	0.94
	marginal R2	0.00	0.01	0.01	**0.02**	**0.03**	**0.08**	**0.24**	**0.39**	**0.61**
CDI	p-values	**0.01**	**0.01**	**0.01**	**0.04**	0.18	0.52	0.76	0.84	0.95
	marginal R2	0.00	0.00	0.00	0.01	**0.02**	**0.51**	**0.81**	**0.88**	**0.93**
BDI	p-values	**0.01**	**0.01**	**0.02**	**0.05**	0.26	0.58	0.75	0.83	0.94
	marginal R2	0.00	0.00	0.00	0.01	**0.04**	**0.26**	**0.62**	**0.68**	**0.81**
DNFCI	p-values	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.04**	0.17	0.27	0.57
	marginal R2	0.00	0.00	0.00	0.01	**0.04**	**0.33**	**0.67**	**0.76**	**0.94**

Figure 3. Number of factors selected by AH criteria for the rolling window of 120 months and the expanding window

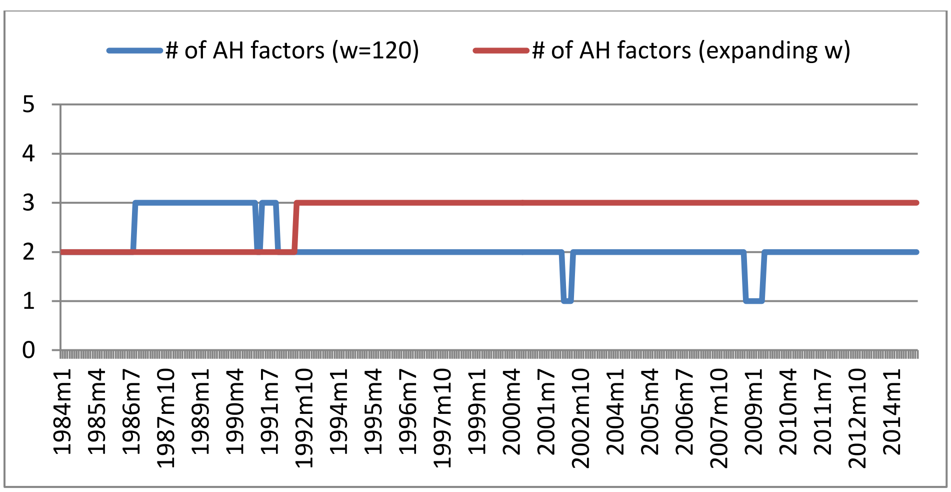

Table 5. DM pairwise tests of left tail QWPS of AR and FAVAR models

Notes: Bolded figures indicate t-stats corresponding to p-values <=0.05 (if negative) or p-values >=095 (if positive) of pairwise tests of left tail QWPS of model column-left tail QWPS of model row. Suffixes –R and –E indicate estimation under a rolling window and an expanding window respectively.

Panel A. IPG (Industrial Production Growth)

Horizon				t-stats			
		AR-R	FAVAR(x)-R	FAVAR(5)-R	AR-E	FAVAR(x)-E	FAVAR(5)-E
3	AR-R	.					
months	FAVAR(x)-R	-1.02	.				
	FAVAR(5)-R	-0.47	1.39	.			
	AR-E	-1.35	0.54	-0.11	.		
	FAVAR(x)-E	**-1.96**	-1.25	-2.21	-1.61	.	
	FAVAR(5)-E	**-2.54**	**-2.69**	**-3.68**	**-2.42**	-1.51	.
	EWP	**-4.18**	**-3.78**	**-4.63**	**-4.10**	-0.94	0.45
6	AR-R	.					
months	FAVAR(x)-R	-0.88	.				
	FAVAR(5)-R	0.02	**2.18**	.			
	AR-E	**-2.78**	-0.40	-1.39	.		
	FAVAR(x)-E	**-2.07**	-1.36	-2.58	-0.91	.	
	FAVAR(5)-E	**-2.36**	**-2.45**	**-4.59**	-1.46	-0.82	.
	EWP	**-5.01**	**-3.94**	**-5.08**	**-3.36**	-0.77	-0.04
12	AR-R	.					
months	FAVAR(x)-R	-0.36	.				
	FAVAR(5)-R	1.82	**3.61**	.			
	AR-E	**-2.70**	-1.13	**-3.14**	.		
	FAVAR(x)-E	**-3.33**	**-3.17**	**-5.52**	**-2.71**	.	
	FAVAR(5)-E	**-2.18**	**-2.29**	**-6.52**	-1.36	1.06	.
	EWP	**-5.73**	**-5.95**	**-7.12**	**-3.45**	0.77	-0.31

Panel B. EMG (Employment Growth)

Horizon				t-stats			
		AR-R	FAVAR(x)-R	FAVAR(5)-R	AR-E	FAVAR(x)-E	FAVAR(5)-E
3	AR-R	.					
months	FAVAR(x)-R	**-2.56**	.				
	FAVAR(5)-R	**-2.65**	0.33	.			
	AR-E	**3.91**	**4.73**	**4.94**	.		
	FAVAR(x)-E	-0.19	**2.94**	**2.54**	**-2.19**	.	
	FAVAR(5)-E	0.36	**3.48**	**3.51**	-1.68	0.92	.
	EWP	**-5.15**	-1.70	**-2.31**	**-7.66**	**-4.53**	**-5.65**
6	AR-R	.					
months	FAVAR(x)-R	**-3.43**	.				
	FAVAR(5)-R	**-2.33**	1.45	.			
	AR-E	**4.94**	**6.02**	**4.82**	.		
	FAVAR(x)-E	0.91	**4.95**	**3.52**	**-1.83**	.	
	FAVAR(5)-E	1.37	**5.16**	**4.39**	-1.35	0.74	.
	EWP	**-4.98**	0.29	-1.33	**-7.72**	**-5.83**	**-6.44**
12	AR-R	.					
months	FAVAR(x)-R	**-3.31**	.				
	FAVAR(5)-R	-1.36	**2.52**	.			
	AR-E	**6.09**	**6.51**	**4.65**	.		
	FAVAR(x)-E	**3.04**	**5.97**	**4.10**	-1.19	.	
	FAVAR(5)-E	**3.13**	**6.32**	**5.04**	-0.82	0.40	.
	EWP	**-4.20**	1.12	-1.68	**-8.04**	**-7.07**	**-7.63**

Table 5 (cont.). DM pairwise tests of left tail QWPS of AR and FAVAR models

Notes: Bolded figures indicate t-stats corresponding to p-values <=0.05 (if negative) or p-values >=095 (if positive) of pairwise tests of left tail QWPS of model column-left tail QWPS of model row. Suffixes –R and –E indicate estimation under a rolling window and an expanding window respectively.

Panel C. CDI (Corporate Sector Distance to Insolvency)

Horizon				**t-stats**			
		AR-R	**FAVAR(x)-R**	**FAVAR(5)-R**	**AR-E**	**FAVAR(x)-E**	**FAVAR(5)-E**
3	**AR-R**	.					
months	**FAVAR(x)-R**	**2.84**	.				
	FAVAR(5)-R	1.82	-0.97	.			
	AR-E	**-2.39**	**-4.58**	**-3.55**	.		
	FAVAR(x)-E	0.65	**-2.25**	-1.32	**2.72**	.	
	FAVAR(5)-E	0.17	**-2.82**	-1.89	**2.26**	-0.88	.
	EWP	**-2.75**	**-6.19**	**-4.99**	0.00	**-3.78**	**-3.34**
6	AR-R	.					
months	FAVAR(x)-R	0.87	.				
	FAVAR(5)-R	0.14	-0.88	.			
	AR-E	**-3.27**	**-3.61**	**-2.94**	.		
	FAVAR(x)-E	0.37	-0.41	0.31	3.45	.	
	FAVAR(5)-E	-0.34	-1.28	-0.48	2.94	-1.16	.
	EWP	**-3.72**	**-5.46**	**-4.20**	**-0.06**	**-4.31**	**-4.31**
12	AR-R	.					
months	FAVAR(x)-R	**-2.09**	.				
	FAVAR(5)-R	**-2.68**	-1.04	.			
	AR-E	**-3.10**	-1.20	-0.38	.		
	FAVAR(x)-E	-1.27	0.69	1.50	1.85	.	
	FAVAR(5)-E	-1.58	0.55	1.49	1.90	-0.28	.
	EWP	**-5.14**	**-2.93**	**-2.04**	-1.81	**-3.42**	**-3.91**

Panel D. BDI (Banking Sector Distance to Insolvency)

Horizon				**t-stats**			
		AR-R	**FAVAR(x)-R**	**FAVAR(5)-R**	**AR-E**	**FAVAR(x)-E**	**FAVAR(5)-E**
3	**AR-R**	.					
months	**FAVAR(x)-R**	**3.42**	.				
	FAVAR(5)-R	**2.99**	-0.08	.			
	AR-E	-0.40	**-3.53**	**-3.52**	.		
	FAVAR(x)-E	0.69	**-2.94**	**-2.80**	1.44	.	
	FAVAR(5)-E	**2.29**	-1.51	-1.41	**3.06**	**4.13**	.
	EWP	**-2.24**	**-5.84**	**-5.64**	**-1.93**	**-4.86**	**-6.68**
6	**AR-R**	.					
months	**FAVAR(x)-R**	1.29	.				
	FAVAR(5)-R	1.87	0.69	.			
	AR-E	0.82	-0.29	-1.06	.		
	FAVAR(x)-E	1.83	0.60	-0.28	0.96	.	
	FAVAR(5)-E	**2.58**	1.44	0.68	1.92	**3.09**	.
	EWP	**-2.13**	**-3.75**	**-4.74**	**-3.79**	**-7.30**	**-7.93**
12	**AR-R**	.					
months	**FAVAR(x)-R**	1.25	.				
	FAVAR(5)-R	**2.85**	1.64	.			
	AR-E	**3.74**	**2.81**	1.55	.		
	FAVAR(x)-E	**3.54**	**2.55**	0.95	-0.87	.	
	FAVAR(5)-E	**4.30**	**3.40**	1.87	0.32	**4.10**	.
	EWP	-0.41	-1.92	**-4.06**	**-6.25**	**-8.22**	**-9.46**

Table 5 (cont.). DM pairwise tests of left tail QWPS of AR and FAVAR models

Notes: Bolded figures indicate t-stats corresponding to p-values <=0.05 (if negative) or p-values >=095 (if positive) of pairwise tests of left tail QWPS of model column-left tail QWPS of model row. Suffixes –R and –E indicate estimation under a rolling window and an expanding window respectively.

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Panel E. DNFCI (Negative change in NFCI)

Horizon				t-stats			
		AR-R	FAVAR(x)-R	FAVAR(5)-R	AR-E	FAVAR(x)-E	FAVAR(5)-E
3	AR-R	.					
months	FAVAR(x)-R	1.03	.				
	FAVAR(5)-R	0.97	-0.14	.			
	AR-E	0.56	-0.51	-0.44	.		
	FAVAR(x)-E	1.44	0.81	0.58	1.28	.	
	FAVAR(5)-E	**3.02**	**2.28**	**2.56**	**2.94**	**3.15**	.
	EWP	-1.20	-1.65	**-2.79**	**-1.81**	**-3.93**	**-5.84**
6	AR-R	.					
months	FAVAR(x)-R	1.75	.				
	FAVAR(5)-R	0.88	-1.07	.			
	AR-E	-1.92	-2.31	**-2.08**	.		
	FAVAR(x)-E	0.04	-0.83	-0.80	1.25	.	
	FAVAR(5)-E	1.71	0.40	1.02	**2.78**	**4.01**	.
	EWP	-1.67	**-2.52**	**-3.62**	0.23	**-1.95**	**-3.93**
12	AR-R	.					
months	FAVAR(x)-R	**2.68**	.				
	FAVAR(5)-R	**2.73**	-0.17	.			
	AR-E	**-2.19**	**-3.05**	**-4.25**	.		
	FAVAR(x)-E	0.51	-1.39	**-2.16**	**2.16**	.	
	FAVAR(5)-E	1.71	-0.25	-0.45	**3.11**	**3.13**	.
	EWP	0.22	**-2.87**	**-4.92**	**2.15**	-1.39	**-2.98**

Table 6. DM pairwise tests of $VaR_{0.10}$ scores of EWP against AR and FAVAR models

Notes: Bolded figures indicate t-stats corresponding to p-values <=0.05 of pairwise test of 10% EWP quantile score – quantile score of model row. Suffixes –R and –E indicate estimation under a rolling window and an expanding window respectively.

	t-stats					
	AR-R	**FAVAR(x)-R**	**FAVAR(5)-R**	**AR-E**	**FAVAR(x)-E**	**FAVAR(5)-E**
IPG						
3 months	**-4.45**	**-2.65**	**-2.48**	**-4.20**	-0.26	1.79
6 months	**-5.57**	**-2.47**	**-3.70**	**-3.90**	-0.30	1.27
12 months	**-6.33**	**-4.01**	**-5.16**	**-3.40**	0.76	0.23
EMG						
3 months	**-4.84**	**-2.20**	**-2.83**	**-7.28**	**-4.18**	**-5.35**
6 months	**-4.36**	-0.43	-1.60	**-7.38**	**-5.31**	**-5.73**
12 months	**-3.34**	0.73	-1.24	**-8.08**	**-6.42**	**-6.71**
CDI						
3 months	**-3.53**	**-5.19**	**-4.38**	**-1.97**	**-4.30**	**-3.53**
6 months	**-4.09**	**-4.13**	**-3.36**	-1.76	**-4.77**	**-4.19**
12 months	**-5.24**	**-2.62**	**-2.70**	**-2.93**	**-4.15**	**-3.89**
BDI						
3 months	**-3.27**	**-6.16**	**-6.04**	**-2.71**	**-2.10**	**-2.57**
6 months	**-3.44**	**-4.99**	**-5.80**	**-3.87**	**-4.64**	**-4.14**
12 months	**-2.37**	**-4.17**	**-6.11**	**-4.95**	**-5.29**	**-5.54**
DNFCI						
3 months	**-2.61**	-0.68	**-2.40**	-1.51	**-2.29**	**-3.40**
6 months	-1.56	-0.89	**-2.36**	1.02	-1.40	**-2.55**
12 months	-0.90	-1.60	**-2.14**	1.62	-0.93	-0.53

Table 7. DM pairwise tests of $VaR_{0.10}$ scores of Quantile Projection models

Notes: Bolded figures indicate t-stats corresponding to p-values <=0.05 (if negative) or p-values >=095 (if positive) of pairwise tests of 10% quantile score of model column-10% quantile score of model row. Suffixes –R and –E indicate estimation under a rolling window and an expanding window respectively.

Panel A. IPG (Industrial Production Growth)

Horizon				t-stats			
		QAR-R	QARF(3)-R	QARF(5)-R	QAR-E	QARF(3)-E	QARF(5)-E
3	QAR-R	.					
months	QARF(3)-R	**-4.72**	.				
	QARF(5)-R	**-3.50**	0.38	.			
	QAR-E	**4.96**	**7.34**	**5.93**	.		
	QARF(3)-E	**-2.01**	2.27	1.48	**-5.24**	.	
	QARF(5)-E	**-3.03**	0.96	0.60	**-6.63**	-1.67	.
	EWPQ	**-5.16**	0.48	0.00	**-8.15**	-1.57	-0.68
6	QAR-R	.					
months	QARF(3)-R	**-1.99**	.				
	QARF(5)-R	-1.63	-0.31	.			
	QAR-E	**6.37**	**4.24**	**3.32**	.		
	QARF(3)-E	-1.71	0.44	0.53	**-4.19**	.	
	QARF(5)-E	**-2.40**	-0.38	0.04	**-5.04**	-1.69	.
	EWPQ	**-5.77**	**-2.65**	-1.40	**-10.46**	**-3.01**	**-2.39**
12	QAR-R	.					
months	QARF(3)-R	**-4.53**	.				
	QARF(5)-R	**-3.43**	0.25	.			
	QAR-E	**4.23**	**6.70**	**5.72**	.		
	QARF(3)-E	**-3.40**	1.20	0.94	**-8.20**	.	
	QARF(5)-E	**-3.99**	0.84	0.61	**-8.78**	-0.92	.
	EWPQ	**-6.64**	0.75	0.34	**-10.77**	-1.13	-0.59

Panel B. EMG (Employment Growth)

Horizon				t-stats			
		QAR-R	QARF(3)-R	QARF(5)-R	QAR-E	QARF(3)-E	QARF(5)-E
3	QAR-R	.					
months	QARF(3)-R	-1.73	.				
	QARF(5)-R	-1.88	-0.61	.			
	QAR-E	**5.69**	**2.93**	**3.06**	.		
	QARF(3)-E	-0.81	1.79	1.93	**-2.06**	.	
	QARF(5)-E	-0.45	2.68	2.99	-1.61	1.15	.
	EWPQ	**-3.08**	-1.30	-0.92	**-4.74**	**-2.70**	**-3.33**
6	QAR-R	.					
months	QARF(3)-R	**-2.00**	.				
	QARF(5)-R	**-2.03**	0.21	.			
	QAR-E	**4.17**	**3.05**	**3.11**	.		
	QARF(3)-E	-0.52	2.10	2.01	-1.76	.	
	QARF(5)-E	-1.67	0.33	0.21	**-2.67**	**-1.98**	.
	EWPQ	**-4.70**	-1.75	**-2.01**	**-5.94**	**-3.61**	-1.72
12	QAR-R	.					
months	QARF(3)-R	**-4.57**	.				
	QARF(5)-R	**-5.29**	-0.94	.			
	QAR-E	**2.42**	**4.55**	**5.39**	.		
	QARF(3)-E	**-3.19**	1.60	**2.55**	**-4.80**	.	
	QARF(5)-E	**-4.13**	1.15	**2.28**	**-4.66**	-1.10	.
	EWPQ	**-7.66**	0.40	1.37	**-6.57**	-1.84	-0.98

Table 7 (cont.). DM pairwise tests of $VaR_{0.10}$ scores of Quantile Projection models

Notes: Bolded figures indicate t-stats corresponding to p-values <=0.05 (if negative) or p-values >=095 (if positive) of pairwise tests of 10% quantile score of model column-10% quantile score of model row. Suffixes –R and –E indicate estimation under a rolling window and an expanding window respectively.

Panel C. CDI (Corporate Sector Distance to Insolvency)

Horizon				t-stats			
		QAR-R	QARF(3)-R	QARF(5)-R	QAR-E	QARF(3)-E	QARF(5)-E
3	QAR-R	.					
months	QARF(3)-R	-1.51	.				
	QARF(5)-R	0.28	1.76	.			
	QAR-E	-1.72	0.60	-1.08	.		
	QARF(3)-E	**-3.46**	-1.08	**-2.26**	**-3.28**	.	
	QARF(5)-E	**-3.21**	-0.41	-1.90	**-2.05**	1.13	.
	EWPQ	**-4.12**	**-3.76**	**-4.23**	**-3.31**	-1.87	**-2.22**
6	QAR-R	.					
months	QARF(3)-R	**-2.31**	.				
	QARF(5)-R	-0.44	1.08	.			
	QAR-E	-0.87	1.79	0.15	.		
	QARF(3)-E	-0.12	**2.16**	0.29	0.30	.	
	QARF(5)-E	-0.37	**2.11**	0.22	0.15	-0.21	.
	EWPQ	**-4.10**	-0.44	-1.27	**-3.60**	**-2.59**	**-4.50**
12	QAR-R	.					
months	QARF(3)-R	-1.88	.				
	QARF(5)-R	0.89	**2.03**	.			
	QAR-E	-1.36	0.91	-1.38	.		
	QARF(3)-E	-0.84	1.19	-1.35	0.18	.	
	QARF(5)-E	-1.26	0.53	-1.71	-0.48	-1.27	.
	EWPQ	**-4.00**	-1.21	**-2.58**	**-3.18**	**-4.84**	**-2.87**

Panel D. BDI (Banking Sector Distance to Insolvency)

Horizon				t-stats			
		QAR-R	QARF(3)-R	QARF(5)-R	QAR-E	QARF(3)-E	QARF(5)-E
3	QAR-R	.					
months	QARF(3)-R	-1.18	.				
	QARF(5)-R	**3.29**	**5.53**	.			
	QAR-E	1.60	**2.72**	**-2.24**	.		
	QARF(3)-E	-1.08	0.13	**-4.26**	**-3.55**	.	
	QARF(5)-E	-1.11	-0.08	**-4.46**	**-3.87**	-0.23	.
	EWPQ	-1.91	-0.88	**-5.76**	**-2.88**	-0.97	-0.52
6	QAR-R	.					
months	QARF(3)-R	0.95	.				
	QARF(5)-R	0.99	0.12	.			
	QAR-E	-1.11	-1.51	-1.77	.		
	QARF(3)-E	-1.61	**-2.09**	**-2.35**	-0.99	.	
	QARF(5)-E	-1.15	-1.74	**-1.99**	-0.22	1.12	.
	EWPQ	**-3.07**	**-3.23**	**-3.55**	-1.88	-1.02	-1.92
12	QAR-R	.					
months	QARF(3)-R	-0.78	.				
	QARF(5)-R	-0.96	-0.43	.			
	AR-E	0.00	0.70	0.89	.		
	QARF(3)-E	**-2.09**	-1.22	-0.69	**-2.04**	.	
	QARF(5)-E	**-2.14**	-1.57	-1.28	**-2.14**	-0.80	.
	EWPQ	**-4.35**	**-3.64**	**-2.24**	**-4.12**	**-2.46**	-1.01

Table 7 (cont.). DM pairwise tests of $VaR_{0.10}$ scores of Quantile Projection models

Notes: Bolded figures indicate t-stats corresponding to p-values <=0.05 (if negative) or p-values >=095 (if positive) of pairwise tests of 10% quantile score of model column-10% quantile score of model row. Suffixes –R and –E indicate estimation under a rolling window and an expanding window respectively.

Panel E. DNFCI (Negative Change in NFCI)

Horizon				t-stats			
		QAR-R	QARF(3)-R	QARF(5)-R	QAR-E	QARF(3)-E	QARF(5)-E
3	QAR-R	.					
months	QARF(3)-R	-1.22	.				
	QARF(5)-R	-1.71	**-2.12**	.			
	QAR-E	**5.37**	**9.31**	**9.02**	.		
	QARF(3)-E	0.90	**5.45**	**6.99**	**-5.01**	.	
	QARF(5)-E	0.83	**4.67**	**7.13**	**-4.76**	-0.37	.
	EWPQ	1.90	**7.41**	**9.83**	**-4.74**	**2.20**	**2.53**
6	QAR-R	.					
months	QARF(3)-R	-1.78	.				
	QARF(5)-R	**-2.55**	**-2.98**	.			
	QAR-E	**4.79**	**14.38**	**13.97**	.		
	QARF(3)-E	0.06	**3.95**	**6.14**	**-5.94**	.	
	QARF(5)-E	-0.45	**2.50**	**5.40**	**-6.60**	**-2.02**	.
	EWPQ	-0.97	**2.90**	**5.65**	**-12.41**	**-2.46**	-0.82
12	QAR-R	.					
months	QARF(3)-R	**-3.20**	.				
	QARF(5)-R	**-3.46**	-1.38	.			
	QAR-E	**3.57**	**14.19**	**13.05**	.		
	QARF(3)-E	-0.80	**5.67**	**7.16**	**-6.45**	.	
	QARF(5)-E	-1.29	**3.95**	**5.21**	**-7.09**	**-2.48**	.
	EWPQ	-1.89	**5.32**	**6.84**	**-11.33**	**-2.86**	-0.87

Table 8. $VaR_{0.10}$ scores of EWPQ forecasts/ $VaR_{0.10}$ scores of EWP forecasts

(***** denotes significance of DM tests of
numerator forecast score—denominator forecast score)

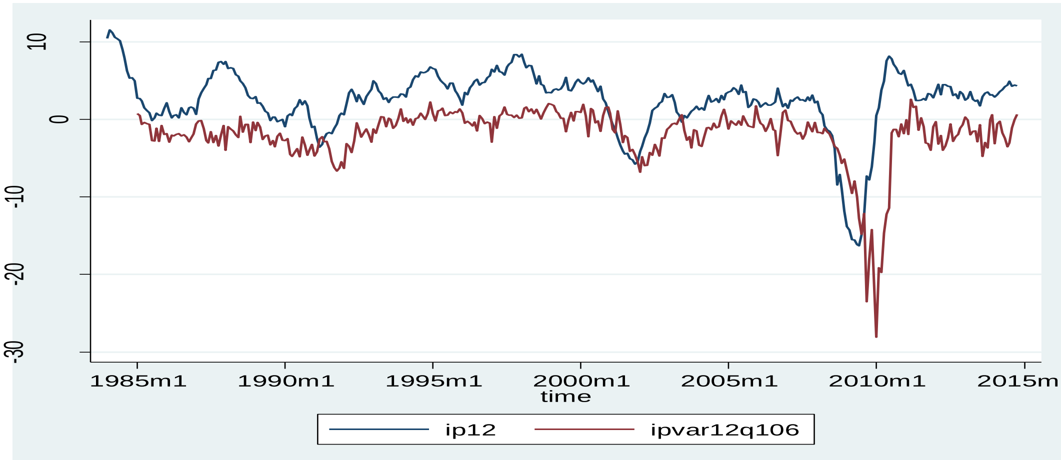
Forecast horizon	3 months	6 month	12 months
IPG (Industrial Production growth)	0.90*	0.81*	0.84*
EMG (Employment Growth)	0.78*	0.68*	0.66*
CDI (Corporate Sector DI)	0.88*	0.91*	0.86*
BDI (Banking Sector DI)	0.77*	0.69*	0.56*
DNFCI (Negative change in NFCI)	1.02	0.95*	0.81*

Table 9. Coverage ratios of the EWP and EWPQ $VaR_{0.10}$ forecasts

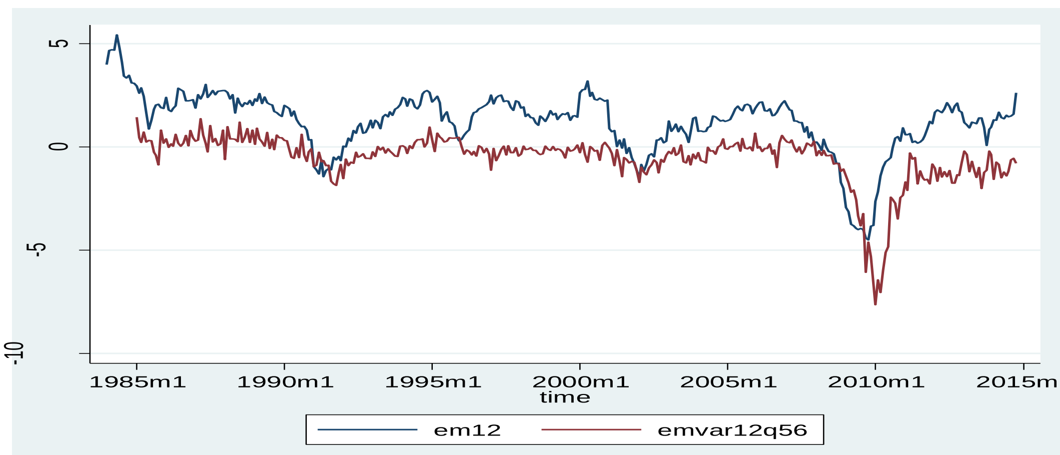
			EWP				*EWPQ*	
	Forecast Horizon		***months***				***months***	
		3	6	12		3	6	12
IPG (Industrial Production Growth)	1984:1-2014:12	0.09	0.14	0.18		0.05	0.09	0.11
	2007:1-2015:12	0.13	0.17	0.24		0.10	0.12	0.15
EMG (Employment Growth)	1984:1-2014:10	0.16	0.22	0.27		0.10	0.12	0.14
	2007:1-2015:10	0.30	0.34	0.42		0.11	0.19	0.21
CDI (Corporate Sector DI)	1984:1-2014:10	0.18	0.20	0.24		0.13	0.06	0.15
	2007:1-2015:10	0.20	0.23	0.26		0.09	0.06	0.17
BDI (Banking Sector DI)	1984:1-2014:10	0.23	0.28	0.36		0.14	0.16	0.18
	2007:1-2015:10	0.27	0.36	0.45		0.07	0.23	0.20
DNFCI (negative change in NFCI)	1984:1-2014:10	0.12	0.12	0.13		0.04	0.05	0.07
	2007:1-2015:10	0.17	0.24	0.29		0.11	0.13	0.15

Figure Set 1. EWPQ $VaR_{0.10}$ forecasts at 12 month horizon

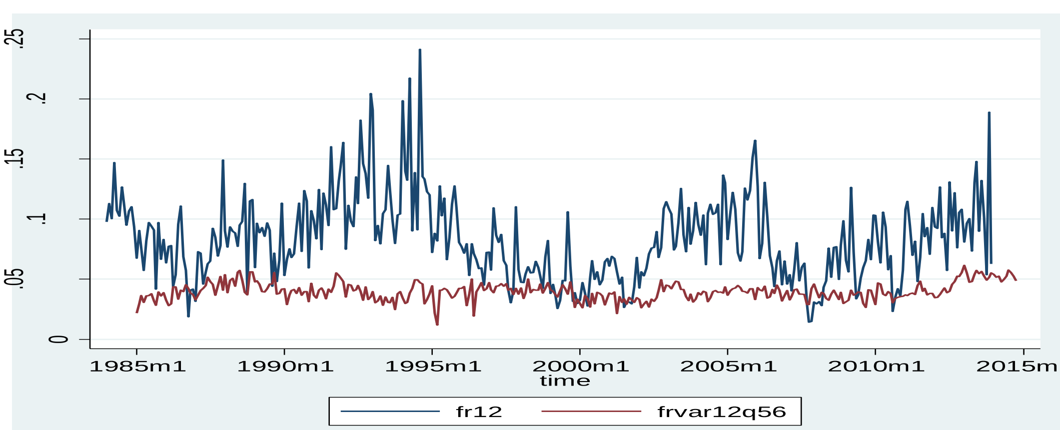
IPG and *Industrial Production-at-Risk* ($VaR_{0.10}(IPG)$)



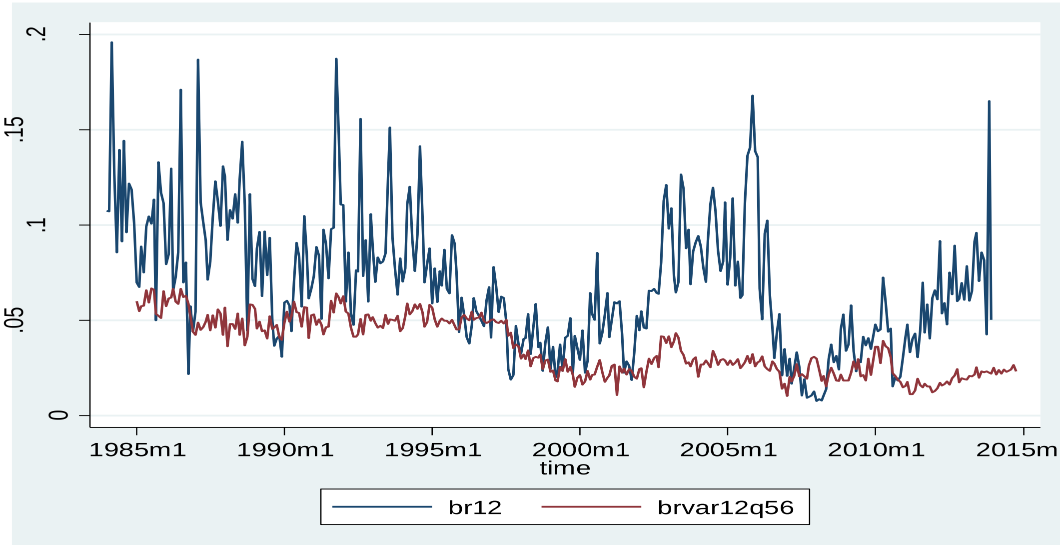
EMG and *Employment-at-Risk* ($VaR_{0.10}(EMG)$)



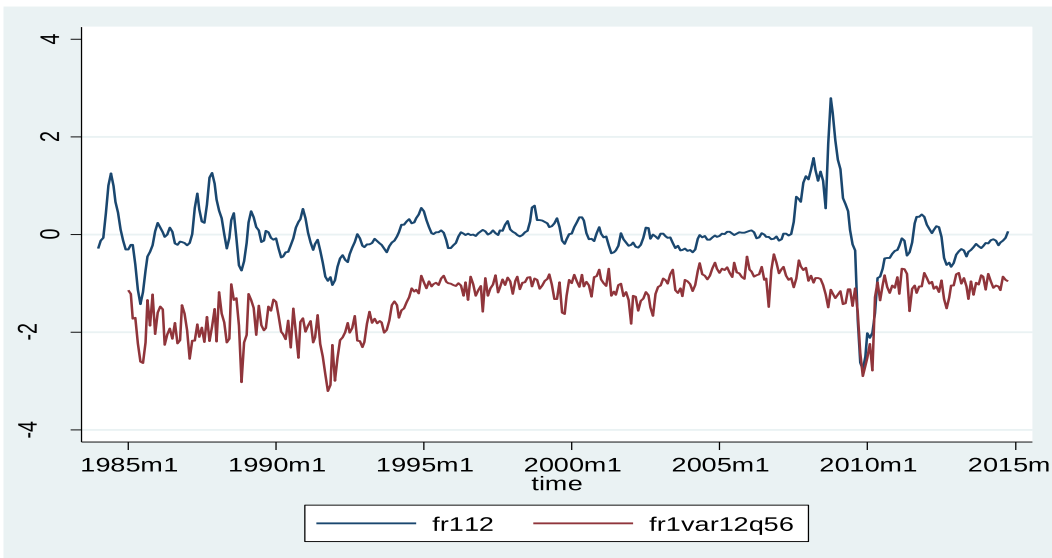
CDI and *Corporate Sector-at-Risk* ($VaR_{0.10}(CDI)$)



BDI and *Banking Sector-at-Risk* ($VaR_{0.10}(BDI)$)



DNFCI and *Financial Markets-at-Risk* ($VaR_{0.10}(DNFCI)$)



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DATA APPENDIX

The data range of all variables 1973:1-2014:12. The format of the tables is as follows: group, series number, transformation code, series mnemonic (id), and series description. The column "tcode" denotes the following transformations: (1) no transformation, (2) first difference, (3) first difference of logarithms. Application of transformations was implemented trough standard unit root tests. All series are taken from the FRED-MD database, except those marked in *italics* (taken from DataStream), and in ***bold-italics*** (taken from the Fed Chicago website).

Group 1	#	Tcode	Id	description
	1	3	RPI	Real Personal Income
	2	3	W875RX1	RPI ex. Transfers
	3	3	INDPRO	IP Index
	4	3	IPFPNSS	IP: Final Products and Supplies
	5	3	IPFINAL	IP: Final Products
	6	3	IPCONGD	IP: Consumer Goods
	7	3	IPDCONGD	IP: Durable Consumer Goods
	8	3	IPNCONGD	IP: Nondurable Consumer Goods
	9	3	IPBUSEQ	IP: Business Equipment
	10	3	IPMAT	IP: Materials
	11	3	IPDMAT	IP: Durable Materials
	12	3	IPNMAT	IP: Nondurable Materials
	13	3	IPMANSICS	IP: Manufacturing
	14	3	IPB51222S	IP: Residential Utilities
	15	3	IPFUELS	IP: Fuels
	16	1	NAPMPI	ISM Manufacturing: Production
	17	2	CAPUTLB00004S	Capacity Utilization: Manufacturing

Group 2	#	tcode	Id	description
	1	3	CLF16OV	Civilian Labor Force
	2	3	CE16OV	Civilian Employment
	3	2	UNRATE	Civilian Unemployment Rate
	4	2	UEMPMEAN	Average Duration of Unemployment
	5	3	UEMPLT5	Civilians Unemployed <5 Weeks
	6	3	UEMP5TO14	Civilians Unemployed 5-14 Weeks
	7	3	UEMP15OV	Civilians Unemployed >15 Weeks
	8	3	UEMP15T26	Civilians Unemployed 15-26 Weeks
	9	3	UEMP27OV	Civilians Unemployed >27 Weeks
	10	3	CLAIMSx	Initial Claims
	11	3	PAYEMS	All Employees: Total nonfarm
	12	3	USGOOD	All Employees: Goods-Producing

	13	3	CES1021000001	All Employees: Mining and Logging
	14	3	USCONS	All Employees: Construction
	15	3	MANEMP	All Employees: Manufacturing
	16	3	DMANEMP	All Employees: Durable goods
	17	3	NDMANEMP	All Employees: Nondurable goods
	18	3	SRVPRD	All Employees: Service Industries
	19	3	USTPU	All Employees: TT&U
	20	3	USWTRADE	All Employees: Wholesale Trade
	21	3	USTRADE	All Employees: Retail Trade
	22	3	USFIRE	All Employees: Financial Activities
	23	3	USGOVT	All Employees: Government
	24	2	CES0600000007	Hours: Goods-Producing
	25	2	AWOTMAN	Overtime Hours: Manufacturing
	26	2	AWHMAN	Hours: Manufacturing
	27	1	NAPMEI	ISM Manufacturing: Employment
	28	3	CES0600000008	Ave. Hourly Earnings: Goods
	29	3	CES2000000008	Ave. Hourly Earnings: Construction
	30	3	CES3000000008	Ave. Hourly Earnings: Manufacturing

Group 3	#	tcode	Id	description
	1	3	HOUST	Starts: Total
	2	3	HOUSTNE	Starts: Northeast
	3	3	HOUSTMW	Starts: Midwest
	4	3	HOUSTS	Starts: South
	5	3	HOUSTW	Starts: West
	6	3	PERMIT	Permits
	7	3	PERMITNE	Permits: Northeast
	8	3	PERMITMW	Permits: Midwest
	9	3	PERMITS	Permits: South
	10	3	PERMITW	Permits: West

Group 4	#	tcode	Id	description
	1	3	DPCERA3M086SBEA	Real PCE
	2	3	CMRMTSPLx	Real M&T Sales
	3	3	RETAILx	Retail and Food Services Sales
	4	1	NAPM	ISM: PMI Composite Index
	5	1	NAPMNOI	ISM: New Orders Index
	6	1	NAPMSDI	ISM: Supplier Deliveries Index
	7	1	NAPMII	ISM: Inventories Index
	8	3	AMDMNOx	Orders: Durable Goods
	9	3	ANDENOx	Orders: Nondefense Capital Goods

	10	3	AMDMUOx	Unfilled Orders: Durable Goods
	11	3	BUSINVx	Total Business Inventories
	12	2	ISRATIOx	Inventories to Sales Ratio
	13	2	*USCNFCONQ*	*Conference Board Consumer Confidence Index*

Group 5	id	tcode	Id	description
	1	3	M1SL	M1 Money Stock
	2	3	M2SL	M2 Money Stock
	3	3	M2REAL	Real M2 Money Stock
	4	3	AMBSL	St. Louis Adjusted Monetary Base
	5	3	TOTRESNS	Total Reserves
	6	3	NONBORRES	Nonborrowed Reserves
	7	3	BUSLOANS	Commercial and Industrial Loans
	8	3	REALLN	Real Estate Loans
	9	3	NONREVSL	Total Nonrevolving Credit
	10	2	CONSPI	Credit to PI ratio
	11	3	MZMSL	MZM Money Stock
	12	3	DTCOLNVHFNM	Consumer Motor Vehicle Loans
	13	3	DTCTHFNM	Total Consumer Loans and Leases
	14	3	INVEST	Securities in Bank Credit

Group 6	#	tcode	Id	description
	1	2	FEDFUNDS	Effective Federal Funds Rate
	2	2	CP3M	3-Month AA Comm. Paper Rate
	3	2	TB3MS	3-Month T-bill
	4	2	TB6MS	6-Month T-bill
	5	2	GS1	1-Year T-bond
	6	2	GS5	5-Year T-bond
	7	2	GS10	10-Year T-bond
	8	2	AAA	Aaa Corporate Bond Yield
	9	2	BAA	Baa Corporate Bond Yield
	10	1	COMPAPFF	CP - FFR spread
	11	1	TB3SMFFM	3 Mo. - FFR spread
	12	1	TB6SMFFM	6 Mo. - FFR spread
	13	1	T1YFFM	1 yr. - FFR spread
	14	1	T5YFFM	5 yr. - FFR spread
	15	1	T10YFFM	10 yr. - FFR spread
	16	1	AAAFFM	Aaa - FFR spread
	17	1	BAAFFM	Baa - FFR spread
	18	3	TWEXMMTH	Trade Weighted U.S. FX Rate
	19	3	EXSZUS	Switzerland / U.S. FX Rate

	#	tcode	Id	description
	20	3	EXJPUS	Japan / U.S. FX Rate
	21	3	EXUSUK	U.S. / U.K. FX Rate
	22	3	EXCAUS	Canada / U.S. FX Rate

Group 7	#	tcode	Id	description
	1	3	PPIFGS	PPI: Finished Goods
	2	3	PPIFCG	PPI: Finished Consumer Goods
	3	3	PPIITM	PPI: Intermediate Materials
	4	3	PPICRM	PPI: Crude Materials
	5	3	Oilprice	Crude Oil Prices: WTI
	6	3	PPICMM	PPI: Commodities
	7	1	NAPMPRI	ISM Manufacturing: Prices
	8	3	CPIAUCSL	CPI: All Items
	9	3	CPIAPPSL	CPI: Apparel
	10	3	CPITRNSL	CPI: Transportation
	11	3	CPIMEDSL	CPI: Medical Care
	12	3	CUSR0000SAC	CPI: Commodities
	13	3	CUUR0000SAD	CPI: Durables
	14	3	CUSR0000SAS	CPI: Services
	15	3	CPIULFSL	CPI: All Items Less Food
	16	3	CUUR0000SA0L2	CPI: All items less shelter
	17	3	CUSR0000SA0L5	CPI: All items less medical care
	18	3	PCEPI	PCE: Chain-type Price Index
	19	3	DDURRG3M086SBEA	PCE: Durable goods
	20	3	DNDGRG3M086SBEA	PCE: Nondurable goods
	21	3	DSERRG3M086SBEA	PCE: Services

Group 8	#	tcode	Id	description
	1	*3*	*TOTMKUS(PI)*	*US-DS Market - PRICE INDEX*
	2	*3*	*TOTMKUS(PE)*	*US-DS Market - PER*
	3	*2*	*TOTMKUS(DY)*	*US-DS Market - DIVIDEND YIELD*
	4	*3*	*TOTLIUS(PI)*	*US-DS NON-FINANCIAL - PRICE INDEX*
	5	*3*	*TOTLIUS(PE)*	*US-DS NON-FINANCIAL - PER*
	6	*2*	*TOTLIUS(DY)*	*US-DS NON-FINANCIAL - DIVIDEND YIELD*
	7	*3*	*INDUSUS(PI)*	*US-DS Industrials - PRICE INDEX*
	8	*3*	*INDUSUS(PE)*	*US-DS Industrials - PER*
	9	*2*	*INDUSUS(DY)*	*US-DS Industrials - DIVIDEND YIELD*
	10	*3*	*CNSMGUS(PI)*	*US-DS Consumer Gds - PRICE INDEX*
	11	*3*	*CNSMGUS(PE)*	*US-DS Consumer Gds - PER*
	12	*2*	*CNSMGUS(DY)*	*US-DS Consumer Gds - DIVIDEND YIELD*
	13	*3*	*FINANUS(PI)*	*US-DS Financials - PRICE INDEX*

	#	tcode	Id	description
	14	*3*	*FINANUS(PE)*	*US-DS Financials - PER*
	15	*2*	*FINANUS(DY)*	*US-DS Financials - DIVIDEND YIELD*
	16	*3*	*TECNOUS(PI)*	*US-DS Technology - PRICE INDEX*
	17	*3*	*TECNOUS(PE)*	*US-DS Technology - PER*
	18	*2*	*TECNOUS(DY)*	*US-DS Technology - DIVIDEND YIELD*
	19	*3*	*BANKSUS(PI)*	*US-DS Banks - PRICE INDEX*
	20	*3*	*BANKSUS(PE)*	*US-DS Banks - PER*
	21	*2*	*BANKSUS(DY)*	*US-DS Banks - DIVIDEND YIELD*
	22	*3*	*INSURUS(PI)*	*US-DS Insurance - PRICE INDEX*
	23	*3*	*INSURUS(PE)*	*US-DS Insurance - PER*
	24	*2*	*INSURUS(DY)*	*US-DS Insurance - DIVIDEND YIELD*
	25	*3*	*RLESTUS(PI)*	*US-DS Real Estate - PRICE INDEX*
	26	*3*	*RLESTUS(PE)*	*US-DS Real Estate - PER*
	27	*2*	*RLESTUS(DY)*	*US-DS Real Estate - DIVIDEND YIELD*

Group 9	*#*	*tcode*	*Id*	*description*
	1	*1*	*TOTMKUS(PI)*	*US-DS Market - Distance to Insolvency*
	2	*1*	*TOTLIUS(PI)*	*US-DS NON-FINANCIAL -Distance to Insolvency*
	3	*1*	*INDUSUS(PI)*	*US-DS Industrials - Distance to Insolvency*
	4	*1*	*CNSMGUS(PI)*	*US-DS Consumer Gds - Distance to Insolvency*
	5	*1*	*FINANUS(PI)*	*US-DS Financials - Distance to Insolvency*
	6	*1*	*TECNOUS(PI)*	*US-DS Technology - Distance to Insolvency*
	7	*1*	*BANKSUS(PI)*	*US-DS Banks - Distance to Insolvency*
	8	*1*	*INSURUS(PI)*	*US-DS Insurance - Distance to Insolvency*
	9	*1*	*RLESTUS(PI)*	*US-DS Real Estate - Distance to Insolvency*
	10	2	***NFCI***	***Fed Chicago National Financial Conditions Index***

TABLES APPENDIX

Table A.1. RMSE, Uniform, Right Tail and Left Tail QWPS of density forecasts of AR and FAVAR models (real variables)

Model	AR-R	FAVAR(x)-R	FAVAR(5)-R	AR-E	FAVAR(x)-E	FAVAR(5)-E	EWP	minimum
Variable								across
IPG								rows
			A. 3 month horizon					
RMSE	1.18	1.11	1.13	1.15	1.10	1.04	1.05	**1.04**
Uniform QWPS	61.36	60.08	62.36	59.84	58.55	56.52	55.63	**55.63**
Right tail QWPS	18.04	17.94	18.88	17.50	17.84	17.25	16.82	**16.82**
Left tail QWPS	19.92	18.98	19.52	19.41	18.06	17.26	17.31	**17.26**
			B. 6 month horizon					
RMSE	2.26	2.10	2.18	2.10	2.08	1.96	1.96	**1.96**
Uniform QWPS	115.32	111.53	116.97	106.70	105.88	102.92	99.43	**99.43**
Right tail QWPS	33.09	31.85	33.84	29.44	30.27	29.54	28.45	**28.45**
Left tail QWPS	38.62	36.99	38.64	36.41	34.99	33.55	32.73	**32.73**
			C. 12 month horizon					
RMSE	4.32	3.81	4.05	3.92	3.61	3.36	3.39	**3.36**
Uniform QWPS	215.25	198.77	218.29	198.07	181.29	176.18	172.03	**172.03**
Right tail QWPS	61.79	56.05	62.67	53.86	50.59	49.08	48.81	**48.81**
Left tail QWPS	73.41	67.70	73.82	69.29	62.04	59.79	57.88	**57.88**
EMG			**A. 3 month horizon**					
RMSE	0.46	0.39	0.40	0.45	0.42	0.42	0.40	**0.39**
Uniform QWPS	26.12	23.41	23.14	27.43	25.72	25.60	22.40	**22.40**
Right tail QWPS	7.80	7.23	6.97	7.73	7.67	7.32	6.81	**6.81**
Left tail QWPS	8.52	7.32	7.40	9.60	8.43	8.71	6.91	**6.91**
			B. 6 month horizon					
RMSE	0.76	0.63	0.65	0.75	0.72	0.72	0.66	**0.63**
Uniform QWPS	41.81	35.92	36.74	44.45	42.37	43.00	35.99	**35.92**
Right tail QWPS	11.96	10.68	10.48	11.59	11.63	11.66	10.43	**10.43**
Left tail QWPS	14.20	11.73	12.37	16.64	14.96	15.33	11.79	**11.73**
			C. 12 month horizon					
RMSE	1.34	1.14	1.18	1.36	1.32	1.30	1.19	**1.14**
Uniform QWPS	71.37	59.87	63.52	76.17	73.11	74.13	60.42	**59.87**
Right tail QWPS	18.94	16.42	16.98	17.82	18.50	18.76	16.10	**16.10**
Left tail QWPS	25.93	21.06	22.73	30.95	27.65	27.96	21.53	**21.06**

Table A.2 RMSE, Uniform, Right Tail and Left Tail QWPS of density forecasts of AR and FAVAR models (financial variables)

Model	**AR-R**	**FAVAR(x)-R**	**FAVAR(5)-R**	**AR-E**	**FAVAR(x)-E**	**FAVAR(5)-E**	**EWP**	**minimum across rows**
Variable								
CDI			**A. 3 month horizon**					
RMSE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	**0.03**
Uniform QWPS	1.91	2.07	1.99	1.80	1.93	1.94	1.82	**1.80**
Right tail QWPS	0.63	0.68	0.64	0.59	0.64	0.65	0.60	**0.59**
Left tail QWPS	0.55	0.61	0.59	0.52	0.57	0.56	0.52	**0.52**
			B. 6 month horizon					
RMSE	0.03	0.04	0.04	0.03	0.03	0.03	0.03	**0.03**
Uniform QWPS	2.08	2.15	2.11	1.92	2.09	2.06	1.95	**1.92**
Right tail QWPS	0.68	0.71	0.70	0.63	0.69	0.67	0.64	**0.63**
Left tail QWPS	0.61	0.62	0.61	0.55	0.61	0.60	0.55	**0.55**
			C. 12 month horizon					
RMSE	**0.04**	**0.04**	**0.04**	0.04	0.04	0.04	0.04	**0.04**
Uniform QWPS	2.31	2.27	2.20	2.13	2.21	2.24	2.14	**2.13**
Right tail QWPS	0.76	0.77	0.73	0.70	0.72	0.74	0.71	**0.70**
Left tail QWPS	0.68	0.64	0.63	0.62	0.66	0.65	0.60	**0.60**
BDI			**A. 3 month horizon**					
RMSE	0.03	0.03	0.03	0.03	0.03	0.04	0.03	**0.03**
Uniform QWPS	1.84	1.93	1.94	1.84	1.97	2.07	1.84	**1.84**
Right tail QWPS	0.58	0.57	0.58	0.58	0.63	0.65	0.59	**0.57**
Left tail QWPS	0.56	0.64	0.63	0.55	0.57	0.60	**0.53**	**0.53**
			B. 6 month horizon					
RMSE	0.03	0.03	0.03	0.04	0.04	0.04	0.04	**0.03**
Uniform QWPS	2.08	2.15	2.15	2.19	2.28	2.36	2.09	**2.08**
Right tail QWPS	0.64	0.66	0.65	0.67	0.70	0.72	0.66	**0.64**
Left tail QWPS	0.65	0.68	0.69	0.67	0.69	0.71	0.62	**0.62**
			C. 12 month horizon					
RMSE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	**0.04**
Uniform QWPS	**2.29**	2.35	2.39	2.60	2.63	2.69	2.39	**2.29**
Right tail QWPS	**0.70**	0.71	0.70	0.76	0.78	0.80	0.73	**0.70**
Left tail QWPS	**0.72**	0.75	0.79	0.83	0.82	0.84	0.72	**0.72**
DNFCI			**A. 3 month horizon**					
RMSE	0.32	0.44	0.35	0.33	0.35	0.39	0.31	**0.31**
Uniform QWPS	14.42	17.14	15.82	15.15	16.32	18.03	14.11	**14.11**
Right tail QWPS	3.91	5.43	4.48	4.18	4.65	5.19	3.93	**3.91**
Left tail QWPS	5.06	5.24	5.26	5.15	5.39	5.90	4.77	**4.77**
			B. 6 month horizon					
RMSE	0.45	0.74	0.51	0.44	0.42	0.47	0.42	**0.42**
Uniform QWPS	20.33	26.17	22.28	19.98	20.64	23.15	19.17	**19.17**
Right tail QWPS	5.52	8.76	6.41	5.55	5.93	6.82	5.48	**5.48**
Left tail QWPS	7.11	7.66	7.34	6.76	6.81	7.44	6.38	**6.38**
			C. 6 month horizon					
RMSE	0.60	0.83	0.68	0.58	**0.53**	0.61	0.55	**0.53**
Uniform QWPS	28.19	31.90	30.89	27.53	27.45	30.98	26.31	**26.31**
Right tail QWPS	7.77	9.72	8.69	7.77	7.62	9.08	7.33	**7.33**
Left tail QWPS	9.87	10.16	10.37	9.30	9.39	10.00	9.05	**9.05**