ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Improving Tail Risk Forecasts with a Quantile Projection Neural Network

Bachelor Thesis: International Bachelor Econometrics and Operations Research

Replicates and Extends: Forecasting tail risk (De Nicolo and Lucchetta 2017)

Supervisor: Bram van Os MSc, Second assessor: dr. Yutao Sun

Name student: Hagesteijn, Donald

Student ID number: 477622

Date final version: 5 July 2020

Abstract

In this paper, I investigate the accuracy of and the reliability of the $VaR_{0.05}$ forecasts of US real and financial risk indicators. I explore the following models: direct and iterated auto-regressive models, quantile projections and neural network quantile projections. I also investigate the effect of adding factors containing information about the US economy to the set of explanatory variables and the effect of pooling the forecasts. All estimation was done pseudo-real-time and implemented on the period January 1973 until December 2014. This yielded the following empirical findings: the equally weighted pool of non-factor-augmented quantile projections are the most reliable and significantly more accurate than the other models except for one indicator of financial risk. There the equally weighted pool of non-factor-augmented neural network quantile projections was superior across all variables and forecast horizons.

Contents

1 Introduction

The focus of this research is to identify a reliable early warning system (EWS) in the form of multi-period tail risk forecasts of real and financial variables. Here, the value at risk (VaR) represents the tail risk of a variable. JPMorgan popularised the VaR in the 1980s. Each VaR has a probability level of α between 0 and 1, which represents the value the variable exceeds with probability $1-\alpha$. Stated otherwise, the VaR_α represents the quantile of the distribution of the data-generating-process. If we could predict the VaRs accurately, then we could identify periods of increased risk beforehand. However, the problem here is that it is impossible to know the exact distribution of future data-generating-processes. Using the past realisations I aim to identify models that can capture the future tail-distributions of the variables adequately.

Constructing models to identify periods of extreme risk beforehand accurately has practical applications for corporate and governmental agencies. For example, a government could alter its monetary policies before a period of extreme risk such that the economic damage from potential crises can be minimised. On the other hand, financial institutions such as pension funds could hedge their assets and adapt their investment strategy to minimise a potential financial loss. From a scientific standpoint, it will be intriguing to see to what extent the relations in the quantile projections are non-linear.

This research replicates the research done by De Nicolò and Lucchetta (2017), which aims to develop an early warning system for periods with extreme tail risk. Their empirical evidence shows that the pooled linear quantile projections have superior forecasting power concerning the tail risk of real and financial risk indicators. In this research, I allow for non-linear relationships between the future tail risks and the predictors using a particle swarm optimised quantile regression neural network. In the current literature, this model has only been used to forecast the realised variance of financial time series in

The data set I use to identify which models result in the most accurate VaR forecast contains two indicators of real risk and three indicators of financial risk. I adopt industrial production growth and total employment growth as indicators of real risk. Moreover, as indicators of financial risk, I use the change in the National Financial Condition Index, constructed by the Federal Reserve Bank of Chicago and the portfolio distance-to-insolvency measures of corporate and banking sectors. I use monthly data, and the sample period spans from January 1973 to December 2014. I start this research by replicating the research of De Nicolò and Lucchetta (2017). Therefore, I first implement direct and iterative auto-regressive models. Then, I investigate how their forecasting accuracy compares to linear quantile-projections. I also investigate how adding factors, containing information about the US economy, to the set of explanatory variables affects the forecasting performance and to what extend pooled forecasts are superior to individual forecasts. To measure accuracy, I use (weighted probability) quantile scores. Then, as an extension, to model non-linear relationships in the quantile projections, I implement a particle swarm optimised quantile regression neural network in a similar setup as the other models.

By implementing the research specified above, I arrive at the following empirical findings: The superiority of direct vs iterative auto-regressive models varies across the variables and forecast horizons; The quantile projections result in more reliable and more accurate forecasts for all variables except DNFCI; The neural network quantile projections are less accurate and less reliable compared to the linear quantile projections for all variables except DNFCI; Pooling forecasts result in more accurate predictions; Adding factors tot the set of explanatory variables and removing three lags (from 5 lags to 2 lags) worsens the accuracy of the forecasts across all models, all variables and all forecast horizons.

The structure of this report is as follows: In Section 2, I discuss the connection between the current literature and the research question. I discuss the data in Section 3. Then, in Section 4, the methods used are presented. Finally, I discuss the main findings in Section 5 and state a conclusion in Section 6.

2 Literature

The focus of this research is to identify an early warning system for real and financial risk which takes the form of a model that is capable of accurately predicting the future value-at-risks of real and financial risk indicators. Therefore, the main research question is ”Which models result in the most accurate VaR forecasts?”. This question is answered using the following sub-questions: How do workhorse auto-regressive models compare to quantile projections?; To what extend does adding factors containing information about the US economy to the set of explanatory variables improve forecasting performance?; To what extend are pooled forecasts able to outperform individual forecasts? and How does the tail risk forecasting performance of quantile regression neural networks compare to linear quantile projections?

An elaborate review of models used to measure and track indicators of systematic financial tail risk is reported in Bisias et al. (2012). However, these methods do not focus on real economy variables or the risk in the financial sector; neither do they explore their the out-of-sample forecast performance such that they do not develop an early warning system. Modelling tail risk of real variables was covered by Acemoglu et al. (2015). However, forecasting the tail risk was not considered. Also, they evaluated models for shocks in the tail risk and thus are not applicable in regular situations.

De Nicolò and Lucchetta extend their previous research Lucchetta and De Nicoló (2012) by developing an early warning system as a set of multi-period tail risk forecasts of real and financial risk measures.

First, they compare the multi-period forecast performance of auto-regressive models against quantile projections(QP). They find that the QP forecasts are significantly more accurate most of the time and otherwise not significantly different. As noted by Komunjer (2013), to make quantile projections, fewer assumptions are needed, such that the variables we wish to forecast are not required to have a symmetric distribution. Second, De Nicolò and Lucchetta compare the forecasting performance of equally-weighted pools of forecasts against individual forecasts. Their research shows that pooled forecasts are significantly superior to or not significantly different from individual forecasts. Hendry and Clements (2004) shows this is likely to occur when the mean of data-generating-process varies across time. Due to business cycles, a non-constant mean of the data-generating-process is likely to occur in the data. Lastly, they use scoring rules to investigate the out-of-sample accuracy of the tail risk forecasts. One of there results was the superior accuracy of the QP forecast over the direct and indirect auto-regressive models.

However, they restricted their research to linear quantile projections. To allow for non-linear relations in the QPs, I use a quantile regression neural network trained using partial swarm optimisation. Pradeepkumar and Ravi (2017) apply this model to financial time series and show this model often outperforming GARCH and machine learning-based models for predicting volatility. I investigate whether this performance carries over to tail forecasts of real and financial risk indicators.

3 Data

As a part of this research, I replicate the research done by De Nicolò and Lucchetta (2017) using the same data. I wish to predict the VaRs of the following five series: the log change in the industrial production index (IPG); the log change in total employment (EMG); the distance to insolvency of a value-weighted portfolio consisting of non-financial firms (CDI); the distance to insolvency of a value-weighted portfolio consisting of banks (DBI) and the negative first differences of the National Financial Condition Index (DNFCI). The VaRs of IPG and EMG represent the tail risk of real activity, the VARs of CDI and BDI represent financial tail risks, and DNFCI represents the tail risk in financial markets.

As stated by De Nicolò and Lucchetta (2017), CDI and BDI are the distance-to-insolvency (DI) measures of corporate and banking sectors. Atkeson et al. (2017) introduced the distance-to-insolvency measure, it represents a firms equity cushion relative to the volatility of the value of its assets, and it bases on Leland (1994). The volatility of a firms assets is estimated using the equity volatility. The CDI and BDI measures are obtained by taking the DI of a value-weighted portfolio of all the companies in the Datastream equity indexes of non-financial firms and banks, respectively. The volatility of a firms equity is estimated by the monthly average of the squared daily returns.

The National Financial Condition Index is constructed by the Federal Reserve Bank of Chicago and is based on more than 100 indicators of risk in the financial system. It is shown by Brave and Butters (2011) that the NFCI can identify well-known periods of financial stress. They also report how to calculate the NFCI. However, in the current literature, there are inconsistent conclusions concerning the usefulness of financial condition indexes as early warning signals as noted by Aramonte et al. (2013). In Table and , I depict the descriptive statistics and the correlations of the five variables.

Table 1: Descriptive statistics of the variables

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	491	0.002	0.253	-1.389	1.281

Table 2: Correlations of the variables

	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	-0.2363*	-0.1565*	0.0301	0.0443	1

* means significantly different from zero at 5%.

I use monthly data over the period January 1973 until December 2014. I used the data provided by De Nicolò and Lucchetta (2017), which are obtained from the data archive of the Journal of Applied Econometrics volume 32 Issue 1. However, specific series need a transformation to the (log of the) first differences as described in Table of the appendix. The variables IPG, EMG, CDI and BDI contain no missing observations. The last year of the variable DNFCI is missing. Therefore, this last year is not taken into account when forecasting the DNFCI.

I obtain the factors used as explanatory variables by applying principal component analysis (PCA) to the correlation matrix of 164 monthly time series concerning the US economy. These series were collected by McCracken and Ng (2016) and can be obtained from DataStream and the FRED-MD database. The 164 series are divided into nine groups, of which a summary description is reported in Table of the appendix. Also, there are 25 months which have at least one missing observation resulting in a total of 48 missing observations which are not taken into account when calculating the correlation matrix. To choose the optimal number of factors at each point in time, I implement the AH criterion as introduced by Ahn and Horenstein (2013), which maximises the ratio of two neighbouring eigenvalues arranged in descending order. However, this criterion frequently selects an extremely high number of factors. Also, McCracken and Ng (2016) notes a decrease in explanatory power after the fifth factor. Therefore I take only the first six eigenvalues into account such that a maximum of five factors can be selected. The AH criterion selects three factors when the factors are created using the whole period of the data set and three and five factors explain 0.34% and 0.42% of the total variation in the data, respectively. The explanatory power of the factors obtained using the whole period of the data is depicted in Table 3.

Table 3: A Table containing the R-squareds of regressions of the variables on each factor, factor combination and factor combination + AR(5) terms

	F1	F2	F3	F4	F5	F1-F3	F1-F5	F1-F3+AR(5)	F1-F5+AR(5)
IPG	0.28	0.44	0.01	0.02	0.07	0.73	0.82	0.76	0.82
EMG	0.18	0.12	0.01	0.01	0.01	0.31	0.33	0.33	0.36
CDI	0.01	0.12	0.04	0.15	0.04	0.17	0.36	0.46	0.52
BDI	0.06	0.02	0.15	0.16	0.00	0.23	0.39	0.56	0.60
DNFCI	0.21	0.00	0.00	0.03	0.03	0.22	0.28	0.58	0.60

4 Methodology

To replicate the research of De Nicolò and Lucchetta (2017), I implement three methods to make quantile forecasts: a direct AR model; an iterated AR and factor-augmented VAR model(FAVAR) with a linear autoregressive conditional heteroskedasticity (GARCH) model for the volatility; projections utilizing a quantile regression(QP) together with the direct AR model I investigate the explanatory power of the factors on the future tail risk by adding factors to the models and comparing their forecast accuracy. To explore whether aggregated forecasts are superior to individual forecasts, I create four equally weighted pools(EWPs): two containing the direct AR and iterated FAVAR models specified with and without factors where the AH criterion selects the number of factors; two containing the QP models with and without factors. Their motivations behind these models are as follows: the empirical findings of Marcellino et al. (2006) and Pesaran et al. (2011) show that the superiority of the direct and iterated AR and FAVAR models depend on both the series considered and the forecasting horizon. I introduce the linear GARCH specification in the iterated AR and FAVAR forecasts as it allows us to model the time-varying volatility that is often encountered in the considered series. This choice is also supported by the research of Ghysels et al. (2009) in which they note the superiority of iterated forecasts for second moments over constant specifications. This is especially interesting as Acemoglu et al. (2015) found that time-varying variance models can explain the differential behaviour in the tails of real variables. I investigate the performance of equally weighted pools since Geweke and Amisano (2012) found that EWPs are superior to individual forecasts in terms of density forecasts. I investigate whether this also holds for tail forecasts. I estimate the factor-augmented models with AH factors. For each model, I use two types of windows to construct the forecasts. The first window is a rolling window of 120 months which allows us to account for time-varying in parameters and possible structural breaks. The second window is an expanding window having an initial size of 120 months, and adding one observation sequentially at each forecasting date. To observe whether the qualitative conclusions are uniform concerning different forecast horizons, I use three forecast horizons, namely 3, 6 and 12 months. Next I define the set of variables I aim to forecast as $Y_t = \{IPG_t, EMG_t, DBI_t, CDI_t, DNFCI_t\}$, with $y_t \in Y_t$ and F_t as a vector containing the PCA factors.

4.1 Direct AR Forecasts

The functional form of the model is as follows:

$$y_{t+h} = A + B(L)F_t + C(L)y_t + \varepsilon_{t+h} \tag{1}$$

here F_t and y_t lagged values of the factors and the variable itself respectively and h is the forecast horizon and ε_{t+h} is the error term. The VaR_α of y_{t+h} is constructed as follows:

$$VaR_\alpha(y_{t+h}) = Q_\alpha(y_{t+h}) = \hat{y}_{t+h} + \hat{\sigma}_t F^{-1}(\alpha) \tag{2}$$

here $\hat{\sigma}_t$ is the standard deviation of the differences between the forecasts of y_{t+h} and the realised values inside the estimation window and the $F^{-1}(\alpha)$ represents the inverse cumulative distribution function (cdf) of the Gaussian distribution.

4.2 Iterated Forecasts with Time-Varying Volatility (FAVAR)

The functional form of the model is as follows:

$$\begin{bmatrix} F_t \\ y_t \end{bmatrix} = \begin{bmatrix} A(L) & B(L) \\ a(L) & b(L) \end{bmatrix} \begin{bmatrix} F_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ u_{yt} \end{bmatrix} \tag{3}$$

where F represents the vector the factors, y is the variable itself, η_t is the error vector of the factors and u_{yt} is the error term of the variable we wish to predict. Similar to the direct AR model, the VaR_α of y_{t+h} is calculated as follows:

$$VaR_\alpha(y_{t+h}) = Q_\alpha(y)_{t+h} = \hat{y}_{t+h} + \hat{\sigma}_{t+h}F^{-1}(\alpha) \tag{4}$$

Where $F^{-1}(\alpha)$ represents the inverse cdf of the Gaussian distribution and the $\hat{\sigma}_{t+h}$ is estimated using a linear GARCH(1,1) model described by:

$$\begin{aligned} u_{yt} &= \sigma_{yt}\varepsilon_{yt} \\ \sigma_{yt} &= a + b\sigma_{yt-1} + c|u_{yt-1}| \end{aligned} \tag{5}$$

To estimate the parameters in equation we assume a time-independent Gaussian distribution with a zero mean for ε_{yt}. The IPG and EMG series are represented in percentage changes, CDI and BDI in levels and DNFCI in first differences. Therefore the h step ahead forecast for CDI is just the iterated forecast. However, for IPG, EMG and DNFCI the variable forecasts are given by $\hat{y^*}_{t+h} = \sum_{i=1}^{h} \hat{y}_{t+i}$ and the volatility forecasts are proxied by $\hat{\sigma^*}_{t+h} = \sqrt{\sum_{i=1}^{h} \hat{\sigma^2}_{t+i}}$ as done in Ghysels et al. (2009) and Andersen et al. (2010).

4.3 Quantile Projections (QPs)

Using OLS, one aims to explain the mean of a dependent variable given explanatory variables. However, by changing the loss function, one can explain a quantile of the dependent variable. The loss function I therefore have to use is as follows: $\frac{1}{T-h}\sum_{t=1}^{T-h}\rho_\alpha(y_{t+h} - \hat{y}_{t+h})$, where $\hat{y}_{t+h} = X_t'\beta(\alpha)$ and $\rho_\alpha(u) = u(\alpha - I\{u < 0\})$ and α is the probability that the realised variable should be lower than the quantile projection forecast. I use a linear model here such that the VaR_α of y_{t+h} at probablility level α is given by

$$VaR_\alpha(y_{t+h}) = Q_\alpha(y_{t+h}) = X_t'\hat{\beta}(\alpha) \tag{6}$$

where $\hat{\beta}(\alpha)$ are the parameters that minimize the linear quantile function.

4.4 Neural Networks

Artificial neural networks (ANNs) have been proven highly capable of modelling complex relations between input and the desired output in the fields of language translation, image recognition, advertisement selection and game playing like poker and the Chinese board game go. The power of neural networks stems from their capability to combine relationships. It aggregates simple linear relations into simple non-linear relations which then can be used to mimic complex non-linear relations. Recursively, even more, complex relationships can be modelled.

The inspiration of ANNs came from biological neural networks where neurons are connected through synapses. In our brains, input signals (for example, vision) are fired trough a net of neurons. Then, the signal is transformed depending on the nature of the synapses and neurons. This process is mimicked in ANN. There, the weights represent the synapses, and the nature of the neuron is determined by its bias parameter and activation function.

A neural network consists of an input layer, hidden layers and an output layer. A layer consist of nodes that have a specific value, a node is also called a neuron. Here, I use the diagram in Figure 1 to explain how a neural network calculates output. The values of nodes in the input layer are simply the explanatory variables. Then the values of nodes in the hidden layers are calculated by taking a weighted average of the nodes in the previous layer plus a bias and filling that into an activation function $f(x)$. Then, the node in the output layer is calculated in the same way. Neural networks can differ in the number of layers they have, how many nodes are in each layer and which node has what activation function. Each node can have any activation function. However, it is conventional that each node in a layer has the same activation function but that the activation functions in different layers can differ. The parameters of a neural network are the weights and biases. To

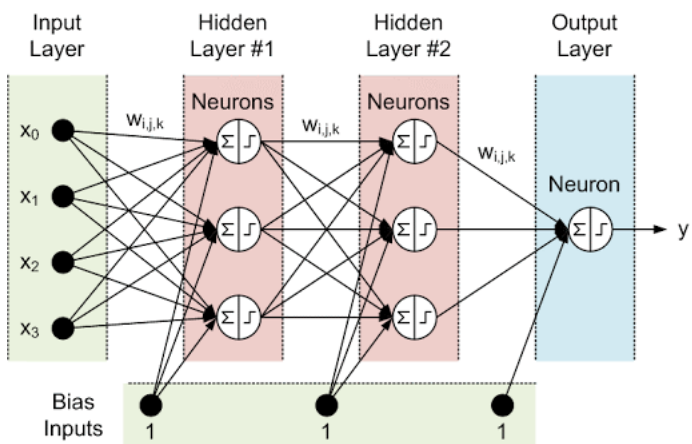

Figure 1: A diagram of the structure of a feed-forward neural network which has four nodes in its input layer as well as in its two hidden layers and one node in its output layer

estimate these parameters, an objective function that evaluates the goodness-of-fit needs to be constructed. After that, one can estimate the optimal weights and biases using an optimisation algorithm.

4.5 Neural Network Quantile Projections

The drawback of using a linear quantile projection model is that it is by definition not able to capture non-linear relations between the explanatory variables and the quantile forecast. To explore to what extend allowing for non-linear relations improves forecasting accuracy, I evaluate the forecasting performance of a quantile regression neural network(QRNN). Specifically, I explore a particular version of the quantile regression neural network implemented by Pradeepkumar and Ravi (2017). It is called the particle swarm optimised quantile regression neural network(PSOQRNN). They show that this model is often able to outperform GARCH and machine learning-based prediction models for realised variance forecasting. They evaluate performance in terms of mean squared error, directional change statistic and Thiel's inequality coefficient. I implement this method to observe whether its favourable performance carries over to the accuracy of quantile forecasts. The neural network is trained by minimising the same loss function used for the linear quantile projections described in the quantile projection Section. However, here $\hat{y}_{t+h}$ is estimated using a feed-forward neural network. The neural network consists of an input layer with the number of nodes equal to the number of predictors, one hidden layer with an equal number of nodes as the input layer and an output layer with one node, as shown in Figure 2 As done by Pradeepkumar and Ravi (2017), I choose the hyper-

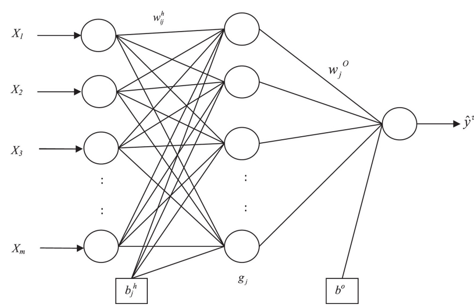

Figure 2: The structure of the particle swarm optimisation quantile regression neural network as displayed in Pradeepkumar and Ravi (2017)

bolic tangent function as the activation function for the hidden layer. Such that the value of the nodes in the hidden layer are calculated as follows:

$$n_{jt} = tanh(\sum_{j=1}^{m} w_{ij}^{h} X_{i,t} + b_j)$$

Where $n_{j,t}$ is the value of the j^{th} node from above in the hidden layer at time t, $w_{i,j}^{h}$ is the weight node j gives to input node i, b_j is the bias at node j and m is the number of nodes in the input layer. Ultimately the VaR forecasts are calculated as follows:

$$VaR_\alpha(y_{t+h}) = Q_\alpha(y_{t+h}) = \sum_{j=1}^{m} w_j^o n_{jt} + b^o$$

Where w_j^o is the weight given to node j in the hidden layer and b^o is the introduced bias. The weights and biases are estimated, by implementing a particle swarm optimisation algorithm with an inertia coefficient of

0.9 and a cognitive and social coefficient of 0.3 and 0.5, respectively. These values were chosen via trial and error on a subset of the data. Finding the optimal parameters is often referred to as training the neural network. For each forecast, a neural network is trained using the data in its estimation window. A common pitfall when training neural networks is overfitting which means that the parameters are tweaked ”too well” for the training data such that it focuses more on the errors between the actual relationship and the data than the real relationship itself as displayed in Figure 3 However, if the neural network is under trained, one runs

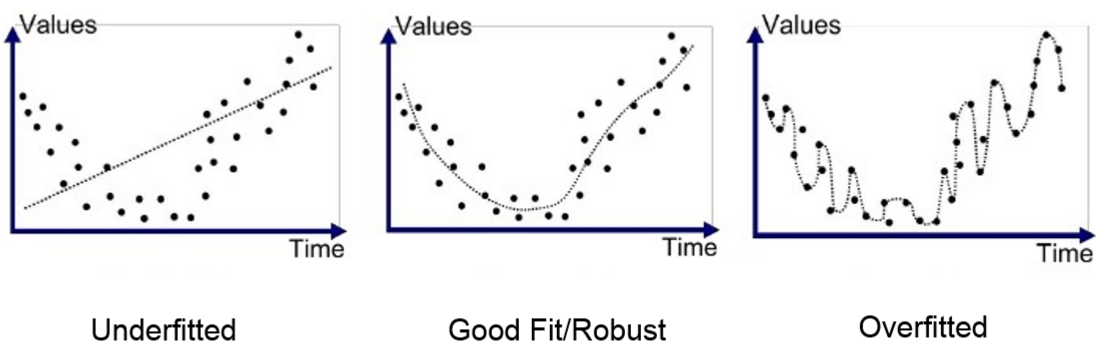

Figure 3: Examples of an under fitted, a good fitted and an overfitted model, the line represents the model and the dots represent the training data

the risk of underfitting, which means that the model is too simple. To find a balance between under and overfitting, I investigate how much the objective function decreases per iteration for small subsets of the data. This yielded 70 iterations with 100 particles.

4.6 Particle Swarm Optimisation

Introduced by Kennedy and Eberhart (1995), particle swarm optimisation is a method to find the optimal location of a set of parameters with respect to an objective function. It is inspired from the so-called ”swarm intelligence” observed in a bee swarm or a school of fish and uses multiple entities called particles and uses the so-far-best location of a particle and of all the particles to update their movement.

The locations of n particles are initially randomly generated across the search space and are then updated iteratively. In each iteration, the new location ($\overrightarrow{X_i^{t+1}}$) of a particle is calculated by adding its velocity ($\overrightarrow{V_i^{t+1}}$) to its current location as depicted in equation 7. Its velocity is calculated by multiplying the previous velocity by the inertia scalar w, then add the cognitive coefficient c times a random variable (r_1) on the unit interval times the difference between the so-far-best location of the particle and its current location. Finally, add the social coefficient s multiplied by another random variable (r_2) on the unit interval times the difference between the so-far-best location of all particles and its current location as described in equation 8.

$$\overrightarrow{X_i^{t+1}} = \overrightarrow{X_i^t} + \overrightarrow{V_i^{t+1}} \tag{7}$$

Where i is the particle's identification number.

$$\overrightarrow{V_i^{t+1}} = w\overrightarrow{V_i^t} + cr_1(\overrightarrow{P_i^t} - \overrightarrow{X_i^t}) + sr_2(\overrightarrow{G_i^t} - \overrightarrow{X_i^t}) \tag{8}$$

The number of particles, inertia, the cognitive component, social component and the number of iterations are chosen beforehand, and the cognitive and social component stays constant. However, the inertia is decreased from its initial value to zero linearly during the iterative process.

4.7 Forecast Evaluation

To compare the accuracy of tail forecasts, I use the quantile-weighted probability score (QWPS) that was introduced by Gneiting and Ranjan (2011). Using the QWPS, I can evaluate the accuracy of density forecasts within a region of the distribution, like its tails. I also use it to evaluate the accuracy of quantile projections like VaRs. The functional form of the continuous QWPS is defined as follows:

$$QWPS(f,y) = \int_0^1 QS(F^{-1}(\alpha), y, \alpha) w(\alpha) d\alpha \tag{9}$$

Here f is the density forecast,y is the realised value, F is the cdf chosen for the forecast variable such that $F^{-1}(\alpha)$ becomes the quantile projection at probability level α, $w(\alpha)$ is between zero and one and is a function to weigh the importance of a quantile which I define here as $w(\alpha) = (1-\alpha)^2$ and $QS(F^{-1}(\alpha), y, \alpha)$ represents the quantile score(QS) defined as:

$$QS(F^{-1}(\alpha), y, \alpha) = 2(I\{y \leq F^{-1}(\alpha)\} - \alpha)(F^{-1}(\alpha) - y) \tag{10}$$

with $I\{\}$ representing the indicator function. Both the QWPS and QS are orientated such that lower values indicate more accurate predictions. To evaluate the predictive ability of VaR_α forecasts I set $w(\alpha)$ to 1 for a certain probability level and 0 for all other values such that it collapses to the quantile score. To then find out whether one set of forecasts is significantly more accurate or different, I use the Diebold and Mariano (2002) test (DM) of equal forecasting performance of two left tail QWPSs or quantile scores. Under the null hypotheses of equal scores and some regularity conditions, the differences between the scores are asymptotically standard normal. Since a lower QWPS and QS are preferred, a forecast m is significantly more accurate than h if the DM statistic is significantly negative.

5 Results

In this section, I present and compare the results of the different models. The results are obtained via Python version 2.7. First, I discuss the results for the AR models. Secondly, I discuss the results of the QP models. Thirdly, I compare the performance of the EWPs of factor-augmented AR models and QP models. Fourthly, I present the results of the neural network quantile projections and compare them to the models of De Nicolò and Lucchetta (2017). The estimation of parameters and factors are done pseudo-real time such that they are re-estimated for each estimation window.

5.1 Results for AR Models

Tables 9 and 10 of the Appendix notates the left tail QWPSs of the real and financial variables respectively for all three forecast horizons and the following models: the factor- and not factor-augmented direct and indirect models estimated using a rolling or an expanding window and their equally weighted pools. An asterisk implies that that model is significantly superior to the other models in that column according to a DM test at a 5% probability level. If multiple values in a column have an asterisk, it means that those models are superior to the other models and do not significantly differ from each other.

I observe that for the real variables, the EWPs of the direct models strongly or weakly dominate the EWPs of the indirect models. For the financial variables, the superiority of either the direct or indirect models depends on the variable and forecast horizon. This aligns with the findings of Marcellino et al. (2006) and Pedersen et al. (2012) who state that superiority direct or iterated forecasts differ across variables and forecast horizons.

For the real variables, the EWPs of the models with factors do not outperform the EWP models without factors with two exceptions. For the financial variables EWPs, adding factors result in less accurate forecasts for CDI and BDI and more accurate forecasts for DNFCI without exceptions. This contradicts the results of De Nicolò and Lucchetta (2017), as they observe a lowered QWPS when adding factors to the EWPs, for all the models and forecast horizons.

When comparing EWPs to individual models, I observe, EWP models being significantly superior or not significantly different from an individual forecast for 10 out of the 15 columns (5 variables x 3 forecast horizons). This implies that the pooling of models result in more accurate forecasts and evens with the results of Geweke and Amisano (2012), who find that EWPs enhance forecasting performance.

For each variable and forecast horizon, Table 4 shows the test statistics of a DM test of equal performance applied to the left tail QWPSs of the EWP models. If the test statistic is negative and significant, then the model in the row is significantly more accurate than the model in the column. If the test statistic is positive and significant, then the model in the column is significantly more accurate than the model in the row.

Table 4: DM pair-wise tests of left tail QWPS of EWPs of AR models

Forecast horizon	3 months			6 months			12 months		
	AR-I	AR-D	FAAR-D	AR-I	AR-D	FAAR-D	AR-I	AR-D	FAAR-D
IPG									
AR-D	-5.64*			-1.19			1.21		
FAAR-D	-4.48*	0.89		-2.17*	-2.51*		-1.90*	-6.50*	
FAVAR-I	2.47*	5.71*	4.96*	2.87*	2.69*	3.68*	2.52*	0.85	3.91*
EMG									
AR-D	-7.24*			-4.21*			-2.21*		
FAAR-D	-5.33*	2.74*		-2.04*	2.24*		-1.41	0.60	
FAVAR-I	3.77*	8.52*	7.23*	4.72*	6.96*	5.38*	5.61*	6.01*	5.16*
CDI									
AR-D	-1.53			0.56			1.32		
FAAR-D	0.63	2.65*		1.69*	2.27*		1.40	0.95	
FAVAR-I	1.79*	2.53*	0.56	2.35*	1.79*	0.18	3.92*	2.25*	1.50
BDI									
AR-D	-1.42			1.84*			2.74*		
FAAR-D	1.13	3.45*		3.66*	4.72*		2.82*	2.25*	
FAVAR-I	3.15*	3.96*	1.31	4.58*	3.68*	0.47	6.38*	5.64*	3.35*
DNFCI									
AR-D	-2.47*			2.43*			0.67		
FAAR-D	-2.68*	-1.19		1.48	-1.81*		0.35	-0.49	
FAVAR-I	-0.35	2.24*	2.46*	-1.07	-3.57*	-2.76*	-3.00*	-4.55*	-3.75*

* indicates the model in the row is significantly more accurate compared to the model in the column with $p \leq 0.05$ (if negative) or the model in the column is significantly more accurate compared to the model in the row with $p \geq 0.95$ (if positive).

By comparing the direct models (AR-D and FAAR-D) to the indirect models (AR-I and FAVAR-I), I observe that the direct models are often significantly superior to the indirect models (13 times significantly superior vs 5 times significantly inferior). De Nicolò and Lucchetta (2017) find similar results: 12 times significantly superior vs 9 times significantly inferior. This also aligns with the findings of Marcellino et al. (2006) and Pedersen et al. (2012).

By comparing the models without factors (AR-D and AR-I) to the models with factors (FAAR-D and FAVAR-I), I observe that the models are most of the time significantly more accurate than the models with factors (19 times significantly superior vs 4 times significantly inferior). The models with factors have a gain in explanatory power due to its added explanatory variables. However, they also have a loss in explanatory power since it uses fewer lags (2 vs 5). This finding differs from De Nicolò and Lucchetta (2017). They find the models with the factors tend to improve the forecasting performance (12 times significantly superior vs

5 times significantly inferior) regardless of the loss of the three lags.

5.2 Results for Quantile Projections

Table 11 of the Appendix shows the average quantile scores of $VaR_{0.05}$ forecasts for the real and financial variables for the following models: the factor- and not factor-augmented quantile projections estimated using a rolling or an expanding window and their equally weighted pools. Similar to Tables 9 and 10, an asterisk implies that a model is significantly superior to the other models in that column, according to a DM test at a 5% probability level. If multiple values in a column have an asterisk, it means that those models are superior to the other models and do not significantly differ from each other.

With one exception, I observe the following: the EWPs of the models with factors do not outperform the EWP models without factors. This again contradicts the results of De Nicolò and Lucchetta (2017), who find the factor-augmented models outperforming the non-factor-augmented models.

When comparing the pooled forecasts to the individual forecasts, I observe, EWP models being significantly superior or not significantly different from individual forecasts for 11 out of the 15 columns (5 variables x 3 forecast horizons). This implies that the pooling of models result in more accurate forecasts and again evens with the results of Geweke and Amisano (2012), who find that EWPs enhance forecasting performance.

Table 5 depicts the ratios of the average quantile scores of the EWP QP model to the EWP AR model. Left, for the situation where the models are not factor-augmented. And right, where the models are, factor augmented. An asterisk means that the two models have significantly different forecasting performance, as tested by a DM test of equal performance at a 5% significance level.

Table 5: Ratios of $VaR_{0.05}$ average of the quantile scores of the EWP of QP models to the EWP of AR models and the EWP of factor-augmented QP models to the EWP of factor-augmented (V)AR models

	EWP QPAR vs EWP AR			EWP FA-QPAR vs EWP FA-(V)AR		
Forecast horizon	3 months	6 months	12 months	3 months	6 months	12 months
IPG	1.01	0.90	0.94	0.99	1.02	1.05
EMG	1.08	1.08	1.01	1.06	1.19	1.21
CDI	0.80*	0.83*	0.83*	0.91*	0.95	0.97
BDI	0.80*	0.74*	0.78*	0.86*	0.82*	0.91
DNFCI	1.58*	1.56*	1.93*	1.49*	2.22*	2.39*

* means the DM test of equal predictive performance is rejected at a 5% significance level.

performance, a ratio below one implies that the QP model is superior. I observe the EWP of QP models to be not significantly different for the variables IPG and EMG. I also observe that the EWP of QP models is significantly more accurate than the EWP of AR models or not significantly different for the variables CDI and BDI. Contrary, the EWP of AR models is significantly superior to the EWP of QP models for the variable DNFCI. Implying that the superiority of QP models over AR models depends on the variable to which the model is applied. This differs from De Nicolò and Lucchetta (2017), who find that QPs are significantly superior or not significantly different to AR models across each variable and forecast horizon.

5.3 Results for the Neural Network Quantile Projections

Table 12 of the Appendix reports the average quantile scores of the $VaR_{0.05}$ forecasts for the real and financial variables of the following models: the factor- and not factor-augmented neural network quantile projections estimated using a rolling or an expanding window and their equally weighted pools. Similar to Tables 9, 10 and 11, an asterisk implies that that model is significantly superior to the other models in that column according to a DM test at a 5% probability level. If multiple values in a column have an asterisk, it means that those models are superior to the other models and do not significantly differ from each other.

Similar to the AR and QP models, the EWPs of neural network quantile projections with factors do not outperform the EWP neural network quantile projections without factors, with one exception.

The results concerning the superior forecasting performance of pools over individual models is the same as for quantile for the projections, I observe, EWP models being significantly superior or not significantly different from an individual forecast for 10 out of the 15 columns (5 variables x 3 forecast horizons). This again implies that the pooling of models result in more accurate forecasts and again evens with the results of Geweke and Amisano (2012), who find that EWPs enhance forecasting performance.

In Table 13 of the Appendix, I include the comparison between the neural network quantile projections and its (linear) quantile projections equivalent, in the form of the ratios of $VaR_{0.05}$ the average quantile scores of neural network QP models to QP models. Hence, a ratio lower than one implies that the neural network quantile projections are superior. Similar to Table 5, an asterisk means that the two models have significantly different forecasting performance, as tested by a DM test of equal performance at a 5% significance level.

For the variables, IPG, EMG, CDI and BDI, the neural network quantile projections are significantly inferior or not significantly different from the quantile projections 69 out of the 72 times (4 variables times 6 models times 3 forecast horizons). However, for the DNFCI, I observe that the neural network quantile projections are significantly superior or not significantly different from the quantile projections for all models and forecast horizons. This implies that the use of neural network quantile projections vs linear quantile projections depend on the variable which VaR one is trying to predict.

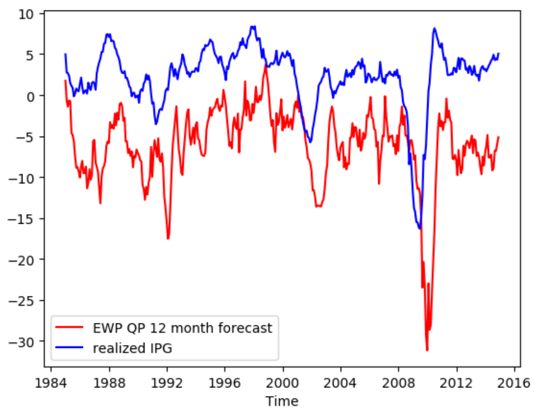

Figure 4: IPG and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of the quantile projections without factors

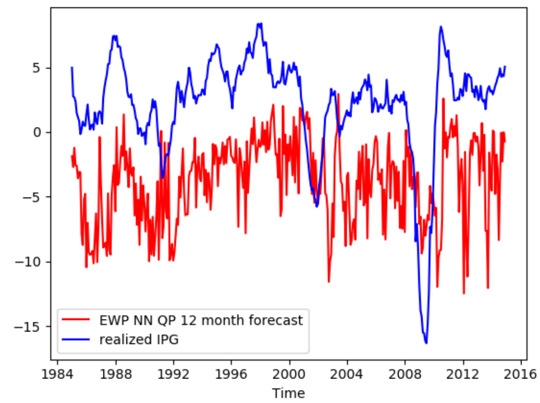

Figure 5: IPG and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of neural network quantile projections without factors

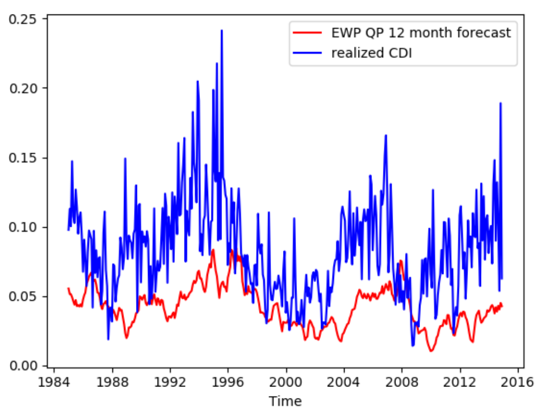

Figure 6: CDI and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of quantile projections without factors

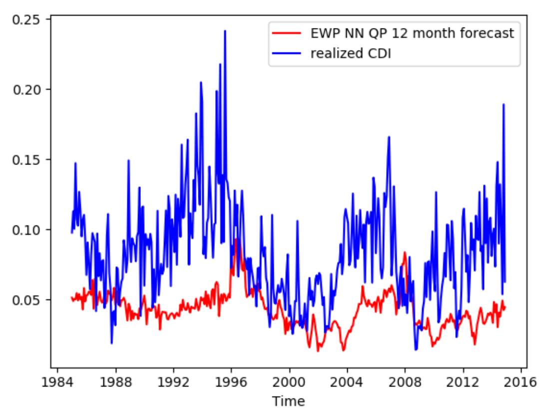

Figure 7: CDI and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of neural network quantile projections without factors

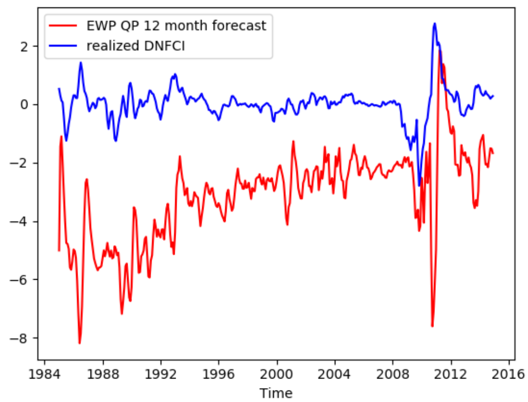

Figure 8: DNFCI and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of quantile projections without factors

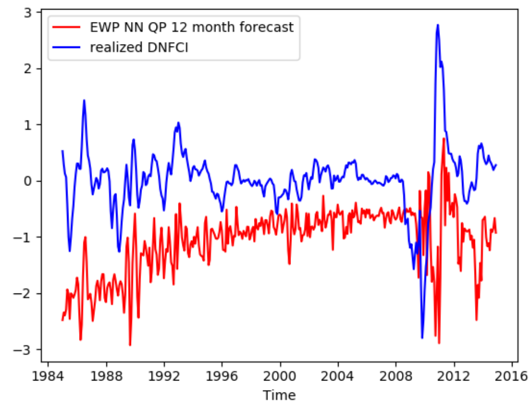

Figure 9: DNFCI and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of neural network quantile projections without factors

Since for both the EWPs of quantile projetions and neural network quantile projections, the EWPs without factors are better, I investigate those further, I display the graphs of the quantile projections and the neural network quantile projections at $\alpha = 0.05$ vs their realized variables over the period 1985m1-2014m12 of IPG, CDI and DNFCI in Figures 4, 5, 6, 7, 8 and 9. Their equivlent of the variables EMG and BDI are found in the Appendix and show simmilar traits to IPG and CDI respectively.

It stands out that the neural network quantile projection forecasts are much more disruptive compared to the forecast of the previous month, resulting in ”spiky graphs”. These are not beneficial since they are not accompanied by a change in the realized value and therefor result in noisy forecasts. This could be the result of a neural network that is not properly trained as its forecasts depend more on noise than the true signal. For the variables that are not in levels but (log) change, I also observe that of the neural network quantile projections, the range of the forecast of the period 1985m1-2014m12 is smaller compared to the quantile projections and that they do not model crises period 2007-2009 well.

5.4 Comparing Factor-Augmented and Non Factor-Augmented EWPs

To depict the forecasting accuracy of the models with factors vs the models without factors more clear, I include the ratios of the average quantile scores of the $VaR_{0.05}$ forecasts, of the EWPs of non-factor-augmented models to EWPs of factor-augmented models in Table 6. For all models: AR, QPs and neural network QPs, I observe, solely, that the EWPs without factors are significantly superior or not significantly different from the EWPs with factors. This implies that added the factors to the explanatory variables can not compensate for the loss of the three lags (from 5 to 2). Again, this result does not align with the findings of De Nicolò and Lucchetta (2017).

Table 6: Ratios the average of the quantile scores of the $VaR_{0.05}$ of EWP of models without factors to EWP of factor-augmented models

	EWP AR vs EWP FA-(V)AR			EWP QPAR vs EWP FA-QPAR		
Forecast horizon	3 months	6 months	12 months	3 months	6 months	12 months
IPG	0.93	0.94	1.03	0.95	0.82	0.91
EMG	0.93*	0.95	0.99	0.95	0.86*	0.83*
CDI	1.05	1.00	0.95	0.03*	0.57*	0.86*
BDI	0.92*	0.91*	0.92*	0.86*	0.82*	0.79*
DNFCI	0.97	1.01	0.98	1.03	0.71*	0.79*

	EWP NN QPAR vs EWP FA- NN QPAR		
Forecast horizon	3 months	6 months	12 months
IPG	0.64*	0.83	0.87
EMG	0.68*	0.73*	0.81
CDI	0.57*	0.69*	0.69*
BDI	0.55*	0.71*	0.88
DNFCI	0.76	0.97	1.02

* means the DM test of equal predictive performance is rejected at a 5% significance level.

5.5 Comparing Reliability

In Tables 14 and 15 of the Appendix, the coverage ratios of the EWPs of AR models, the EWPs of QP models and the EWPs of neural network QP models are shown both non-factor-augmented and factor-augmented respectively, over the period 1984m1-2014m12 and 2007m1-2014m12. To investigate the reliability of the forecasts, I show the coverage ratios over an extended period (1984m1-2014m12) and a period were the financial crisis of 2007-2009 is more dominantly present (2007m1-2014m12). If the coverage ratios of the two periods are similar, it means that the model is robust and its forecasting accuracy does not drop in crises periods. However, if the coverage ratios of the second period are much higher, then model is less reliable in periods of crisis. As proper risk estimating models are most important in periods of crises, this would make the model unreliably. Since the models aim to forecast the 5% value at risk, a coverage ratio lower (higher) than 5% indicate the model over (under) estimates the risk.

The EWPs of AR models with and without factors tend to have coverage ratios close to 0.05 when evaluating the whole period. However, when evaluating the period where the financial crisis more present, 2007m1-2014m12, I observe a dramatic increase in the coverage ratios for the variables IPG, EMG and DNFCI. This implies that, fore those variables, (factor-augmented) AR models underestimate the risk and thus not reliable in crisis periods for IPG, EMG and DNFCI.

The EPW of the QP models with and without factors tend to have lower coverage ratios than 0.05 and thus over-estimate the risk. However, for the variables CDI and BDI, for a forecast horizon of 12, the coverage ratios increases to 0.19 and 0.25 respectively, meaning that the model is not robust to a crisis period for those two variables and that forecasting horizon.

The coverage ratios of the EWP of the neural network quantile projections with and without factors are higher than 0.05 with 6 exceptions out of the 60. Also, the coverage ratios increase when the financial crisis is a bigger part of the period. This implies that neural net quantile projections under-estimate the risk and under-estimates it even more in crisis periods.

5.6 Discussion of the Replication

The data I use has the same descriptive statistics and correlations for all variables except DNFCI. This implies that at least for those four variables, I should be able to obtain the same results. A Reason to not obtain the same results is non-linear optimisation, De Nicolò and Lucchetta (2017) does not provide which optimisation techniques they use; however, this difference should be insignificant. Nonetheless, qualitative I observe the same results as in De Nicolò and Lucchetta (2017), except for my observation that factor-augmented models perform worse than non-factor-augmented models. This implies that I calculate the factors differently.

6 Conclusion and Further Research

To answer the main research question: "Which models result in the most accurate VaR forecasts?", I investigate the accuracy and reliability of the $VaR_{0.05}$ forecasts of the following models: direct and iterative auto-regressive models, quantile projections and neural network quantile projections. I also investigate the effect of pooling forecasts and or adding factors containing information about the US economy to the set of explanatory variables.

My empirical evidence implies the following: The superiority of direct vs iterative auto-regressive models varies across the variables and forecast horizons; The quantile projections result in more reliable and more accurate forecasts for all variables except DNFCI; The neural network quantile projections are less accurate and less reliable compared to the linear quantile projections for all variables except DNFCI; Pooling forecasts result in more accurate predictions; Adding factors tot the set of explanatory variables and removing three lags (from 5 lags to 2 lags) worsens the accuracy of the forecasts across all models, all variables and all forecast horizons.

To answer the research question: For the variables, IPG, EMG, CDI and BDI, the equally weighted pools of the non-factor-augmented quantile projections result in the most accurate and reliable $VaR_{0.05}$ forecasts. For the variable DNFCI, the equally weighted pool of the non-factor-augmented neural network quantile projections is the most accurate. However, when looking at the reliability, the linear quantile projections outperform the neural network quantile projections. All the qualitative conclusions align with the results of De Nicolò and Lucchetta (2017). Except for their observations that factor-augmented models are superior to non-factor-augmented models. This implies that I calculate the factors differently.

The finding that neural network quantile projections have superior forecasting ability for the variable DNFCI is motivating to extend this research to other risk indicating variables. Neural networks can take many forms and can use many optimisation algorithms. Even with this research, the applicability of neural networks in risk forecasting remains a vastly unexplored field. One extension of this research is to decrease the ”spikiness” of the neural network quantile projection risk forecasts by adding a penalisation term for ”spikiness” to the neural network's objective function. This could also force the model to be more dependent on the relationship between the future quantiles and its explanatory variables, instead of the random parts of the distribution.

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7 Appendix

Table 7: Description of the data set

Group	Summary description	Number 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

Table 8: Table A5. Model specifications

PANEL A. AR MODELS

#	model identifier	volatility	estimation	# of factors	AR lags	est. window	Equally Weighted Pools	
							pools	EWPs
			AR models (no factors)				(1,2)	AR-I
1	AR-I-RW	linear GARCH(1,1)	iterated	0	5	rolling	(3,4)	AR-D
2	AR-I-EW	linear GARCH(1,1)	iterated	0	5	expanding	(5,6)	FAAR-D
3	AR-D-RW	in-sample	direct	0	5	rolling	(7,8)	FAVAR-I
4	AR-D-EW	in-sample	direct	0	5	expanding		
			Factor-augmented models					
5	FAAR-D-AH-RW	in-sample	direct	AH optimal	2	rolling		
6	FAAR-D-AH-EW	in-sample	direct	AH optimal	2	expanding		
7	FAVAR-I-AH-RW	linear GARCH(1,1)	iterated	AH optimal	2	rolling		
8	FAVAR-I-AH-EW	linear GARCH(1,1)	iterated	AH optimal	2	expanding		

Panel B. QUANTILE PROJECTIONS

#	model identifier	volatility	estimation	# of factors	AR lags	est. window	Equally Weighted Pools	
			QAR models (no factors)				pools	EWPs
1	QAR-RW			0	5	rolling	(1,2)	QAR
2	QAR-EW			0	5	expanding	(3,4)	FAQAR
			Factor-augmented models					
3	FAQAR-AH-RW			AH optimal	2	rolling		
4	FAQAR-AH-EW			AH optimal	2	expanding		

Table 9: Average Left Tail QWPS of AR and FAVAR Models

PANEL A. Real Variables

		IPG			EMG		
		3m	6m	12m	3m	6m	12m
#	AR models (no factors)						
1	AR-I-RW	19.67	37.99	74.80	8.24	14.51	28.19
2	AR-I-EW	19.97	37.19	72.35*	8.00	13.81	26.58*
3	AR-D-RW	15.28*	34.72*	74.69	6.23*	12.55*	26.06*
4	AR-D-EW	16.23	37.35	79.02	6.16*	12.46*	25.64*
pools	Equally Weighted Pools						
(1,2)	AR-I	19.65	37.28	73.28	8.09	14.13	27.34
(3,4)	AR-D	15.52*	35.50	75.82	6.16*	12.43*	25.63*
	Factor-augmented models						
5	FAAR-D-AH-RW	16.02*	34.20*	71.98	6.63	13.46	27.12
6	FAAR-D-AH-EW	16.49	35.52	68.64*	6.48	13.22	25.97*
7	FAVAR-I-AH-RW	21.51	41.69	79.65	9.03	16.67	32.22
8	FAVAR-I-AH-EW	20.83	39.91	76.06	8.77	15.99	31.31
pools	Equally Weighted Pools						
(5,6)	FAAR-D	15.86*	33.69*	68.61*	6.48	13.11	25.99*
(7,8)	FAVAR-I	20.80	40.38	77.63	8.83	16.25	31.71

An asterisk indicates that a model is significantly more accurate than any other model in that column according to a DM test at a 5% probability level. When multiple values in a column have an asterisk it means that those models are superior to the other models in that column and do not significantly differ from each other.

Table 10: Average Left Tail QWPS of AR and FAVAR Models

PANEL B. Financial Variables

		CDI			BDI			DNFCI		
		3m	6m	12m	3m	6m	12m	3m	6m	12m
#	AR models (no factors)									
1	AR-I-RW	0.539	0.545	0.579	0.514	0.518	0.588	5.456	7.475*	10.462
2	AR-I-EW	0.525	0.535*	0.549*	0.489*	0.491*	0.541*	5.669	7.373*	10.597
3	AR-D-RW	0.517	0.562	0.604	0.478*	0.526	0.606	4.308*	7.838	10.993
4	AR-D-EW	0.498*	0.533*	0.561*	0.488	0.53	0.589	5.18	9.05	11.779
pools	Equally Weighted Pools									
(1,2)	AR-I	0.53	0.538*	0.562	0.499	0.501	0.56	5.523	7.357*	10.363
(3,4)	AR-D	0.506	0.545	0.581	0.479*	0.523	0.592	4.546	8.202	10.681
	Factor-augmented models									
5	FAAR-D-AH-RW	0.559	0.593	0.62	0.524	0.576	0.635	4.347*	7.653	10.151
6	FAAR-D-AH-EW	0.533	0.555	0.576*	0.533	0.575	0.622	5.269	9.047	12.47
7	FAVAR-I-AH-RW	0.571	0.592	0.65	0.555	0.579	0.686	5.489	7.139*	9.126*
8	FAVAR-I-AH-EW	0.546	0.563	0.612	0.545	0.589	0.704	6.064	7.724	10.133
pools	Equally Weighted Pools									
(5,6)	FAAR-D	0.543	0.571	0.592	0.52	0.568	0.621	4.455*	7.908	10.557
(7,8)	FAVAR-I	0.556	0.575	0.628	0.545	0.577	0.691	5.418	7.055*	9.214*

An asterisk indicates that a model is significantly more accurate than any other model in that column according to a DM test at a 5% probability level. When multiple values in a column have an asterisk it means that those models are superior to the other models in that column and do not significantly differ from each other.

Table 11: Average Quantile Scores of Quantile Projections at $\alpha = 0.05$

PANEL A. Real Variables

		IPG			EMG		
		3m	6m	12m	3m	6m	12m
#	Quantile Projections (no factors)						
1	QP-RW	0.2402*	0.4597*	1.1449	0.1028*	0.2014*	0.4203
2	QP-EW	0.2705	0.5298	1.1253	0.1013*	0.2031*	0.3938*
	Factor-augmented Quantile Projections						
3	FAQP-AH-RW	0.3052	0.6997	1.3872	0.1092*	0.2629	0.5129
4	FAQP-AH-EW	0.2497*	0.5428	1.3258*	0.1056*	0.2220*	0.4506
pools	Equally Weighted Pools						
(1,2)	EWP QP	0.2505	0.4801*	1.0902*	0.1008*	0.1992*	0.3847*
(3,4)	EWP FAQP	0.2641*	0.5843	1.1919*	0.1058*	0.2314	0.4636

PANEL B. Financial Variables

		CDI			BDI		
		3m	6m	12m	3m	6m	12m
#	Quantile Projections (no factors)						
1	QP-RW	0.004914*	0.005070*	0.005542	0.004862*	0.004950*	0.006570
2	QP-EW	0.004877*	0.005116*	0.005176*	0.004831*	0.004978*	0.005745*
	Factor-augmented Quantile Projections						
3	FAQP-AH-RW	0.005775	0.006367	0.007509	0.005422	0.006058	0.008534
4	FAQP-AH-EW	0.005879	0.006439	0.007244	0.006408	0.006617	0.007907
pools	Equally Weighted Pools						
(1,2)	EWP QP	0.004888*	0.005077*	0.005338	0.004829*	0.004911*	0.006151
(3,4)	EWP FAQP	0.005362	0.005784	0.006575	0.005618	0.005988	0.007778

		DNFCI		
		3m	6m	12m
#	Quantile Projections (no factors)			
1	QP-RW	0.1038*	0.1742*	0.2790*
2	QP-EW	0.1361	0.2247	0.4097
	Factor-augmented Quantile Projections			
3	FAQP-AH-RW	0.1170*	0.2636	0.4402
4	FAQP-AH-EW	0.1288	0.3115	0.4892
pools	Equally Weighted Pools			
(1,2)	EWP QP	0.1166	0.1877	0.3243
(3,4)	EWP FAQP	0.1136*	0.2658	0.4110

An asterisk indicates that a model is significantly more accurate than any other model in that column according to a DM test at a 5% probability level. When multiple values in a column have an asterisk it means that those models are superior to the other models in that column and do not significantly differ from each other.

Table 12: Average Quantile Scores of Neural Network Quantile Projections at $\alpha = 0.05$

PANEL A. Real Variables

		IPG			EMG		
		3m	6m	12m	3m	6m	12m
#	Quantile Projections (no factors)						
1	NN QP-RW	0.2727	0.6985	1.7467	0.0952	0.2232	0.5255
2	NN QP-EW	0.2383*	0.6193*	1.0815*	0.0817*	0.1865*	0.4301*
	Factor-augmented Quantile Projections						
3	NN FAQP-AH-RW	0.4208	0.8891	1.8850	0.1297	0.2865	0.6738
4	NN FAQP-AH-EW	0.4332	0.8260	1.4457	0.1477	0.3132	0.5136
pools	Equally Weighted Pools						
(1,2)	EWP NN QP	0.2280*	0.5801*	1.2266	0.0850*	0.1860*	0.4379*
(3,4)	EWP NN FAQP	0.3588	0.6957	1.4065	0.1245	0.2559	0.5381

PANEL B. Financial Variables

		CDI			BDI		
		3m	6m	12m	3m	6m	12m
#	Quantile Projections (no factors)						
1	NN QP-RW	0.005856	0.005774	0.006785	0.005445	0.006706	0.008441
2	NN QP-EW	0.005060*	0.005447*	0.005315*	0.005091*	0.005326*	0.006142*
	Factor-augmented Quantile Projections						
3	NN FAQP-AH-RW	0.011553	0.009522	0.011268	0.012377	0.009678	0.009517
4	NN FAQP-AH-EW	0.010752	0.009632	0.009856	0.009555	0.011445	0.011350
pools	Equally Weighted Pools						
(1,2)	EWP NN QP	0.005367	0.005412*	0.005878	0.005122*	0.005841	0.007050
(3,4)	EWP NN FAQP	0.009430	0.007868	0.008523	0.009255	0.008231	0.007972

		DNFCI		
		3m	6m	12m
#	Quantile Projections (no factors)			
1	NN QP-RW	0.0748*	0.1442	0.2444
2	NN QP-EW	0.0874	0.1313*	0.1725*
	Factor-augmented Quantile Projections			
3	NN FAQP-AH-RW	0.1095	0.1559	0.2189
4	NN FAQP-AH-EW	0.1144	0.1486	0.1905*
pools	Equally Weighted Pools			
(1,2)	EWP NN QP	0.0770*	0.1314*	0.1904*
(3,4)	EWP NN FAQP	0.1010	0.1360*	0.1873*

An asterisk indicates that a model is significantly more accurate than any other model in that column according to a DM test at a 5% probability level. When multiple values in a column have an asterisk it means that those models are superior to the other models in that column and do not significantly differ from each other.

Table 13: Ratios the average quantile scores of the $VaR_{0.05}$ forecasts of neural network QP models to QP models

	PANEL A. Real Variables						
			IPG			EMG	
		3m	6m	12m	3m	6m	12m
#	Quantile Projections (no factors)						
1	NN QP-RW vs QP-RW	1.14	1.52*	1.53*	0.93	1.11	1.25
2	NN QP-EW vs QP-EW	0.88*	1.17*	0.96	0.81*	0.92	1.09
	Factor-augmented Quantile Projections						
3	NN FAQP-AH-RW vs FAQP-AH-RW	1.38*	1.27	1.36*	1.19	1.09	1.31
4	NN FAQP-AH-EW vs FAQP-AH-EW	1.73*	1.52*	1.09	1.40*	1.41*	1.14
pools	Equally Weighted Pools						
(1,2)	EWP NN QP vs EWP QP	0.91	1.21*	1.13	0.84*	0.93	1.14
(3,4)	EWP NN FAQP vs EWP FAQP	1.36*	1.19	1.18	1.18	1.11	1.16
	PANEL B. Financial Variables						
			CDI			BDI	
		3m	6m	12m	3m	6m	12m
#	Quantile Projections (no factors)						
1	NN QP-RW vs QP-RW	1.19*	1.14*	1.22*	1.12*	1.35*	1.28*
2	NN QP-EW vs QP-EW	1.04	1.06*	1.03	1.05	1.07*	1.07*
	Factor-augmented Quantile Projections						
3	NN FAQP-AH-RW vs FAQP-AH-RW	2.00*	1.52*	1.50*	2.28*	1.60*	1.12
4	NN FAQP-AH-EW vs FAQP-AH-EW	1.83*	1.49*	1.36*	1.49*	1.73*	1.44*
pools	Equally Weighted Pools						
(1,2)	EWP NN QP vs EWP QP	1.10*	1.07*	1.10*	1.06	1.19*	1.15*
(3,4)	EWP NN FAQP vs EWP FAQP	1.76*	1.26*	1.29*	1.65*	1.37*	1.03
			DNFCI				
		3m	6m	12m			
#	Quantile Projections (no factors)						
1	NN QP-RW vs QP-RW	0.72*	0.83*	0.88			
2	NN QP-EW vs QP-EW	0.64*	0.58*	0.42*			
	Factor-augmented Quantile Projections						
3	NN FAQP-AH-RW vs FAQP-AH-RW	0.94	0.59*	0.50*			
4	NN FAQP-AH-EW vs FAQP-AH-EW	0.89	0.48*	0.39*			
pools	Equally Weighted Pools						
(1,2)	EWP NN QP vs EWP QP	0.66*	0.70*	0.59*			
(3,4)	EWP NN FAQP vs EWP FAQP	0.89	0.51*	0.46*			

* means the DM test of equal predictive performance is rejected at a 5% significance level.

Table 14: Coverage Ratios of Equally Weighted Pools of $VaR_{0.05}$ Forecasts of AR, QP and neural network QP models without factors

	Model:	EWP AR			EWP QP			EWP NN QP		
Variable	Forecast Horizon:	3m	6m	12m	3m	6m	12m	3m	6m	12m
IPG	1984:1-2014:12	0.02	0.03	0.06	0.01	0.02	0.03	0.05	0.04	0.08
	2007:1-2014:12	0.06	0.11	0.15	0.04	0.06	0.12	0.10	0.12	0.19
EMG	1984:1-2014:12	0.03	0.04	0.06	0.03	0.03	0.04	0.06	0.06	0.09
	2007:1-2014:12	0.07	0.08	0.15	0.04	0.02	0.01	0.06	0.13	0.20
CDI	1984:1-2014:12	0.08	0.06	0.05	0.06	0.07	0.06	0.08	0.10	0.10
	2007:1-2014:12	0.07	0.05	0.06	0.07	0.08	0.11	0.07	0.12	0.15
BDI	1984:1-2014:12	0.03	0.03	0.04	0.07	0.08	0.08	0.11	0.12	0.13
	2007:1-2014:12	0.00	0.00	0.10	0.06	0.12	0.18	0.11	0.14	0.20
DNFCI	1984:1-2014:12	0.04	0.04	0.05	0.01	0.01	0.01	0.04	0.04	0.05
	2007:1-2014:12	0.11	0.13	0.20	0.05	0.04	0.05	0.11	0.14	0.23

Table 15: Coverage Ratios of Equally Weighted Pools of $VaR_{0.05}$ Forecasts of AR, QP and neural network QP models with factors

	Model:	EWP FA(V)AR			EWP FA-QP			EWP NN FA-QP		
Variable	Forecast Horizon:	3m	6m	12m	3m	6m	12m	3m	6m	12m
IPG	1984:1-2014:12	0.03	0.04	0.04	0.03	0.03	0.05	0.08	0.08	0.13
	2007:1-2014:12	0.06	0.12	0.15	0.04	0.06	0.11	0.12	0.14	0.20
EMG	1984:1-2014:12	0.02	0.03	0.04	0.03	0.03	0.04	0.09	0.10	0.13
	2007:1-2014:12	0.10	0.11	0.17	0.05	0.04	0.02	0.17	0.17	0.27
CDI	1984:1-2014:12	0.05	0.03	0.03	0.01	0.00	0.14	0.06	0.05	0.05
	2007:1-2014:12	0.06	0.01	0.02	0.02	0.01	0.19	0.06	0.05	0.04
BDI	1984:1-2014:12	0.01	0.01	0.02	0.03	0.03	0.14	0.10	0.10	0.09
	2007:1-2014:12	0.00	0.00	0.04	0.08	0.04	0.25	0.12	0.12	0.13
DNFCI	1984:1-2014:12	0.04	0.04	0.05	0.03	0.02	0.01	0.04	0.04	0.07
	2007:1-2014:12	0.08	0.14	0.21	0.07	0.07	0.01	0.08	0.15	0.19

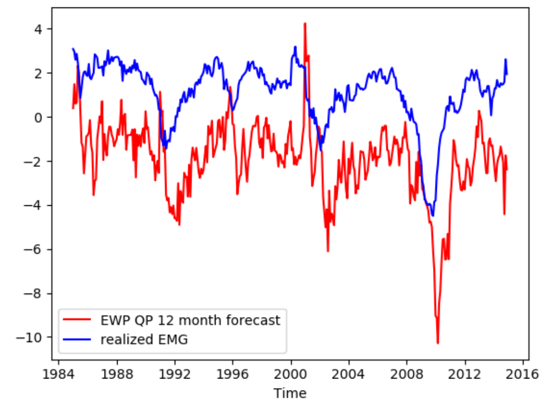

Figure 10: EMG and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of quantile projections without factors

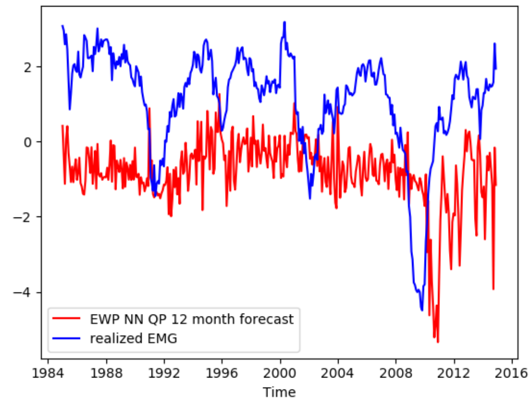

Figure 11: EMG and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of neural network quantile projections without factors

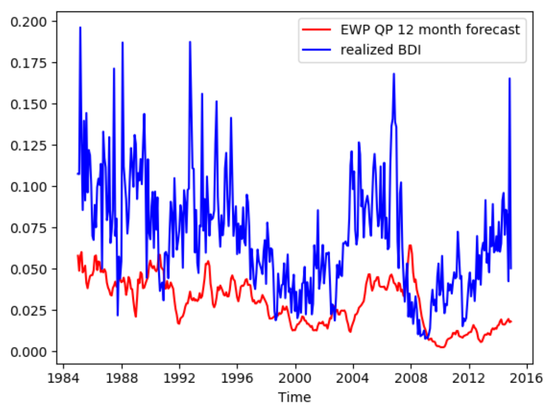

Figure 12: BDI and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of quantile projections without factors

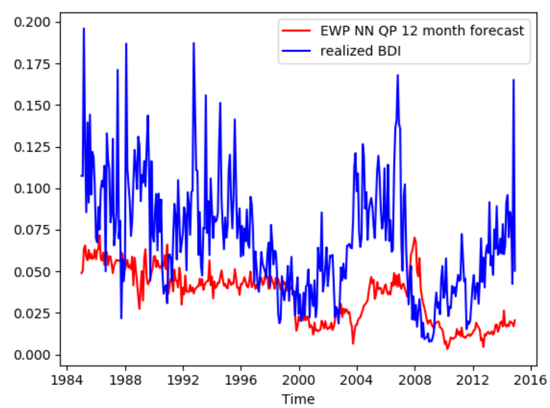

Figure 13: BDI and its 12 month ahead $VaR_{0.05}$ forecast, obtained using an equally weighted pool of neural network quantile projections without factors

Data transformation

The raw data can be downloaded from:
`http://qed.econ.queensu.ca/jae/2017-v32.1/de_nicolo-lucchetta/`. However how the data should be transformed is denoted with the transformation code (tcode) in the following table. (1) means no transformation, (2) means the first difference and (3) means the first difference of the natural logarithm.

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

	#	tcode	id	description
	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

	#	tcode	id	description
	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	#	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

Group	#	tcode	id	description
	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
	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

	#	tcode	id	description
	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
	14	3	FINANUS(PE)	US-DS Financials - PER

	#	tcode	id	description
	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	dimarket	US-DS Market - Distance to Insolvency
	2	1	dinonfinancial	US-DS NON-FINANCIAL -Distance to Insolvency
	3	1	diindustrials	US-DS Industrials - Distance to Insolvency
	4	1	diconsumerg	US-DS Consumer Gds - Distance to Insolvency
	5	1	difinancials	US-DS Financials - Distance to Insolvency
	6	1	ditechnology	US-DS Technology - Distance to Insolvency
	7	1	dibanks	US-DS Banks - Distance to Insolvency
	8	1	diinsurance	US-DS Insurance - Distance to Insolvency
	9	1	direalestate	US-DS Real Estate - Distance to Insolvency
	10	2	NFCI	Fed Chicago National Financial Conditions Index