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IDENTIFYING US BUSINESS CYCLE REGIMES USING FACTOR AUGMENTED NEURAL NETWORK MODELS

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Abstract

We propose a factor augmented neural network model to identify the current state (instead of future) of the US business cycle. Dynamic factors are extracted from a large-scale data set consisted of 122 variables. Then, these dynamic factors are fed into neural network models for predicting the current business cycle regime. First, we show that our proposed method determines US business cycle regimes quite accurately in sample and out of sample without taking account of the historical data availability. Then in a pseudo real time exercise, we also show that our neural network models identify business cycle regimes in a timely and accurate manner. Finally, our results indicate that neural network models outperform probit models.

Keywords: Dynamic Factor Model; Neural Network; Recession; Business Cycle
JEL: E37, E32, C38

1 Introduction

Whether the US in a recession or an expansion at any given time is crucial information for all economic agents in the US and around the globe. Especially, identifying the start of a recession as early as possible may help policy makers to take necessary precautions for the economy. However, the business cycle dating committee of the National Bureau of Economic Research (NBER) which currently maintains the chronology of the US business cycle has historically announced business cycle turning points with a significant delay. Therefore over the years, many business cycle dating methodologies have been proposed in the literature.[1] In this study, we propose a factor augmented neural network (NN) model to determine the

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[1]See Hamilton (2011) for a survey of models that aim to identify turning points in real time.

business cycle regime of the current period in real time. We predict recessions and expansions via a factor augmented NN in two steps. In the first step, we use the dynamic factor model (DFM) proposed by Giannone et al. (2008) to extract a handful of dynamic factors from a large number of data series. In the second step, we feed these dynamic factors into NNs to determine recession and expansion periods in real time.

Predicting economic variables by factors extracted from large/medium-scale data sets is a widespread approach in the literature[2] but this isn't still common for predicting business cycle regimes for future or current periods. In one of the notable studies, Fossati (2016) uses factor augmented probit and Markov switching models to determine current business conditions. For predicting future business cycle regimes, Bellégo and Ferrara (2009) extract static factors from 13 variables and feed them into a probit model to forecast Euro Area recessions. Chen et al. (2011) also follow a similar factor augmented probit approach using a data set including 131 variables to predict recessions in the US economy. Furthermore, Fossati (2015) also forecasts US recessions using the factor augmented probit approach but he uses dynamic factors instead of static ones and a smaller data set. Finally, Christiansen et al. (2014) use the factor augmented probit to test the predictive ability of sentiment variables for US recessions.

Except Giusto and Piger (2017) which use a simple machine learning algorithm known as Learning Vector Quantization to identify turning points for the US business cycle, other studies that use factors to predict current or future recession and expansion periods utilize parametric models. Given that true data generating process is unknown, a non-parametric approach may be more appropriate for predicting US business cycle regimes. Our interest lies in non-parametric NN algorithms. NNs have been successfully applied to problems in computer science, engineering, medical, and financial applications. However, NNs are rarely used for predicting business cycle regimes in real time. One notable exception is the study of Qi (2001) which uses a two-layered NN model for 1 to 8 quarter ahead out of sample business cycle state predictions. Qi (2001) uses NNs with one or two variables to obtain predictions for the US business cycle regimes. Compared to Qi (2001), we use a large-scale data set consisted of 122 variables and focus on identifying the business cycle regime of the current month instead of forecasting whether there will be a recession or expansion in coming periods because our model is based on the nowcasting methodology of Giannone et al. (2008) which is best suited for obtaining predictions of the target variable for the present or the

[2] See Eickmeier and Ziegler (2008) for a meta analysis of factor forecast applications for output and inflation and see Banbura et al. (2013) for factor nowcasting applications for output.

very recent past.

In this study, we use factor augmented NN models with 8 different estimation techniques and two different combination methods to identify the business cycle regime of the current period. As a competing model, we utilize a probit model. We extract factors from a data set consisted of 122 variables. As we don't have vintage data for these 122 variables, we use final revised data to conduct our analysis. First, we show that most of the NN models follow the NBER's business cycle chronology quite accurately in sample and out of sample without taking account of the historical data availability. Then, we test the identification performance of our models by replicating the historical data availability in each estimation period. Our results show that most factor augmented NN models determine US business cycle regimes in a timely and accurate manner both for expansion and recession periods. Given that the NBER announces turning points of the US business cycle with a significant lag and most dating methodologies fail to determine US business cycle regimes in a timely fashion as shown by Hamilton (2011), our proposed methodology can be helpful for both policy makers and market participants to infer the current state of the economy without much delay. Finally, these NN models clearly outperform the probit model especially in recession periods.

The remainder of this paper is as follows. Section 2 introduces the methodology. Section 3 describes the data set. Section 4 presents the empirical results, and section 5 concludes.

2 The methodology

In this study, we use NNs to determine business cycle regimes. Before utilizing NNs, we perform dimensionality reduction by employing a DFM because using full data set can cause overfitting of NNs and lead to poor prediction performance due to irrelevant and noisy variables. A DFM is appropriate for reducing the dimension of a macroeconomic data set because a small number of factors is enough to capture most of the dynamics among macroeconomic data series.[3]

[3]See Sargent and Sims (1977) and Giannone et al. (2005).

2.1 The dynamic factor model

Let's assume that standardized and filtered n monthly series $x_t = (x_{1,t}, x_{2,t}, \ldots, x_{n,t})', t = 1, 2, \ldots, T$ as in Giannone et al. (2008) have the following approximate dynamic factor model:

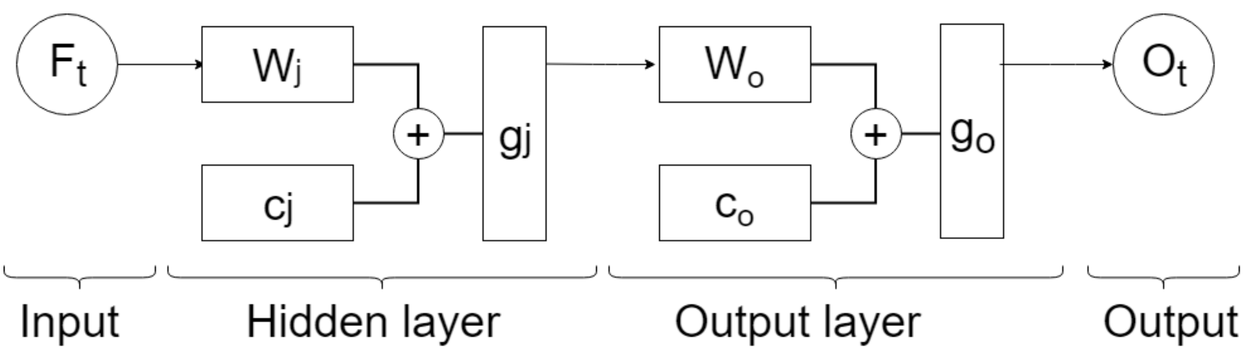
$$x_t = \mu + \Lambda f_t + \xi_t; \quad \epsilon_t \sim \mathbb{N}(0, \Sigma_\xi), \tag{1}$$

$$f_t = \Phi(L) f_{t-1} + B\eta_t; \quad \eta_t \sim \mathbb{N}(0, I_q), \tag{2}$$

where μ is a constant, Λ is an nxr matrix of factor loadings, $f_t = (f_{1,t}, f_{2,t}, \ldots, f_{r,t})'$ are unobserved common factors that satisfy $r \ll n$, and ξ_t is an idiosyncratic component assumed to be multivariate white noise with diagonal covariance matrix Σ_ξ. As shown in the equation 2, f_t is assumed to follow a vector autoregression process driven by q dimensional vector of common shocks, η_t, that follows a white-noise process. B is an rxq matrix of full rank q with $q \leqslant r$ and $\varphi(L)$ is an rxr lag polynomial matrix.

Following Giannone et al. (2008), we use a two-step estimation approach to obtain common factors. In the first step, the initial estimate of common factors are obtained by the principal component analysis and then parameters of the model are estimated via OLS using only the balanced part of the data set. In the second step, estimates of common factors are obtained via Kalman smoother for both the balanced and unbalanced part of the data set.[4]

Figure 1: A two layered feed forward NN



2.2 The neural network model

After obtaining common factors, we feed those into NNs to identify US business cycle regimes. Let y_t be a categorical variable that shows NBER recession periods as 1 and NBER expansion

[4]See Doz et al. (2011) for the properties of the two-step estimator.

periods as 0. Then, we use the following two layered feed forward NN model which is also represented in the figure 1:

$$O_t = g_o(W_o g_j(W_j \hat{F}_t + c_j) + c_o), \tag{3}$$

where $O_t = (1 - y_t, y_t)$ is the output, $\hat{F}_t$ are estimated dynamic factors that are standardized to zero mean and unit variance, W_j is an sxr matrix of weights in the hidden layer, W_o is a 2xs matrix of weights in the output layer, c_j is an sx1 vector of ones in the hidden layer, c_o is a 2x1 vector of ones in the output layer, g_j is a tan-sigmoid transfer function, and g_o is a soft-max transfer function. Finally, s is the number of neurons in a hidden layer.

There are various backpropagation algorithms to train a NN model. In general, a backpropagation algorithm first assign initial values to weights, then the initial output is calculated using initial weights. Afterwards, the initial output is compared with actual values using a loss function, and the error values are propagated backwards via gradients to neurons in previous layers. The backprogation algorithm uses these error values to update the weights. Another set of outputs is calculated using new weights and this process continues until the error threshold, the minimum performance gradient, or the maximum number of iterations is reached. We use the following backpropagation algorithms in our study:

- Gradient descent (GD), GD with momentum (GDM), GD with momentum and adaptive learning rate (GDML): The GD algorithm is a basic widely used algorithm to train a NN model. The basic update equation of the GD algorithm is as follows: $\Delta W_k = -\alpha_k * g_k$. Each weight W is updated in the descending gradient direction according to a learning rate. GD can be further improved by using momentum training as follows: $\Delta W_k = -\alpha_k * g_k + p * W_{k-1}$, where p is the momentum parameter and W_{k-1} is the previous weight compared to W_k. Finally, adaptive learning rate can also be incorporated into the GDM by increasing the learning rate if error decreases or by decreasing the learning rate if error increases more than a factor.

- Resilient backpropagation (RB): In a NN with sigmoid functions, gradients can have very small values and this may prevent weights to reach their optimal values. Therefore, RB aims to prevent this by using the sign of the gradient instead of the gradient's value. The updating equation of the weights is similar to GD with variable learning rate.

- Conjugate gradient backpropagation with Fletcher-Reeves updates (CGFR) and conjugate gradient backpropagation with Polak-Ribiere updates (CGPR): In GD algorithms, weights are adjusted according to steepest descent direction but this doesn't always yield the fastest convergence. Conjugate gradient algorithms aim to solve this problem by performing a search along conjugate directions. Weights are updated according to the following equation: $\Delta W_k = \alpha_k * p_k$, where $p_k = g_k + \beta_k p_{k-1}$ with $p_0 = -g_0$. In this way, the search continues by combining the steepest descent direction and the previous search direction. CGFR and CGPR are differentiated according to β_k. In CGFR, $\beta_k = \frac{g_k^T g_k}{g_{k-1}^T g_{k-1}}$ and in CGPR, $\beta_k = \frac{\Delta g_k^T g_k}{g_{k-1}^T g_{k-1}}$.

- Broyden–Fletcher–Goldfarb–Shanno Quasi-Newton backpropagation (BFGS): The Newton method is an alternative to the conjugate gradient methods for fast optimization. According to the Newton method, weights are calculated as follows: $\Delta W_k = H_k^{-1} * g_k$, where H_k is the Hessian matrix. However, calculating Hessian matrix is complex and expensive for NN models. Instead of calculating second order partial derivatives, we use the popular BFGS method that update an approximate Hessian matrix at each iteration.

- Levenberg-Marquardt backpropagation (LM): Like the BFGS, the LM algorithm was developed to reach the speed of the Newton's method without calculating the second derivatives. Weights in the LM algorithm are updated as follows in a Newton-like manner: $\Delta W_k = (H_k^a + \mu I)^{-1} * g_k$, where the approximate Hessian matrix, H_k^a is calculated using the Jacobian matrix, $H_k^a = J^T J$, and μ is a scalar.

The detailed description of the RB algorithm is given in Riedmiller and Braun (1993) and for other algorithms see Demuth et al. (2014).

After obtaining estimated weights, the prediction for the current period obtained at time t, $\hat{O}_{t,t} = (\text{Prob}(\hat{y}_{t,t} = 0|\hat{F}_t), \text{Prob}(\hat{y}_{t,t} = 1|\hat{F}_t))$, are computed as follows:

$$\hat{O}_{t,t} = g_o(\hat{W}_o g_j(\hat{W}_j \hat{F}_t + \hat{c}_j) + \hat{c}_o). \tag{4}$$

As the loss function, we use the mean squared errors (MSE). For stopping criteria, we set the error term goal as 10^{-5}, the minimum performance gradient as 10^{-7} and the maximum number of iterations as 1000. Furthermore, we use an early stopping technique with 6 maximum cross-validation failures to prevent overfitting.[5]

[5]We use the Matlab 2017a Neural Network Toolbox to train these NN models. Otherwise stated, default parameters of the Neural Network Toolbox are used for all backpropagation algorithms.

3 The data set

Our data set is based on the large-scale data set of McCracken and Ng (2016) (FRED-MD) version December 2016 including data for output, income, labor market, housing, consumption, orders, inventories, money, credit, interest rates, exchange rates, prices, and stock market. We choose this data set because it is publicly available to all researchers, it is updated monthly, and revisions are handled by data specialists. We choose 122 timely variables with enough observations to estimate common factors from this data set. All variables are transformed appropriately to ensure stationary. Variables and their applied transformations are shown in the Appendix A.

In this study, our aim is predict recession and expansion periods in the US economy. As a result, our dependent variable is a binary categorical variable that shows recession periods as 1 and other periods as 0. We determine recession and expansion periods according to the Business Cycle Dating Committee of the NBER which currently maintains a chronology of the US business cycle.[6] According to NBER's dating of trough and peak points of the US economy, we define an expansion as a period following a trough until a peak is announced. Remaining periods are defined as recession.

4 Empirical results

In this section, we first show how well NN models fit the data in sample and out of sample without taking account of the historical data availability. Then, we determine the business cycle regime of the current month recursively using a pseudo real time data set.

To evaluate the prediction performance of models, the quadratic probability score (QPS), which is equivalent to the MSE for probability predictions, is used. The QPS is defined as follows:

$$\mathrm{QPS}_t = 2/T \sum_{t=1}^{T} (\mathrm{Prob}(\hat{y}_t = 1 | \hat{F}_t) - y_t)^2. \tag{5}$$

[6] Instead of a regular definition of an economic recession in terms of two consecutive quarters of decline in real GDP, the committee doesn't have a fixed definition of a recession. They analyze a broad range of economic indicators including real manufacturing and trade sales, industrial production index, real personal income less transfers, aggregate hours of work in the total economy, payroll survey employment, household survey employment, as well as monthly and quarterly GDP to assess contraction and expansion dates.

The QPS' range is between 0 and 2 and smaller values indicate better forecasting performance.

We also present the accuracy of models in recession (expansion) periods as the number of correct predictions in recession (expansion) periods divided by the number of recession (expansion) periods. We define the correct prediction for recession and expansion periods as $\text{Prob}(\hat{y}_t = 1|\hat{F}_t) \geq 0.5$ and $\text{Prob}(\hat{y}_t = 1|\hat{F}_t) < 0.5$, respectively.

To extract factors, we use a DFM with $r = 2$, $q = 2$, $p = 1$ as in Giannone et al. (2008).[7] For each NN model, the neuron structure in the hidden layer is determined according to the performance of the NN model in the initial estimation period. We test the number of neurons up to 10 and choose the neuron structure that minimizes the QPS in the initial estimation period.

NN models are sensitive to initial weights. Therefore, we run NNs 100 times in each estimation window to ensure robustness of the results. From 100 NNs, we obtain the final output using two different methods. In the first method, we use equal weights to combine outputs of all 100 NN models. In the second method, we classify the output of each NN model as 1 if $\text{Prob}(\hat{y}_t = 1|\hat{F}_t) \geq 0.5$, or 0 otherwise, then we combine outputs of all 100 NNs using equal weights. We call the first method as the regular method and the latter one as the modified method. As the competing model, we use a probit model that use dynamic factors as the input.

4.1 The fit of models

To evaluate the goodness of the fit, we present predictions of NNs for the whole sample. The data set contains the period between 1960:07-2009:12[8]. To be in line with the out of sample identification exercise performed in the next section, the estimation period is restricted to the period covering 1960:07-1989:12 and the rest is used for the test period.

To utilize the early stopping technique, the first 70% of the estimation period is used for training and the rest of the estimation period is reserved for cross-validation.[9] Finally, we

[7]Determining the specification for a DFM is a difficult job. Alternatively, one can also use information criteria such as Bai and Ng (2002) and Bai and Ng (2007) to determine the specification of the DFM. However as stated by Bańbura and Rünstler (2011), these criteria usually indicate a large number of factors, leading volatile forecasts. Therefore, we follow a simple approach and use the specification of Giannone et al. (2008) which is a quite good specification in these kinds of forecasting exercises for the US economy.

[8]We lose some data at the beginning of the sample due to transformations.

[9]For the probit model, we don't use cross-validation.

use weights calculated in the training period (1960:07-1980:11) to calculate outputs in the cross-validation period (1980:12-1989:12) and the test period (1990:01-2009:12).

The table 1 shows QPSs of models in the estimation period and the test period. The best result in the estimation period are obtained from the NN model with the LM algorithm using the modified combination method. Except NN models estimated by the GD and the GDM, all other NN models have similar QPSs and outperform the probit model in the estimation period. The NN model with the RB algorithm using the modified combination method have the best result in the test period. Similar to the estimation period, NN models estimated by the GD and the GDM have very poor prediction performance in the test period. In general, all other NN models except the GD and the GDM have similar performance in this period. Interestingly in test period, the prediction performance of the probit model is on par with that of NN models.

Tables 2 and 3 show the accuracy of models in the estimation period and the test period both during recession and expansion periods. In the estimation period during recessions, the accuracy of NN models is between 90.17% and 80.33% except the GD and the GDM. On the other hand, the accuracy of the probit model in the estimation period during recessions is 75.41% which is lower than most of the NN models. In test period during recessions, most of the models' accuracy is 86.49%. In the table 2, NN models estimated by the GD and the GDM perform poorly in the test period as expected. For expansion periods, the accuracy of all models is very high, above 96%.

To analyze the accuracy of models better, we also present figures 2 and 3 that show predictions from NN models using both regular and modified combination method and the probit model for the estimation period and the test period. Figures 2 and 3 show that factor augmented models seems to capture recession periods quite well especially in test period. In the estimation period, models cannot capture the second half of the 1982 recession. Some models also fail to capture a few recession periods in the 1970 recession. Furthermore, NN models show false positives in July and August 1989. Moreover, NN models combined by the modified method is much smoother than those combined by the regular method. NN models also seem to capture the NBER's business cycle chronology better than the probit model. The GD and the GDM fail to predict recession periods as expected. Finally thanks to the early stopping rule, there is no sign of overfitting in NN models.

4.2 Pseudo real time performance of models

In the previous section, we ignore historical data availability to assess the fit of models over the whole data sample. In this section, we analyze the real time performance of models. Unfortunately as we don't have the vintage data for all 122 variables, we ignore historical data revisions and use the final revised data. Therefore, we evaluate the pseudo real time performance of models. We assume that predictions are produced once per month after the CPI data has been released, i.e., around the 15th day of each month. According to this assumption, we construct a stylized calendar for data series in the FRED-MD data set and replicate historical data availability every time we estimate models and produce predictions. The appendix shows the publication lag for each data series in the FRED-MD data set.

The publication lag of the NBER business cycle chronology is not as straightforward as other data series because NBER historically announced turning points of the business cycle with a delay of between 4 and 21 months and didn't release any official announcements that helps us to update the information set between turning point announcements. To replicate historical data availability and update our information set continuously despite the lack of any official NBER announcements during long expansion periods, we implement the following set of assumptions similar to Giusto and Piger (2017): (1) the date of a turning point is known once it is announced by the NBER; (2) a peak will be announced by the NBER with a maximum publication lag of 12 months and (3) after a peak is announced by the NBER, the recession will last at least six months starting from the announced peak.

In this exercise, we predict the business cycle regime of the current period in each period recursively from 1990:01 to 2009:12. The initial estimation period is between 1960:07-1989:12. In each iteration, the first 70% of the estimation period is used for training and the rest of the estimation period is reserved for cross-validation.

The table 4 presents QPSs of NN models and the probit model. The table 4 clearly shows that the best model is the NN model with the RB algorithm using the modified combination method. This was expected as this model is the best model in the previous exercise for the test sample. NN models with the CGFR, the CGPR and the BFGS using the modified combination method also have very high prediction performance. These four models have better performance that their counterparts using the regular combination as the modified combination method provide much smoother predictions as it is seen in figures 2 and 3. As in the previous exercise, the GD algorithms perform very poorly. Furthermore, most of the

NN models clearly outperform the probit model.

The table 5 shows the accuracy of models both during recession and expansion periods. For recession periods, NN models using the CGPR algorithm has highest accuracy. These NN models classify 91.89% of recession periods correctly. NN models estimated by the RB and the CGFR for both combination methods, the NN model estimated by the BFGS using the modified combination method, and the NN model estimated by the LM using the regular combination method also have very high accuracy, 89.19%. However, the probit model has an accuracy of 56.17% for recession periods. As expected, NN models estimated by the GD methods have very poor performance during recession periods. For expansion periods, the accuracy of all models are very high, above 97%.

Figures 4 and 5 present predictions of NN models using both the regular method and the modified method and the probit model. NN models show the beginning of the 1990 recession a few months late compared to the NBER's chronology. On the other, most NN models identify the peak of the 2001 crisis and the financial crisis of 2007-2008 quite accurately. For troughs, NN models identify them with a small lag. Except NN models estimated by the GD algorithms, most NN models follows the NBER's chronology quite accurately. Given that the NBER announces turning points with a significant delay and most dating methodologies fail to determine US business cycle regimes in a timely fashion as shown by Hamilton (2011), NN models provide timely and accurate information on the current state of the US business cycle. However, the probit model perform very poorly compared to NN models by totally missing the 2001 crisis.

5 Conclusion

In this study, we propose a factor augmented neural network model to determine the current state of the US business cycle. We estimate the factor augmented neural network in two steps. In the first step, we use a dynamic factor model (DFM) to extract two common factors from a large-scale data set. In the second step, we feed these factors into NN models to obtain the current state of the US business cycle.

First, we evaluate the fit of models over the whole data sample by ignoring historical data availability. Then, we assess the identification performance of NN models by taking account of historical data availability. Results show that most NN models except those estimated by the GD algorithms capture the most of the NBER's business cycle chronology quite well. However, NN models calculated using GD type algorithms perform very poorly. Furthermore, most NN models perform better that the probit model which fail to capture 2001 recession in the pseudo real time exercise. Given that the NBER identify turning points with a significant delay, NN models can be used to obtain timely information on the current state of the business cycle.

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Tables and figures

Table 1: QPSs of models for the estimation and test periods

	Regular Combination		Modified Combination	
	Estimation Period	Test Period	Estimation Period	Test Period
GD	0.079	0.052	0.072	0.049
GDM	0.079	0.053	0.072	0.050
GDML	0.044	0.025	0.049	0.028
RB	0.043	0.024	0.048	0.019
CGFR	0.041	0.022	0.042	0.022
CGPR	0.040	0.023	0.042	0.022
BFGS	0.041	0.022	0.043	0.022
LM	0.041	0.023	0.039	0.026
Probit	0.054	0.023	0.054	0.023

Note: GD, GDM, GDML, RB, CGFR, CGPR, BFGS, and LM are the NN models estimated by the gradient descent (GD), GD with momentum (GDM), GD with momentum and adaptive learning rate (GDML), resilient backpropagation (RB), conjugate gradient backpropagation with Fletcher-Reeves updates (CGFR), conjugate gradient backpropagation with Polak-Ribiere updates (CGPR), Broyden–Fletcher–Goldfarb–Shanno Quasi-Newton backpropagation (BFGS), and Levenberg-Marquardt backpropagation (LM) algorithms, respectively. Probit is the probit model. Estimation period is between 1960:07-1989:12 and the test period is between 1990:01-2009:12. The regular method indicates that 100 NNs are combined using equal weights. The modified method indicates that the output of each NN model is first classified as 1 if $\text{Prob}(\hat{y}_t = 1|\hat{F}_t) \geq 0.5$, or 0 otherwise, then outputs of 100 NNs are combined using equal weights. For the probit model, we don't use any combination method to obtain the final output. Therefore, results for the probit model under the regular combination and the modified combination are same.

Table 2: The accuracy of models for the estimation and test periods during recession periods

	Regular Combination		Modified Combination	
	Estimation Period	Test Period	Estimation Period	Test Period
GD	47.541	35.135	55.738	40.541
GDM	47.541	35.135	55.738	40.541
GDML	85.246	86.486	90.164	86.486
RB	88.525	86.486	80.328	86.486
CGFR	83.607	86.486	81.967	86.486
CGPR	90.164	86.486	81.967	86.486
BFGS	83.607	86.486	80.328	86.486
LM	83.607	86.486	80.328	78.378
Probit	75.410	86.486	75.410	86.486

Note: For abbreviations and definitions see notes under the table 1.

Table 3: The accuracy of models for the estimation and test periods during expansion periods

	Regular Combination		Modified Combination	
	Estimation Period	Test Period	Estimation Period	Test Period
GD	99.659	100.000	99.659	100.000
GDM	99.659	100.000	99.659	100.000
GDML	96.928	98.030	96.246	97.537
RB	96.246	97.537	96.587	99.015
CGFR	97.270	98.522	97.270	98.522
CGPR	96.587	97.537	97.270	98.522
BFGS	97.270	98.030	96.587	98.522
LM	97.270	98.030	97.952	99.507
Probit	97.611	99.507	97.611	99.507

Note: For abbreviations and definitions see notes under the table 1.

Table 4: QPSs of models for the pseudo real time exercise (1990:01-2009:12)

	Regular Combination	Modified Combination
GD	0.156	0.158
GDM	0.156	0.158
GDML	0.105	0.165
RB	0.069	0.053
CGFR	0.067	0.059
CGPR	0.065	0.057
BFGS	0.069	0.060
LM	0.069	0.080
Probit	0.088	0.088

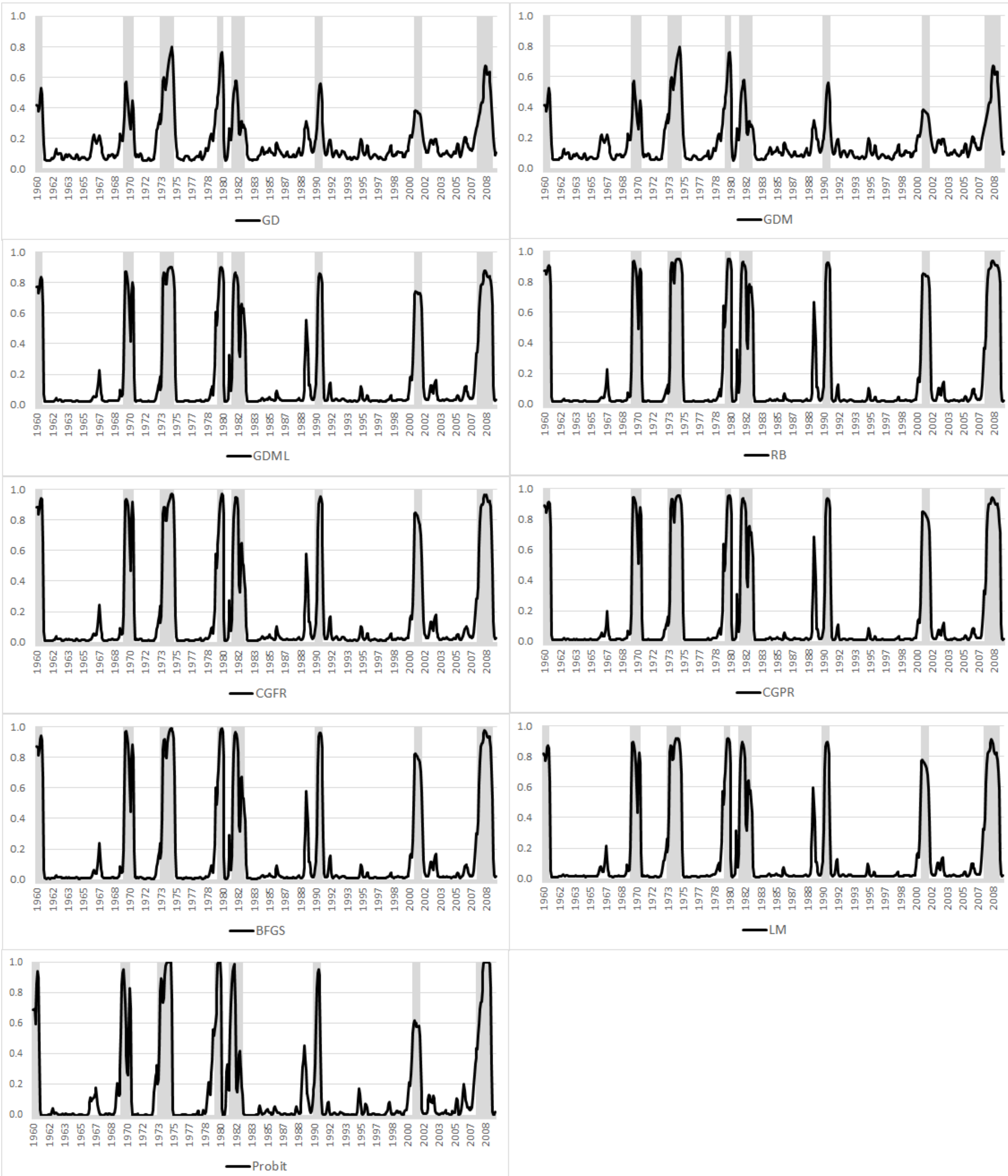
Note: For abbreviations and definitions see notes under the table 1.

Table 5: The accuracy of model under recession and expansion periods for the pseudo real time exercise (1990:01-2009:12)

	Recession Periods		Expansion Periods	
	Regular Comb.	Modified Comb.	Regular Comb.	Modified Comb.
GD	8.108	16.216	100.000	100.000
GDM	8.108	16.216	100.000	100.000
GDML	59.459	16.216	98.030	99.507
RB	89.189	89.189	97.537	98.522
CGFR	86.486	89.189	97.537	98.030
CGPR	91.892	91.892	97.537	98.030
BFGS	83.784	89.189	97.537	98.030
LM	89.189	72.973	98.030	99.015
Probit	56.757	56.757	99.507	99.507

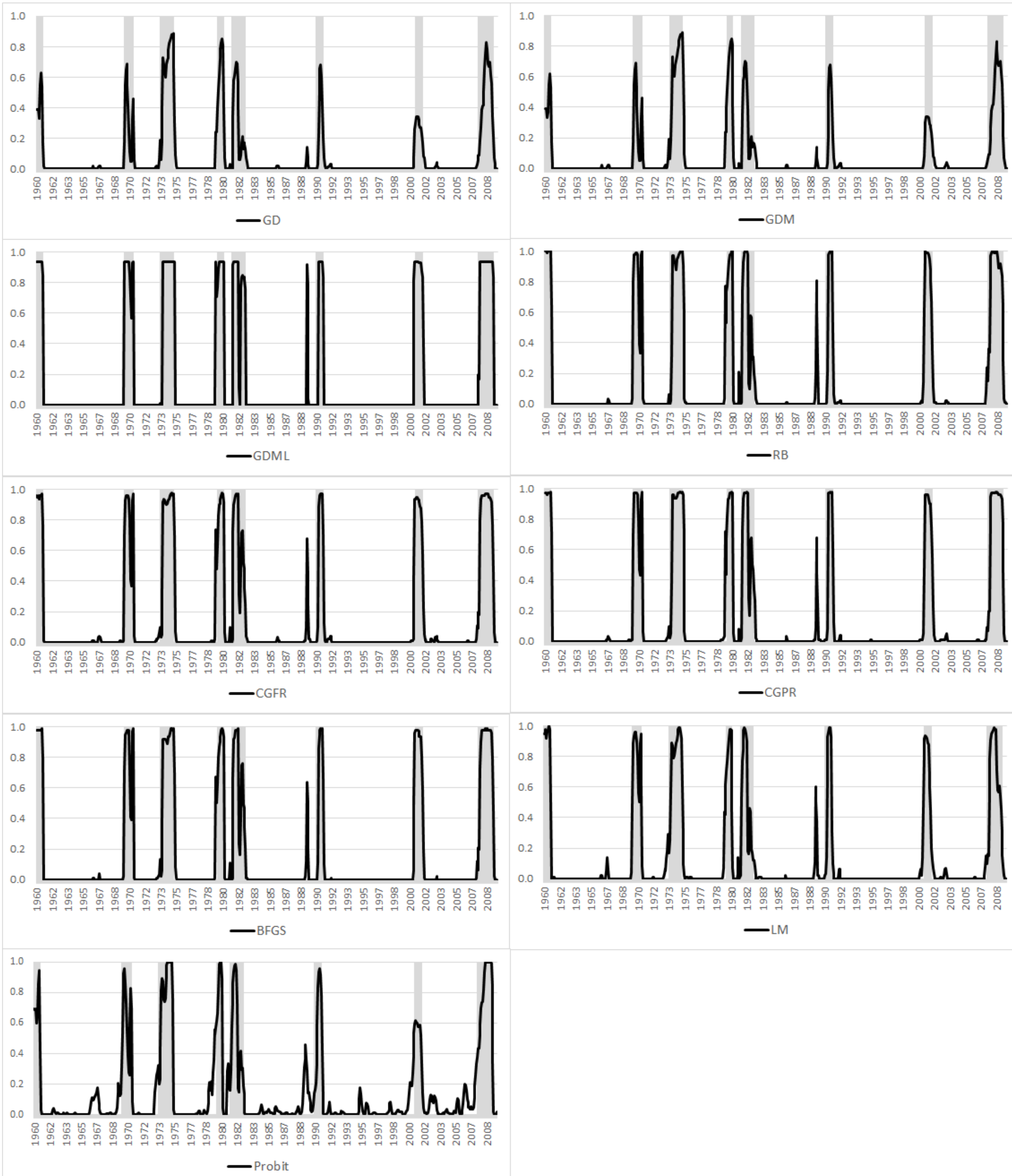
Note: For abbreviations and definitions see notes under the table 1. “Comb.” is the combination.

Figure 2: NN models using the regular combination and the probit model (1960:07-2009:12)



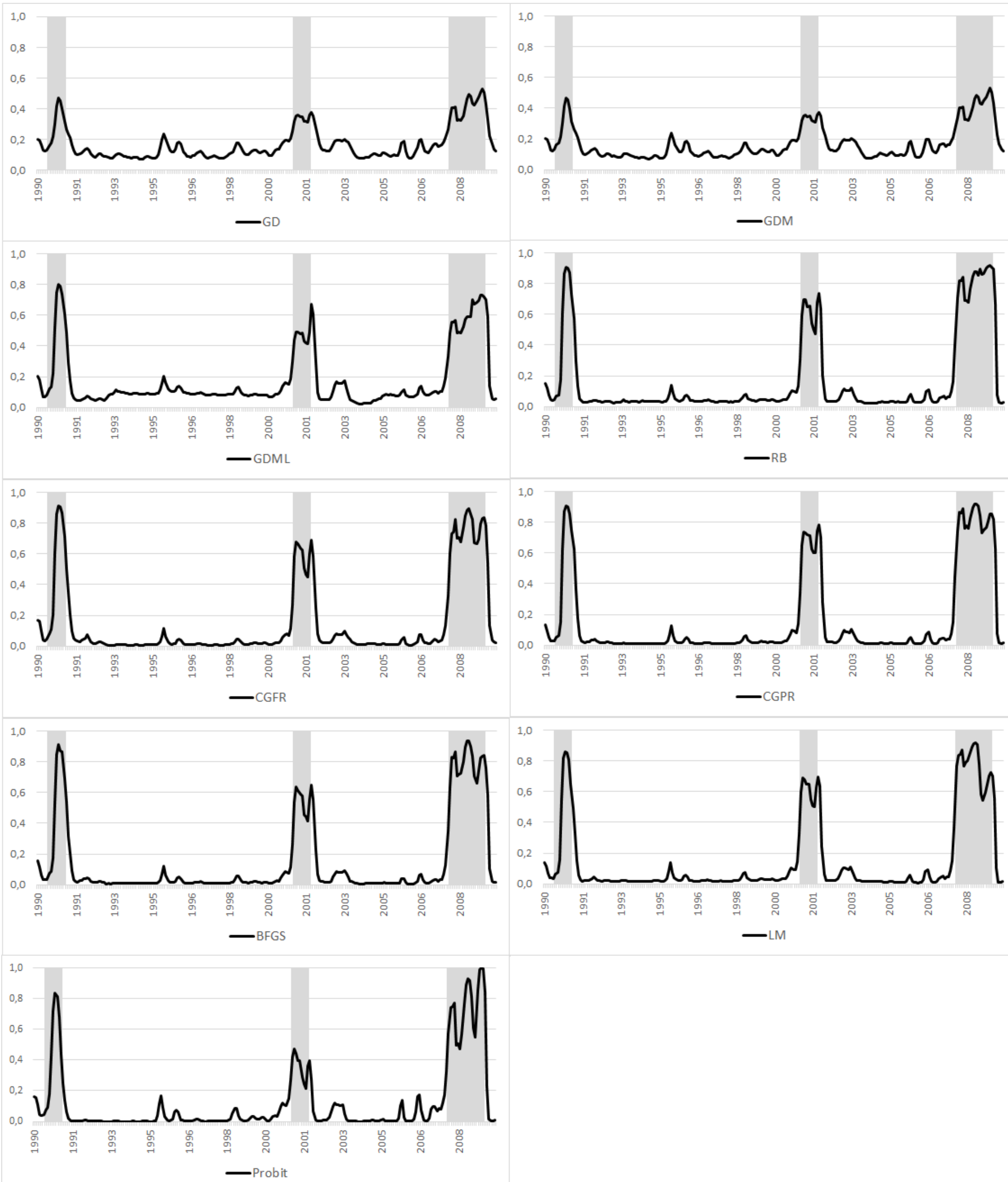
Note: For abbreviations and definitions see notes under the table 1.

Figure 3: NN models using the modified combination and the probit model (1960:07-2009:12)



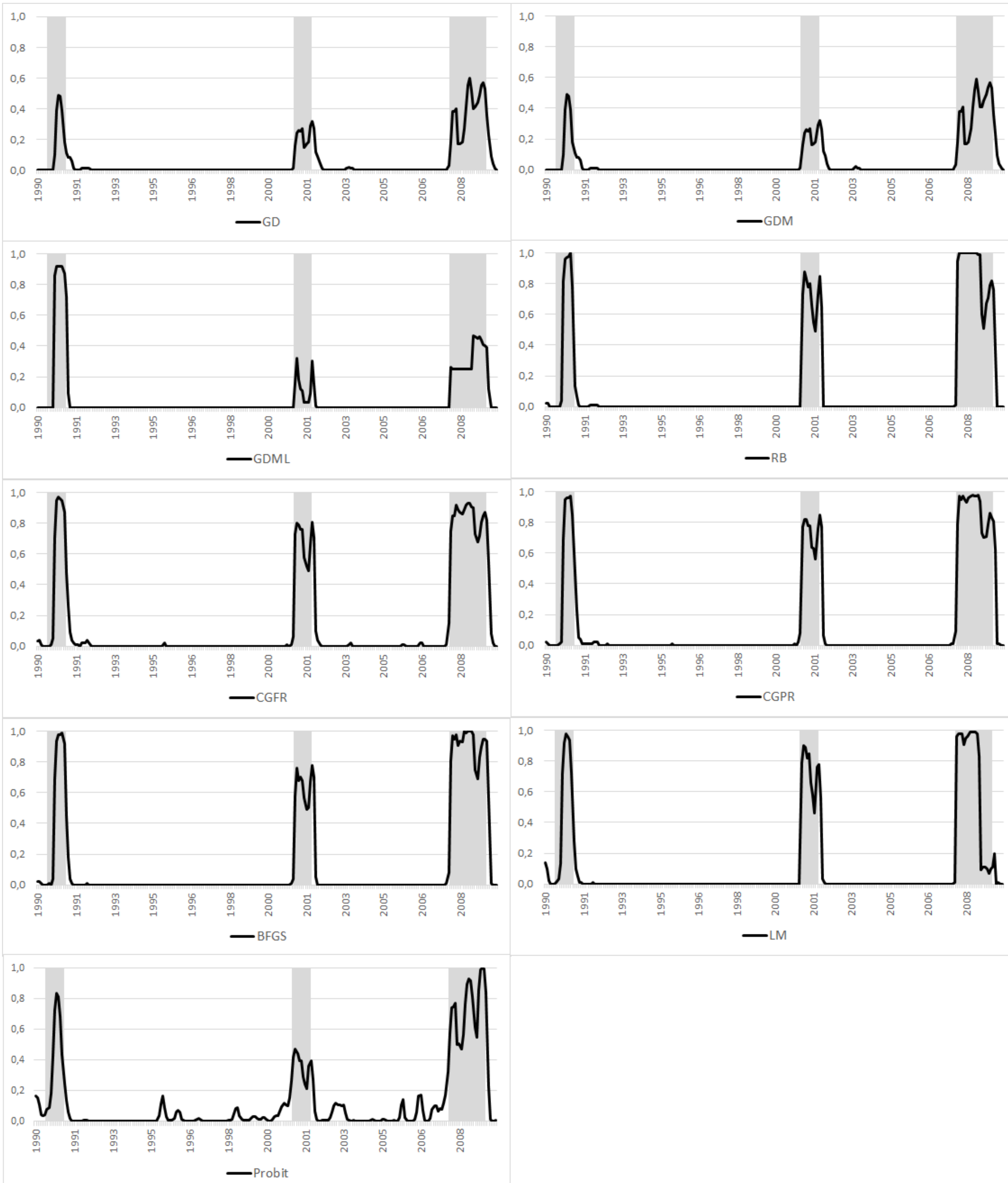
Note: For abbreviations and definitions see notes under the table 1.

Figure 4: NN models using the regular combination and the probit model for the pseudo real time exercise (1990:01-2009:12)



Note: For abbreviations and definitions see notes under the table 1.

Figure 5: NN models using the modified combination and the probit model for the pseudo real time exercise (1990:01-2009:12)



Note: For abbreviations and definitions see notes under the table 1.

Appendix A: the description of the data set

Code	Description	Transformation	Lag
RPI	Real Personal Income	1	2
W875RX1	Real personal income excluding current transfer receipts	1	2
DPCERA3M086SBEA	Real personal consumption expenditures (chain-type quantity index)	1	2
CMRMTSPLx	Real Manufacturing and Trade Industries Sales	1	3
RETAILx	Real Retail and Food Services Sales	1	2
INDPRO	Industrial Production Index	1	2
IPFPNSS	Industrial Production: Final Products and Nonindustrial Supplies	1	2
IPFINAL	Industrial Production: Final Products (Market Group)	1	2
IPCONGD	Industrial Production: Consumer Goods	1	2
IPDCONGD	Industrial Production: Durable Consumer Goods	1	2
IPNCONGD	Industrial Production: Nondurable Consumer Goods	1	2
IPBUSEQ	Industrial Production: Business Equipment	1	2
IPMAT	Industrial Production: Materials	1	2
IPDMAT	Industrial Production: Durable Materials	1	2
IPNMAT	Industrial Production: Nondurable Materials	1	2
IPMANSICS	Industrial Production: Manufacturing (SIC)	1	2
IPB51222S	Industrial Production: Residential utilities	1	2
IPFUELS	Industrial Production: Fuels	1	2
CUMFNS	Capacity Utilization: Manufacturing (SIC)	2	2
CLF16OV	Civilian Labor Force	1	1
CE16OV	Civilian Employment Level	1	1
UNRATE	Civilian Unemployment Rate	2	1
UEMPMEAN	Average (Mean) Duration of Unemployment	2	1
UEMPLT5	Number of Civilians Unemployed for Less Than 5 Weeks	1	1
UEMP5TO14	Number of Civilians Unemployed for 5 to 14 Weeks	1	1
UEMP15OV	Number of Civilians Unemployed for 15 Weeks and Over	1	1
UEMP15T26	Number of Civilians Unemployed for 15 to 26 Weeks	1	1
UEMP27OV	Number of Civilians Unemployed for 27 Weeks and Over	1	1
CLAIMSx	Initial Claims	1	1
PAYEMS	All Employees: Total Nonfarm Payrolls	1	1
USGOOD	All Employees: Goods-Producing Industries	1	1
CES1021000001	All Employees: Mining and Logging: Mining	1	1
USCONS	All Employees: Construction	1	1
MANEMP	All Employees: Manufacturing	1	1
DMANEMP	All Employees: Durable Goods	1	1
NDMANEMP	All Employees: Nondurable goods	1	1
SRVPRD	All Employees: Service-Providing Industries	1	1
USTPU	All Employees: Trade, Transportation and Utilities	1	1
USWTRADE	All Employees: Wholesale Trade	1	1
USTRADE	All Employees: Retail Trade	1	1
USFIRE	All Employees: Financial Activities	1	1
USGOVT	All Employees: Government	1	1
CES0600000007	Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing	2	1
AWOTMAN	Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing	2	1
AWHMAN	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	2	1
HOUST	Housing Starts: Total: New Privately Owned Housing Units Started	1	2
HOUSTNE	Housing Starts in Northeast Census Region	1	2
HOUSTMW	Housing Starts in Midwest Census Region	1	2
HOUSTS	Housing Starts in South Census Region	1	2
HOUSTW	Housing Starts in West Census Region	1	2
PERMIT	New Private Housing Units Authorized by Building Permits	1	2
PERMITNE	New Private Housing Units Authorized by Building Permits in the Northeast Census Region	1	2
PERMITMW	New Private Housing Units Authorized by Building Permits in the Midwest Census Region	1	2
PERMITS	New Private Housing Units Authorized by Building Permits in the South Census Region	1	2
PERMITW	New Private Housing Units Authorized by Building Permits in the West Census Region	1	2
AMDMNOx	Manufacturers' New Orders: Durable Goods	1	2
ANDENOx	New Orders for Nondefense Capital Goods	1	2
AMDMUOx	Value of Manufacturers' Unfilled Orders for Durable Goods Industries	1	2
BUSINVx	Total Business Inventories	1	2
ISRATIOx	Total Business: Inventories to Sales Ratio	2	2

Code	Description	Transformation	Lag
M1SL	M1 Money Stock	1	1
M2SL	M2 Money Stock	1	1
M2REAL	Real M2 Money Stock	1	2
AMBSL	St. Louis Adjusted Monetary Base	1	1
TOTRESNS	Total Reserves of Depository Institutions	1	1
NONBORRES	Reserves of Depository Institutions, Nonborrowed	1	1
BUSLOANS	Commercial and Industrial Loans, All Commercial Banks	1	1
REALLN	Real Estate Loans, All Commercial Banks	1	1
NONREVSL	Total Nonrevolving Credit Owned and Securitized, Outstanding	1	2
CONSPI	Nonrevolving consumer credit to Personal Income	1	2
S&P 500	S&P 500	1	1
S&P: indust	S&P 500 Industries	1	1
S&P div yield	S&P dividend yield	1	1
FEDFUNDS	Effective Federal Funds Rate	2	1
CP3Mx	3-Month AA Financial Commercial Paper Rate	2	1
TB3MS	3-Month Treasury Bill: Secondary Market Rate	2	1
TB6MS	6-Month Treasury Bill: Secondary Market Rate	2	1
GS1	1-Year Treasury Constant Maturity Rate	2	1
GS5	5-Year Treasury Constant Maturity Rate	2	1
GS10	10-Year Treasury Constant Maturity Rate	2	1
AAA	Moody's Seasoned Aaa Corporate Bond Yield	2	1
BAA	Moody's Seasoned Baa Corporate Bond Yield	2	1
COMPAPFFx	3-Month Commercial Paper Minus Federal Funds Rate	0	1
TB3SMFFM	3-Month Treasury Bill Minus Federal Funds Rate	0	1
TB6SMFFM	6-Month Treasury Bill Minus Federal Funds Rate	0	1
T1YFFM	1-Year Treasury Constant Maturity Minus Federal Funds Rate	0	1
T5YFFM	5-Year Treasury Constant Maturity Minus Federal Funds Rate	0	1
T10YFFM	10-Year Treasury Constant Maturity Minus Federal Funds Rate	0	1
AAAFFM	Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate	0	1
BAAFFM	Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate	0	1
EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	1	1
EXJPUSx	Japan / U.S. Foreign Exchange Rate	1	1
EXUSUKx	U.S. / U.K. Foreign Exchange Rate	1	1
EXCAUSx	Canada / U.S. Foreign Exchange Rate	1	1
WPSFD49207	PPI: Finished Goods	3	1
WPSFD49502	PPI: Finished Consumer Goods	3	1
WPSID61	PPI: Intermediate Materials	3	1
WPSID62	PPI: Crude Materials	3	1
OILPRICEx	Crude Oil, spliced WTI and Cushing	3	1
PPICMM	PPI: Metals and metal products	3	1
CPIAUCSL	CPI: All Items	3	1
CPIAPPSL	CPI: Apparel	3	1
CPITRNSL	CPI: Transportation	3	1
CPIMEDSL	CPI: Medical Care	3	1
CUSR0000SAC	CPI: Commodities	3	1
CUUR0000SAD	CPI: Durables	3	1
CUSR0000SAS	CPI: Services	3	1
CPIULFSL	CPI: All Items Less Food	3	1
CUUR0000SA0L2	CPI: All items less shelter	3	1
CUSR0000SA0L5	CPI: All items less medical care	3	1
PCEPI	Personal Consumption Expenditures: Chain-type Price Index	3	2
DDURRG3M086SBEA	Personal consumption expenditures: Durable goods (chain-type price index)	3	2
DNDGRG3M086SBEA	Personal consumption expenditures: Nondurable goods (chain-type price index)	3	2
DSERRG3M086SBEA	Personal consumption expenditures: Services (chain-type price index)	3	2
CES0600000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing	3	1
CES2000000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Construction	3	1
CES3000000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing	3	1
MZMSL	MZM Money Stock	1	1
DTCOLNVHFNM	Consumer Motor Vehicle Loans Owned by Finance Companies, Outstanding	1	3
DTCTHFNM	Total Consumer Loans and Leases Owned and Securitized by Finance Companies, Outstanding	1	3
INVEST	Securities in Bank Credit at All Commercial Banks	1	1
VXOCLSx	VXO	1	1

Note: The column "Code" shows the code of the variable in the FRED-MD database. The column "Lag" shows the publication lag of the variable. The column "Transformation" denotes the following data transformation for a series: (0) No Transformation; (1) monthly growth rate; (2) monthly differences; (3) monthly differences of the yearly growth rate.