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SHORT-TERM FORECASTING OF U.S. BUSINESS CYCLE REGIMES USING FACTOR AUGMENTED NEURAL NETWORK MODELS

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Short-Term Forecasting of U.S. Business Cycle Regimes Using Factor Augmented Neural Network Models

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Abstract

We propose a factor augmented neural network model to obtain short-term predictions of U.S. business cycle regimes. First, dynamic factors are extracted from a large-scale data set consisting of 122 variables. Then, these dynamic factors are fed into neural network models for predicting recession and expansion periods. We show that the neural network model provides good in sample and out of sample fits compared to the popular Markov switching dynamic factor model. We also perform a pseudo real time out of sample forecasting exercise and show that neural network models produce accurate short-term predictions of U.S. business cycle phases.

Keywords: Dynamic Factor Model; Neural Network; Recession

JEL: E37, E31

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. As it is shown by the financial crisis of 2007-2008, it is still hard for both practitioners and researchers to determine the state of the economy in a timely manner.

As an alternative to previous business cycle prediction approaches, we propose a factor augmented neural network (NN) model. 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

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number of data series. By utilizing a DFM, we also obtain future values of input variables. In the second step, we feed these dynamic factors into NNs to predict recession and expansion periods.

Forecasting economic and financial variables by factors extracted from large/medium-scale data sets is a widespread approach in the literature, but this isn't still common for predicting recession and expansion periods. In one of the few studies on this subject, 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.

All of the literature that uses factors to predict recessions utilizes parametric probit models. Given that true data generating process is unknown, a non-parametric approach may be more appropriate for predicting U.S. 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 forecasting recessions. One notable exception is the study of Qi (2001) which uses a two-layered NN model for out of sample recession prediction. However, he only uses NNs with one or two variables and doesn't utilize a larger data set. By using NNs with large data sets for forecasting recession and expansion periods, we aim to improve the methodology of our predecessors.

Factors derived from the DFM proposed by Giannone et al. (2008) are mainly used for now-casting GDP in the literature (e.g., Angelini et al., 2011; Barhoumi et al., 2010; D'Agostino et al., 2012; Matheson, 2010) and the prediction power of these factors quickly deteriorates in longer forecasting horizons. Therefore, we aim to obtain short-term predictions for the U.S. business cycle regimes.

In this study, we first show that our proposed method follow the National Bureau of Economic Research's (NBER) business cycle chronology quite accurately given the final revised data. For the whole sample period, we compare probabilities obtained from the NN model with those obtained from a dynamic factor Markov switching (DFMS) model and show that the NN model fits the data much better. Then, we perform a pseudo real time out of sample forecasting exercise. Our results show that one month ahead predictions obtained from a factor augmented NN model identify US business cycle states quite accurately.

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 predict recession and expansion periods. Before utilizing NNs, we perform dimensionality reduction by employing a DFM. Using full data set would probably cause overfitting of NNs and lead to poor forecasting 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.[1] Furthermore, we use a DFM to obtain predictions for input variables.

2.1 The dynamic factor model

Let's assume that standardized n monthly series $x_t = (x_{1,t}, x_{2,t}, \ldots, x_{n,t})', t = 1, 2, \ldots, T$ which are transformed to represent their quarterly counterparts[2] have the following approximate dynamic factor model as in Giannone et al. (2008):

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

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

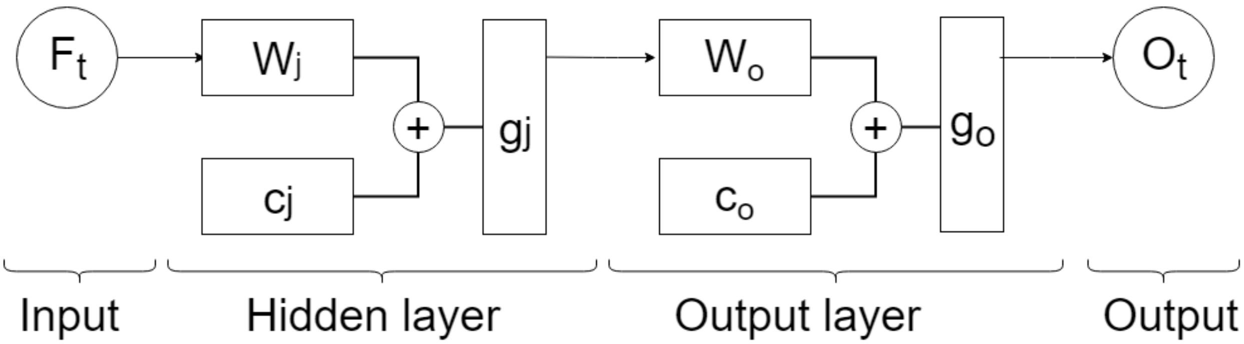
where μ is a constant, Λ is an nxr matrix of factor loadings, $f_t = (f_{1,t}, f_{2,t}, \ldots, f_{r,t})'$ are unobserved common factors that satisfy $r \ll n$, and ξ_t is an idiosyncratic component assumed to be multivariate white noise with diagonal covariance matrix Σ_ξ. As shown in equation 2, f_t 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.

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

[2]This is needed to reduce noise in monthly factors. Noisy data significantly reduces the prediction power of NN models.

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.[3,4]

Figure 1: A two layered feed forward NN



2.2 The neural network model

Let y_t be a categorical variable that shows NBER recession periods as 1 and NBER expansion periods as 0. Then, we use the following two-layered feed forward NN model which is also represented in 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.

Accordingly, h-step ahead iterated out of sample predictions obtained at time t, $\hat{O}_{t+h,t} = (\text{Prob}(\hat{y}_{t+h,t} = 0|\hat{F}_t), \text{Prob}(\hat{y}_{t+h,t} = 1|\hat{F}_t))$, are computed as follows:

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

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

[4] Publication delays of input variables cause unbalancedness at the end of the data set.

We train the NN model using a Levenberg-Marquardt backpropagation algorithm. In a backpropagation algorithm initial values are first assigned to weights, then the initial output is calculated using initial weights. Afterwards, the initial output is compared with actual values using mean squared errors (MSE), and the error values are propagated backwards 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 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.

3 The data set

We use the large-scale data set of McCracken and Ng (2016) (FRED-MD) to predict recession and expansion periods for the US economy. We choose this data set because it is publicly available to all researchers, it is updated monthly, and revisions are handled by data specialists. By using a public database that is updated and maintained regularly, we make sure that researchers can reproduce our results easily.

As of December 2016, the FRED-MD data set consists of 128 monthly indicators, including data for output, income, labor market, housing, consumption, orders, inventories, money, credit, interest rates, exchange rates, prices, and stock market. We remove three variables from the data set[5] because they don't have enough observations to estimate dynamic factors. Furthermore, we remove three more variables[6] that lag more than 3 months in the data set because we prefer all variables to be timely. We end up with a data set consisting of 122 variables. Applied transformations to the data series are shown in the appendix.

In this study, our aim is predict recession and expansion periods in the US economy. The Business Cycle Dating Committee of the NBER currently maintains a chronology of the US business cycle. 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

[5]These are new orders for consumer goods, the trade weighted U.S. Dollar index: major currencies, and the consumer sentiment index.

[6]These are the help wanted index for United States, the ratio of help wanted/number of unemployed, and the price-earnings ratio: S&P composite common stock.

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. 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 and then we perform an out of sample forecasting exercise.

To extract factors, we use a DFM with $r = 2$ and $q = 2$ as in Giannone et al. (2008). Then, we construct four different NNs according to four different lag structures, $1 \leq p \leq 4$. By following such a methodology, we analyze whether various lag lengths of common factors affect the prediction accuracy of NN models.

NN models are sensitive to initial weights. Therefore, we run NNs 100 times in each estimation window to ensure robustness of the results.[7] 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 $\text{Prob}(\hat{y}_{t+h} = 1|\hat{F}_{t+h}) > 0.5$, or 0 otherwise, then we combine outputs of all 100 NNs using equal weights. We call the first method as the direct method and the latter one as the modified method.

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:

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

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

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

[7]All results are reproducible, same 100 seeds are used for each estimation period.

neurons up to 10 and choose the neuron structure that minimizes the QPS of the direct method in the initial estimation period.

4.1 The fit of the model

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 forecasting 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. Finally, we use the 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).[9]

Table 1: QPSs of NN models in the estimation period and the test period

NN model	QPS (Estimation)		QPS (Test)	
	Direct	Modified	Direct	Modified
p=1, s=2	0.035	0.035	0.024	0.023
p=2, s=2	0.036	0.033	0.023	0.021
p=3, s=1	0.023	0.026	0.021	0.023
p=4, s=4	0.031	0.023	0.024	0.019

Note: Specifications of NN models are shown in the first column. p shows the number of lags in factors and s shows the number of neurons in the hidden layer. The direct method indicates that NNs are combined using equal weights. The modified method indicates that the output of each NN model is first classified as 1 if $\text{Prob}(\hat{y}_{t+h} = 1|\hat{F}_{t+h}) > 0.5$, or 0 otherwise, then outputs of NNs are combined using equal weights.

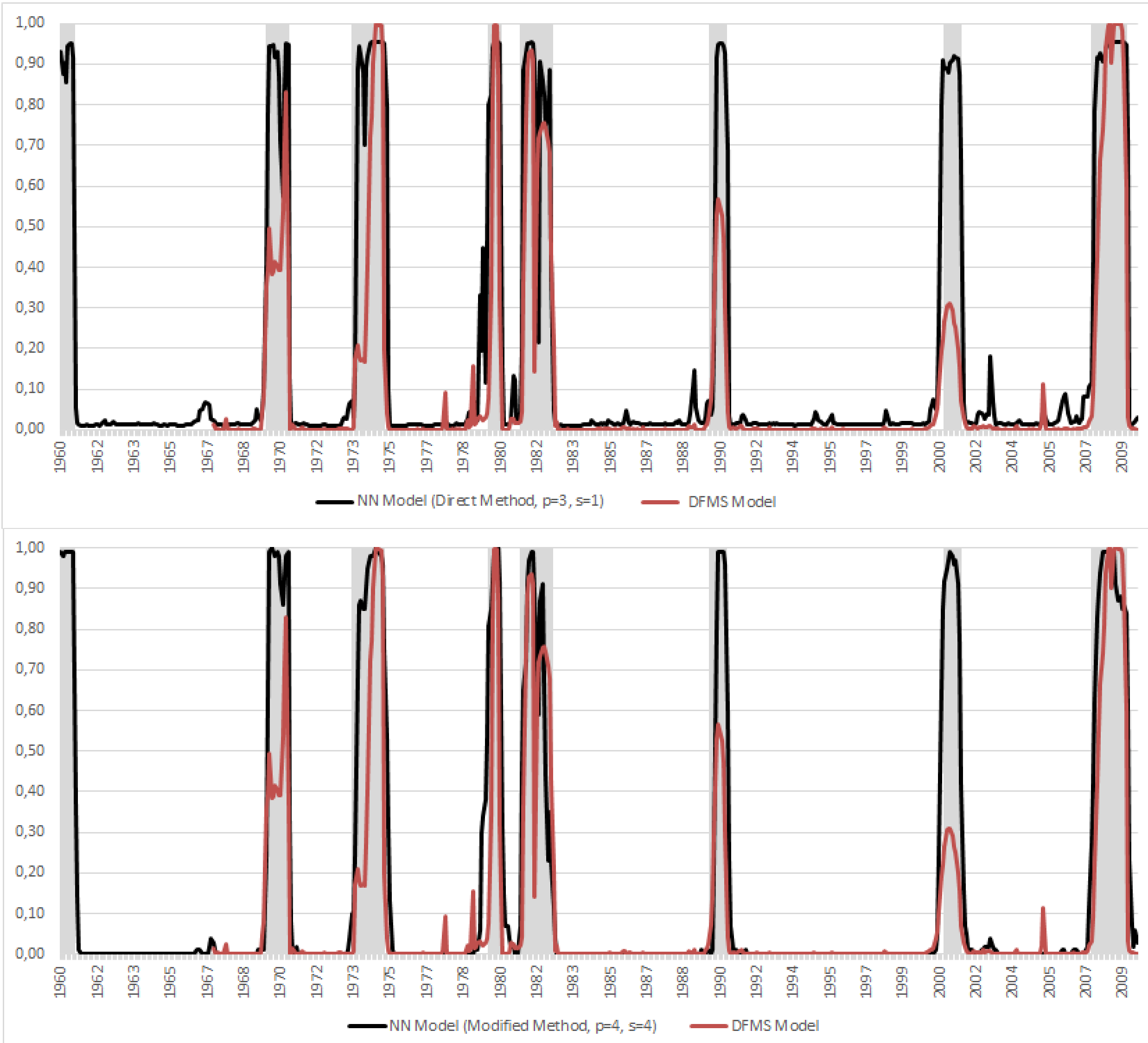
Table 1 shows QPSs of neural network models in the estimation period and the test period. The best results in the estimation period are obtained from the NN model with 4 lags using the modified combination method and the NN model with 3 lags using the direct combination method. The NN model with 4 lags using the modified combination method also has the best prediction accuracy in the test period. Generally, all models have similar QPSs in the test period. Differences between forecasting performances of models are much larger in the training period.

Figure 2 shows predictions derived from the best NN model for both the direct method and

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

[9]To reinforce the training process, we remove some false positives in the estimation period.

Figure 2: NN models and the DFMS model



Note: Specifications of NN models are shown in the parentheses. p shows the number of lags in the factors and s shows the number of neurons in the hidden layer. The direct method indicates that NNs are combined using equal weights. The modified method indicates that the output of each NN model is first classified as 1 if $\text{Prob}(\hat{y}_{t+h} = 1|\hat{F}_{t+h}) > 0.5$, or 0 otherwise, then outputs of NNs are combined using equal weights. Recession periods are shaded in gray.

the modified method. To analyze NN models' the goodness of the fit better, we also present smoothed recession probabilities derived from a DFMS model which is one of the popular approaches in the literature. The DFMS was based on Chauvet (1998) and the smoothed recession probabilities are calculated using Bayesian estimation techniques developed in Kim and Nelson (1998).[10] The DFMS model uses four monthly variables: non-farm payroll

[10]See Chauvet and Piger (2008) for a detailed discussion of this model.

employment, the index of industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales.

Figures 2 shows that the NN model seems to capture recession periods quite well. There are only a few issues in this model. The NN model indicates an early trough for the 1982 crisis and identifies the peak before the 1990 crisis a few months late compared to the NBER chronology. Still, the prediction performance of the NN model especially in the test period is quite well and the NN model performs much better than the DFMS model. Thanks to the early stopping rule, there is no sign of overfitting in the NN model.

4.2 Out of sample forecasting

We estimate NNs recursively with the initial estimation sample covering 1960:07-1989:12. In each estimation period, the first 70% of the estimation period is used for training and the rest of the estimation period is reserved for cross-validation.

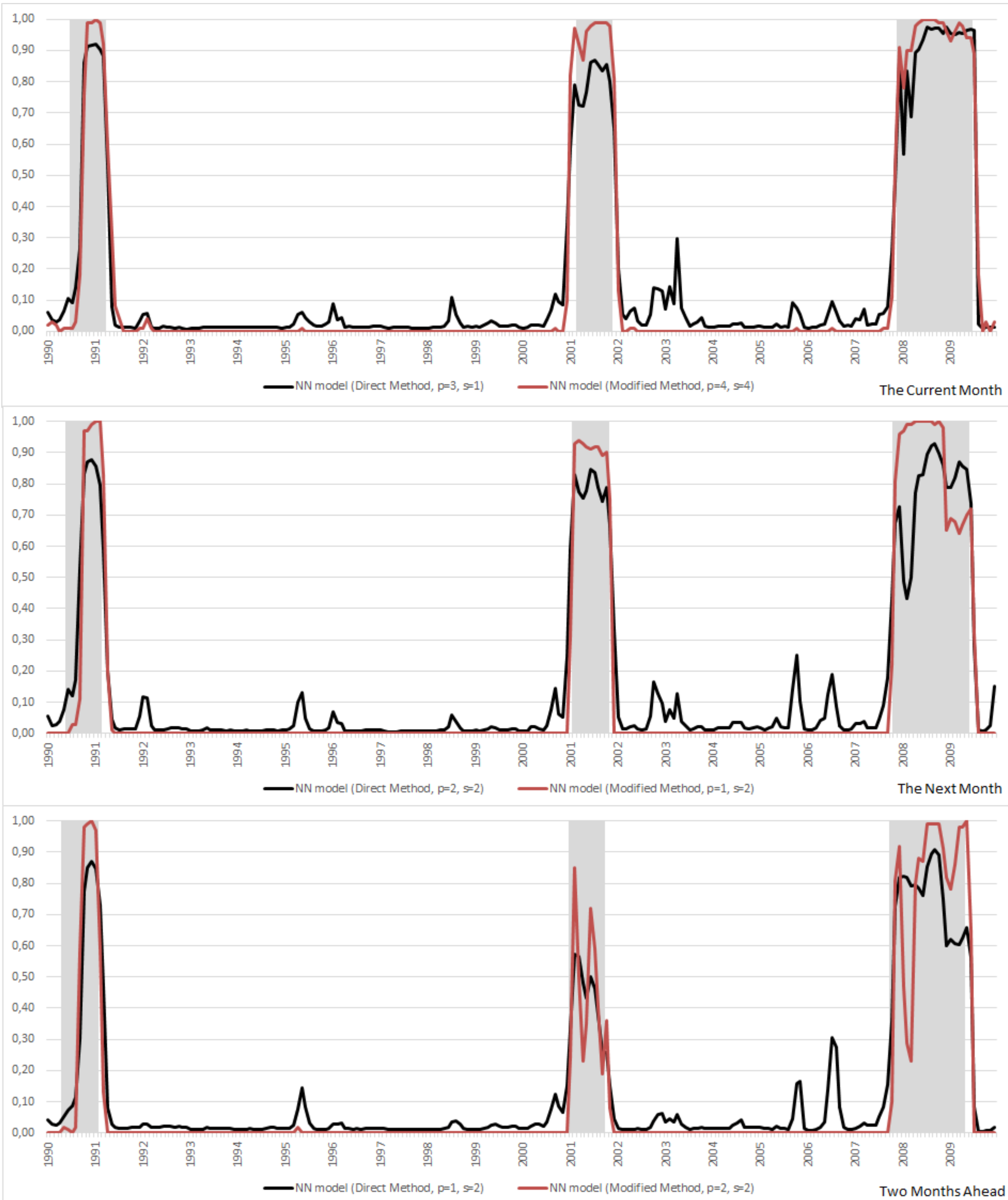
For out of sample forecasting exercise, we assume that predictions are produced once per month after CPI data has been released, i.e., around the 15th day of each month. According to this assumption, we construct a stylized calendar for data series in the FRED-MD data set to replicate historical data availability. The appendix shows publication lags 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. To replicate historical data availability, we implement the following set of assumptions similar to Giusto and Piger (2017). A peak will be announced by the NBER with a maximum publication lag of 12 months and after a peak is announced by the NBER, the recession will last at least six months starting from the announced peak.

Our main aim in this exercise is to conduct short-term predictions of business cycle regimes. Therefore, we only predict business cycle phases for the current month, the next month, and two months ahead in each estimation period.

Table 2 presents QPSs for the current month, the next month, and two months ahead business cycle state predictions of NN models. For the current month, the NN model with 3 lags using the direct combination method has the best prediction performance. For the next month, NN models with 1 and 2 lags using the modified combination method have the lowest QPS. Interestingly, best models for the next month have the similar forecasting

Figure 3: The current month, the next month, and two months ahead predictions of the best NN models both for direct and modified method



Note: Specifications of NN models are shown in the parentheses. p shows the number of lags in the factors and s shows the number of neurons in the hidden layer. The direct method indicates that NNs are combined using equal weights. The modified method indicates that the output of each NN model is first classified as 1 if $\text{Prob}(\hat{y}_{t+h} = 1|\hat{F}_{t+h}) > 0.5$, or 0 otherwise, then outputs of NNs are combined using equal weights. Recession periods are shaded in gray. The forecasting horizon is displayed in the lower left corner of each panel.

accuracy compared to the best model for the current month. However, predictions for two months ahead are worse than those for the current month and the next month.

Table 2: QPSs of NN models for the current month, next month, and two months ahead predictions

NN model	QPS (Direct Method)			QPS (Modified Method)		
	h=1	h=2	h=3	h=1	h=2	h=3
p=1, s=2	0.057	0.061	0.088	0.058	0.054	0.107
p=2, s=2	0.061	0.058	0.089	0.066	0.054	0.096
p=3, s=1	0.053	0.073	0.106	0.059	0.079	0.137
p=4, s=4	0.059	0.070	0.101	0.055	0.064	0.117

Note: Specifications of NN models are shown in the first column. p shows the number of lags in the factors and s shows the number of neurons in the hidden layer. The direct method indicates that NNs are combined using equal weights. The modified method indicates that the output of each NN model is first classified as 1 if $\text{Prob}(\hat{y}_{t+h} = 1|\hat{F}_{t+h}) > 0.5$, or 0 otherwise, then outputs of NNs are combined using equal weights. h shows the forecasting horizon.

Figures 3 presents the current month, the next month, and two months ahead predictions of the best NN models both for the direct method and the modified method. Figure 3 shows that predictions of NN models for the current month and the next month are pretty accurate. However, NNs still classify some periods inaccurately. NNs identify the peak before the 1990 crisis late and the peak before the 2001 crisis early. The prediction performance of NNs for the 2007-2008 crisis is much more accurate. Furthermore, NNs usually predict trough points with 1 month lag. In spite of these minor misses, figure 3 shows that the factor augmented NN model has strong prediction power, especially compared to other models such as Christiansen et al. (2014) or Fornaro (2016). Figure 3 also shows that two months ahead predictions aren't as accurate as one step and current month predictions. Two months ahead predictions don't capture the 2001 crisis very accurately. Furthermore, two month ahead predictions don't yield additional information compared to one month ahead predictions for the 1990 crisis or the 2007-2008 crisis.

One can question whether the prediction power of NN models is better than that of ordinary probit models. In table 3, we compare best NN models with the corresponding probit models. In the current month predictions, probit models and NNs have the similar forecasting performance. On the other hand, the prediction power of NNs is substantially higher than that of probit models for the next month. QPS of the best NN model is 27% lower than that of the best probit model for the next month. QPS of the best NN model is 24.3% lower than that of the best probit model for two months ahead.

Table 3: The ratio of the NN model's QPS to the probit model's QPS

NN/Probit	QPS		
	h=1	h=2	h=3
p=1	0.005	-0.339	-0.243
p=2	0.113	-0.268	-0.261
p=3	-0.005	-0.122	-0.119
p=4	-0.023	-0.260	-0.247
Best	-0.005	-0.270	-0.243

Note: This table presents ratios of best NN models' QPSs to the corresponding probit models' QPSs. Last row show the QPS ratio of best NN model and best probit model for a given forecasting horizon. The lag structure of NN models and probit models are shown in the first column. p shows the number of lags in the factors. h shows the forecasting horizon.

5 Conclusion

In this study, we propose a factor augmented neural network model to predict recession and expansion periods. 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 probabilities of business cycle regimes.

First, we show that NN models fit the data quite well. The fit of NN models is even better than the fit of the DFMS model which is one of the most popular approaches in the literature. Second, we perform an out of sample forecasting exercise. Our results show that NN models can predict recession and expansion periods accurately for the current month and the next month. However, the prediction power of NN model seems to deteriorate in longer forecasting horizons.

Compared to probit models, NN models' main benefit is seen in the next month and two months ahead predictions. For the next month and two months ahead predictions, QPSs of the best NN models is 27% and 24.3% lower than those of the best probit models, respectively.

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Appendix: description of the data set

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.

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