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The Treasury Bill Rate, the Great Recession, and Neural Networks Estimates of Real Business Sales

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Abstract

This paper analyzes out-of-sample forecasts of real total business sales. We study monthly data from January 1970 to June 2012. The predictor variable, 3-month Treasury bill interest rate, was used with both the regression (used as a benchmark) and neural network models. The neural network models', trained in supervised learning with the Levenberg-Marquardt backpropagation through time algorithm, prediction accuracy was confirmed with correlation coefficient and root mean square tests. The activation function used for the focused gamma models of the time-lag recurrent networks in both the hidden and output layers was tanh. The forecast period ranged from January 2006 to June 2012 thus encompassing the past recession. The real business sales variable is one of the indicators used as a coincident index of the U.S. business cycle, and is included among the variables studied by the Federal Reserve to formulate monetary policy. It is thus an important indicator surrogating for real GDP, which is reported quarterly and with a longer time delay. Our analysis shows that recent recessions have increased in duration, so that using a 36-month change to approximate an average cycle in estimating and forecasting is more relevant and accurate than past usage of a 24-month change.

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Keywords: Real Total Aggregate Sales; Neural Network Models; 3-Month Treasury Bills; Recession; Multistep Predication; U.S. Business Cycle.

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1. Introduction

The economic and financial crisis of 2007-2009 known as the "Great Recession" is the most severe downturn experienced in the United States since the Depression of the late 1920's through 1930's. The recovery from the recent recession is also notable by taking longer than any other post World War II recovery. By June 2012, three years after the trough of the recession was called, indicators such as sales, industrial production and unemployment were performing far below their comparative values in previous upturns. Records made available by the Federal Reserve showed that up to the very start of the Great Recession the Federal Reserve was unaware of the forthcoming crisis and was primarily focused on incipient inflation as a problem[1].

Post-event analysis revealed that the mainstream academic and financial communities saw the recession as unpredictable. Among the reasons were securitization that promoted advances in financial innovations and changes in banking practices over the late 1990's and early part of this century as well as the emergence of a shadow banking sector, since both were viewed as fostering unforeseen structural changes in the economy[2]. Nevertheless, some professionals did forecast elements of the crisis well in advance[3]. In addition, the recession was also forecasted by interest rates and the interest rate spread (albeit the spread performed weakly), which are predictors of business cycle recessions. This study seeks to support the latter proposition that the economic downturn itself was predictable and that the predictions were feasible for well over twenty months in advance.

The interest rate and the interest rate spread are used to forecast economic conditions including recessions, real GDP, total real sales, and total inventories. The reason interest rates have predictive ability over aggregate macroeconomic variables is because they reflect the monetary policy of the Federal Reserve. Monetary expansion stimulates the economy with a time lead by lowering interest rates. Monetary contractions have the opposite effect: increased money results in rising interest rates, which over time act to reduce economic growth. Recent work on the predictive ability of the interest rate spread includes Rudebusch[4], Abdymomunov[5] and Gilchrist et al[6]. A detailed survey of the spread literature as a forecaster is found in Wheelock and Wohar[7]. Seminal studies that focused on interest rate as a predictor includes Zarnowitz[8] and King and Watson[9]. More recent works are attributable to Joseph et al[10] and Stock and Watson[11].

A lessening of the ability of the spread to forecast recent real GDP and sales[12] appears to be concurrent with a change in the length of business cycles' durations. The National Bureau of Economic Research (NBER) reported that of the 12 recessions in the U.S. since 1945; the first 9 had an average half-cycle of peak-to-peak and trough-to-trough of 26.6 months durations[13]. When the last 3 recessions from 1990 to date are also included, the duration increases to 35.4 months, thus lending further credence to the Gorton et al[2] observation of possible structural changes in the economy. Several past studies on interest rate forecasting ability have used a 24-month change/cycle in the dependent and independent variables based on the NBER data from 1945 to 1990, but as the NBER's updated information through 2013 showed, the average length of the cycles has been steadily increasing since the 1990's, and the average half-cycle reported by the NBER is now closer to 36 months. Some examples of studies using the 24-month cycle included Larrain[14,15] and Joseph et al[2,16].

The intention of this study is to generate predictions of both the downturn and recovery of the Great Recession. The hypothesis is that models based on the 36-month cycle are statistically more stable, and will outperform those based on 24-month cycle assumptions as they will produce forecasts that more closely conform to the National Bureau of Economic Research's updated information on business cycles. The forecasts generated from these two types of models under the neural network scheme will be subsequently benchmarked against similar forecasts produced by regression models. The accuracy of the forecasts will be determined using correlation, root mean square error, mean absolute error, mean error, mean absolute percent error, percent of correct direction, and Thiel inequality coefficient statistics.

2. Methods and Materials

The data consists of real total business sales (RTBS), which is the aggregate of all manufacturing, wholesale and retail sales in the U.S., reported on a monthly basis by the U.S. Department of Commerce, Bureau of the Census. RTBS is often used as a surrogate for the gross domestic product (GDP) since their correlation is 0.98, and it is available much earlier and more frequently than the GDP. The second time series used is the U.S. 90-day monthly

Treasury bill, as reported by the Federal Reserve Bank of St. Louis. Both variables were subjected to smoothing by a 3 month moving average.

We attempted to forecast a time period amply encompassing the Great Recession and the ensuing recovery, but we did so with the inverted interest rate, not the spread. Chinn et al[12] found robustness in the interest rate as compared to the spread, and we hope to confirm these findings with our empirical results. Forecasting future economic conditions, especially economic downturns, is important to the business community and to the country overall because downturns are damaging to financial markets, savings and retirement funds of individuals, and national employment. Our analysis seeks to analyse forecasts based on both 36-month and 24-month cycle data for real business sales and interest rates.

The dependent variable is 36 month percent changes/cycles in RTBS and the independent variable is the 36 month backward difference/cycles of the 3-month inverted U.S. Treasury bill interest rate (T-bill). The same structure holds for training and forecasts of 24-month changes/cycles in RTBS and the T-bill. The lead of the 36-month cycle T-bill is 28 months while the lead of the 24-month cycle T-bill is 22 months over RTBS. Since the data are smoothed by a 3-month moving average, the effective lead is 25 and 19 months, respectively.

Two types of modelling were used for both the 24-month cycle and the 36-month cycle tests. One was a regression model[17] used as a benchmark for the other type, which was a neural network model. These models were developed in Microsoft Excel and NeuroDimension NeuroSolutions version 6 software platforms respectively. The particular neural network models used were the focused gamma neural network[18] of the time lag recurrent network class. By definition, the focused gamma neural network model is dynamic and contains a short-term input memory structure. The gamma models' setup, parameters and statistics are shown in Table 1, parts (a) & (b). They consisted of three layers. One input with a tapped delay line gamma memory structure that included a depth of three, two taps, and two weights; one hidden layer with two processing elements and 10 weights; and an output with one processing element and three weights. The weights were updated in the batch mode of supervised learning control and both hidden and output layers used the hyperbolic tangent activation function. The supervised learning algorithm employed was Levenberg-Marquardt backpropagation through time[18,19].

Table 1a & b. Focused gamma neural network setup

Cycles	Network	Multistep Ahead	Inputs	Hidden Layer	Output Layer	Supervised Learning Control		
24 Month	Gamma	23	1	1	1	Thr=0.0001	Increment	Batch
36 Month	Gamma	29	1	1	1	Thr=0.0001	Increment	Batch

Note: Both the hidden and output layers used the tanh activation function and Levenberg-Marquardt algorithm for weight updates; [Thr] stands for threshold.

Training							Testing		
Cycles	Date	RMSE	Correlation	PEs	Taps	Tap Delay	Date	RMSE	Correlation
24 Month	Feb 70 - Dec 05	0.1459	0.96	3	2	1	Jan 06 - Jun 12	0.0256	0.95
36 Month	Feb 70 - Dec 05	0.1643	0.94	3	2	1	Jan 06 - Jun 12	0.0184	0.96

Note: Depth of samples = 3; trajectory length = 143; total weights =15.

Table 2. 24 and 36-month cycle regression statistics and parameters

Date	Cycle	Correlation		Variables	Coefficient	Standard Err.	t-value	P-value
Feb 70 - Dec 05	24 Month	0.7056		Intercept	0.0567	0.0021	27.06	8.10E-95
				T-Bill	0.0157	0.0008	20.63	3.50E-66
Feb 70 - Dec 05	36 Month	0.5471		Intercept	0.0891	0.0028	31.55	7.50E-11
				T-Bill	0.0123	0.0009	13.52	5.50E-35

The parameters and statistics of the 24 and 36-month cycle regression estimations for the period covering February 1970 to December 2005 are shown in Table 2. The 24-month cycle regression model exhibited higher correlation and t-value for the T-Bill than the 36-month cycle regression model. However, noted in the forecast section, the 36-month cycle regression model will have substantially better performance in forecasting than the 24-month cycle model. Such incongruence between estimation and forecasting performance in regression models is not uncommon.

The effective data set, once smoothing, differencing, and shifting for the forecast horizon were taken into account, encompassed the period from February 1970 to June 2012 of monthly samples. As shown in Table 1, the training period used for the models was from February 1970 to December 2005, totalling 431 samples for the regression models and 429 samples with a trajectory length of 143 samples per exemplar for the gamma neural network models. This training period included five recessions and recoveries so that the parameters for out-of-sample forecasting models used to generate the 'Great Recession' cycle had statistical antecedents. Nevertheless, the amplitude of the forecast cycle was the largest since the 1920-1930's Great Depression, and has no parallel in the training data. This feature should be taken into account when interpreting both regression and neural network forecasts. The testing (or forecasting) was done from January 2006 to June 2012 for the 78 samples.

3. Results and Discussion

Table 3 shows the performance statistics used to evaluate the neural network and regression forecasts. Since any single forecast performance valuation measure is subject to some weakness, eight traditional performance statistics were used. In all eight categories, the gamma 36-month cycle neural network model outperformed the gamma 24-month cycle model. The 36-month cycle had a slightly higher correlation at 0.9607 compared to 0.9484 to the 24-month cycle model. The correlation statistics showed the least advantage of all statistical measures for the gamma 36 model. However, the other seven measures showed significant differences in the quality of the forecast evaluation. Thus, in the next lowest parameter, the root mean square error (RMSE), the 36-month cycle gamma model came in at 0.0184, which was 39% higher than the 24-month cycle gamma model's RMSE of 0.0256, and the percent of correct direction (POCD) measure of 0.8572 was 40% higher than that of the 24-month cycle neural network forecast. This meant that POCD accurately captured 85.72 percent of the 36-month cycle forecasts' direction compared to the 24-month cycle's 61.04 percent. The 36-month cycle's forecast performance measured by POCD improved by 71 percent over the 24-month cycle's predictions.

Table 3. Forecast Statistics: Neural Networks and Regression models: Jan 2006 to Jun 2012

Model	Correlation	RMSE	Theil 1	Theil 2	MAD	POCD	Mean Error	MAPE
Gamma 36	0.9607	0.0184	0.0955	0.1744	0.0134	0.8572	0.0078	37.09
Gamma 24	0.9484	0.0256	0.3529	1.0908	0.0207	0.6104	-0.0524	94.71
Ratios Stats.	0.99	1.39	3.70	6.25	1.54	0.71	6.72	2.55
Regression 36	0.7103	0.0654	0.3656	1.15	0.038	0.7922	-0.0507	170.05
Regression 24	0.1613	0.1012	0.8533	11.63	0.0744	0.5325	-0.0573	246.89

Major differences in the evaluation of the two neural network models became more pronounced when the next two statistics were considered. In terms of the mean absolute percent error (MAPE), the gamma 36-month cycle was at 37.09, a 155 percent improvement over the gamma 24-month cycle's MAPE of 94.71. An even bigger discrepancy was found by comparing the models' mean errors. The 36-month cycle had a mean error of 0.0078, much smaller than the 24-month cycle's 0.0524, which translated into an improvement for the 36-month cycle of 572 percent.

The Theil inequality coefficient (Theil) statistics come in U1 and U2 versions. Under U1, the 36-month cycle model (0.0955) outperformed the 24-month cycle (0.3529) by 270 percent. When U2 was used as the predictive measure, the 36-month cycle model (0.1744) outperformed the 24-cycle (1.0908) once more, but by a much larger factor, 525 percent. A question is which Theil statistic described predictive accuracy better, with analysts recurrently choosing one over the other, or reporting both. Bliemel[20] favored U2 and advised that U1 can mislead. U1 ranges between zero (denoting a perfect forecast) and 1 (denoting a no change naïve forecast). If, however, the forecast is worse than a naïve forecast, the U1 value would be calculated as lower than 1. The U2 does not have this problem and does not appear to have other statistical issues. The Theil U2 also has a lower limit of zero and an upper bound of 1 denoting a naïve forecast, and values higher than the upper bound 1 denoting worse than naïve forecasts.

With regard to the neural network and regression models' forecasts, Table 3 above shows that the baseline regression forecasts did confirm that the 36-month cycle analysis of real business sales data yielded better results than the 24-month cycle approach, with all prediction measures favoring the longer cycle. However, both regression models did poorly compared to the neural network approach. In both the 36-month cycle and the 24-month cycle analyses, the regression models' forecasts seriously underperformed the predictions of the gamma neural network models. Since the 36-month cycle approach appeared dominant in the predictive results over the 24-month cycle approach, the comparison of predictive performance will be limited to the gamma 36-month cycle and regression 36 models. One reason for the less than stellar performance of the regression models is that many financial and economic relationships appear, on closer inspection, to be of a nonlinear nature[16,21].

Gamma 36's correlation at 0.9607 is 35.25 percent greater than regression 36's at 0.7103. Gamma 36's RMSE at 0.0184 outperformed regression 36's RMSE of 0.0654 by 255 percent. In terms of mean absolute deviation (MAD) and mean error, gamma 36 improved on regression 36 by factors of 184 and 550 percent, respectively. The POCD captured by gamma 36 is 85.72 percent compared to 79.22 percent for regression 36, an improvement of only 8 percent while the MAPE of gamma 36-month cycle (37.09) showed a 358 percent improvement over that of regression 36. Finally, gamma 36 had better predictive measures with both Theil statistics. Its U1 was better by a factor of 282 percent, while its U2 was 559 percent larger than regression 36.

A visual inspection of the forecasts added to the statistical analyses since it revealed properties of the predictions not readily apparent in the single number measures of Table 3. Figures 1 and 2 compare the forecasts generated by both the regression and neural network models from January 2006 to June 2012. Figure 1 shows the 24-month cycle

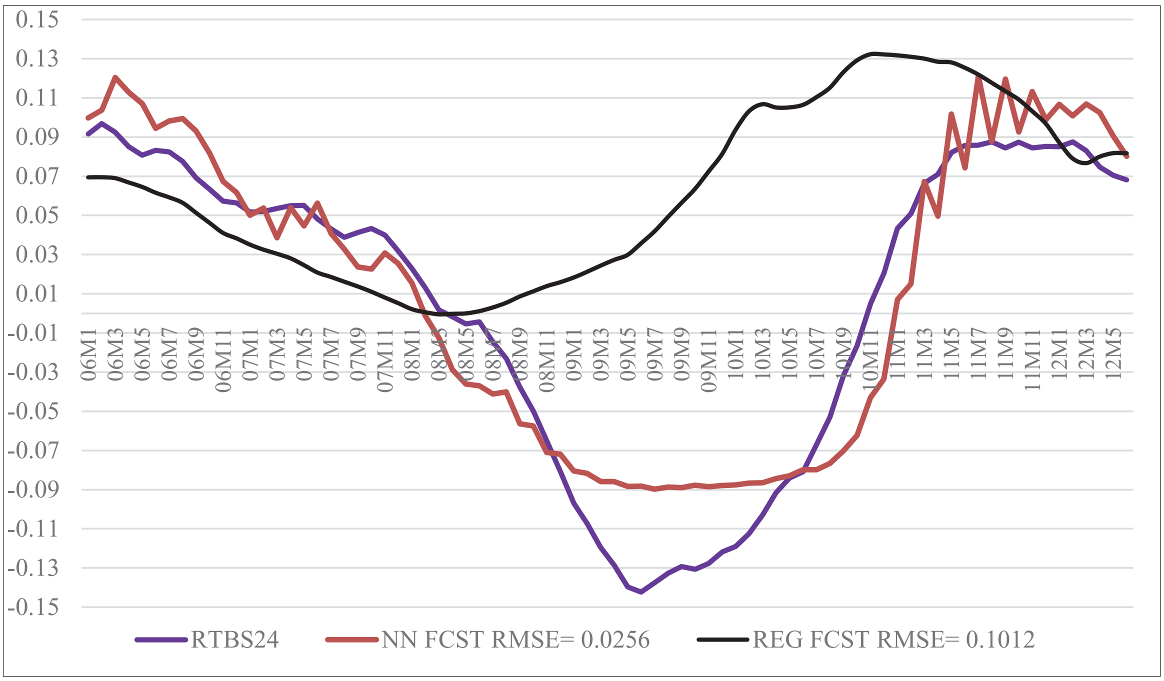

Fig. 1. 24-month cycle sales forecasts with neural network and regression modes --Jan 2006 -Jun 2012.

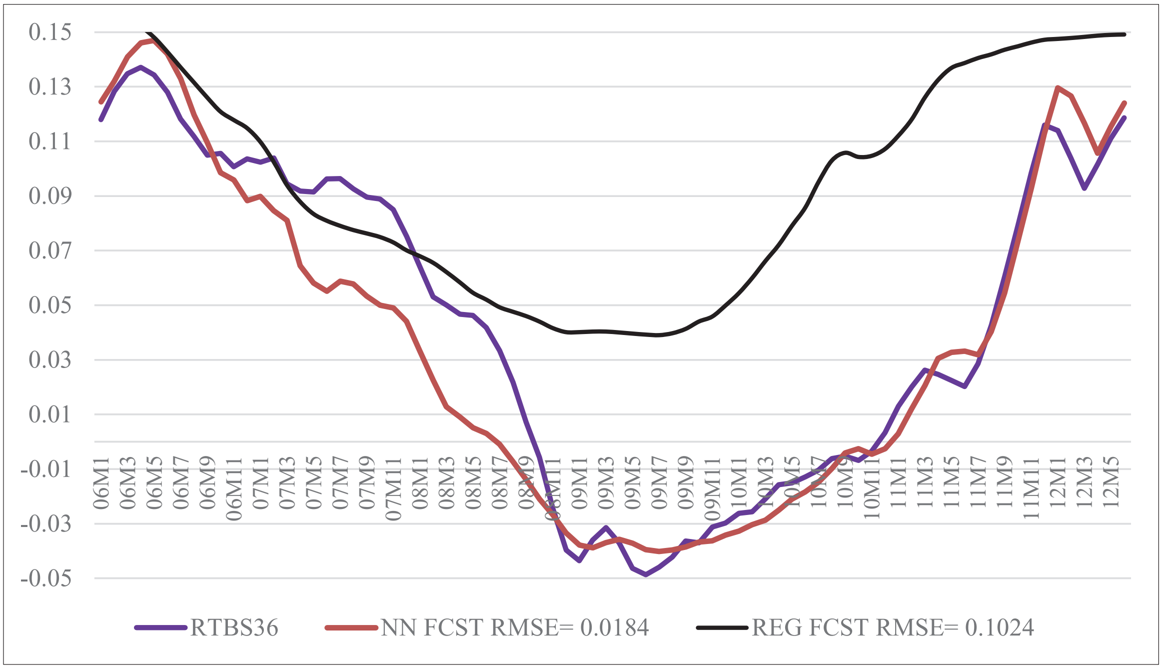

Fig. 2. 36-month cycle sales forecasts with neural network and regression models --Jan 2006 to 2012.

forecasts. It is readily apparent that the regression forecast did not closely follow the path of the actual data; it produced only positive values during one of the most severe recessions, and completely missed the trough. The neural network forecast, while an improvement over the regression forecast, also missed capturing the severity of the economic downturn as evidenced by the visible gap between the trough of the actual data and the flat neural network forecast well above it. The plot of the actual data has a ‘V’ shape while the plot of the gamma 24-month cycle forecast has a ‘U’ shape and is higher. This might in part be due to the amplitude of the forecast recession and recovery, which has no counterpart in the training data, as previously discussed in Section 2.

Figure 2 shows the 36-month cycle forecasts. Compared to Fig. 1, the forecasts shown in Fig. 2 captured the pattern of the actual data much better resulting in improved fits. The regression 36 predictions were still positive, but were much more in phase with the actual data than those of regression 24. Nonetheless they underperformed both neural network models. There was substantial improvement in the neural network forecast, with gamma 36 patterning the depth of the recession and the ensuing recovery accurately. The neural network forecast is now also ‘V’ shaped as is the actual data, and fits the trough tightly. It does, however, somewhat overstate the beginning fall of the economic downturn. The statistical results tend to show that the 36-cycle neural network forecast is far better able to cope with the amplitude of the Great Recession’s sharp decline and recovery than that generated by the 24-cycle neural network model.

4. Conclusion

Our analysis showed that the neural network models outperformed their baseline regression counterparts. There was weak to no support for a 24-month cycle analytical framework for the U.S. business cycle from the regression and neural network models, respectively. In contrast, the 36-month cycle hypothesis is more strongly supported by the neural network model, while the 36-month cycle regression, which underperformed the comparable neural network model, also lent some backing to the longer business cycle hypothesis. The results shown in this paper consequently appear to be in line with the NBER’s data since 1990 on business cycle durations. The NBER’s most recent data encompassing the 12 recessions in the U.S. since 1945 yielded a 35.4 month half-cycle. The same data estimated prior to 1990 averaged to a 26.6 month duration. They also validated Qi and Zhang[21] finding that appropriate "differencing is the most effective" method for neural network modeling and out-of-sample forecasting of "real-world time series," which are typically nonlinear and stochastic. The predictor variable, U.S. 3-month T-bill, was 36 month backward difference and the predicted variable, RTBS, was subjected to 36 month percent change during the preprocessing of the raw data. The empirical findings of this study were concordant with Gorton's[2] assertion that financial innovations, securitization, and the emergence of a shadow banking system have brought about structural changes in the U.S. economy. Additionally, this work also followed Chinn & Kucko[12], who found robustness in the interest rate as compared to the spread. The closeness of fit of the 36-month cycle neural network model's forecast showed that the prediction of the most recent economic slowdown that began in late 2007/ early 2008 was feasible well before the event, and lent credence to Schlefer's[3] references to professionals that did forecast elements of the crisis well in advance.

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