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Predictive Ability of the Interest Rate Spread Using Neural Networks

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Abstract

Interest rates are commonly used as predictors of future economic conditions as measured by industrial production, real gross domestic product and real total business sales (RTBS), as well as through the prediction of recessions in the economy. Recession forecasting is mainly characterized by probit categorical analysis, and there appear to be hardly any neural network research in this area. This paper contributes to the recession forecasting literature using interest rate spreads (the difference between the average yields on 10 year U.S. Treasury bonds and on 3 month U.S. Treasury bills) to forecast the 2007 to 2009 recession with neural network models referenced against regression models. It is shown that neural network models out-performed regression models as evidenced by the R-squared and mean square error performance metrics. Unlike other studies, the change in interest rates is used to compute the interest rate spread. The targeted variable is RTBS. The interest rate spread variable was used to generate three input variables comprising 23, 26, and 29 month leads respectively over RTBS.

Keywords Real total business sales; Recession forecasting; Neural networks; Multiple regression; 3-month Treasury bills.

Introduction

For over twenty years the interest rate spread (the difference between long term and short term interest rates) was known to be a generally reliable forecaster of future economic conditions. This is attested to by surveys of the literature which analyze studies that research the analytic and predictive power of the spread and of interest rates in

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general. These literature surveys include Wheelock and Wohar (2009), Berk and van Bergeijk (1998), and Plosser and Rouwenhorst (1993). The consensus in many recent research studies is that the spread does play a significant role in anticipating real economic growth as exemplified by real gross domestic product (real GDP), real total business sales (RTBS), and industrial production, among others; and that the spread can also forecast inflation and consumption. Most important, while the spread's ability to forecast these variables, particularly output growth, has diminished somewhat over the years, its ability in forecasting recessions has remained remarkably stable.

Monetary Policy Links Explaining the Spread's Predictive Capabilities

Why are interest rate spread and interest rates in general predictors of longer term economic activity? The principal reason lies in the fact that interest rates are very closely linked to the Federal Reserve's monetary policy. Changes in the Federal Reserve's monetary policy are used to manage the growth of the U.S. economy and to steer it through the business cycle with minimum disruption. The Federal Reserve will enforce policies that result in so called "tight" monetary conditions, where credit is relatively more difficult to get because it causes interest rates to rise. Conversely, the Federal Reserve can seek "loose" monetary conditions, where credit is relatively easier to get since it causes interest rates to fall. The Federal Reserve uses these policies in a countercyclical manner. When the economy is beginning to "heat" up and output and inflation are beginning to increase at a fast rate, the Federal Reserve puts on the "brakes" to slow the economy by raising interest rates. When the economy shows signs of slowing down, the Federal Reserve lowers interest rates to stimulate consumption and investment and make the economy grow faster. There is, however, a substantial time delay between the implementation of a Federal Reserve interest rate change and its effect on the economy. King and Watson (1996) found that the time delay between interest rate change and when it starts to affect economic growth is approximately fifteen to eighteen months, while Dotsey (1998) found that the interest rate spread begins to influence economic growth after 24 months.

Two Distinct Types of Spread Forecasts

The literature on the topic is naturally divided into two distinct tracks. On the one hand, researchers have extensively analyzed how well the spread forecasts output growth. This involves the analysis of time series data. Most of the empirical evidence for the interest rate spread's effectiveness in forecasting is based on linear regression models, though some analyses are based on GARCH and nonlinear regression. Of relevance to this paper is work done by Tkacz (2001) who uses neural networks to forecast quarterly Canadian real GDP growth and Shaaf (2000) who also uses neural networks to forecast U.S. quarterly output growth. Both studies found that out-of-sample simulations outperformed forecasts from linear models. An overall finding in the literature is that the spread does forecast output growth -- that is, the ups and downs of the economy on a "continuous" or more strictly, discrete, basis (quarter to quarter) -- but that its accuracy has decreased over time.

The second track, which researchers follow in analyzing the forecasting ability of the interest rate spread, is how well the spread forecasts recessions. This, in most cases, is not treated as a continuous or discrete forecast, but is instead treated as a forecast of an abrupt transition. This is, nevertheless, a valuable forecast since a warning of an upcoming recession can help business, government, and consumers mitigate its impact. The effect of an unanticipated recession can bring about severe dislocations to the human and physical capital of a nation as witnessed by the 2007-2009 economic disruption. The studies of the interest rate spread in anticipating recessions are mostly based on probit models, where the dependent variable is treated as categorical, and is composed of zeros and ones. We found hardly any evidence of neural network studies analyzing the predictive power of the interest rate spread regarding recessions. A notable exception is Qi (2001) who used neural networks to study the predictive abilities of 27 different economic and financial variables, including interest rates and interest rate spreads, with regard to recessions in the U.S. economy and found that interest rate spread surpassed the other variables in predicting recessions. Therefore, the use of neural networks to study the relative predictive ability of interest rate spread in relationship to economic recessions is reasonable. Moreover, there is a growing use in the application of neural networks and other artificial/computational intelligence models in economic and financial forecasting. Some examples include Joseph et al (2010) who compared the forecasting performance of neural networks relative to multiple regression in predicting Standard and Poor's 500 stock index earnings yield, Pacelli et al (2011) who used neural networks to successfully forecast Euro/USD exchange rate, and Angelini et al (2008) who used neural networks to successfully assess the credit risk of Italian small businesses. Furthermore, Angelini et al reported on the overall areas in economics and finance where neural networks are applied. They included classification and discrimination (e.g., credit risk assessment, stock classification, and bank failure prediction); time series prediction (e.g., stock prices and indexes, currency prices, options, financial crashes forecast, and economic crises warnings); function approximation and optimization (e.g., portfolio selection and investment project return prediction). Other works of neural networks in economics and finance include Kingdon (1997) and Trippi and Turban (1993). Kingdon concentrated on the design and implementation of neural network models and genetic algorithms based adaptive systems for modeling financial time series while Trippi and Turban edited a compendium of articles from different authors that focused on such topics as financial decision making, bond rating, mortgage underwriting judgments, nonlinear structure of financial markets, and the testability of arbitrage pricing theory.

Empiricism

The interest rate variables used to construct the spread are the monthly average yield on the 10 year U.S. Treasury Bond and the monthly average yield on the 3 month U.S. Treasury bill. Both data sets are from the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of Saint Louis. The variable used to depict the recession in the U.S. economy is monthly data of RTBS, also known as real manufacturing and trade sales, and is reported by the Bureau of Economic Analysis and U.S. Department of Commerce. RTBS is one of the indicators used by the National Bureau of Economic Research to date recessions and has a correlation of 0.99 to real GDP. We use RTBS because it is a monthly data series, whereas real GDP is reported quarterly and thus presents fewer observations.

The full data set starts in August 1964 and ends in June 2009. RTBS is seasonally adjusted. All data samples are three month moving averages that smoothed the volatility in the data. RTBS and the interest rate spread are 24 month changes in both data series, with RTBS as the dependent variable and three differently timed spread leads as the independent variables. The spread has a long and variable lead on RTBS, as determined by correlation analysis, and its highest correlations are distributed over a period ranging from 23 to 29 months. Accordingly, the spread is used as an independent variable with three leads: 23, 26, and 29 months. The spacing between the leads and the ensuing use of three leading variables is similar to the lagged polynomial regressions used by most researchers (Wheelock and Wohar, 2009, p. 425), which uses three quarter lags, corresponding to our three month separations. This methodology also helps to potentially avoid multicollinearity issues in the ensuing regression analysis that is used as a comparison for neural networks in this study. The preprocessed data set reduces to 483 samples covering the period from April 1969 to June 2009.

Wheelock and Wohar (2009) state that "it remains to be seen how incorporating data for the recession that began in 2007 affects the performance of forecasting models that use the term spread to predict economic activity…." The goal of the current analysis is to answer this question and test the predictive ability of the spread regarding the 2007-2009 recession. This recession officially started December 2007 and ended June 2009, as stated by the National Bureau of Economic Research. However, the slowdown in growth of the economy, as reflected by a steady decrease in the growth rate, was evident since January 2006. Accordingly, the out-of-sample data set over which we test both the regression and neural network models' forecasting performance starts as of this date, January 2006, and ends in June 2009.

One difference of this work from most others that use the spread to forecast recessions is the use of discrete numeric data rather than categorical (0, 1) data or a probit type model. That is, here the actual economic data for each month of the 42 month downturn in economic activity is forecasted. This makes the forecast of this study relatively more informative because it predicts the real dollar magnitude of the recession, and not just its likely occurrence, as categorical analysis is limited to do. Put another way, the methodology used herein tells how substantial the magnitude of the recession is likely to be. Probit and other categorical analyses cannot. A second difference of this work relates to the use of a neural network approach, benchmarked against a regression approach

Experiments

The experiments were similarly conducted in two separate regimens for both the regression analysis and the neural network forecasting. In the first regimen, the regression analysis and the neural network models were estimated from 441 samples that spanned April 1969 to December 2005. These models were then tested on 23 samples that covered January 2006 to November 2007. For the second regimen, the models were estimated from 464 samples and tested on 19 samples covering the respective periods of April 1969 to November 2007 and December 2007 to June 2009. The two neural network models were designed in NeuroSolutions version 5.0. The models were of the time-delay neural network (TDNN) with *tanh* activation functions and batch weight updates under supervised learning rule using the Levenberg-Marquardt backpropagation algorithm (Principe et al, 2000). Each model had three inputs, one hidden layer, and one output layer. The input memories had 10 taps and a depth of 3. The respective models had two and three processing elements in the hidden layer and one processing element in the output layer.

The linear regression models estimated using the NCSS 2000 statistical software package are described by equations $y_1(t) = 0.057 + 0.016x_{23}(t) + 0.007x_{26}(t) + 0.003x_{29}(t)$ and $y_2(t) = 0.056 + 0.015x_{23}(t) + 0.007x_{26}(t) + 0.004x_{29}(t)$, where y signifies RTBS with the subscripts indicating the first and second regimens of the experiments, while explanatory variable x denotes interest rate spread (or spread) with its subscripts 23, 26, and 29 specifying the respective leads over RTBS, thereby resulting in three separate explanatory variables. Although the high correlations between spreads x_{23} and x_{26} and x_{26} and x_{29} seem to suggest incipient multicollinearity (Koop, 2006), multicollinearity analyses based on eigenvalues of centered correlations showed no evidence of multicollinearity in either regimen of the experiment.

Results and Discussion

Overall, the neural network models outperformed the multiple regression models as demonstrated by the performance statistics of in-sample model estimations and the corresponding out-of-sample testing in Table 1 and the out-of-sample forecasts of Figure 1. However, there is an exception. The regression models yielded relatively better MSE when fitted with the training data – 0.0001 compared to 0.0448 and 0.0476 respectively for the neural network models. Otherwise, the neural network models provided superior performance. This better in-sample performance of the regression models is suggestive of some degree of overfitting of the data since the out-of-sample forecasting performance is relatively less impressive. Under both training and testing, the R-squares associated with the neural network models' estimation and forecasting of RTBS are higher than the corresponding ones for the regression models. In addition, the MSEs associated with the neural network models' forecasting of RTBS yielded reasonably lower values than the regression models. For example, associated with the training set and testing set of regimen 1 of the experiment are R-squares of 0.6416 and 0.7797 for the neural network models compared to R-squares of 0.4468 and 0.7567 for the regression models. These findings indicate that the explanatory variables in the interest rate spread of the neural networks models have relatively stronger influence on the variations in RTBS. Moreover, the MSEs resulting from the forecasting of RTBS during the testing period of regimen 1 and regimen 2 are 0.0002 and 0.0005 for the neural network models compared to 0.0008 and 0.0014 for the regression models. That is, the MSEs associated with the neural network models are lower by at least a factor of 2.8, demonstrating the superior performance of the neural network forecasts.

The MSEs of the overall forecast of 42 monthly samples of data, which is the combined total of the forecasts of regimen 1 (23 months, from January 2006 to November 2007) and regimen 2 (19 months, from December 2006 to June 2009 -- the end of the recession), are 0.0004 for the neural network models and 0.0011 for the regression models. When these two MSEs are compared, it is found that the neural network models' overall MSE is lower than the regression model MSE by about a factor of 3. When the overall relative MSE of the aggregate neural network forecast is considered in conjunction with the comparatively better overall R-square value of 0.8757 (higher than the corresponding regression forecast value by 0.3262), it is clear from the MSE and the R-square statistics that the neural network models' forecasting performance is much better than the regression models' forecasting.

Figure 1 validates the performance statistics of Table 1 by showing that the overall neural network forecast outperformed the multiple regression forecast. Of particular importance is that the overall regression models' forecast shows a major discrepancy from the actual course of the recession since it starts to indicate a steady upturn beginning in April 2008 (month 28 of Figure 1). This upturn continues steadily through the end of the forecast period, whereas the official end of the recession was not until June 2009 (or month 42). The overall neural network models' forecast, instead, parallels the downward trajectory of the actual RTBS and turns upward, moving closely with the actual RTBS at a decreasing rate beginning February 2009 (or month 38), and reaching essentially zero

Table 1

Performance Statistics

Models	R-Squared			MSE		
	Training	Testing	Overall*	Training	Testing	Overall*
TDNN	0.6416	0.7797		0.0448	0.0002	
	0.6288	0.5314	**0.8757**	0.0476	0.0005	**0.0004**
Regression	0.4468	0.7567		0.0001	0.0008	
	0.4673	0.3398	**0.5495**	0.0001	0.0014	**0.0011**

*Overall refers to the aggregate forecast of the 42 samples over the two testing periods.

Note: Two regimens of training and testing for the two types of models where the upper row signifies regimen 1 (23 months) and the second row signifies regimen 2 (19 months) for each type of model.

growth (-0.0015) by the end of the recession in June 2009.

While there is more volatility in the neural network forecast compared to the smoother performance of the regression forecast, the neural network forecast is closer to the actual RTBS data. Moreover, the volatility in the neural network forecast does not appear to be too consequential since the overall forecast is made up of two forecast periods: the first predicting 23 months, from January 2006 (month 1) to November 2007 (month 23), and the second anticipating 19 months, from December 2007 (month 24) to June 2009 (month 42). A review of Figure 1 shows that the neural network forecast indicates the long term trend of RTBS for both periods more closely than the regression forecast.

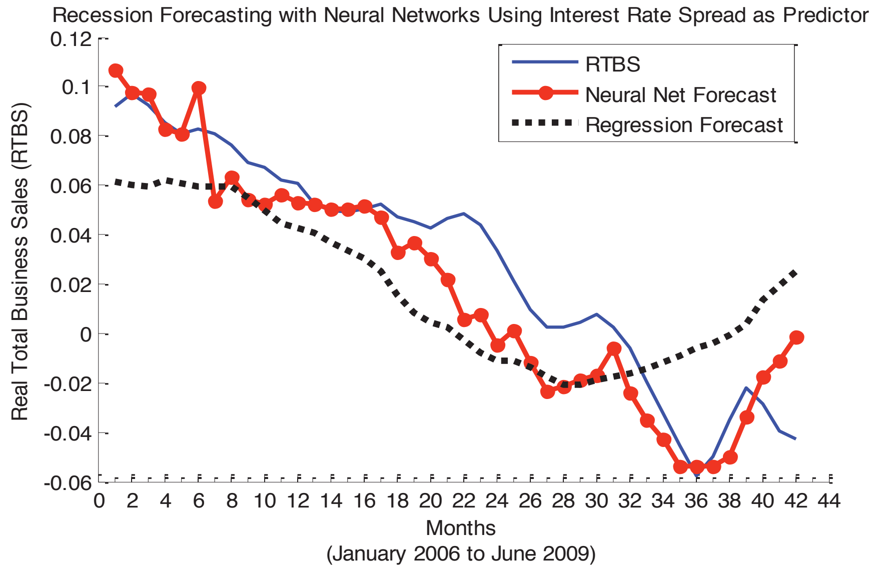

Figure 1: Recession forecasting with Neural networks relative to multiple regression.

Conclusion

This study has demonstrated that neural network modeling and forecasting of economic recessions by means of interest rate spread are viable, and more effective than multiple regression analyses. With the neural network models, interest rate spread had relatively more impact on the variance of RTBS and the MSE was about one third of that associated with the corresponding regression models. Moreover, it should be stated that the neural network models are more sophisticated in design and better suited for the data sets that are believed to be nonlinear and time varying such as the economic and financial time series of this study.

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