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# Forecasting Purchasing Managers' Index with Compressed Interest Rates and Past Values

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**Abstract**

The purchasing managers' index (PMI) is a simple subjective survey about the state of the manufacturing sector of the national economy. It's an early indicator of the nation's economic strength with effects extending into federal monetary policy and the financial markets. It is a composite index comprising the weighted average of new orders, production, employment, supplier deliveries, and inventories. It has been established that inverted interest rates in 3-month Treasury bills is a predictor of PMI. This study extended the work on the compression of economic and financial predictor variables as well as the relative efficiency of temporal nonlinear neural network models in forecasting economic time series variables. It showed that compressed interest rates and PMI past values are also effective predictors of the future values of PMI. Less than 30% of the wavelet packets coefficients of interest rates were involved in accomplishing the forecasting task. The correlation, root mean square error, normalized root mean square error, mean absolute deviation, and Theil inequality metrics were used to determine the efficacy of the forecasts. The overall PMI forecast produced by the neural network models was relatively better than that produced by the regression models on all metrics except Theil inequality.



*Keywords* Compressed interest rate; 3-month Treasury bills; Purchasing managers' index; Neural networks; Robust regression; Models.

## Introduction

Purchasing managers' index (PMI) is a monthly seasonally adjusted weighted composite diffusion index of five indicators of economic activities in the manufacturing sector (Harris, 1991; Koenig, 2002; Lindsey & Pasvur, 2005; Raedels, 1990; Peláez, 2003). The five indicators are weighted as follows: 30% for new orders, 25% for production,

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20% for employment, 15% for supplier deliveries, and 10% for inventories. The PMI is a subjective index, based on the reports from manufacturing firms' purchasing managers. Its advantages include timeliness; reliability; and a predictor of changes in industrial production, real gross domestic product (GDP), real inventories, real sales, sales/inventory ratio, federal funds rate, foreign exchange returns, and in monetary policy (Berge & Jorda, 2011; Neely & Day, 2010; Ozyldirim et al, 2011). Some of PMI's disadvantages are its subjective nature and the unaccounted economic impact of surveyed firms in survey responses. The PMI's diffusion aspect makes it behave like a leading indicator. Koenig (2002) said that diffusion indices provide no information on the intensity of a time dependent relative change in values or a firms' economic impact. Moreover, Harris (1991) found that PMI "is helpful in predicting contemporaneous manufacturing activity;" and "deserves at least part of its reputation as a key economic indicator."

The PMI is not only subjective and simple but it is also enduring and meritorious as a forecasting tool of important economic variables (Peláez, 2003; Simpson & Ramchander, 2008). Because of the relative importance of the PMI's ability to predict future economic activities including changes in real GDP and the growth rate, some researchers have called for improving its statistical robustness and quantification to give it greater accuracy and signaling power (Peláez, 2003). Moreover, other researchers see value in being able to accurately forecast the PMI so as to gain insight into the economy's future direction and present models to accomplish this task (Larrain, 2007; Lindsey & Pasvur, 2005; Raedels, 1990).

Economic forecasting falls into two general groups: qualitative and quantitative, where the qualitative forecasting may merely involve intuition and speculative judgments while the quantitative forecasting could involve sophisticated statistical analyses (Granger and Newbold, 1973; Wisner & Stanley, 1994; Wolstenholme, 1999; Goodwin, 2002; Lindsey & Pasvur, 2005). The increased use of strategic planning and the need for cost containment among corporate managers necessitate hybrid forecasting strategies that integrate the right mix of qualitative and quantitative forecasting since both strategies have complementary strengths and weaknesses, and the fact that forecasting is a human activity (Wisner & Stanley, 1994; Wolstenholme, 1999; Goodwin, 2002; Lindsey & Pasvur, 2005). Nonetheless, business managers and decision makers are overly reliant on short term bias prone subjective forecasting because of their lack of training and familiarity in using more accurate statistical forecasting methods (Wolstenholme, 1999; Goodwin, 2001). When economists and business managers use statistical forecasting methods, they tend to overly favor regression analyses (Koop, 2006; Lindsey & Pasvur, 2005; Septhon, 2009; Wisner & Stanley, 1994). However, the increasing use of computers, data repositories, and ubiquitous data over the last 20 years are demanding more computational and automatic ways to efficiently mine, analyze, and forecast future economic conditions to provide information that afford a competitive advantage to firms in this ever changing dynamic business environment.

There is a limited but increasing use of neural network modeling techniques in various areas of economic forecasting (Larrain, 2007). This study is an extension of Larrain's 2007 work on the relative forecasting of PMI with inverted 3-month T-bill interest rate using neural network models. The out-of-sample forecast in this study subsumes the 36 months covering September 2002 to August 2005 in Larrain's (2007) work: it covers 159 months inclusive of May 1997 to July 2010. This study also differs from Larrain's in that its forecast horizon is 12 months instead of 10; it uses past values of PMI as one of the explanatory variables; the explanatory interest rate variable is compressed to within 15% of its wavelet packet coefficients (Mix & Olejniczak, 2003); and it uses robust multiple regression (DuMouchel and O'Brien, 1989) instead of the regular linear regression as a basis of comparison for the time lagged recurrent neural network focused gamma models (Principe et al, 2000; Haykin, 1999). The performance measures used to test the accuracy of the forecasts are correlation and root mean square error for the individual forecasts and correlation (r ), root mean square error (RMSE), normalized root mean square error (NRMSE), mean absolute deviation (MAD), and Theil inequality (Theil) for the overall forecasts.

## Materials and Procedures

The raw interest rate and PMI data consisted of 552 monthly samples dated from August 1964 to July 2010. They were shown through scatter plots (Koop, 2006) to be generally not linearly related to each other even after preprocessing by compression, filtering, 12 month backward differencing, and mean removal. Their power spectral densities were concentrated within relatively few low frequency indices. The zero mean raw interest rate variable reached its highest power spectral density of 50.15 at index 2 and then rapidly tapered off to a spectral density of

0.93 at index 28 while the zero mean raw PMI, similarly, reached its highest power spectral density of 174.3 at index 8 and then rapidly tapered off to a spectral density of 5.53 at index 45. The power spectral densities of interest rate and PMI after the preprocessing showed similar behaviors. The power spectral density investigations were performed with Mathworks Matlab signal processing toolbox using Welch's method inclusive of Chebyshev window. All the preprocessing and processing of the interest rate and the PMI data sets were done using a combination of Matlab version 7.12.0.635 (R2011a), Microsoft Excel 2010, and NeuroDimension NeuroSolutions version 6.06. For example, Excel and NeuroSolutions were for the neural network modeling and forecasts while Excel and Matlab for the multiple regression modeling and forecasts.

The interest rate compression and the PMI denoising were done using similar Matlab wavelet toolbox main menu setup. The one dimensional wavelet packet with the discrete approximation of Meyer wavelet (*dmey*) and the *Shannon* entropy criterion was used. For the interest rate compression, the decomposition level was three (3), the threshold method was balanced sparsity norm, and the global threshold was 4.07 while for the PMI denoising the decomposition level was four (4), the threshold method was the soft fixed form threshold with unscaled white noise structure, and the global threshold was 3.66. Only 12.58% of the compressed interest rate wavelet packet coefficients were required to recover 99.51% of the total energy into the compressed interest rate. Thereafter, the 12 month backward first differencing and mean removal techniques were applied to the compressed interest rate and the denoised PMI, thereby reducing the interest rate and PMI changes from 552 to 540 monthly samples.

For both levels and differences, interest rate preceded PMI by 11 months at maximum values of 0.391 and 0.601 respectively. Since the Hurst exponent value of 0.572 exceeded 0.5 for the PMI changes, the PMI changes are predictable. While the skewness with kurtosis and the Jacque-Bera test values for interest rate and PMI levels showed that they were not representing samples from normal distributions at the 1% significance level, the skewness with kurtosis and the Jacque-Bera test values for interest rate and PMI changes appeared to be near normal from the near zero skewness values of -0.027 and 0.069 and near 3.0 kurtosis values of 3.651 and 3.748 respectively, and the Jacque-Bera test being statistically significant at the 5% level. Since the absolute magnitude of PMI changes was about five times that of interest rate changes, interest rate changes were scaled up by a factor of 5 to conveniently align interest rate with PMI values to facilitate easy visual comparison.

Because of the 11 months lead of compressed interest rate changes over denoised PMI changes at their maximum correlation of 0.601, the forecast horizon for PMI was set to 12 months, where compressed interest rate changes and past values of denoised PMI changes were the predictor variables and denoised PMI was the response variable predicted to be 12 months in the future. By aligning the predictor and response variables while compensating for the forecast horizon, these variables were reduced from 540 samples to 528 samples with the response variable covering the period of August 1966 to July 2010 and the predicted response covering the out-of-sample forecast period of May 1997 to July 2010 in increments of 45, 50, 39, and 36 monthly samples for the testing subsets, where the overlapped two samples of the ending of the first and the beginning of the second increments, six samples of the ending of the second and the beginning of the third increments, and three samples of the ending of the third and the beginning of the fourth increments were averaged. The initial training subset covered the period of August 1965 to April 1996; subsequent training subsets were then increased in increments of 43, 44, and 36 monthly samples respectively making the fourth training subset 492 monthly samples. Two types of models were used in the prediction process: focused gamma time-lagged recurrent neural network and robust multiple regression (Principe et al, 2000; Haykin, 1999; DuMouchel & O'Brien, 1989). The general model describing the focused gamma neural network is the following:

$$y(t+h)=\varphi_0\left(\sum_{j=1}^{M} w_j \varphi_1\left(\sum_{k=1}^{R}\sum_{l=1}^{D}\Big(w_{jk}(0)x_k(t)+w_{jk}(l)\big((1-\mu)x_{kl}(t-1)+\mu x_{kl-1}(t-1)\big)\Big)+b_j\right)+b_0\right)$$

where M, R, D, b, h, and $\mu$ are the number of processing elements in the hidden layer, number of inputs, number of taps, bias, forecast horizon, and feedback parameter, respectively. The activation functions for the hidden and output layers are $\varphi_1$ and $\varphi_0$ respectively. The focused gamma neural network models had two inputs and two input weights; input memory with four taps and tap delays of 1, 1, 1, and 2 respectively as well as a depth of six and trajectory lengths of 41, 103, 57, and 82 respectively; one hidden layer with three processing elements and 27 weights and biases; and one output layer with one processing element and four weights and biases. The hidden and output layers used the *tanh* activation function. The models were trained in supervised batch learning mode with the help of the Levenberg-Marquardt backpropagation through time algorithm. The general form of the model describing the robust regression is the following:

$$y(t+h) = a_1 x_1(t) + a_2 x_2(t)\ ,\ t \geq 1$$

where the set of coefficients for ($a_1$, $a_2$) corresponding to $x_1$ for interest rate and $x_2$ for PMI over the four training intervals are {(0.694, -0.402); (0.702, -0.409); (0.674, -0.414); (0.648,-0.425)}. The coefficients were computed using the iteratively reweighted least squares algorithm with the logistic weighting function until their estimates converged within a specified limit.

## Results and Discussion

In the experiments of this study, both standard and relative performance measures were used to judge the relative efficacy of the focused gamma neural network and the robust regression models forecasts and the overall forecasts. For the overall forecasts two standard (RMSE and MAD) and three relative (r, NRMSE, Theil) performance measures were used. The performance measures and the visual examination of the forecasted PMI show that the neural network models performed better (see Table 1 and Fig. 1). Of the two sets of four PMI forecasts that make up the two overall PMI forecasts of Fig. 1, the set of four relating to the neural network models show relatively lower RMSE values on three of the four regimens (2-4) and higher correlations for two of the regimens (2 & 4). The differences in the RMSE values of neural network and regression models are 0.782, 0.653, and 3.742 in favor of

Table 1

Performance Measures

| Models | Model Testing | | Aggregated Forecast of Models | | | |
|---|---|---|---|---|---|---|
| | RMSE | Correlation | RMSE (NRMSE) | Correlation | MAD | Theil |
| Neural Network | 3 836 | 0 841 | | | | |
| | 5 563 | 0 866 | | | | |
| | 2 515 | 0 684 | | | | |
| | 7 560 | 0 791 | **5.088 (0.646)** | **0.803** | **3.715** | **0.687** |
| Regression | 3 781 | 0 848 | | | | |
| | 6 345 | 0 642 | | | | |
| | 3 168 | 0 728 | | | | |
| | 11 302 | 0 405 | **6.851 (0.869)** | **0.545** | **5.177** | **0.476** |

Note: Four regimens of training and testing, the uppermost row signifies regimen 1 of each model type.

the neural network models. For regimen 1, the difference in the RMSE values of 0.055 between the two types of models favors the regression model. This suggests that for the regimen 1 forecast, the regression model performed only marginally better than the neural network model, while in the other three regimens, the neural network models' overall performance was relatively much better. A similar finding is evident in the correlation results. In regimens 2 and 4, the correlations between the PMI forecasts of the neural network models and the actual PMI exceeded those for the regression models by 0.224 and 0.386 respectively, whereas in regimen 1 and 3, the correlations relating to the neural networks models are less than the regression models by 0.007 and 0.044 respectively. The overall forecast generated by the neural network models show better performance in terms of relatively higher correlation and lower RMSE, NRMSE, and MAD (see Table 1): the related positive differences between the two forecasts in favor of neural network are 0.258, 1.763, 0.223, and 1.462.

Visual assessment of the neural network and regression forecasts confirmed the findings of most of the performance measures. While both forecasts mostly follow the general patterns of the actual PMI data, the neural network generated forecast captured more of the details as well as alignment with the PMI data. However, neither the neural network nor the regression models were able to capture the abrupt fall in PMI of -10.47 units over the six month period of July 2008 to December 2008. PMI bottomed out in December 2008, and thereafter increased over the next several months until it peaked in March 2010. The overall downturn in PMI actually started in December 2007 (see Fig. 1, month 128), the same month that the recent 2007/2009 recession started (Joseph et al, 2010). Whereas PMI started to show evidence of an upturn in the economy in January 2009, the neural network forecast of PMI showed the upturn starting much earlier, June 2008; this upturn evident in the neural network forecast reached its peak value at the same time as the actual PMI. The regression forecast started its general upturn much earlier than the neural network forecast, March 2007, and continued until it peaked in November 2009, four months earlier than the peaks of the neural network forecast and the actual PMI. Therefore, the regression forecast did not capture any part of the recent recession evident in PMI between December 2007 and December 2008. The neural network forecast captured some of it between January 2008 and June 2008, but not much.

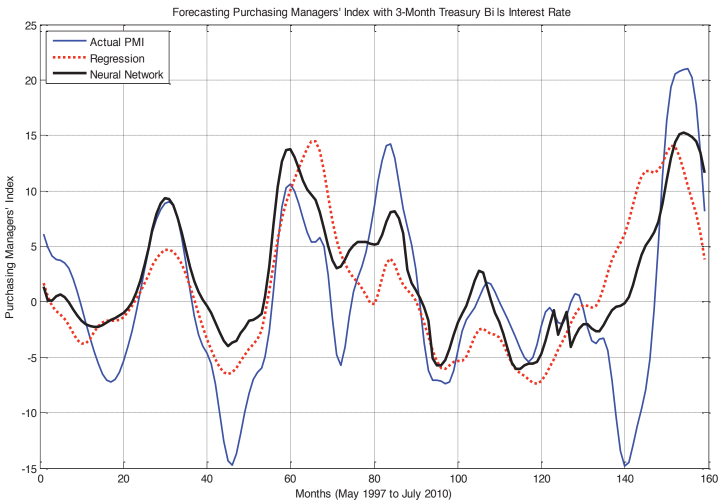


Figure 1: The overall out-of-sample forecasts of the purchasing managers' index with focused gamma neural network and robust regression models.

Why did the forecasts generally miss the downturn in PMI that corresponded to the first half of the recent recession? Part of the answer might lie in the relationship between 3-month T-bills interest rate and PMI over the period of December 2005 and December 2008. The countercyclical behavior of interest rate on the economy suggests that generally low interest rates stimulate spending in the economy while high interest rates curtail it. While the maximum correlation between inverted 3-month T-bill interest rate and PMI occurred when interest rate is leading by 11 months, some of the differences between the dominant lead/lag peaks as well as troughs of these two economic variables are greater or less than 11 months. In December 2005, interest rate peaked (inverted interest rate troughed) and PMI experienced a dominant trough in December 2008; this is 21 months after interest rate peaked. Thus, a 12 month forecast horizon may have been inadequate to predict the first half of the recession, since interest rate was able to trough while PMI was declining between July 2008 and December 2008.

Using inverted T-bills interest rate as the predictor, Larrain (2007) forecasted PMI with the focused gamma neural network and regression models. His neural network models were more complex: 24 processing elements compared to three in the experiments of this work. Over the period (September 2002 to August 2005) of Larrain's out-of-sample forecasts, the RMSE statistics for the neural network forecast in this work is greater than that obtained by Larrain by 2.31 and a correlation of 0.803 is obtained. Over the three year period of the neural network forecast, the two results are generally comparable, but the forecast here shows better alignment and trending with the actual PMI.

## Conclusion

The neural network forecasts were generally better than the regression forecasts. However, neither the neural network nor the regression forecasts adequately captured the downturn in PMI that was evidence of the recent 2007/2009 economic recession. The use of more adaptive forecasting horizons reflective of the complex relationship between interest rate and PMI would probably be helpful since these variables were found to be generally not linear. Future work will investigate this premise. Furthermore, results obtained in this work for September 2002 to August 2005 are comparable to those of Larrain (2007) in showing that interest rate is a viable predictor of PMI.

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