Announcement Effects of Macro Economic Variables on Stock Market Returns and Volatility- A Neural Network Approach

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We study the effects of macroeconomic variables on stock returns and volatility using a Neural Network approach. Neural network models can discover nonlinear complex patterns with the ability to process high levels of data. Neural networks can be used for any type of similar data sets with the ability to process and uncover similar data patterns, and provide a result. In this paper, we use a learning neural network model to find the relationship and strength of six widely used macroeconomic variables on stock market returns and volatility. Results indicate the three most influential variables are announcements of inflation, unemployment, and national income.

INTRODUCTION

Changes in macroeconomic variables can potentially affect firm cash flows and risk. The effect of macroeconomic variables on stock returns has long been a subject of academic research. Numerous studies have examined this issue including Bodie (1976), Fama (1981), Chen, Roll and Ross (1986), Chan, Karceski and Lakonishok (1998), and Flannery and Protopapadakis (2002). Chan, Chen and Hsieh (1985) and Chen, Roll and Ross (1986) found that the growth rate of industrial production, the expected inflation rate, unexpected inflation, bond default risk premiums and term structure spread influence stock market returns. Bodie (1976) and Fama (1981) find a negative relationship between the rate of inflation and monetary growth on stock returns.

Flannery and Protopapadakis (2002) find that the consumer price index (CPI), the producer price index (PPI), monetary aggregates (M1 or M2), the employment report, the balance of trade, housing starts, and affect stock market returns and/or volatility. Chan, Karceski and Lakonishok (1998) do not find any empirical evidence supporting the assertion that macroeconomic variable announcements affects or influence stock returns. Flannery and Protopapadakis (2002) find six macroeconomic variables that affect aggregate stock returns.

In this paper, we extend the previous research by using a neural network model[1]. The foundation of neural networks is the structure of the information processing system. A neural network is composed of many highly interconnected processing elements which are called neurons. The neural network system uses human-like learning techniques to solve problems. The learning process of the neural network is called training because of the way in which it resembles the way that the human brain processes information. The primary advantage of such a model is the fact that neural networks do not impose any structure on the data, which makes them very useful and appealing in situations where the effect or impact of one variable or variables is considered in relation to other variables which may or may not have emerged from the data prior to or during the study and may create further opportunities in the research.

Most forecasting techniques used today are based upon traditional linear or nonlinear statistical models, such as regression analysis.[2] Although these models are useful and have been utilized for many years to generate predictions, the models are somewhat limited in their ability to forecast in certain situations. Neural network models have the ability to detect nonlinear relationships while still allowing for high levels of noisy data and chaotic components. Another advantage of neural networks is the when they are properly trained, they can be considered experts for both the project for which they were designed and subsequent new projects. This network structure can even be used to provide projections given new situations and answer "what if" questions.

We choose the following six variables, money supply (M2), the consumer price index (CPI), the producer price index (PPI), industrial production, the unemployment rate and the balance of trade to study the nature of the relationship that exists between the announcement of these variables and stock market returns and volatility. The choice of these variables is based on the existing empirical studies in this area. Studies report significant relations of stock returns with money supply (Berkman (1978), Urich and Wachtel (1981), Roley (1983), Thornton (1989), and McQueen and Roley (1993) and with industrial production, Roley and Troll (1983), Harvey and Huang (1990), and McQueen and Roley (1993) The research has been extended to producer price effects (Urich and Wachtel (1983), Smirlock (1986), Dwyer and Hafer (1989) and Edison (1996). (Smirlock (1986), Hardouvelis (1988), McQueen and Roley (1993) and Edison (1996) and another focus was unemployment (Hardouvelis (1988), Cook and Korn (1991) McQueen and Roley (1993) and Edison (1996) and with balance of trade (Flannery and Protopapadakis, 2002).

The back-propagation neural network model is used to find the strength of relationship that exists between the six macro variables and the S&P 500 Stock Index and volume changes. The model is used in two stages: the training stage and the testing stage. The results show the following contribution order of the six variables on the S&P 500 Index: 1) Unemployment Rate 2) Consumer Price Index 3) Industrial production 4) Money Supply 5) Producer production index 6) Balance of trade. As for the S&P 500 volume changes, contribution order is as follows: 1) Industrial Production 2) Consumer Price Index 3) Unemployment rate 4) Producer Price Index 5) Money supply 6) Balance of trade. We test the robustness of the results in the testing stage and find the results to hold.

The paper proceeds as follows. Following a literature review in section 1, a brief introduction on the back-propagation neural network model is given in section 2. Data and methodology are discussed in section 3. Section 4 presents results, while Section 5 provides summary and concluding remarks.

LITERATURE REVIEW

Numerous studies analyze the effect of new information about fundamentals on stock market prices. Some studies report a weak relationship between announcements of macroeconomic news and stock price response, while others find this relationship to be strong. Schwert (1981) finds that the daily response of stock prices to news about inflation is weak and slow. These findings are confirmed by Pearce and Roley (1985). Using survey data, they observe little evidence that the stock market responds to macroeconomic news, except for money supply and the discount rate. In addition, Chen, Roll and Ross (1986) find that the covariance between stock returns, industrial production, and other measures of real economic activity are weak, while growth rate of industrial production, expected inflation, unexpected inflation, bond default risk premium and term structure spread affect stock returns.

McQueen and Roley (1993) find evidence of asymmetric market response to news across business cycles, after controlling for different stages in the business cycle. They find that 3.9 percent of the daily variation in the S&P 500 Index is explained by the news announcements of macroeconomic variables. They attribute the failure to find a stronger relationship to the shortcoming of the constant-coefficient models being estimated. Boyd, Jagannathan and Hu (2002) also find that macro news has distinct time-varying effects on equity returns. They examine the impact of unemployment announcement surprises on the S&P 500 return over 1948-1995 and conclude that high unemployment raises stock prices during an economic expansion but lowers stock value during a contraction. They hypothesize that higher unemployment predicts both lower interest rates and lower corporate profits, and conclude that the relative importance of these two effects vary over the business cycle. The weak relation between macroeconomic news announcements and stock market response can be attributed to the noisy nature of the realized variables that are used as measures of change in expectations. This noise reflects the fact that most macroeconomic data are preliminary when they are released and are subject to many subsequent revisions. In many cases these revisions are substantial and significant both statistically and economically.

Cutler, Poterba and Summers (1989) find that it is difficult to identify the information that could account for the largest price movement in the stock market. Their findings indicate that in most cases, the information cited by the press as causing the market move "is not particularly important".

DATA AND METHODOLOGY

The objective of the paper is to identify linkages between stock market movements and changes in the 6 real economic variables. The 6 variables are: money supply (M2), the consumer price index (CPI), the producer price index (PPI), industrial production, the unemployment rate and the balance of trade. The monthly data from 1980 to 2016 is from the Federal Reserve Bank of St. Louis. The Percentage Change is calculated using the change between the current month and the previous month's data. The U.S. Stock market movement is proxied by S&P 500 returns and trading volume. The percentage change in the S&P 500 index is calculated using the percentage change of the previous month's last day's index value and the current month's first day index value. Table 1 gives a complete description of the variables used in this study.

TABLE 1
DESCRIPTION OF VARIABLES

The range of the data is from 1980-2016. The S&P 500 index and volume is calculated using the percentage change between the last day of the month and the first day of the next month. The monthly percentage changes of M2, CPI, PPI, IP, UER and BT are the percentage changes between last month and the next month.

Symbol	Variable	Definition
SP	S&P 500 Stock index	1-day percentage change at the announcement date
SPVOL	S&P 500 Index Volume	1-day volume change at the announcement date
M2	M2 Money Stock	M2 monthly percentage change
CPI	Consumer Price Index	CPI monthly percentage change
PPI	Producer Price Index	PPI monthly percentage change
IP	Industrial Production	IP monthly percentage change
UER	Unemployment Rate	Unemployment rate monthly percentage change
BT	Balance of Trade	Balance of trade monthly percentage change

The purpose of this paper is to find the extent to which each of the six variables affect stock returns. To perform this analysis, we use a back-propagation neural network system. The main advantage of this system is its lack of any structural form on the data. The model does not assume any type of relationship that might exist between the S&P 500 return and volume and any of the 6 variables. The purpose of the model is to find if such a relationship exists and to what degree each variable affects the stock market movement. To carry on the analysis, we divide the sample into two sub-periods 1980 to 2000 is the training and adaptive period and 2001-2016 is the testing period.

The architecture of the neural network back-propagation model is a 2 level network with 6 input variables and 1 output variable. The same model is used to test for 2 different outputs, the S&P 500 Index and Volume. The transfer function used in the model is the regular sigmoid function.

The training period 1980-2000 has 252 data points for each of the 6 monthly announcements. The 6 variables produce 1512 data points as inputs to the model. The network is run two times, each for the S&P index and volume. Table 2 shows that the correlation between actual and predicted values for training data is 0.892 for the S&P Index change, while Table 3 reports a correlation of 0.798 for the S&P Volume change. The testing period 2001-2016 has 192 data points for each of the 6 monthly announcements. Overall there are 1152 inputs. Again, the network is run twice, the first one having the output as the S&P Index change, and the second time the volume change. In Table2, the correlation between the actual and the predicted data for the S&P Index change is 0.875 and in Table 3 the correlation between the actual and the predicted values of the volume change is 0.759.

TABLE 2
NETWORK PARAMETERS FOR S&P 500 INDEX

The network parameters for the training period are calculated using the 1980-2000 period. The testing period is from 2001-2016.

	Standard Dev.	Bias	Max Error	Correlation
Training Period	276.3722	-2.04	104.35	0.892
Testing Period	325.8452	17.03	589.72	0.875

TABLE 3
NETWORK PARAMETERS FOR S&P 500 VOLUME

The network parameters for the training period are calculated using the 1980-2000 period. The testing period is from 2001-2016.

	Standard Dev.	Bias	Max Error	Correlation
Training Period	301.179	-1.24	118.36	0.798
Testing Period	405.314	14.52	478.891	0.759

ANALYSIS OF RESULTS

Tables 4 to 7 display contribution of input variables. For the training period, we note that the UER's announcement contributes the most to the change in the index (21.9%), followed by CPI (20.71%) and IP (20.34%). The remaining 3 variables provide significantly less contribution. The order of contribution for the same variables on S&P Volume is IP at 21.45%, followed by CPI with 19.45% and UER with 19.36%. The top 3 contributing variables to the S&P 500 Index and volume remain the same, with their rankings being slightly different.

The same analysis is done using the same model with the weights taken from the training period to test model performance. The testing period, 2001-2016, shows similar contribution patterns. For the contribution percentage of variables on the S&P 500 Index change, the top 3 are IP at 20.84% followed by PPI at 19.05% and UER at 17.23%. As for the contribution percentages to the S&P 500 Volume change, the top 3 are the PPI at 20.73% followed by UER at 19.81% and CPI at 17.91%.

The above results show us the contribution of the 6 variables on the stock market returns and volatility if we assume that on the announcement day, the stock market is affected by those 6 variables. The training period gives us the contributions of each of the variables under the assumption that there is a cause-effect relationship between the inputs and the output. The testing period gives us the contribution of each of the variables, with an already established cause-effect relationship from the training period. The weights that each node gives from the training period are used in the testing period to see if the use of those weights, will yield the same percentage contribution from each variable.

The neural network model defines the relative strength of the macroeconomic variables on S&P Stock market returns and volatility for the 1980-2016 periods. The previous research has found that there is a relationship between the announcement of macroeconomic variables and stock market return and volatility. However, the strength of such relationship was not defined. A learning neural network model gives us the strength of each of the influencing variables. In this paper, the comparative strength of variable announcement effect on the S&P 500 Index and Volume has been established.

We utilized industrial production as a proxy for national income. An increase in industrial production induces an increase in corporate earnings, thus enhancing the present value of the firm and increasing national disposable income which should lead to more retail investment in the stock market. The opposite will cause a fall in the stock market.

The consumer price index and the producer price index are both proxies for the rate of inflation. Like Bodie (1976) and Fama (1981) we find that the stock market is negatively affected by relatively high rates of inflation. Combining the contributions of CPI and PPI gives us about 40% of the overall contribution that inflation rates have on changes in the S&P 500 Index and Volume.

The unemployment rate is another measure of the health of the economy. A high unemployment rate results in less financial security, thus less investment. The announcement of high levels of unemployment will result in lower S&P levels.

TABLE 4
THE PERCENTAGE CONTRIBUTION OF EACH NODE ON OUTPUT (S&P 500 INDEX) FOR TRAINING PERIOD (1980-2000)

Layer	Node	% Contribution
1	M2	14.23
1	CPI	20.71
1	PPI	12.68
1	IP	20.34
1	UER	21.9
1	BT	10.14
2	1	71.26
2	2	28.74

TABLE 5
THE PERCENTAGE CONTRIBUTION OF EACH NODE ON OUTPUT (S&P 500 VOLUME) FOR TRAINING PERIOD (1980-2000)

Layer	Node	% Contribution
1	M2	12.87
1	CPI	19.45
1	PPI	15.63
1	IP	21.45
1	UER	19.36
1	BT	11.24
2	1	81.23
2	2	18.77

TABLE 6
THE PERCENTAGE CONTRIBUTION OF EACH NODE ON OUTPUT (S&P 500 INDEX) FOR TESTING PERIOD (2001-2016)

Layer	Node	% Contribution
1	M2	17.58
1	CPI	16.42
1	PPI	19.05
1	IP	20.84
1	UER	17.23
1	BT	8.88
2	1	34.71
2	2	65.29

TABLE 7
THE PERCENTAGE CONTRIBUTION OF EACH NODE ON OUTPUT (S&P 500 VOLUME) FOR TESTING PERIOD (2001-2016)

Layer	Node	% Contribution
1	M2	14.06
1	CPI	17.91
1	PPI	20.73
1	IP	13.62
1	UER	19.81
1	BT	13.87
2	1	28.67
2	2	71.33

SUMMARY AND CONCLUSION

The current study aims to augment and extend the literature studying the linkage between real macroeconomic variables and stock market movements. The variables were selected to conform to previous literature which found a strong relationship between these variables and stock market returns. The consumer price index, producer price index, industrial production (proxy for national output), M2 money supply, unemployment rate and the balance of trade were the variables chosen for this study.

The utilization of a back-propagation neural network model in the training and the testing phases gave consistent output patterns for the 6 macroeconomic variables. Our study revealed that inflation, industrial production and unemployment are the three highest contributing variables to stock market return and volatility. Our results confirm the conclusions of prior studies on the effect of the macroeconomic variable announcement effect on stock market returns and volatility. However, the originality of the paper lies in the use of the neural network model added to prior research efforts by showing the percentage contribution of each variable's announcement effect on the S&P 500 Index and Volume.

ENDNOTES

1. Please see Appendix 1 for a brief description of the Neural Network model.
2. Econometric approaches taken by researchers in this area include simple one factor models (Pearce and Roley 1985), conditional models (McQueen and Roley 1993) and models of simultaneous impact on level and conditional volatility using GARCH to detect such factors from the conditional variance (Flannery and Protopapadakis 2002)

APPENDIX 1
Neural Network Models

Definition of a Neural Network

A neural network is an information processing paradigm that is inspired by the way human brains process information. Neural networks have a large appeal to many researchers due to their natural similarity to the structure of the brain, a characteristic not shared by more traditional systems.

In much the same way that the human brain is made up of interconnected neurons, neural networks are comprised of interconnected processing elements called units. Neural network units respond to input signals in much the same way that neurons in the human brain respond.

Neural networks can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new set of facts and to answer, "what if" questions. A neural network can be viewed as a black box with the ability to predict an output pattern when it is fed a recognizable input pattern. The neural network must first be "trained" by letting it process a large number of input patterns and providing it with the output for each pattern so that it can learn from the input-output relationships. Once trained, the neural network will have the ability to recognize similarities when new input patterns are fed to it, and it can predict output patterns based on its training.

Neural networks have the ability to detect similarities in inputs, even though a particular input may never have been provided to the network before. This property allows for excellent interpolation capabilities, especially when the input data is noisy (not exact). Neural networks may be used as a direct substitute for autocorrelation, multivariable regression, linear regression, trigonometric and other regression techniques.

Neural networks are superior to more traditional statistical techniques in that they possess the ability to represent both linear and non-linear relationships and to learn these relationships directly from the data that is processed during the training stage. Traditional linear models are simply inadequate when it comes to modeling data that contains non-linear characteristics.

A neural network consists of four main parts:

1. Processing units, with each unit having a particular activation level at any point in time.
2. Weighted interconnections between the different processing units with a deterministic function about how the activation of one unit will provide to input for another unit.
3. An activation rule that is based on the input data at a unit to produce a new output data or activation instruction for another unit.
4. A learning rule that functions as an adjusting measure how to calibrate the weights for a given input/output pair.

Learning in a Neural Network

Learning is the ultimate goal in a neural network architecture. Therefore, the choice of a learning algorithm is the most important problem in neural network development. Learning in a neural network setting allows a processing unit to change its input/output behavior in response to changes in the environment. In general, the activation rule is fixed and is embedded with the initial network construction. In addition, the input/output set cannot be changed to influence the input/output behavior, the weights corresponding to that input set can to be calibrated. The neural network can be calibrated at a training stage where, weights are modified in response to the input/output sets. Several learning rules are available for neural network models. A supervised learning environment is one where the network is provided with the correct answer for the output during training stage. The unsupervised learning environment is one where there is no external teacher present, and the network learns the optimal output on its own.

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