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# Two Essays on the Effect of Macroeconomic News on the Stock Market

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TWO ESSAYS ON THE EFFECT OF MACROECONOMIC NEWS ON THE STOCK MARKET

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# ABSTRACT

## TWO ESSAYS ON THE EFFECT OF MACROECONOMIC NEWS ON THE STOCK MARKET



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This dissertation uses macroeconomic variables. In the first essay I use macroeconomic variables to determine if these variables affect the market's returns and volatilities, and in the second essay I examine whether the 11-month returns can be explained by these variables.

Using macroeconomic variables and forecasts of these variables on a quarterly basis from the Survey of Professional Forecasters, I first develop macroeconomic surprise variables. The macroeconomic surprise variables are then modified by dispersion of forecasts to adjust for surprises from uncertainty. Dispersion adjusted forecast surprises have not been used extensively in the literature. I also use a monetary shock variable. The market index I look at is the S&P 500. Among the results obtained from OLS regressions are that S&P 500 returns are influenced by inflation surprises and S&P 500 volatilities are influenced by industrial production surprises. Based on extant theory, macroeconomic variables are supposed to influence asset prices. This paper contributes to identifying variables that previously were not seen as responsible for affecting asset markets.

Macroeconomic variables are also used to study the 11-month returns in the other January effect. The other January effect was folklore up until Cooper, McConnell, Ovtchinnikov (2006) confirmed it with statistical evidence. There has been a lot of controversy about the other January effect. Essentially, if the return in January of a particular year is positive (negative) the next 11-month return will be positive (negative). I show that a simple macroeconomic variable such as term premium which is the difference of long term interest rate and short term interest rate can be equally effective as a predictor for the next 11-months of returns. In addition to replicating the original study on a different time period, I show that the other January effect is not as predictive as expected, the results show that the other January effect is driven by negative Januarys and that positive Januarys do not predict returns. In addition conditioning, the January returns on various macroeconomic variables shows that the January effect works for the market value weighted index and not the market equal weighted index.

Members of Dissertation Committee: Dr. Larry Filer
Dr. Kenneth Yung

I dedicate this dissertation to my mother and father for supporting me in all my endeavors, for being an inspiration to me, and for instilling in me the value of education.

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# TWO ESSAYS ON THE EFFECT OF MACROECONOMIC NEWS ON THE STOCK MARKET

## INTRODUCTION

A stock market index is used in many studies to determine how the markets react to various risk factors, and these risks are usually determined by the effect news has on asset markets. Many studies have failed to determine conclusively how macroeconomic news affects markets. Chen, Roll and Ross (1986) say "A rather embarrassing gap exists between the theoretically elusive importance of systematic 'state variables' and my complete ignorance of their identity. The co-movements of asset prices suggest the presence of underlying exogenous influences, but we have not yet determined which economic variables, if any, are responsible." On the other hand Cooper, McConnell and Ovtchinnikov (2006), determine that "the return from the month of January is a powerful predictor of the returns over the remaining months of the year." This result seems to show that something other than macroeconomic news could predict stock markets into the future.

There has been a large body of research which looks into how macroeconomic variables affect stock market returns; however, the results obtained so far have not been consistent. One of the earliest papers that tried to determine a relationship between macroeconomic news and stock returns was McQueen and Roley (1993); they found that news effects were determined by states of the economy. Following Andersen and Bollerslev (1997), a number of papers have tried to relate high frequency conditional volatility with macroeconomic news using their GARCH model. Only a couple of papers

Arnold and Vrugt (2008, 2010) have looked at macroeconomic news and market volatilities using low frequency data. This paper extends their research which looked at how market volatility is affected by fundamental uncertainty at low frequencies, by incorporating macroeconomic surprises.

In general, studies that focus on the effects of surprises from macroeconomic variables adopt the following approach:

$$\delta_m^t = A_m^t - F_m^t \tag{1}$$

where, $\delta_m^t$ denotes the surprise or forecast error in macroeconomic variable m at time t, $A_m^t$ is the actual realized value of the macroeconomic announcement, and $F_m^t$ the median or mean value of a professional forecast survey. While this approach is simple and intuitive, it ignores the uncertainty associated with the forecasts.

Some researchers, for example Wongswan (2006) standardized surprises by dividing it by the standard deviation of analyst forecasts. To date, however, extant literature focuses almost exclusively on the impact from the mean forecasting errors or shocks on financial markets, but I posit the results would be more powerful if I accounted for forecasters' uncertainty in my calculations. For example, would a 10% surprise with 75% uncertainty be as powerful as a 5% surprise with 10% uncertainty? It is easy to see that the 5% surprise would have a more powerful effect on the markets than the 10% surprise. Therefore, when uncertainty is small you would expect a large reaction to surprise in the market.

In addition to looking at macroeconomic forecast errors, a monetary shock variable is used to determine its effects, if any, on the stock market. I follow Romer and Romer (2004) series of shock variables using a narrative approach, I convert it to a monthly series. Using both the macroeconomic forecast errors and monetary shock variables, I run regressions to determine if these variables have any effect at all on the S&P 500 returns and volatilities.

Arnold and Vrugt (2008, 2010) in their studies use macroeconomic uncertainty as determined by dispersion of forecasters' forecasts. They look at the effect of macroeconomic uncertainty on market volatility and find that forecasters' uncertainty does account for market volatility to a certain extent. As far as the stock market is concerned, they find that the effect disappears after 1997.

The main findings are that inflation surprise as given by the GDP deflator is significant when index returns are the dependent variable and industrial production surprise is significant when index volatility is the dependent variable, these results are stronger in the contemporaneous regressions. Monetary shocks do not seem to have any effect on either index returns or volatilities.

In the next essay, I look at the Other January Effect (hereafter OJE) as studied by Cooper, McConnell, and Ovtchinnikov (2006) (hereafter CMO). CMO document an interesting new seasonality in U.S. stock returns. The 11-month holding period returns from February to December, conditional on positive January returns are significantly higher than those, conditional on negative January returns. CMO call it the Other January Effect (OJE) to distinguish it from the well-known January Effect that documents strong positive returns in small-cap firms in January. For value weighted excess market returns over their primary 1940 to 2003 sample, they find that the spread between the average 11-month return following positive January returns and the average 11-month return following negative January returns is a significant 14.7%. The spread is even more sizable using equal weighted market returns. CMO also report that the OJE cannot be explained by business cycles, investor sentiment, presidential cycles, or the Fama-French three-factor models.

To determine whether the OJE is truly a new puzzle among a growing list of anomalies in the finance literature or simply a statistical fluke, Stivers, Sun, and Sun (2009) study the OJE using new international, style, and sub-period evidence. They hypothesize that, if the OJE is related to a pervasive and persistent behavioral bias, then one should expect the OJE to show up in the international equity markets and to persist over time. Using data from 22 countries, Stivers, Sun and Sun show that OJE is not a widespread phenomenon. This suggests that OJE is unlikely to be driven by ubiquitous psychological biases similar to the momentum phenomenon documented by Jegadeesh and Titman (1993) and the related international evidence as in Griffin, Ji, and Martin (2003). Stivers, Sun and Sun interpret their results as evidence that OJE is a temporary anomaly in the sense of Schwert (2003).

Intriguingly, Stivers, Sun and Sun also find that the international OJE spreads and the OJE spreads in disaggregate U.S.-style portfolios are more related to the U.S. market level January return, rather than the respective country-specific or portfolio-specific January return. Further, although they do not formally test for the relation between some macroeconomic variables and the OJE, Stivers, Sun and Sun in untabulated results find that, compared to other months, the January return is the only month that is reliably informative about both the subsequent credit spread change and the subsequent industrial production growth, and in a manner that is consistent with the OJE return spread. Taken together, the evidence from Stivers, Sun and Sun also appears consistent with the hypothesis that there might be an undiscovered linkage between the OJE and some well-known macroeconomic variables.

Some readers might argue that in CMO's original study, they report essentially no relation between commonly used business cycle variables and the OJE. However CMO's study in this respect is somewhat limited in terms of both scope and depth. For example, CMO summarize the relation between business cycle variables and the OJE in only one table. In light of the evidence from Stivers, Sun and Sun and given the importance of understanding the nature and sources of the OJE and its bearing on the efficient market hypothesis, a detailed analysis of the OJE and its relation with various macroeconomic variables appears overdue and warranted.

I provide new evidence that the OJE is more closely related to macroeconomic variables than previously reported in the literature. Specifically, I show that similar to the January return dummy used by CMO, a dummy variable that captures the slope of the yield curve can also predict subsequent 11-month returns from February to December. The return spread for this yield curve dummy is comparable to the January dummy and is significant for value weighted market index. More interestingly, after controlling for the yield curve dummy, January return no longer appears to provide useful information about subsequent returns as the return spreads become negative. I also find that a dummy variable that is defined as the intersection of both the January and the yield curve dummy is a more powerful predictor of the 11-month returns from February to December.

Beyond the yield curve dummy, I further provide a comprehensive study of the role of macroeconomic variables in a standard predictive regression setting. Similar to CMO, the regressors that I choose are lagged macroeconomic variables including term premium, dividend yield, default premium, and detrended three-month Treasury bill yield. I also consider some variations by using non-detrended three-month Treasury bill yield. I find several interesting results. Consistent with the hypothesis that macroeconomic variables do have predictive power for subsequent February to December returns, adjusted $R^2$ values of predictive regressions that exclude the January dummy range from 15% to 26%. Adding the January dummy elevates the adjusted $R^2$ values to a range of 23% to 33%. This confirms that January returns contain useful and independent information. However, it also shows that the January dummy is neither unique nor dominant in terms of its predictive value. Last but not the least, I find that after controlling for the information in macroeconomic variables, the OJE return spreads does not appear to be ubiquitous to all the market indexes.

The remainder of this dissertation is organized as follows. The next chapter looks into the relationship of macroeconomic and monetary shock variables with the S&P 500. Chapter three looks at how the OJE results may not be the result of January returns at all. And, the final chapter concludes and provides suggestions for future research.

# MACROECONOMIC SURPRISES AND MONETARY SHOCK EFFECTS ON THE S&P 500

## I. DISCUSSION AND RELATED LITERATURE

Almost all the current literature that focuses on survey forecasts of economic forecasts use some variation of the GARCH model. The forecasts they use most often rely on the Money Market Survey (MMS) forecasts that are given by professionals on a weekly basis.

Using 17 macroeconomic variables, Flannery and Protopapadakis (2002) find that Balance of Trade, Unemployment, Housing starts, and a monetary aggregate affect conditional volatility when using high frequency data. There have not been many studies that tie macroeconomic surprises to volatilities at low frequencies. The main reason for there being a few studies is that while forecasts are made at low frequencies, asset prices evolve at high frequencies. In the Flannery and Protopapadakis model, returns are mainly affected by measures of inflation and also by a monetary aggregate.

Kim, Mckenzie and Faff (2004) look at how various macroeconomic announcement shocks affect the stock, bond and treasury markets using a GARCH model; for stocks they found that consumer and producer price inflation affects conditional returns and volatility. Brenner, Pasquariello, and Subrahmanyam (2009) look at daily conditional returns, volatility and co-movements of three financial markets: stock, corporate bonds and treasury bonds. They show that returns react asymmetrically to the information content of surprise announcements. In addition unemployment and retail sales news was also found to heighten stock market volatility. Schemling and

Schrimpf (2011) show that survey based inflation expectations are able to forecast future stock returns in many international equity markets, but they only consider inflation expectations as their independent variable.

Looking into market volatility, Arnold and Vrugt (2008) show that US stock market volatility is significantly related to the dispersion in economic forecasts of SPF participants. These authors try to follow Schwert (1989), who looks into the relationship between market volatility and macroeconomic volatility. Engel and Rangel (2008) discuss volatility in a GARCH framework showing that breaking up return volatilities into low frequency and high frequency components would help model forecasts of volatility dependent on macroeconomic surprises which are generally low frequency. The paper shows that levels of GDP and interest rates and the volatility of inflation are primary causes of low frequency market volatility. Engle, Ghysels and Sohn (2009) using Garch-MIDAS find that return volatility at the daily level is affected by inflation and industrial production growth. They find that greater inflation leads to higher stock market volatility and greater industrial production leads to lower volatility, but they do not test any other variables. Adrian and Rosenberg (2008) show that the Long-Run component of market risk is highly correlated with industrial production growth innovations.

The importance of dispersion is highlighted by Lahiri and Sheng (2010) who show that "forecast uncertainty equals disagreement plus the variance of future aggregate shocks that accumulate over the horizon." They use Survey of Professional Forecasters data for output growth and inflation to come to their conclusion. These results are stronger in stable periods of the market than in volatile periods and also at short horizons. Anderson, Ghysels and Juergens (2009) find that uncertainty, measured by beta weighted variance of forecasts of mean market returns by professional forecasters is able to predict returns better than volatility based risk measures. In evaluating forecast data from sources like Survey of Professional Forecasters, Ang, Bekaert and Wei (2007) examine different models of forecasting U.S. inflation and their main conclusion is that surveys outperform other forecasting methods. Stark (2010) looks at the accuracy of SPF forecasts and finds that the "surveys' accuracy falls sharply at quarterly horizons beyond the first," which is why I use only forecasts over the quarterly horizon.

Finally, the reason I find it interesting to use a monetary shock variable along with macroeconomic surprises is because Bernanke and Kuttner (2005) show that an unanticipated 25 basis point cut in Federal funds rate target is associated with an approximate 1% increase in broad stock indexes. They looked at the fed futures contract to determine unanticipated changes in Federal funds target rate. Also, Chen (2007) shows that S&P 500 index returns is affected by monetary policy to a larger extent during bear markets and that tightening monetary policy tends to shift the markets into a bear market regime. Chen uses Markov-switching models to test the asymmetric effects. In addition to the above two authors, Bjornland and Leitemo (2009) show that real stock prices fall by seven to nine percent due to a monetary policy shock in a VAR model.

The aim of the next sub-chapter of the thesis is to make progress in finding the elusive link between macroeconomic and monetary surprises with asset returns and volatilities that are alluded to theoretically, but have been elusive in empirical studies as stated by Chen, Roll, and Ross (1986). I specify various models and run regressions to find if the independent variables influence the dependent variable.

## II. DATA AND VARIABLE CONSTRUCTION

### A. Macroeconomic Variables and the SPF data

I obtain the Survey of Professional Forecasters (hereafter SPF) data from Federal Reserve Bank of Philadelphia. According to the bank's website, the SPF is the oldest quarterly survey of macroeconomic forecasts in the United States. It began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990. The SPF data set has been used successfully in both the economics and finance literature.

The SPF forecast data is available in quarterly format. The sample I use is from the fourth quarter of 1968 to the fourth quarter of 2009, with a total of 165 quarterly observations for each variable. Although the data covers a wide variety of economic and financial variables, many of the variables do not have complete historical data over the whole sample period. Therefore, I focus on six macroeconomic variables of interest: nominal GDP, unemployment rate, corporate profits, industrial production, GDP price index (GDP deflator), and housing starts. Note that the measurement of corporate profits has changed in the SPF. Prior to 2006, it is measured as nominal corporate profits after tax excluding inventory valuation adjustment (IVA) and capital consumption adjustment (CCAdj). Beginning with the survey of 2006:Q1, however, this variable includes IVA and CCAdj. SPF projections are available for both levels and growth rates. I focus exclusively on the growth rates of these variables the only exception being unemployment rate. According to SPF documentation, annualized growth rates are calculated as follows:

$$g = 100\left[\left(\frac{x_t}{x_{t-1}}\right)^4 - 1\right] \tag{2}$$

where, $g$ denotes the annualized growth rate and $x$ denotes the level of the macroeconomic variable of interest. It should be noted that SPF usually contains forecasts for the prior quarter, the current quarter, as well as up to four quarters after the current quarter. The current quarter is ended as the quarter in which the survey is conducted. The survey usually comes out late in the second to third week of the middle month of each quarter. I focus only on the current quarter's forecast in this paper.

To measure forecasting errors, I match the SPF projections against the actual realized values of macroeconomic variables obtained from St. Louis Federal Reserve Bank. I construct annualized growth rates of these variables in the same manner as in SPF. I then take the difference between the actual values and the mean forecast values as my measure of forecasting errors.

Consistent with previous findings in the literature, I find that SPF provides reasonably good projections. Among the six macroeconomic variables of interest, the mean forecasting errors (standard deviations) are: GDP growth (gdp) 0.6663% (2.6676%), unemployment rate (unemp) -0.0283% (0.1542%), industrial production (ip) -0.00285% (3.7910%), housing starts (housing) 7.049% (25.468%), corporate profits (cp) 5.0903% (25.02%), and GDP price index (pgdp) 0.0791% (1.1317). Hence, except for housing starts and corporate profits, SPF projections appear almost flawless in terms of its accuracy. Time series plots of these forecasting errors are shown in Figure 1.

[Insert Figure 1 here]

B. Measuring Forecast Uncertainty

A unique feature of the SPF data is that not only does it provide the average forecasts, but it also reports a measure of uncertainty of these forecasts. This uncertainty measure is defined by the cross-sectional forecasting dispersion. More specifically dispersion is the difference between the 75th percentile and the 25th percentile of the SPF projections. Given the cross-sectional forecasting dispersion, I proceed to calculate the adjusted forecasting error as follows:

$$d_t^m = \frac{\delta_t^m}{disp_t^m + \varepsilon_t^m} \tag{3}$$

where, $d_t^m$ is the uncertainty adjusted measure of forecasting error of a macroeconomic variable m at time t. $\delta_t^m$ is the unadjusted forecasting error defined as the difference between the SPF projection and the actual value of the macroeconomic variable m. $disp_t^m$ denotes the cross-sectional forecasting dispersion. $\varepsilon_t^m$is set to zero whenever $disp_t^m \neq 0$, and $\varepsilon_t^m$ is set to a small quantity when $disp_t^m = 0$. Among the six macroeconomic variables, the dispersion measures for GDP growth, corporate profits, and housing starts never have a zero value. Therefore $\varepsilon_t^m = 0$ in these three cases. For the other three macroeconomic variables that do have observations of zero dispersion, I set $\varepsilon_t^m = 0.01$ for unemployment rate, and 0.1 for both industrial production and GDP price index. Note that the mean of dispersion of the three variables are 0.1557 (unemployment rate), 3.3715 (industrial production), and 1.0990 (GDP price index) respectively. Time series plots for forecast uncertainty or dispersion are shown in Figure 2 and Figure 3 has the time series plots for uncertainty adjusted forecasting errors of macroeconomic variables.

[Insert Figure 2 here]

[Insert Figure 3 here]

C. Romer Monetary Shocks

For the monetary shock variable I use the variables provided by Crowe and Barakchian (2010), they follow the narrative approach derived in Romer and Romer (2004). Essentially, Romer and Romer look at the quantitative and narrative records that are available for the decisions that the Federal Reserve makes regarding federal funds rate. These records around FOMC meetings are then quantified and regressed against the Federal Reserve's internal forecasts. In other words, the change in intended funds rate around FOMC meetings are regressed against intended funds rate against level of intended funds before changes associated with the meetings, inflation, real output growth and unemployment rate, the residuals is the unanticipated monetary shock variable, this variable is then converted to a monthly time series depending on the month in which the FOMC meeting occurred, if two meetings occurred in a particular month the shocks are summed and if no meeting occurred the shock was 0 for that particular month. This variable is available from March of 1969 to June of 2008. The time series plot of monetary shock variable is provided in Figure 4. This data set has a mean of 0 and a standard deviation of 0.2952.

[Insert Figure 4 here]

D. S&P Returns and Volatilities

S&P 500 daily price data is acquired from Yahoo Finance database, the prices are adjusted for dividends and splits, this data is then converted to daily returns, daily returns are then converted to monthly and quarterly returns in addition to deriving monthly and quarterly volatilities. The volatility is the standard deviation in the return data for a month or a quarter. Table 1 provides the summary statistics of the data.

[Insert Table 1 here]

III. EMPIRICAL RESULTS

A. Regression Results with Adjustment for Uncertainty in Macroeconomic news

To see if any of my macroeconomic surprises that have been adjusted for uncertainty have an effect on S&P 500 returns during the current quarter, I run following regressions, the adjusted macroeconomic surprises are contemporaneous in the first regression and the adjusted macroeconomic surprises are lagged in the second regression. Table 2, Panel A reports the results of the following two regressions:

$$R_t = \beta_0 + \beta_1 d_t^{gdp} + \beta_2 d_t^{unemp} + \beta_3 d_t^{ip} + \beta_4 d_t^{housing} + \beta_5 d_t^{cp} + \beta_6 d_t^{pgdp} + \varepsilon_t \tag{4}$$

$$R_t = \beta_0 + \beta_1 d_{t-1}^{gdp} + \beta_2 d_{t-1}^{unemp} + \beta_3 d_{t-1}^{ip} + \beta_4 d_{t-1}^{housing} + \beta_5 d_{t-1}^{cp} + \beta_6 d_{t-1}^{pgdp} + \varepsilon_t \quad (5)$$

$R_t$, is the S&P 500 return for each quarter t. As shown in equation (3), $d_t^m$ is the dispersion adjusted forecasting error for the macroeconomic variable m at time t. The cross-sectional forecasting dispersion is measured as the difference between the 75$^{th}$ and the 25$^{th}$ percentile of the SPF projections. My interpretation of adjusted forecasting error is in essence a "weighted" measure of forecasting errors. For example, a large macroeconomic forecast error with a large degree of uncertainty and therefore the macroeconomic forecast error has a smaller impact than a large macroeconomic forecast error with a small degree of uncertainty. I argue that by using uncertainty-adjusted forecasting errors, we can better depict how investors react to macroeconomic news.

The results in Table 2, Panel A show that both the contemporaneous and lagged relationships have very small $R^2$ values (7% for the contemporaneous regression and 2% for the lagged regression), with the gross domestic product price deflator (pgdp) having a negative explanatory power at the 5% level for the contemporaneous regression and 1% level for the lagged relationship. This seems to be in line with various previous studies (Flannery and Protopapadakis, 2002) that mainly look at inflation using both consumer price index and producer price index.

[Insert Table 2 here]

The next set of regressions look at these same adjusted macroeconomic forecast errors, but the dependent variable here is the quarterly volatility $Vol_t$ of the S&P 500. The results for the following equations are shown in Table 2, Panel B.

$$Vol_t = \beta_0 + \beta_1 d_t^{gdp} + \beta_2 d_t^{unemp} + \beta_3 d_t^{ip} + \beta_4 d_t^{housing} + \beta_5 d_t^{cp} + \beta_6 d_t^{pgdp} + \varepsilon_t \tag{6}$$

$$Vol_t = \beta_0 + \beta_1 d_{t-1}^{gdp} + \beta_2 d_{t-1}^{unemp} + \beta_3 d_{t-1}^{ip} + \beta_4 d_{t-1}^{housing} + \beta_5 d_{t-1}^{cp} + \beta_6 d_{t-1}^{pgdp} + \varepsilon_t \tag{7}$$

The $R^2$ values are better in these equations than in the level equations with $R^2$ for the contemporaneous relationships being 16% and the $R^2$ for the lagged relationship being 5%. At the 1% level both equations (6) and (7) show industrial production (ip) to be significant. In the Garch-MIDAS model where the authors Engle, Ghysels and Sohn (2009) try to see how low frequency macroeconomic variables affect daily returns and conditional volatilities, they find that both inflation and industrial production affect conditional volatilities, this study however does not test other macroeconomic variables and each macro variable's effect on the market is tested separately and not conjointly.

B. Testing raw forecasts

In this section I test whether the SPF forecasts have any effect on S&P 500 returns or volatilities. Instead of using quarterly returns and volatilities, I use monthly returns and volatilities. The forecasters usually provide their quarterly forecasts late in the second to third week of the middle month of each quarter. The forecast variable $f_t^m$ represents the mean of the SPF forecasts of a particular quarter, with m representing one of the macro-variables and t representing the quarter. I run the following regressions with the results reported in Table 3.

$$R_{t,30-day} = \beta_0 + \beta_1 f_t^{gdp} + \beta_2 f_t^{unemp} + \beta_3 f_t^{ip} + \beta_4 f_t^{housing} + \beta_5 f_t^{cp} + \beta_6 f_t^{pgdp} + R_{t-1,30-day} + \varepsilon_t \tag{8}$$

$$Vol_{t,30-day} = \beta_0 + \beta_1 f_{t-1}^{gdp} + \beta_2 f_{t-1}^{unemp} + \beta_3 f_{t-1}^{ip} + \beta_4 f_{t-1}^{housing} + \beta_5 f_{t-1}^{cp} + \beta_6 f_{t-1}^{pgdp} + Vol_{t-1,30-day} + \varepsilon_t \quad (9)$$

where, $R_{t,30-day}$ and $Vol_{t,30-day}$ are the S&P 500 returns and volatilities for the middle month of each quarter respectively, $R_{t-1,30-day}$ and $Vol_{t-1,30-day}$ are the S&P 500 returns and volatilities for the first month of each quarter. A lagged dependent variable is used to subsume any autocorrelation that may be present in the dependent variable. The $R^2$ is 8% for the return regression and 55% for the volatility regression, however, in the volatility regression only nominal GDP and the GDP price index seem to have any explanatory power at the 10% significance level, most of the explanatory power comes from the regression constant and the lagged dependent variable.

[Insert Table 3 here]

C. Relationship between S&P 500 and Volatilities of Macroeconomic forecast error

Here, I follow Arnold and Vrugt (2008) to calculate the volatilities of dispersion adjusted macroeconomic forecast error variables. I use an AR (1) – model to collect the residuals of the dispersion adjusted macroeconomic forecast errors $d_t^m$ and call it $\varepsilon_t^m$, the absolute value of this $|\varepsilon_t^m|$ is taken as the volatility $v_t^m$. $v_t^m$ is used in regression the results of which appear in Panel A of Table 4. In Panel B, I use a variation of $v_t^m$, where $\sigma_t^m = \sum_{i=t-3}^{t} v_i^m$.

$$R_t = \beta_0 + \beta_1 v_t^{gdp} + \beta_2 v_t^{unemp} + \beta_3 v_t^{ip} + \beta_4 v_t^{housing} + \beta_5 v_t^{cp} + \beta_6 v_t^{pgdp} + \beta_7 R_{t-1} + \varepsilon_t \quad (10)$$

$$Vol_t = \beta_0 + \beta_1 v_t^{gdp} + \beta_2 v_t^{unemp} + \beta_3 v_t^{ip} + \beta_4 v_t^{housing} + \beta_5 v_t^{cp} + \beta_6 v_t^{pgdp} + \beta_7 Vol_{t-1} + \varepsilon_t \quad (11)$$

$$R_t = \beta_0 + \beta_1 \sigma_t^{gdp} + \beta_2 \sigma_t^{unemp} + \beta_3 \sigma_t^{ip} + \beta_4 \sigma_t^{housing} + \beta_5 \sigma_t^{cp} + \beta_6 \sigma_t^{pgdp} + \beta_7 R_{t-1} + \varepsilon_t \quad (12)$$

$$Vol_t = \beta_0 + \beta_1 \sigma_t^{gdp} + \beta_2 \sigma_t^{unemp} + \beta_3 \sigma_t^{ip} + \beta_4 \sigma_t^{housing} + \beta_5 \sigma_t^{cp} + \beta_6 \sigma_t^{pgdp} + \beta_7 Vol_{t-1} + \varepsilon_t \quad (13)$$

[Insert Table 4 here]

The result for equation 10 seems to be the strongest, and shows that S&P 500 may be influenced by volatilities of forecast errors in nominal GDP and GDP price index at the 5% level of significance and by industrial production at the 1% level of significance, the $R^2$ for this equation is 10%. Industrial production also appears to be statistically significant in equation (11), which has S&P 500 volatility as the dependent variable. Autocorrelation in the equations presented above is controlled using a lag of the dependent variable which is significant in the index volatility equations, these results are in Table 4. Arnold and Vrugt (2008) run the volatility equations but with dispersion being used as an independent variable along with volatility calculated with the AR(1) – model on the actual macroeconomic variables, they also break up the regression into two sub-periods, one covering 1969 to 1996 and the other from 1997 to 2004. In their results they find that uncertainty from dispersion of analysts' forecasts in the 1969 to 1996 period is significant for nominal GDP and corporate profits when they do not sum up the previous quarters volatilities. After summing the macroeconomic volatilities for four quarters they find the regression is significant for nominal GDP and unemployment but in the period 1997 to 2004 they find no significant relationships. My results for equations (12) and (13) are not as strong as those for equations (10) and (11), for S&P 500 returns GDP price index is significant at the 5% level and for S&P 500 volatility Industrial production is significant at the 10% level.

D. S&P 500 index and Monetary Shocks

Here I look at whether monthly monetary shock variable ($Monetary_t$) is able to determine S&P 500 returns and volatilities in contemporaneous regressions given by the following equations. The monetary shock variable is got from data provided by Crowe and Barakchian (2010), Crowe and Barakchaian follow the Romer and Romer (2004) paper to derive monetary shock using the narrative approach. The results are presented in Table 5.

$$R_t = \beta_0 + \beta_1 Monetary_t + \beta_2 R_{t-1} + \varepsilon_t \tag{14}$$

$$Vol_t = \beta_0 + \beta_1 Monetary_t + \beta_2 Vol_{t-1} + \varepsilon_t \tag{15}$$

$R_t$ and $Vol_t$ here, are the monthly returns and volatilities of the S&P 500. Surprisingly, for the full sample period monetary shocks do not seem to have any effect on S&P 500 index returns or volatilities. As before, in the volatility equation the lagged dependent variable is highly significant showing that volatility is auto-correlated. Bernanke and Kuttner (2005) regress CRSP value weighted returns on expected and unexpected components of monthly fed funds rate changes and they find a statistically significant negative response to unanticipated rate increases and little or no response to the anticipated actions, their sample time period was from May 1989 to December 2002, the adjusted $R^2$ for their regression is 7%. I also do sub-period analysis to correspond with Bernanke and Kuttner's paper. My results don't change much from the full sample regression. Panel A of Table 5 has the full sample period regression, Panel B is pre 1989 and Panel C is post 1989.

[Insert Table 5 here]

A. Regression Results with Adjustment for Uncertainty in Macroeconomic news and Monetary Shocks

In my final set of regression equations, I add the monetary shock variable. The monetary shock variable is the monthly monetary shock variable provided by Crowe and Barakchian (2010) which is summed over 3 months to make it a quarterly variable, this quarterly monetary shock variable is added to equations (4), (5), (6) and (7) resulting in the following equations, whose results are presented in Table 6.

$$R_t = \beta_0 + \beta_1 d_t^{gdp} + \beta_2 d_t^{unemp} + \beta_3 d_t^{ip} + \beta_4 d_t^{housing} + \beta_5 d_t^{cp} + \beta_6 d_t^{pgdp} + \beta_1 Monetary_t + \varepsilon_t \tag{16}$$

$$R_t = \beta_0 + \beta_1 d_{t-1}^{gdp} + \beta_2 d_{t-1}^{unemp} + \beta_3 d_{t-1}^{ip} + \beta_4 d_{t-1}^{housing} + \beta_5 d_{t-1}^{cp} + \beta_6 d_{t-1}^{pgdp} + \beta_1 Monetary_{t-1} + \varepsilon_t \tag{17}$$

$$Vol_t = \beta_0 + \beta_1 d_t^{gdp} + \beta_2 d_t^{unemp} + \beta_3 d_t^{ip} + \beta_4 d_t^{housing} + \beta_5 d_t^{cp} + \beta_6 d_t^{pgdp} + \beta_1 Monetary_t + \varepsilon_t \tag{18}$$

$$Vol_t = \beta_0 + \beta_1 d_{t-1}^{gdp} + \beta_2 d_{t-1}^{unemp} + \beta_3 d_{t-1}^{ip} + \beta_4 d_{t-1}^{housing} + \beta_5 d_{t-1}^{cp} + \beta_6 d_{t-1}^{pgdp} + \beta_1 Monetary_{t-1} + \varepsilon_t \tag{19}$$

As expected, the results do not change substantially with the addition of the monetary shock variable; GDP price index remains significant in both the contemporaneous and lagged relations. When the dependent variable is S&P 500 index returns, however, industrial production also becomes significant at the 10% level in the contemporaneous equation.

[Insert Table 6 here]

When S&P 500 index volatility is the dependent variable industrial production is significant in both the contemporaneous and lagged relations at the 1% level, $R^2$ increases to 25% in the contemporaneous relation while $R^2$ is 3% in the lagged relationship.

# MACROECONOMIC VARIABLES AND THE OTHER JANUARY EFFECT

## I. BACKGROUND DISCUSSION AND DATA DESCRIPTION

Calendar effects in financial markets are often viewed as a refutation of market efficiency. Some of the well-known examples include: the January effect (Keim, 1983 and Reinganum, 1983), the weekend effect (French, 1980), the sell-in-May effect (Bouman and Jacobsen, 2002), and the turn-of-the-month effect (Ariel, 1987). These and other seasonal effects, if unexplained, pose a serious challenge to the efficient market hypothesis since it is difficult to understand why arbitrage forces cannot correct such blatant violations of market efficiency.

The other January Effect (OJE) is a recent addition to this growing list of calendar related anomalies. It is also known as the January barometer among Wall Street practitioners, who primarily focus on using raw January returns as a predictor for stock market's performance for the remainder of the year.

Cooper, McConnell, Ovtchinnikov (2006) (CMO) notes that this effect was first documented in Yale Hirsch's Stock Trader's Almanac in the early 1970s. However among academicians, it had received little attention until CMO, who provide the first rigorous econometric test of the effect using both excess and raw returns.

CMO show that the return spread for the 11-month following positive and negative Januaries are highly significant. In addition, CMO find no evidence that the OJE can be explained by business cycle variables, the Presidential Cycle in stock returns, or investor sentiment. Thus, although CMO document strong statistical results, they are agnostic about its potential explanations.

Most of the evidence from international tests of the OJE refutes its presence, for example Bohl and Salm (2007) show that the OJE was only present in 3 out of 14 countries they examined and that the effect does not appear to exist after 1980. Easton and Pinder (2007) replicate the CMO study over 44 countries and found limited evidence for this effect in 5 of those countries at the 5% level of significance. Marshall and Vishaltanachoti (2008) find that OJE cannot be seen in 22 equity markets of the 23 which they studied and conclude that it only works superficially in the U.S. markets. The persistence of the January dummy variable is of concern to Marshall and Vishaltanachoti (2008) brought their attention from a paper by Powell, Shi, Smith and Whaley (2007). Marshall and Vishaltanachoti (2010) show that the OJE does not outperform a passive 12-month buy and hold strategy. However, Brown and Luo (2006) after determining that the OJE is more useful only when January is a down month, proceed to extend the OJE to 12 months following January and find these results stronger than 11-month results for the OJE.

Stivers, Sun and Sun (2009) confront the issue by examining the international, style, and sub-period evidence. They hypothesize that the OJE could be driven by three primary potential explanations. First, the OJE might be attributable to an internationally priced risk factor. If so, one would expect that the OJE would also exist in international markets and that the OJE should persist over time. Second, if the OJE is related to a pervasive and persistent behavioral bias, then one should also expect the OJE to show up in the international equity markets and to persist over time. Third, the OJE could be a temporary anomaly in the sense of Schwert (2003). In this case an anomaly might simply be a statistical aberration with no underlying economic explanation or alternatively be tied to a specific period of history, as the realized returns were responding to the economic and trading environment at the time. Presumably, the anomalous price behavior is unlikely to persist under this scenario. Stivers, Sun and Sun find little evidence that the OJE is pervasive in international markets. Stivers, Sun and Sun also find that OJE has weakened somewhat in recent sub-period samples, especially for equal weighted index raw returns. Taken together, they conjecture that the OJE is likely to be a "temporary anomaly".

It is noteworthy that Stivers, Sun and Sun (2009) also document an interesting OJE spillover effect from the U.S. to other countries. In their Table 4, they find that for eight major markets (Australia,Canada, France, Germany, Italy, Japan, Sweden, and the U.K.) the own-country OJE effect is essentially non-existent, with an average return spread of only 0.72%. In contrast, conditional on the sign of U.S. market January returns, the average return spread is 10.83%. Thus Stivers, Sun and Sun conclude that the OJE phenomenon in these eight major countries is more related to the U.S. January return, rather than the own country's January return. Similar results (Tables 5 and 7) are also evident in U.S. industry, book-to-market, and size-based portfolios. It is shown that OJE spreads are stronger when conditioning upon the market-level January return than when conditioning upon the respective own-portfolio January return.

Hence, the OJE appears to be mainly a U.S. market-oriented phenomenon. But what drives this result? One possibility is that market performance in January could be influenced by portfolio decisions made by long-term investors who rebalance their portfolios after a careful review of the state of the U.S. economy. Thus, for example, if these “smart money” investors decide that the economic outlook is bearish and determine to reduce their exposure to the stock market for the coming year, then the exodus of these investors on the margin is likely to result in a negative January return, and vice versa. Given its importance and size, the performance of U.S. market should in turn exert a big impact on global markets as well as industry, book-to- market, and size-based portfolios. If this transmission mechanism holds true and “smart money” investors act on available economic information, then one way to test this hypothesis is to see if lagged macroeconomic variables have predictive power for returns in the post-January months. In addition, it is interesting to see if after controlling for the lagged macroeconomic variables, the OJE is still prominent. I present empirical results addressing these issues in the following section.

Following CMO, I mainly focus on the OJE using U.S. market data. Specifically, I use monthly value weighted and equal weighted index returns from the Center for Research in Security Prices (CRSP). I define a January dummy variable that is equal to 1 if the January CRSP return is positive and 0 otherwise. Conditional on the January dummy, I calculate the following 11-month holding period return from February to December. The difference in the average 11- month returns following positive and negative Januaries is called the return spread. I repeat the calculations using both raw returns and excess returns; excess returns are obtained by subtracting the 1-month risk-free rate from raw returns.

I collect macroeconomic variables from Federal Reserve Bank at St. Louis and CRSP, focusing on the following commonly used variables: term premium defined as the difference between the yields on the 10-year and 1-year Treasury notes, dividend yield constructed from value weighted CRSP index as in Fama and French (1988), default premium is calculated as the difference between yields on Moody's BAA and AAA rated corporate bonds, and for short-term interest rate, I use the 3-month Treasury bill rate. My sample period is from 1954 to 2009, this period was selected based on the availability of macroeconomic data.

## II. EMPIRICAL RESULTS

In this section, I present my main empirical results. First I investigate if a dummy variable that represents the shape of the yield curve has similar predictive power for the 11-month returns from February to December, and if so what is its relation to the January dummy variable. Second, I report predictive regression results using standard macroeconomic variables as regressors. I compare the predictive power of these macroeconomic variables to that of the January dummy variable. Finally, I test if information contained in January returns, which are orthogonal to macroeconomic variables, still carry predictive power for the subsequent 11-month returns.

### A. Return Spreads from the Slope of Yield Curve

From the perspective of an investor who relies on the OJE to make portfolio decisions, a trading strategy suggested by CMO is to go long stocks if January market return is positive and switch to T-bills otherwise. Such a strategy has the advantage of being simple to identify in real time and easy to implement. Likewise, my goal here is to see if I can come up with a macroeconomic variable to generate real time trading signals that are easy to follow without any ambiguity. Among the commonly used macroeconomic variables, the term premium appears to be a good choice. Note that the sign of term premium indicates the slope of the yield curve. Namely when the term premium is positive, the slope of the yield curve is positive and vice versa. The reason for choosing this variable is twofold. First, the slope of the yield curve is a well-known predictor of business cycles (Wheelock and Wohar, 2009). In particular, downward sloping yield curves are quite successful in predicting future recessions. Second, this yield curve variable is simple to construct and can be easily adopted for real time investment decisions. Later, I show that yield curve is not the optimal variable in terms of its predictive power for the following 11-month returns from February to December. Similar to the January dummy variable in the OJE, I construct a dummy variable based on the sign of the yield curve, which is equal to 1 if the term premium in December of the prior year is positive and 0 otherwise.

The standard methodology in the literature is to estimate a simple regression model using the dummy variable of interest as the regressor. I estimate the following five regression models:

$$r_t = \propto + \beta D_t^{Jan} + \varepsilon_t \tag{20}$$

$$r_t = \propto + \beta D_t^{TP} + \varepsilon_t \tag{21}$$

$$r_t = \propto + \beta D_t^{Jan-TP} + \varepsilon_t \tag{22}$$

$$r_t = \propto + \beta D_t^{TP-Jan} + \varepsilon_t \tag{23}$$

$$r_t = \propto \; + \beta D_t^{TPxJan} + \varepsilon_t \tag{24}$$

where $r_t$ is the 11-month holding period return from February to December in year t, $D_t^{Jan}$ a January dummy. $D_t^{TP}$ is the yield curve dummy variable. To see if the OJE is still significant after controlling for the slope of the yield curve, I define a new dummy variable $D_t^{Jan-TP}$ that equals one if $D_t^{Jan}$ = 1 and $D_t^{TP}$= 0, and equals zero otherwise. For comparison, I also include a dummy variable $D_t^{TP-Jan}$ that equals one if $D_t^{TP}$ = 1 and $D_t^{Jan}$ = 0. Finally, $D_t^{TPxJan}$ is a dummy variable that equals one if $D_t^{Jan}$= 1 and $D_t^{TP}$ = 1, and equals zero otherwise.

[Insert Table 7 here]

The results are reported in Table 7. Consistent with CMO, Panel A shows that the OJE appears to be quite strong in my sample period from 1954 to 2009. For instance, the return spreads for value weighted and equal-weight index excess returns are 12.54% and 14.76% respectively. The results based on raw returns are similar albeit slightly weaker, especially for equal weighted index. Interestingly, the results reported in Panel B indicate that the yield curve dummy also has predictive power for the 11-month returns from February to December. For example, based on the excess value weighted index, the average 11-month return following a positive (negative) yield curve is 8.50% (−3.24%) with a significant return spread of 11.73%. These results are comparable to the January dummy variable. Overall, the yield curve dummy variable appears to work well for the value weighted index, but loses statistical significance in the case of equal weighted index returns.

In panel C, I report the return spreads for the January dummy after controlling for the yield curve dummy. I find that when the dummy variable $D_t^{Jan-TP}$ is equal to one, namely when the January return is positive and the yield curve is negative, the average 11-month return is quite small. For example, it is only -5.23% and -2.73% for value weighted and equal weighted index excess returns respectively. In the case when $D_t^{Jan}$ is equal to zero, the average 11-month return is large and negative. For example, it is -7.13% and -9.59% for value weighted and equal weighted index excess returns respectively. Therefore, the return spreads turn out to be negative, albeit not statistically significant. In panel D, I reverse the roles of the January and yield curve dummies. I find the average 11-month return is low when yield curve is positive and January return is negative, and high otherwise. Thus the results from panels C and D show that these two effects are quite interdependent.

The results from Panel E confirms the observation that January Dummy and Term Premium dummy are interdependent. It shows that when both January and yield curve dummies are positive, the average 11-month return from February and December is substantially higher than the case when either one of the dummy variables is negative. This result show's that the return spreads become even stronger than when using either the January or the yield curve dummy alone. For instance, the spreads are 13.96% and 12.96% for value weighted and equal weighted index excess returns respectively, and are highly significant. Taken together, the results based on the shape of the yield curve appear to be consistent with the notion that the OJE is at least partially related to macroeconomic variables.

B. Predictive regressions

While the results from the yield curve dummy variable are revealing, they are somewhat limited due to the focus on only one macroeconomic variable. Hence I proceed to test the relation between a set of commonly used macroeconomic variables and the OJE in a predictive regression setting. The predictors include dividend yield, term premium, default premium, and short-term interest rate. The choices of these variables follow CMO as well as extensive literature on stock return predictability. It should be noted that CMO focus exclusively on the detrended 3-month Treasury bill rate as a proxy for the short-term interest rate variable. To detrend the T-bill yield, CMO divide the monthly T-bill yields by the average of the previous 12 monthly observations. Presumably CMO perform the detrending because of the high autocorrelation in monthly T-bill yields, which might be a concern when monthly interest rates are used. However in the stock return predictability literature, it is very common to use non-detrended short rate (Bossaerts and Hillion, 1999). In the current context, since OJE requires only annual observations, it is likely to be less problematic to use non-detrended short rate. Hence I include both types of short rates in the following regression analysis.

Formally, I run variations of the following regression model to determine the relation between OJE and lagged macroeconomic variables.

$$\begin{aligned} R_t^{FEB,DEC} = {} & \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DIV_{t-1} + \beta_3 DEF_{t-1} \\ & + \beta_4 DYLD_{t-1} + \beta_5 YLD_{t-1} + \alpha_1 D_t^{JAN} + \alpha_2 R_t^{JAN} \\ & + \varepsilon_t \end{aligned} \tag{25}$$

where, $R_t^{FEB,DEC}$ is the 11-month return from February to December in year t. The regressors are mostly lagged macro variables term premium (TERM), dividend yield

(DIV), default premium (DEF ), detrended three-month T-bill yield (DYLD) and its non-detrended counterpart (YLD). The main result here is that the regression has more explanatory power when YLD is used instead of DYLD and this explanatory power increases when the January Dummy is used. However, using the January returns instead of the January dummy has less explanatory power. Panel A reports the value weighted excess return regression results; the adjusted $R^2$ without the January dummy but with T-bill yield is 19.45% while it is 31.66% when the January dummy is used, these results are slightly less when January Macro Variables are used in the regression, this is true for Panels B, C, and D. The adjusted $R^2$ without January dummy in Panel B for raw value weighted returns are 15.34% and with the January dummy is 22.74%. The adjusted $R^2$ without January dummy in Panel C for raw equal weighted excess returns are 25.08% and with the January dummy is 33.19%. And finally for Panel D, the adjusted $R^2$ without the January dummy 21.21% and with the January dummy is 29.09%, all these results are for the case where the macroeconomic regressors are for December of the previous year.

[Insert Table 8 here]

To sum up, the results from Table 8, I find that lagged dividend yield and non-detrended short-term interest rate have predictive power that are comparable to the January dummy variable for the subsequent 11-month returns from February to December. In addition, default premium appears to have predictive power for equal weighted index returns but not value weighted returns, presumably because small-cap stocks are more sensitive to default risk. Interestingly, macroeconomic variables (DIV and YLD) are capable of explaining a substantial amount of variation in the subsequent 11-month returns. Thus it appears that January dummy is neither unique nor predominant in terms of its predictive power. Moreover, my results show that part of the reason that CMO find no explanatory power for macroeconomic variable is probably due to the fact that they chose detrended rather than non-detrended short term interest rate.

C. Comparison with CMO's Results

So far, I establish in a regression setting, macroeconomic variables do have predictive power for the 11-month returns from February to December. This appears at odds with the analysis from CMO. However, CMO do use a different methodology. In their approach, CMO first run a regression where lagged macroeconomic variables are the regressors and the 11-month post-January return is the dependent variable. They then calculate the 11-month predicted return using the estimated coefficients and the realized observations of the macroeconomic variables. Next, they sort years according to whether the 11-month predicted return is above or below the mean predicted return over the sample period and then sort years according to whether the January returns are predicted to be positive or negative. CMO argue that if macroeconomic variables can explain the OJE, then by sorting the observations according to high and low 11-month predicted returns, the spread between post-January excess returns following positive and negative Januarys should be insignificant, but they do not find this to be true. In fact, they find the return spreads after the sorting procedure is still highly significant. The returns they use for the return spread is abnormal returns which is the difference between the actual and predicted 11-month market returns.

To understand the differences between CMO and my findings based on the regression analysis, I adopt the same sorting procedure used by CMO. There are some minor differences. First, CMO's sample period is from 1940 to 2003, while mine is from 1954 to 2009. Second, CMO only report the results based on abnormal returns (residuals from the predictive regression), whereas I report the results for both abnormal returns and the raw returns. Last but not least, CMO's predictive regression uses only the detrended short-term interest rate. I instead report results using both detrended and non-detrended short-term interest rates.

[Insert Table 9 here]

Panel A of Table 9 reports the results based on the set of predictors chosen by CMO. First I estimate the following regression.

$$R_t^{FEB,DEC} = \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DIV_{t-1} + \beta_3 DEF_{t-1} + \beta_4 DYLD_{t-1} + \varepsilon_t \tag{26}$$

where $R_t^{FEB,DEC}$ is the 11-month post-January return, and the regressors are lagged (from December of the prior year) macro variables: term premium (TERM), dividend yield (DIV), default premium (DEF), and detrended three-month T-bill yield (DYLD). Following CMO, I sort the data according to E[R], the predicted 11-month returns from the regression. I report the mean returns (in percentage) for four scenarios where E[R] ≥ median E[R] or E[R] < median E[R] and the return in January is positive or negative. I include results based on the abnormal returns (residuals) as well as the full holding period returns using CRSP value weighted excess returns (VWR − $R_f$ ), value weighted raw return (VWR), equal weighted excess returns (EWR − $R_f$ ), and equal weighted raw returns (EWR). The results based on abnormal returns are largely inconsistent with CMO. Significant differences of the means of abnormal and raw returns in positive and negative

Januarys are only found in cases where E[R] < median E[R] , and where value weighted excess returns, equal weighted excess returns and equal weighted returns are regressed against macroeconomic variables. All these results are significant at the 5% level.

Next I look at the following equation to see if replacing detrended yield with the non-detrended yield makes any difference to the results above.

$$R_t^{FEB,DEC} = \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DIV_{t-1} + \beta_3 DEF_{t-1} + \beta_4 YLD_{t-1} + \varepsilon_t \tag{27}$$

Here again the results are not substantially different from the detrended case, most significant results are obtained where E[R] < median E[R]. In Panel B of Table 9, I find statistically significant differences in abnormal means and raw means in value weighted excess returns, equal weighted excess returns and equal weighted returns. The results are consistent, except in the case where E[R] ≥ median E[R], the abnormal mean of value weighted returns is significant. The statistically significant difference is driven by negative January returns.

To sum up, the results are inconsistent with the results of CMO. Furthermore, replacing detrended T-bill yield with non-detrended T-bill yield does not change the results. The time period of CMO's study and the time period used in my regression may account for the fact that I do not observe the OJE results that were shown by CMO. It also appears that the OJE is driven by negative Januarys.

D. The OJE after controlling for macroeconomic effects

Next I test directly if incremental information from January returns has predictive power for the next 11-month returns beyond those provided by macroeconomic variables. My goal is to determine whether the OJE is prominent after controlling for the macroeconomic variables on January returns. To this end, I first regress January returns on lagged macroeconomic variables. Based on my regression results, I pick the following lagged regressors from December of the prior year: term premium (TERM ), dividend yield (DIV), default premium (DEF), and three-month T-bill yield (YLD). Note that I replace DYLD with YLD because of my earlier finding that it has more predictive power for the post-January returns. Thus the first model that I consider is as follows:

$$R_t^{JAN} = \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DIV_{t-1} + \beta_3 DEF_{t-1} + \beta_4 YLD_{t-1} + \varepsilon_t \tag{28}$$

where $R_t^{JAN}$ is the CRSP index return in January of year t. The OLS residuals $\varepsilon_t$ contains the incremental information in January returns since OLS residuals are, by construction, orthogonal to the regressors (in this case lagged macroeconomic variables). Thus the second step is to calculate the returns spreads based on the signs of $\varepsilon_t$. Following CMO, I classify the Januarys in my sample into positive ($\varepsilon_t > 0$) and negative ($\varepsilon_t \leq 0$) Januarys. I report the mean returns for the post-January 11-month returns following positive and negative Januarys, as well as the return spreads and their associated p-values.

[Insert Table 10 here]

Panel A of Table 10 reports the results for this approach. Interestingly, I find that after controlling for lagged macroeconomic variables from December of the prior year, it appears that the OJE is no longer significant for equal weighted CRSP index returns. The return spreads are 7.47% and 8.20% for excess and raw returns respectively, but neither is statistically significant. For value weighted index returns, however, the returns spreads are still over 10% and statistically significant. Thus the lagged macroeconomic variable in December of the prior year appears to be a sufficient control for equal weighted index but not sufficient for value weighted index.

I do not restrict myself to December of the prior year's variables but also use January of the current year's macroeconomic variables as the January dummy is got from returns in January of the current year. I use December of prior year's macroeconomic variables in my previous regressions largely to be consistent with CMO, who focus on this timing convention. Since the OJE uses information up to January of a given year to predict post-January returns in the same year, it appears reasonable to use macroeconomic variables up to January of the same year. At least, this would put January return and other macroeconomic variables on a level playing field, and would not introduce any "look-ahead" bias. Therefore, I proceed to run the following regression.

$$R_t^{JAN} = \beta_0 + \beta_1 TERM_t + \beta_2 DIV_t + \beta_3 DEF_t + \beta_4 YLD_t + \varepsilon_t \qquad (29)$$

where, the regressors are the macroeconomic variables in January of year t. Thus the residuals from this regression contain information from January returns that are uncorrelated with macroeconomic variables up to January of year t. I then proceed to categorize the Januarys in my sample into positive and negative Januarys according to the signs of $\varepsilon_t$. I report the mean post-January 11-month holding period returns following positive and negative Januarys and their spreads in Panel B of Table 10. The result here is not much different from that of the previous model (28). The spreads are 9.46% and 10.00% for value weighted CRSP excess index returns and raw index returns respectively, and 7.47% and 8.20% for equal weighted CRSP excess index returns and raw index returns.

Since the dividend yield is constructed by using price information, some readers might be concerned that the results from model (29) are driven by the fact that January dividend yield shares the same price information as the market return in January. To alleviate this concern, I rerun the regression but exclude dividend yield from the model. The resulting regression is below:

$$R_t^{JAN} = \beta_0 + \beta_1 TERM_t + \beta_3 DEF_t + \beta_4 YLD_{t-1} + \varepsilon_t \tag{30}$$

where, the regressors are the same as in model (29) other than the exclusion of January dividend yield. The results are shown in Panel C of Table 10. I find that the January return spreads are quite similar to those reported in Panel B: 9.70% and 10.12% for value weighted CRSP excess index returns and raw index returns, and 13.19% and 10.34% for equal weighted CRSP excess index returns and raw index returns. Once again the results are significant for the value weighted returns but not for the equal weighted returns.

I further examine the robustness of these results by dividing the sample into three sub-periods. The first sub-period is from 1954 to 1973, which is around the time when first public documentation of the OJE was published in Yale Hirsh's Stock Trader's Almanac. This could be labeled as the pre-discovery period. The other two sub-periods are from 1974 to 1993 and from 1994 to 2009. Panel A in Table 11 shows the results for following model:

$$R_t^{JAN} = \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DEF_{t-1} + \beta_3 YLD_{t-1} + \beta_4 TERM_t + \beta_5 DEF_t + \beta_6 YLD_t + \varepsilon_t \quad (31)$$

The main results from the above model is that for the entire sample period, the value weighted excess return is significant with spread of 9.92% with January returns as the dependent variable. When the January dummy is used the spread is 12.77%. For the sample period of 1974 to 1993, I obtain a statistically significant spread of 11.39% using the January dummy as the dependent variable.

[Insert Table 11 here]

Significant results are also obtained for the entire sample, using the value weighted return as the dependent variable with a mean spread of 10.83% and when the dummy variable is used as the dependent variable, the spread is 9.56%. However, significant results are not obtained for the sub-periods.

For the case of equal weighted excess returns using the January dummy as the dependent variable, I get significant results using both the entire sample period and the 1954 to 1973 sub-period. The mean spreads are 13.24% and 30.60% respectively.

And finally, when only the equal weighted return is used with the January dummy as the dependent variable, significant means spread is found only for 1954 to 1973 sub-period with a mean spread of 30.49%.

Summing up, the OJE is not consistently found in all sub-periods, however, it has to be cautioned the number of years available for sub-period analysis is very small. Following my earlier result using the term premium dummy, the OJE seems to be predominant in CRSP value weighted excess and value weighted returns.

# CONCLUSION

Reviewing the results obtained from the two different studies, in the first study on how macroeconomic variables affect a market index, I observe that there is much room for future research. Looking at the effect of macroeconomic forecast errors on the S&P 500 index I find that industrial production is an important variable in contemporaneous relationships and this variable in other studies is noticeable by its absence, with some authors justifying why they do not observe its effect in their studies. In the second study where I look at the other January Effect, conflicting results were obtained; the macroeconomic variables do not seem to entirely subsume the OJE but it appears that these macroeconomic variables could be used to predict future returns much like the OJE, I also found that the OJE does not conform to the original results of CMO when the 11-month returns are conditioned on macroeconomic variables.

Regressing S&P 500 index returns on SPF dispersion adjusted macroeconomic forecast errors, I find that the GDP deflator has some explanatory power. When looking at S&P 500 volatilities, I find that industrial production explains volatility along with the GDP deflator. When I look at forecasters' ability to forecast volatility, I do not find forecasters able to predict either returns or volatilities above the 5% level of significance.

When using volatility in the surprises as the regressor, I find that the GDP deflator has significant explanatory power on S&P 500 returns and volatility. Volatility of industrial production forecast error also show significant explanatory power on S&P 500 returns and volatility. Volatility of nominal GDP has some explanatory power when the S&P 500 returns are regressed against it.

Monetary Shocks do not seem to have any effect on S&P 500 returns or volatilities. This is a surprise since previous researchers find that monetary shocks cause the stock market as a whole to react. Finally, I observe that my results are robust to the addition of the monetary shock variable to my regressions where S&P 500 returns and volatilities are the dependent variables and macroeconomic variables are independent variables.

Though I observe a couple of macroeconomic variables using dispersion adjusted surprises, this thesis suggests many different future avenues for research. Among them the search for evidence in international markets, the attempt to reconcile low frequency observations of macroeconomic data with high frequency market data, and to check what effect dispersion adjusted macroeconomic forecast errors have on different markets.

In the next essay, I look at how the macroeconomic variables, among them term premium, dividend yield, default premium and short term interest rate may help explain the OJE. The results of this thesis is among the various studies that seem to show that the OJE may be an artifact of the time period of data studied or is an artifact of the statistical methodology used to determine its existence.

I show that term premium has all the qualities of the January barometer and the regression results show significant spreads when using term premium as a predictor for the OJE.

Regression results also showed that short term yields explain the OJE much like the January dummy. However, the January dummy is not subsumed by the macroeconomic variables in these regressions.

In replicating the original study of Cooper, McConnell and Ovtchinnikov (2006), I found the OJE is strangely absent after accounting for macroeconomic variables in most of the CRSP indices, I also see that the OJE could be attributed to the negative Januaries is some of the regressions.

Inconclusive results were obtained when tried to account for the other January Effect by first conditioning the January returns with macroeconomic variables. Essentially using the value weighted excess and value weighted raw returns supported the existence of the OJE but not when using equal weighted excess or equal weighted raw returns. The results add to the literature that questions the validity of the other January Effect.

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Table 1. Summary Statistics

This table reports the summary statistics for the following variables: S&P 500 index return, S&P 500 index volatility, forecasting errors, dispersion adjusted forecasting errors, and absolute value of residual from AR(1)-model of dispersion adjusted forecasting errors for six macroeconomic variables. The macroeconomic variables include GDP growth (gdp), unemployment rate (unemp), industrial production (ip), housing starts (housing), corporate profits (cp), and GDP price index (pgdp). $\delta^m$ stands for the unadjusted forecasting errors for macro variable m. $d^m$ stands for the uncertainty adjusted forecasting errors. $\upsilon^m$ denotes the absolute value of residuals from AR(1)-model. The sample period is from 1968:Q4 to 2009:Q4.

| | Mean | Minimum | Maximum | Std. Dev. | Skewness | Ex. kurtosis |
|---|---|---|---|---|---|---|
| SP500 returns | 1.8115 | -26.1163 | 21.5869 | 8.3700 | -0.4890 | 0.8469 |
| SP500 volatility | 0.0094 | 0.0040 | 0.0422 | 0.0050 | 3.2829 | 15.9599 |
| $\delta^{gdp}$ | 0.6663 | -7.4993 | 11.7349 | 2.6676 | 0.5853 | 2.1506 |
| $\delta^{unemp}$ | -0.0283 | -0.4167 | 0.4351 | 0.1542 | 0.5493 | 0.3426 |
| $\delta^{ip}$ | -0.0029 | -9.9918 | 10.3921 | 3.7910 | 0.0362 | 0.0278 |
| $\delta^{housing}$ | 7.0490 | -43.0449 | 144.0520 | 25.4681 | 1.5312 | 5.8846 |
| $\delta^{cp}$ | 5.0903 | -59.5078 | 102.9220 | 25.0203 | 0.8386 | 2.6535 |
| $\delta^{pgdp}$ | 0.0791 | -3.6283 | 3.6975 | 1.1317 | 0.3122 | 0.3059 |
| $d^{gdp}$ | 0.3632 | -4.3023 | 5.3721 | 1.5493 | 0.2516 | 0.9626 |
| $d^{unemp}$ | -0.3621 | -19.0909 | 42.4324 | 4.1038 | 5.9899 | 73.1461 |
| $d^{ip}$ | -0.0418 | -40.2766 | 73.9176 | 7.0010 | 5.8342 | 80.6510 |
| $d^{housing}$ | 0.3731 | -3.5250 | 5.1591 | 1.2239 | 0.5365 | 1.2924 |
| $d^{cp}$ | 0.2467 | -7.5599 | 6.1122 | 1.9010 | -0.3964 | 3.5835 |
| $d^{pgdp}$ | 0.1273 | -2.4730 | 22.5088 | 2.0657 | 7.7827 | 81.8232 |
| $\upsilon^{gdp}$ | 1.1626 | 0.0006 | 5.0545 | 1.0244 | 1.4494 | 2.1592 |
| $\upsilon^{unemp}$ | 1.3395 | 0.0007 | 42.5053 | 3.8709 | 8.2467 | 79.1839 |
| $\upsilon^{ip}$ | 1.8922 | 0.0076 | 73.9318 | 6.7498 | 8.7647 | 83.8720 |
| $\upsilon^{housing}$ | 0.8614 | 0.0015 | 4.3715 | 0.7477 | 1.7491 | 4.3975 |
| $\upsilon^{cp}$ | 1.2802 | 0.0003 | 7.5028 | 1.3766 | 2.1952 | 5.5410 |
| $\upsilon^{pgdp}$ | 0.9686 | 0.0021 | 21.9254 | 1.7936 | 9.8711 | 112.1610 |

Table 2. S&P 500 Index and Surprises in Macroeconomic News Adjusted for Forecasting Uncertainty: Contemporaneous and Lagged relations

Panel A. This table reports the results for the following OLS regressions:

$$R_t = \beta_0 + \beta_1 d_t^{gdp} + \beta_2 d_t^{unemp} + \beta_3 d_t^{ip} + \beta_4 d_t^{housing} + \beta_5 d_t^{cp} + \beta_6 d_t^{pgdp} + \varepsilon_t$$

$$R_t = \beta_0 + \beta_1 d_{t-1}^{gdp} + \beta_2 d_{t-1}^{unemp} + \beta_3 d_{t-1}^{ip} + \beta_4 d_{t-1}^{housing} + \beta_5 d_{t-1}^{cp} + \beta_6 d_{t-1}^{pgdp} + \varepsilon_t$$

where, $R_t$ is the S&P 500 index return in quarter t. $d = \frac{\delta}{disp}$ is the forecasting error variable adjusted for forecasting uncertainty, where δ denotes the differences between actual values of macroeconomic variables and SPF forecasts, and disp is the cross-sectional forecasting dispersion measure defined as the difference between the 75th percentile and the 25th percentile of the SPF projections. The macroeconomic forecast errors included are nominal GDP (gdp), unemployment rate (unemp), industrial production (ip), housing starts (housing), corporate profits (cp), and GDP price index (pgdp). Heteroscedasticity and autocorrelation consistent t-statistics, $R^2$ and adjusted $R^2$ values are also reported. *, **, and *** denote significance levels at 10%, 5%, and 1% respectively. The sample period is from 1968:Q4 to 2009:Q4 for contemporaneous and 1969:Q1 to 2009:Q4 for lagged.

| | Contemporaneous Relationship | | Lagged Relationship | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | 0.0152** | 2.0013 | 0.0158** | 2.2150 |
| gdp | 0.0222 | 0.3744 | 0.0051 | 1.1140 |
| unemp | -0.0058 | -0.4863 | -0.0003 | -0.3684 |
| ip | -0.0019 | -1.5744 | -0.0063 | -0.6892 |
| housing | 0.0089 | 1.5440 | 0.0042 | 0.8212 |
| cp | -0.0037 | -1.2247 | -0.0028 | -0.8771 |
| pgdp | -0.0049** | -2.1796 | -0.0039*** | -3.0790 |
| $R^2$ | 0.0698 | | 0.0280 | |
| Adj. $R^2$ | 0.0344 | | -0.0915 | |

Table 2. (Continued)

Panel B. This table reports the results for the following OLS regressions:

$$Vol_t = \beta_0 + \beta_1 d_t^{gdp} + \beta_2 d_t^{unemp} + \beta_3 d_t^{ip} + \beta_4 d_t^{housing} + \beta_5 d_t^{cp} + \beta_6 d_t^{pgdp} + \varepsilon_t$$

$$Vol_t = \beta_0 + \beta_1 d_{t-1}^{gdp} + \beta_2 d_{t-1}^{unemp} + \beta_3 d_{t-1}^{ip} + \beta_4 d_{t-1}^{housing} + \beta_5 d_{t-1}^{cp} + \beta_6 d_{t-1}^{pgdp} + \varepsilon_t$$

where, $Vol_t$ is the S&P 500 index volatility in quarter t. $d = \frac{\delta}{disp}$ is the forecasting error variable adjusted for forecasting uncertainty, where δ denotes the differences between actual values of macroeconomic variables and SPF forecasts, and disp is the cross-sectional forecasting dispersion measure defined as the difference between the 75th percentile and the 25th percentile of the SPF projections. The macroeconomic forecast errors included are nominal GDP (gdp), unemployment rate (unemp), industrial production (ip), housing starts (housing), corporate profits (cp), and GDP price index (pgdp). Heteroscedasticity and autocorrelation consistent t-statistics, $R^2$ and adjusted $R^2$ values are also reported. *, **, and *** denote significance levels at 10%, 5%, and 1% respectively. The sample period is from 1968:Q4 to 2009:Q4 for contemporaneous and 1969:Q1 to 2009:Q4 for lagged.

| | Contemperaneous Relationship | | Lagged Relationship | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | 0.0096*** | 12.5472 | 0.0096*** | 12.9098 |
| gdp | -0.0004 | -0.8649 | -0.0005 | -1.1301 |
| unemp | -0.0000 | -0.2470 | -0.0000 | -0.5721 |
| ip | 0.0003*** | 3.1566 | 0.0000*** | 3.8984 |
| housing | -0.0003 | -0.9905 | -0.0004 | -1.3315 |
| cp | 0.0001 | 0.7089 | 0.0002* | 1.7370 |
| pgdp | -0.0002** | -2.0360 | -0.0001 | -0.8363 |
| $R^2$ | 0.1629 | | 0.0541 | |
| Adj. $R^2$ | 0.1311 | | 0.0179 | |

Table 3. 30-day S&P 500 index with Macroeconomic forecasts and lagged dependent variable

This table reports the results for the following OLS regressions:

$$R_{t,30-day} = \beta_0 + \beta_1 f_t^{gdp} + \beta_2 f_t^{unemp} + \beta_3 f_t^{ip} + \beta_4 f_t^{housing} + \beta_5 f_t^{cp} + \beta_6 f_t^{pgdp} + R_{t-1,30-day} + \varepsilon_t$$

$$Vol_{t,30-day} = \beta_0 + \beta_1 f_{t-1}^{gdp} + \beta_2 f_{t-1}^{unemp} + \beta_3 f_{t-1}^{ip} + \beta_4 f_{t-1}^{housing} + \beta_5 f_{t-1}^{cp} + \beta_6 f_{t-1}^{pgdp} + Vol_{t-1,30-day} + \varepsilon_t$$

where, $R_{t,30-day}$ is the S&P 500 index return in the middle month of quarter t and $Vol_{t,30-day}$ is the S&P 500 index volatility in the middle month of quarter t. $R_{t-1,30-day}$ is the S&P 500 index return in the first month of quarter t and $Vol_{t-1,30-day}$ is the S&P 500 index volatility in the first month of quarter t. $f'$s are the forecasts of the SPF forecasters. The macroeconomic forecasts included are nominal GDP (gdp), unemployment rate (unemp), industrial production (ip), housing starts (housing), corporate profits (cp), and GDP price index (pgdp). Heteroscedasticity and autocorrelation consistent t-statistics, $R^2$ and adjusted $R^2$ values are also reported. *, **, and *** denote significance levels at 10%, 5%, and 1% respectively. The sample period is from 1968:Q4 to 2009:Q4.

| | S&P 500 Returns | | S&P 500 Volatility | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | -0.0240 | -1.4640 | 0.0053** | 2.5392 |
| gdp | 0.0041 | 0.8622 | -0.0006* | -1.8369 |
| unemp | 0.0043 | 1.5163 | 0.0001 | 0.4520 |
| ip | -0.0024 | -1.0760 | 0.0001 | 0.5548 |
| housing | 0.0000 | 0.1089 | 0.0000 | -0.5365 |
| cp | 0.0002 | 0.3989 | 0.0000 | 1.2867 |
| pgdp | -0.0049 | -0.9555 | 0.0005* | 1.6861 |
| S&P 500 Lag | 0.1664** | 2.4721 | 0.4640*** | 3.4318 |
| $R^2$ | 0.0769 | | 0.5551 | |
| Adj. $R^2$ | 0.0358 | | 0.5352 | |

Table 4. S&P 500 Index and Volatilities of Macroeconomic News Adjusted for Forecasting Uncertainty and lagged dependent variable

Panel A. This table reports the results for the following OLS regressions:

$$R_t = \beta_0 + \beta_1 \upsilon_t^{gdp} + \beta_2 \upsilon_t^{unemp} + \beta_3 \upsilon_t^{ip} + \beta_4 \upsilon_t^{housing} + \beta_5 \upsilon_t^{cp} + \beta_6 \upsilon_t^{pgdp} + \beta_7 R_{t-1} + \varepsilon_t$$

$$Vol_t = \beta_0 + \beta_1 \upsilon_t^{gdp} + \beta_2 \upsilon_t^{unemp} + \beta_3 \upsilon_t^{ip} + \beta_4 \upsilon_t^{housing} + \beta_5 \upsilon_t^{cp} + \beta_6 \upsilon_t^{pgdp} + \beta_7 Vol_{t-1} + \varepsilon_t$$

where, $R_t$ is the S&P 500 index return for the quarter t and $Vol_{t,}$ is the S&P 500 index volatility for the quarter t. $\upsilon$ is the absolute value of residuals collected from AR(1)-model of $d$, $d = \frac{\delta}{disp}$ is the forecasting error variable adjusted for forecasting uncertainty, where δ denotes the differences between actual values of macroeconomic variables and SPF forecasts, and *disp* is the cross-sectional forecasting dispersion measure defined as the difference between the 75th percentile and the 25th percentile of the SPF projections. The volatilities macroeconomic forecast errors included are nominal GDP (gdp), unemployment rate (unemp), industrial production (ip), housing starts (housing), corporate profits (cp), and GDP price index (pgdp). Heteroscedasticity and autocorrelation consistent t-statistics, $R^2$ and adjusted $R^2$ values are also reported. *, **, and *** denote significance levels at 10%, 5%, and 1% respectively. The sample period is from 1969:Q1 to 2009:Q4.

| | S&P 500 Returns | | S&P 500 Volatility | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | 0.0432*** | 2.7252 | 0.0021 | 1.4674 |
| gdp | -0.0145** | -2.3327 | 0.0010 | 1.5187 |
| unemp | 0.0013 | 0.6692 | 0.0000 | -0.1135 |
| ip | -0.0026*** | -4.5741 | 0.0003*** | 2.8194 |
| housing | -0.0036 | -0.4026 | -0.0001 | -0.2023 |
| cp | -0.0008 | -0.1580 | 0.0002 | 1.1561 |
| pgdp | -0.0031** | -2.3618 | 0.0000 | -0.0031 |
| S&P 500 Lag | 0.1263 | 1.5598 | 0.5791*** | 5.9317 |
| $R^2$ | 0.0966 | | 0.5222 | |
| Adj. $R^2$ | 0.0561 | | 0.5008 | |

Table 4. (Continued)

Panel B. This table reports the results for the following OLS regressions:

$$R_t = \beta_0 + \beta_1\sigma_t^{gdp} + \beta_2\sigma_t^{unemp} + \beta_3\sigma_t^{ip} + \beta_4\sigma_t^{housing} + \beta_5\sigma_t^{cp} + \beta_6\sigma_t^{pgdp} + \beta_7 R_{t-1} + \varepsilon_t$$

$$Vol_t = \beta_0 + \beta_1\sigma_t^{gdp} + \beta_2\sigma_t^{unemp} + \beta_3\sigma_t^{ip} + \beta_4\sigma_t^{housing} + \beta_5\sigma_t^{cp} + \beta_6\sigma_t^{pgdp} + \beta_7 Vol_{t-1} + \varepsilon_t$$

where, $R_t$ is the S&P 500 index return for the quarter t and $Vol_{t,}$ is the S&P 500 index volatility for the quarter t. $\sigma$ is a rolling summation of 4 quarters of the absolute value of residuals collected from AR(1)-model of $d$, $d = \frac{\delta}{disp}$ is the forecasting error variable adjusted for forecasting uncertainty, where δ denotes the differences between actual values of macroeconomic variables and SPF forecasts, and *disp* is the cross-sectional forecasting dispersion measure defined as the difference between the 75th percentile and the 25th percentile of the SPF projections. The macroeconomic forecast errors included are nominal GDP (gdp), unemployment rate (unemp), industrial production (ip), housing starts (housing), corporate profits (cp), and GDP price index (pgdp). Heteroscedasticity and autocorrelation consistent t-statistics, $R^2$ and adjusted $R^2$ values are also reported. *, **, and *** denote significance levels at 10%, 5%, and 1% respectively. The sample period is from 1970:Q1 to 2009:Q4.

| | S&P 500 Returns | | S&P 500 Volatility | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | 0.0548 | 1.4331 | 0.0057** | 2.4884 |
| gdp | -0.0039 | -1.1555 | -0.0001 | -0.4794 |
| unemp | 0.0006 | 0.9711 | 0.0000 | -0.9239 |
| ip | 0.0003 | 0.9522 | 0.0000* | -1.8055 |
| housing | 0.0008 | 0.1374 | -0.0006 | -1.4731 |
| cp | -0.0026 | -0.9295 | 0.0002 | 1.0039 |
| pgdp | -0.0039** | -2.2883 | 0.0001 | 1.2040 |
| S&P 500 Lag | 0.0691 | 0.8347 | 0.5732*** | 5.4488 |
| $R^2$ | 0.0500 | | 0.3883 | |
| Adj. $R^2$ | 0.0062 | | 0.3601 | |

Table 5. S&P 500 index and Monetary Shocks with Lagged Dependent variable.

This table reports the following regressions:

$$R_t = \beta_0 + \beta_1 Monetary_t + \beta_2 R_{t-1} + \varepsilon_t$$

$$Vol_t = \beta_0 + \beta_1 Monetary_t + \beta_2 Vol_{t-1} + \varepsilon_t$$

where, $R_t$ is the S&P 500 index return for a month. $Vol_t$ is the S&P 500 index volatility for a month. $Monetary_t$ is the change in the actual federal funds rate controlling for forecasts, converted to monthly and is a shock variable. Heteroscedasticity and autocorrelation consistent t-statistics, $R^2$ and adjusted $R^2$ values are also reported. *, **, and *** denote significance levels at 10%, 5%, and 1% respectively. In Panel A the sample period is from 1969:M4 to 2008:M6. In Panel B the sample period is from 1969:M4 to 1988:M12. In Panel C the sample period is from 1989:M1 to 2008:M6.

Panel A: 1969:M4 to 2008:M6.

| | S&P 500 Returns | | S&P 500 Volatility | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | 0.0062*** | 3.0037 | 0.0041*** | 5.5581 |
| Monetary | -0.0117 | -1.2775 | -0.0004 | -0.7483 |
| S&P 500 Lag | 0.0179 | 0.3613 | 0.5224*** | 6.5177 |
| $R^2$ | 0.0064 | | 0.2760 | |
| Adj. $R^2$ | 0.0022 | | 0.2730 | |

Panel B: 1969:M4 to 1988:M12.

| | S&P 500 Returns | | S&P 500 Volatility | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | 0.0049 | 1.6072 | 0.0049*** | 6.0528 |
| Monetary | -0.0133 | -1.2805 | -0.0001 | -0.2154 |
| S&P 500 Lag | 0.0498 | 0.6970 | 0.4129*** | 5.0518 |
| $R^2$ | 0.0137 | | 0.1711 | |
| Adj. $R^2$ | 0.0051 | | 0.164 | |

Table 5. (Continued)

Panel C: 1989:M1 to 2008:M6

| | S&P 500 Returns | | S&P 500 Volatility | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | 0.0076*** | 2.7959 | 0.0033*** | 6.6229 |
| Monetary | -0.0046 | -0.2554 | -0.0024* | -1.8585 |
| S&P 500 Lag | -0.0283 | -0.4363 | 0.6357*** | 11.431 |
| $R^2$ | 0.0011 | | 0.4357 | |
| Adj. $R^2$ | -0.0076 | | 0.4308 | |

Table 6. S&P 500 Index and Surprises in Macroeconomic News Adjusted for Forecasting Uncertainty: Contemporaneous and Lagged relations

Panel A. This table reports the results for the following OLS regressions:

$$R_t = \beta_0 + \beta_1 d_t^{gdp} + \beta_2 d_t^{unemp} + \beta_3 d_t^{ip} + \beta_4 d_t^{housing} + \beta_5 d_t^{cp} + \beta_6 d_t^{pgdp} + \beta_1 Monetary_t + \varepsilon_t$$

$$R_t = \beta_0 + \beta_1 d_{t-1}^{gdp} + \beta_2 d_{t-1}^{unemp} + \beta_3 d_{t-1}^{ip} + \beta_4 d_{t-1}^{housing} + \beta_5 d_{t-1}^{cp} + \beta_6 d_{t-1}^{pgdp} + \beta_1 Monetary_{t-1} + \varepsilon_t$$

where, $R_t$ is the S&P 500 index return in quarter t. $d = \frac{\delta}{disp}$ is the forecasting error variable adjusted for forecasting uncertainty, where δ denotes the differences between actual values of macroeconomic variables and SPF forecasts, and disp is the cross-sectional forecasting dispersion measure defined as the difference between the 75th percentile and the 25th percentile of the SPF projections. $Monetary_t$ is the change in the actual federal funds rate controlling for forecasts, converted to quarterly. The macroeconomic forecast errors included are nominal GDP (gdp), unemployment rate (unemp), industrial production (ip), housing starts (housing), corporate profits (cp), and GDP price index (pgdp). Heteroscedasticity and autocorrelation consistent t-statistics, $R^2$ and adjusted $R^2$ values are also reported. *, **, and *** denote significance levels at 10%, 5%, and 1% respectively. The sample period is from 1969:Q2 to 2008:Q2 for contemporaneous and 1969:Q3 to 2008:Q3 for lagged.

| | Contemporaneous Relationship | | Lagged Relationship | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | 0.018*** | 2.6199 | 0.0178*** | 2.7015 |
| Monetary | -0.0007 | -0.1236 | 0.0024 | 0.6556 |
| S&P 500 Lag | -0.0007 | -0.5626 | -0.0003 | -0.4966 |
| ip | -0.002* | -1.6703 | -0.0006 | -0.6013 |
| housing | 0.0076 | 1.3432 | 0.0045 | 0.8793 |
| cp | -0.0041 | -1.3009 | -0.0046* | -1.668 |
| pgdp | -0.0048** | -2.044 | -0.0034*** | -2.6336 |
| Monetary | -0.0093 | -1.1011 | -0.0065 | -0.6953 |
| $R^2$ | 0.0811 | | 0.0316 | |
| Adj. $R^2$ | 0.0379 | | -0.0139 | |

Table 6. (Continued)

Panel B. This table reports the results for the following OLS regressions:

$$Vol_t = \beta_0 + \beta_1 d_t^{gdp} + \beta_2 d_t^{unemp} + \beta_3 d_t^{ip} + \beta_4 d_t^{housing} + \beta_5 d_t^{cp} + \beta_6 d_t^{pgdp} + \beta_1 Monetary_t + \varepsilon_t$$

$$Vol_t = \beta_0 + \beta_1 d_{t-1}^{gdp} + \beta_2 d_{t-1}^{unemp} + \beta_3 d_{t-1}^{ip} + \beta_4 d_{t-1}^{housing} + \beta_5 d_{t-1}^{cp} + \beta_6 d_{t-1}^{pgdp} + \beta_1 Monetary_{t-1} + \varepsilon_t$$

where, $Vol_t$ is the S&P 500 index volatility in quarter t. $d = \frac{\delta}{disp}$ is the forecasting error variable adjusted for forecasting uncertainty, where δ denotes the differences between actual values of macroeconomic variables and SPF forecasts, and disp is the cross-sectional forecasting dispersion measure defined as the difference between the 75th percentile and the 25th percentile of the SPF projections. $Monetary_t$ is the change in the actual federal funds rate controlling for forecasts, converted to quarterly. The macroeconomic forecast errors included are nominal GDP (gdp), unemployment rate (unemp), industrial production (ip), housing starts (housing), corporate profits (cp), and GDP price index (pgdp). Heteroscedasticity and autocorrelation consistent t-statistics, $R^2$ and adjusted $R^2$ values are also reported. *, **, and *** denote significance levels at 10%, 5%, and 1% respectively. The sample period is from 1969:Q2 to 2008:Q2 for contemporaneous and 1969:Q3 to 2008:Q3 for lagged.

| | Contemporaneous Relationship | | Lagged Relationship | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| const | 0.0089*** | 19.5413 | 0.0091*** | 17.7717 |
| Monetary | 0.0001 | 0.6298 | 0.0000 | 0.0695 |
| S&P 500 Lag | 0.0000 | -0.4979 | 0.0000 | -0.9828 |
| ip | 0.0003*** | 3.3029 | 0.0001*** | 5.2029 |
| housing | -0.0001 | -0.3683 | -0.0003 | -1.0119 |
| cp | 0.0000 | 0.1073 | 0.0002 | 1.2159 |
| pgdp | -0.0001 | -1.3018 | -0.0001 | -0.6075 |
| Monetary | -0.0004 | -0.9983 | -0.0004 | -0.9316 |
| $R^2$ | 0.2529 | | 0.0324 | |
| Adj. $R^2$ | 0.2178 | | -0.0131 | |

Table 7. The OJE and Term Premium: 1954 to 2009

This table reports the OJE with term premium (TP) results using monthly CRSP value weighted (VWR) and equal-weight (EWR) index returns from 1954 to 2009. TP is defined as the difference between yields on 10-year and 1-year Treasures. I include results for both raw returns and excess returns. $R_f$ denotes the monthly risk-free rate. I estimate the following five models:

$$\text{Model 20: } r_t = \propto + \beta D_t^{Jan} + \varepsilon_t$$

$$\text{Model 21: } r_t = \propto + \beta D_t^{TP} + \varepsilon_t$$

$$\text{Model 22: } r_t = \propto + \beta D_t^{Jan-TP} + \varepsilon_t$$

$$\text{Model 23: } r_t = \propto + \beta D_t^{TP-Jan} + \varepsilon_t$$

$$\text{Model 24: } r_t = \propto + \beta D_t^{TPxJan} + \varepsilon_t$$

where $r_t$ is the 11-month return over February to December in year t, $D_t^{Jan}$ is the January dummy that equals one if the January return for the CRSP index is positive and is zero otherwise. $D_t^{TP}$ is the term premium dummy variable that equals one when term premium is positive and zero otherwise. $D_t^{Jan-TP}$ is a dummy variable that equals one if $D_t^{Jan}$ = 1 and $D_t^{TP}$ = 0, and equals 0 otherwise. $D_t^{Jan-TP}$ is a dummy variable that equals one if $D_t^{TP}$ = 1 and $D_t^{Jan}$ = 0, and equals 0 otherwise. $D_t^{TPxJan}$ is a dummy variable that equals one if $D_t^{Jan}$ = 1 and $D_t^{TP}$ = 1, and equals 0 otherwise. Panel A to E report the results for Models 1 to 5 respectively. For each panel, I report the mean returns for the two cases where the dummy variables equal one and zero. The return spreads and their t-statistics (in parentheses) are also included. N denotes the number observations for each value of the dummy variables. *, **, and *** denote significance levels at 10%, 5%, and 1% respectively.

Panel A: Model 20

| | VMR – $R_f$ | VWR | EWR – $R_f$ | EWR |
|---|---|---|---|---|
| Mean Return (%),$D_t^{Jan}$ = 1 | 10.70 | 14.16 | 9.31 | 12.89 |
| N | 34 | 35 | 42 | 44 |
| Mean Return (%),$D_t^{Jan}$= 0 | -1.84 | 4.15 | -5.45 | 0.27 |
| N | 22 | 21 | 14 | 12 |
| Spread (%) | 12.54 | 10.02 | 14.76 | 12.62 |
| t-value | (3.03)*** | (2.32)** | (2.09)** | (1.67) |

Table 7. (Continued)

Panel B: Model 21

| | $VMR - R_f$ | VWR | $EWR - R_f$ | EWR |
|---|---|---|---|---|
| Mean Return (%),$D_t^{TP} = 1$ | 8.50 | 12.82 | 7.87 | 12.08 |
| N | 43 | 43 | 43 | 43 |
| Mean Return (%),$D_t^{TP} = 0$ | -3.24 | 2.44 | -1.83 | 3.92 |
| N | 13 | 13 | 13 | 13 |
| Spread (%) | 11.73 | 10.37 | 9.70 | 8.17 |
| t-value | (2.38)** | (2.08)** | (1.31) | (1.09) |

Panel C: Model 22

| | $VMR - R_f$ | VWR | $EWR - R_f$ | EWR |
|---|---|---|---|---|
| Mean Return (%),$D_t^{Jan-TP} = 1$ | 1.10 | 2.08 | 3.33 | 8.10 |
| N | 6 | 7 | 9 | 10 |
| Mean Return (%),$D_t^{Jan-TP} = 0$ | 6.33 | 11.60 | 6.06 | 10.64 |
| N | 50 | 49 | 47 | 46 |
| Spread (%) | -5.23 | -9.51 | -2.73 | -2.54 |
| t-value | (-0.74) | (-1.46) | (-0.32) | (-0.30) |

Panel D: Model 23

| | $VMR - R_f$ | VWR | $EWR - R_f$ | EWR |
|---|---|---|---|---|
| Mean Return (%),$D_t^{TP-Jan} = 1$ | 0.55 | 4.66 | -2.26 | 3.71 |
| N | 15 | 15 | 10 | 9 |
| Mean Return (%),$D_t^{TP-Jan} = 0$ | 7.68 | 12.51 | 7.33 | 11.43 |
| N | 28 | 28 | 23 | 22 |
| Spread (%) | -7.13 | -7.85 | -9.59 | -7.72 |
| t-value | (-1.47) | (-1.62) | (-1.17) | (-0.90) |

Panel E: Model 24

| | $VMR - R_f$ | VWR | $EWR - R_f$ | EWR |
|---|---|---|---|---|
| Mean Return (%),$D_t^{TPxJan} = 1$ | 12.75 | 16.87 | 10.94 | 14.30 |
| N | 28 | 28 | 33 | 34 |
| Mean Return (%),$D_t^{TPxJan} = 0$ | -1.21 | 3.63 | -2.02 | 3.83 |
| N | 28 | 28 | 23 | 22 |
| Spread (%) | 13.96 | 13.55 | 12.96 | 10.47 |
| t-value | (3.54)*** | (3.41)*** | (2.09)** | (1.64) |

Table 8. Macroeconomic Variables and OJE

This table reports the results from variations of the following regression:

$R_t^{FEB,DEC} = \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DIV_{t-1} + \beta_3 DEF_{t-1} + \beta_4 DYLD_{t-1} + \beta_5 YLD_{t-1} + \alpha_1 D_t^{JAN} + \alpha_2 R_t^{JAN} + \varepsilon_t$ where $R_t^{FEB,DEC}$ is the 11-month return from February to December in year t. The regressors are lagged macro variables from December of the prior year. They include term premium (TERM), dividend yield (DIV), default premium (DEF), three-month T-bill yield (YLD) and its de-trended version (DYLD). $R_t^{JAN}$ is the market index return in the January of year t, and $D_t^{JAN}$ is the January dummy for the year t. I also estimate the same model but use macro variables in January of t as the regressors. The sample period is from 1954 to 2009. $\bar{R}^2$ denotes the adjusted $R^2$ value of the regressions, and t-statistics are reported in parenthesis. Panels A to D report the results for value weighted excess returns (VWR – $R_f$), value weighted returns (VWR), equal weighted excess returns (EWR – $R_f$), and equal weighted returns (EWR) respectively.

Panel A: VWR - $R_f$

| | December Macro Variables | | | | January Macro Variables | | |
|---|---|---|---|---|---|---|---|
| TERM | 2.4071 | -0.6948 | -0.8677 | -1.0317 | -0.3254 | -0.5941 | -0.7954 |
| | (1.06) | (-0.30) | (-0.41) | (-0.46) | (-0.13) | (-0.27) | (-0.33) |
| DIV | 4.9320 | 6.1039 | 5.3240 | 5.3450 | 5.7730 | 5.7055 | 5.4536 |
| | (2.31) | (3.02) | (2.83) | (2.60) | (2.69) | (2.93) | (2.59) |
| DEF | 0.1645 | 6.3740 | 7.8669 | 6.8759 | 6.3034 | 7.4794 | 6.4490 |
| | (0.03) | (1.48) | (1.97) | (1.62) | (1.35) | (1.76) | (1.41) |
| DYLD | -0.0582 | | | | | | |
| | (-0.53) | | | | | | |
| YLD | | -2.6292 | -2.5324 | -2.6548 | -2.5058 | -2.4386 | -2.5539 |
| | | (-2.83) | (-2.96) | (-2.90) | (-2.67) | (-2.86) | (-2.79) |
| $D_t^{JAN}$ | | | 0.1183 | | | 0.1269 | |
| | | | (3.18) | | | (3.43) | |
| $R_t^{JAN}$ | | | | 0.6071 | | | 0.7085 |
| | | | | (1.53) | | | (1.82) |
| $\bar{R}^2$ (%) | 7.29 | 19.45 | 31.66 | 21.53 | 16.96 | 31.43 | 20.57 |

Table 8. (Continued)

Panel B: VWR

| | December Macro Variables | | | | January Macro Variables | | |
|---|---|---|---|---|---|---|---|
| TERM | 1.7899 | -0.3854 | -0.3998 | -0.7361 | -0.0562 | -0.1938 | -0.5593 |
| | (0.80) | (-0.16) | (-0.18) | (-0.32) | (-0.02) | (-0.08) | (-0.23) |
| DIV | 5.4627 | 6.2820 | 5.6622 | 5.5062 | 5.9533 | 5.8990 | 5.6176 |
| | (2.59) | (3.02) | (2.83) | (2.61) | (2.70) | (2.84) | (2.60) |
| DEF | 2.4117 | 5.9535 | 7.3129 | 6.4750 | 5.8855 | 7.2499 | 6.0476 |
| | (0.46) | (1.35) | (1.72) | (1.48) | (1.23) | (1.60) | (1.29) |
| DYLD | -0.0207 | | | | | | |
| | (-0.19) | | | | | | |
| YLD | | -1.7077 | -1.6645 | -1.7871 | -1.5953 | -1.6041 | -1.7096 |
| | | (-1.79) | (-1.83) | (-1.90) | (-1.65) | (-1.77) | (-1.81) |
| $D_t^{JAN}$ | | | 0.0972 | | | 0.1096 | |
| | | | (2.43) | | | (2.75) | |
| $R_t^{JAN}$ | | | | 0.6240 | | | 0.7524 |
| | | | | (1.53) | | | (1.89) |
| $\bar{R}^2$ (%) | 10.08 | 15.34 | 22.74 | 17.51 | 12.44 | 22.44 | 16.61 |

Panel C: EWR – $R_f$

| | December Macro Variables | | | | January Macro Variables | | |
|---|---|---|---|---|---|---|---|
| TERM | 2.3705 | -2.2678 | -3.4669 | -2.4914 | -1.2046 | -2.8693 | -1.7539 |
| | (0.73) | (-0.71) | (-1.14) | (-0.79) | (-0.36) | (-0.89) | (-0.52) |
| DIV | 5.9397 | 7.7022 | 7.4087 | 7.0783 | 7.2743 | 7.7750 | 7.1240 |
| | (1.94) | (2.72) | (2.77) | (2.49) | (2.42) | (2.76) | (2.40) |
| DEF | 2.5263 | 15.1203 | 18.0940 | 14.8626 | 14.8464 | 18.0787 | 14.2066 |
| | (0.33) | (2.51) | (3.13) | (2.49) | (2.27) | (2.90) | (2.19) |
| DYLD | -0.1690 | | | | | | |
| | (-1.07) | | | | | | |
| YLD | | -4.4856 | -4.4016 | -4.5425 | -4.2127 | -4.2376 | -4.2982 |
| | | (-3.45) | (-3.59) | (-3.53) | (-3.21) | (-3.44) | (-3.31) |
| $D_t^{JAN}$ | | | 0.1650 | | | 0.1788 | |
| | | | (2.68) | | | (2.84) | |
| $R_t^{JAN}$ | | | | 0.5542 | | | 0.5929 |
| | | | | (1.39) | | | (1.47) |
| $\bar{R}^2$ (%) | 11.16 | 25.08 | 33.19 | 26.42 | 22.59 | 32.00 | 24.32 |

Table 8. (Continued)

Panel D: EWR

| | December Macro Variables | | | | January Macro Variables | | |
|---|---|---|---|---|---|---|---|
| TERM | 1.7246 | -2.0403 | -3.6172 | -2.2696 | -0.9935 | -2.7842 | -1.5737 |
| | (0.53) | (-0.62) | (-1.14) | (-0.69) | (-0.28) | (-0.82) | (-0.45) |
| DIV | 6.5719 | 8.0021 | 7.8637 | 7.3768 | 7.5704 | 8.1499 | 7.4155 |
| | (2.15) | (2.75) | (2.84) | (2.52) | (2.45) | (2.76) | (2.42) |
| DEF | 4.7369 | 14.8479 | 17.7801 | 14.5931 | 14.5672 | 16.6484 | 13.9013 |
| | (0.62) | (2.40) | (2.97) | (2.37) | (2.16) | (2.57) | (2.08) |
| DYLD | -0.1344 | | | | | | |
| | (-0.85) | | | | | | |
| YLD | | -3.6223 | -4.1695 | -3.7272 | -3.3538 | -3.8876 | -3.4959 |
| | | (-2.71) | (-3.24) | (-2.80) | (-2.48) | (-2.97) | (-2.61) |
| $D_t^{JAN}$ | | | 0.1714 | | | 0.1701 | |
| | | | (2.57) | | | (2.49) | |
| $R_t^{JAN}$ | | | | 0.5588 | | | 0.6229 |
| | | | | (1.35) | | | (1.50) |
| $\bar{R}^2$ (%) | 9.59 | 21.21 | 29.02 | 22.48 | 18.40 | 25.96 | 20.35 |

Table 9. Macroeconomic Variables and subsequent 11-month return from February to December

This table reports the results based on the following regression where the dependent variable is the 11-month return from February to December. The regressors are lagged (from December of the prior year) macro variables term premium (TERM), dividend yield (DIV), default premium (DEF), and the de-trended three-month T-bill (DYLD). The sample period is from 1954 to 2009. E[R] denotes the excess 11-month returns from the regression. I report the mean returns (in percentage) from four scenarios where E[R] ≥ median E[R] or E[R] < median E[R] and the returns in January is positive or negative. I include the results based on the abnormal returns (residuals) and the full holding period returns based on CRSP value-weight excess returns (VWR – $R_f$), value weighted raw return (VWR), equal weighted excess returns (EWR – $R_f$), and equal weighted raw returns (EWR). The return spreads and the associated p-values (in parentheses) are also included. Panel A reports the results for the predicted model where the de-trended three-month T-bill is included. Panel B reports the results for the predictive model where non-de-trended three-month T-bill (YLD) is included.

Table 9. (Continued)

Panel A: $R_t^{FEB,DEC} = \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DIV_{t-1} + \beta_3 DEF_{t-1} + \beta_4 DYLD_{t-1} + \varepsilon_t$

| | 11- month holding period abnormal return | | | | 11- month holding period raw returns | | | |
|---|---|---|---|---|---|---|---|---|
| | Pos Jan | Neg Jan | Spread | p-value | Pos Jan | Neg Jan | Spread | p-value |
| VWR - $R_f$ | | | | | | | | |
| E[R] ≥ median E[R] | 1.876 | -7.404 | 9.280 | (0.1657) | 12.381 | 3.800 | 8.581 | (0.2649) |
| E[R] < median E[R] | 8.358 | -6.807 | 15.166 | (0.0165) | 8.294 | -5.059 | 13.354 | (0.0354) |
| VWR | | | | | | | | |
| E[R] ≥ median E[R] | 2.808 | -4.653 | 7.461 | (0.1354) | 18.650 | 11.051 | 7.600 | (0.1968) |
| E[R] < median E[R] | 4.394 | -6.816 | 11.210 | (0.1123) | 8.835 | -1.029 | 9.863 | (0.1578) |
| EWR - $R_f$ | | | | | | | | |
| E[R] ≥ median E[R] | 1.521 | -4.513 | 6.034 | (0.6714) | 13.905 | 12.474 | 1.430 | (0.9364) |
| E[R] < median E[R] | 5.771 | -13.564 | 19.335 | (0.0390) | 3.754 | -15.409 | 19.162 | (0.0217) |
| EWR | | | | | | | | |
| E[R] ≥ median E[R] | -2.618 | 2.522 | -5.140 | (0.7209) | 14.428 | 26.450 | -12.022 | (0.5512) |
| E[R] < median E[R] | 8.802 | -15.411 | 24.212 | (0.0233) | 11.047 | -12.817 | 23.864 | (0.0147) |

Table 9. (Continued)

Panel B: $R_t^{FEB,DEC} = \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DIV_{t-1} + \beta_3 DEF_{t-1} + \beta_4 YLD_{t-1} + \varepsilon_t$

| | 11- month holding period abnormal return | | | | 11- month holding period raw returns | | | |
|---|---|---|---|---|---|---|---|---|
| | Pos Jan | Neg Jan | Spread | p-value | Pos Jan | Neg Jan | Spread | p-value |
| VWR - $R_f$ | | | | | | | | |
| E[R] ≥ median E[R] | 1.753 | -2.419 | 4.172 | (0.4628) | 13.101 | 10.023 | 3.078 | (0.6529) |
| E[R] < median E[R] | 8.028 | -10.150 | 18.178 | (0.0027) | 7.654 | -10.049 | 17.703 | (0.0026) |
| VWR | | | | | | | | |
| E[R] ≥ median E[R] | 2.939 | -6.049 | 8.989 | (0.0720) | 18.708 | 10.889 | 7.820 | (0.2484) |
| E[R] < median E[R] | 4.325 | -5.790 | 10.114 | (0.1355) | 8.103 | 0.000 | 8.102 | (0.2260) |
| EWR - $R_f$ | | | | | | | | |
| E[R] ≥ median E[R] | 1.032 | -9.350 | 10.383 | (0.2880) | 15.298 | 7.508 | 7.790 | (0.5886) |
| E[R] < median E[R] | 6.642 | -13.675 | 20.317 | (0.0101) | 3.327 | -18.409 | 21.736 | (0.0059) |
| EWR | | | | | | | | |
| E[R] ≥ median E[R] | 2.223 | -9.442 | 11.665 | (0.2524) | 20.445 | 11.253 | 9.192 | (0.5306) |
| E[R] < median E[R] | 4.624 | -17.388 | 22.013 | (0.0347) | 5.994 | -15.101 | 21.095 | (0.0434) |

Table 10. The OJE after Controlling for Macroeconomic Effects

This table reports the OJE after controlling for Macroeconomic Variables using monthly CRSP value weighted (VWR) and equal weighted (EWR) index returns. I include results for both raw and excess returns $R_f$ denotes the monthly risk-free rate. I estimate the following regression models:

Model 28: $R_t^{JAN} = \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DIV_{t-1} + \beta_3 DEF_{t-1} + \beta_4 YLD_{t-1} + \varepsilon_t$

Model 29: $R_t^{JAN} = \beta_0 + \beta_1 TERM_t + \beta_2 DIV_t + \beta_3 DEF_t + \beta_4 YLD_t + \varepsilon_t$

Model 30: $R_t^{JAN} = \beta_0 + \beta_1 TERM_t + \beta_3 DEF_t + \beta_4 YLD_{t-1} + \varepsilon_t$

Where $R_t^{JAN}$ is the stock index return in January of year t. The regressors in Model 1 are lagged macroeconomic variables, term variable ($TERM_t$), dividend yield ($DIV_{t-1}$), default premium ($DEF_{t-1}$), and the three-month T-bill yield ($YLD_{t-1}$) from December of year t – 1. In Model 2 the regressors are contemporaneous macroeconomic variables, term variable ($TERM_t$), dividend yield ($DIV_t$), default premium ($DEF_t$), and the three-month T-bill yield ($YLD_t$) from January of year. In Model 3, I use the same contemporaneous regressors of Model 2 having removed dividend yield ($DIV_t$). I report the post-January 11-month returns following positive ($\varepsilon_t \geq 0$) and negative ($\varepsilon_t < 0$) Januarys. The return spreads and their P-values (in parenthesis) are also included. N denotes the number of observations. I include results from the sample of 1954 to 2009.

Panel A: Model 28

| | VWR-$R_f$ | VMR | EWR-$R_f$ | EWR |
|---|---|---|---|---|
| Mean Returns (Positive January)% | 10.55 | 15.44 | 7.99 | 12.86 |
| N | 30 | 30 | 27 | 27 |
| Mean Returns (Negative January)% | 0.26 | 4.60 | 3.42 | 7.70 |
| N | 26 | 26 | 29 | 29 |
| Spread % | 10.29 | 10.85 | 4.57 | 5.16 |
| p-value | (0.0201) | (0.0139) | (0.4676) | (0.4145) |

Table 10. (Continued)

Panel B: Model 29

| | VWR-$R_f$ | VMR | EWR-$R_f$ | EWR |
|---|---|---|---|---|
| Mean Returns (Positive January)% | 10.33 | 15.23 | 9.49 | 14.43 |
| N | 29 | 29 | 27 | 27 |
| Mean Returns (Negative January)% | 0.88 | 5.23 | 2.02 | 6.23 |
| N | 27 | 27 | 29 | 29 |
| Spread % | 9.46 | 10.00 | 7.47 | 8.20 |
| p-value | (0.0304) | (0.02197) | (0.2349) | (0.1937) |

Panel C: Model 30

| | VWR-$R_f$ | VMR | EWR-$R_f$ | EWR |
|---|---|---|---|---|
| Mean Returns (Positive January)% | 10.28 | 15.11 | 9.15 | 12.77 |
| N | 30 | 30 | 41 | 42 |
| Mean Returns (Negative January)% | 0.58 | 4.99 | -4.03 | 2.43 |
| N | 26 | 26 | 15 | 14 |
| Spread % | 9.70 | 10.12 | 13.19 | 10.34 |
| p-value | (0.0291) | (0.0225) | (0.1121) | (0.2337) |

Table 11. The OJE after Controlling for Macroeconomic Effects, Robustness Check

This table reports the OJE after controlling for Macroeconomic Variables using monthly CRSP value weighted (VWR) and equal weighted (EWR) index returns. I include results for both raw and excess returns $R_f$ denotes the monthly risk-free rate. I estimate the following regression model:

Model 31: $R_t^{JAN} = \beta_0 + \beta_1 TERM_{t-1} + \beta_2 DEF_{t-1} + \beta_3 YLD_{t-1} + \beta_4 TERM_t + \beta_5 DEF_t + \beta_6 YLD_t + \varepsilon_t$

Where $R_t^{JAN}$ is the stock index return in January of year t. The regressors in Model are lagged and contemporaneous macroeconomic variables, term variable ($TERM_{t-1}$), default premium ($DEF_{t-1}$), three-month T-bill yield ($YLD_{t-1}$), term variable ($TERM_t$), default premium ($DEF_t$), and the three-month T-bill yield ($YLD_t$) t-1 terms are from December of the previous year and t terms are January of the present year. I also estimate an alternative model where the dependent variable is the January dummy $D_t^{JAN}$. I report the post-January 11-month returns following positive ($\varepsilon_t \geq 0$) and negative ($\varepsilon_t < 0$) Januarys. The return spreads and their P-values (in parenthesis) are also included. N denotes the number of observations. I include results from the sample of 1954 to 2009 as well as 3 sub-sample periods. Panels A, B, C, and D report the results for the value weighted index excess returns, value weighted raw returns, equal weighted excess returns, and equal weighted raw returns respectively.

Panel A: VWR - $R_f$

| | $R_t^{JAN}$ | | | | $D_t^{JAN}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | 54 to 09 | 54 to 73 | 74 to 93 | 94 to 09 | 54 to 09 | 54 to 73 | 74 to 93 | 94 to 09 |
| Mean Return (Pos Jan) % | 10.38 | 8.18 | 7.16 | 9.09 | 10.79 | 11.10 | 9.57 | 11.40 |
| N | 30 | 10 | 10 | 11 | 34 | 11 | 10 | 11 |
| Mean Return (Neg Jan) % | 0.46 | 6.41 | 0.59 | 2.59 | -1.98 | 2.64 | -1.82 | -5.09 |
| N | 26 | 10 | 10 | 7 | 22 | 9 | 10 | 5 |
| Spread % | 9.92 | 1.77 | 6.57 | 6.50 | 12.77 | 8.47 | 11.39 | 16.49 |
| p-value | (0.0230) | (0.8119) | (0.2593) | (0.5770) | (0.0081) | (0.2749) | (0.0473) | (0.2626) |

Table 11. (Continued)

Panel B: VWR

| | $R_t^{JAN}$ | | | | $D_t^{JAN}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | 54 to 09 | 54 to 73 | 74 to 93 | 94 to 09 | 54 to 09 | 54 to 73 | 74 to 93 | 94 to 09 |
| Mean Return (Pos Jan) % | 15.44 | 11.62 | 14.89 | 12.61 | 14.16 | 14.44 | 12.89 | 15.29 |
| N | 30 | 10 | 10 | 11 | 34 | 11 | 11 | 11 |
| Mean Return (Neg Jan) % | 4.60 | 9.68 | 6.73 | 5.74 | 4.60 | 6.02 | 8.27 | -2.90 |
| N | 26 | 10 | 10 | 7 | 22 | 9 | 9 | 5 |
| Spread % | 10.83 | 1.93 | 8.16 | 6.87 | 9.56 | 8.42 | 4.62 | 18.19 |
| p-value | (0.0127) | (0.7858) | (0.1798) | (0.5673) | (0.0398) | (0.2559) | (0.4417) | (0.2250) |

Panel C: EWR - $R_f$

| | $R_t^{JAN}$ | | | | $D_t^{JAN}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | 54 to 09 | 54 to 73 | 74 to 93 | 94 to 09 | 54 to 09 | 54 to 73 | 74 to 93 | 94 to 09 |
| Mean Return (Pos Jan) % | 6.92 | 15.79 | 5.02 | 1.54 | 10.11 | 16.53 | 8.33 | 7.10 |
| N | 24 | 8 | 10 | 10 | 37 | 13 | 11 | 10 |
| Mean Return (Neg Jan) % | 4.14 | -0.84 | 3.57 | 10.35 | -3.13 | -14.09 | -0.64 | 6.95 |
| N | 31 | 12 | 10 | [illegible] | 19 | 7 | 9 | 6 |
| Spread % | 2.79 | 16.62 | 1.45 | -8.80 | 13.24 | 30.62 | 8.98 | 0.15 |
| p-value | (0.6504) | (0.1246) | (0.8681) | (0.4968) | (0.0584) | (0.0021) | (0.3010) | (0.9933) |

Table 11. (Continued)

Panel D: EWR

| | $R_t^{JAN}$ | | | | $D_t^{JAN}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | 54 to 09 | 54 to 73 | 74 to 93 | 94 to 09 | 54 to 09 | 54 to 73 | 74 to 93 | 94 to 09 |
| Mean Return (Pos Jan) % | 12.76 | 19.15 | 12.35 | 4.63 | 12.42 | 19.76 | 8.85 | 10.36 |
| N | 25 | 8 | 10 | 10 | 36 | 13 | 12 | 10 |
| Mean Return (Neg Jan) % | 8.11 | 2.37 | 10.07 | 13.67 | 6.17 | -10.73 | 14.76 | 10.15 |
| N | 31 | 12 | 10 | 10 | 20 | 7 | 8 | 6 |
| Spread % | 4.65 | 16.78 | 2.28 | -9.04 | 6.24 | 30.49 | -5.91 | 0.21 |
| p-value | (0.4498) | (0.1202) | (0.8027) | (0.4853) | (0.3761) | (0.0019) | (0.5179) | (0.9903) |

Figure 1. Forecasting Errors of Macroeconomic Variables

This figure plots the time series for SPF forecasting errors of for following macroeconomic variables: GDP, Unemployment Rate, Industrial Production, Housing Starts, Corporate Profits, and GDP Price Index.

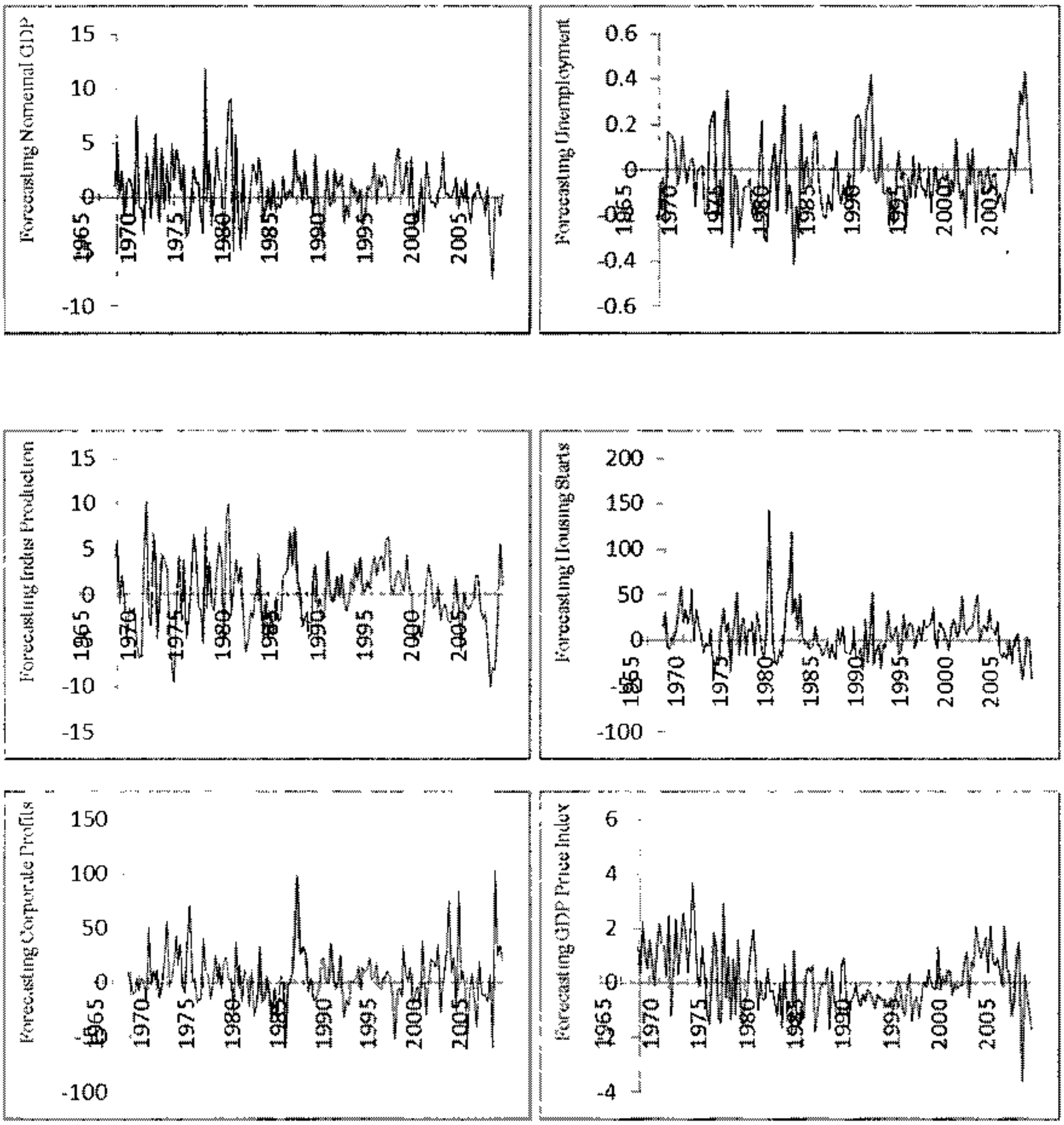


Figure 2. Forecasting Uncertainty of Macroeconomic Variables

This figure plots the time series for SPF forecasting uncertainty of for following macroeconomic variables: GDP, Unemployment Rate, Industrial Production, Housing Starts, Corporate Profits, and GDP Price Index.

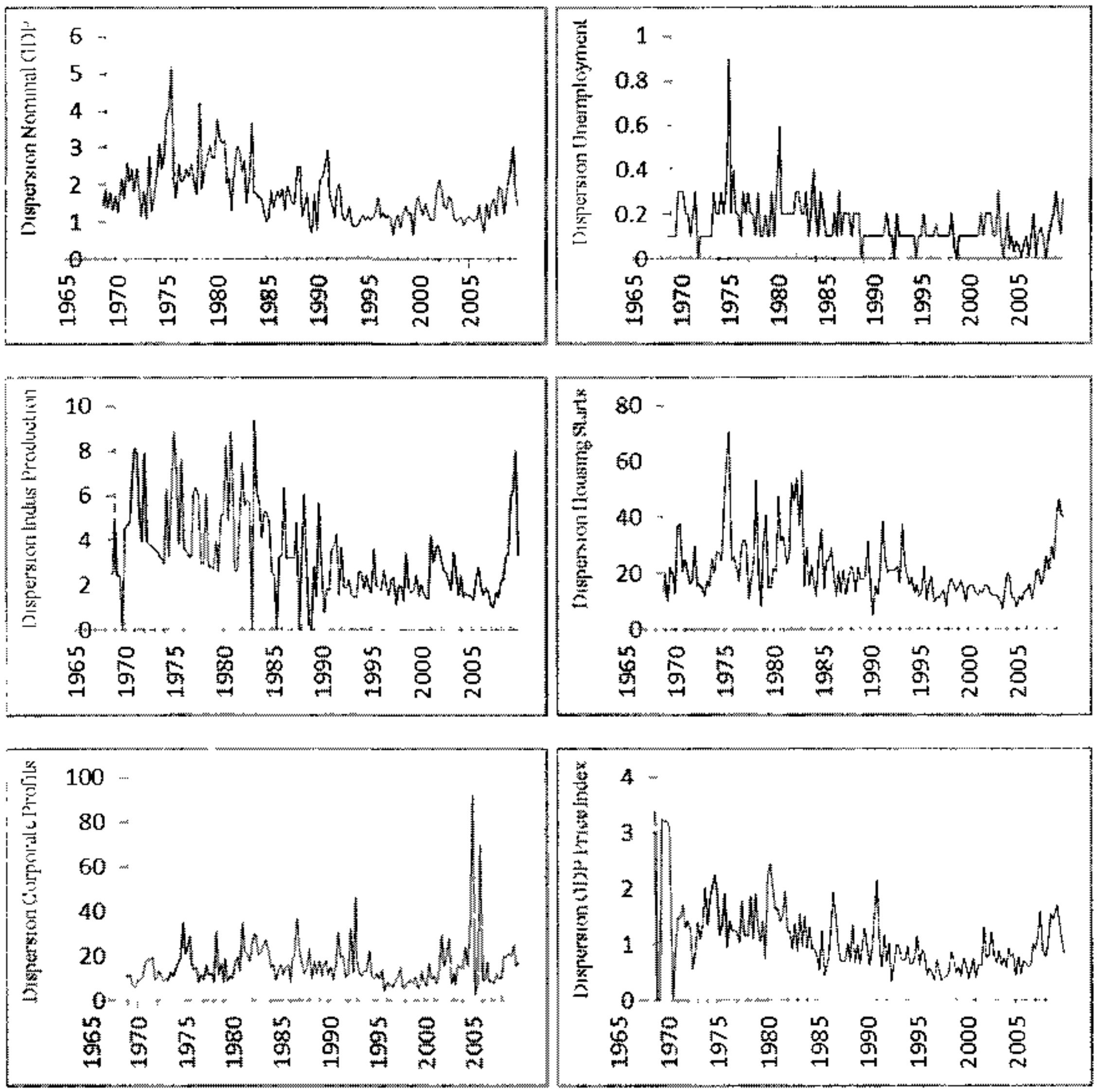


Figure 3. Uncertainty Adjusted Forecasting Errors of Macroeconomic Variables

This figure plots the time series for SPF forecasting errors adjusted for forecasting uncertainty for following macroeconomic variables: GDP, Unemployment Rate, Industrial Production, Housing Starts, Corporate Profits, and GDP Price Index.

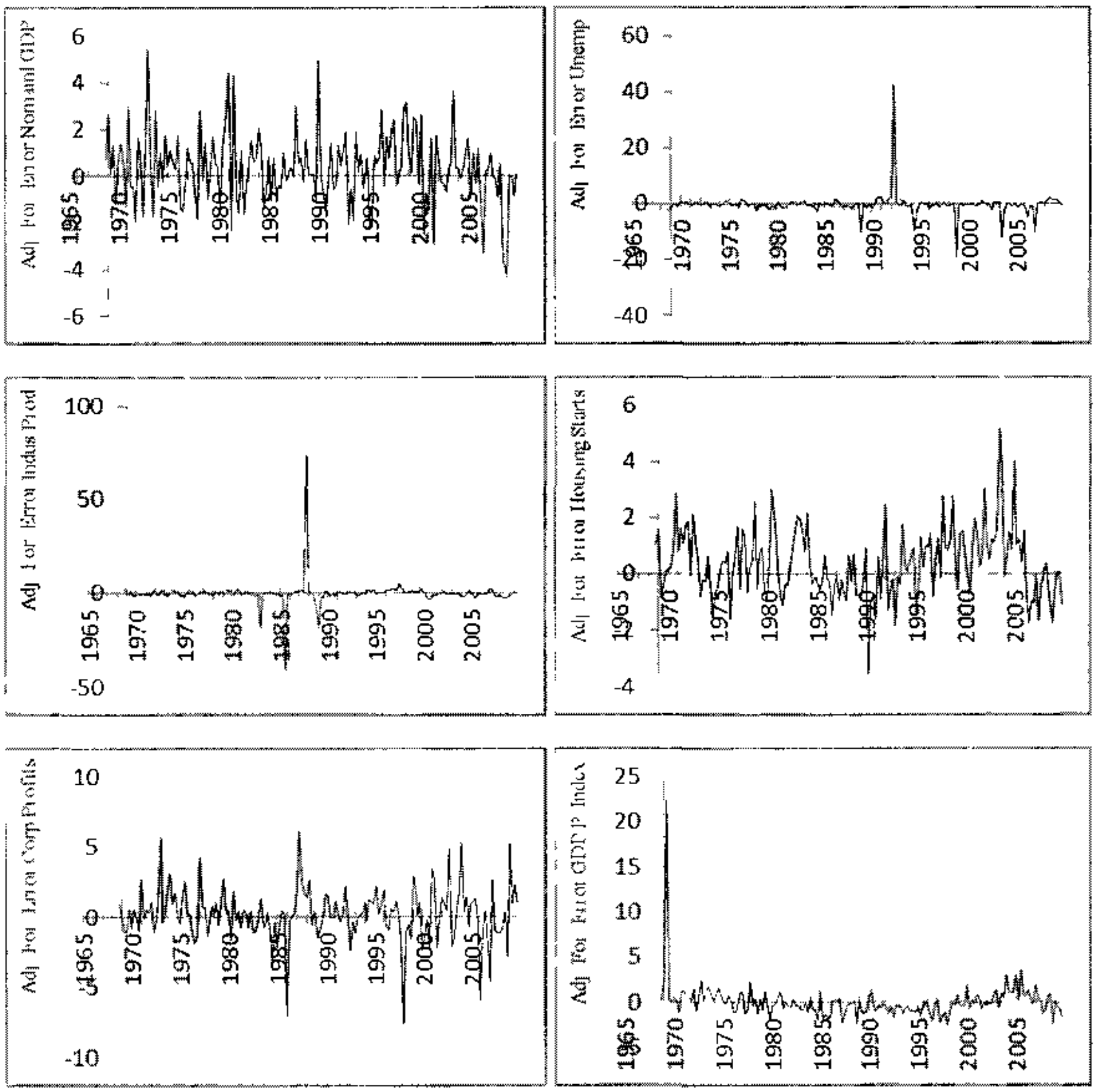
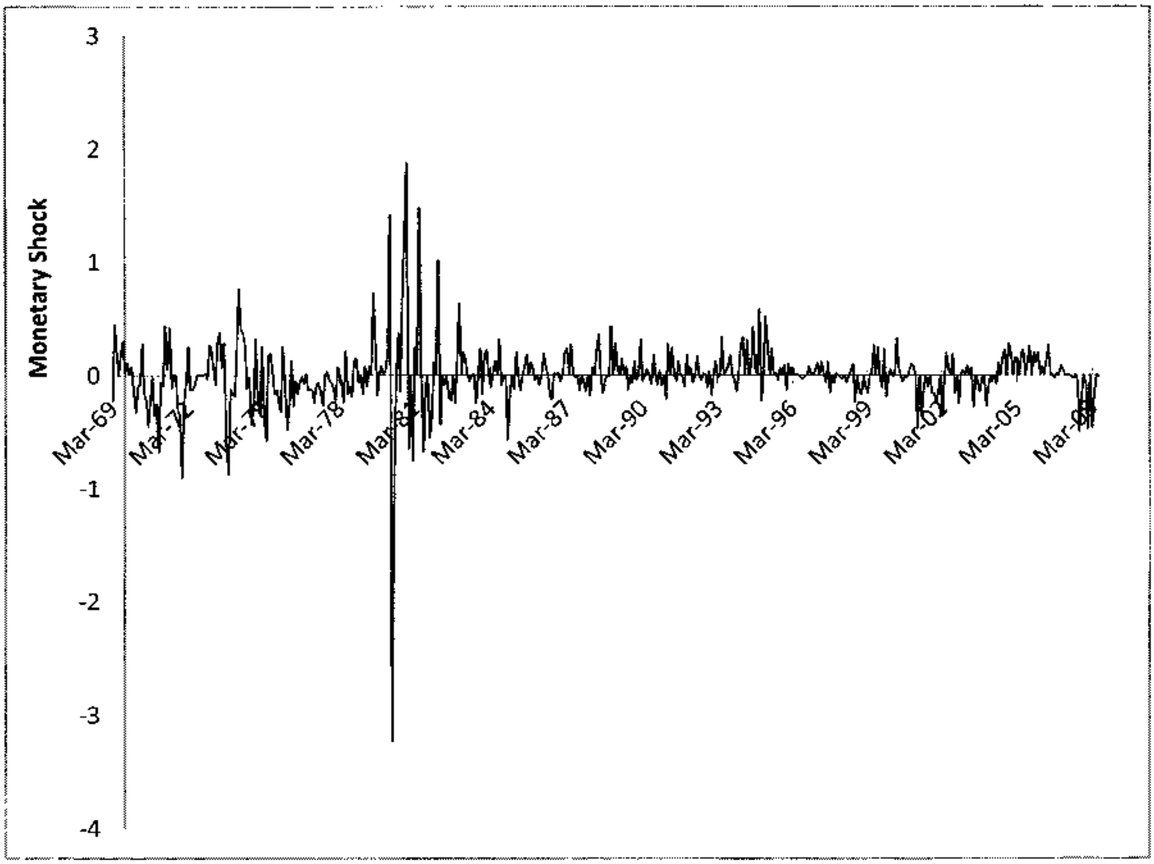


Figure 4. Monetary Shock Variable

This figure plots the monetary shock variable provided by Crowe and Barakchian (2010)



# VITA

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