

Exceeding Expectations: Economic Forecasts and Underreaction to Macroeconomic Announcements

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Abstract

Existing research relies on the assumption of rational expectations and argues that only unexpected macroeconomic announcements affect stock prices. By utilizing survey forecasts of macroeconomic statistics, we find that market participants' expectations are not rational. They systematically under-predict macroeconomic statistics and their forecast errors are predicted by past macroeconomic announcements. Most importantly, we find that the stock market does not see through this bias, i.e. we find statistically significant stock price effects of *expected* components of macroeconomic surprises. We suggest a behavioral explanation for this result since investors overweight the importance of historical information and do not make the necessary adjustments after the arrival of new information.

1. Introduction

In the past several decades, a large body of research has examined the effect of macroeconomic announcements on the stock market. While these papers differ from each other in terms of the macroeconomic factors and time periods they examine, most of them use a similar statistical model. Mainly, stock prices are regressed on the unexpected component of macroeconomic announcements, often referred to as forecast errors or surprises in this literature. Surprises are calculated as the difference between the released statistic and its expected value, which is usually measured with survey forecasts of financial market participants. Pearce and Roley (1985) were one of the first to implement this approach. They argued that while theoretically, both the expected and the unexpected components of economic announcements could affect stock prices, the empirical evidence of their study supported the Efficient Market Hypothesis (EMH) and showed that only unexpected economic news affected the S&P 500 returns during the 1977-1982 period.

Since the Pearce and Roley study, research papers have only looked at the relationship between stock prices and the unexpected component of macroeconomic announcements, thereby relying on the assumption of rational expectations and efficient markets. However, recent research in behavioral finance has shown that the behavior of stock prices is not always consistent with EMH.¹ In particular, a large subset of this research examines the stock price effects of public announcements and provides empirical evidence that stock prices may not only respond to new information [Bernard and Thomas (1989, 1990), Birz (2014), Gilbert et. al (2012), Huberman and Regev (2001), Tetlock (2011)]. Given this evidence, it is at least worth considering that there are some investors who may not be able to extract the unanticipated

¹ Hirshleifer (2001) and Barberis and Thaler (2003) provide a detailed literature review of research on market efficiency and behavioral finance.

² Please refer to Gennaioli, Ma, and Shleifer (2016) for extensive review of papers on the rationality of expectations.

component of macroeconomic announcements, resulting in them trading on expected or historic economic information.

Moreover, even if investors calculate the surprise component of macroeconomic announcements by subtracting their expected values from the released statistics, these expectations may not be formed rationally, and therefore, these surprises may not be an accurate measure of new information [Aggarwal et al. (2005), Campbell and Sharpe (2009)].

A growing literature in macroeconomics and finance employs survey data to measure expectations of economic agents. For example, Gennaioli, Ma, and Shleifer (2016) claim that expectations impact behavior of individuals and survey data provides an invaluable insight into how these expectations are formed. Consequently, the authors argue that rational expectations should not be automatically assumed since the availability of survey expectations data allows to test whether this is a plausible assumption. Interestingly, many recent papers that employ surveys to understand behavior of economic agents reject the assumption of rationality and find that while expectations predict behavior, they are often biased and inefficient [Ang, Bekaert, and Wei (2007), Campbell and Sharpe (2009), Frankel and Froot (1987), Gennaioli, Ma, and Shleifer (2016), Greenwood and Shleifer (2014), Piazzesi, Solamano, and Schneider (2015), Soules (2004)]².

Research on stock price effects of macroeconomic news has also recognized the importance of survey forecasts to measure expectations of market participants. For more than three decades, researchers have been using Money Market Services (MMS) survey of market participants to measure investors' expectations of macroeconomic statistics [e.g. Andersen, Bollerslev, Diebold, and Vega (2003, 2007), Balduzzi, Elton, and Green (2001), Campbell and

² Please refer to Gennaioli, Ma, and Shleifer (2016) for extensive review of papers on the rationality of expectations.

Sharpe (2009), Flannery and Protopapadakis (2002), McQueen et. al (1993)]. While some tested these forecasts for rationality and found systematic errors in market participants' expectations, most papers in this literature do not test whether these errors impact stock prices.³

Thus, the objective of our paper is two-fold. First, we perform several tests to determine whether survey expectations of macroeconomic statistics are formed rationally. To do this, we follow the methodology of the papers referenced above, as well as the methodology of Aggarwal et al. (2005), who specifically test rationality of MMS surveys. We find that while these expectations do predict economic statistics, they tend to be biased. Specifically, they systematically under-predict actual economic statistics and the forecast errors, i.e. surprises, are predicted by the values of past macroeconomic announcements.

These findings are consistent with a broader finance and economics literature that documents statistically significant correlations between survey expectations and past data [e.g. Bacchetta et al. (2009), De Bondt (1993), Gennaioli, Ma, and Shleifer (2016), Greenwood and Shleifer (2014), Nordhaus (1987)]. Moreover, the findings are also consistent with Campbell and Sharpe (2009), who focus on MMS forecasts and adopt a model similar to Aggarwal et al. (2005). They find evidence of “anchoring bias” – macroeconomic surprises are correlated with the values of past macroeconomic announcements – and investigate whether the bias impacts the bond market.

Similarly to Campbell and Sharpe (2009), we believe that our result implies that market participants underweight new information and put too much weight on historical announcements when they forecast macroeconomic statistics. More importantly, since the market participants' expectations are biased towards past data, then the forecast errors, which are commonly used by

³ Campbell and Sharpe (2009), who find that MMS forecasters make systematic errors, examine whether biased expectations impact the bond market.

researchers to measure macroeconomic surprises, do not only capture the unexpected component of macroeconomic announcements.

Consequently, our second and main objective is to examine whether the stock market can see through this bias. Specifically, we test whether stock prices are correlated with the component of surprises predicted by past announcements or whether stock prices only respond to truly new information, i.e. unanticipated components of these surprises. We test our hypothesis in two ways. First, we econometrically decompose the value of the surprise into the component formed by past announcements and the component that contains unanticipated information, and then compare both components to stock prices. Our findings show that the stock market does not see through the bias. We find statistically and economically significant relationship between the S&P 500 returns and the component of the surprises formed by the past announcements.

In our second approach, we implement the unrestricted model proposed by Pearce and Roley (1985, p. 62). In other words, we do not assume that the stock price effect of expected macroeconomic information is statistically equal to zero. Similarly to the results of the first approach, we find that expected macroeconomic information impacts stock prices regardless of whether it is measured with survey forecasts or the average value of past announcements.

In summary, our paper provides two significant contributions to existing research. First, we contribute to the research on asset price effects of macroeconomic news, which currently documents that surprises contain only new information and that only unexpected macroeconomic information affects stock prices. [Andersen et al. (2007), Boyd et. al. (2005), Chen, Roll, and Ross (1986), Jain (1988), McQueen and Roley (1993), Pearce and Roley (1985)]. While we are not the first to find that survey expectations of macroeconomic announcements are biased towards historical announcements, to our knowledge, we are first to find that the stock market

does not see through this bias, i.e. that the historical component of economic surprises may also affect stock prices. This finding may mean that investors, perhaps due to the effects of systematic cognitive biases, underweight the importance of new information and trade on *expected* or historical macroeconomic information embedded in these forecasts.

Interestingly, our findings also indicate that not only individual and unsophisticated investors are prone to judgment and decision-making errors, which was the belief of some early papers in behavioral finance. MMS forecast, the most popular source of economic forecasts in this literature, surveys market participants that include economists and strategists from major commercial banks, top brokerage houses, consulting firms and fund management companies.

Our second contribution is to the debate on the importance of survey data for research in finance. Gennaioli et al. (2016, p. 380) point out that survey data is not viewed as a valuable source of information in finance research, and therefore, they are not often used. Similarly to Gennaioli et al. (2016) and Greenwood and Shleifer (2014), we find that survey expectations provide insight into investor behavior and their subsequent impact on financial markets.

Throughout the paper, we focus on monthly nonfarm payroll employment (NFE) releases. We do this for two reasons. First, the existing research argues that employment announcements are the most influential announcements for asset prices among all macroeconomic releases [Andersen and Bollerslev (1998), Andersen et al. (2007), Carnes et al. (1991), Lahaye et al. (2011)]. Second, very little is known about the rationality of NFE forecasts and their impact on stock prices. Aggarwal et al. (2005) find systematic errors in MMS forecasts of various macroeconomic statistics, however they do not look at NFE statistics and they do not consider whether these errors impact asset prices. Campbell and Sharpe (2009), who find that MMS forecasts of NFE statistics are biased, argue that employment announcements have the

biggest impact on financial markets. However, they only consider the bond market.

2. Data

The expectations on NFE statistics are measured with survey forecasts collected by MMS, the most popular source of economic forecasts in existing literature on stock price effects of macroeconomic news. Every Friday, MMS surveys market participants on the variables scheduled to be released during the following week. Thus, in the case of NFE, MMS forecasts are made public 5 days before the official releases. The surveys are conducted in the morning by phone, email or fax and the results of the surveys become available in the late afternoon. MMS data were purchased from Haver Analytics. According to Haver Analytics, MMS conducts weekly surveys of market participants, which include professionals from major commercial banks, brokerage houses, consulting firms and fund management companies.⁴

The Bureau of Labor Statistics releases the official data on NFE at 8:30 AM on the first Friday of each month. The data were obtained from FRED database at the Federal Reserve Bank of St. Louis. Table 1 provides summary statistics on the released NFE data, their MMS forecasts, and surprises calculated as the difference between statistics and MMS forecasts.

The time series of closing prices on the S&P 500 were obtained from CRSP for the period between January 1, 1992 and December 31, 2008. We exclude the post-2008 time period in order to avoid contamination with confounding effects of expansionary monetary policy and quantitative easing (QE) programs, which have dominated equity markets since the end of 2008. However, in Appendix A1, we provide robustness tests using the entire sample, as well the

⁴ According to Haver Analytics, MMS has the most complete history of consensus data (forecast survey medians) and “as first reported” (unrevised) actuals of major macroeconomic indicators for the U.S., Canada, 20 European countries, Japan, Australia and several Asian countries.

detailed discussion on sample selection. Moreover, in our 17-year sample, four NFE release days coincided with Good Friday, during which the stock market was closed. Consequently, the sample consists of 200 observations.⁵

3. Testing Rationality of Survey Expectations.

One of the most common tests of rational expectations in existing research is to regress realized statistics on their ex ante survey forecasts. For example, Ang, Bekaert, and Wei (2007), Mehra (2002), and Thomas (1999) use this method to test whether survey forecasts of inflation are biased. Following the same approach, Gennaioli et al. (2016) test the rationality of CFO and analyst survey expectations of future earnings growth. Aggarwal et al. (2005) examine the rationality of MMS forecasts using the above stated method. Consequently, we follow these researchers and use the same specification:

$$NFE_t = \alpha_0 + \alpha_1 NFE_t^e + \varepsilon_t \quad (1)$$

where NFE_t denotes realized value of nonfarm employment released at time t . NFE_t^e denotes ex ante forecasts of nonfarm employment, and ε_t is an error term.⁶

Rational expectations implies that $\alpha_0 = 0$ and $\alpha_1 = 1$. We test this hypothesis and report the results in Table 2, Panel A. As indicated by both coefficients, the hypothesis that expectations are rational is rejected at the 1% level. We also report the results of the Wald test that both coefficients simultaneously equal to zero. This hypothesis is also rejected at the 1% level. Moreover, $\alpha_1 > 1$ implies that forecasters systematically under-predict NFE statistics.

⁵ The following days of unemployment and NFE releases coincided with Good Friday: April 1, 1994; April 5, 1996; April 2, 1999; April 6, 2007.

⁶ Because of a small sample size, we compute bootstrapped standard errors for all regressions in the paper in order to provide more accurate statistical inference (see Efron (1979)). We also estimate the model with Newey-West standard errors as a robustness check. The statistical significance remains the same. These results are not reported here but can be made available by request.

This result is consistent with Aggarwal et al. (2005). While they do not look at NFE series, they find systematic biases in expectations of other macroeconomic statistics by utilizing MMS forecasts and the model in equation (1) [(Aggarwal et al. (2005), pg. 107]. Furthermore, the authors argue that the results of this test are meaningful only if both realized NFE and expected NFE are stationary. Alternatively, if both series follow the unit root process, then the statistical inference from the rationality test in equation (1) may lead to erroneous conclusions and the additional cointegration tests need to be performed.

To examine the stability of our data, we utilize the augmented Dickey-Fuller model (ADF) and test NFE statistics and their forecasts for stationarity. The results, which are reported in Panel B of Table 2, show that both realized and forecasted NFE are stationary in levels and first differences. For each tested series, the null hypothesis that the series follows a unit root process is rejected at the 1% level.

In addition to the rationality test in equation (1), existing research conducts other tests to examine the nature of the biases that may impact forecasters. As previously mentioned, a number of these papers find that forecasters tend to overweight the importance of old information. According to the rational expectations hypothesis, forecast errors – the difference between the realized data and the expected data – should be unpredictable, i.e. they should be orthogonal to all available and previously released information. To test this hypothesis, researchers regress forecast errors on past data using the following specification:

$$Y_t - E(Y_t) = \gamma_0 + \gamma_1 Y_{t-m} + v_t \quad (2)$$

The rational expectations hypothesis is rejected if γ_1 is statistically different from 0. For example, Gennaioli et al. (2016, pg. 417) follow this approach and find that forecast errors of CFOs predicting earnings growth are correlated with past profitability and GDP growth. Based

on this result, the authors argue that CFO expectations of earnings growth are not rational. Bacchetta et al. (2009) use survey data and find that forecast errors in excess returns on stock, forex, and bond markets are predictable by previously released data relevant to these financial markets. Frankel and Froot (1987) reject rational expectations after finding that exchange rate forecast errors are predicted by lagged spot rates. Consequently, we also employ the model in equation (2) as our second test of rational expectations. Specifically, we examine whether NFE surprises are predicted by past NFE announcements.

There is already some evidence that the forecast errors derived from MMS surveys may be correlated with past economic announcements. For example, Aggarwal et al. (2005) show that these errors, often referred as surprises in this literature, may be correlated with values of previous five economic announcements.⁷ In a similar model, Campbell and Sharpe (2009) document that NFE surprises are correlated with the average value of the three previous announcements.⁸

Given this evidence, we also examine whether NFE surprises are predicted by the values of the previous three announcements, as well as the previous five announcements. We utilize the following specification:

$$NFE_t - E(NFE_t) = \gamma_0 + \gamma_1 \overline{NFE}_{-m} + v_t \quad (3)$$

where $\overline{NFE}_{-m}$ is either the average value of previous three announcements or the average value of previous five announcements. To ensure that the results are not impacted by a small number of outliers, we follow previous research and use Huber (1981) M-estimator that produces robust

⁷ Aggarwal et al. (2005) run the following regression: $Y_t = \beta_0 + \beta_1 E(Y_t) + \beta_2 Y_t^{AR} + \varepsilon_t$. Please note that if $E(Y_t)$ is subtracted from both sides, then Aggarwal et al. (2005) model become similar to the model in a broader literature (i.e. the model in our equation 2 and equation 3). Y_t^{AR} is derived from a simple AR model with 5 lags of past economic announcements. The authors reject rationality based on the fact that β_2 is positive and statistically significant.

⁸ Campbell and Sharpe (2009) explain that their model is somewhat different from Aggarwal et al. (2005) due to the objectives of their study.

estimates in the presence of outliers [for example, see Garcia (2012)].

The results are reported in Table 3. In the first two rows, we show two regressions examining whether NFE surprises are affected by three lags of past announcements and five lags, respectively. In both cases, γ_1 is statistically significant at the 1% level, which implies that NFE forecasts are biased and can be systematically predicted by past announcements. Moreover, the coefficients from both regressions indicate that anywhere between 14% and 17% of market participants' forecasts is based on the values of past announcements.

Contrary to the findings of Campbell and Sharpe (2009) with respect to other macroeconomic variables, our findings show that the forecasters of NFE do not seem to be sophisticated enough to treat later lags as less important. This is indicated by the fact that the coefficient on $\overline{NFE}_{-5}$ is not lower than the coefficient on $\overline{NFE}_{-3}$. In fact, this evidence may be consistent with findings of other papers that forecasters exhibit extrapolative behavior. Specifically, our result may indicate that market participants follow trends and are more likely to rely on past announcements if the trend persists for a longer time period. Finally, in the third row, we check the robustness of our result by following Aggarwal et al. (2005). Instead of the average values of the previous five NFE announcements, we use the forecast from a simple AR model with 5 lags. The results are even stronger than those with the average values of the previous five releases shown in the second row.

4. Does the Stock Market See Through the Bias?

Historically, existing research on stock price effects of macroeconomic news utilized the following specification:

$$R_t = \beta_0 + \beta_1 S_t + \epsilon_t \quad (4)$$

where R_t denotes the difference in closing prices during the release day of macroeconomic statistics. S_t denotes surprises calculated as the difference between the released statistic and its expected value measured with surveys that are collected earlier. To ensure easy interpretations, it is customary in the existing literature to standardize surprises as in Andersen, Bollerslev, Diebold, and Vega (2003, 2007):

$$S_{k,t} = \frac{(A_{k,t} - F_{k,t})}{\sigma_k} \quad (5)$$

where $A_{k,t}$ is the value of the released statistic k , $F_{k,t}$ is the expected value of the statistic k provided by MMS forecasts, and σ_k denotes the sample standard deviation of $A_{k,t} - F_{k,t}$.

As mentioned before, by utilizing the specification in equation (4), researchers make a significant assumption that the stock market is informationally efficient, i.e., that expectations ($F_{k,t}$) are rational and surprises ($S_{k,t}$) only capture unexpected and new information. However, as we show in the previous section, NFE expectations are not formed rationally, and surprises are predicted by past announcements. This means that surprises do not only contain only unexpected and new information.

In this section, we test whether the stock market can see through this bias, i.e. whether the market participants and stock prices only respond to new information. In our first test, we follow Campbell and Sharpe (2009) and econometrically decompose the value of the surprise (S_t) into the component predicted by past announcements and the residual component of the surprise that represents unexpected information. We then compare both components to stock returns using the following specification:

$$R_t = \beta_0 + \beta_1 S_t^e + \beta_2 (S_t - S_t^e) + \epsilon_t \quad (6)$$

where R_t denotes the percentage change in the closing price on the S&P 500 at time t , the

release day of the NFE statistics, and the closing price at time $t-1$. S_t^e represents the expected or stale component of each NFE surprise predicted by the model in equation (3):

$$S_t^e \equiv \widehat{NFE_t - NFE_t^e} = \gamma_0 + \gamma_1 \overline{NFE_{-m}} + v_t,$$

where $\overline{NFE_{-m}}$ is either the average value of previous three announcements or the average value of previous five announcements).⁹ S_t is the NFE surprise calculated as the difference between the announced value of the release and the forecast as in equation (5). Therefore, $S_t - S_t^e$ denotes the unexpected component of the surprise S_t and represents the “true” measure of new information.

In equation (6), we test EMH and the type of information that affects stock prices. If $\beta_1 = 0$, then the stock market is informationally efficient. This would mean that market participants can anticipate biased expectations and do not trade on stale information. Alternatively, if β_1 is statistically different from zero, this would indicate that the stock market does not see through the bias and that some investors trade on past macroeconomic announcements. The results are shown in Table 4.

In regressions (1) and (2), $\beta_1 > 0$ and the coefficients are statistically significant at the 1% level. For example, a one-standard deviation increase in the predictable component of NFE surprise increases S&P 500 returns by 1.26%. These results are also robust to standard time series controls. In regressions (3) and (4), we include two lags of S&P 500 returns to control for residual autocorrelation, a January dummy to control for the “January effect,” and a Friday dummy to control for the “weekend effect”. We also ensure that our results are not driven by past return-volume interactions as in Campbell, Grossman and Wang (1993). Therefore, we include two lags of S&P 500 returns multiplied by the detrended natural logarithm of S&P 500 volume for the same time period as part of the control variables. The results do not change even after we

⁹ For consistency purposes and ease of interpretation, we standardized both the surprise and past announcements in equation (3) by dividing them by their standard deviation.

include these control variables. In both regressions, the coefficient on S_t^e is greater than zero and it remains statistically significant at least at the 5% level. In summary, the results of Table 4 indicate that stock prices are impacted by predictable component of NFE surprises, which implies that some investors overweight the importance of historic information and that the stock market may be informationally inefficient.

To ensure that the above results are not driven by a choice of an econometric model, we continue to examine whether stock prices are affected by stale information on NFE by implementing a different model, i.e. the Pearce and Roley unrestricted model. Pearce and Roley (1985) postulate that theoretically, both the expected and the unexpected components of economic announcements could affect stock prices and present the following model:

$$R_t = \delta_0 + \delta_1 S_t + \delta_2 F_t + \epsilon_t \quad (7)$$

where R_t denotes closing stock returns on the release day of the macroeconomic statistics. F_t is the expected value of each statistics measured with MMS forecasts that are available prior to the release of macroeconomic statistics, and S_t denotes the surprise. Pearce and Roley (1985) then assume that the stock market is informationally efficient ($\delta_2 = 0$) and proceed to test the restricted model ($R_t = \delta_0 + \delta_1 S_t + \epsilon_t$).

Given the results presented earlier in this section, we hypothesize that some investors may overweight the importance of past information when they trade on macroeconomic factors. As a result, expected information about NFE may also impact stock returns, in which case we should observe a statistically significant correlation between stock returns and MMS forecasts on NFE in equation (7), i.e., $\delta_2 \neq 0$. The results, which are reported in regressions (1) and (4) of Table 5, show that the coefficient on F_t is greater than zero, and is statistically significant at least

at the 5% level.¹⁰

Moreover, in the remaining regressions of Table 5, we examine whether stock returns are correlated with past announcements in a simpler setting than the one presented in Table 4. In univariate regressions (2) and (5), we find a statistically significant correlation between the S&P 500 returns on the NFE release day and the average value of the previous three announcements. In regressions (3) and (6), we find the impact of the past five NFE announcements on the contemporaneous S&P 500 returns, and the coefficients are statistically significant at the 1% level. In summary, these results confirm the result of Table 4 in showing that the stock market participants may trade on stale information and that the stock prices may be informationally inefficient.

5. Behavioral Explanation

The results of Tables 2 - 5 suggest a behavioral explanation for stock price effects of expected economic announcements. According to EMH, only new economic information should impact stock prices. In contrast, our findings show that NFE forecast errors are predicted by past announcements and the stock market responds to the stale component of NFE surprises. These results suggest that some investors may overvalue the importance of historical information for forecasting future economic conditions and stock returns, even after new information is already publicly available. Research in experimental psychology may explain this type of behavior.

Edwards (1968) finds that individuals do not update their beliefs enough or as much as

¹⁰ Previous research on stock price effects of macro news finds that the effect of macroeconomic surprises may vary with the state of the business cycle. Therefore, we also check whether the effect of stale NFE news is state dependent. The results, reported in the Appendix Table B1, confirm the results in Table 4. The coefficient on S_t^e is statistically different from zero at the 1% level in expansions. None of the coefficients are statistically significant in recession. However, since there are only 19 months of recession in the sample, this result may be a consequence of insufficient statistical power.

Bayesian agent would after the arrival of new information. In his experiment, individuals tend to underweight new data and tend to rely more on past data. The author calls this tendency a *conservatism bias*. In behavioral finance literature, Barberis et al. (1998, p. 315), who find evidence of underreaction, argue that conservatism bias could explain why individuals may disregard the “full information content” of new public announcements and rely more on past data. Hirshleifer (2001, p. 1536) believes that conservatism bias is a form of *anchoring bias*.

Tversky and Kahneman (1974) explain that anchoring is when people rely too much on some initial value or starting point (anchor) to make estimates. Even if the anchor is relevant, the bias arises when people do not update their estimates sufficiently. Previously discussed Campbell and Sharpe (2009) argue that the fact that MMS forecasts are biased towards past announcements is evidence that market participants are susceptible to anchoring bias. Consequently, we believe that our results also suggest a behavioral explanation for the informational inefficiency arising when stock prices respond to NFE announcements.

Finally, these results also shed light on the type of agents that make systematic judgment errors. Traditionally, research in behavioral finance has argued that only unsophisticated investors may be susceptible to errors. Since MMS survey participants include economists and strategists from major financial institutions, our findings suggest that sophisticated market participants overweight the importance of past announcements when they trade on NFE.

4. Conclusion

In this paper, we find that survey expectations of NFE announcements are not rational. Specifically, NFE surprises are predicted by values of the past NFE announcements. Furthermore, we document that the predicted component of these surprises impacts stock prices, which suggests that some investors trade on stale information and that stock prices may be

informationally inefficient. We believe our results may be explained by behavioral theories documented by studies in experimental psychology [Edwards (1968), Tversky and Kahneman (1974)] and behavioral finance [Barberis et al. (1998), Hirshleifer (2001)] suggesting that some investors tend to overweight the importance of historical information and do not make the necessary adjustments after the arrival of new information.

Moreover, our findings provide direction for future research. Haver Analytics informs that MMS survey participants include professionals from major financial institutions. Our results then suggest that finance professional may also be susceptible to systematic judgment errors. Of course, a lack of further information about the surveyed individuals makes it impossible to determine the degree of their sophistication and training in finance. However, at minimum, our findings provide evidence against the notion that individuals who are employed by financial institutions are completely rational and motivate future work on rationality of institutional investors.

Similarly to other research papers, we believe that while expectations determine behavior of individuals, their common systematic errors may also impact the aggregate activity. For example, Gennaioli, Ma, and Shleifer (2016) hypothesize that judgment errors may lead to recessions and downturns in financial and housing markets. Therefore, similarly to these authors, we also believe that future research should be devoted to improving macroeconomic and financial models to account for biased expectations among economic agents.

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Table 1
Summary Statistics: Nonfarm Payroll Employment: Forecasts, Releases, and Surprises
(1992-2008)

<i>NFE</i> (Δ in thousands)	Mean	Std. Dev.	Min	Max	Obs.
<i>MMS Forecasts</i>	127.14	114.39	-324	375	200
<i>Releases</i>	132.75	237.24	-732	1226	200
<i>Surprises</i>	5.61	183.77	-684	1056	200

Table 2
Rational Expectations Test 1

Panel A shows the results of a regression relating realized NFE statistics to their survey forecasts:

$$NFE_t = \alpha_0 + \alpha_1 NFE_t^e + \varepsilon_t$$

where NFE_t denotes realized value of nonfarm employment released at time t , NFE_t^e denotes ex ante forecasts of nonfarm employment. Wald p-val. denotes p values from Wald test that $\alpha_0 = -\alpha_1$. N = number of observations, p-values are reported in the parentheses. * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level. Panel B reports results of augmented Dickey-Fuller test of both realized and forecasted NFE using the following specification:

$$Y_t - Y_{t-1} = \gamma_0 + \gamma_1 Y_{t-1} + \gamma_2 \Delta Y_{t-1} + \gamma_3 \Delta Y_{t-2} + \nu_t.$$

Where Y is either realized or forecasted NFE. DF critical values are from Fuller (1996) tables. t statistics are reported in brackets, *** indicates rejection of the null hypothesis that a series has a unit root at the 1% level.

Panel A: Realized NFE Statistics and Survey Expectations					
NFE_t	α_0	α_1	Wald p-val. ($H_0: \alpha_0 + \alpha_1 = 0$)	N	R ²
	-40.19*** (0.01)	1.36*** (0.00)	0.00	200	0.43

Panel B: Testing Stationarity of Realized and Forecasted NFE			
Augmented Dickey-Fuller	Levels	First Difference	
Realized NFE	-0.63***	-1.49***	
[t-stat]	[-9.20]	[-24.09]	
Expected NFE	-0.16***	-1.27***	
[t-stat]	[-3.67]	[-18.31]	
DF Critical values	1% [-3.477]	5% [-2.83]	10% [-2.573]

Table 3
Rational Expectations Test 2: Surprises and Past Announcements

The table shows the results of 3 regression relating realized NFE surprises to past NFE announcements:

$$NFE_t - NFE_t^e = \gamma_0 + \gamma_1 \overline{NFE_{-m}} + v_t$$

where $NFE_t - NFE_t^e$ denotes NFE surprise, i.e. unexpected component of NFE announcement. $\overline{NFE_{-m}}$ denotes either the average value of previous three announcements or the average value of previous five announcements. NFE^{AR} is a forecast from the AR model with 5 lags. Wald p-val. denotes p values from Wald test $H_0: \beta_0 + \beta_1 = 0$. N = number of observations, p-values are reported in the parentheses, and standard errors are in brackets. * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

R_t	γ_0	γ_1	Wald p-val. ($\gamma_0 = -\gamma_1$)	N	R ²
$\overline{NFE_{-3}}$	-20.03* [11.54] (0.08)	0.14*** [0.05] (0.00)	0.00	200	0.03
$\overline{NFE_{-5}}$	-23.81** [12.37] (0.05)	0.17*** [0.05] (0.00)	0.00	200	0.03
NFE^{AR}	-32.30** [12.84] (0.02)	0.24*** [0.07] (0.00)	0.00	200	0.04

Table 4
The Effect of Expected and Unexpected Employment Information on Stock Prices

The table shows the results of 4 regressions with following specification:

$$R_t = \beta_0 + \beta_1 S_t^e + \beta_2 (S_t - S_t^e) + \epsilon_t$$

S_t^e denotes the component of the surprise that is predicted by past information: $NFE_t - E_t(NFE_t) = \gamma_0 + \gamma_1 \overline{NFE_{-m}} + v_t$, where $\overline{NFE_{-m}}$ denotes either the average value of the previous three announcements ($\overline{NFE_{-3}}$) or the average value of the previous five announcements ($\overline{NFE_{-5}}$). $(S_t - S_t^e)$ denotes the unexpected component of the surprises. N = number of observations, p-values are reported in the parentheses, and standard errors are in brackets. Controls include two lags of S&P 500 returns, a January dummy, a Friday dummy, and two lags of return-volume interactions as in Campbell, Grossman and Wang (1993). * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

R_t	$\overline{NFE_{-3}}$	$\overline{NFE_{-5}}$	$\overline{NFE_{-3}}$	$\overline{NFE_{-5}}$
	(1)	(2)	(3)	(4)
β_1	1.26*** [0.47] (0.01)	1.53*** [0.44] (0.00)	1.15** [0.53] (0.03)	1.34*** [0.50] (0.01)
β_2	-0.017 [0.066] (0.80)	-0.027 [0.064] (0.68)	-0.021 [0.066] (0.75)	-0.028 [0.064] (0.66)
Controls	No	No	Yes	Yes
N	200	200	200	200
R ²	0.02	0.04	0.08	0.09

Table 5
The Effect of Expected and Unexpected Employment Information on Stock Prices

The table shows the results of 6 regressions explaining the effect of macroeconomic factors on stock returns. R_t is the difference between the closing price on the S&P 500 at time t , the day of UN and NFE announcements, and the closing price at time $t-1$. F_t denotes expected NFE measured with MMS survey forecasts. S_t denotes surprises on NFE calculated as in Andersen, Bollerslev, Diebold, and Vega (2003, 2007). $\overline{NFE}_{-3}$ denotes either the average value of the previous three announcements. $\overline{NFE}_{-5}$ is the average value of the previous five announcements. Controls include two lags of S&P 500 returns, a January dummy, a Friday dummy, and two lags of return-volume interactions as in Campbell, Grossman and Wang (1993). N = number of observations, p-values are reported in the parentheses, and standard errors are in brackets. * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

R_t	(1)	(2)	(3)	(4)	(5)	(6)
F_t	0.238*** [0.090] (0.01)			0.215** [0.091] (0.02)		
S_t	-0.028 [0.067] (0.64)			-0.031 [0.067] (0.64)		
$\overline{NFE}_{-3}$		0.188** [0.077] (0.02)			0.171** [0.076] (0.02)	
$\overline{NFE}_{-5}$			0.252*** [0.076] (0.01)			0.220*** [0.076] (0.01)
Controls	No	No	No	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	200	200	200	200	200	200
R ²	0.04	0.02	0.04	0.09	0.08	0.09

Table 6
The Effect of Expected and Unexpected NFE on Future Stock Prices

The table shows the results of 4 regressions with following specification: $R_{t+n} = \beta_0 + \beta_1 S_t^e + \beta_2 (S_t - S_t^e) + \epsilon_t$. R_{t+1} is the difference between the closing price on the S&P 500 at time $t+1$, and the closing price at time t , the release day of UNE and NFE announcements. R_{t+2} , R_{t+3} , R_{t+4} , and R_{t+5} denote S&P 500 returns on the second day, third day, fourth day and fifth day since the release of NFE announcements. S_t^e denotes the component of the surprise that is predicted by past information: $NFE_t - E_t(NFE_t) = \gamma_0 + \gamma_1 \overline{NFE}_{-m} + \nu_t$, where $\overline{NFE}_{-m}$ denotes either the average value of the previous three announcements ($\overline{NFE}_{-3}$) or the average value of the previous five announcements ($\overline{NFE}_{-5}$). $(S_t - S_t^e)$ denotes the unexpected component of the surprises. N = number of observations, p-values are reported in the parentheses, and standard errors are in brackets. Controls include two lags of S&P 500 returns, a January dummy, a Friday dummy, and two lags of return-volume interactions as in Campbell, Grossman and Wang (1993). * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

	$\overline{NFE}_{-3}$					$\overline{NFE}_{-5}$				
	R(t+1)	R(t+2)	R(t+3)	R(t+4)	R(t+5)	R(t+1)	R(t+2)	R(t+3)	R(t+4)	R(t+5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β_1	1.00	0.12	1.06	0.06	0.08	0.90	0.33	0.80	-0.07	0.26
	[0.65]	[0.62]	[0.65]	[0.71]	[0.53]	[0.58]	[0.55]	[0.59]	[0.69]	[0.50]
	(0.13)	(0.85)	(0.11)	(0.93)	(0.87)	(0.12)	(0.60)	(0.18)	(0.93)	(0.06)
β_2	0.01	0.017	-0.019	-0.08	0.06	0.00	0.16	-0.017	-0.08	0.06
	[0.06]	[0.08]	[0.06]	[0.08]	[0.05]	[0.06]	[0.08]	[0.06]	[0.07]	[0.06]
	(0.87)	(0.33)	(0.76)	(0.28)	(0.25)	(0.89)	(0.55)	(0.78)	(0.30)	(0.29)
N	200	200	200	200	200	200	200	200	200	200
R ²	0.02	0.02	0.02	0.00	0.00	0.02	0.02	0.02	0.00	0.00

Appendix A: Sample Details

Previous literature on equity effects of macroeconomic factors established the fact that the impact of interest rates on equity prices offsets equity effects of real economic variables such as GDP, industrial production, unemployment and employment [Andersen et. al (2007), Boyd et. al (2005), McQueen et. al (1993)].¹¹ Furthermore, previous research showed that U.S. interest rates “dominate” U.S. and international stock prices over real economic variables during the Fed’s policy implementation [Andersen et. al (2007)]. For example, Andersen et. al (2007) show that during the recession of 1998, following Russian default crisis and the collapse of Long Term Capital Management (LTCM) hedge fund, the Fed’s actions ended up decreasing interest rates, which led to higher stock prices despite bad economic conditions.¹²

Specifically to the recent financial crisis, recent research shows a structural change in the way economic variables affect equity markets after 2008 as a result of QE programs [Kontonikas et.al (2013), Löffler and Posch (2013)]. When “bad” real-sector economic reports trigger the expansionary monetary policy (or market’s expectation of such policy), the subsequent effect of lower interest rates on stock prices contaminates the effect of real variables, making it difficult to disentangle the two. Since the financial crisis produced a myriad of QE programs, which dominated daily trading on equity markets, we decided to exclude the post-2008 period from the

¹¹ For example, “bad” employment reports, which, *ceteris paribus*, lead to lower stock prices, may trigger the expansionary monetary policy (or market’s expectation of such policy) resulting in lower interest rates and higher stock prices. As a result, while stock prices respond to employment announcements, from the econometric prospective, the cumulative effect may be statistically equal to zero or stock prices may even be higher [Andersen et. al (2007), Boyd et. al (2005), McQueen et. al (1993)].

¹² Lucca and Moench (2012) is another interesting study that also confirms the dominance of interest rates in the equity markets. In particular, they show that that between 1994 and 2011, 80% of equity premium may be explained by trading around FOMC announcements.

main results in order to capture equity effects of NFE and unemployment rate without any contamination.

With that said, we include additional tests to show that our results are robust for the entire sample: 1992-2012. Kontonikas et.al (2013) show that the financial crisis and QE create a structural change in the data during 09/2007-12/2009 period, resulting in statistically insignificant coefficients on economic announcements if the structural break is not properly modeled. In Panel A of Table A1, we do the same. Similarly to Kontonikas et.al (2013), we show that our results from Table 4 are not statistically significant for the 1992-2012 period if we do not account for the structural break during 2007-2009 financial crisis.

In Panel B of Table A1, we use Kontonikas et.al (2013) model to correct for the structural break. The results for the non-crisis period then become statistically significant at the 1% level for the entire sample, similarly to those shown in Table 4.

Since Kontonikas et.al (2013) use a sample that spanned until 2009, they only look at the 2007-2009 period as a reason for the structural break. However, Mamaysky (2014) makes a strong case that QE had a tremendous effect on daily equity returns during 2008-2012 period as well. Lucca and Moench (2012) also confirm a large impact of FOMC and QE announcements in a sample that spans until 2011. Given the evidence of this recent research, we decided to exclude the post-2008 period from our main results to avoid a potential contamination of lower interest rates resulting from QE and monetary policy.

Table A1**S&P 500 Effects of Macroeconomic Forecasts and Surprises (1992-2012)**

Panel A shows the results of 4 regressions explaining the effect of NFE on stock returns using the specification that does not account for the structural change related to 2007-2009 crisis: $R_t = \beta_0 + \beta_1 S_t^e + \beta_2 (S_t - S_t^e) + \text{Controls} + \epsilon_t$. Panel B shows the results of regressions with the specification that accounts for the structural change of 2007-2009 crisis $R_t = \beta_0 + D^{crisis}(\beta_1 S_t^e + \beta_2 (S_t - S_t^e)) + (1 - D^{crisis})(\beta_3 S_t^e + \beta_4 (S_t - S_t^e)) + \text{Controls} + \epsilon_t$ where S_t^e denotes the component of the surprise that is predicted by past information: $NFE_t - E_t(NFE_t) = \gamma_0 + \gamma_1 \overline{NFE}_{-m} + \nu_t$, $\overline{NFE}_{-m}$ denotes either the average value of the previous three announcements ($\overline{NFE}_{-3}$) or the average value of the previous five announcements ($\overline{NFE}_{-5}$). $(S_t - S_t^e)$ denotes the unexpected component of the surprises. D^{crisis} denotes a dummy variable that takes on the value of 1 during the crisis period and 0 otherwise. Controls include two lags of S&P 500 returns, a January dummy, a Friday dummy, and two lags of return-volume interactions as in Campbell, Grossman and Wang (1993). N = number of observations, p-values are reported in the parentheses, and standard errors are in brackets. * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

Panel A: Not Accounting For the Structural Change During 2007-2009 Period

R_t	$\overline{NFE}_{-3}$ (1)	$\overline{NFE}_{-5}$ (2)	$\overline{NFE}_{-3}$ (3)	$\overline{NFE}_{-5}$ (4)
S_t^e	0.58 [0.90] (0.52)	0.90 [0.76] (0.24)	0.33 [0.94] (0.73)	0.63 [0.78] (0.42)
$S_t - S_t^e$	0.01 [0.051] (0.78)	0.01 [0.06] (0.92)	0.003 [0.051] (0.95)	- 0.01 [0.06] (0.89)
Controls	No	No	Yes	Yes
N	200	200	200	200
R ²	0.01	0.01	0.02	0.03

Panel B: Accounting For the Structural Change During 2007-2009 Period

R_t	$\overline{NFE}_{-3}$ (1)	$\overline{NFE}_{-5}$ (2)	$\overline{NFE}_{-3}$ (3)	$\overline{NFE}_{-5}$ (4)
Non-Crisis Period				
$S_t^e * (1 - D^{crisis})$	2.24** [0.96] (0.02)	2.64*** [0.73] (0.00)	2.07** [1.05] (0.05)	2.44*** [0.79] (0.00)
$(S_t - S_t^e) * (1 - D^{crisis})$	0.02 [0.05] (0.66)	0.00 [0.05] (0.99)	0.01 [0.05] (0.91)	0.02 [0.05] (0.77)
Crisis Period				
$S_t^e * D^{crisis}$	-2.03 [1.74] (0.24)	-1.72 [1.52] (0.26)	-2.37 [1.90] (0.21)	-1.96 [1.61] (0.22)
$(S_t - S_t^e) * D^{crisis}$	-0.33 [0.48] (0.49)	-0.36 [0.50] (0.47)	-0.35 [0.44] (0.43)	-0.40 [0.46] (0.38)
Controls	No	No	Yes	Yes
N	200	200	200	200
R ²	0.04	0.05	0.06	0.07

Table B1**The Effect of Expected and Unexpected Employment Information on Stock Prices, Controlling for the State of the Business Cycle**

The table shows the results of 4 regressions with following specification:

$$R_t = \beta_0 + D^{recession}(\beta_1 S_t^e + \beta_2 (S_t - S_t^e)) + (1 - D^{recession})(\beta_3 S_t^e + \beta_4 (S_t - S_t^e)) + Controls + \epsilon_t$$

S_t^e denotes the component of the surprise that is predicted by past information: $NFE_t - E_t(NFE_t) = \gamma_0 + \gamma_1 \overline{NFE}_{-m} + v_t$, where $\overline{NFE}_{-m}$ denotes either the average value of the previous three announcements ($\overline{NFE}_{-3}$) or the average value of the previous five announcements ($\overline{NFE}_{-5}$). $(S_t - S_t^e)$ denotes the unexpected component of the surprises. $D^{recession}$ denotes a dummy variable that takes on the value of one during recessions calculated using NBER index. Controls include two lags of S&P 500 returns, a January dummy, a Friday dummy, and two lags of return-volume interactions as in Campbell, Grossman and Wang (1993). N = number of observations, p-values are reported in the parentheses, and standard errors are in brackets. * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

R_t	$\overline{NFE}_{-3}$ (1)	$\overline{NFE}_{-5}$ (2)	$\overline{NFE}_{-3}$ (3)	$\overline{NFE}_{-5}$ (4)
Expansions				
β_1	1.48*** [0.51] (0.00)	1.70*** [0.48] (0.00)	1.39*** [0.55] (0.01)	1.51*** [0.49] (0.00)
β_2	0.03 [0.07] (0.68)	0.01 [0.07] (0.78)	0.03 [0.07] (0.72)	0.02 [0.07] (0.79)
Recessions				
β_3	0.19 [2.62] (0.94)	0.59 [2.69] (0.83)	-0.22 [2.94] (0.94)	0.34 [3.13] (0.91)
β_4	-0.52 [0.56] (0.36)	-0.55 [0.52] (0.30)	-0.44 [0.58] (0.44)	-0.50 [0.54] (0.35)
Controls	No	No	Yes	Yes
N	200	200	200	200
R ²	0.04	0.06	0.09	0.10