# Forecasting the Macroeconomy:

# Analysts versus Economists

by

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*This draft is preliminary and incomplete. Please do not cite without the authors' permission.*

This version: November 3, 2011

We thank Joseph Piotroski, Ivan Marinovic, the participants of a research seminar at Harvard Business School and accounting brownbag seminars at University of Maryland and Stanford University for their helpful comments and suggestions.

## ABSTRACT

We investigate whether sell-side analysts and economists behave differently when forecasting the macroeconomy by examining analysts' *aggregate* earnings forecasts and economists' real GDP growth forecasts. We document that the two sets of forecasts are highly correlated, suggesting that that they contain a non-trivial set of common macroeconomic information. However, the efficiency with which analysts and economists incorporate the same set of macroeconomic news into their forecasts is different. In particular, we find strong evidence of analysts *underreacting* to *negative* macroeconomic news—aggregate earnings forecast errors are predictably more negative following *negative* macroeconomic news, with the extent of *underreaction* more pronounced for more pro-cyclical and larger firms. In contrast, economists do not exhibit such underreaction—GDP growth forecast errors are *not* predictable using the same set of macroeconomic news. Further, the stock market appears to overweight aggregate earnings forecasts in forming its expectation about the economy—the market returns surrounding the first few "bellwether" firms' earnings announcements are predictably more negative following quarters with worse macroeconomic news.

## 1 Introduction

Expectations have long been ascribed a central role in macroeconomics (Pigou 1927; Friedman 1968; and Lucas 1973). In the U.S., two sets of forecasters play a crucial role in shaping the expectations about the economy—sell-side analysts (hereafter, analysts), who forecast corporate earnings, and economists, who forecast macroeconomic indicators. Together their forecasts affect a large spectrum of economic decisions, from consumer spending, portfolio asset allocation, and firm investment to the Federal Reserve's monetary policy, and hence the extent to which the two sets of forecasts reflect similar or different information about the macroeconomy has important implications. Yet we know little about whether there are differences in how analysts and economists form their expectations about the macroeconomy, and more importantly, how such differences, if any, affect the market's expectations. In this paper we attempt to fill this void by addressing the following questions: 1) Do analysts' *aggregate* earnings forecasts and economists' real GDP growth forecasts contain common information about the macroeconomy? 2) Do analysts and economists differ in the efficiency with which they incorporate macroeconomic news into their forecasts? If they do, what is the source of the difference? 3) Does the market weight the macroeconomic information in analysts' and economists' forecasts efficiently?

Given the nature of macroeconomic forecasts, there is little doubt that real GDP growth forecasts contain information about future macroeconomic conditions; this is not necessarily the case, however, for aggregate earnings forecasts. Evidence from prior research suggests that while analysts revise their forecasts around the announcements of certain macroeconomic news (Hess and Kreutzman 2010), in aggregate their forecasts are not sensitive to changing macroeconomic conditions (Darrough and Russell 2002; McKinsey 2010). Anecdotal evidence supports this view. For instance, following the recent economic downturn, the financial press has been replete with reports on the disconnect between analysts' and economists' forecasts—while economists have "ratcheted down their forecasts for overall economic growth," analysts have "remained remarkably optimistic despite the dangers that may lie ahead" (New York Times 2011). It is therefore unclear to what extent aggregate earnings forecasts reflect macroeconomic expectations.

Perhaps the more interesting question is whether analysts and economists *efficiently* incorporate the same set of macroeconomic news into their forecasts. Prior literature suggests that the efficiency of a forecast depends on the forecaster's incentive structure and inherent cognitive biases (i.e., overconfidence). The literature on analysts' incentives finds that firm-specific earnings forecasts tend to be overly optimistic, with analysts overweighting (underweighting) positive (negative) news to attract underwriting business, generate brokerage revenue, or (in the pre-RegFD era) gain access to management (e.g., Dugar and Nathan 1995; Cowen, Groysberg, and Healy 2006; Francis and Philbrick 1993, Easterwood and Nutt 1999).[1] In theory, if such incentive-driven optimism also affects how analysts forecast macroeconomic information, we should observe *underreaction* to negative and *overreaction* to positive macroeconomic news. Fewer studies in the macro literature examine the effect of incentives on macroeconomic forecast efficiency, and they largely focus on reputation-driven incentives to herd or issue extreme forecasts (e.g., Lamont 2002; Ehrbeck and Waldmann 1996). Nevertheless, it is clear that in general economists' incentives do not mirror those of analysts, and absent analysts' revenue- and client-driven incentives, economists are less likely to exhibit similar inefficiencies (i.e., *underreaction* to negative and *overreaction* to positive macroeconomic news) in their forecasts.

Cognitive biases, in contrast, tend to be "hard-wired"—they are common to all humans, analysts and economists alike (e.g., Griffin and Tversky 1992). In particular, both sets of forecasters might be overconfident in their forecasting ability, overweighting their private information and underweighting public signals (e.g., Daniel, Hirshleifer, and Subrahmanyam 1999), in which case both analysts and economists should *underreact* to macro news (positive *and* negative) that is publicly observable. Cognitive biases can be mitigated at least in part, however, by the use of decision aids (e.g., Bonner, Libby, and Nelson 1996). Because economists are more likely to use decision tools (e.g., econometric modeling) than analysts (e.g., Batchelor and Dua 1991), the extent of underreaction should be lower among economists. Given the different predictions under the incentive and cognitive bias arguments, whether and how aggregate earnings and real GDP forecasts differ in their efficiency is ultimately an empirical question.

We examine the information content and efficiency of *aggregate* earnings and real GDP growth forecasts using a sample of quarterly EPS forecasts from I/B/E/S and real GDP growth forecasts from the Survey of Professional Forecasters over the 1984 to 2010 period. We measure aggregate earnings as the sum of firm-specific consensus earnings forecasts scaled by the sum of lagged book values of equity. The aggregation of individual earnings forecasts essentially

[1] Groysberg, Healy, and Maber (2011) document that analysts' compensation depends primarily on their celebrity status and investment-banking contributions. They find no evidence that it is related to earnings forecast accuracy; job turnover, however, appears to be significantly influenced by forecast accuracy.

diversifies away the firm-specific (idiosyncratic) forecast components, which facilitates comparison of analysts' and economists' responses to a *common* set of macroeconomic news. We choose to focus on real GDP growth forecasts because real GDP growth is one of the most comprehensive and closely watched macroeconomic indicators, and more importantly, it has been identified in prior literature as one of the common factors in earnings (Ball, Sadka, and Sadka 2009). For both aggregate earnings and real GDP growth, we examine quarterly forecasts made either for the current or the next calendar quarter. We focus on these short-term forecasts because they have been shown to be most accurate for both sets of forecasters (e.g., Braun and Yaniv 1992; Darrough and Russell 2002).

We first document a significant and positive correlation (0.55) between realized real GDP growth and aggregate earnings, which suggests that real GDP growth is an important common factor in earnings in our sample. We also find that each set of forecasts is potentially useful to the other set of forecasters—current-quarter aggregate earnings (real GDP growth) forecasts are significantly positively correlated with realized real GDP growth (aggregate earnings), with correlations of 0.43 (0.57). These significant correlations suggest that even though the two sets of forecasts are different (analysts forecast earnings *levels* and economists forecast real GDP *growth rates*), they share a common component and hence it is reasonable to compare their information content and efficiency with respect to macroeconomic information.

Next, we compare the information content of the two sets of forecasts by documenting the contemporaneous association between forecast revisions and macroeconomic news (proxied by the revisions in counterpart forecasts and market returns). Not surprisingly, we find a significant and positive association between revisions in real GDP growth forecasts and all measures of macroeconomic news. In contrast, aggregate earnings forecast revisions are significantly positively associated with real GDP forecast revisions but are not significantly associated with market returns.[2] When we partition macroeconomic news into "positive" and "negative" news, we find a strong positive association between forecast revisions and *negative* news for both real GDP growth and aggregate earnings. The association between forecast revisions and *positive* news, however, is generally insignificant. These findings suggest that both sets of forecasts are informative mostly about "bad" macroeconomic news.

[2] The lack of a significantly positive association is likely due to the low power of our tests as the slopes from reversed returns-forecast revision regressions are significantly positive for aggregate earnings forecast revisions.

To explore analysts' and economists' forecast efficiency, we examine the predictability of their forecast errors with respect to positive and negative macroeconomic news. We find little evidence of significant underreaction to *positive* news in both aggregate earnings and real GDP growth forecasts. For *negative* news, we find a positive and significant association with aggregate earnings forecasts, suggesting that analysts *underreact* to negative macroeconomic news, whereas we do not find evidence of similar underreaction for economists—the association between real GDP growth forecast errors and negative news is consistently insignificant. Additional analysis shows that analysts' underreaction is more pronounced for more procyclical and larger firms. Taken together, these results suggest that in aggregate analysts are not efficient at incorporating macroeconomic information (in particular, negative macroeconomic news) into their earnings forecasts, and that the documented underreaction is more likely to be driven by their incentives to be optimistic than underlying cognitive biases.

Finally, we investigate whether the stock market is fixated on analysts' aggregate earnings forecasts in forming its aggregate earnings expectations. We find that the market returns surrounding earnings announcements of the first few "bellwether" firms are significantly more negative in quarters following worse macroeconomic news. In short, the stock market does not appear to see through and adjust for analysts' underreaction to negative news at the aggregate level and hence is consistently surprised by lower-than-expected earnings following the quarters with negative macroeconomic news.

Our study contributes to several strands of literature. First, despite the large number of studies on analyst forecasts, we know little about the properties of *aggregate* earnings forecasts, and more importantly, about whether analysts tend to behave differently than economists in forming their expectations about the macroeconomy. Our study adds to this literature by documenting the information content of aggregate earnings forecasts and providing evidence that analysts and economists do indeed behave differently with respect to macroeconomic news. In particular, while we find pervasive evidence of analysts underreacting to negative macroeconomic news in their aggregate earnings forecasts, we do not find such underreaction present in economists' real GDP growth forecasts. These findings also suggest that analysts' revenue- or client-driven incentives are the likely source of their inefficiency. Further, the extant literature on analyst forecast efficiency generally does not distinguish between inefficiencies with respect to firm-specific versus macro-level information. Our results suggest that the previously documented firm-level inefficiencies are driven at least in part by the inefficient incorporation of macroeconomic information.

Second, our study contributes to the growing literature on the information content of aggregate earnings by documenting that aggregate earnings forecasts reflect macroeconomic information and hence can serve as a proxy for the market's expectation of aggregate earnings (as proposed by Sadka and Sadka 2009). However, one should exercise caution when using aggregate earnings forecasts because of the time-varying, optimistic biases embedded in the forecasts. Such optimism also has implication for studies that rely on aggregate earnings forecasts to measure market risk premiums (Claus and Thomas 2001; Pastor, Sinha, and Swaminathan 2008) or market-wide discount rate or cash flow news (Da and Warachka 2011; Chen and Zhao 2010)—since the documented biases are correlated with macroeconomic news and stages of the business cycle, failure to adjust for them can lead to finding spurious results (e.g., a spuriously higher market risk premium during recessions).

Third, our study complements the macro forecasting literature by showing that economists tend to behave differently than analysts in forecasting the macroeconomy, at least with respect to the set of macroeconomic news we examine. Our evidence suggests that economists are relatively efficient in their forecasts of real GDP growth compared to analysts' forecasts of aggregate earnings.

Taken together, our results have implications for both the producers and the users of real GDP growth and aggregate earnings forecasts. For instance, our results shed light on whether collaboration among analysts and economists may lead to improved forecasts. In addition, to the extent that government institutions such as the Federal Reserve Board use these forecasts as inputs in their monetary policy decisions, our results may have policy implications; for instance, the potential benefit of enhancing the efficiency of the forecasting process is likely to be greater during economic downturn when the need to exit from a period of significant monetary easing becomes more pronounced. Similarly, our study should help organizations involved in forecasting and policymaking on a multi-country basis, such as the International Monetary Fund or the Inter-American Development Bank, identify and eliminate potential sources of forecast errors.

The rest of the paper is organized as follows. Section 2 reviews prior literature on analysts' and economists' forecasts. Section 3 outlines our research design and formulates our predictions.

Section 4 describes our sample and main variables. Section 5 presents our empirical results. Section 6 concludes.

# 2 Prior Literature

## 2.1 Information Content of Forecasts

***Analysts' Aggregate Forecasts***

Prior research on sell-side analyst forecasts generally concludes that earnings forecasts for individual firms contains value-relevant information (e.g., Givoly and Lakonishok 1979; Lys and Sohn 1990) that is used by the stock market in pricing stocks (Francis and Soffer 1997; Frankel, Kothari, and Weber 2006). Whether *aggregate* analyst forecasts contain information about the macroeconomy, however, is unclear.

On the one hand, prior research shows that earnings contain a large non-diversifiable component (Ball and Brown 1967; Ball, Sadka, and Sadka 2009) and are pro-cyclical at the aggregate level (Lucas 1977; Stock and Watson 1999), suggesting that aggregate analyst forecasts contain macroeconomic information. Hess and Kreutzman (2010) further document a significant analyst reaction (in the form of individual earnings forecast revisions) around major macroeconomic news announcements. Similarly, several analyst surveys report macroeconomic conditions as important inputs in analysts' stock valuations (Chugh and Meador 1984; Moyes, Saadouni, Simon, and Williams 2001), and economic trends are frequently cited in analyst reports (Previts, Bricker, Robinson, and Young 1994; Abdolmohammadi, Simnett, Thibodeau, and Write 2006).

On the other hand, Darrough and Russell (2002) fail to find a downward adjustment in aggregate earnings forecasts in response to the market crash of 1987 and the Asian crisis of 1997. Similarly, industry research (McKinsey 2010) finds that long- and medium-term analyst forecasts vary little with the business cycle. Prior research (e.g., Kothari, Lewellen, and Warner 2006) further documents a negative association between aggregate returns and earnings, suggesting that changes in aggregate earnings are dominated by aggregate discount rate news rather than aggregate cash flow news.[3]

Given the mixed evidence on whether analysts adjust their earnings expectations over the business cycle and the ambiguous relation between aggregate earnings and stock market returns, the extent to which aggregate earnings forecasts reflect macroeconomic information (as well as the nature of such information) remains an open empirical question.[4]

***Economists' Forecasts***

Unlike aggregate earnings forecasts, macroeconomic forecasts are inextricably linked to the underlying macroeconomic indicators and hence there is little doubt as to whether they contain information about the macroeconomy. In addition, prior research finds that economists' macroeconomic forecasts are more accurate than purely statistical forecasts. For example, Ang, Bekaert, and Wei (2007) find that consensus forecasts from economist surveys (the Livingston, Michigan, and SPF surveys) outperform other forecasting approaches in predicting inflation out of sample, and Wieland and Wolters (2011) find that professional real GDP growth forecasts from Greenbook and SPF outperform most popular forecasting models during recessionary periods.

The evidence with respect to how the stock market interprets macroeconomic news, however, is mixed. While there is evidence of a positive association between long-horizon stock market returns and contemporaneous innovations in real (non-monetary) economic indicators (e.g., Chen, Roll, and Ross 1986; Fama 1990), the evidence on short-window announcement returns is less clear.[5] Pearce and Roley (1985), for example, do not find a statistically significant association between forecast surprises for the industrial production index and announcement-day stock returns. In contrast, Birz and Lott (2011) find the news coverage of changes in GDP growth significantly

[3] What drives a negative association between aggregate earnings and returns is still an open question. For example, recent research argues that the negative relation can be driven in part by the inability to identify an appropriate proxy for aggregate earnings expectations (Sadka and Sadka 2009).

[4] It is possible that the perceived lack of adjustment to business cycles may be due to the inherent difficulty of forecasting business conditions (Fildes and Stekler 2002). In this study, we control for the inherent difficulty of business cycle forecasting by using macroeconomists' forecasts as a natural benchmark to assess the macroeconomic information content of sell-side analysts' forecasts.

[5] The evidence on the market reaction to monetary economic indicators is more robust. For example, using unexpected changes in the Federal funds rate to measure policy surprises, several studies show that monetary shocks are negatively related to stock market prices (e.g., Bernanke and Kuttner 2005; Gurkaynak, Sack, and Swanson 2005).

affects stock returns.[6] Additional evidence shows that stock market reactions to news about macroeconomic fundamentals is asymmetric. For example, Boyd, Hu, and Jagannathan (2005) find that bad news about employment causes stock prices to rise during expansions and fall during contractions, and Andersen, Bollerslev, Diebold, and Vega (2007) and Albuquerque and Vega (2009) find similar results using high frequency data for a wide range of announcements.

Taken together, the above findings suggest that macroeconomic forecasts are informative for the stock market and that their information content depends on prevailing macroeconomic conditions. Our study complements this stream of literature by examining whether and how economists differ from analysts in incorporating macroeconomic information into their forecasts.

## 2.2 Forecast Efficiency

***Analysts' Aggregate Forecasts***

A large body of research suggests that analysts' forecasts are inefficient at the firm level. First, analysts tend to be optimistic, with the degree of optimism varying with analysts' incentives to attract underwriting business (Dugar and Nathan 1995; Lin and McNichols 1998), generate brokerage revenue (Cowen, Groysberg, and Healy 2006), or maintain access to management (Francis and Philbrick 1993).[7] Second, analysts tend to underreact to information contained in recent earnings changes, forecast revisions, and stock returns (Abarbanell and Bernard 1992; Elliott, Philbrick, and Weidman 1995; Ali, Klein, and Rosenfeld 1992), with some studies reporting stronger underreaction to negative news (Abarbanell and Bernard 1992) and others reporting overreaction to positive news (Easterwood and Nutt 1999).

The extant literature on analyst forecasting behavior in general does not distinguish between firm-specific and macro-level information. It is possible, however, that the efficiency in processing firm-specific and macro-level information is different. Prior evidence suggests, for example, that analysts tend to specialize in certain industries (Gilson, Healy, Noe, and Palepu 2001) and that

[6] In addition, Gilbert (2011) finds that an empirical relation between stock returns on macroeconomic news announcement days and the *future* revisions of the released data; the sign of the relation differs across the business cycle.

[7] Alternative explanations for optimistic bias in analysts' forecasts include self-censoring and non-quadratic loss functions. For instance, McNichols and O'Brien (1997) suggest that analysts prefer to drop coverage of a firm to issuing unfavorable forecasts. The extent to which this self-selection argument applies to reactions to unfavorable macroeconomic news is unclear. Basu and Markov (2004) and Gu and Wu (2003) suggest that analysts' forecasts appear to biased because analysts are not minimizing mean squared errors in their forecasts.

stock prices incorporate industry-wide information produced by analysts to a greater extent than firm-specific information (Piotroski and Roulestone 2004).[8] Because idiosyncratic information is averaged out when earnings are aggregated, the efficiency of aggregate earnings forecasts depends only on the efficiency with which analysts process macroeconomic information. This implies that if analysts are more efficient in processing macroeconomic information (or simply adopt macro forecasts produced by professionals as assumed by Basu, Markov, and Shivakumar 2010), the forecast inefficiencies found at the firm level may not be present at the aggregate level.

Empirically, there is little evidence on whether analysts are efficient in processing macroeconomic information. Ackert and Hunter (1995) show that between 1984 and 1990, firm-specific quarterly earnings forecasts did not fully incorporate information in previous-quarter nominal GNP changes but were efficient with respect to prior S&P 500 returns and changes in other macroeconomic variables, including inflation, unemployment, oil prices and corporate profits. Darrough and Russell (2002) find that between 1987 and 1999, aggregate earnings forecasts were significantly more optimistic than top-down forecasts and exhibited higher autocorrelation in forecast revisions, although the top-down forecasts were less efficient on average. And Basu, Markov, and Shivakumar (2010) find that earnings forecasts do not fully incorporate information about future firm-specific exposure to inflation. We add to these studies by investigating whether *aggregate* analyst forecasts are efficient with respect to macroeconomic information. More importantly, we explore whether any existing inefficiencies are common to both analysts and economists.

### *Economists' Forecasts*

An important body of literature explores the rationality of macroeconomic forecasts based on survey data collected by professional forecasters, including the Blue Chip survey, the Livingston survey, and the Survey of Professional Forecasters (SPF). Given the context of this study, we focus our review on the work that pertains to forecasts of real output (GDP/GNP) growth in the U.S.[9]

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[8] These papers represent only one side of the debate in the literature on the relative informativeness of industry-wide and firm-specific information produced by sell-side analysts. Papers that suggest greater usefulness of firm-specific information include Mikhail, Walther, and Willis (1997) and Liu (2011).

[9] U.S. economists are on average more accurate and less biased than economists abroad (e.g., Batchelor 2007). In addition, there is less evidence of biased and inefficient forecasts of real GDP/GNP growth compared to, for example, forecasts of inflation.

The overall evidence on the efficiency of real GDP forecasts is mixed. For example, while Batchelor and Dua (1991) find little evidence that forecast errors are serially correlated, Davies and Lahiri (1995) find the opposite and reject informational efficiency for up to half of the survey participants. The evidence on whether GDP growth forecasts incorporate other publicly available information is equally mixed. Brown and Maital (1981) find that six-month-ahead real GNP growth forecasts are efficient with respect to several macroeconomic indicators.[10] Baghestani and Kianian (1993), in contrast, find that errors in real GNP growth forecasts even for the current or next quarters are not orthogonal to previously available macroeconomic information. More recently, Schuh (2001) shows that SPF forecasters tend to underpredict GDP significantly when inflation and nominal interest rates are unusually low, and vice versa. Finally, while there is anecdotal evidence that economists tend to be optimistic (Zarnowitz 1985; Smalhout 2000), prior research does not find evidence of optimistic biases in real GDP/GNP growth forecasts over sufficiently long time periods (Schuh 2001; Batchelor 2007).[11] Our study adds to these findings by providing additional evidence on whether economists are efficient with respect to macroeconomic information, particularly when compared with analysts.

In the next section, we provide a simple framework that illustrates the basic intuition behind the two sets of forecasts and we discuss how differences in analysts' and economists' underlying incentives and cognitive biases can yield different forecast efficiency in aggregate earnings and real GDP growth.

# 3 Research Design

## 3.1 Framework for Empirical Tests

Assume there are N firms in the economy, and earnings for every firm $i$ ($X_i$) consist of a common component and a firm-specific (idiosyncratic) component:

$$X_{i,t} = \beta_i \cdot M_t + \varepsilon_{i,t}, \quad i=1 \text{ to N}, \tag{1}$$

[10] Brown and Maital (1981), however, find that 12-month-ahead forecasts do not incorporate information in money growth efficiently.

[11] Zarnowitz (1985) argues that "predicting a general downturn is always unpopular, and predicting it prematurely ahead of others may prove quite costly to the forecaster and his customers". Smalhout (2000) cites Gary Shilling, a private forecaster, explaining that "Most economists are paid to be cheerleaders. Whistle blowers are unemployable".

where $M$ is the common factor in earnings, $\beta_i$ is firm $i$'s sensitivity to the common factor, and $\varepsilon_i$ is the idiosyncratic factor in earnings, which has zero expected mean.

The conditional expectation of each firm's earnings based on all available information at time $t$ is given by:

$$\mathrm{E}_t\,(X_{i,\,t+1} \mid I_t) = \beta_i \cdot M^*_{t+1} + \varepsilon^*_{i,\,t+1}, \tag{2}$$

where $M^*$ and $\varepsilon^*$ represent the expectations for $M$ and $\varepsilon$ that are formed efficiently at time $t$ conditional on all available information $I_t$.

Based on our earlier discussions, analysts may form inefficient forecasts of both the common and the firm-specific components of earnings (we assume that earnings sensitivities to the common factor, $\beta_i$, are publicly observed and known to analysts):

$$\mathrm{F}_t\,(X_{i,\,t+1} \mid I_t) = \beta_i \cdot M^A_{t+1} + \varepsilon^A_{i,\,t+1}, \tag{3}$$

where $M^A$ and $\varepsilon^A$ represent analysts' forecasts, that is, expectations for $M$ and $\varepsilon$ that are formed conditional on analysts' information set, $A_t$.

The expected forecast error (actual minus forecast) is then given by:

$$\mathrm{E}_t(FE_{i,\,t+1} \mid I_t) = \beta_i \cdot [M^*_{t+1} - M^A_{t+1}] + \varepsilon^*_{i,\,t+1} - \varepsilon^A_{i,\,t+1}. \tag{4}$$

When N is sufficiently large, the aggregate forecast error (i.e., the weighted average of all firms' forecast errors) depends only on the common component of forecast errors because the idiosyncratic component converges to zero. Hence, the expected aggregate forecast error can be re-written as:

$$\mathrm{E}_t(FE^{AGG}_{t+1} \mid I_t) = \overline{\beta_i} \cdot [M^*_{t+1} - M^A_{t+1}], \tag{5}$$

where $FE^{AGG}_{t+1}$ is the aggregate (weighted-average) forecast error and $\overline{\beta_i}$ is the weighted-average exposure to the common factor in earnings.

Economists, on the other hand, only forecast the common factor, e.g., real GDP growth. Like analysts, they can also produce inefficient forecasts, which are denoted by $M^{E}_{t+1}$. Economists' expected forecast error is thus equal to:

$$E_t(FE^{ECON}_{t+1} | I_t) = M^{*}_{t+1} - M^{E}_{t+1}. \tag{6}$$

Two observations about the above framework are important. First, from equation (5) it is clear that only the inefficient use of market-wide information (as opposed to firm-specific information) can bias *aggregate* earnings forecasts. Second, from equations (5) and (6) we can see that although analysts forecast corporate earnings while economists (in our setting) forecast real GDP growth, we can directly compare their forecasting behavior as long as real GDP growth is an important factor that is correlated with aggregate earnings.

Next, we describe our empirical predictions and the corresponding statistical tests.

### 3.2 Predictions for Forecast Inefficiencies: Analysts vs. Economists

Prior research in the analyst and macro forecasting literatures attributes forecasters' inefficiency primarily to two explanations: incentives to deviate from efficient forecasts and cognitive biases (overconfidence). Our predictions are based on these two explanations.

#### *Incentives to be Optimistic*

The incentives-based explanation argues that analysts strategically bias their forecasts by over- (under-) weighting positive (negative) information to produce optimistically biased forecasts (Chen and Jiang 2006). Although prior research does not distinguish between inefficient reactions to firm-specific and macroeconomic news, the on-average optimistic bias in analysts' forecasts suggests that some of the strategic under- (over-) reaction is likely to occur in response to recent macroeconomic news. In that case, aggregate forecast errors should be positively (negatively) associated with negative (positive) macroeconomic news.

Economists' incentives to deviate from efficient forecasts are not as widely researched in the macro forecasting literature, with the exception of the reputation-driven incentives to make extreme forecasts in search of publicity. For instance, Lamont (2002) finds that more established economists are more likely to deviate from consensus, which leads to lower accuracy.[12] Similarly, Laster, Bennett, and Geoum (1999) find that economists that belong to industrial corporations produce forecasts closest to consensus, while economists from independent forecasting firms deliver forecasts furthest away from consensus.[13] Given that there is little evidence to suggest that economists face a similar set of revenue- or client-driven incentives as their analyst counterparts, we expect to observe less strategic under- (over-) reaction to bad (good) news in real GDP forecasts. Accordingly, our first prediction is as follows:

*Prediction 1. If analysts behave strategically by over- (under-) weighting prior positive (negative) macroeconomic news, aggregate earnings forecast errors should be positively (negatively) associated with prior negative (positive) macroeconomic news. We expect no such asymmetric association between economists' forecast errors in real GDP growth and prior macroeconomic news.*

Empirically, incentive-driven over- and underreaction can be detected by regressing forecast errors (*FE*) on recent positive ($NEWS^{M+}$) and negative ($NEWS^{M-}$) macroeconomic news:

$$FE_{t+1} = b_1 NEWS_t^{M+} + b_2 NEWS_t^{M-} \tag{7}$$

The slope estimates $b_1$ and $b_2$ converge in probability to zero if analysts' or economists' reactions to positive and negative news are similarly efficient. Over- (under-) reaction to positive (negative) news would result in a negative (positive) $b_1$ ($b_2$).

[12] Stark (1997) does not find the Lamont (2002) result using anonymous SPF data. The difference may be due to the fact that reputation incentives do not affect confidential forecasts.
[13] Other studies suggest that assuming asymmetrical loss functions may explain why economists' forecasts appear to be inefficient (Elliot, Komunjer, and Timmermann 2005). However, asymmetrical loss assumptions appear to be less applicable to real GDP growth forecasts than budget deficit forecasts (e.g., the penalty associated with over- or undershooting a policy target) as in Elliot et al.

*Cognitive Biases: Overconfidence*

The overconfidence explanation for inefficient forecasts (Easterwood and Nutt 1999, Ehrbeck and Waldmann 1996)[14] argues that if analysts or economists exhibit overconfidence biases with respect to processing macroeconomic information, i.e., if they underweight public signals and overweight their private prior information, their forecast errors should be positively associated with recent macroeconomic news, both positive and negative. Our second prediction is therefore as follows:

*Prediction 2. If analysts (economists) are prone to overconfidence biases in processing macroeconomic information, their forecast errors in aggregate earnings (real GDP growth) should be positively associated with recent macroeconomic news.*

Although cognitive biases are considered to be hard-wired in humans (e.g., Griffin and Tversky 1992), they can be mitigated by the use of decision aids (e.g., Bonner, Libby, and Nelson 1996). The use of decision aids is likely different between economists and analysts. Most economists use a combination of econometric modeling and expert judgment (e.g., Batchelor and Dua 1991) in forming macroeconomic forecasts. While there is little direct evidence on forecasting techniques used by sell-side analysts, research shows that analysts are more likely to use simple heuristics based on long-term growth, the PEG model, or industry comparables in determining target prices (Bradshaw 2004, Demirakos, Strong, and Walker 2004). To the extent that analysts use less rigorous forecasting techniques than economists, analysts' forecasts are likely to be more influenced by cognitive biases. Our last prediction is thus as follows:

*Prediction 3. If greater reliance on formal prediction methods alleviates cognitive biases for economists, forecast errors in real GDP growth should be less positively associated with past macroeconomic news compared to forecast errors in aggregate earnings.*

[14] Overall underreaction to recent news is also consistent with efficient Bayesian updating under uncertainty (Markov and Tamayo 2006). Specifically, when analysts have to learn prior distribution parameters by observing earnings realizations, analyst forecast errors can be ex-post predictable and positively autocorrelated. Given that the inherent task of macroeconomic forecasting is the same for analysts and economists, under this explanation we should expect to see similar underreaction to recent news for both sets of forecasters.

Empirically, underreaction can be detected by a linear regression of forecast errors (actual minus forecast), *FE*, on recent macroeconomic news, $NEWS^M$:

$$FE_{t+1} = b\ NEWS_t^M. \tag{8}$$

The slope estimate $b$ converges to zero if efficient weight is assigned to $NEWS^M$ in updating the forecast. If analysts or economists underreact to new macroeconomic information, $b$ is expected to be positive.

Note that inefficiency driven by overconfidence implies similar underreaction to both positive and negative news, while inefficiency driven by incentives to be optimistic implies underreaction only to negative news. Thus, the slope estimates $b_1$ and $b_2$ in equation (7) should both be negative due to overconfidence.

# 4 Sample Selection and Variable Measurement

Our analyses use aggregate earnings and real GDP growth forecasts issued between the fourth quarter of 1984 and the fourth quarter of 2010. Earnings forecasts are obtained from I/B/E/S and real GDP growth forecasts come from the Survey of Professional Forecasters (SPF) maintained by the Philadelphia Federal Reserve.[15] The diagram in Figure 1 depicts the variable measurement timeline and Appendix A summarizes variable definitions.

## 4.1 Real GDP Growth

The SPF real GDP growth forecasts are produced by a range of economists both affiliated and unaffiliated with financial institutions.[16] The forecasts are solicited once a quarter following publication of the advance GDP number from the previous quarter and are released to the public

[15] I/B/E/S detailed forecast files start in 1983. Prior to the fourth quarter of 1984, the number of quarterly earnings forecasts is insufficient to calculate aggregate earnings forecasts.
[16] SPF only classifies economists' affiliation as with financial versus nonfinancial institutions. Financial institutions include insurance companies, banks, and companies that manage financial assets. Nonfinancial institutions include manufacturers, universities, and pure research and consulting firms. (SPF Documentation: http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/spf-documentation.pdf).

on average two weeks later.[17,18] Our tests use median consensus forecasts made in quarter *t* for the current and next quarters, denoted *FGDP0* and *FGDP1*, respectively.[19]

We obtain realized real GDP growth values from the Philadelphia Federal Reserve's real-time estimates database.[20] We choose to use realized GDP growth values that correspond to the first (advance) report released by the Bureau of Economics and Statistics. Realized real GDP growth rates for the current and next quarters are labeled *GDP0* and *GDP1*, respectively.

Real GDP growth forecast surprises for the current and next quarters are calculated as *SURP_FGDP0 = GDP0 – FGDP0* and *SURP_FGDP1 = GDP1 – FGDP1*, respectively.

## 4.2 Aggregate Earnings

We construct aggregate earnings forecasts in two steps. First, we use individual analysts' EPS forecasts from I/B/E/S's detailed dataset to construct a consensus median forecast for every firm at the end of each calendar quarter. In calculating the consensus forecast we include only those forecasts that were issued or updated after the current quarter's release of the real GDP growth forecast.

Second, we estimate the aggregate earnings forecast as:

$$FEARN_t = \frac{\sum_{i=1}^{N} FEPS_{i,t} \cdot SHARES_{i,t}}{\sum_{i=1}^{N} BV_{i,t-1}},$$

where $FEPS_{i,t}$ is the consensus median EPS forecast for firm *i* at the end of quarter *t*; $SHARES_{i,t}$ is number of shares outstanding from I/B/E/S; $BV_{i,t-1}$ is book value of equity at the end of the most recent quarter from Compustat; and *N* is the number of firms with available consensus median forecasts (we only use firms with fiscal quarters ending in March, June, September and December) at the end of quarter *t*.

Aggregate forecasts consist, on average, of 1,800 firm-specific forecasts. We label aggregate forecasts for current- and next-quarter earnings as *FEARN0* and *FEARN1*, respectively.

[17] In recent years, approximately 45 economists contribute their real GDP growth forecasts to SPF each quarter; in the earlier part of our sample the number of contributors was less than 20.
[18] Prior to 1992, SPF collected real GNP forecasts.
[19] SFP reports annualized growth rates. We convert them back to quarterly growth rates.
[20] Using the Philadelphia Federal Reserve's real-time database ensures the best matching between the realized and forecasted values (Stark 2010).

Realized aggregate earnings are computed using realized earnings per share values from I/B/E/S as:

$$EARN_t = \frac{\sum_{i=1}^{N} EPS_{i,t} \cdot SHARES_{i,t}}{\sum_{i=1}^{N} BV_{i,t-1}},$$

where $EPS_{i,t}$ is the realized EPS value for firm $i$ and quarter $t$; $SHARES_{i,t}$ is number of shares outstanding from I/B/E/S; $BV_{i,t\text{-}1}$ is book value of equity for the end of the most recent quarter from Compustat; and $N$ is the number of firms with available realized EPS values. We only use firms with fiscal quarters ending in March, June, September and December, for which we have consensus forecast data.

We label realized aggregate earnings for the current and next quarters as *EARN0* and *EARN1*, respectively.

Aggregate earnings forecast surprises for the current and next quarters are calculated as differences between realized aggregate earnings and their corresponding forecasts, that is, *SURP_FEARN0 = EARN0 – FEARN0** and *SURP_FEARN1 = EARN1 – FEARN1**, respectively. *FEARN0** and *FEARN1** are aggregate earnings forecasts computed using only those consensus forecasts with corresponding non-missing realized earnings from I/B/E/S.[21]

### 4.3 Macroeconomic News

We use three measures of macroeconomic news: revisions in aggregate earnings forecasts, revisions in real GDP growth forecasts, and returns on the CRSP value-weighted index.

We calculate revisions in forecasts made both for the current and the next quarters. Specifically, for each calendar quarter $t$, a revision in the real GDP growth forecast for the current (next) quarter is calculated as the difference between the real GDP growth forecast for quarter $t$ ($t$+1) made in quarter $t$ and the real GDP growth forecast for quarter $t$ ($t$+1) made in quarter $t$-1. We label forecast revisions for the current (next) quarter as *ΔFGDP0* (*ΔFGDP1*).

Similarly, for each calendar quarter $t$, a revision in the aggregate earnings forecast for the current (next) quarter is calculated as the difference between the aggregate earnings forecast for

[21] These aggregate forecasts constrained by realized earnings availability are highly correlated (correlations exceed 0.999) with aggregate forecasts calculated using all available firm-specific consensus forecasts and on average deviate from them by less then 0.3%.

quarter $t$ ($t$+1) made in quarter $t$ and the aggregate earnings forecast for quarter $t$ ($t$+1) made in quarter $t$-1. We hold the firm composition constant across forecasts for the same fiscal quarter issued in quarters $t$-1 and $t$. As a result, forecast revisions are computed using a smaller number of individual forecasts compared to forecast levels. Aggregate forecast revisions for the current (next) quarter consist, on average, of 1,500 (1,444) firm-specific forecasts. We label forecast revisions for the current (next) quarter as *ΔFEARN0* (*ΔFEARN1*). Some of our tests require estimating lagged revisions in aggregate earnings forecasts for the current (next) quarter. These revisions, labeled as *lΔFEARN0* (*lΔFEARN1*), are calculated as the differences between the aggregate earnings forecast for quarter $t$ ($t$+1) made in quarter $t$-1 and the aggregate earnings forecast for quarter $t$ ($t$+1) made in quarter $t$-2.

The return on the CRSP value-weighted index is simply a buy-and-hold return calculated over three months coinciding with the forecast revision period of either real GDP growth forecasts or aggregate earnings forecasts. We label these returns *lMKTRET* and *MKTRET*, respectively. See Figure 1 for the measurement timeline. In the tests of real GDP growth forecast efficiency, the return estimation period is lagged by an additional month to ensure that return data are available to surveyed economists.

# 5 Empirical Results

## 5.1 Descriptive Statistics

### *Forecasts and Realized Values*

Panel A of Table 1 presents descriptive statistics for forecasts and realized values of aggregate earnings and real GDP growth. We find that for our sample, average real GDP growth is about 0.6% *per quarter* (roughly 2.4% annualized), and average aggregate earnings (i.e., aggregate return on equity) is roughly 3.7%. The mean forecasts are similar in magnitude to the corresponding realized values.

Panel B of Table 1 reports correlations between forecasts and realized values, with Pearson (Spearman) correlations below (above) the diagonal. Because the two sets of correlations are qualitatively similar, we focus our discussion on the Pearson correlations. Several of the correlations are worth noting. First, the correlation between real GDP growth

(*GDP0*) and aggregate earnings (*EARN0*) is 0.55, suggesting that real GDP growth is an important macroeconomic factor in earnings for our sample. Second, the two sets of forecasts are also significantly positively correlated—the correlation between current-quarter forecasts of real GDP growth (*FGDP0*) and aggregate earnings (*FEARN0*) is 0.49. The co-movement of the two realized series and their respective forecasts is depicted in Panels A and B of Figure 1. The plot clearly reflects the high correlations reported earlier. The figure also clearly shows that both aggregate earnings and real GDP growth are sensitive to the business cycle. Third, both sets of forecasts are highly correlated with their corresponding realized values—the correlation between *EARN0* and *FEARN0* is 0.86 and that between *GDP0* and *FGDP0* 0.75 Finally, the correlation between real GDP growth (aggregate earnings) forecasts and aggregate earnings (real GDP growth) is 0.57 (0.43), suggesting that the forecasts issued by economists (analysts) are useful for predicting aggregate earnings (real GDP growth).

Overall, the correlations between realized and forecasted real GDP growth and aggregate earnings are economically and statistically significant. Such significant correlations suggest that, even though analysts forecast earnings levels and economists forecast real GDP growth rates, it is reasonable to compare their forecasting behavior within the framework described in Section 3.1.

***Forecast Revisions and Forecast Errors***

Panel A of Table 2 presents descriptive statistics for aggregate earnings and real GDP growth forecast surprises and forecast revisions. On average, revisions in both current- and one-quarter-ahead aggregate earnings forecasts (Δ*FEARN0* and Δ*FEARN1*) and real GDP growth forecasts (Δ*FGDP0* and Δ*FGDP1*) are significantly negative, suggesting that both analysts and economists "walk down" their forecasts. The economists' revised forecasts tend to be either pessimistic or unbiased—the mean real GDP growth forecast errors (*SURP_FGDP0* and *SURP_FGDP1*) are positive or insignificant. In contrast, analysts' revised forecasts continue to be optimistic despite the downward revisions—the mean forecast errors for aggregate earnings (*SURP_FEARN0* and *SURP_FEARN1*) are significantly negative. Further, the absolute forecast errors are larger for one-quarter-ahead forecasts than for current-quarter forecasts for both aggregate earnings and real GDP growth, which is consistent with evidence in prior research that shorter-horizon forecasts tend to be more accurate (e.g., Braun and Yaniv 1992; Darrough and Russell 2002).

Panel A (B) of Figure 3 plots the surprises (revisions) in both forecast series. Panel A shows that aggregate earnings forecasts are optimistic in 75% of the sample quarters, whereas real GDP growth forecasts observe an almost even split (55%). Panel B shows that revisions in aggregate earnings forecasts are negative in 85% of the sample quarters, relative to only 48% of quarters with negative revisions in real GDP growth forecasts. In short, Figure 3 demonstrates the pervasiveness of "walk down" behavior and optimism in aggregate earnings forecasts relative to real GDP growth forecasts.

Panels B and C of Table 2 present the time-series correlations for forecast revisions and surprises, respectively. To the extent that forecast errors and forecast revisions from previous periods are known to the forecaster, neither forecast errors nor forecast revisions should be serially correlated. Panel B of Table 2 shows that aggregate earnings forecast revisions are strongly positively autocorrelated—the correlation between current-quarter (one-quarter-ahead) forecast revisions for quarter *t* and *t*-1, *l*Δ*FEARN0* and Δ*FEARN0* (*l*Δ*FEARN1* and Δ*FEARN1*), are 0.52 (0.37). The autocorrelations in real GDP growth forecast revisions are substantially lower—the corresponding correlations between *l*Δ*FGDP0* and Δ*FGDP0* (*l*Δ*FGDP1* and Δ*FGDP1*) are 0.22 (0.13). Panel C of Table 2 indicates that aggregate earnings forecast errors are also significantly autocorrelated—the correlation between aggregate earnings surprises for quarters *t*-1 and *t* (*lSURP_FEARN0* and *SURP_FEARN0*) is 0.48. In contrast, the correlation between real GDP growth surprises for quarters *t*-1 and *t* (*lSURP_FGDP0* and *SURP_FGDP0*) is insignificantly different from zero (0.01). Overall, the real GDP growth forecasts produced by economists appear to be more efficient than the aggregate earnings forecasts produced by analysts.[22]

### 5.2 Information Content of Forecasts

Next, we investigate the macroeconomic content of the two sets of forecasts, i.e., the extent to which analysts and economists update their forecasts in response to changing macroeconomic conditions. We expect the information content of the two forecasts to be similar

[22] Note that aggregate earnings forecast surprises (real GDP growth forecast revisions) from the previous quarter may not be publicly known at the time analysts (economists) issue forecasts. Autocorrelations in forecast surprises (forecast revisions) should thus be interpreted with caution when analyzing analysts' (economists') forecast efficiency.

to the extent that aggregate earnings and real GDP growth have a common macroeconomic component.

To compare the information content of the two sets of forecasts, we regress revisions in aggregate earnings and real GDP growth forecasts on contemporaneous macroeconomic news:

$$\Delta F = Intercept + b\ NEWS, \tag{9}$$

where *ΔF* is an aggregate earnings or real GDP growth forecast revision (forecast issued in quarter *t* minus forecast issued in quarter *t*-1) for the current quarter (*t*) or the next quarter (*t*+1); and *NEWS* is one of the contemporaneously estimated macroeconomic news variables. News contemporaneous with *aggregate earnings forecast revisions* include real GDP growth forecast revisions (*ΔFGDP0* and *ΔFGDP1*) or returns on the value-weighted market index (*MKTRET*). News contemporaneous with *real GDP growth forecast revisions* include lagged revisions in aggregate earnings (*lΔFEARN0* and *lΔFEARN1*) or lagged returns on the value-weighted market index (*lMKTRET*). Detailed variable descriptions are provided in the Appendix.

Table 3 reports the results of the information content regressions. We find that economists' and analysts' forecast revisions are strongly positively related, suggesting that both sets of forecasts embed common information.[23] The association between real GDP forecast revisions and aggregate market returns is positive and statistically significant, while that between aggregate earnings forecast revisions and market returns is insignificantly positive. The lack of a significantly positive association for aggregate earnings forecast revisions is surprising, given that aggregate earnings forecasts are presumably more relevant for stock prices than real GDP growth forecasts.[24]

As mentioned in Section 2, prior literature documents that the information content of macroeconomic announcements varies with the sign of the announced news, with negative and

[23] Note that the overlap in the periods over which aggregate earnings and real GDP growth forecast revisions are measured is not perfect.

[24] Possible explanations for the lack of a significantly positive relationship include 1) less timely aggregate earnings forecast revisions, 2) a larger discount-rate-news component in aggregate earnings forecasts, and 3) lack of power to detect a significant association due to small sample size. Results from reversed returns–forecast revision regressions (untabulated) support the third explanation (lack of power)— the slopes in the reversed regressions are significantly positive for aggregate earnings forecast revisions.

positive news eliciting different market reactions.[25] Accordingly, we next investigate whether the information content of economists' and analysts' *forecasts* is also asymmetric with respect to the incorporation of "good" and "bad" news. Toward that end, we estimate the following regression with macroeconomic news partitioned into positive and negative news variables:

$$\Delta F = Intercept + b_0\, I\_NEG\_NEWS + b_1\, POS\_NEWS + b_2\, NEG\_NEWS, \qquad (10)$$

where *ΔF* is an aggregate earnings or real GDP growth forecast revision (forecast issued in quarter *t* minus forecast issued in quarter *t*-1) for the current quarter (*t*) or the next quarter (*t*+1); *I_NEG_NEWS* is equal to one if the *NEWS* measure is negative, and zero otherwise; *POS_NEWS* is an interaction term between a positive news indicator and the *NEWS* variable, calculated as (1 - *I_NEG_NEWS*)**NEWS* ; *NEG_NEWS* is an interaction term between the negative news indicator and the *NEWS* variable, calculated as *I_NEG_NEWS* **NEWS*; and *NEWS* is one of the contemporaneous macroeconomic news measures as previously defined.

The results reported in Table 3 suggest that economists as well as analysts consistently revise their forecasts only in response to *unfavorable* macroeconomic news.[26] In particular, while the coefficient on *NEG_NEWS* is significantly positive across all regression specifications, the coefficient on *POS_NEWS* is not significantly positive in any regression. Moreover, in two regressions—current-quarter aggregate earnings forecast revisions regressed on market returns, and current-quarter real GDP growth forecast revisions regressed on one-quarter-ahead earnings forecast revisions—the coefficient on *POS_NEWS* is significantly negative.

Prior research suggests several rational explanations for an asymmetric reaction to news of different signs, including an asymmetric increase in uncertainty upon receiving bad or good news (e.g., Veronesi 1999) or worst-case scenario inferences due ambiguity aversion (e.g., Epstein and Schneider 2008). The former explanation suggests that investors require an additional risk premium for increased uncertainty about the underlying state of the economy upon receiving negative (positive) news during good (bad) economic times, which exacerbates a

[25] The disproportionately strong reaction to negative news has been documented in several markets in response to several news sources. For example, Andersen, Bollerslev, Diebold, and Vega (2003) document an asymmetric response to macro news in the foreign exchange market, while Hautsch and Hess (2002) find asymmetry in the T-bond market response to macro news announcements.

[26] Note that there are only 15 (25) quarters in which *lΔFEARN0* (*lΔFEARN1*) are positive. The sign of the association with positive lagged aggregate earnings forecast revisions should thus be interpreted with caution.

negative (dampens a positive) price reaction. The latter explanation suggests that investors interpret news signals using the worst-case scenario approach. The worst-case scenario associated with observing a negative (positive) signal is that the signal is precise (imprecise), in which case investors overreact to negative news and underreact to positive news. In our setting, this argument translates into a larger (smaller) negative (positive) forecast revision in response to adverse (favorable) macroeconomic news.[27]

Overall, analysts' and economists' forecasts exhibit both similarities—they reflect overlapping information sets and tend to be revised to a greater extent in response to negative macroeconomic news—and differences—the association between forecast revisions and macroeconomic news is generally stronger for real GDP growth forecasts.

### 5.3 Forecast Efficiency

To explore whether analysts and economists fully incorporate macroeconomic information into their forecasts, we examine the predictability of their forecast errors by estimating the following regression corresponding to equation (8) from Section 3.2:

$$SURP = Intercept + b\ NEWS, \tag{11}$$

where *SURP* is the current-quarter (one-quarter-ahead) forecast error in aggregate earnings or real GDP growth, calculated as the realized value for quarter $t$ ($t$+1) minus the current-quarter (one-quarter-ahead) forecast issued in quarter $t$; and *NEWS* is one of the lagged macroeconomic news measures. We use real GDP growth forecast revisions (*ΔFGDP0* and *ΔFGDP1*) and the return on the value-weighted market index (*MKTRET*) as proxies for macroeconomic news to predict errors in aggregate earnings forecasts, and *lagged* aggregate earnings forecast revisions (*lΔFEARN0* and *lΔFEARN1*) and the *lagged* return on the value-weighted market index (*lMKTRET*) as proxies for macroeconomic news to predict errors in real GDP growth (see Section 4.3 for a detailed discussion of the variable measurement timeline).

Table 4 reports the results of estimating regression (11). We find strong evidence of underreaction in aggregate earnings forecasts—aggregate earnings surprises are predictable using most measures of macroeconomic news. Specifically, errors in current-quarter (one-

[27] Veronesi's (1999) model only explains the asymmetric *price* reaction since it relies on the presence of discount rate news. The ambiguity-aversion scenario is thus more relevant in our setting.

quarter-ahead) forecasts are significantly positively associated with all news measures with the exception of market returns (one-quarter-ahead real GDP growth forecast revisions). In contrast, there is little evidence of overall underreaction in real GDP growth forecasts—only current-quarter real GDP growth surprises are predictable using lagged aggregate market returns. Overall, aggregate earnings forecasts are substantially less efficient compared to real GDP growth forecasts, with analysts significantly underreacting to recent macroeconomic news. Such a difference in underreaction patterns is inconsistent with analysts and economists being subject to the same set of cognitive biases. Rather, this difference suggests either that the formal forecasting techniques used by economists mitigate the extent of their overconfidence, or that overconfidence is not an important factor in forecast efficiency in general.

To shed light on the source of forecast inefficiency, and in particular, on whether the documented analyst underreaction is driven at least in part by incentives to be optimistic (resulting in underreaction only to negative news), we estimate the following regression, which corresponds to equation (7) from Section 3.2:

$$SURP = Intercept + b_0 \, I\_NEG\_NEWS + b_1 \, POS\_NEWS + b_2 \, NEG\_NEWS, \qquad (12)$$

where *SURP* is the current-quarter (one-quarter-ahead) forecast error in aggregate earnings or real GDP growth; *NEWS* is one of the lagged macroeconomic news measures, as previously defined; *I_NEG_NEWS* is equal to one if the news is negative and zero otherwise; *POS_NEWS* is an interaction term between *I_POS_NEWS* and *NEWS*, where *I_POS_NEWS* is equal to one if the news is positive and zero otherwise; and *NEG_NEWS* is an interaction term between *I_NEG_NEWS* and *NEWS*.

Table 4 reports the results of estimating regression (12). In the aggregate earnings forecast error regressions, the coefficient on *NEG_NEWS* is mostly significant and positive, suggesting that analysts consistently underreact to *negative* news.[28] The coefficient on *POS_NEWS* is generally insignificantly different from zero, suggesting that analysts underreact *only* to negative macroeconomic news. This result is consistent with the biases in aggregate

[28] The underreaction to negative news is statistically significant in all cases, except when one-quarter-ahead aggregate earnings surprises are regressed on revisions in current-quarter real GDP forecasts or market returns. In both of these cases, however, forecast errors are more positively associated with negative news; the lack of statistical significance may be due to low statistical power of the tests.

earnings forecasts being driven at least in part by analysts' revenue- or client-driven incentives to produce optimistic forecasts.

In contrast, we do not find evidence of similar asymmetric underreaction to macroeconomic news—the coefficient on *NEG_NEWS* is insignificantly different from zero for all macroeconomic news measures.[29] Overall, we find that analysts are consistently less efficient at incorporating *adverse* macroeconomic information into their forecasts compared to economists. The documented differences in efficiency are thus likely driven by analysts' incentives to be optimistic.

### 5.4 Stock Market Implications

Our results thus far suggest that economists' real GDP growth forecasts are more efficient than analysts' aggregate earnings forecasts, especially with respect to incorporating negative macroeconomic news. In this section we investigate whether the stock market adjusts for underreaction in aggregate earnings forecasts when pricing stocks. If the stock market is fixated on analysts' forecasts and similarly fails to fully adjust earnings expectations downwards following negative news, then we expect the stock market to be negatively "surprised" when lower-than-expected realized earnings are announced, with the magnitude of the surprise proportional to the magnitude of the negative news.

To test for such market underreaction out of sample, we sort quarters into "portfolios" based on the distribution of each of the macroeconomic news proxies over the past 20 years. More specifically, we split all news realizations into positive and negative partitions and then determine the 30% and 70% breakpoints within the two partitions. This procedure allows us to sort quarters into six portfolios: below 30%, between 30% and 70%, and above 70% for negative and positive news realizations. Note that because we require at least 15 quarters with non-missing news of the same sign to determine the breakpoints, we cannot sort quarters based on positive aggregate earnings forecast revisions and negative market returns.

We first examine whether such partitioning reasonably predicts aggregate earnings and real GDP growth forecast errors. Given the results from our inefficiency tests, we expect only

[29] We find underreaction in real GDP growth forecasts with respect to *positive* market returns, and *overreaction* with respect to positive changes in current-quarter aggregate earnings forecasts. However, these results are not robust across the two real GDP growth forecast horizons and thus are difficult to interpret. We also find that real GDP growth forecast surprises are predictable using positive lagged revisions in real GDP growth forecasts for the same horizon. These results need to be interpreted with caution, however, because consensus real GDP growth forecasts for the current quarter are not available to economists when they issue their forecasts.

partitioning within *negative* and *most recent* forecast revisions or market returns to predict aggregate earnings surprises, and only partitioning within *lagged* market returns to predict real GDP forecast surprises. The results, reported in Table 5, are generally consistent with out-of-sample predictability of aggregate earnings surprises. In particular, aggregate earnings surprises are predictable using negative revisions in one-quarter-ahead real GDP growth forecasts and weakly predictable using negative revisions in aggregate earnings forecasts. In contrast, real GDP growth surprises are predictable in the hypothesized direction only using lagged market returns.

To test whether the market is fixated on aggregate earnings forecasts, we examine market return predictability using the previously described quarter partitions. As in the aggregate earnings surprise predictability tests, we only expect partitioning within *negative* and *most recent* forecast revisions or market returns to predict market returns.

We first examine whether such partitioning predicts market returns realized over the next quarter (*MKTRET1*). The results, reported in Table 5, suggest that although market returns following the most negative macroeconomic news are more negative than market returns following the least negative macroeconomic news, the difference in returns is not statistically significant. The lack of statistical significance may be due to low statistical power of our tests—full-quarter returns incorporate many information signals in addition to earnings-related news. Accordingly, we next investigate whether our sample partitions can predict market returns *attributable to earnings news* released during the next quarter. To do this, we calculate market returns on the days when the first few S&P500 firms announce their earnings during the next quarter.[30] Specifically, we identify the dates on which the first five, ten, or fifteen S&P500 firms announce their earnings during each calendar quarter; we then calculate returns attributable to earnings announcements as average daily market returns earned during the identified announcement days. The resulting average announcement date market returns are labeled *ANNRET5*, *ANNRET10*, and *ANNRET15*, respectively.

The results, reported in Panels A and B of Table 5, suggest that our sample partitions robustly predict announcement-day market returns for the first few S&P500 earnings announcers.

[30] Measuring market returns on the days when the first few S&P500 firms make earnings announcements assumes that these are the bellwether stocks and that the stock market infers expected performance of the whole economy (or a stock's industry) from their performance. The literature suggests that some stocks are indeed treated as bellwethers by both analysts and investors (Hameed, Morck, Shen, and Yeung 2010).

For example, for the first fifteen S&P 500 earnings announcers, the announcement-day market returns are 0.4% to 0.7% lower in the "below 30%" quarters (i.e., quarters following most negative macroeconomic news) than in the "above 30%" quarters (i.e., quarters following the least negative macroeconomic news), where news is proxied by revisions in real GDP growth or aggregate earnings forecasts. Overall, the stock market does not appear to see through analysts' optimistic biases at the aggregate level and hence is consistently surprised by lower-than-expected aggregate earnings following quarters with negative macroeconomic news.

While there is no evidence of underreaction to negative macroeconomic news in economists' real GDP growth forecasts, our forecast efficiency tests suggest that economists may underreact to information contained in *positive* lagged market returns. Accordingly, we investigate whether partitions based on positive lagged market returns predict both the market returns realized over the next quarter and the returns attributable to real GDP growth announcements. The announcement-day market returns (labeled *GANNRET*) are estimated on the day when the Bureau of Economics and Statistics announces the initial (advance) real GDP growth estimates for the current quarter. Panel C of Table 5 reports the results. We find no evidence of market return predictability either for the full-quarter returns (which is not surprising) or around the real GDP growth announcement dates. The latter finding is consistent with the lack of a price reaction to real (i.e., non-monetary) macroeconomic indicator announcements documented in prior research (Pearce and Roley 1985).

Overall, the return predictability evidence is consistent with the stock market overweighting overly optimistic analyst forecasts in forming aggregate earnings expectations, and as a consequence being predictably negatively surprised by earnings released in the quarters following negative macroeconomic news.

## 5.5 Additional Analyses

### *Cross-sectional Forecast Efficiency Tests*

In this section, we examine whether the documented inefficiency in aggregate earnings forecasts varies with two firm attributes: earnings sensitivity to aggregate earnings (i.e., earnings cyclicality) and firm size.

To the extent that the inefficiency in aggregate earnings forecasts arises from analysts underreacting to macroeconomic news, the degree of underreaction should be more pronounced for firms that are more pro-cyclical (i.e., for firms whose earnings are more sensitive to macroeconomic news). Further, analysts following larger firms may be more overconfident in their *private* macroeconomic information if they believe that larger firms are more representative of the industry or the entire economy. If analysts' underreaction arises from their overconfidence (i.e., underweighting *public* macroeconomic information), and the degree of overconfidence is positively associated with firm size, then we expect to see more pronounced underreaction for larger firms.

We use accounting betas to measure earnings cyclicality. Accounting betas are estimated as the slopes from regressing firm-specific seasonal net operating profit changes (scaled by four-quarter-lagged total assets) on market-level seasonal net operating profit changes using the past twelve quarters of data.[31] We use total assets from Compustat for the latest quarter before the consensus forecast date to measure firm size.

To test whether the extent of analysts' forecast inefficiency with respect to macroeconomic information varies with earnings cyclicality and firm size, we partition our sample into terciles based on either their accounting betas or size. Within each tercile, we calculate aggregate forecast errors following the same algorithm discussed in Section 4.2. We then estimate the following regression, which is analogous to regression (9), using forecast errors aggregated within each subsample:

$$SURP^{S} = Intercept + b\ NEWS, \tag{9a}$$

where $SURP^S$ is the $t$+1 forecast error for a given sample partition, and *NEWS* is one of the recent macroeconomic news variables, as previously defined.

Table 6 reports the slope estimates for regression (9a) for the various sample partitions using the same set of macroeconomic news measures.[32] When the sample is partitioned based on accounting betas, we find that the least pro-cyclical firms (those in the lowest accounting beta

[31] Market-level seasonal net operating profit changes are calculated by summing changes in net operating profits across all firms in a given quarter and dividing by the corresponding sum of four-quarter-lagged total assets.
[32] Due to a smaller number of observations in some of the earlier quarters, the regressions are based on shorter time series and use 90 (92) quarters for aggregate surprises partitioned on accounting betas (firm size).

tercile) are the least likely to underreact to recent macroeconomic news—the coefficient on *NEWS* is consistently lower (and in most cases, substantially lower) in the "Low" partition than in the "Mid" and "High" partitions. With the exception of one specification, the coefficient on *NEWS* for the "HIGH" partition is either higher or roughly the same as that for the "MID" partition. Overall, the results suggest that the forecasts made for the least pro-cyclical firms exhibit the least underreaction to macroeconomic news.

When the sample is partitioned based on firm size, we find that in eight out of ten regressions the slope coefficients on *NEWS* are monotonically increasing with firm size, suggesting that aggregate earnings forecasts exhibit greater underreaction for larger firms. These results are somewhat surprising given that prior research on firm-specific forecast efficiency finds that forecasts for larger firms tend to be less biased (e.g., Lim 2001) and are updated more quickly in response to new information (e.g., Zhang 2008).

### *Forecasting Performance over the Business Cycle*

Recent anecdotal evidence suggests that there is a disconnect between economists' and analysts' forecasts following the recession of 2008-2009. In particular, the evidence suggests that analysts are consistently more optimistic than economists about the outlook of the economy (e.g., Wall Street Journal 2011; New York Times 2011).[33] In this section, we provide preliminary descriptive evidence on whether analysts' and economists' forecast accuracy does indeed vary over the business cycle.

Panel A of Figure 3 plots the forecast errors in analysts' and economists' forecasts of aggregate earnings and real GDP growth, respectively, over our sample period; the quarters classified as recessionary by NBER are highlighted in the figure. Casual observation suggests that on average both analysts and economists are more negatively surprised during recessions

[33] For example, according to the WSJ (2011) article, "The U.S. economy has slowed noticeably in recent weeks, prompting economists to ratchet down their estimates for growth… But individual stock analysts have remained noticeably upbeat.… The disconnect between analysts on the one hand and strategists and economists on the other comes largely because analysts are largely focused on their individual companies and industries." A NY Times (2011) article conveys a similar message: "Amid all the grim economic data and a chorus of warnings of a fresh recession, one group on Wall Street has remained remarkably optimistic despite the dangers that may lie ahead—the research analysts who track individual companies. Typically bullish in the best of times, this group has barely budged on its expectations for earnings in the second half of 2011, even as the economists and strategists at the big brokerage firms have steadily ratcheted down their forecasts for overall economic growth."

than expansions. Descriptive statistics reported in Table 7 support this observation: both economists' and analysts' forecast errors are significantly more negative during recessions. This finding is not surprising given the inherent difficulty in predicting recessions (Fildes and Stekler 2002). More surprising, however, is the finding that the accuracy of economists' forecasts of current-quarter real GDP growth is not significantly different over the business cycle. Unlike the absolute forecast errors of aggregate earnings, the average absolute forecast errors in real GDP growth are not statistically significantly *larger* during recessions (i.e., the one-quarter-ahead GDP growth forecasts are less efficient during recessions). Thus, while both sets of forecasters tend to be more negatively surprised during recessions, economists appear to demonstrate relatively better short-horizon forecast accuracy.[34]

From Panel B of Figure 2 and Panel B of Figure 3, it is obvious that both economists and analysts respond to recessionary periods by significantly revising their forecasts downwards. The corresponding statistical analysis presented in Panel C of Table 7 confirms this observation—both analysts' and economists' forecast revisions are significantly more negative during recessions. The frequency of negative revisions also increases for both sets of forecasters during recessions, although the increase in frequency is statistically significant only for the economists, with the percentage of negative revisions in current- (next-) quarter GDP growth forecasts significantly higher during recessions compared to expansions—90% (82%) versus 59% (44%), respectively. The corresponding percentages for negative revisions in aggregate earnings forecasts for the current (next) quarter are 100% (100%) versus 87% (83%), respectively. Unfortunately, given the small number of recessionary quarters in our sample, it is difficult to test whether analysts are more inefficient at incorporating macroeconomic news during recessions relative to economists. However, given the concentration of negative macroeconomic news during recessions and analysts' overall underreaction to such news, one might conjecture that analyst forecast inefficiencies are indeed more pronounced during recessionary periods.

## 6 Conclusion

In this paper, we investigate whether sell-side analysts and economists behave differently when forecasting the macroeconomy by comparing analysts' *aggregate* earnings forecasts and

[34] An important caveat is that our sample period spans only three NBER recessions (August 1990 - March 1991, April 2001 - November 2001, and January 2008 - June 2009), which limits the generalizability of our findings.

economists' real GDP growth forecasts. We find that while there is a significant common component across the two sets of forecasts, their accuracy and efficiency differ drastically. Specifically, we find that aggregate earnings forecasts are persistently optimistic and analysts tend to underreact to negative news, with the extent of underreaction more pronounced for more procyclical and larger firms. In contrast, real GDP growth forecasts are on average unbiased and economists do not appear to underreact to negative news. Such difference in forecast efficiency is likely driven by analysts' revenue- or client-driven incentives to be optimistic. We further find that the stock market inefficiently weights the two sets of forecasts in forming earnings expectations. In particular, the market returns surrounding the first few "bellwether" firms' earnings announcements are predictably more negative following quarters with worse macroeconomic news. This finding is consistent with the market not sufficiently adjusting its earnings expectations downwards due to overweighting (underweighting) insufficiently (sufficiently) downward-adjusted forecasts by analysts (economists).

Our findings are subject to several caveats. First, in this study we examine forecast efficiency with respect to macroeconomic information that is *common* to both sets of forecasts (i.e., macroeconomic information that is an important earnings factor). As a result, our findings may not generalize to macroeconomic information that is not relevant for aggregate earnings. Second, we use a single product of analysts' research (i.e., earnings forecasts), and a single product of economists' research (i.e., real GDP growth forecasts). Incorporating recommendations and forecasts with respect to other economic indicators may enrich the analysis and help further distinguish between the determinants of forecasting behavior. Finally, our sample period is relatively short, including only 105 quarters (with three recessions). As a consequence, we are unable to perform tests conditional on the stage of the business cycle, which limits the extent to which our findings can be extrapolated to other time periods with different business-cycle composition. In addition, some of our tests may lack statistical power to detect economically important relationships due to the small sample size.

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## Appendix. Variable Definitions

*FGDP0* (*FGDP1*) – consensus median forecast of real GDP growth for quarter *t* (*t*+1) made in quarter *t* from the Survey of Professional Forecasters (SPF).

*GDP0* (*GDP1*) – realized real GDP growth for quarter *t* (*t*+1) based on initial figures from the Bureau of Economics and Statistics.

*FEARN0* (*FEARN1*) – aggregate consensus earnings forecast for quarter *t* (*t*+1) made in quarter *t*, calculated as the sum of firm-specific consensus median earnings forecasts divided by the sum of the book values of equity for the latest quarter from Compustat. Firm-specific consensus median forecasts are calculated using I/B/E/S forecasts outstanding at the end of calendar quarter *t* that were issued or revised following the most recent SPF forecast issuance.

*EARN0* (*EARN1*) – realized aggregate earnings for quarter *t* (*t*+1), calculated as the sum of firm-specific realized earnings from I/B/E/S divided by the sum of the book values of equity for the latest quarter from Compustat before consensus forecast issuance. Only realized earnings of the firm-quarters for which we have forecasts enter the calculation.

*SURP_FGDP0* (*SURP_FGDP1*) – surprise (realized minus forecasted) in real GDP growth for quarter *t* (*t*+1) relative to the forecast made in quarter *t*.

*SURP_FEARN0* (*SURP_FEARN1*) – surprise (realized minus forecasted) in aggregate earnings for quarter *t* (*t*+1) relative to the forecast made in quarter *t*. The realized and forecasted aggregate figures are based on the same set of firms.

*lSURP_FGDP0* – surprise (realized minus forecasted) in real GDP growth for quarter *t*-1 relative to the forecast made in quarter *t*-1.

*lSURP_FEARN0* – surprise (realized minus forecasted) in aggregate earnings for quarter *t*-1 relative to the forecast made in quarter *t*. The realized and forecasted aggregate figures are based on the same set of firms.

*ΔFGDP0* (*ΔFGDP1*) – revision in real GDP growth forecasts for quarter *t* (*t*+1) made between quarters *t*-1 and *t*.

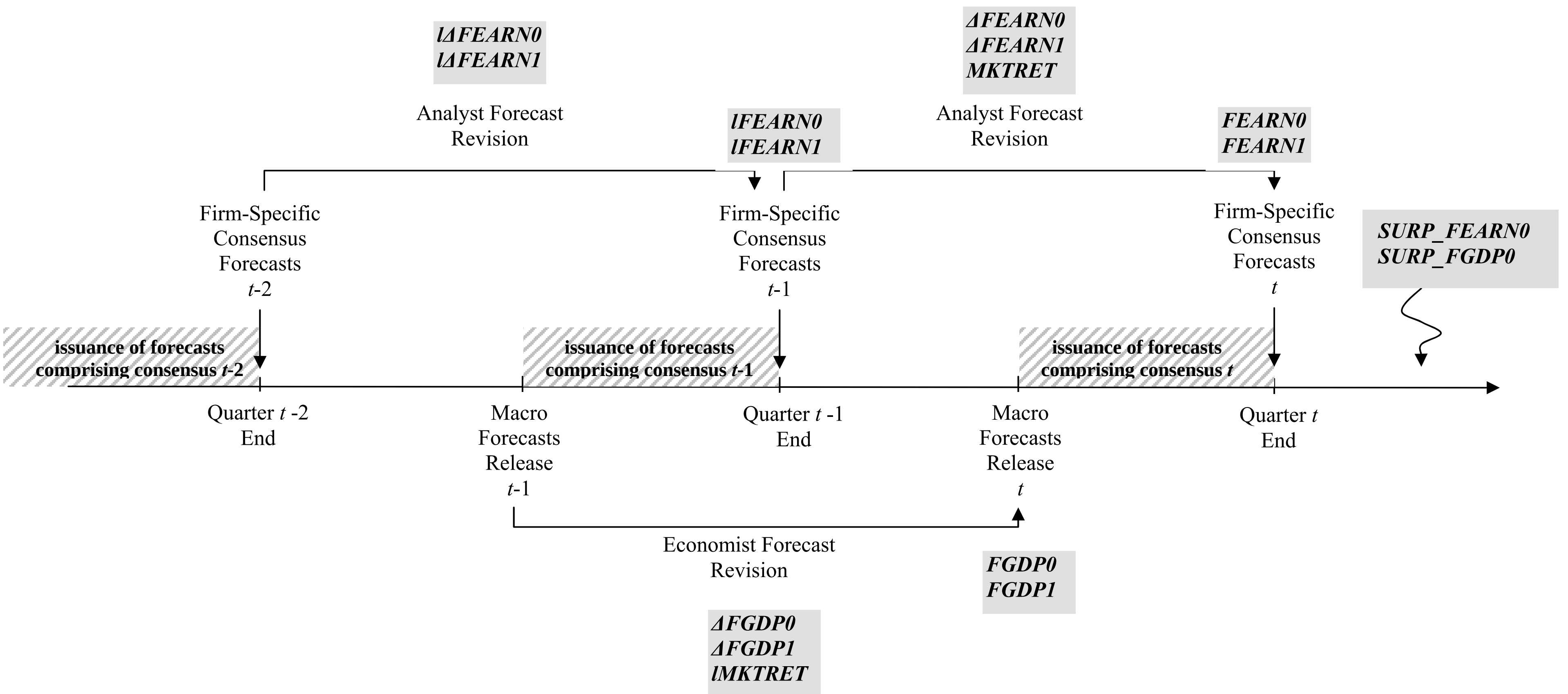
*ΔFEARN0 (ΔFEARN1)* – revision in aggregate earnings forecasts for quarter *t* (*t*+1) made between quarters *t*-1 and *t*. Firm composition is held constant.

*lΔFGDP0 (lΔFGDP1)* – revision in real GDP growth forecasts for the current (next) quarter made between quarters *t*-2 and *t*-1. Firm composition is held constant.

*lΔFEARN0 (lΔFEARN1)* – revision in aggregate earnings forecasts for the current (next) quarter made between quarters *t*-2 and *t*-1. Firm composition is held constant.

*MKTRET* (*lMKTRET*) – return on CRSP value-weighted index in quarter *t* (over the three months ending in the month of GDP forecast issuance in quarter *t*). In the tests of real GDP growth forecast efficiency, the return estimation period is lagged by an additional month.

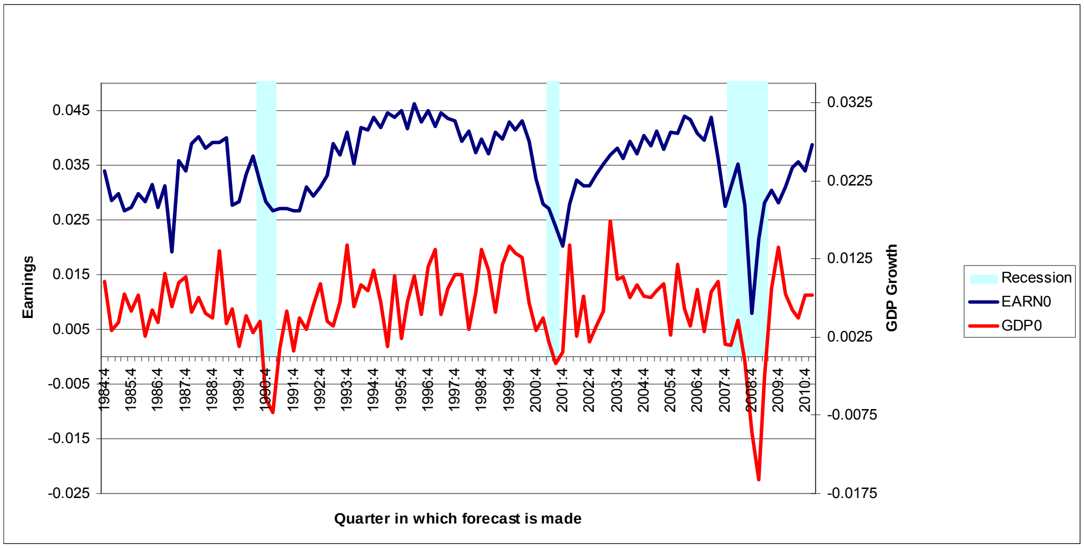
**Figure 1. Variable Measurement Timeline**



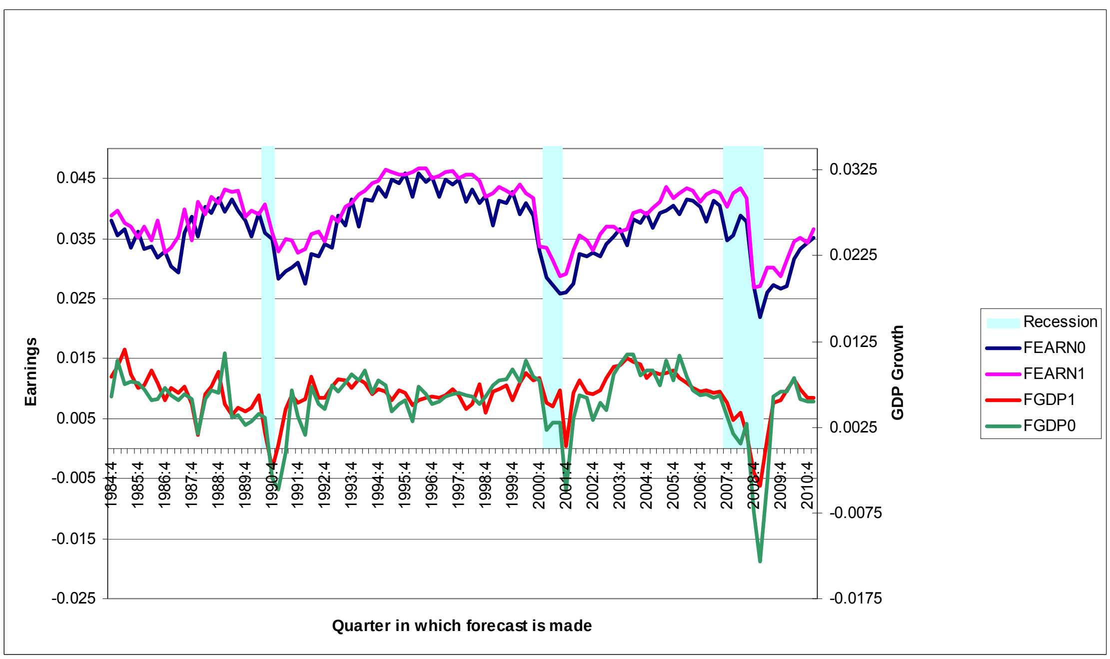
# Figure 2. Aggregate Earnings and Real GDP Growth

The figure spans 105 quarters from 4:1984 to 4:2010. Panel A plots realized aggregate earnings (EARN0) and real GDP growth (GDP0) for quarter *t*. Panel B plots the consensus median forecast of real GDP growth for quarter *t* (*t*+1) made in quarter t, *FGDP0* (*FGDP1*), and the aggregate consensus earnings forecast for quarter *t* (*t*+1) made in quarter *t*, *FEARN0* (*FEARN1*).

## Panel A. Realized Aggregate Earnings and Real GDP Growth



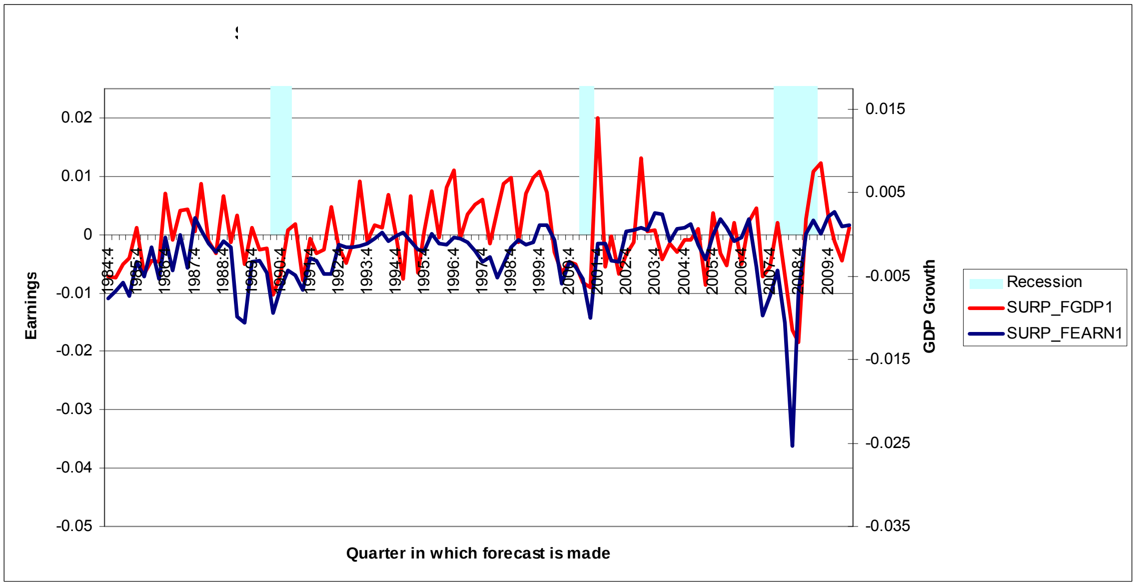

## Panel B. Aggregate Earnings and Real GDP Growth Forecasts



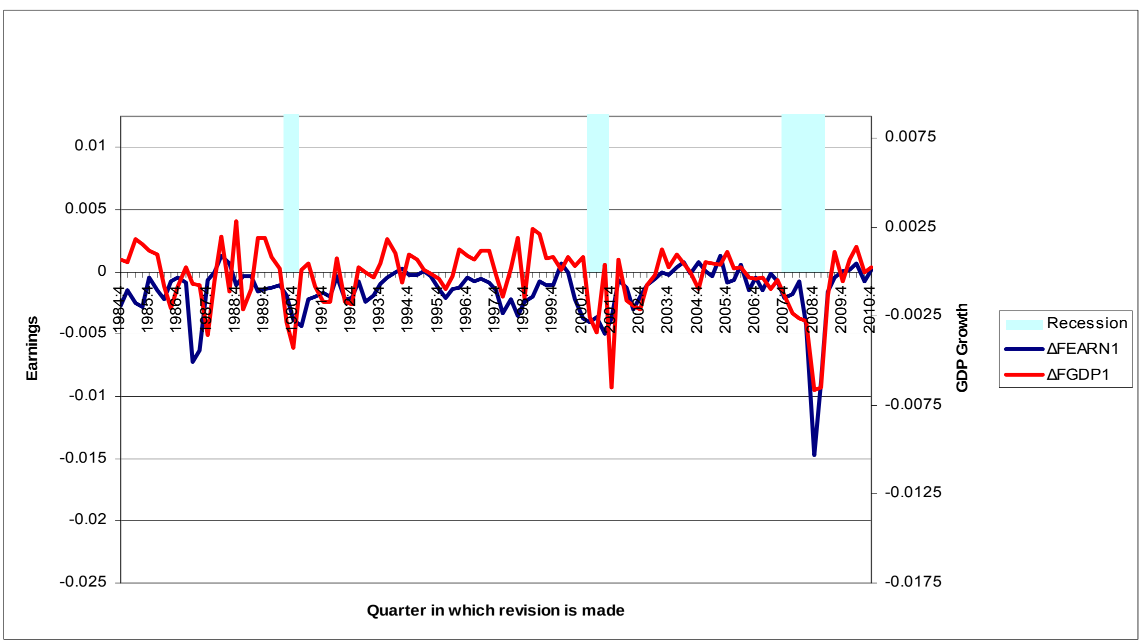
## Figure 3. Aggregate Forecast Revisions and Surprises

The figure spans 105 quarters from 4:1984 to 4:2010 (the plot in Panel A spans 104 quarters ending in 3:2010). Panel A plots surprises in real GDP growth and aggregate earnings forecasts for quarter *t*+1 relative to forecasts made in quarter *t*, *SURP_FGDP1* and *SURP_FEARN1*, respectively. Panel B plots revisions between quarters *t*-1 and *t* in the real GDP growth and aggregate earnings forecasts for quarter *t*+1, *ΔFGDP1* and *ΔFEARN1*, respectively.

### Panel A. Surprises in Aggregate Earnings and Real GDP Growth Forecasts




### Panel B. Revisions in Aggregate Earnings and Real GDP Growth Forecasts



## Table 1. Aggregate Earnings and Real GDP Growth: Forecasts and Realized Values

The table contains descriptive statistics and correlations among forecasts and corresponding realized values for a sample of 105 quarters from 4:1984 to 4:2010. Variables are defined as follows: *GDP0* (*GDP1*) – realized real GDP growth for quarter *t* (*t*+1). *EARN0* (*EARN1*) – realized aggregate earnings for quarter *t* (*t*+1). *FGDP0* (*FGDP1*) – consensus median forecast of real GDP growth for quarter *t* (*t*+1) made in quarter *t. FEARN0* (*FEARN1*) – aggregate consensus earnings forecast for quarter *t* (*t*+1) made in quarter *t*. The Pearson (Spearman) correlations in Panel B are reported below (above) the diagonal. The numbers in parentheses are corresponding *p*-values.

### Panel A. Descriptive Statistics

| | Nobs | Mean | StdDev | 1% | 5% | 25% | Med | 75% | 95% | 99% |
|---|---|---|---|---|---|---|---|---|---|---|
| **Realized values:** | | | | | | | | | | |
| ***GDP0*** | 105 | 0.0063 | 0.005 | -0.010 | -0.001 | 0.004 | 0.006 | 0.009 | 0.014 | 0.014 |
| ***GDP1*** | 105 | 0.0062 | 0.005 | -0.010 | -0.001 | 0.004 | 0.006 | 0.009 | 0.014 | 0.014 |
| ***EARN0*** | 105 | 0.0351 | 0.007 | 0.019 | 0.027 | 0.030 | 0.036 | 0.041 | 0.044 | 0.045 |
| ***EARN1*** | 104 | 0.0357 | 0.007 | 0.015 | 0.026 | 0.030 | 0.037 | 0.042 | 0.045 | 0.046 |
| **Forecasts:** | | | | | | | | | | |
| ***FGDP0*** | 105 | 0.0056 | 0.004 | -0.007 | -0.003 | 0.004 | 0.006 | 0.008 | 0.010 | 0.011 |
| ***FGDP1*** | 105 | 0.0063 | 0.003 | -0.003 | 0.001 | 0.005 | 0.007 | 0.008 | 0.010 | 0.011 |
| ***FEARN0*** | 105 | 0.0365 | 0.005 | 0.026 | 0.027 | 0.033 | 0.037 | 0.041 | 0.045 | 0.046 |
| ***FEARN1*** | 105 | 0.0390 | 0.005 | 0.027 | 0.030 | 0.035 | 0.040 | 0.043 | 0.046 | 0.047 |

### Panel A. Correlation among Realized Values and Forecasts

| Spearman \ Pearson | *GDP0* | *GDP1* | *EARN0* | *EARN1* | *FGDP0* | *FGDP1* | *FEARN0* | *FEARN1* |
|---|---|---|---|---|---|---|---|---|
| ***GDP0*** | - | 0.45 | 0.55 | 0.51 | 0.75 | 0.59 | 0.43 | 0.41 |
| | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| ***GDP1*** | 0.26 | - | 0.48 | 0.60 | 0.43 | 0.49 | 0.30 | 0.26 |
| | (0.01) | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) |
| ***EARN0*** | 0.46 | 0.41 | - | 0.82 | 0.57 | 0.42 | 0.86 | 0.82 |
| | (0.00) | (0.00) | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| ***EARN1*** | 0.46 | 0.51 | 0.86 | - | 0.48 | 0.37 | 0.67 | 0.67 |
| | (0.00) | (0.00) | (0.00) | | (0.00) | (0.00) | (0.00) | (0.00) |
| ***FGDP0*** | 0.54 | 0.32 | 0.43 | 0.46 | - | 0.86 | 0.49 | 0.44 |
| | (0.00) | (0.00) | (0.00) | (0.00) | | (0.00) | (0.00) | (0.00) |
| ***FGDP1*** | 0.30 | 0.29 | 0.24 | 0.25 | 0.74 | - | 0.30 | 0.26 |
| | (0.00) | (0.00) | (0.01) | (0.01) | (0.00) | | (0.00) | (0.01) |
| ***FEARN0*** | 0.36 | 0.31 | 0.89 | 0.73 | 0.32 | 0.10 | - | 0.93 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.32) | | (0.00) |
| ***FEARN1*** | 0.33 | 0.24 | 0.83 | 0.73 | 0.27 | 0.06 | 0.92 | - |
| | (0.00) | (0.01) | (0.00) | (0.00) | (0.01) | (0.56) | (0.00) | |

## Table 2. Forecast Revisions and Forecast Surprises

The table contains descriptive statistics and correlations among forecast surprises and forecast revisions for a sample of 105 quarters from 4:1984 to 4:2010. Variables are defined as follows: *ΔFGDP0* (*ΔFGDP1*) – revision between quarters *t*-1 and *t* in the real GDP growth forecast for quarter *t* (*t*+1). *ΔFEARN0* (*ΔFEARN1*) – revision between quarters *t*-1 and *t* in the aggregate earnings forecast for quarter *t* (*t*+1). *SURP_FGDP0* (*SURP_FGDP1*) – surprise (realized minus forecasted) in real GDP growth for quarter *t* (*t*+1) relative to the forecast made in quarter *t*. *SURP_FEARN0* (*SURP_FEARN1*) – surprise (realized minus forecasted) in aggregate earnings for quarter *t* (*t*+1) relative to the forecast made in quarter *t*. |*SURP_FGDP0*|, |*SURP_FGDP1*|, |*SURP_FEARN0*| and |*SURP_FEARN1*| are absolute values of surprises. *ΔFGDP0* (*ΔFGDP1*) – revision between quarters *t*-1 and *t* in the real GDP growth forecast for quarter *t* (*t*+1). *ΔFEARN0* (*ΔFEARN1*) – revision between quarters *t*-1 and *t* in the aggregate earnings forecast for quarter *t* (*t*+1). *lΔFEARN0 (lΔFEARN1)* – revision between quarters *t*-2 and *t*-1 in the aggregate earnings forecast for quarter *t* (*t*+1). *lSURP_FGDP0* – surprise (realized – forecasted) real GDP growth for quarter *t*-1 relative to the forecast made in quarter *t*-1. *lSURP_FEARN0* – surprise (realized minus forecasted) aggregate earnings for quarter *t*-1 relative to the forecast made in quarter *t*-1. The Pearson (Spearman) correlations in Panels B and C are reported below (above) the diagonal. The numbers in parentheses are corresponding *p*-values.

### Panel A. Descriptive Statistics for Forecast Revisions and Surprises

| | Nobs | Mean | *t*-stat | *p*-value | StdDev | 1% | 5% | 25% | Med | 75% | 95% | 99% |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Forecast revisions:** | | | | | | | | | | | | |
| ***ΔFGDP0*** | 105 | -0.0008 | -3.10 | (0.00) | 0.003 | -0.010 | -0.004 | -0.002 | -0.001 | 0.001 | 0.002 | 0.004 |
| ***ΔFGDP1*** | 105 | -0.0003 | -1.70 | (0.09) | 0.002 | -0.006 | -0.003 | -0.001 | 0.000 | 0.001 | 0.002 | 0.002 |
| ***ΔFEARN0*** | 105 | -0.0020 | -8.62 | (0.00) | 0.002 | -0.010 | -0.006 | -0.003 | -0.001 | -0.000 | 0.001 | 0.002 |
| ***ΔFEARN1*** | 105 | -0.0015 | -7.29 | (0.00) | 0.002 | -0.009 | -0.004 | -0.002 | -0.001 | -0.000 | 0.001 | 0.001 |
| **Forecast surprises:** | | | | | | | | | | | | |
| ***SURP_FGDP0*** | 105 | 0.0007 | 2.14 | (0.03) | 0.003 | -0.005 | -0.004 | -0.002 | 0.000 | 0.003 | 0.006 | 0.009 |
| ***SURP_FGDP1*** | 105 | -0.0001 | -0.22 | (0.83) | 0.004 | -0.011 | -0.006 | -0.003 | -0.001 | 0.003 | 0.008 | 0.009 |
| ***SURP_FEARN0*** | 105 | -0.0015 | -4.21 | (0.00) | 0.004 | -0.012 | -0.009 | -0.003 | 0.000 | 0.000 | 0.002 | 0.003 |
| ***SURP_FEARN1*** | 104 | -0.0035 | -6.45 | (0.00) | 0.006 | -0.015 | -0.014 | -0.006 | -0.002 | 0.000 | 0.003 | 0.004 |
| **Absolute forecast surprises:** | | | | | | | | | | | | |
| \|***SURP_FGDP0***\| | 105 | 0.0028 | 14.47 | (0.00) | 0.002 | 0.000 | 0.000 | 0.001 | 0.002 | 0.004 | 0.007 | 0.009 |
| \|***SURP_FGDP1***\| | 105 | 0.0034 | 12.92 | (0.00) | 0.003 | 0.000 | 0.000 | 0.001 | 0.003 | 0.005 | 0.008 | 0.013 |
| \|***SURP_FEARN0***\| | 105 | 0.0025 | 8.45 | (0.00) | 0.003 | 0.000 | 0.000 | 0.000 | 0.002 | 0.003 | 0.009 | 0.012 |
| \|***SURP_FEARN1***\| | 104 | 0.0043 | 8.90 | (0.00) | 0.005 | 0.000 | 0.000 | 0.001 | 0.003 | 0.006 | 0.014 | 0.015 |

### Panel B. Correlation among Forecast Revisions

| **Spearman \ Pearson** | ***ΔFGDP0*** | ***ΔFGDP1*** | ***ΔFEARN0*** | ***ΔFEARN1*** | ***lΔFGDP0*** | ***lΔFGDP1*** | ***lΔFEARN0*** | ***lΔFEARN1*** |
|---|---|---|---|---|---|---|---|---|
| ***ΔFGDP0*** | - | 0.72 | 0.64 | 0.60 | 0.22 | 0.22 | 0.42 | 0.37 |
| | | (0.00) | (0.00) | (0.00) | (0.02) | (0.03) | (0.00) | (0.00) |
| ***ΔFGDP1*** | 0.54 | - | 0.59 | 0.55 | 0.37 | 0.13 | 0.49 | 0.41 |
| | (0.00) | | (0.00) | (0.00) | (0.00) | (0.18) | (0.00) | (0.00) |
| ***ΔFEARN0*** | 0.44 | 0.32 | - | 0.78 | 0.42 | 0.31 | 0.52 | 0.56 |
| | (0.00) | (0.00) | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| ***ΔFEARN1*** | 0.47 | 0.32 | 0.75 | - | 0.35 | 0.22 | 0.57 | 0.37 |
| | (0.00) | (0.00) | (0.00) | | (0.00) | (0.03) | (0.00) | (0.00) |
| ***lΔFGDP0*** | 0.17 | 0.34 | 0.30 | 0.23 | - | 0.37 | 0.54 | 0.57 |
| | (0.08) | (0.00) | (0.00) | (0.02) | | (0.00) | (0.00) | (0.00) |
| ***lΔFGDP1*** | 0.16 | -0.02 | 0.16 | 0.05 | 0.32 | - | 0.14 | 0.21 |
| | (0.10) | (0.83) | (0.10) | (0.64) | (0.00) | | (0.16) | (0.03) |
| ***lΔFEARN0*** | 0.24 | 0.27 | 0.61 | 0.62 | 0.31 | 0.09 | - | 0.75 |
| | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.37) | | (0.00) |
| ***lΔFEARN1*** | 0.18 | 0.20 | 0.59 | 0.45 | 0.38 | 0.18 | 0.77 | - |
| | (0.06) | (0.04) | (0.00) | (0.00) | (0.00) | (0.07) | (0.00) | |

**Panel C. Correlation among Forecast Surprises**

| Spearman \ Pearson | *SURP_ FGDP0* | *SURP_ FGDP1* | *SURP_ FEARN0* | *SURP_ FEARN1* | *lSURP_ FGDP0* | *lSURP_ FEARN0* |
|---|---|---|---|---|---|---|
| ***SURP_FGDP0*** | - | 0.27 | 0.19 | 0.18 | 0.01 | 0.05 |
| | | (0.01) | (0.05) | (0.06) | (0.88) | (0.59) |
| ***SURP_FGDP1*** | 0.22 | - | 0.32 | 0.50 | 0.01 | 0.15 |
| | (0.02) | | (0.00) | (0.00) | (0.96) | (0.14) |
| ***SURP_FEARN0*** | 0.16 | 0.23 | - | 0.59 | 0.11 | 0.48 |
| | (0.10) | (0.02) | | (0.00) | (0.28) | (0.00) |
| ***SURP_FEARN1*** | 0.16 | 0.43 | 0.68 | - | 0.09 | 0.31 |
| | (0.10) | (0.00) | (0.00) | | (0.39) | (0.00) |
| ***lSURP_FGDP0*** | -0.04 | 0.03 | 0.09 | 0.17 | - | 0.19 |
| | (0.70) | (0.74) | (0.37) | (0.09) | | (0.05) |
| ***lSURP_FEARN0*** | -0.01 | 0.13 | 0.59 | 0.51 | 0.17 | - |
| | (0.95) | (0.18) | (0.00) | (0.00) | (0.08) | |

## Table 3. Information Content of Forecasts

The table reports results of regressing forecast revisions on various news proxies for a sample of 105 quarters from 4:1984 to 4:2010. The dependent variables are defined as follows: *ΔFGDP0* (*ΔFGDP1*) –revision between quarters *t*-1 and *t* in the real GDP growth forecast for quarter *t* (*t*+1). *ΔFEARN0* (*ΔFEARN1*) –revision between quarters *t*-1 and *t* in the aggregate earnings forecast for quarter *t* (*t*+1). The *NEWS* proxies are *ΔFGDP0* (*ΔFGDP1*) as previously defined; *MKTRET* – return on the CRSP value-weighted index in quarter *t*; *lΔFEARN0 (lΔFEARN1)* – revision between quarters *t*-2 and *t*-1 in the aggregate earnings forecast for quarter *t* (*t*+1); and *lMKTRET* – return on the CRSP value-weighted index over the three months ending in the month of the GDP forecast issuance in quarter *t*. *NEG_NEWS* is set equal to the corresponding news variable if it is non-positive, and zero otherwise. *POS_NEWS* is set equal to the corresponding news variable if it is positive, and zero otherwise. *I_NEG_NEWS* is an indicator equal to one if the corresponding news variable is non-positive. *t*-statistics based on standard errors with Newey-West adjustment for autocorrelation are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

### Panel A. Information Content of Aggregate Earnings Forecasts

| | ***Dependent Variable = ΔFEARN0*** | | | | | | ***Dependent Variable = ΔFEARN1*** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***NEWS = ΔFGDP0*** | | ***NEWS = ΔFGDP1*** | | ***NEWS = MKTRET*** | | ***NEWS = ΔFGDP0*** | | ***NEWS = ΔFGDP1*** | | ***NEWS = MKTRET*** | |
| ***NEWS*** | 0.602 | | 0.822 | | 0.008 | | 0.500 | | 0.665 | | 0.008 | |
| | (4.08)*** | | (3.20)*** | | (1.39) | | (3.36)*** | | (2.63)*** | | (1.59) | |
| ***NEG_NEWS*** | | 0.790 | | 1.371 | | 0.023 | | 0.612 | | 1.048 | | 0.027 |
| | | (3.45)*** | | (4.46)*** | | (1.61) | | (2.38)** | | (2.64)*** | | (1.93)* |
| ***POS_NEWS*** | | 0.066 | | -0.069 | | -0.006 | | 0.151 | | -0.167 | | -0.001 |
| | | (0.27) | | (-0.16) | | (-1.94)* | | (0.91) | | (-0.57) | | (-0.48) |
| ***I_NEG_NEWS*** | | 0.000 | | 0.001 | | -0.000 | | -0.000 | | 0.000 | | 0.001 |
| | | (0.11) | | (1.30) | | (-0.20) | | (-0.04) | | (0.46) | | (1.50) |
| ***Intercept*** | -0.002 | -0.001 | -0.002 | -0.001 | -0.002 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.002 | -0.000 |
| | (-6.39)*** | (-2.53)** | (-6.89)*** | (-2.44)** | (-4.79)*** | (-1.61) | (-5.73)*** | (-2.23)** | (-6.71)*** | (-1.94)* | (-4.71)*** | (-0.24) |
| **Nobs** | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 |
| **Adj. $R^2$** | 0.646 | 0.668 | 0.615 | 0.678 | 0.455 | 0.519 | 0.569 | 0.577 | 0.527 | 0.576 | 0.399 | 0.480 |

### Panel B. Information Content of Real GDP Growth Forecasts

| | ***Dependent Variable = ΔFGDP0*** | | | | | | ***Dependent Variable = ΔFGDP1*** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***NEWS = lΔFEARN0*** | | ***NEWS = lΔFEARN1*** | | ***NEWS = lMKTRET*** | | ***NEWS = lΔFEARN0*** | | ***NEWS = lΔFEARN1*** | | ***NEWS = lMKTRET*** | |
| ***NEWS*** | 0.509 | | 0.413 | | 0.008 | | 0.405 | | 0.319 | | 0.006 | |
| | (4.21)*** | | (2.56)** | | (1.76)* | | (7.05)*** | | (3.15)*** | | (2.22)** | |
| ***NEG_NEWS*** | | 0.541 | | 0.558 | | 0.017 | | 0.410 | | 0.405 | | 0.016 |
| | | (4.19)*** | | (4.52)*** | | (1.94)* | | (6.72)*** | | (5.44)*** | | (3.04)*** |
| ***POS_NEWS*** | | -0.498 | | -0.346 | | 0.002 | | -0.279 | | -0.036 | | 0.000 |
| | | (-0.80) | | (-2.33)** | | (0.32) | | (-0.60) | | (-0.51) | | (0.05) |
| ***I_NEG_NEWS*** | | -0.000 | | -0.001 | | 0.000 | | -0.000 | | -0.000 | | 0.000 |
| | | (-0.30) | | (-1.69)* | | (0.37) | | (-0.94) | | (-0.71) | | (0.88) |
| ***Intercept*** | 0.000 | 0.000 | -0.000 | 0.000 | -0.001 | -0.000 | 0.000 | 0.001 | -0.000 | 0.000 | -0.000 | 0.000 |
| | (0.05) | (0.64) | (-1.54) | (1.43) | (-2.91)*** | (-0.56) | (2.07)** | (2.35)** | (-0.03) | (2.93)*** | (-1.74)* | (0.92) |
| **Nobs** | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 |
| **Adj. $R^2$** | 0.234 | 0.225 | 0.191 | 0.244 | 0.143 | 0.162 | 0.249 | 0.238 | 0.178 | 0.199 | 0.114 | 0.184 |

## Table 4. Forecast Error Predictability

The table reports results of regressing forecast surprises on various lagged news proxies for a sample of 105 quarters from 4:1984 to 4:2010. The dependent variables are defined as follows: *SURP_FGDP0* (*SURP_FGDP1*) – surprise (realized minus forecasted) in real GDP growth for quarter *t* (*t*+1) relative to the forecast made in quarter *t*. *SURP_FEARN0* (*SURP_FEARN1*) – surprise (realized minus forecasted) in aggregate earnings for quarter *t* (*t*+1) relative to the forecast made in quarter *t*. The *NEWS* proxies are *ΔFGDP0* (*ΔFGDP1*) – revision between quarters *t*-1 and *t* in the real GDP growth forecast for quarter *t* (*t*+1); *ΔFEARN0* (*ΔFEARN1*) –revision between quarters *t*-1 and *t* in the aggregate earnings forecast for quarter *t* (*t*+1); *MKTRET* – return on the CRSP value-weighted index in quarter *t*; *lΔFEARN0 (lΔFEARN1)* – revision between quarters *t*-2 and *t*-1 in the aggregate earnings forecast for quarter *t* (*t*+1); *lMKTRET* – return on the CRSP value-weighted index over the three months ending in the month *preceding* the GDP forecast issuance in quarter *t*. *NEG_NEWS* is set equal to the corresponding news variable if it is non-positive, and zero otherwise. *POS_NEWS* is set equal to the corresponding news variable if it is positive, and zero otherwise. *I_NEG_NEWS* is an indicator equal to one if the corresponding news variable is non-positive. *t*-statistics based on standard errors with Newey-West adjustment for autocorrelation are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

### Panel A. Predictability of Errors in Earnings Forecasts

| | ***Dependent Variable = SURP_FEARN0*** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ***News = ΔFGDP0*** | | ***News = ΔFGDP1*** | | ***News = ΔFEARN0*** | | ***News = ΔFEARN1*** | | ***News = MKTRET*** | |
| ***NEWS*** | 0.599 | | 0.611 | | 0.928 | | 0.999 | | 0.009 | |
| | (4.14)*** | | (1.71)* | | (7.36)*** | | (7.81)*** | | (1.25) | |
| ***NEG_NEWS*** | | 0.495 | | 1.339 | | 0.961 | | 0.951 | | 0.031 |
| | | (2.18)** | | (3.68)*** | | (7.86)*** | | (6.49)*** | | (1.92)* |
| ***POS_NEWS*** | | 0.098 | | -1.775 | | 0.682 | | -0.996 | | 0.000 |
| | | (0.43) | | (-2.17)** | | (1.10) | | (-1.54) | | (0.02) |
| ***I_NEG_NEWS*** | | -0.002 | | -0.000 | | 0.000 | | -0.002 | | 0.001 |
| | | (-2.08)** | | (-0.56) | | (0.35) | | (-2.67)*** | | (1.19) |
| ***Intercept*** | -0.001 | 0.000 | -0.001 | 0.001 | 0.000 | 0.000 | 0.000 | 0.002 | -0.002 | -0.001 |
| | (-2.33)** | (0.22) | (-2.42)** | (1.00) | (0.91) | (0.07) | (0.07) | (3.32)*** | (-2.85)*** | (-1.71)* |
| **Nobs** | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 |
| **Adj. $R^2$** | 0.285 | 0.289 | 0.205 | 0.326 | 0.465 | 0.458 | 0.430 | 0.432 | 0.174 | 0.210 |

| | ***Dependent Variable = SURP_FEARN1*** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ***News = ΔFGDP0*** | | ***News = ΔFGDP1*** | | ***News = ΔFEARN0*** | | ***News = ΔFEARN1*** | | ***News = MKTRET*** | |
| ***NEWS*** | 0.475 | | 0.656 | | 0.985 | | 0.899 | | 0.015 | |
| | (2.82)*** | | (1.66) | | (4.60)*** | | (3.37)*** | | (1.89)* | |
| ***NEG_NEWS*** | | 0.031 | | 0.970 | | 0.878 | | 0.731 | | 0.020 |
| | | (0.15) | | (2.12)** | | (3.93)*** | | (2.85)*** | | (1.11) |
| ***POS_NEWS*** | | -0.155 | | -0.392 | | -1.032 | | -2.997 | | 0.005 |
| | | (-0.46) | | (-0.45) | | (-1.56) | | (-2.86)*** | | (0.68) |
| ***I_NEG_NEWS*** | | -0.004 | | -0.000 | | -0.003 | | -0.005 | | -0.001 |
| | | (-2.61)** | | (-0.17) | | (-3.08)*** | | (-3.61)*** | | (-0.34) |
| ***Intercept*** | -0.003 | -0.001 | -0.003 | -0.002 | -0.001 | 0.001 | -0.002 | 0.002 | -0.004 | -0.003 |
| | (-4.11)*** | (-1.19) | (-4.26)*** | (-2.03)** | (-2.20)** | (2.09)** | (-2.66)*** | (2.19)** | (-4.27)*** | (-3.96)*** |
| **Nobs** | 104 | 104 | 104 | 104 | 104 | 104 | 104 | 104 | 104 | 104 |
| **Adj. $R^2$** | 0.308 | 0.337 | 0.304 | 0.300 | 0.406 | 0.422 | 0.359 | 0.377 | 0.315 | 0.307 |

## Panel B. Predictability of Errors in Real GDP Growth Forecasts

| | *Dependent Variable = SURP_FGDP0* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ***News = ΔFGDP0*** | | ***News = ΔFGDP1*** | | ***News = lΔFEARN0*** | | ***News = lΔFEARN1*** | | ***News = lMKTRET*** | |
| ***NEWS*** | 0.128 | | -0.008 | | -0.072 | | 0.111 | | 0.008 | |
| | (1.05) | | (-0.04) | | (-0.41) | | (0.93) | | (2.06)** | |
| ***NEG_NEWS*** | | -0.002 | | 0.106 | | 0.031 | | 0.173 | | -0.005 |
| | | (-0.01) | | (0.32) | | (0.19) | | (1.35) | | (-0.48) |
| ***POS_NEWS*** | | 0.881 | | 0.109 | | -3.205 | | 0.160 | | 0.013 |
| | | (1.80)* | | (0.21) | | (-2.22)** | | (0.76) | | (1.78)* |
| ***I_NEG_NEWS*** | | 0.001 | | 0.001 | | -0.000 | | 0.001 | | -0.001 |
| | | (0.86) | | (0.51) | | (-0.30) | | (0.78) | | (-0.75) |
| ***Intercept*** | 0.001 | -0.000 | 0.001 | 0.000 | 0.001 | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 |
| | (2.27)** | (-0.25) | (2.02)** | (0.61) | (1.43) | (1.20) | (2.30)** | (0.49) | (1.37) | (0.39) |
| **Nobs** | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 |
| **Adj. $R^2$** | 0.033 | 0.042 | 0.023 | 0.007 | 0.026 | 0.044 | 0.029 | 0.015 | 0.054 | 0.059 |

| | *Dependent Variable = SURP_FGDP1* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ***News = ΔFGDP0*** | | ***News = ΔFGDP1*** | | ***News = lΔFEARN0*** | | ***News = lΔFEARN1*** | | ***News = lMKTRET*** | |
| ***NEWS*** | 0.045 | | 0.349 | | -0.179 | | -0.123 | | 0.007 | |
| | (0.14) | | (0.82) | | (-1.51) | | (-0.95) | | (0.88) | |
| ***NEG_NEWS*** | | -0.007 | | 0.646 | | -0.196 | | -0.226 | | 0.019 |
| | | (-0.01) | | (0.85) | | (-1.45) | | (-1.34) | | (1.20) |
| ***POS_NEWS*** | | 0.267 | | 1.319 | | 1.237 | | -0.052 | | -0.000 |
| | | (0.46) | | (2.60)** | | (1.01) | | (-0.13) | | (-0.00) |
| ***I_NEG_NEWS*** | | 0.000 | | 0.002 | | 0.001 | | -0.001 | | 0.000 |
| | | (0.10) | | (2.04)** | | (0.55) | | (-0.66) | | (0.29) |
| ***Intercept*** | -0.000 | -0.000 | 0.000 | -0.001 | -0.000 | -0.001 | -0.000 | 0.000 | -0.000 | 0.000 |
| | (-0.11) | (-0.35) | (0.01) | (-1.71)* | (-0.72) | (-1.28) | (-0.39) | (0.24) | (-0.52) | (0.14) |
| **Nobs** | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 | 105 |
| **Adj. $R^2$** | -0.018 | -0.037 | 0.000 | 0.009 | -0.011 | -0.029 | -0.015 | -0.029 | -0.003 | -0.008 |

## Table 5. Out-of-sample Forecast Surprise and Return Predictability

The table documents predictability of aggregate earnings and real GDP growth surprises and market returns based on the magnitude of recent news. The surprise and return variables are defined as follows: *SURP_FEARN0* (*SURP_FGDP*) – surprise (realized minus forecasted) in aggregate earnings (real GDP growth) for quarter *t* relative to the forecast made in quarter *t*. *MKTRET1* – value-weighted return on the CRSP market index over quarter *t*+1. *ANNRET5, ANNRET10* and *ANNRET15* – average value-weighted return on the CRSP market index on the days of the first five, 10, and 15 earnings announcements of S&P 500 firms in calendar quarter *t*+1. *GANNRET* – value-weighted return on the CRSP market index on the day the initial real GDP growth estimate is announced in calendar quarter *t*+1. Returns are measured on the next business day if announcements were made on a weekend. All quarters are first partitioned by the sign of the recent news, and then within each sign they are sorted into three groups—below 30th percentile, between 30th and 70th percentiles, and above 70th percentile—based on the magnitude of recent news relative to the breakpoints from a historical distribution. The breakpoints are estimated from the past 20 years of data with at least 15 quarters having non-missing news of the same sign. The news variables include *ΔFGDP0* (*ΔFGDP1*) –revision between quarters *t*-1 and *t* in the real GDP growth forecast for quarter *t* (*t*+1); *MKTRET* – return on the CRSP value-weighted index in quarter *t*; *lΔFEARN0 (lΔFEARN1)* – revision between quarters *t*-2 and *t*-1 in the aggregate earnings forecast for quarter *t* (*t*+1); *lMKTRET* – return on the CRSP value-weighted index over the three months ending in the month of the GDP forecast issuance in quarter *t*. The table reports mean values of surprises and returns within each news partition. '1-3' denotes a difference between means from below 30th percentile and above 70th percentile partitions. *t*-statistics for the differences are reported below. *p*-values for the differences are reported in parentheses.

### Panel A. Partitions Based on Past Revisions in Real GDP Growth Forecasts

| | Partitions Based on *ΔFGDP0* | | | | | | Partitions Based on *ΔFGDP1* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Nobs | *SURP_ FEARN0* | *MKT RET1* | *ANN RET5* | *ANN RET10* | *ANN RET15* | Nobs | *SURP_ FEARN0* | *MKT RET1* | *ANN RET5* | *ANN RET10* | *ANN RET15* |
| **Negative Revisions:** | | | | | | | | | | | | |
| **1 (Below 30%)** | 14 | -0.004 | 0.024 | -0.004 | -0.004 | -0.004 | 12 | -0.005 | -0.007 | -0.007 | -0.007 | -0.005 |
| **2 (30% - 70%)** | 28 | -0.002 | 0.032 | 0.001 | -0.001 | -0.001 | 16 | -0.001 | 0.032 | 0.001 | -0.001 | -0.002 |
| **3 (Above 30%)** | 20 | -0.002 | 0.029 | 0.001 | 0.000 | 0.000 | 20 | -0.001 | 0.040 | 0.001 | 0.000 | 0.001 |
| **1 - 3** | | -0.002 | -0.005 | -0.004 | -0.003 | -0.004 | | -0.004 | -0.047 | -0.008 | -0.007 | -0.005 |
| | | -1.09 | -0.13 | -1.25 | -1.27 | -1.79 | | -2.32 | -1.24 | -2.44 | -2.17 | -2.50 |
| | | (0.28) | (0.89) | (0.22) | (0.21) | (0.08) | | (0.03) | (0.22) | (0.02) | (0.04) | (0.02) |
| **Positive Revisions:** | | | | | | | | | | | | |
| **1 (Below 30%)** | 7 | 0.000 | 0.017 | 0.000 | -0.001 | 0.000 | 19 | 0.000 | 0.003 | 0.001 | -0.001 | -0.001 |
| **2 (30% - 70%)** | 12 | 0.001 | 0.019 | 0.001 | 0.002 | 0.001 | 16 | 0.000 | 0.031 | 0.001 | 0.001 | 0.000 |
| **3 (Above 30%)** | 8 | 0.001 | 0.016 | 0.002 | 0.000 | 0.000 | 14 | -0.002 | 0.051 | 0.002 | 0.001 | 0.000 |
| **1 - 3** | | -0.001 | 0.001 | -0.002 | -0.002 | 0.000 | | 0.002 | -0.047 | 0.000 | -0.002 | -0.001 |
| | | -1.47 | 0.02 | -0.49 | -0.52 | 0.06 | | 1.49 | -1.77 | -0.07 | -0.95 | -0.46 |
| | | (0.16) | (0.99) | (0.63) | (0.61) | (0.96) | | (0.15) | (0.09) | (0.95) | (0.35) | (0.65) |

### Panel B. Partitions Based on Past Revisions in Earnings Forecasts

| | Partitions based on *ΔFEARN0* | | | | | | Partitions Based on *ΔFEARN1* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Nobs | *SURP_ FEARN0* | *MKT RET1* | *ANN RET5* | *ANN RET10* | *ANN RET15* | Nobs | *SURP_ FEARN0* | *MKT RET1* | *ANN RET5* | *ANN RET10* | *ANN RET15* |
| **Negative Revisions:** | | | | | | | | | | | | |
| **1 (Below 30%)** | 23 | -0.004 | 0.008 | -0.005 | -0.005 | -0.005 | 18 | -0.003 | 0.007 | -0.007 | -0.006 | -0.005 |
| **2 (30% - 70%)** | 29 | -0.001 | 0.021 | 0.001 | 0.000 | -0.001 | 34 | -0.002 | 0.038 | 0.002 | 0.000 | -0.001 |
| **3 (Above 30%)** | 28 | 0.000 | 0.047 | 0.003 | 0.002 | 0.001 | 24 | 0.000 | 0.031 | 0.001 | 0.001 | 0.001 |
| **1 - 3** | | -0.004 | -0.039 | -0.008 | -0.007 | -0.006 | | -0.004 | -0.024 | -0.008 | -0.007 | -0.006 |
| | | -5.00 | -1.54 | -2.94 | -3.39 | -3.67 | | -3.56 | -0.82 | -2.71 | -3.06 | -3.16 |
| | | (0.00) | (0.13) | (0.01) | (0.00) | (0.00) | | (0.00) | (0.42) | (0.01) | (0.00) | (0.00) |

**Panel C. Partitions Based on Past Returns**

| | Partitions Based on *lMKTRET* | | | | Partitions Based on *MKTRET* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Nobs | *SURP_ FGDP0* | *MKT RET1* | *GANN RET* | Nobs | *SURP_ FEARN0* | *MKT RET1* | *ANN RET5* | *ANN RET10* | *ANN RET15* |
| **Positive Returns:** | | | | | | | | | | |
| **1 (Below 30%)** | 19 | 0.000 | 0.011 | 0.003 | 18 | -0.001 | 0.016 | 0.000 | 0.000 | -0.001 |
| **2 (30% - 70%)** | 25 | 0.002 | 0.034 | -0.002 | 25 | 0.000 | 0.014 | 0.000 | -0.001 | 0.000 |
| **3 (Above 30%)** | 15 | 0.002 | 0.018 | 0.002 | 20 | -0.001 | 0.048 | 0.003 | 0.001 | 0.001 |
| **1 - 3** | | -0.002 | -0.007 | 0.001 | | 0.000 | -0.033 | -0.003 | -0.002 | -0.003 |
| | | -2.13 | -0.24 | 0.19 | | 0.10 | -1.46 | -2.23 | -1.22 | -1.99 |
| | | (0.04) | (0.81) | (0.85) | | (0.92) | (0.15) | (0.03) | (0.23) | (0.05) |

## Table 6. Cross-sectional Forecast Efficiency Tests

The table reports slope estimates from regressing aggregate earnings surprises computed for sub-samples of firms on recent news proxies. To compute aggregate surprises, each quarter the firms are sorted into terciles based on the magnitude of their accounting betas (Panel A) or total assets (Panel B). Aggregate surprises are then calculated within each tercile using the same procedure as the overall aggregate earnings surprise calculation. "Low", "Mid", and "High" refer to regressions using aggregate surprises calculated using observations within the first, second, and third terciles, respectively, of the accounting betas (Panel A) or total assets (Panel B) distributions. Accounting betas are the slopes from regressions of seasonal changes in the firm's quarterly net operating profits (scaled by four-quarter-lagged total assets) on the corresponding market aggregate. Regressions require past 12 quarters of data. Total assets for the latest quarter before the consensus forecast date are from Compustat. The *NEWS* variables include *ΔFGDP0* (*ΔFGDP1*) –revision between quarters *t*-1 and *t* in the real GDP growth forecast for quarter *t* (*t*+1); *MKTRET* – return on the CRSP value-weighted index in quarter *t*; *lΔFEARN0 (lΔFEARN1)* – revision between quarters *t*-2 and *t*-1 in the aggregate earnings forecast for quarter *t* (*t*+1); *lMKTRET* – return on the CRSP value-weighted index over the three months ending in the month of the GDP forecast issuance in quarter *t*. *t*-statistics based on standard errors with Newey-West adjustment for autocorrelation are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

### Panel A. Partitioning Firms by Past Accounting Betas

| Partition | *Dependent Variable = SURP_FEARN0* | | | | | *Dependent Variable = SURP_FEARN1* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *NEWS =* | | | | | *NEWS =* | | | | |
| | *ΔFGDP0* | *ΔFGDP1* | *ΔFEARN0* | *ΔFEARN1* | *MKTRET* | *ΔFGDP0* | *ΔFGDP1* | *ΔFEARN0* | *ΔFEARN1* | *MKTRET* |
| **Low** | 0.086 | 0.070 | 0.412 | 0.273 | 0.000 | 0.299 | 0.529 | 0.520 | 0.557 | 0.009 |
| | (1.09) | (0.44) | (5.11)*** | (5.66)*** | (0.06) | (2.88)*** | (2.26)** | (4.18)*** | (4.38)*** | (1.52) |
| **Mid** | 0.511 | 0.640 | 0.651 | 0.923 | 0.013 | 0.356 | 0.725 | 0.837 | 1.066 | 0.020 |
| | (2.78)*** | (1.99)* | (5.34)*** | (4.54)*** | (1.81)* | (2.45)** | (2.33)** | (5.17)*** | (2.95)*** | (3.10)*** |
| **High** | 0.534 | 0.570 | 0.546 | 0.649 | 0.012 | 0.739 | 1.470 | 0.900 | 1.013 | 0.020 |
| | (2.28)** | (1.17) | (6.41)*** | (5.31)*** | (1.37) | (2.54)** | (2.86)*** | (5.72)*** | (4.03)*** | (1.87)* |

### Panel B. Partitioning Firms by Size

| Partition | *Dependent Variable = SURP_FEARN0* | | | | | *Dependent Variable = SURP_FEARN1* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *NEWS =* | | | | | *NEWS =* | | | | |
| | *ΔFGDP0* | *ΔFGDP1* | *ΔFEARN0* | *ΔFEARN1* | *MKTRET* | *ΔFGDP0* | *ΔFGDP1* | *ΔFEARN0* | *ΔFEARN1* | *MKTRET* |
| **Low** | 0.148 | 0.036 | 0.654 | 0.249 | 0.008 | 0.133 | 0.199 | 0.612 | 0.171 | 0.017 |
| | (0.82) | (0.11) | (1.66) | (0.78) | (1.42) | (0.65) | (0.56) | (1.30) | (0.50) | (2.16)** |
| **Mid** | 0.268 | 0.247 | 1.015 | 0.840 | 0.010 | 0.218 | 0.567 | 0.839 | 0.880 | 0.011 |
| | (1.78)* | (0.87) | (5.72)*** | (5.98)*** | (1.94)* | (1.37) | (1.93)* | (2.90)*** | (3.20)*** | (1.89)* |
| **High** | 0.625 | 0.829 | 0.951 | 1.034 | 0.013 | 0.494 | 0.990 | 0.999 | 1.008 | 0.023 |
| | (3.75)*** | (2.17)** | (7.68)*** | (7.17)*** | (1.37) | (2.85)*** | (2.43)** | (4.85)*** | (3.41)*** | (2.94)*** |

## Table 7. Descriptive Statistics over the Business Cycle

The table compares average values of forecasts, realized values, forecast revisions, signed and absolute surprises and proportion of negative revisions for recessionary and expansionary quarters from 4:1984 to 4:2010. Quarters are classified into "Recession" or "Expansion" based on NBER's business cycle classification for the end of the quarter date. Variables are defined as follows: *GDP0* (*GDP1*) – realized real GDP growth for quarter *t* (*t*+1). *EARN0* (*EARN1*) – realized aggregate earnings for quarter *t* (*t*+1). *FGDP0* (*FGDP1*) – consensus median forecast of real GDP growth for quarter *t* (*t*+1) made in quarter *t*. *FEARN0* (*FEARN1*) – aggregate consensus earnings forecast for quarter *t* (*t*+1) made in quarter *t*. *SURP_FGDP0* (*SURP_FGDP1*) – surprise (realized minus forecasted) in real GDP growth for quarter *t* (*t*+1). *SURP_FEARN0* (*SURP_FEARN1*) – surprise (realized minus forecasted) in aggregate earnings for quarter *t* (*t*+1) relative to the forecast made in quarter *t*. |*SURP_FGDP0*|, |*SURP_FGDP1*|, |*SURP_FEARN0*| and |*SURP_FEARN1*| are absolute values of surprises. *ΔFGDP0* (*ΔFGDP1*) –revision between quarters *t*-1 and *t* in the real GDP growth forecast for quarter *t* (*t*+1). *ΔFEARN0* (*ΔFEARN1*) –revision between quarters *t*-1 and *t* in the aggregate earnings forecast for quarter *t* (*t*+1). %*NEGΔFGDP0*, %*NEGΔFGDP1*, %*NEGΔFEARN0* and %*NEGΔFEARN1* denote percentage of negative revisions. 'Expansion-Recession' denotes a difference between means values within expansion and recession quarters. *t*-statistics for the differences are reported below. *p*-values for the differences are reported in parentheses.

### Panel A. Mean Forecasts and Realized Values over the Business Cycle

| | Number of quarters | *GDP0* | *GDP1* | *EARN0* | *EARN1* | *FGDP0* | *FGDP1* | *FEARN0* | *FEARN1* |
|---|---|---|---|---|---|---|---|---|---|
| **Expansion** | 94 | 0.007 | 0.007 | 0.036 | 0.037 | 0.006 | 0.007 | 0.037 | 0.040 |
| **Recession** | 11 | -0.003 | -0.002 | 0.026 | 0.024 | -0.002 | 0.001 | 0.031 | 0.035 |
| **Expansion - Recession** | | 0.010 | 0.010 | 0.010 | 0.013 | 0.008 | 0.006 | 0.006 | 0.005 |
| ***t*-statistic** | | 7.81 | 7.44 | 4.92 | 6.27 | 8.67 | 8.68 | 3.88 | 3.19 |
| ***p*-value** | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

### Panel B. Forecast Accuracy over the Business Cycle

| | Number of quarters | *SURP_FGDP0* | *SURP_FGDP1* | *SURP_FEARN0* | *SURP_FEARN1* | \|*SURP_FGDP0*\| | \|*SURP_FGDP1*\| | \|*SURP_FEARN0*\| | \|*SURP_FEARN1*\| |
|---|---|---|---|---|---|---|---|---|---|
| **Expansion** | 94 | 0.001 | 0.000 | -0.001 | -0.003 | 0.003 | 0.003 | 0.002 | 0.004 |
| **Recession** | 11 | -0.001 | -0.004 | -0.005 | -0.011 | 0.002 | 0.006 | 0.005 | 0.011 |
| **Expansion - Recession** | | 0.002 | 0.004 | 0.003 | 0.008 | 0.001 | -0.003 | -0.003 | -0.007 |
| ***t*-statistic** | | 1.86 | 3.09 | 3.18 | 4.89 | 1.03 | -3.32 | -3.05 | -5.34 |
| ***p*-value** | | (0.07) | (0.00) | (0.00) | (0.00) | (0.31) | (0.00) | (0.00) | (0.00) |

### Panel C. Forecast Revisions over the Business Cycle

| | Number of quarters | *ΔFGDP0* | *ΔFGDP1* | *ΔFEARN0* | *ΔFEARN1* | *%NEG ΔFGDP0* | *%NEG ΔFGDP1* | *%NEG ΔFEARN0* | *%NEG ΔFEARN1* |
|---|---|---|---|---|---|---|---|---|---|
| **Expansion** | 94 | 0.000 | 0.000 | -0.002 | -0.001 | 0.585 | 0.436 | 0.872 | 0.830 |
| **Recession** | 11 | -0.004 | -0.003 | -0.006 | -0.005 | 0.909 | 0.818 | 1.000 | 1.000 |
| **Expansion - Recession** | | 0.003 | 0.003 | 0.005 | 0.003 | -0.324 | -0.382 | -0.128 | -0.170 |
| ***t*-statistic** | | 4.49 | 6.19 | 7.49 | 5.91 | -2.12 | -2.45 | -1.26 | -1.49 |
| ***p*-value** | | (0.00) | (0.00) | (0.00) | (0.00) | (0.04) | (0.02) | (0.21) | (0.14) |