Top-Down vs. Bottom-Up Index Forecasts: Are Equity Strategists Strategically Pessimistic?

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Abstract

This study examines the distinct role of equity strategists in forecasting aggregate earnings and market returns. Unlike traditional firm-level analysts who focus on individual stocks, strategists provide macroeconomic insights to inform investors' decision making. We compare strategists' top-down S&P 500 EPS forecasts with bottom-up forecasts made by sell-side equity analysts. While both forecasts move in tandem, they often deviate from each other. We find that strategists' divergence from bottom-up forecasts varies systematically with macroeconomic conditions. In turn, strategists' divergence has predictive value for future aggregate earnings surprises and aggregate stock returns, consistent with sell-side analysts and investors underreacting to the information contained in strategists' index forecasts. We also find that the predictive ability is concentrated during periods of macroeconomic uncertainty. Overall, investors and policy makers can benefit when they use both bottom-up and top-down forecasts in combination when forming expectations for aggregate earnings.

1. Introduction

The role of equity strategists is to inform investors' decisions in allocating their assets between equities versus other asset classes, such as bonds. They provide insights into the broader economic context, helping investors understand the relative attractiveness of different asset classes under various macroeconomic conditions. Additionally, they play a crucial role in advising active investors on how to outperform the stock market by identifying and recommending sector rotation strategies, which involve shifting investments between different industry sectors based on anticipated economic trends and cyclical changes within the market. This within-stock market asset allocation aims to exploit the varying performance of different sectors as the economic environment evolves (Bradshaw 2012; Kadan et al. 2012). Strategists often possess significant expertise in macroeconomic trends, allowing them to interpret and predict how factors such as GDP growth, inflation, interest rates, and global economic developments will impact the overall stock market. Strategists work alongside in-house economists, who focus on broader macroeconomic trends and indicators, such as GDP growth, unemployment rates, and monetary policy (Hugon et al. 2007), and interpret these trends in the context of the equity markets and investment decisions. In this study, we shed light on strategists' distinct role in predicting future aggregate earnings and market returns.

In their reports, strategists produce index-level EPS forecasts and index-level target prices. The EPS forecasts for the entire stock market, such as those for the S&P 500 index, serve as a foundation for their overall market outlook. These forecasts are analogous to the EPS forecasts that bottom-up analysts use for individual stocks, which are key inputs in the valuation process.[1] By providing an aggregate view of expected earnings for the index, strategists help investors gauge the potential earnings power of the market as a whole. Strategists also provide index-level target prices, which offer a projection of where they believe the index will trade at a future date based on their economic and market analysis. This target price takes into account various factors, including anticipated changes in earnings, interest rates, and broader economic conditions. These projections help investors set their expectations for market performance and adjust their investment strategies accordingly.

Notably, aggregate earnings forecasts for the S&P 500 are a key macroeconomic indicator. The Federal Reserve Board periodically assesses the US financial system and evaluates how elevated stock market valuation is by comparing the aggregate earnings forecasts for the S&P 500 Index and the index price (i.e., S&P 500 Index's P/E ratio) (Federal Reserve Board 2018). We study two groups of forecasters who issue earnings forecasts for the index: (1) equity strategists who issue index-level earnings forecasts using a top-down approach (i.e., top-down forecasts); and (2) sell-side equity analysts who follow and issue earnings forecasts for individual constituent companies, that are aggregated to the index level (i.e., bottom-up forecasts). Darrough and Russell (2002) provide a preliminary comparison of these two types of aggregate earnings forecasts and conclude that, while both top-down and bottom-up forecasts are optimistic, strategists' top-down forecasts are significantly less optimistic than bottom-up forecasts, on average. We refer to this as market strategists' relative pessimism with respect to the bottom-up forecast. We investigate whether strategists' divergence from bottom-up forecasts varies systematically over time and contains information that is useful for investors.

[1] We use the terms strategists, market strategists, and equity strategists interchangeably throughout the paper. While strategists are technically a subset of equity analysts employed by sell-side brokerages, we limit our use of the terms "analyst" and "sell-side analyst" to refer to non-strategist analysts who issue firm-specific equity research.

Prior research on the usefulness of the forecasts and recommendations produced by market strategists is limited. As noted above, Darrough and Russell (2002) is perhaps the most in-depth prior examination of strategists' index-level EPS forecasts, focused on the average bias and accuracy of strategists' EPS forecasts from 1987 – 1999. Darrough and Russell (2002) propose that firm-level analysts' cognitive biases and incentives to curry favor with management may explain the excess optimism of bottom-up EPS forecasts relative to market strategists' top-down forecasts, but they do not analyze whether the difference between top-down and bottom-up forecasts contains useful information. Kadan et al. (2012) examine brokerage-level industry recommendations and find that strategists' industry recommendations have incremental investment value relative to analysts' firm-level investment recommendations. We are not aware of any prior research that assesses the investment value of market strategists' index-level forecasts, or their incremental value relative to aggregating bottom-up analysts' firm-level forecasts.

If the excess optimism of bottom-up EPS forecasts is due to firm-level analysts' relatively stable incentives to curry favor with management, one might expect top-down and bottom-up EPS forecasts to move in lockstep together over time, but with a constant upwards bias in bottom-up EPS forecasts. On the other hand, if individual analysts have cognitive biases that cause them to adopt management's optimistic "insider" perspective of the firm's prospects, they may underreact to negative external information, such as macroeconomic news (Kahneman and Lovallo 1993; Darrough and Russell 2002). Consistent with this, Hugon et al. (2016) find that individual analysts underreact to negative macroeconomic information contained in GDP forecast revisions. If market strategists are better able to incorporate macroeconomic information in their forecasts, then the relative pessimism of top-down EPS forecasts compared with bottom-up forecasts may vary with macroeconomic indicators and contain useful forward-looking information for future aggregate earnings surprises and market returns.

We analyze quarterly differences in top-down vs. bottom-up one-year-ahead S&P 500 EPS forecasts from 2Q 2003 to 2Q 2019. Our primary variable of interest is *Diff_EPS*, defined as the difference between the top-down and bottom-up forecast issued in the same month, scaled by the ending index value of the S&P 500 in the previous month. Consistent with Darrough and Russell (2002), we find that the average value of *Diff_EPS* is -0.3% during our more recent sample period, indicating that the top-down forecast is generally lower than the bottom-up forecast computed in the same month. However, we observe significant variation in the level of *Diff_EPS* over time, such that *Diff_EPS* has an interquartile range from -0.4% to -0.2% relative to the level of the S&P 500 index, and even becomes positive in some months of our sample period (see Figure 2).

Our first set of tests investigates the time-series determinants of strategists' relative pessimism. Kadan et al. (2012) suggest that strategists exhibit across-industry expertise (i.e., successful sector rotation strategy) based on their responsiveness to macroeconomic trends and industry cyclicality. Given strategists' responsiveness to macroeconomic trends, we hypothesize and find that macroeconomic news explains the variation in strategists' divergence from bottom-up forecasts. Specifically, *Diff_EPS*, is positively related to proxies for industrial profit margins (i.e., the spread between CPI and PPI), and negatively related to measures of unemployment and monetary policy as proxied by the federal funds rate. These results support the idea that strategists deviate from bottom-up forecasts when they see significant changes in macroeconomic trends that are not embedded in bottom-up forecasts.

We next evaluate whether the macroeconomic information embedded in strategists' relative pessimism has predictive ability for future capital market outcomes. If strategists incorporate macroeconomic and index-wide news that affects corporate earnings not captured in bottom-up analysts' estimates, then strategists' deviation from bottom-up forecasts will signal market-wide unexpected earnings. Additionally, if investors' aggregate expectations align more with bottom-up analysts' market expectations, the information embedded in *Diff_EPS* may also signal imminent stock market movements as investors update their expectations in response to macroeconomic news.

Our findings confirm these predictions. We find that *Diff_EPS* is predictive of future aggregate earnings surprises. We also find that *Diff_EPS* is positively associated with the one- to three-month ahead returns of major stock market indices. Overall, we conclude that strategists' interpretations of macroeconomic news relative to bottom-up analysts have significant information content. Further analyses suggest that strategists' superior predictive ability is more pronounced when macroeconomic uncertainty is high. We find that the main results are concentrated during recession periods and periods when the CBOE volatility index (i.e., the VIX) is elevated.

Interestingly, our results above hold not only for S&P 500 Index constituents, but also for smaller non-constituent firms. This suggests that the macroeconomic information contained in strategists' outputs is also relevant for smaller firms outside the index that are exposed to the same macroeconomic trends, and that investors can benefit from strategists' information production when they invest in firms with poorer information environments due to lack of analyst following.

The findings thus far suggest that strategists' relative pessimism varies systematically with macroeconomic trends and has significant information content in predicting future earnings surprises and stock returns. Implicit in these findings is the notion that top-down forecasts are more accurate than bottom-up forecasts. To substantiate this idea, we examine the quality of top-down and bottom-up forecasts. We find a consistent pattern where top-down forecasts remain less optimistic and, consequently, more accurate than bottom-up forecasts leading up to earnings realization (see Figure 3). This reaffirms our overarching conclusion that strategists effectively incorporate macroeconomic signals and provide higher-quality forecasts than their bottom-up counterparts.

Our findings contribute to the literature in several ways. First, we contribute to the sell-side analyst literature. This literature has extensively examined the forecasting behavior of (bottom-up) analysts, but generally overlooked equity strategists. Our results highlight the distinct and complementary roles of strategists and bottom-up analysts. While bottom-up analysts excel in detailed, firm-level analysis, strategists bring an essential macroeconomic perspective that enhances the overall understanding of the market. This combination of insights is crucial for developing robust earnings expectations and investment strategies, especially during periods of heightened uncertainty. Two notable exceptions are Darrough and Russell (2002), who document strategists' relative forecast pessimism compared with bottom-up analysts, and Kadan et al. (2012) who find that investors can benefit when they consider both analysts' within-industry expertise and strategists' across-industry expertise. We suggest a potential mechanism for these findings by identifying important forward-looking macroeconomic signals embedded into strategists' outputs that market participants often overlook.

In this regard, our findings also contribute to prior research on bottom-up analysts' response to macroeconomic news. Consistent with prior research, our results suggest that bottom-up analyst forecasts are inefficient with respect to macroeconomic news (Basu et al. 2010; Hugon et al. 2016). However, we show that strategists' forecasts are more efficient at incorporating the aggregate earnings impact of macroeconomic shocks than bottom-up analysts. While prior work has focused on the inefficiency of bottom-up analysts' individual or firm-level forecasts with respect to incorporating the implications of revisions in specific macroeconomic indicators (i.e., expected inflation or GDP growth), we take a holistic approach to evaluating the aggregate (i.e., index-level) information content of bottom-up analysts' forecasts relative to another set of forecasters, market strategists. Controlling for individual macroeconomic signals, we find that strategists' top-down EPS forecasts are more efficient than aggregate bottom-up EPS forecasts in incorporating the overall impact of macroeconomic news on corporate earnings, leading to predictable future aggregate earnings surprises. Furthermore, investors appear to overweight bottom-up analysts forecasts, leading to predictable future index returns.

2. Background and Literature Review

2.1 Market Strategists

Market strategists focus on the equity market as a whole in contrast to traditional (firm-level) analysts who cover individual stocks. Thus, the role of market strategists is to inform investors' decisions in allocating their assets between equities versus other asset classes, such as bonds (i.e., across-asset class allocation), rather than to issue recommendations or earnings forecasts on specific companies. Also, strategists issue industry-level recommendations to identify booms and slumps in industries in support of sector rotation strategies (i.e., within stock market asset allocation).

Prior research documents that successful market timing by active investors can generate abnormal returns (Jiang et al. 2007; Chen and Liang 2007), especially during times of macroeconomic uncertainty, and that portfolios based on sector rotation strategies generate abnormal returns (Kadan et al. 2012). Accordingly, investors value market strategists with significant expertise in macroeconomic trends and industry cyclicality. Indeed, *Institutional Investor* magazine's annual all-star analyst rankings include a "macro portfolio strategy" section to honor strategists who exhibit superior market timing and sector rotation strategies.

In the 2009 poll, for example, one strategist was recognized for his ability in predicting S&P 500 index returns: *"Levkovich turned bullish on U.S. stocks last November and predicted that the S&P 500 index, then at 752.44, would top 1,000 this year. The index first topped the thousand-point mark in early August and closed the month at 1,020.62."*[2] Another strategist was applauded for a successful sector rotation strategy: *"The 40-year-old strategist told clients in January to dump defensive stocks such as telecommunications and health care companies and load up on consumer discretionary stocks… Through August the health care and telecommunications sectors trailed the broad market by 4.1 and 16.6 percentage points, respectively, and consumer discretionary stocks outpaced the market by 7.8 points."*[3]

In their reports, strategists produce three main outputs: index-level EPS forecasts, index-level target prices, and within-index industry recommendations. Appendix 1 Panel A provides an example of the summary page of a typical Bank of America (BofA) strategist's report. Notably, the report provides the strategist's top-down forecast ("BofA Strategy") alongside both the FactSet bottom-up consensus EPS forecast and a bottom-up forecast based on the individual

[2] https://www.institutionalinvestor.com/article/b150nxnl71vq08/macro-portfolio-strategy
[3] https://www.institutionalinvestor.com/article/b150qb090vqr8n/macro-portfolio-strategy

forecasts of BofA's firm-level sell-side analysts for the S&P 500 constituents. The strategist's top-down forecast differs from both the FactSet consensus and BofA's own individual analysts. The difference between BofA's strategists and its own individual analysts might be viewed as surprising, given that BofA's strategists and analysts share the same information and human resources, and that strategists often consult with their brokerages' analysts about their outlook for the industries/stocks that the bottom-up analysts cover.

However, strategists' top-down approach to forecasting may lead to different forecast outcomes due to strategists' differential expertise and job responsibilities. For example, strategists' responsiveness to macroeconomic trends, in particular, help them identify where bottom-up forecasts might be wrong. Appendix 1 Panel B provides an example illustrating how strategists pinpoint a specific macroeconomic factor that makes bottom-up forecasts seem overly optimistic. The title of the report, "*Q3 preview: bottom-up to start looking more challenging,*" first summarizes the bottom-up forecasts' detachment from reality. The strategist then states, "*PMI momentum softened during Q3. Global composite PMI is down 3 points in Q3 vs Q2, suggesting that earnings growth is likely to be outright negative*." This example succinctly shows why strategists deviate from bottom-up analysts and raises an interesting question of whether the divergence relative to bottom-up analysts systematically varies with macroeconomic factors and has investment values.

2.2 Inefficiency of Bottom-Up Analysts Incorporating Macroeconomic Information

While we are not aware of prior literature examining market strategists' response to macroeconomic fluctuations relative to that of bottom-up analysts, prior literature does examine bottom-up analysts' response to macroeconomic news. Basu et al. (2010) find that changes in inflation expectations predict future forecast errors for up to three-quarters ahead and conclude that sell-side analysts underutilize inflation information in their earnings estimates. The authors suggest this inefficiency could be due to irrationality of analysts, similar to those of Kahneman and Lovallo (1993), and/or the cost of incorporating inflation expectations into estimates exceeding the benefits of improved accuracy.

Other studies have examined bottom-up analysts' ability to incorporate GDP growth expectations into their earnings estimate. Hann et al. (2012) find that, in the aggregate, bottom-up analysts fail to incorporate negative macroeconomic news from economists' real GDP growth revisions. Additionally they document that investors appear to base their expectations of aggregate earnings on bottom-up analysts forecasts, such that they are surprised by the lower earnings reported by bellwether firms. Hugon et al. (2016) examine individual bottom-up analysts' underreaction to negative macroeconomic news at the firm-quarter level. They find that bottom-up analysts are inefficient at incorporating negative GDP growth expectations in their forecasts, but that this inefficiency is attenuated when the analysts' brokerage employs an economist.

Notably, economists are a separate group of forecasters who issue forecasts for macroeconomic indicators such as real GDP growth. While economists focus on predicting economy-wide indicators such as GDP growth or unemployment, strategists synthesize macroeconomic information, such as that produced by economists, and use it to inform their index-level earnings expectations. We predict that, to the extent that strategists are able to better synthesize macroeconomic information than bottom-up analysts, fluctuations in their relative pessimism with respect to bottom-up EPS forecasts will be associated with changes in macroeconomic indicators and contain information about aggregate future earnings surprises. To the extent that investors overweight bottom-up analysts' expectations, strategists' relative pessimism may also predict future returns.

2.3 Top-down EPS versus Bottom-up EPS

Darrough and Russell (2002) examine differences in the forecasts of strategists and bottom-up analysts from 1987 to 1999. They find while both types of analysts are optimistic in their forecasts, bottom-up analysts tend to be more optimistic than top-down analysts. Darrough and Russell (2002) attribute differences between strategists' and analysts' forecasts to bottom-up analysts' cognitive biases and incentives. The cognitive-based explanation predicts that bottom-up analysts develop bonds with the management of the companies they follow such that they behave as "insiders" in the forecasting process and are "more likely to hear the good news on a company's prospects and to discount any bad news arising from external base-rate data" (Kahneman and Lovallo 1993). Bottom-up analysts also have incentives to issue optimistic forecasts to maintain access to management or to generate investment banking opportunities for the brokerage (Brown et al. 2015). Strategists are less susceptible to these biases and incentives since they do not develop relationships with individual firms.

Darrough and Russell (2002) also compare the accuracy of top-down vs. bottom-up EPS forecasts and find that top-down analysts are more accurate at longer horizons, but bottom-up analysts become more accurate at shorter horizons of six months or less. During Darrough and Russell's (2002) sample period, strategists issued forecasts on a GAAP basis whereas sell-side analysts issued forecasts of operating ('street') earnings. Thus, Darrough and Russell (2002) speculate that their accuracy results may arise from difficulties in strategists' task of forecasting non-operating items. Darrough and Russell (2002) also discuss the possibility that analysts' and strategists' optimism may change over time, but conclude that they do not have sufficient data to formally test such changes. They note the possibility that bottom-up analysts' optimism could deteriorate towards the end of their sample period as analysts began playing the "walk down game" (e.g. Kasznik and McNichols 2002), as well as the possibility that changes in strategists' optimism could vary with macroeconomic fluctuations.

Our more recent data allows us to further examine these possibilities raised by Darrough and Russell (2002). Based on our interviews with strategists, during our sample period both analysts and strategists forecast "street" earnings. Thus, an exclusion of a certain accounting item from EPS number does not drive differences between top-down and bottom-up EPS in our data. If bottom-up analysts' forecasts have shifted towards playing the "walk down" to provide beatable EPS forecasts, we may find that their relative optimism has declined in more recent years. We are also able to examine whether changes in strategists' relative pessimism vary with macroeconomic fluctuations.

3. Data and Variable of Interest

3.1 Data Description

We collect consensus top-down and bottom-up annual EPS forecasts from the Refinitiv database. Specifically, we obtain the top-down and bottom-up EPS consensus forecast for the S&P 500 index from the Refinitiv Datastream/Eikon.[4] The S&P 500 top-down EPS consensus is the mean of individual strategists' forecasts provided to Refinitiv each month. Refinitiv Datastream/Eikon provides top-down EPS consensus for FY1 through FY2 under the ticker symbol SPX. Unlike the top-down consensus, which is a cross-sectional mean of individual strategists' forecasts, the bottom-up EPS consensus for the index is the value-weighted average

[4] Refinitiv used to provide these forecasts under the ticker symbol SAP5 as part of the I/B/E/S history files, but discontinued providing the series in 2005.

of EPS consensus for each index constituent in the S&P 500 index. At the end of each month, Refinitiv takes the consensus EPS forecasts of individual stocks in the index for FY1 through FY2 from I/B/E/S and calculates the weighted average of the consensus forecasts, where the weight is based on the market value of each firm in the index.

Figure 1 shows the tab in the Refinitiv Eikon platform displaying the trends of top-down (the violet line) and bottom-up consensus (the orange line) for the S&P 500 index for FY2024. Investors observe and compare these series in real time to track overall earnings trends of the S&P 500 firms and assess how top-down and bottom-up approaches lead to differential forecasts for the same set of firms in the index.

The macroeconomic variables used in our analyses come from a variety of sources. For each quarter, we use the most recent available variables to ensure that these variables are available to investors and analysts. We access inflation, unemployment, and consumer sentiment data from the Federal Reserve Economic Data (FRED) database. We also use the Survey of Professional Forecasters (SPF) forecast of the growth rate in real GDP, obtained from the Philadelphia Federal Reserve website. The Purchasing Managers' Index ("PMI") and the Chicago Board of Trade Federal Funds Futures Rate ("FFFR") are obtained from Refinitiv Datastream. Finally, we access investor sentiment data (Baker and Wurgler 2006) from Jeffrey Wurgler's personal website.[5] In the aggregate return predictability tests, we add three predictors that are known to predict market returns: (Goyal et al. 2023). These variables are aggregate accruals (Hirshleifer et al. 2009), the growth rate in personal consumption expenditures, and the growth rate in industrial production (Møller et al. 2015). We access these predictors from Amit Goyal's personal

[5] https://pages.stern.nyu.edu/~jwurgler/

website.[6] Following Li et al. (2023), we detrend all the control variables using the Baxter and King (1999) filter to focus on variations over the business cycle. Other firm-level data used in our analyses come from I/B/E/S, CRSP, and Compustat.

Our sample period covers from 2Q 2003 to 2Q 2019 which results in 65 quarter observations for our aggregate, index-level analyses and 200,441 firm-quarter observations in our firm-level analyses. We begin in 2Q 2003 because top-down EPS forecasts are not available prior to this period in Refinitiv Datastream and end in 2Q 2019 because we lose last three years' of observations when detrending the macroeconomic variables.

3.2 Addressing Non-Stationarity in Aggregate EPS Forecasts

Our raw aggregate EPS forecasts, whether top-down or bottom-up, are non-stationary and highly persistent. This non-stationarity poses significant challenges when drawing inferences about the dynamic relationship between index-level EPS forecasts and future capital market outcomes as non-stationary data can lead to spurious regression results. To address these challenges, we shift our focus to the difference between top-down and bottom-up EPS forecasts. By examining the differential between these two sets of forecasts, we mitigate the issues associated with their non-stationarity. Using one forecast type as a natural benchmark for the other allows us to better isolate and understand the unique information each forecast provides, providing a clearer view of how divergences in these forecasts relate to future market outcomes.

Our measure of strategists' relative pessimism is the difference between top-down and bottom-up analysts' next-twelve-month EPS forecasts in quarter *t*, *Diff_EPS*, defined as:

[6] https://sites.google.com/view/agoyal145

$$Diff\_EPS_t = \frac{TD\_EPS_t - BU\_EPS_t}{SP\_INDEX_{t-1}}$$

where *TD_EPS* and *BU_EPS* are the next-twelve-month top-down and bottom-up S&P 500 EPS forecasts as of quarter *t*, respectively, and *SP_INDEX* is the closing value of the S&P 500 index in the previous month.

In any given quarter, strategists and analysts provide annual EPS forecasts for FY1 and FY2, the current and subsequent fiscal years, respectively. To construct the index level top-down and bottom-up EPS forecast for the next twelve months at any given quarter, we annualize the FY1 and FY2 forecasts by calculating a time weighted average. Specifically, at each month-end, we assign a percentage weight to each fiscal year forecast by calculating the number of months left until the current year-end. For example, for the September 30, 2011 observation, we assign a 25% (3/12) weight to the 2011 EPS forecast and a 75% weight to the 2022 EPS forecast to obtain a 12-month forward forecast.

Figure 2, Panel A plots *TD_EPS* and *BU_EPS* over our sample period. Both sets of forecasts broadly move together and generally increase over time, but the difference between the two series varies non-monotonically. Figure 2, Panel B, plots the scaled differences between the two sets of forecasts (i.e., *Diff_EPS*). On average, *Diff_EPS* is negative during our sample period, consistent with Darrough and Russell's (2002) finding that strategists' top-down EPS forecasts are pessimistic relative to analysts' bottom-up forecasts. However, the degree of strategists' relative pessimism fluctuates over time, including a few periods in which strategists are relatively optimistic compared to bottom-up analysts (i.e. months in which *Diff_EPS* is positive).

3.3 Time-Series Model Selection

Selecting the appropriate time-series model is a critical step in analyzing and forecasting financial data. The choice of model can significantly impact the accuracy of predictions and the validity of inferences drawn from the data. In this section, we outline the criteria and process for choosing the most suitable time-series model for our analysis of EPS forecasts and their relationship with future market outcomes.

To select an appropriate time series model for our study, we follow prior research (e.g., Hann et al. 2021) and first test the stationarity of key time-series variables. Since our main focus in this study is the predictive ability of *Diff_EPS* for future aggregate earnings surprises (UE_{t+1}) and market returns ($Ret_{t+\tau}$), we test the stationarity of these variables in Table 1 using the augmented Dickey-Fuller test (with one lag and a time trend). Given that the null hypothesis under the Dickey-Fuller test is that a unit root exists, a significant Dickey-Fuller test statistic would indicates stationarity. We find that the p-values for the Dickey-Fuller test statistics for all series are less than 0.01, indicating that these series are stationary (untabulated).

Next, we select the time series models that best fit the time series variables. Given our data is quarterly, we follow Hann et al.'s (2021) model selection process and consider the following four models: AR(1), ARIMA(0,0,0) × $(1,0,0)_4$, ARIMA(1,0,0) × $(1,0,0)_4$, and AR(4). The first model assumes autocorrelation only at the first lag, the second model assumes only a seasonal autocorrelation, and the third model is a combination of the first two. The last model, AR(4), is the least restrictive of the set and allows for non-zero autocorrelations at all four lags.

We select the model that best fits the data based on two criteria: Akaike information criterion (AIC) and Bayesian information criterion (BIC). Table 1 reports the AICs and BICs of the four time-series models for the considered series and highlights the best-performing models in bold. Overall, the AR(1) model tends to dominate the other models based on the AIC and BIC. Since we include macroeconomic variables as well as return predictors in our AR models as controls, we estimate the ARMAX regressions with AR(1) term throughout our paper.[7]

4. Empirical Results

4.1 Determinants of Strategists' Relative Pessimism

We first study the time-series determinants of strategists' relative pessimism (i.e. *Diff_EPS*). To examine whether strategists' relative pessimism varies with macroeconomic indicators, we estimate the following equation using OLS:

$$Diff\_EPS_t = \beta_0 + \beta_1 Inf\_Spread_{t-1} + \beta_2 GDP\_FCST_{t-1} + \beta_3 Unemp_{t-1} + \beta_4 PMI_{t-1} + \beta_5 FFFR_{t-1} + \beta_6 Cons\_Sent_{t-1} + \beta_7 Inv\_Sent_{t-1} + \varepsilon_t \quad [1]$$

Our determinants include macroeconomic signals commonly used by prior research (e.g., Bonsall et al. 2013) and cited by strategists in their research reports. We first consider inflation spread, Inf_Spread_{t-1}, calculated as the difference between Consumer Price Index (CPI) and Producer Price Index (PPI). To the extent that CPI and PPI captures output prices and input prices, respectively, the spread between the two inflation indexes captures expected changes in corporate profit margins. Prior work finds bottom-up analysts' earnings forecasts do not fully reflect a firm's inflation exposure (Basu et al. 2010), which leads to a prediction that strategists' EPS forecasts will better incorporate the inflation expectations embedded in Inf_Spread_{t-1}.

[7] For simplicity, Hann et al. (2021) do not consider series with moving-average terms. Including moving-average terms in our models tends to result in worse fits, as indicated by higher values of AIC and BIC. Therefore, we exclude moving-average terms from our analysis.

GDP_FCST_{t-1} is the most recent 12-month forecast of real GDP growth from the Philadelphia Survey of Professional Forecasters, and $Unemp_{t-1}$ is the U.S. Bureau of Labor Statistics unemployment rate from the prior month. Hann et al. (2012) find bottom-up analysts underreact to real GDP growth news and unemployment forecast revisions although Hugon et al. (2016) point out that the underreaction can be mitigated to some degree when they have access to an in-house economist, particularly when GDP news is negative. Both inputs are important for strategist's forecasts as higher GDP growth (unemployment) positively (negatively) affects corporate earnings in aggregate. Given prior literature finds bottom-up analysts tend to underreact to these signals, we expect strategists to incorporate GDP growth expectations and unemployment into their estimates more timely.

$FFFR_{t-1}$ is the federal funds futures rate from the prior month to proxy for the expectations of changes in monetary policy with higher (lower) values representing a tightening (loosening) in monetary policy expectations. The federal funds rate can affect corporate profits through at least two channels. It directly affects firms' borrowing costs and/or indirectly affects firms' revenue as the Federal Reserve controls economic activities through monetary policy. An increase (a decrease) in the federal funds rate will negatively (positively) affect corporate profits through both of these channels as it will increase (decrease) borrowing costs and slow down (stimulate) the economy.

Our final three determinants capture managers', consumers', and investors' sentiment about economic conditions. PMI_{t-1} is the Purchasing Managers' Index from the prior month to capture the expectations of the economic conditions from firms in the manufacturing, construction, and service industries, while $Cons\_Sent_{t-1}$ and Inv_Sent_{t-1} are sentiment indices from the prior month of consumers and investors, respectively (Baker and Wurgler 2006). All variables in Eq. (1) are standardized to have a mean of zero and standard deviation of one. All continuous variables throughout the paper are winsorized at the 1% and 99% levels.

We report the results of estimating our determinants model in Table 3 with our dependent variables of interest, $Diff\_EPS_t$. A one-standard deviation increase in Inf_Spread_{t-1} is associated with a 0.589 standard deviation increase (t-stat = 3.633) in $Diff\_EPS_t$ indicating strategists become relatively more optimistic than bottom-up analysts in response to inflation expectations and corporate margins consistent with our expectation given the findings of Basu et al. (2010). In contrast, a one standard deviation increase in $FFFR_{t-1}$ is associated with a 0.445 standard deviation decrease (t-stat = -3.292) in $Diff\_EPS_t$ as strategists revise their forecasted EPS down more in response to contractionary monetary policy expectations. Similarly, strategists appear to respond more to increases in unemployment , displaying relatively greater pessimism compared to bottom-up analysts (coef = -0.445 t-stat = -3.292) consistent with the findings of Hann et al. (2012) that bottom-up analysts fail to timely incorporate negative macroeconomic news.

Taken together, these findings extend Darrough and Russell (2002) by validating that strategists' relative pessimism systematically varies with a number of relevant macroeconomic indicators. However, these results do not indicate whether strategists' differential response to macroeconomic indicators contains value-relevant information. For this to be the case, strategists' pessimism should both vary with macroeconomic indicators and have incremental predictive value for relevant future outcomes. We test this idea in the following sections.

4.2 Predictive Value of Strategists' Relative Pessimism

We next study the information content of the difference between top-down and bottom-up forecasts in predicting future aggregate earnings surprises and whether investors incorporate the strategists' information efficiently in their expectations. If variation in *$Diff\_EPS_t$* reflects relevant macroeconomic news that is incorporated in strategists' forecasts but not fully reflected in bottom-up analysts' forecasts, it may predict future aggregate earnings surprises relative to the bottom-up EPS forecast. Additionally, if investors' aggregate expectations align with those of bottom-up analysts, the information embedded in *$Diff\_EPS_t$* may also predict future market returns.

Accordingly, we test whether *$Diff\_EPS_t$* is predictive of future aggregate earnings surprises and market returns using the following models:

$$UE_{t+1} = \beta_0 + \beta_1 Diff\_EPS_t + Controls + \varepsilon_t \qquad [2]$$

$$Ret_{t+\tau} = \beta_0 + \beta_1 Diff\_EPS_t + Controls + Return\ Predictors + \varepsilon_t \qquad [3]$$

where UE_{t+1} is aggregate earnings surprises, calculated as the value-weighted average of all firms' earnings surprises (UE_{it+1}) announced in the next quarter, with weights based on market value as of quarter-end.[8] Individual firm unexpected earnings, UE_{it+1}, are calculated as actual earnings less the most recent analyst consensus forecast, scaled by the stock price. Following Konchitchki and Patatoukas (2014), we remove firm-quarter observations that fall in the top and bottom one percentile of UE_{it+1} each quarter before aggregating them into UE_{t+1}. $Ret_{t+\tau}$ is the value-weighted cumulative returns for major stock indices in the upcoming one to three months. We use returns for all stocks in the CRSP (All CRSP), a large-cap index (S&P 500), a mid-cap index (S&P 400), and a small-cap index (S&P 600). In both regression equations, we control for the macroeconomic signals identified in our determinants analysis (*Controls*) to identify if

[8] We note that value-weighted averages align better with our main independent variable, *$Diff\_EPS_t$*, as the index-level EPS is a value-weighted average of individual constituents' EPS. However, our inference remains similar when we use equal-weighted averages.

$Diff\_EPS_t$ contains incrementally meaningful information. For the return test, we also include variables known to predict equity market premium, $Accrual_{t-1}$, $GPCE_{t-1}$, and GPI_{t-1}, to ensure that the results are not driven by these variables (Goyal et al. 2023).

In Table 4, we report the results of our unexpected earnings analysis. In Column (1), we do not find a significant association between $Diff\_EPS_t$ and aggregate unexpected earnings for the full sample. In Columns (2) and (3), we estimate the predictive ability of $Diff\_EPS_t$ on aggregate earnings surprise for the S&P 500 and non-S&P 500 separately. We find our measure of strategists' relative pessimism is predictive of future aggregate earnings surprises only for S&P 500 (coef = 0.267 t-stat = 2.048) but not for non-S&P 500 firms. This result is consistent with the prediction that top-down analysts' forecasts contain macroeconomic news not incorporated into bottom-up analysts' estimates for earnings announced in the subsequent earnings season for the S&P 500 firms.

In Table 5, we turn to the return predictability of $Diff\_EPS_t$. In Panel A, we find that $Diff\_EPS_t$ is positively associated with one- to three-month ahead total market returns and statistically significant at 1%. This suggests that when strategists' EPS forecasts become less (more) pessimistic relative to those issued by bottom-up analysts, the stock market performs better (worse) in the next one to four months. Economically, a one standard deviation increase in $Diff\_EPS_t$ is associated with a one-month ahead cumulative return of 2.0%, a two-month ahead cumulative return of 2.8%, and a three-month ahead cumulative return of 2.5%, suggesting that investors initially underreact to the macroeconomic signals embedded into strategists' forecasts, taking months to fully incorporate $Diff\_EPS_t$ information into stock prices.

Next, we examine S&P 500 returns and non-S&P 500 returns separately. Panel B documents the return predictability of $Diff\_EPS_t$ for S&P 500 returns. We find that $Diff\_EPS_t$ is positively associated with one- to three-month ahead S&P 500 returns, consistent with the total market returns reported in Panel A. The economic magnitudes mirror Panel A's findings. For non-S&P 500 returns, we examine the S&P 400 (mid-cap) and S&P 600 (small-cap) indices in Panels C and D. We find that $Diff\_EPS_t$ is positively associated with one- to three-month ahead returns of these two indices. Economically, a one standard deviation increase in $Diff\_EPS_t$ *is* associated with a one-month ahead cumulative return of 2.8% (3.3%) and a three-month ahead cumulative return of 3.0% (3.4%) for the S&P 400 (S&P 600) index. The economic magnitude for non-S&P 500 firms is larger than that S&P 500 firms. We interpret this result as an indication that smaller firms outside the S&P 500 index are exposed to the same macroeconomic trends affecting the larger index constituents. Additionally, these smaller firms are experiencing are economically linked to the S&P 500 index constituents.

As described earlier, we include the AR(1) term in all regression models to account for potential autocorrelation in our dependent variables. In most cases, the AR(1) terms remain statistically insignificant, suggesting that the autocorrelation of our dependent variables is not significant. The lack of significant autocorrelation in our dependent variables aligns with the nature of earnings surprises and market returns, both of which are influenced by new, unforeseen information rather than by historical data trends. Firstly, our dependent variables represent earnings surprises against (bottom-up) analyst forecasts rather than raw earnings levels. These surprises are inherently less likely to exhibit autocorrelation because they are not driven by predictable, systematic patterns in earnings data but rather by unexpected events or information releases. Secondly, market returns, especially over shorter time horizons, are generally assumed to be influenced by new information and are largely considered to follow a random walk. This implies that today's returns should not be significantly correlated with past returns, making it difficult for past returns to predict future returns consistently. Consequently, the insignificance of the AR(1) terms in our regression models supports the robustness of our findings, indicating that our dependent variables are independent of their lagged values in a time series context.

Taken together, our results are consistent with $Diff\_EPS_t$ containing market-wide value relevant news that investors have not fully incorporated into their expectations similar to the behavior of bottom-up analysts. This suggests that strategists' forecasts capture new and relevant information about the overall market. Furthermore, our results indicate that active investors can benefit from strategists' forecast divergence relative to bottom-up analysts. The divergence between top-down and bottom-up forecasts highlights the different perspectives and methodologies employed by strategists and bottom-up analysts. Strategists often incorporate broader macroeconomic factors and market-wide trends, while bottom-up analysts focus on firm-specific details and fundamentals. When strategists' forecasts significantly diverge from those of bottom-up analysts, it signals that there may be discrepancies in the market's valuation and the underlying economic realities. Active investors, who are typically more engaged in analyzing and acting on such information, can exploit these divergences to make more informed investment decisions. By aligning their strategies with the insights derived from top-down forecasts, active investors can potentially achieve better returns compared to relying solely on bottom-up analyses. The combination of these approaches provides a more comprehensive view of the market.

5. Time-Series Variation

In subsequent analyses, we examine time-series variation in the information content of $Diff\_EPS_t$. Consistent with the findings of Hann et al. (2012) and Hugon et al. (2016) we expect strategists' EPS forecast to be particularly useful during periods of market-wide uncertainty and/or negative macroeconomic news. To operationalize this prediction, we re-estimate our aggregate unexpected earnings and future returns equations interacting $Diff\_EPS_t$ with specific indicator variables that capture periods of economic uncertainty. The first indicator variable, *Recession*, equals one for fiscal periods classified as recessions by the National Bureau of Economic Research (NBER). Recessions typically involve widespread economic downturns, leading to increased uncertainty and volatility in the financial markets. The second indicator variable, *HighVix*, equals one for fiscal periods when the VIX is in the top quintile. The VIX measures the market's expectation of volatility over the next 30 days, with higher values indicating greater uncertainty and risk aversion among investors.

We report the results of this additional analysis for earnings surprises in Table 6. In Panel A Column (1), we find that during recessionary periods strategists' relative pessimism is positively and significantly predictive of future earnings surprises (coef = 0.820 t-stat = 3.265). We find similar results during periods of heightened investor uncertainty in Column (2). In particular when the VIX is elevated, we find $Diff\_EPS_t$ is positive and significantly associated with future earnings surprises (coef = 0.535 t-stat = 1.713). We report the time-series variation solely for the S&P500 firms in our sample for brevity. Untabulated results suggest that the predictive ability of $Diff\_EPS_t$ on earnings surprise for the non-S&P500 firms also exists during periods of uncertainty.

Turning to the return predictability in Panel B, we find the association between $Diff\_EPS_t$ and future aggregate returns is stronger during periods of elevated investor uncertainty. Columns (1)-(3) suggests that during recessions, strategists' relative pessimism significantly predicts cumulative returns for the S&P 500 index. The coefficients for interaction variables range from 0.020 to 0.036 and are generally statistically significant, indicating robust statistical and economical significance. Columns (4)-(6) further illustrate that the return predictability of *Diff_EPS*$_t$ is more pronounced during heightened market uncertainty. While we report the time-series variation only for the S&P 500 firms for brevity, similar conclusions persist when analyzing non-S&P 500 firms (untabulated).

Overall, these results indicate that strategists' responsiveness to macroeconomic signals is particularly useful during periods of heightened uncertainty, such as recessions or times of high market volatility, when the broader economic context significantly impacts firm performance and investor behavior.

6. Additional Analyses

6.1 Comparing Forecast Errors of Top-down and Bottom-up Forecasts

The empirical analyses conducted so far provide evidence that strategists' relative pessimism varies systematically with macroeconomic trends and has significant information content in predicting future earnings surprises and stock returns. Implicit in these findings is the idea that top-down forecasts are more accurate than bottom-up forecasts. In this section, we conduct additional analysis to examine the quality of top-down and bottom-up forecasts.

We first calculate top-down and bottom-up analysts' forecast errors at each monthly forecast horizon to investigate how these forecasts behave over time relative to actual earnings. Following Darrough and Russell (2002), we define forecast errors at each month *t* as:

$$FE_t = \frac{EPS_t - Actual}{Actual}$$

where t = -21, -20, ……, +1. *EPS* is either top-down or bottom-up forecast for the fiscal year and *Actual* is the actual realized earnings.

Figure 2 Panel A plots the mean forecast errors (FE_t) at each monthly forecast horizon leading up to the realization. In this figure, we highlight several key findings. Firstly, there is a noticeable gap in percentage forecast errors between two forecasts, particularly at longer forecast horizons, consistent with Darrough and Russell (2002). For instance, at t = -20, the average bottom-up error is approximately 10%, while the top-down error is 5%. This gap narrows over time as analysts receive more current information as time proceeds. However, Figure 2 shows a significantly different pattern in contrast to Darrough and Russell's (2002) period of 1987-1999. In their era, top-down forecast were more accurate (less accurate) than bottom-up forecasts for longer (shorter) forecast horizon. Thus, there was an intersection of two graphs, FE_t for top-down forecasts and FE_t for bottom-up forecasts, at around t = -7.[9] Yet, during our sample period, we do not find a reversal of relative accuracy: top-down forecasts consistently remain less optimistic and, consequently, more accurate than bottom-up forecasts over the entire period.

In panel B, we conduct a difference in means test between strategists' and bottom-up analysts' forecast errors at 2-year and 1-year horizons. We find the difference between strategists' and bottom-up analysts' FE_t are statistically significant at both forecast horizons. These differences in forecast errors indicate that top-down analysts are significantly less optimistic, consistent with the trends in Panel A. Notably, the difference for the 1-year horizon, 0.0096, is smaller than that for the 2-year horizon, 0.0461, suggesting that bottom-up analysts "walk down" their forecasts more rapidly.

Overall, this analysis reaffirms our conclusion that strategists incorporate macroeconomic signals and provide higher-quality forecasts than their bottom-up counterparts for aggregate EPS.

[9] P. 146, Figure A1, Darrough and Russell (2002)

6.2 Firm Level Analysis

To better understand how the entire market-level information embedded in strategists' relative pessimism, $Diff\_EPS_{t,}$ is transmitted to individual stocks, we investigate whether $Diff\_EPS_t$ is associated with earnings surprises and short-window earnings announcement returns for individual firms in the upcoming earnings season. As strategists incorporate macroeconomic signals that bottom-up forecasts might have overlooked into EPS forecasts, index constituents will likely experience earnings surprises. We estimate the following firm-level equation using OLS.

$$UE_{it} \text{ or } CAR_{[-1,+1]} = \beta_0 + \beta_1 Diff\_EPS_t + \beta_2 Size_{it} + \beta_3 BTM_{it} + \beta_4 AnalystFollow_{it} + \beta_5 Loss_{it}$$

$$+ \beta_6 EarningsPersist_{it} + \beta_7 Leverage_{it} + Macro\ Controls + Firm\ FE + Year\ FE + \varepsilon_{it} \quad [4]$$

UE_{it} is firm *i's* earnings surprise for the quarter and $CAR_{[-1,+1]}$ is the buy-and-hold abnormal return in the three day window around the upcoming quarterly earnings announcement. We include firm characteristic controls such as firm size, analyst following, earnings persistence, book-to-market ratio, loss and leverage. We also include macroeconomic variables used on the previous analyses and firm and year fixed effects. Formal definitions of the firm-level variables can be found in Appendix 2.

If $Diff\_EPS_t$ carries meaningful macroeconomic information not reflected in bottom-up analysts' expectations, we predict that larger values of $Diff\_EPS_t$ indicate higher relative optimism and thus positive firm-level earnings surprises. Likewise, if strategists become relatively pessimistic, it will signal negative cash flow news not reflected in bottom-up analysts' expectations. Therefore, we predict a positive coefficient on β_1 when the dependent variable is unexpected earnings. Turning to investors' reaction, if investors align their expectations more with bottom-up analysts' guidance, we expect the information content of *Diff_EPS*$_t$ regarding macroeconomic news will not be reflected in the price of the individual stock. Accordingly, if investors perceive the positive (negative) earnings surprise as more persistent due to positive (negative) macroeconomic trends reflected in the strategist's forecast, we expect a positive coefficient on β_1 when the dependent variable is the abnormal return around the earnings announcement.

We report the results of estimating our earnings surprise and abnormal announcement returns models in Table 7 Panel A and B, respectively. In Column (1) of Panel A, we find the coefficient on *Diff_EPS*$_t$ is positive and statistically significant at the 10% level (coef = 0.007 t-stat= 1.722) for the full sample indicating that as strategists revise their EPS estimates upwards (downwards) relative to bottom-up analysts' forecasts, then firms in our sample will experience positive (negative) earnings surprises. In Column (2) and (3), we subsample our analysis by firms in the S&P 500 and those not in the S&P 500. We find the coefficient on *Diff_EPS*$_t$ remains positive and statistically significant at 10% level only for Column (3). The insignificant coefficient in Column (2) might appear inconsistent with the aggregate-level findings for the S&P 500 firms reported in Column (2) of Table 4. To reconcile this discrepancy, it important to note that while Table 4 used value-weighted average earnings surprises, our firm-level OLS analysis treats each firm-quarter earnings surprise equally, effectively equal-weighting earnings surprises.

In Panel B, we report the results of our earnings announcement return analysis. The coefficients on *Diff_EPS*$_t$ are positive and statistically significant at the 1% level in Column (2) only with respective t-stats of 2.728. The coefficients indicate that a one standard deviation increase in *Diff_EPS*$_t$ is associated with incremental abnormal announcement returns of approximately 0.2%. These results are consistent with investors failing to incorporate the information contained in strategists' index-level EPS forecasts into their firm-specific earnings expectations, and then being positively (negatively) surprised around earnings announcements, on average, during periods when prior $Diff\_EPS_t$ is relatively high (low).

Consistent with our longer-window analyses in the aggregate level, our firm-level analysis reaffirms that strategists' forecasts effectively predict future earnings surprises and short-window earnings announcement returns. This coherence across the aggregate- and firm-level bolsters our conclusion regarding the predictive power of strategists' forecasts.

7. Conclusion

Aggregate earnings forecasts for the S&P 500 are a key macroeconomic indicator as the Federal Reserve Board uses them to guide their monetary policy. We study two groups of forecasters who issue earnings forecasts for the index and investigate whether strategists' relative pessimism compared to bottom-up analysts' aggregate forecasts varies systematically over time and contains information that is useful for investors. We find that strategists' relative pessimism varies systematically with macroeconomic conditions. In turn, strategists' relative pessimism has predictive value for future aggregate earnings surprises and aggregate returns for major stock indices, consistent with sell-side analysts and investors underreacting to the information contained in strategists' index forecasts.

While there is some evidence that (bottom-up) analysts underreact to macroeconomic news, the macroeconomic signals embedded in strategists' top-down forecasts have been largely overlooked in the literature. Our findings contribute to understanding the role of strategists in mitigating their fellow analysts' underreaction to macroeconomic signals, which has important implications for investors and policy makers. Investors can benefit when they use both bottom-up and top-down forecasts in combination when they form expectations for aggregate earnings. Policy makers can also make more informed and timelier decisions when they incorporate strategists' forecasts into their assessments of the economy.

Given limited academic research on strategists, future research could shed light on strategists' role in capital markets. Do strategists' forecasts predict future macroeconomic outcomes, such as GDP growth or monetary policy? Do strategists' other outputs, such as target prices for S&P 500, have incremental information over other metrics known to generate abnormal returns? Do firm managers respond to strategists' outputs when issuing management forecasts? We leave these questions for future research.

Appendix 1. Variable Definitions

Variable	Definition
$Diff\_EPS_t$	The 12-month forward top-down consensus EPS forecasts for the S&P 500 index minus bottom-up EPS forecasts for the index, scaled by the previous month's S&P 500 index price.
UE_{it}	Actual earnings less analysts' most recent mean consensus scaled by price.
UE_t	Aggregate earnings surprises, calculated as the value-weighted average of all firms' earnings surprises (*UE_{it}*) announced in the next three months, with weights based on market value as of quarter-end
$Ret_{t+\tau}$	Return for stock indices in the next τ month(s)
$CAR_{[-1,+1]}$	The buy-and-hold cumulative abnormal return relative to the value-weighted CRSP market index around the earnings announcement.
FE_t	The difference between forecasted EPS and realized EPS, scaled by the realized EPS
$Size_{it}$	Natural log of the market value of equity from the most recent quarter-end period.
BTM_{it}	The ratio of the book value of equity to the market value of equity from the most recent quarter-end period.
$AnalystFollow_{it}$	The natural logarithm of one plus the number of analysts covering the firm prior to the most recent quarter-end period.
$EarningsPersist_{it}$	The coefficient of a regression on earnings scaled by shares outstanding on prior year earnings for the same quarter scaled by shares outstanding.
$Leverage_{it}$	Total debt scaled by total assets from the most recent quarter-end period
$Loss_{it}$	An indicator variable equal to one if the firm reported negative earnings from the most recent quarter-end period.
Inf_Spread_{t-1}	The difference between the Consumer Price Index the Producer Price Index in the prior month. Accessed through FRED.
GDP_FCST_{t-1}	The most recent 12-month ahead forecast of real GDP growth from the Survey of Professional Forecasters. Accessed through Philadelphia Federal Reserve website.
$Unemp_{t-1}$	The unemployment rate in the prior month from the U.S. Bureau of Labor Statistics. Accessed through FRED.
PMI_{t-1}	The Purchasing Managers' Index from the prior month. Accessed through Thomson Datastream.
$FFFR_{t-1}$	The CBoT 30-Day Federal Funds Futures settlement rate from the prior month. Accessed through Thomson Datastream.
$Cons\_Sent_{t-1}$	Michigan Survey of Consumer Sentiment from the prior month. Accessed through FRED.
Inv_Sent_{t-1}	Investor sentiment index from the prior month (Baker and Wurgler 2006). Accessed through Jeffrey Wurglers' personal website.
$Accrual_{t-1}$	Aggregate accruals from the prior year (Hirshleifer et al. 2009)
$GPCE_{t-1}$	The growth rate in personal consumption expenditures from the prior year (Møller and Rangvid 2015)
GPI_{t-1}	The growth rate in personal inductrial production from the prior year (Møller and Rangvid 2015)

$Recession_{t-1}$	Indicator variable equal to one if the month in which *$Diff\_EPS_t$* is measured was classified as a recession by NBER.
$HighVix_{t-1}$	Indicator variable equal to one if the average VIX for the month *$Diff\_EPS_t$* is measured is in the top quintile. We use closing levels of the VIX index for the S&P 500.

Appendix 2. Example Strategist Reports

Panel A: Bank of America

S&P 500 EPS: +46% in 2021, +5% in 2022

We forecast $204 (+46% YoY) in 2021 EPS and $215 (+5%) in 2022, based on 2021/22 GDP growth of 5.9%/5.2%, $67/$74 WTI oil, and $1.17/1.15 EURUSD. See our recent EPS Outlook report for full details.

Exhibit 29: We expect 46% growth in 2021 and 5% growth in 2022– download our Excel model
BofA S&P 500 EPS outlook

All based on current constituents unless specified			Bottom-up Consensus				BofA Analyst estimates				BofA Strategy			
	2019	2020	2021	y/y	2022	y/y	2021	y/y	2022	y/y	2021	y/y	2022	y/y
S&P 500 Pro-forma EPS (Historical Index)	$162.93	$139.72												
S&P 500 Pro-forma EPS (Current Constituents)	$159.39	$143.55	$201.19	44%	$219.58	9%	$204.74	47%	$220.89	8%	$204.00	46%	$215.00	5%
Sector ($ billions)														
Consumer Discretionary	102.9	78.0	124.8	60%	161.0	29%	132.3	70%	165.0	25%	121.2	55%	149.4	23%
Consumer Staples	89.6	92.8	100.5	8%	106.5	6%	100.9	9%	107.4	6%	98.9	7%	101.7	3%
Energy	51.1	(5.9)	60.7	1135%	76.1	25%	58.9	1104%	83.8	42%	60.1	1124%	78.2	30%
Financials	248.6	197.6	308.9	56%	271.0	-12%	309.1	56%	278.9	-10%	318.2	61%	274.9	-14%
Health Care	207.8	230.2	279.5	21%	289.0	3%	282.1	23%	282.2	0%	284.7	24%	292.8	3%
Industrials	122.9	66.5	116.4	75%	155.1	33%	116.9	76%	153.7	31%	116.4	75%	148.0	27%
Information Technology	268.2	295.6	371.1	26%	402.3	8%	369.1	25%	395.1	7%	375.2	27%	400.6	7%
Materials	34.1	31.9	57.1	79%	55.5	-3%	57.1	79%	56.4	-1%	55.1	73%	54.5	-1%
Real Estate	36.3	35.7	40.6	14%	42.8	5%	35.9	1%	39.0	9%	40.9	14%	43.2	6%
Communication Services	132.8	137.1	182.4	33%	201.0	10%	208.9	52%	231.7	11%	184.9	35%	204.2	10%
Utilities	43.1	44.5	45.5	2%	49.0	8%	46.0	3%	50.4	10%	45.4	2%	48.2	6%
S&P 500	1,337.3	1,204.1	1,687.5	40%	1,809.3	7%	1,717.2	43%	1,843.7	7%	1,701.0	41%	1,795.8	6%
S&P 500 ex. Financials	1,088.8	1,006.5	1,378.6	37%	1,538.3	12%	1,408.2	40%	1,564.8	11%	1,382.7	37%	1,520.9	10%
S&P 500 ex. Energy and Financials	1,037.7	1,012.4	1,317.8	30%	1,462.2	11%	1,349.2	33%	1,480.9	10%	1,322.6	31%	1,442.7	9%
S&P 500 ex. Energy	1,286.2	1,210.0	1,626.7	34%	1,733.3	7%	1,658.3	37%	1,759.9	6%	1,640.8	36%	1,717.6	5%
Energy Sector ($bn)	51.1	(5.9)	60.7	1135%	76.1	25%	58.9	1104%	83.8	42%	60.1	1124%	78.2	30%
Avg. Oil Price (wtd. blend of Brent & WTI)	$62/bbl	$42/bbl					~$67/bbl	60%	~$74/bbl	10%	~$67/bbl	60%	~$74/bbl	10%
S&P 500 Dividends (Historical Constituents, $/share)	$58.22	$58.22									$61.00	5%	$68.00	11%
Key Macro Economic Forecasts														
Global GDP growth (real)	2.9%	-3.2%									5.8%		4.8%	
US GDP growth (real)	2.2%	-3.5%									5.9%		5.2%	
FX Rate: US$/Euro (average)	1.12	1.14									1.17		1.15	

Source: BofA US Equity & Quant Strategy, FactSet/First Call; Note: 2021 EPS growth is relative to actual S&P 500 2020 EPS of $139.72

BofA GLOBAL RESEARCH

This figure presents an example of the summary page from a Bank of America strategist's report issued on September 8, 2021. The report provides the strategy (top-down) analyst's EPS forecast for the S&P 500 (outlined in red). The report also provides the FactSet bottom-up consensus EPS forecast for the S&P 500 (outlined in blue).

Panel B: J.P. Morgan

J.P.Morgan

Global Markets Strategy
16 October 2023

Equity Strategy

Q3 preview: bottom-up to start looking more challenging

- Big picture, we argued last Monday that **bond yields are likely peaking**, see "Time to position for the long duration trade". Given that the sharp bond selloff was a problem for equities over the past few months, any turn lower in yields is initially interpreted as a positive by the market. The question is how long will that supportive effect last for, as the next market phase could be "bad will be seen as bad", especially if earnings momentum starts to deteriorate. Within the market, we believe the long duration trade calls for a rebound in ytd lagging bond proxy sectors.
- For Q3 reporting season, the consensus expectations are at +4% and +3% yoy EPS growth ex Energy, for US and Eurozone, respectively. Median stock forecast is broadly for flat growth, on a yoy basis. These projections appear undemanding at face value, but, in contrast to 1H, when most activity metrics were on an improving trend, the **PMI momentum softened during Q3**. Global composite PMI is down 3 points in Q3 vs Q2, suggesting that **earnings growth is likely to be outright negative**.
- In level terms, even though 2023 annual EPS growth projection is flat, 2H US EPS is expected to be 6% above 1H. Beyond potentially weaker volumes, driven by decreasing PMIs, we believe **corporate pricing is likely softening** - see our recent report on this. Weaker pricing at the time of elevated input costs such as wages and rates could lead to margin squeeze.
- **Overall, top-line growth is decelerating smartly**, expected to be at +3% and -2% yoy ex Energy for Q3 in US and Eurozone, respectively. This is a significant slowdown from double-digit gains seen through 2021 and 2022.
- EPS revisions have been more stable so far this year, after a poor 2022, but

Equity Strategy

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After an improvement in 1H, activity momentum is pointing to softer earnings delivery in 2H...

This figure presents an example from a J.P. Morgan strategist's report issued on October 16, 2023.

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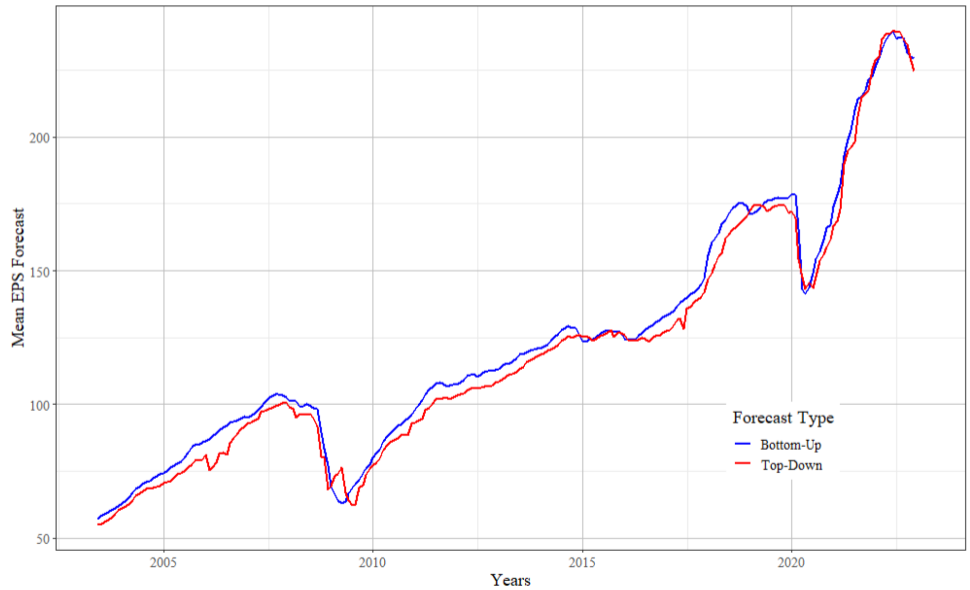
Figure 1: Top-down and Bottom-up EPS forecasts for the S&P 500 in Refinitiv Eikon

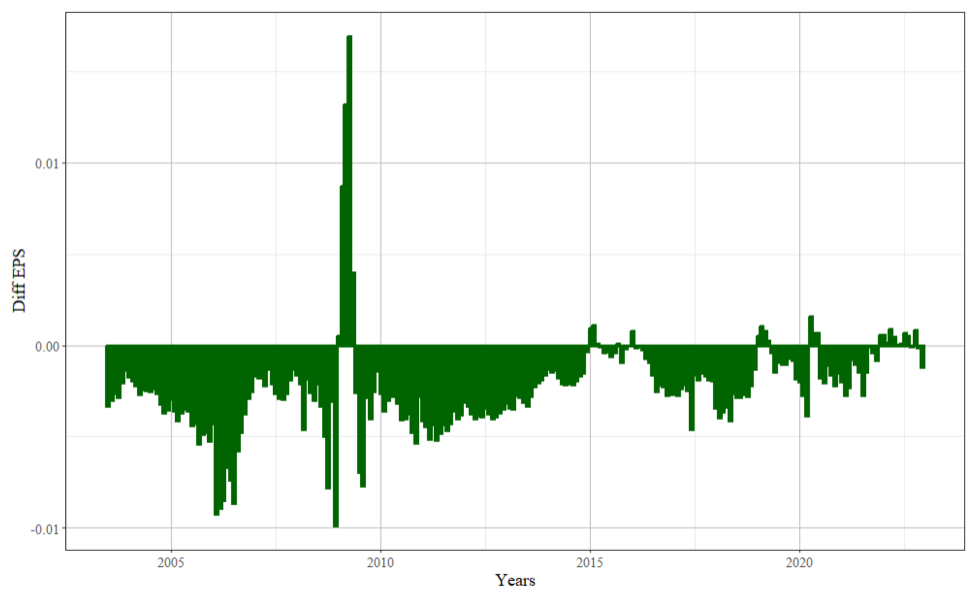
This figure displays the trends of top-down (the violet line) and bottom-up consensus (the orange line) for the S&P 500 index for FY2024.

Figure 2: Time Series of Top-Down and Bottom-Up EPS Forecast

Panel A: Top-Down and Bottom-Up S&P 500 Consensus EPS Forecasts



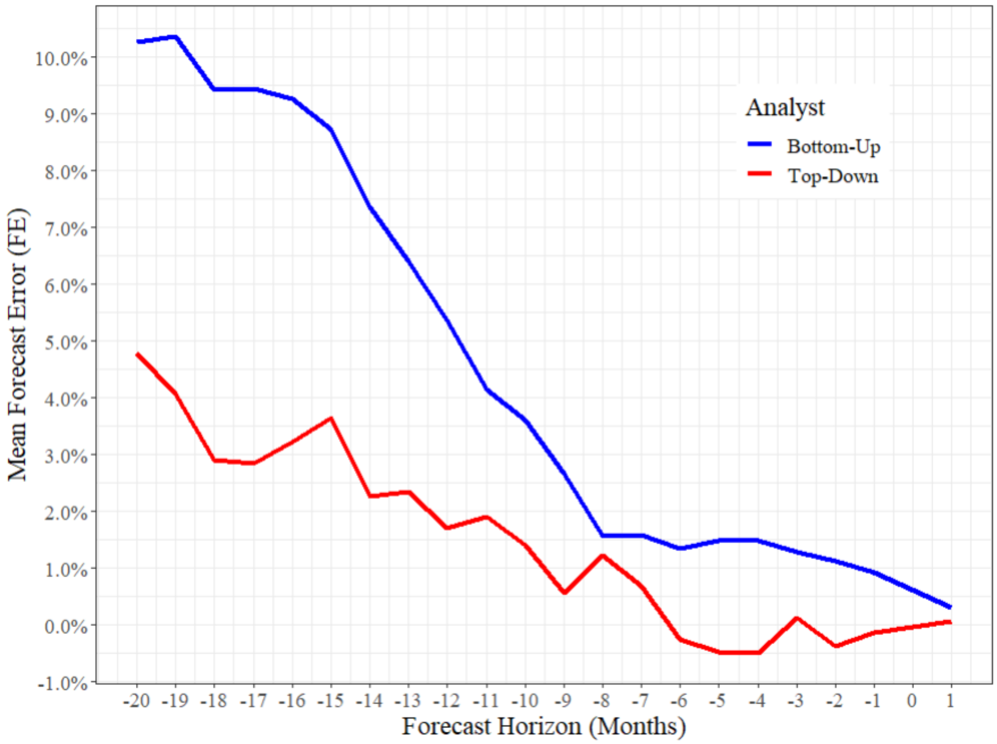
Panel B: Scaled Differences Between Top-Down and Bottom-Up EPS Forecasts (Diff_EPS)



This figure presents monthly values of top-down and bottom-up EPS forecasts for the S&P 500, and the difference between them during our sample period. Panel A plots the two sources of S&P 500 EPS forecasts (TD_EPS_t and BU_EPS_t), and Panel B plots the difference between the top-down and bottom-up EPS forecast as a percentage of the lagged value of the S&P 500 index ($Diff\_EPS_t$).

Figure 3: Forecast Errors of Bottom-Up and Top-Down Forecasts

Panel A: Top-Down and Bottom-Up Mean Forecast Errors by Month Horizon



Panel B: Comparison of Top-Down and Bottom-Up Forecast Errors by Year Horizon

Forecast Errors (FE) 2-Year Horizon			**Forecast Errors (FE) 1-Year Horizon**		
Variable		**Mean**	**Variable**		**Mean**
FE_t (bottom-up EPS)		0.0723	FE_t (bottom-up EPS)		0.0096
FE_t (top-down EPS)		0.0262	FE_t (top-down EPS)		0.0000
	Diff	0.0461		Diff	0.0096
	t-stat	15.66		t-stat	3.04

This figure presents the average forecast errors (FE_t) of top-down and bottom-up EPS forecasts for the S&P 500 at different forecast horizons. Consistent with Darrough and Russell (2002), FE_t is defined as the difference between forecasted EPS and realized EPS, scaled by the realized EPS. Panel A plots the average forecast errors of TD_EPS_t and BU_EPS_t in each of the 21 months prior to the realization. Panel B presents a difference in means test between the forecast errors of TD_EPS_t and BU_EPS_t at a 2-year horizon and a 1-year horizon.

Table 1. Descriptive Statistics

Variables	N	Mean	SD	P25	Median	P75
Aggregate-Level						
$Diff\_EPS_t$	65	-0.003	0.003	-0.004	-0.003	-0.002
Ret_{t+1} – All CRSP	65	0.011	0.044	-0.017	0.015	0.036
Ret_{t+2} – All CRSP	65	0.014	0.061	-0.008	0.022	0.049
Ret_{t+3} – All CRSP	65	0.020	0.071	-0.004	0.026	0.057
Ret_{t+1} – S&P 500	65	0.010	0.045	-0.018	0.015	0.036
Ret_{t+2} – S&P 500	65	0.014	0.062	-0.008	0.021	0.049
Ret_{t+3} – S&P 500	65	0.020	0.072	-0.004	0.026	0.058
Ret_{t+1} – S&P 400	65	0.010	0.055	-0.022	0.013	0.039
Ret_{t+2} – S&P 400	65	0.017	0.073	-0.019	0.024	0.052
Ret_{t+3} – S&P 400	65	0.025	0.084	-0.012	0.036	0.067
Ret_{t+1} – S&P 600	65	0.008	0.061	-0.033	0.010	0.049
Ret_{t+2} – S&P 600	65	0.015	0.081	-0.020	0.014	0.073
Ret_{t+3} – S&P 600	65	0.027	0.089	-0.006	0.034	0.083
UE_t – All	65	-0.001	0.006	-0.001	0.000	0.001
UE_t – S&P 500	65	0.000	0.003	0.000	0.001	0.001
UE_t – non-S&P 500	65	-0.003	0.017	-0.002	0.000	0.000
Inf_Spread_{t-1}	65	-0.007	0.045	-0.036	-0.018	0.016
GDP_FCST_{t-1}	65	2.732	0.603	2.412	2.704	3.019
$Unemp_{t-1}$	65	6.146	1.879	4.700	5.500	7.700
PMI_{t-1}	65	53.815	5.199	51.100	53.600	57.700
$FFFS_{t-1}$	65	1.406	1.661	0.145	0.530	2.135
$Cons\_Sent_{t-1}$	65	83.446	12.028	75.100	86.700	93.700
Inv_Sent_{t-1}	65	-0.241	0.292	-0.394	-0.220	-0.047
$Accrual_{t-1}$	65	-0.045	0.004	-0.048	-0.045	-0.044
$GPCE_{t-1}$	65	0.003	0.004	0.001	0.002	0.006
GPI_{t-1}	65	0.003	0.014	0.001	0.005	0.010
HighVix	65	0.200	0.403	0.000	0.000	0.000
Recession	65	0.092	0.292	0.000	0.000	0.000
Firm-Level						
AnalystFollow	200,803	1.902	0.752	1.386	1.946	2.485
BTM	200,803	0.576	0.496	0.267	0.471	0.756
CAR[-1,+1]	200,803	-0.001	0.083	-0.040	-0.001	0.040
EarningsPersist	200,803	0.270	0.544	-0.062	0.173	0.583
Leverage	200,803	0.229	0.215	0.042	0.187	0.353
Loss	200,803	0.266	0.442	0.000	0.000	1.000
Size	200,803	6.962	1.832	5.632	6.863	8.169
UE_{it}	200,803	-0.004	0.051	-0.001	0.000	0.002

This table provides the descriptive statistics for the variables used in our analyses. Formal definitions of the variables can be found in Appendix 1.

Table 2. Selecting Time-Series Models

	Akaike Information Criterion				Bayesian Information Criterion			
	AR(1)	ARIMA $(0,0,0)\times(1,0,0)_4$	ARIMA $(1,0,0)\times(1,0,0)_4$	AR(4)	AR(1)	ARIMA $(0,0,0)\times(1,0,0)_4$	ARIMA $(1,0,0)\times(1,0,0)_4$	AR(4)
$Diff\_EPS_t$	**-699**	-697	-697	**-699**	**-692**	-690	-687	-685
UE_{t+1} – *All*	**-866**	-853	**-867**	-864	**-858**	-846	**-858**	-850
UE_{t+1} – *S&P 500*	-837	-834	**-847**	-838	-830	-827	**-838**	-824
UE_{t+1} – *non-S&P 500*	**-805**	-800	**-804**	-801	**-798**	-793	-794	-787
Ret_{t+1} – *All CRSP*	-249	**-251**	-249	**-252**	-242	**-244**	-240	-238
Ret_{t+2} – *All CRSP*	**-198**	**-198**	-196	**-197**	**-191**	**-191**	-186	-183
Ret_{t+3} – *All CRSP*	**-169**	**-170**	-168	-164	**-162**	**-163**	-159	-150
Ret_{t+1} – *S&P 500*	-252	**-254**	-252	**-254**	-245	**-247**	-242	-240
Ret_{t+2} – *S&P 500*	**-201**	**-201**	-199	**-200**	**-194**	**-194**	-189	-186
Ret_{t+3} – *S&P 500*	**-172**	**-172**	-170	-167	**-164**	**-165**	-161	-153
Ret_{t+1} – *S&P 400*	-223	-223	-222	**-225**	**-215**	**-216**	-212	-211
Ret_{t+2} – *S&P 400*	**-174**	**-174**	-172	**-175**	**-167**	**-167**	-163	-161
Ret_{t+3} – *S&P 400*	**-142**	**-143**	-141	-139	**-135**	**-136**	-131	-125
Ret_{t+1} – *S&P 600*	**-210**	**-210**	-208	**-211**	**-203**	**-203**	-199	-198
Ret_{t+2} – *S&P 600*	**-160**	**-160**	-158	**-160**	**-153**	**-153**	-149	-145
Ret_{t+3} – *S&P 600*	**-130**	**-131**	-129	-126	**-123**	**-124**	-119	-112

This table reports the Akaike information criterion and Bayesian information criterion for four time-series models: AR(1), ARIMA $(0,0,0) \times (1,0,0)_4$, ARIMA $(1,0,0) \times (1,0,0)_4$, and AR(4).

Table 3. Determinants of Difference between Strategist and Bottom-Up EPS Forecasts

	(1)
	$Diff\_EPS_t$
Inf_Spread_{t-1}	0.589***
	(3.633)
GDP_FCST_{t-1}	-0.140
	(-0.550)
$Unemp_{t-1}$	-0.445***
	(-3.292)
PMI_{t-1}	0.236
	(1.326)
$FFFR_{t-1}$	-0.535***
	(-3.458)
$Cons\_Sent_{t-1}$	0.154
	(0.966)
Inv_Sent_{t-1}	0.120
	(1.139)
AR(1)	-0.233
	(-0.858)
Observations	65
Pseudo R^2	0.314

This table reports the estimated coefficients of our macroeconomic determinants model of $Diff\_EPS_t$. $Diff\_EPS_t$ is calculated as the 12-month forward top-down consensus EPS forecasts (TD_EPS_t) for the S&P 500 index minus bottom-up EPS forecasts (BU_EPS_t) for the index, scaled by the previous month's S&P 500 index price. We estimate the ARMAX regressions with one lag. All variables are standardized in this analysis with formal definitions in Appendix 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity.

Table 4: Predictive Ability of *Diff_EPS* over Future Earnings Surprises

VARIABLES	(1) UE_{t+1} All	(2) UE_{t+1} S&P500	(3) UE_{t+1} non-S&P500
$Diff\_EPS_t$	0.079	0.267**	0.006
	(0.640)	(2.048)	(0.058)
Inf_Spread_{t-1}	-0.135	-0.208	-0.084
	(-1.000)	(-1.287)	(-0.635)
GDP_FCST_{t-1}	-0.325	0.049	-0.385
	(-1.073)	(0.216)	(-1.151)
$Unemp_{t-1}$	0.665***	1.061***	0.370*
	(3.446)	(3.016)	(1.851)
PMI_{t-1}	0.493	-0.107	0.567
	(1.285)	(-0.667)	(1.312)
$FFFR_{t-1}$	0.253**	0.433***	0.134
	(2.278)	(2.757)	(1.452)
$Cons\_Sent_{t-1}$	0.167*	0.501***	0.001
	(1.767)	(2.620)	(0.015)
Inv_Sent_{t-1}	0.058	-0.205**	0.131
	(0.356)	(-2.395)	(0.716)
AR(1)	-0.210	0.165	-0.190
	(-1.432)	(0.817)	(-1.315)
Observations	65	65	65
Pseudo R^2	0.304	0.515	0.196

This table reports the estimated coefficients of our ARMAX model estimated for our full sample, S&P500 sample, and non-S&P500 sample in Columns (1), (2), and (3), respectively. The dependent variable is UE_{t+1} which is the value-weighted average unexpected firm-level earnings surprise based on bottom-up analysts' consensus forecast. Our independent variable of interest is $Diff\_EPS_t$. Control variables are detrended using the Baxter and King (1999) filter. All variables are standardized in this analysis with formal definitions in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity.

Table 5: Predictive Ability of *Diff_EPS* over Future Returns (Aggregate-level)

Panel A. All CRSP Value-Weighted Returns

	(1)	(2)	(3)
		All CRSP	
VARIABLES	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}
$Diff\_EPS_t$	0.020***	0.028***	0.025***
	(4.641)	(4.074)	(4.752)
Inf_Spread_{t-1}	-0.015*	-0.017	-0.004
	(-1.657)	(-1.521)	(-0.279)
GDP_FCST_{t-1}	-0.000	0.013	0.011
	(-0.040)	(0.820)	(0.764)
$Unemp_{t-1}$	0.034***	0.031*	0.044***
	(3.066)	(1.915)	(2.578)
PMI_{t-1}	-0.008	-0.009	-0.012
	(-0.805)	(-0.668)	(-0.890)
$FFFR_{t-1}$	0.026***	0.026**	0.032***
	(3.582)	(2.463)	(2.868)
$Cons\_Sent_{t-1}$	0.006	0.007	0.012
	(0.908)	(0.768)	(1.319)
Inv_Sent_{t-1}	-0.007	-0.004	-0.013
	(-0.971)	(-0.444)	(-1.250)
$Accrual_{t-1}$	0.004	0.006	0.003
	(0.638)	(0.710)	(0.363)
$GPCE_{t-1}$	-0.001	-0.006	-0.015
	(-0.264)	(-0.746)	(-1.578)
GPI_{t-1}	0.001	-0.011	0.002
	(0.076)	(-0.970)	(0.190)
AR(1)	-0.197	-0.100	-0.175
	(-1.576)	(-0.664)	(-1.349)
Observations	65	65	65
Pseudo R^2	0.258	0.287	0.318

This table reports the estimated coefficients of our ARMAX model. The dependent variable is $Ret_{t+\tau}$ where *Ret* is the return to the All CRSP and τ denotes the month relative to current month, *t*. Our independent variable of interest is $Diff\_EPS_t$. Control variables are detrended using the Baxter and King (1999) filter. All independent variables are standardized in this analysis with formal definitions in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity.

Panel B. Large-Cap S&P 500 Returns

	(1)	(2)	(3)
		S&P 500	
VARIABLES	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}
$Diff\_EPS_t$	0.020***	0.028***	0.025***
	(4.647)	(4.079)	(4.743)
Inf_Spread_{t-1}	-0.015	-0.017	-0.003
	(-1.624)	(-1.490)	(-0.256)
GDP_FCST_{t-1}	-0.000	0.014	0.011
	(-0.008)	(0.822)	(0.764)
$Unemp_{t-1}$	0.034***	0.031*	0.045***
	(3.038)	(1.909)	(2.584)
PMI_{t-1}	-0.008	-0.008	-0.012
	(-0.794)	(-0.648)	(-0.878)
$FFFR_{t-1}$	0.026***	0.026**	0.032***
	(3.591)	(2.446)	(2.842)
$Cons\_Sent_{t-1}$	0.006	0.007	0.012
	(0.881)	(0.759)	(1.344)
Inv_Sent_{t-1}	-0.007	-0.004	-0.013
	(-0.974)	(-0.426)	(-1.243)
$Accrual_{t-1}$	0.004	0.006	0.003
	(0.625)	(0.692)	(0.340)
$GPCE_{t-1}$	-0.002	-0.007	-0.015
	(-0.268)	(-0.763)	(-1.578)
GPI_{t-1}	0.001	-0.011	0.002
	(0.069)	(-0.958)	(0.186)
AR(1)	-0.194	-0.096	-0.169
	(-1.557)	(-0.635)	(-1.280)
Observations	65	65	65
Pseudo R^2	0.259	0.290	0.321

This table reports the estimated coefficients of our ARMAX model. The dependent variable is $Ret_{t+\tau}$ where *Ret* is the return to the S&P 500 and τ denotes the month relative to current month, *t*. Our independent variable of interest is $Diff\_EPS_t$. Control variables are detrended using the Baxter and King (1999) filter. All independent variables are standardized in this analysis with formal definitions in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity.

Panel C. Mid-Cap S&P 400 Returns

VARIABLES	(1) Ret_{t+1}	(2) *S&P 400* Ret_{t+2}	(3) Ret_{t+3}
$Diff\_EPS_t$	0.028***	0.036***	0.030***
	(4.961)	(4.943)	(5.363)
Inf_Spread_{t-1}	-0.022**	-0.028**	-0.010
	(-2.238)	(-2.169)	(-0.623)
GDP_FCST_{t-1}	0.002	0.028	0.015
	(0.167)	(1.557)	(0.911)
$Unemp_{t-1}$	0.048***	0.041**	0.056***
	(3.610)	(2.166)	(2.632)
PMI_{t-1}	-0.014	-0.028*	-0.022
	(-1.242)	(-1.929)	(-1.473)
$FFFR_{t-1}$	0.038***	0.036***	0.032**
	(4.638)	(3.080)	(2.511)
$Cons\_Sent_{t-1}$	0.002	0.007	0.016
	(0.186)	(0.624)	(1.521)
Inv_Sent_{t-1}	-0.008	-0.011	-0.012
	(-1.074)	(-1.074)	(-1.052)
$Accrual_{t-1}$	0.009	0.010	0.008
	(1.452)	(1.174)	(0.946)
$GPCE_{t-1}$	-0.004	-0.010	-0.019
	(-0.680)	(-1.080)	(-1.637)
GPI_{t-1}	-0.000	-0.007	0.002
	(-0.005)	(-0.615)	(0.151)
AR(1)	-0.233*	-0.175	-0.195*
	(-1.724)	(-1.180)	(-1.676)
Observations	65	65	65
Pseudo R^2	0.295	0.303	0.322

This table reports the estimated coefficients of our ARMAX model. The dependent variable is $Ret_{t+\tau}$ where *Ret* is the return to the S&P 400 and τ denotes the month relative to current month, *t*. Our independent variable of interest is $Diff\_EPS_t$. Control variables are detrended using the Baxter and King (1999) filter. All independent variables are standardized in this analysis with formal definitions in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity.

Panel D. Small-Cap S&P 600 Returns

VARIABLES	(1) Ret_{t+1}	(2) S&P 600 Ret_{t+2}	(3) Ret_{t+3}
$Diff\_EPS_t$	0.033***	0.041***	0.034***
	(5.477)	(4.636)	(4.787)
Inf_Spread_{t-1}	-0.028***	-0.036**	-0.017
	(-2.604)	(-2.409)	(-0.963)
GDP_FCST_{t-1}	0.003	0.032	0.025
	(0.174)	(1.464)	(1.247)
$Unemp_{t-1}$	0.051***	0.040*	0.049**
	(3.469)	(1.915)	(2.144)
PMI_{t-1}	-0.015	-0.033*	-0.027
	(-1.174)	(-1.919)	(-1.524)
$FFFR_{t-1}$	0.042***	0.037***	0.029**
	(4.790)	(2.634)	(1.998)
$Cons\_Sent_{t-1}$	-0.001	0.009	0.015
	(-0.107)	(0.703)	(1.329)
Inv_Sent_{t-1}	-0.014	-0.015	-0.012
	(-1.570)	(-1.209)	(-0.972)
$Accrual_{t-1}$	0.010	0.011	0.007
	(1.301)	(1.127)	(0.720)
$GPCE_{t-1}$	-0.002	-0.011	-0.024*
	(-0.248)	(-0.930)	(-1.829)
GPI_{t-1}	-0.001	-0.007	0.000
	(-0.125)	(-0.535)	(0.006)
AR(1)	-0.220*	-0.145	-0.151
	(-1.717)	(-0.979)	(-1.249)
Observations	65	65	65
Pseudo R^2	0.330	0.306	0.309

This table reports the estimated coefficients of our ARMAX model. The dependent variable is $Ret_{t+\tau}$ where *Ret* is the return to the S&P 600 and τ denotes the month relative to current month, *t*. Our independent variable of interest is $Diff\_EPS_t$. Control variables are detrended using the Baxter and King (1999) filter. All independent variables are standardized in this analysis with formal definitions in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity.

Table 6: Time-Series Variation

Panel A. Future Earnings Surprises

VARIABLES	(1) UE_{t+1} *S&P 500*	(2) UE_{t+1} *S&P 500*
$Diff\_EPS_t$	-0.410*	-0.165
	(-1.701)	(-0.502)
Recession	3.365***	
	(2.879)	
Recession × $Diff\_EPS_t$	0.820***	
	(3.265)	
HighVix		0.069
		(0.106)
HighVix × $Diff\_EPS_t$		0.535*
		(1.713)
Inf_Spread_{t-1}	-0.348	-0.141
	(-0.933)	(-0.868)
GDP_FCST_{t-1}	0.449	0.066
	(1.081)	(0.313)
$Unemp_{t-1}$	0.945	0.834***
	(1.237)	(2.637)
PMI_{t-1}	-0.303	-0.089
	(-1.212)	(-0.393)
$FFFR_{t-1}$	0.641	0.228
	(1.440)	(1.139)
$Cons\_Sent_{t-1}$	0.949***	0.565*
	(2.774)	(1.819)
Inv_Sent_{t-1}	-0.504**	-0.174*
	(-2.237)	(-1.654)
AR(1)	0.754***	0.202
	(4.865)	(0.536)
Observations	65	65
Pseudo R^2	0.624	0.557

This table reports the time-series variation of our ARMAX model for our full sample. The dependent variable is UE_{t+1} which is the value-weighted average unexpected firm-level earnings surprise for the S&P 500 firms based on bottom-up analysts' consensus forecast. We interact $Diff\_EPS_t$ with the following indicator variables: *Recession* and *HighVix*. *Recession* is an indicator variable equal to one if the period was classified as a recession by the NBER, zero otherwise. *HighVix* is an indicator variable equal to one if the VIX is in the top quintile, zero otherwise. Control variables are detrended using the Baxter and King (1999) filter. All variables are standardized in this analysis with formal definitions in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity.

Panel B. Future Returns

	(1)	(2)	(3)	(4)	(5)	(6)
				S&P 500		
VARIABLES	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}
$Diff\_EPS_t$	0.009	0.005	0.008	0.004	0.001	0.010
	(1.286)	(0.461)	(0.699)	(0.542)	(0.134)	(0.838)
Recession	-0.010	-0.011	-0.062			
	(-0.269)	(-0.186)	(-1.345)			
$Recession \times Diff\_EPS_t$	0.020	0.036**	0.033*			
	(1.529)	(2.132)	(1.800)			
HighVix				0.038**	0.041	0.050*
				(2.287)	(1.175)	(1.671)
$HighVix \times Diff\_EPS_t$				0.020**	0.034***	0.018
				(2.080)	(3.014)	(1.364)
Inf_Spread_{t-1}	-0.013	-0.013	-0.001	-0.016**	-0.018	-0.005
	(-1.588)	(-1.266)	(-0.122)	(-1.960)	(-1.588)	(-0.398)
GDP_FCST_{t-1}	-0.001	0.012	-0.002	0.011	0.025	0.026
	(-0.108)	(0.729)	(-0.141)	(0.949)	(1.600)	(1.583)
$Unemp_{t-1}$	0.025**	0.013	0.029	0.017	0.007	0.024
	(2.404)	(0.804)	(1.613)	(1.278)	(0.362)	(1.158)
PMI_{t-1}	-0.008	-0.008	-0.007	-0.015	-0.016	-0.021
	(-0.888)	(-0.664)	(-0.611)	(-1.417)	(-1.122)	(-1.397)
$FFFR_{t-1}$	0.019***	0.012	0.018	0.017**	0.012	0.023*
	(2.642)	(1.134)	(1.474)	(2.011)	(1.025)	(1.759)
$Cons\_Sent_{t-1}$	0.007	0.010	0.005	0.016**	0.021*	0.024**
	(0.740)	(0.751)	(0.386)	(2.269)	(1.767)	(2.296)
Inv_Sent_{t-1}	-0.007	-0.005	-0.009	-0.011	-0.009	-0.018
	(-0.986)	(-0.495)	(-0.829)	(-1.415)	(-0.833)	(-1.624)
$Accrual_{t-1}$	0.002	0.002	0.003	-0.001	-0.000	-0.002
	(0.317)	(0.231)	(0.367)	(-0.094)	(-0.013)	(-0.242)
$GPCE_{t-1}$	0.001	-0.002	-0.010	-0.003	-0.007	-0.019*
	(0.113)	(-0.277)	(-1.101)	(-0.611)	(-0.750)	(-1.698)
GPI_{t-1}	0.001	-0.011	0.001	-0.001	-0.013	0.001
	(0.082)	(-1.167)	(0.060)	(-0.130)	(-1.212)	(0.055)
AR(1)	-0.303	-0.218	-0.337**	-0.149	-0.016	-0.091
	(-1.477)	(-0.947)	(-2.313)	(-0.792)	(-0.061)	(-0.516)
Observations	65	65	65	65	65	65
Pseudo R^2	0.297	0.346	0.371	0.356	0.372	0.374

This table reports the time-series variation of our ARMAX. The dependent variable is $Ret_{t+\tau}$ where *Ret* is the return to the S&P 500 index and τ denotes the month relative to current month, *t*. We interact $Diff\_EPS_t$ with *Recession*, which is an indicator variable equal to one if the period was classified as a recession by the NBER, zero otherwise. *HighVix* is an indicator variable equal to one if the VIX is in the top quintile, zero otherwise. Control variables are detrended using the Baxter and King (1999) filter. All independent variables are standardized in this analysis with formal definitions in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity.

Table 7. Firm-level Analysis

Panel A. Earnings Surprise

VARIABLES	(1) UE_{t+1} All CRSP	(2) UE_{t+1} S&P 500	(3) UE_{t+1} non-S&P 500
$Diff\_EPS_t$	0.008*	-0.004	0.010*
	(1.722)	(-0.830)	(1.898)
Size	0.039*	0.004	0.046*
	(1.675)	(0.155)	(1.714)
BTM	-0.073***	-0.074***	-0.071***
	(-6.629)	(-2.843)	(-5.959)
AnalystFollow	-0.003	0.007	-0.002
	(-0.352)	(0.958)	(-0.178)
EarningsPersist	-0.005	0.011*	-0.007
	(-1.250)	(1.961)	(-1.465)
Leverage	-0.039***	-0.008	-0.044***
	(-4.565)	(-0.908)	(-4.536)
Loss	-0.437***	-0.179***	-0.464***
	(-32.552)	(-7.030)	(-32.110)
Inf_Spread_{t-1}	-0.011*	0.008	-0.014*
	(-1.665)	(1.125)	(-1.915)
$FFFR_{t-1}$	0.040***	0.031**	0.040***
	(3.069)	(2.094)	(2.620)
$Unemp_{t-1}$	-0.030	-0.028	-0.028
	(-1.420)	(-1.489)	(-1.109)
PMI_{t-1}	-0.015***	-0.006	-0.017***
	(-3.400)	(-1.193)	(-3.296)
GDP_FCST_{t-1}	0.057***	0.031***	0.063***
	(6.871)	(2.744)	(6.591)
$Cons\_Sent_{t-1}$	-0.017**	-0.004	-0.019**
	(-2.550)	(-0.632)	(-2.386)
Inv_Sent_{t-1}	0.009*	-0.000	0.011*
	(1.889)	(-0.084)	(1.948)
Observations	200,441	29,948	170,477
R-squared	0.204	0.158	0.206
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table reports the estimated coefficients of our firm-level earnings surprise model estimated for our full sample, S&P500 sample, and non-S&P500 sample in Columns (1), (2), and (3), respectively. The dependent variable is UE_{it+1} which is the reported earnings less bottom-up analysts' most recent consensus. Our independent variable of interest is $Diff\_EPS_t$. All continuous variables are standardized in this analysis with formal definitions in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity and clustered at the firm level.

Panel B. Earnings Announcement CAR[-1,+1]

VARIABLES	(1) *CAR[-1,+1]* All CRSP	(2) *CAR[-1,+1]* S&P 500	(3) *CAR[-1,+1]* non-S&P 500
$Diff\_EPS_t$	0.001	0.002***	0.000
	(1.404)	(2.728)	(0.674)
Size	-0.024***	-0.029***	-0.024***
	(-21.176)	(-10.580)	(-18.964)
BTM	0.003***	0.003*	0.003***
	(5.474)	(1.953)	(5.259)
AnalystFollow	-0.001***	0.000	-0.002**
	(-2.712)	(0.146)	(-2.567)
EarningsPersist	-0.001**	-0.001	-0.001*
	(-2.282)	(-1.433)	(-1.847)
Leverage	-0.002***	-0.000	-0.002***
	(-3.787)	(-0.127)	(-3.684)
Loss	-0.029***	-0.016***	-0.030***
	(-40.263)	(-8.969)	(-39.701)
Inf_Spread_{t-1}	-0.001*	-0.001	-0.001*
	(-1.923)	(-0.564)	(-1.882)
$FFFR_{t-1}$	0.002	0.000	0.002
	(1.437)	(0.173)	(1.479)
$Unemp_{t-1}$	-0.010***	-0.005	-0.011***
	(-5.307)	(-1.370)	(-5.033)
PMI_{t-1}	0.001*	0.001	0.001
	(1.651)	(1.171)	(1.392)
GDP_FCST_{t-1}	-0.002***	-0.001	-0.002***
	(-2.774)	(-0.347)	(-2.671)
$Cons\_Sent_{t-1}$	0.002***	0.002	0.002***
	(3.420)	(1.281)	(3.253)
Inv_Sent_{t-1}	-0.001**	-0.002**	-0.001
	(-1.981)	(-2.552)	(-1.197)
Observations	200,441	29,948	170,477
R-squared	0.072	0.049	0.076
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table reports the estimated coefficients of our firm-level abnormal earnings announcement period returns model estimated for our full sample, S&P500 sample, and non-S&P500 sample in Columns (1), (2), and (3), respectively. The dependent variable is *CAR[-1,+1]* which is the buy-and-hold abnormal return for the three days centered around the earnings announcement. Our independent variable of interest is $Diff\_EPS_t$. All continuous variables, except for $CAR_{[-1,+1]}$, are standardized in this analysis with formal definitions in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity and clustered at the firm level.