Top-Down vs. Bottom-Up Index Forecasts: The Information Content of Equity Strategists' Relative Pessimism*

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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. Finally, a market-timing strategy that exploits the divergence between top-down and bottom-up forecasts generates economically meaningful abnormal returns. 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.

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1. Introduction

Aggregate earnings forecasts for the S&P 500 index are a key macroeconomic indicator.[1] Two types of index-level earnings forecasts are commonly disseminated by forecast data providers (FDPs) and cited in the financial press: (1) index-level forecasts created by aggregating the firm-level forecasts of the equity analysts following the individual constituent companies, (i.e., bottom-up forecasts), and (2) index-level forecasts made directly by equity strategists who issue S&P 500 earnings forecasts using a top-down approach (i.e., top-down forecasts). Equity strategists play a unique role in sell-side brokerage research departments, with a research focus that bridges the gap between economists, who produce forecasts of macroeconomic indicators (e.g., GDP growth), and equity analysts, who follow individual firms. Strategists are responsible for interpreting the implications of macroeconomic news for the equity market as a whole, along with its differential impact across industry sectors. Compared to economists and firm-level equity analysts, relatively little is known about how strategists behave and whether their index-level forecasts provide value to investors. In this study, we examine whether equity strategists' top-down S&P 500 earnings forecasts provide incremental information beyond that produced by economists and firm-level equity analysts. Specifically, we investigate whether strategists' forecast divergence from bottom-up forecasts varies systematically over time and contains incremental information that is useful for investors.

Two prior studies provide motivation for examining the research outputs produced by equity strategists. First, Darrough and Russell (2002) conduct a preliminary comparison of top-down and bottom-up aggregate earnings forecasts from 1987 – 1999 and conclude that, while

[1] 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).

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 strategists' relative pessimism with respect to the bottom-up forecast. Kadan et al. (2012) examine strategists' industry recommendations and find that they 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 equity strategists' index-level forecasts, or their incremental value relative to economists' GDP forecasts and bottom-up index forecasts.

Darrough and Russell (2002) propose that firm-level analysts' incentives to curry favor with management may explain the excess optimism of bottom-up EPS forecasts relative to strategists' top-down forecasts, but do not test this hypothesis. If the excess optimism of bottom-up EPS forecasts is primarily 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 with a constant upwards bias in bottom-up EPS forecasts. Darrough and Russell (2002) further suggest that firm-level analysts' interactions with management may cause them to adopt management's optimistic "insider" perspective of the firm's prospects (Kahneman and Lovallo 1993). To the extent this is true, firm-level analysts may underreact to negative external information, such as macroeconomic news. Consistent with this, Hugon et al. (2016) find that individual analysts underreact to negative macroeconomic information contained in GDP forecast revisions. We propose that, given equity strategists' training and research focus, along with their "outsider" perspective, strategists are better able to incorporate macroeconomic information in their forecasts than firm-level analysts. Accordingly, we predict that 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.

To test these predictions, we analyze quarterly differences in top-down vs. bottom-up one-year-ahead S&P 500 EPS forecasts from 2Q 2003 to 2Q 2022. We create two variables based on the differences in levels and revisions in EPS forecasts between strategists and bottom-up analysts: *Diff_EPS_Level* and *Diff_EPS_Revision*. Specifically, *Diff_EPS_Level* is the difference between the consensus twelve-month forward EPS forecast for the S&P 500 index from strategists and from bottom-up analysts scaled by the previous month's S&P 500 index price, and *Diff_EPS_Revision* is the difference between the consensus quarterly changes in twelve-month forward EPS forecasts from strategists and from bottom-up analysts. We examine both the difference in levels and revisions of EPS forecasts between top-down analysts and bottom-up analysts because they capture distinct signals that may reflect different dimensions of market expectations. While level differences highlight persistent optimism or pessimism between the two groups, revision differences capture the timing and responsiveness of forecast updates to new information.

Consistent with Darrough and Russell (2002), we find that the median value of *Diff_EPS_Level* is -0.3% during our more recent sample period, indicating that the top-down forecast is generally more pessimistic than the bottom-up forecast computed in the same quarter. We observe significant variation in the level of *Diff_EPS_Level* over time, such that *Diff_EPS_Level* has an interquartile range from -0.4% to -0.1%, and even becomes positive in some quarters of our sample period (see Figure 2 Panel A and Panel B). The median percentage change in *Diff_EPS_Revision* is -0.1% with an interquartile range of -0.9% to 0.7%. These simple statistics suggest that, in contrast to the relatively persistent pessimism in levels, strategists revise their EPS forecasts in a manner that fluctuates between relatively more optimism and pessimism compared to bottom-up analysts (see Figure 2 Panel C).

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_Level*, is positively related to proxies for industrial profit margins (i.e., the spread between CPI and PPI) and investor sentiment, and negatively related to the measure of monetary policy as proxied by the federal funds rate. However, we do not observe statistically significant associations between the macroeconomic variables and *Diff_EPS_Revision*. These results lend some support to 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_Level* and/or *Diff_EPS_Revision* 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 both *Diff_EPS_Level* and *Diff_EPS_Revision* are predictive of future aggregate earnings surprises and are positively associated with the three-month ahead returns of the S&P 500 index. When we decompose both signals into their components (i.e., top-down and bottom-up EPS forecast levels and revisions), we find the predictive ability is primarily driven by strategists' EPS forecasts. To further explore the source of this information content, we test whether the predictive ability of these divergence measures is more pronounced when strategists actively revise their forecasts. The results show that revision-based divergence becomes significantly more predictive of both earnings surprises and returns when accompanied by strategists' own forecast revisions, suggesting it reflects timely incorporation of new information. In contrast, level-based divergence shows no such amplification, indicating that it may reflect more persistent or structural differences in outlook between top-down and bottom-up analysts.

Additional analyses further reveal that the return predictability of strategists' forecasts is more pronounced during periods of elevated macroeconomic uncertainty. Overall, we conclude that strategists' interpretations of macroeconomic news relative to bottom-up analysts contain significant information content.

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.

Finally, we explore whether the divergence between strategists' and bottom-up analysts' EPS forecasts contain useful investment information by developing trading strategies based on our two measures of divergence. We combine *Diff_EPS_Level* and *Diff_EPS_Revision* with the strategists' recent revision in EPS forecast to classify their outlook as relatively optimistic or pessimistic compared to the bottom-up analyst. If both components are optimistic (pessimistic), the strategy takes a long position in equities (government treasuries) and a short position in government treasuries (equities).[2] If the signals are mixed, the strategy defaults to holding the S&P 500 index. Our results show that both timing strategies earn higher average monthly portfolio returns, higher Sharpe ratios, and lower maximum drawdowns compared to a strategy that always takes a long position in the S&P 500 index. In market model tests, we confirm these strategies earn statistically significant monthly alphas of 0.6% - 0.7%. Figure 4 plots the cumulative return to each strategy over our sample period. This plot also highlights that our timing strategies outperform the market during economic downturns by signaling a timely reallocation out of equities into traditionally safer investments like government treasuries. In sum, our trading strategy results indicate strategists' relative pessimism contain valuable information for market participants which can be used to improve risk-adjusted returns and reduce downside risk exposure due to economic downturns.

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

[2] We use monthly returns to the S&P 500 ETF (SPY) and to the iShares 1-3 Year Treasury Bond ETF (SHY).

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 can help investors identify aggregate inefficiencies in analysts' bottom-up forecasts. While prior work has focused on the inefficiency of bottom-up analysts' firm-level forecasts with respect to incorporating the firm-specific implications of macroeconomic news, 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, equity strategists. Controlling for individual macroeconomic signals, our findings suggest 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 Equity Strategists

Equity strategists 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.[3] 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.

Equity strategists focus on the equity market as a whole in contrast to traditional (firm-level) analysts who cover individual stocks. Thus, the role of equity 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 equity 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.

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[3] We use the terms 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.

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."*[4] 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."*[5]

In their reports, strategists produce three main outputs: index-level EPS forecasts, index-level target prices, and within-index industry recommendations. Appendix 2 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 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.

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

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 2 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 equity 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 the difference of their EPS forecasts relative 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, the difference in index-level earnings forecasts 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 Variables 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.[6] 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 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 can observe and compare these series in real time to track overall earnings trends of the

[6] 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.

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.[7] In the aggregate return predictability tests, we add three predictors that are known to predict market returns: *Accrual*, *GPCE*, and *GPI* (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 website.[8]

Our sample period covers from 2Q 2003 to 2Q 2022 which results in 77 quarterly observations for our levels-based analyses and 76 quarterly observations for our revisions-based analyses. We begin in 2Q 2003 because top-down EPS forecasts are not available prior to this period in Refinitiv Datastream.

[7] https://pages.stern.nyu.edu/~jwurgler/
[8] https://sites.google.com/view/agoyal145

3.2 Strategists' Divergence from Bottom-up Forecasts

Our measure of strategists' deviation from bottom-up forecasts is the difference between top-down and bottom-up analysts' next-twelve-month EPS forecasts in quarter *t*. We use two complementary measures—one based on forecast levels and the other on forecast revisions—as defined below:

$$Diff\_EPS\_Level_t = \frac{EPS\_Level\_TD_t - EPS\_Level\_BU_t}{SP\_INDEX_{t-1}} \tag{1-1}$$

where $EPS\_Level\_TD_t$ and $EPS\_Level\_BU_t$ are the next-twelve-month top-down and bottom-up S&P 500 EPS forecasts as of quarter t, respectively, and SP_INDEX_{t-1} is the closing value of the S&P 500 index in the previous month.

$$Diff\_EPS\_Revision_t = \left(EPS_{Revision_{TD}}{}_t - EPS_{Revision_{BU}}{}_t\right) \times 100 \tag{1-2}$$

where $EPS\_Revision\_TD_t$ and $EPS\_Revision\_BU_t$ are the quarterly changes of $EPS\_Level\_TD_t$ and $EPS\_Level\_BU_t$, respectively.

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 $EPS\_Level\_TD_t$ and $EPS\_Level\_BU_t$ 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. To illustrate, Figure 2, Panel B, plots the scaled differences between the two sets of forecasts (i.e., $Diff\_EPS\_Level_t$). On average, $Diff\_EPS\_Level_t$ 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. quarters in which $Diff\_EPS\_Level_t$ is positive). The prevalence of strategists' relative pessimism may reflect the fundamental differences in forecasting methodologies between strategists and bottom-up analysts. Strategists top-down approach and "outsider" perspective leads to systematic relative pessimism in expectations about future earnings for the index compared to bottom-up analysts. Therefore, variation in the magnitude of this disagreement may contain useful information for market participants about future earnings and prices of the index constituents if bottom-up analysts and investors continually fail to incorporate macroeconomic trends that are reflected in the views of the strategist.

Figure 2, Panel C, plots the difference in revisions to consensus EPS forecasts from the prior quarter between strategists and bottom-up analysts during our sample period. Overall, this difference largely fluctuates between changing relative optimism and pessimism. Unlike the difference in levels, strategists exhibit more quarters of increasing relative optimism that align with periods of smaller level differences. However, strategists do not consistently revise their EPS forecasts downwards more than bottom-up analysts in a way that would indicate a widening gap in the level of pessimism between forecast levels. Similar to the time series of the differences in levels, the greatest magnitude of the difference in EPS revisions is largest during the Great Recession. Therefore, our second measure of strategists' divergence in expectations about index earnings may also be useful signal of future earnings and prices of the index constituents. Our revision-based measure captures the notion that strategists are more attuned to macroeconomic trends as a result of their top-down approach, and thus, may incorporate this information into their expectations more timely than bottom-up analysts. Even if strategists and bottom-up analysts ultimately agree on the aggregate effect of macroeconomic trends, strategists' timeliness may provide useful information for market participants about future earnings and prices of the index constituents not yet incorporated into the expectations of bottom-up analysts or investors.

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 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 consider the following four time-series models: AR(1), ARIMA(0,0,0) × $(1,0,0)_4$, ARIMA(1,0,0) × $(1,0,0)_4$, and AR(4). The AR(1) model assumes autocorrelation at the first lag, and the ARIMA(0,0,0) × $(1,0,0)_4$ model assumes autocorrelation from only the fourth lag (i.e. the same quarter from one year prior). The third model, ARIMA(1,0,0) × $(1,0,0)_{4,}$ combines the prior two models and allows for non-zero autocorrelation from the most recent quarter and a seasonal autocorrelation. Finally, the AR(4) model allows for autocorrelation from any of the prior four quarters in each series.

We select the model that best fits the data based on two criteria: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Table 2 reports the AIC and BIC values for four time-series models estimated on our key dependent variables, with the best-performing models highlighted in bold. Overall, the AR(1) model outperforms the others for both $Diff\_EPS\_Level_t$ and $Ret_{[t+1,t+3]}$, while the AR(4) model provides a better fit for UE_t. For $Diff\_EPS\_Revision_t$, model selection is less clear-cut: AIC favors the AR(4) model, whereas BIC suggests the AR(1) model. Given its close relation with $Diff\_EPS\_Level_t$, we adopt the AR(1) specification for $Diff\_EPS\_Revision_t$ to maintain consistency. Since we include macroeconomic variables as well as return predictors in our AR models as controls, we estimate ARMAX regressions with customized AR terms throughout our paper.[9]

4. Empirical Results

4.1 Determinants of Strategists' Divergence from Bottom-up Forecasts

We first study the time-series determinants of the difference in EPS forecasts between strategists and bottom-up analysts. To examine whether strategists' relative pessimism varies with macroeconomic indicators, we estimate the following equation using ARMAX:

$$\begin{aligned} &Diff\_EPS\_Level_t \\ &(\text{or } Diff\_EPS\_Revision_t) \end{aligned} \quad \begin{aligned} &= \beta_0 + Inf\_Spread_{t-1} + GDP\_FCST_{t-1} + Unemp_{t-1} + PMI_{t-1} + \\ &FFFR_{t-1} + Cons\_Sent_{t-1} + Inv\_Sent_{t-1} + AR + \varepsilon_t \end{aligned} \qquad (2)$$

[9] 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.

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}.

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. (2) are standardized to have a mean of zero and standard deviation of one.

We report the results of estimating our determinants model in Table 3 Column (1) with our dependent variables of interest, $Diff\_EPS\_level_t$. A one-standard deviation increase in Inf_Spread_{t-1} is associated with a 0.420 standard deviation increase (t-stat = 3.583) in $Diff\_EPS\_level_t$, indicating that 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). Similarly, strategists appear to respond more strongly to increases in investment sentiment, exhibiting relatively less pessimism than bottom-up analysts (coef = 0.270 t-stat = 1.723). In contrast, a one standard deviation increase in $FFFR_{t-1}$ is associated with a 0.375 standard deviation decrease (t-stat = -3.240) in $Diff\_EPS\_level_t$ as strategists revise their forecasted EPS down more than bottom-up analysts in response to contractionary monetary policy expectations. Column (2) presents the same model with $Diff\_EPS\_Revision_t$ as the dependent variable. In this case, we do not find strong evidence that the difference in forecast revisions between top-down and bottom-up analysts varies with macroeconomic indicators.

Overall, we find some evidence that strategists' divergence from bottom-up forecasts systematically varies with several 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, the difference in EPS forecasts between strategists and bottom-up analysts should both vary with macroeconomic indicators and have incremental predictive value for relevant future outcomes. We test this conjecture in the following sections.

4.2 *Predictive Value of Strategists' Divergence from Bottom-up Forecasts*

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 strategists' divergence 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 $Diff\_EPS\_Level_t$ (or $Diff\_EPS\_Revision_t$) may also predict future market returns.

Accordingly, we test whether $Diff\_EPS\_Level_t$ (or $Diff\_EPS\_Revision_t$) is predictive of future aggregate earnings surprises and market returns using the following models:

$$UE_t \text{ (or } Ret_{[t+1,t+3]}) = \beta_0 + Diff\_EPS\_Level_t \text{ (or } Diff\_EPS\_Revision_t) + Controls + \varepsilon_t \qquad (3)$$

where UE_t is aggregate earnings surprises, calculated as the difference between the 12-month forward actual EPS for the S&P 500 index and the bottom-up forecast (i.e., EPS_Actual_t – $EPS\_Level\_BU_t$). $Ret_{[t+1,t+3]}$ is the value-weighted cumulative return for the S&P 500 index, proxied by the SPY ETF, over the next three months.[10] In both regression equations, we control for the macroeconomic signals identified in our determinants analysis (*Controls*) to identify if *Diff_EPS_Level*$_t$ (or *Diff_EPS_Revision*$_t$) 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. Panel A focuses on level-based forecasts (i.e., *Diff_EPS_Level*$_t$) and examines their ability to predict aggregate earnings surprises for the S&P 500. In column (1), the coefficient estimate for *Diff_EPS_Level*$_t$ is positive and statistically significant at 1% (coef = 0.150 t-stat = 2.917). This suggests that differences in index-level earnings forecasts between strategists and bottom-up analysts are predictive of future aggregate earnings surprises.

To identify the source of this predictability, we next decompose *Diff_EPS_Level*$_t$ into its components and examine their individual predictive power. Columns (2) and (3) report results using *EPS_Level_TD*$_t$ (top-down forecasts) and *EPS_Level_BU*$_t$ (bottom-up forecasts) as separate predictors, respectively. Column (2) shows that top-down forecasts are significantly predictive of future earnings surprises, with a coefficient of 0.207 (t-stat = 3.685), significant at the 1% level. In contrast, column (3) shows that the coefficient for bottom-up forecasts is statistically insignificant, indicating that bottom-up forecasts do not meaningfully predict future earnings surprises. Column (4) includes both forecasts simultaneously in the regression. The results show that top-down forecasts remain significantly predictive of future earnings surprises even after controlling for bottom-up forecasts, further reinforcing the notion that the predictive

[10] Using 12-month returns yields slightly weaker but generally consistent results (untabulated).

power of *Diff_EPS_Level*$_t$ is driven primarily by the information embedded in strategists' top-down forecasts.

Panel B examines revision-based forecasts (i.e., *Diff_EPS_Revision*$_t$) and their ability to predict aggregate earnings surprises for the S&P 500. The findings closely mirror those in Panel A. Specifically, the results indicate that revision-based differences between top-down and bottom-up forecasts also have predictive power for future earnings surprises. Overall, the evidence in Table 4 supports the view that top-down analysts' forecasts embed macroeconomic information not yet reflected in bottom-up analysts' estimates for earnings announced in subsequent reporting periods.

As described earlier, we include the AR(1)-AR(4) terms in all regression models to account for potential autocorrelation in our dependent variables. In most cases, these terms are statistically significant, suggesting that the autocorrelation of our dependent variables is significant. Consequently, including the AR terms in our regression models supports the robustness of our findings.

In Table 5, we turn to the return predictability. If investors' aggregate expectations align more closely with those of bottom-up analysts, the information embedded in *Diff_EPS_Level*$_t$ (or *Diff_EPS_Revision*$_t$) may help predict future market returns. In Panel A, we find that *Diff_EPS_Level*$_t$ is positively associated with cumulative market returns over the next three months and statistically significant at the 5% level. This suggests that when strategists become less (more) pessimistic relative to bottom-up analysts, the stock market tends to perform better (worse) in the following quarter. Economically, a one-standard-deviation increase in *Diff_EPS_Level*$_t$ is associated with a quarterly return of 1.6%.

To further understand the source of this predictability, we decompose *Diff_EPS_Level*$_t$ into *EPS_Level_TD*$_t$ (top-down forecasts) and *EPS_Level_BU*$_t$ (bottom-up forecasts). Columns (2) and (3) show that both forecasts are significantly predictive of future returns, each with a similar economic magnitude: a one-standard-deviation increase in either forecast is associated with a 5.8% increase in quarterly returns. In column (4), we include both forecasts in the regression to assess their relative importance. The results indicate that top-down forecasts dominate bottom-up forecasts and remain significantly predictive of future returns when both are included, further reinforcing the idea that the predictive power of *Diff_EPS_Level*$_t$ is mainly driven by the information embedded in strategists' top-down forecasts.

Panel B presents results using revision-based forecasts (i.e., *Diff_EPS_Revision*$_t$) to predict S&P 500 returns. The overall inference is similar to that of Panel A. In column (1), revision-based differences between top-down and bottom-up forecasts also predict future returns (coef = 0.021 t-stat = 2.500). However, the key difference is that bottom-up revisions do not exhibit return predictability either on their own (column 3) or when conditioning on top-down revisions (column 4).

Taken together, these findings suggest that top-down analysts' forecasts contain market-wide, value-relevant information that investors—and particularly bottom-up analysts—have not yet fully incorporated into their expectations. This implies that strategists' forecasts reflect new and relevant insights about the overall market. Moreover, our results suggest that active investors can potentially benefit from the divergence between strategists' and bottom-up analysts' forecasts.

The divergence between top-down and bottom-up forecasts highlights the distinct perspectives and methodologies of the two groups. While strategists incorporate broader macroeconomic trends and market-level factors, bottom-up analysts focus primarily on firm-specific fundamentals. When these forecasts diverge significantly, it may reflect a disconnect between market valuation and underlying economic conditions. Active investors, who are better positioned to analyze and respond to such discrepancies, may be able to exploit this divergence to enhance their investment decisions. By integrating insights from top-down forecasts into their strategies, investors can potentially achieve superior returns relative to strategies that rely solely on bottom-up analyses. In this sense, the combination of both perspectives offers a more comprehensive view of the market.

5. Interaction between Strategists' Own Revisions and Divergence

Thus far, we have shown that strategists' divergence from bottom-up analysts contains significant information about future earnings surprises and market returns. However, a natural question arises: what drives this divergence? Is it primarily due to strategists adjusting their forecasts in response to new macroeconomic information, or is it driven by movements in bottom-up analysts' forecasts? Our earlier "horse race" regressions suggest that the predictive power of the divergence originates largely from the strategists' side. Specifically, top-down forecasts consistently retain predictive power controlling for bottom-up forecasts, whereas bottom-up forecasts do not. To more formally test this idea, we examine whether the predictive ability of the divergence measure is stronger when strategists themselves revise their forecasts.

We introduce an interaction term between the divergence measure ($Diff\_EPS\_Level_t$ or $Diff\_EPS\_Revision_t$) and a revision in strategists' top-down EPS forecasts during the quarter ($EPS\_Revision\_TD_t$). This approach allows us to test whether the informational content of the divergence is conditional on strategists updating their beliefs. Table 6 reports the results of this analysis. Columns (1) and (2) focus on unexpected earnings (UE_t) as the dependent variable. The findings show a mixed pattern. Specifically, the interaction term for the level-based divergence measure yields a negative sign, suggesting that the predictive ability of *Diff_EPS_Level*$_t$ may not be amplified by contemporaneous revisions in top-down forecasts. In contrast, the interaction with the revision-based divergence measure (*Diff_EPS_Revision*$_t$) suggests that its predictive power strengthens when strategists revise their forecasts (coef = 0.070 t-stat = 2.955). These results point to a more nuanced interpretation: while revision-based divergence appears to reflect dynamic and timely information flow from strategists, level-based divergence may capture more persistent or structural differences in outlook between top-down and bottom-up analysts.

Columns (3) and (4) examine the predictive power of the interaction terms for future S&P 500 returns ($Ret_{[t+1,t+3]}$). Consistent with our findings for unexpected earnings, we do not observe significant results for the interaction involving the level-based divergence measure. This suggests that the predictive ability of *Diff_EPS_Level*$_t$ does not vary meaningfully with strategists' own forecast revisions when it comes to return prediction. However, we do find supportive evidence for the revision-based divergence measure. Specifically, the interaction between *Diff_EPS_Revision*$_t$ and *EPS_Revision_TD*$_t$ is positive and statistically significant (coef = 0.012 t-stat = 2.869), indicating that the return predictability of strategists' divergence is stronger when it is accompanied by revisions to their forecasts. These results reinforce our earlier conclusion that revision-based divergence reflects more timely and actionable information embedded in strategists' forecasts.

6. Time-Series Variation

In subsequent analyses, we examine time-series variation in the information content of *Diff_EPS_Level*$_t$ and *Diff_EPS_Revision*$_t$. Consistent with the findings of Hann et al. (2012) and Hugon et al. (2016) we expect strategists' EPS forecast relative to bottom-up analysts' EPS forecasts 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_Level*$_t$ or *Diff_EPS_Revision*$_t$ with 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 quartile. 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 7. In Panel A, we examine *Diff_EPS_Level*$_t$. While we do not find that strategists' responsiveness to macroeconomic signals is particularly useful during periods of heightened uncertainty to predict earnings surprise (columns 1 and 2), we find in column (3) that during recessionary periods strategists' relative pessimism is positively and significantly predictive of future returns (coef = 0.050 t-stat = 3.383). We find similar results during periods of heightened investor uncertainty in column (4). In particular when the VIX is elevated, we find *Diff_EPS_Level*$_t$ is positive and significantly associated with future returns (coef = 0.027 t-stat = 1.954). Turning to the *Diff_EPS_Revision*$_t$ in Panel B, we do not find that the association between *Diff_EPS_Revision*$_t$ and future earnings surprise of aggregate returns is stronger during periods of elevated investor uncertainty.

Overall, we find some evidence that strategists' responsiveness to macroeconomic signals is particularly useful to predict future returns 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.

7. Additional Analysis: 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 3 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 13%, while the top-down error is 7%. This gap narrows over time as analysts receive more current information as time proceeds. However, Figure 3 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.[11] 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, 0.0111, is smaller than that for the 2-year horizon, 0.0489, 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.

8. Trading Strategy

This section examines whether differences between strategists' EPS forecasts and bottom-up analysts' forecasts contain valuable information by analyzing the returns of market timing portfolios. We construct signals based on strategists' divergence from bottom-up analysts to develop a market timing strategy that varies an investor's exposure to equities versus bonds. Equity investments perform well during expansionary economic periods while treasury bonds offer a flight to safety during economic downturns or times of uncertainty. Our expectation is that strategists will better incorporate macroeconomic information and more quickly into their

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

earnings forecasts than bottom-up analysts. Therefore, strategists' relative optimism or pessimism about the earnings of an equity index may provide a timely signal for investors in their asset allocation decisions.

To capture strategists' difference in expectations from bottom-up analysts, we construct two signals that are based on our two different measures of differences between EPS forecasts ($Diff\_EPS\_Level_t$ or $Diff\_EPS\_Revision_t$) and the strategists' revision in EPS forecasts from the prior quarter. When both components are positive (negative), we classify the signal as optimistic (pessimistic) for equities. Operationally, if equity strategists are relatively optimistic (pessimistic), our trading strategy takes a long position in equities (bonds) and a short position in the bonds (equities). For example, if the value of *Diff_EPS_Level* is negative and the strategist has revised their earnings forecast for the index downwards from the prior quarter, we consider this pessimistic in which case the investor in our trading strategy would short the equity index and take a long position in government treasuries. We use monthly returns to the S&P 500 ETF for equity returns and monthly returns to the iShares 1-3 Year Treasury Bond ETF for bond returns. If there is a mismatch of signals, our strategy defaults to holding the S&P 500 index. Finally, our timing strategy applies the signal developed from the prior quarter end to returns over the next three months.

Table 8 presents the results of this analysis. In Panel A, the average monthly return, standard deviation of returns, Sharpe ratio, and maximum drawdown are calculated for each of the two timing strategies and a benchmark strategy that always takes a long position in the S&P 500 index. The average monthly return to a timing strategy that leverages *Diff_EPS_Level* or *Diff_EPS_Revision* as a signal of strategists' relative pessimism is 0.982% or 0.913%, respectively, both of which are higher than the average portfolio return to always being long in the S&P 500 index. Notably, both timing strategies have Sharpe ratios of 0.801 and 0.735, respectively, which are higher than that of the benchmark model (Sharpe Ratio = 0.663) and lower maximum drawdowns.

In Panel B, we present the results of market model regressions of monthly portfolio returns from our two different timing strategies on market returns. In column (1), the intercept for the *Diff_EPS_Level* strategy is statistically significant at the 5% level and suggests the strategy earns an abnormal monthly return of 0.7%. Similarly, in column (2), the intercept for the *Diff_EPS_Revision* strategy is also statistically significant at the 5% level with a comparable monthly alpha of 0.6%. Figure 4 presents the cumulative portfolio returns to each strategy and the benchmark portfolio of a continual long position in the S&P 500 over our sample period. This figure illustrates the superior performance of both timing strategies relative to the S&P 500 index. However, an important caveat to these results is the superior returns to our two timing strategies accrue during recessionary periods suggesting strategists' relative pessimism provides investors with timely signal to reallocate their investments to safer alternatives, such as treasury bonds, in anticipation of economic downturns which is consistent with our results from section 6. In sum, our trading strategy results indicate that strategists' outputs contain value-relevant investment information for market participants which can be used in an asset allocation strategy based on strategists' relative pessimism to improve risk-adjusted returns and reduce downside risk.

9. 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. We demonstrate active investors can utilize the information in strategists' divergence from bottom-up analysts in determining asset allocation between equities and government treasuries to reduce downside exposure during economic downturns.

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
$EPS\_Level\_TD_t$	The 12-month forward top-down consensus EPS forecasts for the S&P 500 index, scaled by the previous month's S&P 500 index price
$EPS\_Level\_BU_t$	The 12-month forward bottom-up consensus EPS forecasts for the S&P 500 index, scaled by the previous month's S&P 500 index price
$Diff\_EPS\_Level_t$	Difference between top-down and bottom-up EPS levels (i.e., $EPS\_Level\_TD_t - EPS\_Level\_BU_t$)
$EPS\_Revision\_TD_t$	Quarterly change in the top-down EPS level (i.e., $EPS\_Level\_TD_t - EPS\_Level\_TD_{t-3}$), scaled by the previous month's S&P 500 index price
$EPS\_Revision\_BU_t$	Quarterly change in the bottom-up EPS level (i.e., $EPS\_Level\_BU_t - EPS\_Level\_BU_{t-3}$), scaled by the previous month's S&P 500 index price
$Diff\_EPS\_Revision_t$	Difference between top-down and bottom-up EPS revisions (i.e., $EPS\_Revision\_TD_t - EPS\_Revision\_BU_t$), multiplied by 100
EPS_Actual_t	The 12-month forward actual EPS for the S&P 500 index, scaled by the previous month's S&P 500 index price
UE_t	Aggregate earnings surprise, calculated as the difference between the 12-month forward actual EPS for the S&P 500 index and the bottom-up forecast (i.e., $EPS\_Actual_t - EPS\_Level\_BU_t$), scaled by the previous month's S&P 500 index level
$Ret_{[t+1,t+3]}$	Return for the S&P 500 index, proxied by the SPY ETF, over the next three months
FE_t	The difference between forecasted EPS and realized EPS, scaled by the realized EPS
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 industrial production from the prior year (Møller and Rangvid 2015)

Recession$_{t-1}$	Indicator variable equal to one if the period was classified as a recession by NBER.
HighVix$_{t-1}$	Indicator variable equal to one if the average VIX for the period is measured is in the top quartile. 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

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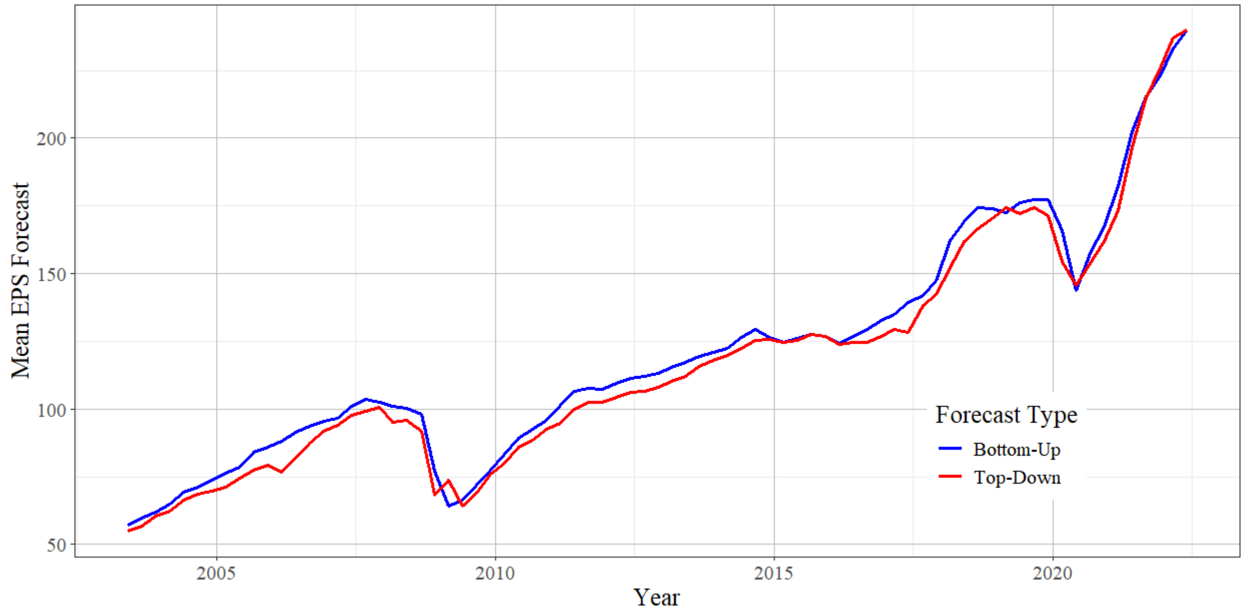
Figure 1: Top-down and Bottom-up EPS forecasts for the S&P 500 in Refinitiv Eikon

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.

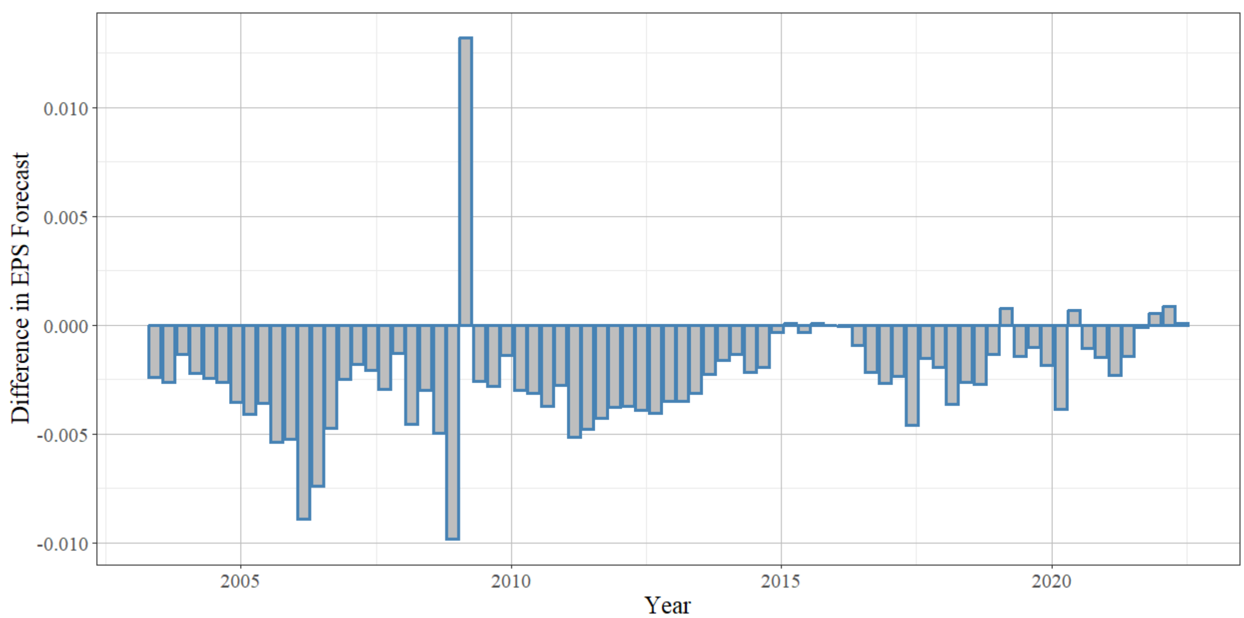
Figure 2: Time Series of Top-Down and Bottom-Up EPS Forecasts

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



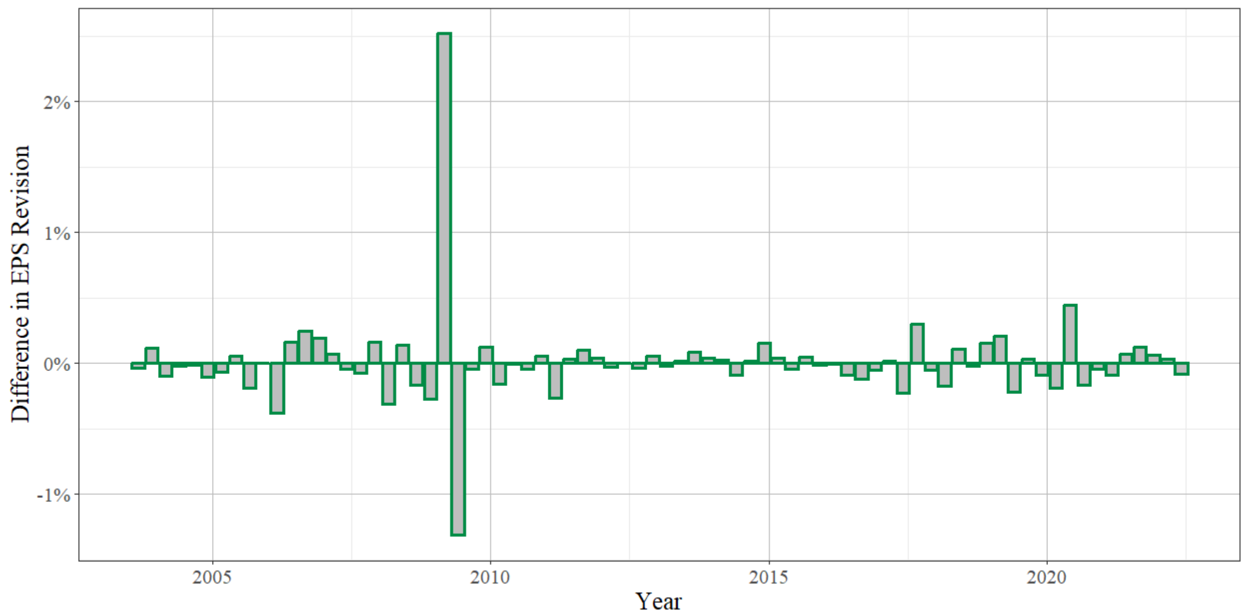
Panel B: Scaled Differences Between Top-Down and Bottom-Up EPS Forecasts

(Diff_EPS_Level)



Panel C: Differences Between Top-Down and Bottom-Up EPS Forecasts Revisions

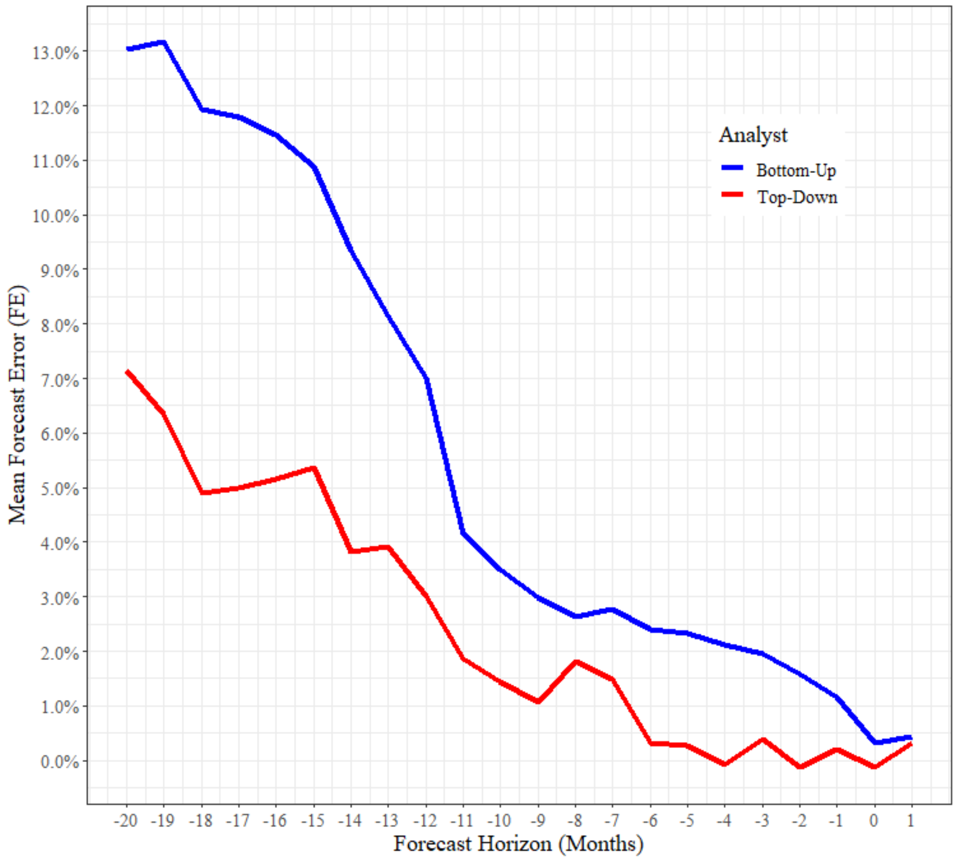
(Diff_EPS_Revision)



This figure presents quarterly 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 ($EPS\_Level\_TD_t$ and $EPS\_Level\_BU_t$), Panel B plots the difference between the mean top-down and bottom-up EPS forecast as a percentage of the lagged value of the S&P 500 index ($Diff\_EPS\_Level_t$), and Panel C plots the difference top-down and bottom-up EPS forecast revision from the prior quarter ($Diff\_EPS\_Revision_t$).

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

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

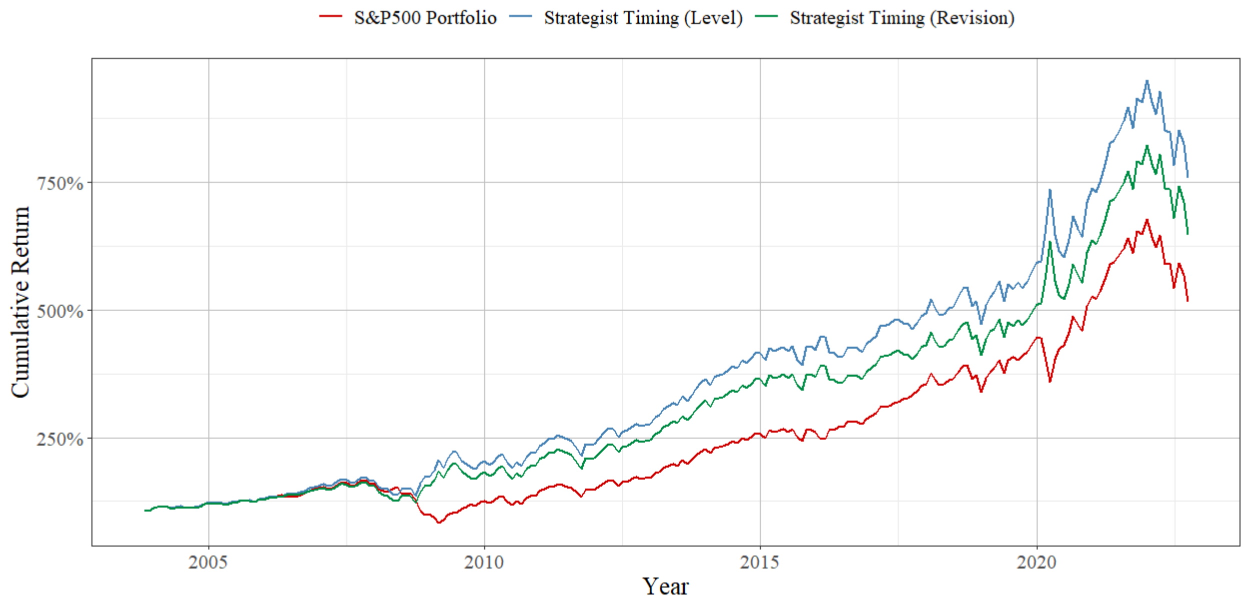


Panel B: Comparison of Top-Down and Bottom-Up Forecast Errors by Year Horizon

Forecast Errors (FE) 2-Year Horizon			**Forecast Errors (FE) 1-Year Horizon**		
Variable		**Mean**	**Variable**		**Mean**
FE_t (bottom-up EPS)		0.0899	FE_t (bottom-up EPS)		0.0157
FE_t (top-down EPS)		0.0410	FE_t (top-down EPS)		0.0046
	Diff	0.0489***		Diff	0.0111***
	t-stat	15.261		t-stat	3.007

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 $EPS\_Level\_TD_t$ and $EPS\_Level\_BU_t$ in each of the 21 months prior to the realization. Panel B presents a difference in means test between the forecast errors of $EPS\_Level\_TD_t$ and $EPS\_Level\_BU_t$ at a 2-year horizon and a 1-year horizon.

Figure 4: Cumulative Returns to Trading Strategy Portfolio



This figure presents cumulative returns to the trading strategy portfolios in our sample period. Our market timing strategy uses signals from the differences in strategists and bottom-up analysts' EPS forecasts to identify periods of strategists' relative optimism/pessimism. When strategists are relatively optimistic (pessimistic), our strategy involves shorting government treasury bonds (the S&P 500 index) and going long in the S&P 500 index (government treasury bonds). We use monthly returns to the S&P 500 ETF for equity returns and monthly returns to the iShares 1-3 Year Treasury Bond ETF for bond returns. The blue line represents the returns to a timing strategy that uses the differences between strategists and bottom-up analysts EPS forecasts and the revision in strategists' EPS forecasts. The green line represents the returns to a timing strategy that uses the differences between strategists and bottom-up analysts EPS forecasts revisions and the revision in strategists' EPS forecasts. The red line represents the returns to a benchmark strategy of always going long in the S&P 500 index.

Table 1. Descriptive Statistics

Variables	N	Mean	SD	P25	Median	P75
$EPS\_Level\_TD_t$	77	0.064	0.010	0.057	0.063	0.069
$EPS\_Level\_BU_t$	77	0.066	0.011	0.059	0.065	0.072
$Diff\_EPS\_Level_t$	77	-0.002	0.003	-0.004	-0.003	-0.001
$EPS\_Revision\_TD_t$	76	0.001	0.004	0.001	0.001	0.003
$EPS\_Revision\_BU_t$	76	0.001	0.004	0.001	0.002	0.003
$Diff\_EPS\_Revision_t$	76	0.007	0.356	-0.088	-0.011	0.065
UE_t	77	-0.003	0.008	-0.004	-0.002	0.002
$Ret_{[t+1,t+3]}$	77	0.025	0.080	-0.004	0.036	0.068
Inf_Spread_{t-1}	77	-0.012	0.056	-0.045	-0.018	0.016
GDP_FCST_{t-1}	77	2.865	0.853	2.408	2.733	3.220
$Unemp_{t-1}$	77	6.066	2.046	4.600	5.400	7.500
PMI_{t-1}	77	54.021	5.319	50.800	54.200	58.100
$FFFR_{t-1}$	77	1.275	1.580	0.130	0.400	2.005
$Cons\_Sent_{t-1}$	77	82.513	12.302	74.100	82.900	92.800
Inv_Sent_{t-1}	77	-0.088	0.558	-0.353	-0.192	-0.001
$Accrual_{t-1}$	77	-0.046	0.005	-0.049	-0.045	-0.044
$GPCE_{t-1}$	77	0.004	0.004	0.001	0.003	0.006
GPI_{t-1}	77	0.003	0.013	0.001	0.005	0.010
HighVix	77	0.247	0.434	0.000	0.000	0.000
Recession	77	0.091	0.289	0.000	0.000	0.000

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)
$Diff\_EPS\_Level_t$	**-690**	-688	-688	-689	**-683**	-681	-678	-675
$Diff\_EPS\_Revision_t$	47	61	48	**43**	**54**	68	57	57
UE_t	-634	-518	-634	**-661**	-627	-511	-624	**-647**
$Ret_{[t+1,t+3]}$	**-166**	**-166**	-165	-161	**-159**	**-159**	-155	-147

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)	(2)
	$Diff\_EPS\_Level_t$	$Diff\_EPS\_Revision_t$
Inf_Spread_{t-1}	0.420***	-0.080
	(3.583)	(-0.544)
GDP_FCST_{t-1}	0.109	0.065
	(1.281)	(1.168)
$Unemp_{t-1}$	-0.315	-0.103
	(-1.329)	(-0.578)
PMI_{t-1}	-0.067	-0.262
	(-0.354)	(-1.213)
$FFFR_{t-1}$	-0.375***	-0.054
	(-3.240)	(-0.618)
$Cons\_Sent_{t-1}$	-0.145	-0.063
	(-0.628)	(-0.348)
Inv_Sent_{t-1}	0.270*	-0.052
	(1.723)	(-0.378)
AR(1)	-0.197	-0.492***
	(-0.739)	(-2.711)
Observations	77	76
Pseudo R^2	0.267	0.290

This table reports the estimated coefficients of our macroeconomic determinants model of $Diff\_EPS\_Level_t$ and $Diff\_EPS\_Revision_t$. $Diff\_EPS\_Level_t$ is the difference between top-down and bottom-up EPS levels for the S&P 500 index as of quarter *t*, scaled by the previous month's S&P 500 index price. $Diff\_EPS\_Revision_t$ is the difference between top-down and bottom-up EPS revisions, multiplied by 100. 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 Strategists' Divergence over Future Earnings Surprises

Panel A. Levels

VARIABLES	(1) UE_t	(2) UE_t	(3) UE_t	(4) UE_t
$Diff\_EPS\_Level_t$	0.150***			
	(2.917)			
$EPS\_Level\_TD_t$		0.207***		0.589***
		(3.685)		(5.115)
$EPS\_Level\_BU_t$			-0.078	-0.741***
			(-0.791)	(-5.168)
Inf_Spread_{t-1}	0.271*	0.113	0.265	0.273***
	(1.776)	(0.289)	(1.422)	(3.043)
GDP_FCST_{t-1}	0.022	-0.058	-0.129	0.005
	(0.154)	(-0.419)	(-0.809)	(0.041)
$Unemp_{t-1}$	0.047	0.186	0.337	0.041
	(0.169)	(1.089)	(1.548)	(0.201)
PMI_{t-1}	-0.002	-0.031	0.032	-0.011
	(-0.019)	(-0.179)	(0.785)	(-0.304)
$FFFR_{t-1}$	-0.158	0.123	0.057	-0.164
	(-0.909)	(0.204)	(0.081)	(-1.075)
$Cons\_Sent_{t-1}$	0.017	-0.055	-0.005	0.004
	(0.129)	(-0.355)	(-0.062)	(0.060)
Inv_Sent_{t-1}	-0.138	-0.080	-0.012	-0.130
	(-1.251)	(-0.729)	(-0.084)	(-1.391)
AR(1)	1.423***	1.631**	1.223**	1.413***
	(3.863)	(2.220)	(2.222)	(7.962)
AR(2)	-0.506	-0.994	-0.329	-0.513
	(-0.558)	(-0.640)	(-0.330)	(-1.177)
AR(3)	0.092	0.463	0.203	0.131
	(0.123)	(0.420)	(0.366)	(0.340)
AR(4)	-0.166	-0.223	-0.262	-0.195
	(-0.744)	(-0.758)	(-1.571)	(-1.377)
Observations	77	77	77	77
Pseudo R^2	0.936	0.899	0.883	0.940

This table reports the estimated coefficients of our ARMAX model. The dependent variable is UE_t, which represents earnings surprises based on bottom-up analysts' consensus forecast. All variables are standardized, and formal definitions are provided 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. Revisions

VARIABLES	(1) UE_t	(2) UE_t	(3) UE_t	(4) UE_t
$Diff\_EPS\_Revision_t$	0.075***			
	(4.089)			
$EPS\_Revision\_TD_t$		0.093***		0.080***
		(3.536)		(2.732)
$EPS\_Revision\_BU_t$			-0.137	-0.116*
			(-0.864)	(-1.784)
Inf_Spread_{t-1}	0.075	0.172	0.052	0.042
	(0.391)	(0.747)	(0.176)	(0.241)
GDP_FCST_{t-1}	-0.040	-0.047	-0.108	-0.042
	(-0.321)	(-0.316)	(-0.664)	(-0.374)
$Unemp_{t-1}$	0.094	0.103	0.293	0.104
	(0.546)	(0.502)	(1.565)	(0.681)
PMI_{t-1}	-0.066	-0.069	0.005	-0.063
	(-1.197)	(-1.109)	(0.053)	(-1.405)
$FFFR_{t-1}$	0.047	-0.096	0.804	0.146
	(0.128)	(-0.324)	(0.456)	(0.298)
$Cons\_Sent_{t-1}$	-0.034	-0.052	-0.059	-0.031
	(-0.668)	(-0.856)	(-0.661)	(-0.655)
Inv_Sent_{t-1}	-0.080	-0.116	0.008	-0.065
	(-0.749)	(-0.947)	(0.078)	(-0.645)
AR(1)	1.766***	1.572***	1.809*	1.844***
	(5.756)	(5.395)	(1.786)	(5.172)
AR(2)	-1.352**	-0.978*	-1.408	-1.510**
	(-2.136)	(-1.670)	(-0.666)	(-2.037)
AR(3)	0.764	0.538*	0.877	0.882
	(1.614)	(1.652)	(0.493)	(1.444)
AR(4)	-0.322**	-0.287***	-0.383	-0.352*
	(-2.048)	(-2.829)	(-0.618)	(-1.696)
Observations	76	76	76	76
Pseudo R^2	0.918	0.914	0.879	0.918

This table reports the estimated coefficients of our ARMAX model. The dependent variable is UE_t, which represents earnings surprises based on bottom-up analysts' consensus forecast. All variables are standardized, and formal definitions are provided 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 Strategists' Divergence over Future Returns

Panel A. Levels

VARIABLES	(1) $Ret_{[t+1,t+3]}$	(2) $Ret_{[t+1,t+3]}$	(3) $Ret_{[t+1,t+3]}$	(4) $Ret_{[t+1,t+3]}$
$Diff\_EPS\_Level_t$	0.016**			
	(1.961)			
$EPS\_Level\_TD_t$		0.058***		0.063**
		(3.412)		(2.491)
$EPS\_Level\_BU_t$			0.059**	-0.007
			(2.547)	(-0.190)
Inf_Spread_{t-1}	0.033**	0.046***	0.048***	0.046***
	(2.250)	(2.888)	(2.838)	(2.859)
GDP_FCST_{t-1}	-0.000	0.037*	0.036*	0.036*
	(-0.034)	(1.940)	(1.749)	(1.740)
$Unemp_{t-1}$	0.032	-0.013	-0.013	-0.012
	(1.635)	(-0.491)	(-0.481)	(-0.418)
PMI_{t-1}	0.012	0.017	0.016	0.017
	(1.133)	(1.594)	(1.423)	(1.606)
$FFFR_{t-1}$	0.021***	0.004	-0.001	0.005
	(2.586)	(0.537)	(-0.082)	(0.511)
$Cons\_Sent_{t-1}$	0.010	0.014	0.015	0.014
	(0.620)	(0.779)	(0.806)	(0.769)
Inv_Sent_{t-1}	0.004	0.017	0.021	0.016
	(0.309)	(1.257)	(1.455)	(1.138)
$Accrual_{t-1}$	0.005	-0.015	-0.021	-0.014
	(0.576)	(-1.587)	(-1.547)	(-1.100)
$GPCE_{t-1}$	-0.009	-0.010	-0.006	-0.010
	(-0.774)	(-0.836)	(-0.494)	(-0.846)
GPI_{t-1}	-0.028***	-0.041***	-0.039***	-0.041***
	(-2.971)	(-3.964)	(-3.610)	(-3.897)
$AR(1)$	-0.276**	-0.253*	-0.229	-0.258*
	(-1.997)	(-1.728)	(-1.495)	(-1.741)
Observations	77	77	77	77
Pseudo R^2	0.329	0.410	0.383	0.410

This table reports the estimated coefficients of our ARMAX model. The dependent variable is $Ret_{[t+1,t+3]}$, which represents return for the S&P 500 index over the next three months. All variables are standardized, and formal definitions are provided 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. Revisions

VARIABLES	(1) $Ret_{[t+1,t+3]}$	(2) $Ret_{[t+1,t+3]}$	(3) $Ret_{[t+1,t+3]}$	(4) $Ret_{[t+1,t+3]}$
$Diff\_EPS\_Revision_t$	0.021**			
	(2.500)			
$EPS\_Revision\_TD_t$		0.026***		0.034***
		(3.070)		(3.299)
$EPS\_Revision\_BU_t$			0.000	-0.016
			(0.023)	(-1.431)
Inf_Spread_{t-1}	0.040**	0.041***	0.038**	0.041***
	(2.561)	(2.623)	(2.324)	(2.723)
GDP_FCST_{t-1}	-0.001	0.000	-0.002	0.001
	(-0.051)	(0.003)	(-0.158)	(0.057)
$Unemp_{t-1}$	0.032*	0.019	0.032	0.024
	(1.661)	(0.980)	(1.567)	(1.230)
PMI_{t-1}	0.018*	-0.003	0.013	0.005
	(1.663)	(-0.214)	(0.839)	(0.370)
$FFFR_{t-1}$	0.016**	0.012*	0.016**	0.013**
	(2.456)	(1.761)	(2.221)	(2.034)
$Cons\_Sent_{t-1}$	0.013	0.003	0.011	0.007
	(0.799)	(0.169)	(0.656)	(0.446)
Inv_Sent_{t-1}	0.013	0.004	0.010	0.008
	(1.001)	(0.348)	(0.765)	(0.649)
$Accrual_{t-1}$	0.000	0.006	-0.001	0.005
	(0.028)	(0.616)	(-0.078)	(0.468)
$GPCE_{t-1}$	-0.010	-0.007	-0.006	-0.010
	(-0.817)	(-0.617)	(-0.514)	(-0.824)
GPI_{t-1}	-0.026***	-0.031***	-0.028***	-0.029***
	(-2.811)	(-3.361)	(-2.770)	(-3.086)
AR(1)	-0.324**	-0.315**	-0.269*	-0.359***
	(-2.230)	(-2.465)	(-1.856)	(-2.608)
Observations	76	76	76	76
Pseudo R^2	0.350	0.356	0.304	0.369

This table reports the estimated coefficients of our ARMAX model. The dependent variable is $Ret_{[t+1,t+3]}$, which represents return for the S&P 500 index over the next three months. All variables are standardized, and formal definitions are provided 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: Interactive Effect of Strategists' Divergence and Top-Down EPS Revisions

VARIABLES	(1) UE_t	(2) UE_t	(3) $Ret_{[t+1,t+3]}$	(4) $Ret_{[t+1,t+3]}$
$Diff\_EPS\_Level_t$	0.353***		0.005	
	(7.840)		(0.455)	
$Diff\_EPS\_Revision_t$		0.147*		0.003
		(1.672)		(0.454)
$EPS\_Revision\_TD_t$	-0.216***	-0.083	0.026*	0.028***
	(-5.133)	(-0.644)	(1.667)	(3.303)
$Diff\_EPS\_Level_t \times EPS\_Revision\_TD_t$	-0.034***		0.002	
	(-2.758)		(0.364)	
$Diff\_EPS\_Revision_t \times EPS\_Revision\_TD_t$		0.070***		0.012***
		(2.955)		(2.869)
Controls	Yes	Yes	Yes	Yes
AR model	AR(4)	AR(4)	AR(1)	AR(1)
Observations	76	76	76	76
Pseudo R^2	0.955	0.928	0.360	0.412

This table reports the estimated coefficients of our ARMAX model. The dependent variables are UE_t, which represents earnings surprises based on bottom-up analysts' consensus forecast, and $Ret_{[t+1,t+3]}$, which represents return for the S&P 500 index over the next three months. All variables are standardized, and formal definitions are provided 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: Effects of Macroeconomic Uncertainty

Panel A. Levels

VARIABLES	(1) UE_t	(2) UE_t	(3) $Ret_{[t+1,t+3]}$	(4) $Ret_{[t+1,t+3]}$
$Diff\_EPS\_Level_t$	0.173***	0.192***	-0.011	-0.003
	(3.229)	(2.710)	(-0.888)	(-0.240)
Recession	0.569***		-0.036	
	(2.990)		(-0.961)	
$Diff\_EPS\_Level_t \times Recession$	-0.004		0.050***	
	(-0.082)		(3.383)	
HighVix		-0.005		0.022
		(-0.072)		(0.961)
$Diff\_EPS\_Level_t \times HighVix$		-0.045		0.027*
		(-0.801)		(1.954)
Controls	Yes	Yes	Yes	Yes
AR model	AR(4)	AR(4)	AR(1)	AR(1)
Observations	77	77	77	77
Pseudo R^2	0.944	0.937	0.420	0.362

This table reports the estimated coefficients of our ARMAX model. The dependent variables are UE_t, which represents earnings surprises based on bottom-up analysts' consensus forecast, and $Ret_{[t+1,t+3]}$, which represents return for the S&P 500 index over the next three months. All variables are standardized, and formal definitions are provided 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. Revisions

VARIABLES	(1) UE_t	(2) UE_t	(3) $Ret_{[t+1,t+3]}$	(4) $Ret_{[t+1,t+3]}$
$Diff\_EPS\_Revision_t$	0.044	0.096*	0.041***	0.045***
	(1.061)	(1.875)	(2.726)	(2.594)
Recession	0.734***		-0.033	
	(3.174)		(-0.672)	
$Diff\_EPS\_Revision_t$ × *Recession*	0.078		-0.024	
	(1.590)		(-1.463)	
HighVix		-0.023		0.029
		(-0.450)		(1.305)
$Diff\_EPS\_Revision_t$ × *HighVix*		-0.022		-0.027
		(-0.451)		(-1.350)
Controls	Yes	Yes	Yes	Yes
AR model	AR(4)	AR(4)	AR(1)	AR(1)
Observations	76	76	76	76
Pseudo R^2	0.922	0.919	0.366	0.374

This table reports the estimated coefficients of our ARMAX model. The dependent variables are UE_t, which represents earnings surprises based on bottom-up analysts' consensus forecast, and $Ret_{[t+1,t+3]}$, which represents return for the S&P 500 index over the next three months. All variables are standardized, and formal definitions are provided in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided). Standard errors are robust to heteroscedasticity.

Table 8: Trading Strategy

Panel A. Comparison of Portfolios

Strategy	Mean Monthly Return	SD Return	Sharpe Ratio	Max Drawdown
Diff_EPS_Level	0.982%	4.245%	0.801	-20.935%
Diff_EPS_Revision	0.913%	4.305%	0.735	-24.675%
S&P500	0.814%	4.254%	0.663	-50.777%

Panel B. Market Model

	(1)	(2)
Signal =	*Diff_EPS_Level*	*Diff_EPS_Revision*
VARIABLES	*Portfolio Return$_t$*	*Portfolio Return$_t$*
Intercept	0.007**	0.006**
	(2.586)	(2.249)
Market Return$_t$	0.363***	0.376***
	(5.874)	(6.010)
Observations	228	228
Adjusted R^2	0.129	0.134

This table reports the performance of portfolios constructed using signals of strategists' relative pessimism to determine asset allocation between equities and treasuries. The timing signal combines the difference between strategists' and bottom-up analysts' EPS forecasts (either *Diff_EPS_Level* or *Diff_EPS_Revision*) and strategists' revision in EPS forecast from the prior quarter. When both components are positive (negative), our trading strategy goes long (short) in equities (treasury bonds) and short (long) treasury bonds (equities). If the components are mixed signals, our strategy defaults to a long position in equities. We use monthly returns to the S&P500 ETF (SPY) and the 1-3 Treasury Bond ETF (SHY). In Panel A, we report the average monthly return, standard deviation of returns, Sharpe ratio, and maximum drawdown for two market timing strategies and a benchmark portfolio that always takes a long position in the S&P500 index. In Panel B, we report the results from market model regressions where the portfolio return to each trading strategy is regressed on the monthly return to market. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-sided).