Attention Is (Mostly) All You Need: Solving the Post-Earnings-Announcement Drift Puzzle*

Odhrain McCarthy†[1]

[1]NYU Stern School of Business at NYU Abu Dhabi

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Abstract

Post-earnings-announcement drift (PEAD) refers to a stock's price drifting in the direction of an earnings surprise after the announcement. I test whether limited attention dampens reactions to earnings surprises, while confirmation bias amplifies reactions to prior-consistent surprises and mutes reactions to prior-inconsistent surprises. Using analyst recommendations as a proxy for investor priors, I find that immediate reactions to prior-inconsistent surprises are weaker, but their PEAD is at least double that of prior-consistent ones. Portfolio strategies conditioned on prior-inconsistent and prior-consistent surprises yield annualized alphas of 12.6% and 1.4%, respectively, compared to 7.1% for an unconditional strategy. Thus, the PEAD is concentrated in prior-inconsistent surprises and, contrary to claims of its decline, persists over time.

JEL Classification: G4, G12, G14

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†otm210@nyu.edu

I Introduction

This paper shows that confirmation bias is a key driver of the post-earnings-announcement drift (PEAD), modulating it depending on prior consistency. Using analyst recommendations as proxies for investors' priors, I show that earnings surprises inconsistent with prior beliefs generate at least twice the PEAD of prior-consistent surprises. In quarterly rebalanced portfolio sorts, the PEAD based on prior-inconsistent surprises yields a Carhart (1997) annual FF-4 alpha of 12.6% compared to 1.4% for prior-consistent surprises. By comparison, the original PEAD long-short strategy, which doesn't condition on investor priors, generates a Carhart (1997) FF-4 alpha of 7.4%.

Investors process an overwhelming amount of financial information in real time. Yet, their attention is limited and selective, shaping how they respond to new information. Nowhere is this more evident than in the post-earnings announcement drift (PEAD) - the tendency for stock prices to continue moving in the direction of an earnings surprise after the announcement (Ball and Brown, 1968; Bernard and Thomas, 1989, 1990). So prominent is the PEAD anomaly in the affront to market efficiency, that Fama (1998) originally referred to it as the "*granddaddy of underreaction events*". Meanwhile, in the last thirty years, 183 articles have been published in top finance and accounting journals on the PEAD, with 58 of those coming in the last five years (Martineau, 2021a).

Despite decades of research, PEAD remains a puzzle (see Fink (2021) for an excellent summary). Existing explanations for the PEAD focus on limited investor attention, showing it is amplified after distraction events such as Fridays or high-news days (Hirshleifer, Lim, and Teoh, 2009; DellaVigna and Pollet, 2009). However, these models struggle to explain why the PEAD persists even after low-distraction environments. This paper proposes a more complete explanation: it's not just whether investors allocate their attention, it's how they allocate their attention that drives the PEAD.

It proposes confirmation bias as a missing attentional mechanism underlying the PEAD. Confirmation bias refers to the tendency of people to selectively attend to information that aligns with their prior beliefs while ignoring contradictory evidence (Nickerson, 1998). It operates through two distinct attention selection processes identified in psychology: top-down and bottom-up at-

tention (Bordalo, Gennaioli, and Shleifer, 2022). Top-down attention is goal-directed, causing individuals to actively seek information that supports their expectations. Bottom-up attention is stimulus-driven, making salient information stand out. For example, a confirmation-biased investor optimistic about Nvidia's prospects will actively seek positive news (top-down) while also perceiving favorable information as more salient (bottom-up).

Building on this foundation, I develop a theoretical framework where a risk-neutral agent values firms based on priors and new information. The agent's prior beliefs about the long-run outcome can be optimistic or pessimistic, and new information arrives in the form of a noisy signal about the short-run shock.[1] The agent exhibits two behavioral frictions - limited attention and confirmation bias. First, the agent underreacts to new information, placing too little weight on signals due to limited attention. Second, relative to this benchmark, the agent also overweights confirming signals and underweights disconfirming signals. These frictions generate testable predictions in the cross-section of immediate price response to announcements and the post-earnings annoncement returns. For instance, relative to the limited attention benchmark, an optimistic agent reacts too strongly (too little) to positive news (negative news) thereby reducing (amplifying) post-announcement abnormal returns.

I test these hypotheses using IBES analyst consensus recommendations as a proxy for investors' priors about a firm. Specifically, I classify investors as optimistic if the consensus recommendation is "Buy" (including "Strong Buy") and as pessimistic if the recommendation is "Hold/Sell".[2] One concern is that analyst ratings might reflect the opposite of marginal investors' actual views - for example, analysts might be optimistic about firms that are undervalued because investors are too pessimistic. However, consistent with Jegadeesh, Kim, Krische, and Lee (2004), I find that Buy firms exhibit characteristics of "glamour" stocks (e.g., low book-to-market ratios, high momentum), indicating these ratings capture investor optimism.

[1] For simplicity, I assume a rational prior. The model can be extended to include irrational priors, though this does not affect the key focus - the interaction between news and priors.

[2] Since 56% of firms in the sample carry a "Buy" recommendation, this classification roughly splits the data in half. In subsequent analyses, I leverage the full distribution of analyst ratings to examine whether the effects strengthen with greater optimism or pessimism.

For initial tests, I sort stocks into deciles based on earnings surprises. Consistent with investor limited attention, firms in the highest decile earn 2.3% in abnormal returns over the next 60 days, while those in the lowest decile earn -1.2%, resulting in a 60-day PEAD of 3.5%—a magnitude in line with prior work (Fink, 2021). If investors do not inherent confirmation bias, we would expect this 60-day PEAD to remain unchanged after conditioning on proxies for their priors. Instead, PEAD strengthens significantly when earnings surprises disconfirm priors. Specifically, the 60-day PEAD rises to 4.7%, with Hold/Sell firms in the top earnings surprise decile earning 2.9% and Buy firms in the bottom decile earning -1.8%. Conversely, when earnings surprises confirm priors, the drift shrinks to 2.3%: Buy firms in the top decile earn 1.7%, while Hold/Sell firms in the bottom decile earn -0.6%. Thus, prior-inconsistent news more than doubles the PEAD relative to prior-consistent news. Multivariate regressions confirm this result, showing statistical significance even after controlling for known PEAD drivers.

Turning to the announcement return response to earnings surprises - commonly referred to as the "Earnings Response Coefficient" (ERC) - confirmation bias implies that the ERC should be stronger for prior-consistent news than for prior-inconsistent news. At first glance, the raw data appears inconsistent with this prediction. However, once I account for well-established determinants of the ERC (Kothari, 2001), the picture changes. In particular, I find that prior-inconsistent earnings surprises are associated with larger pre-announcement abnormal returns, and find evidence this is due to their higher earnings persistence.[3] Accordingly, after controlling for pre-announcement returns, the analysis reveals the ERC is stronger for prior-consistent surprises. Furthermore, when focusing on extreme earnings surprises, the abnormal announcement return response is 0.99% larger for prior-consistent surprises compare to prior-inconsistent surprises.

Two additional results show how striking these results are: portfolio sorts and analyzing PEAD across different subsamples. First, a traditional PEAD portfolio strategy - long top-surprise-quintile and short bottom-surprise-quintile each quarter - yields an annual Carhart (1997) FF-4 alpha of 7.1%. In contrast, A "Prior-Inconsistent PEAD Strategy" (long top-quintile stocks with Hold/Sell ratings and short bottom-quintile stocks with Buy ratings) nearly doubles the alpha to

[3]Concrectely, I find that revisions in analysts' one-year earnings forecasts leading up to the anouncement are significantly larger for prior-inconsistent news, reinforcing the notion of their greater persistence.

12.6%. Meanwhile, a "Prior-Consistent PEAD Strategy" delivers just 1.4%, and is statistically indistinguishable from zero. These results are robust under the CAPM and Fama and French (1993) factor models. Second, my results provide new insights into the time variation in PEAD documented by Martineau (2021a). He finds that the PEAD becomes insignificant for All-but-Microcap stocks after 2006 and for Microcap stocks after 2016.[4] I replicate these findings through 2019, confirming his conclusions over the period he analyzes. However, when extending the sample to 2020–2022, I find that PEAD reemerges strongly across both stock groups. Moreover, when conditioning on whether the earnings surprise confirms or disconfirms analysts' priors, a new pattern emerges: prior-inconsistent surprises exhibit persistent, robust PEAD across all periods and stock groups. Instead, for confirming surprises the PEAD is not present since 1994 for All-but-Microcap stocks and since 2006 for Microcap stocks. Thus, the PEAD is concentrated in prior-inconsistent surprises and, contrary to claims of its decline, persists over time.

A potential concern is that analyst ratings may correlate with omitted variables affecting both announcement responses and post-announcement returns. For instance, Buy firms are often low-book-to-market, high-momentum stocks. I address this by including an extensive set of controls and find that the results remain robust, consistent with research that finds PEAD is a distinct anomaly, not subsumed by other characteristics (Bernard, Thomas, and Wahlen, 1997; Chordia and Shivakumar, 2006; Yan and Zhao, 2011). Furthermore, the confirmation bias hypothesis predicts opposing effects on a firm's immediate stock response to earnings surprises versus its post-announcement effects, posing a challenge for alternative explanations to account for these opposing outcomes. Nonetheless, I also perform several sensitivity analyses of the main results; the robustness of the findings remain.

A natural question is why arbitrageurs do not eliminate this mispricing. Two key explanations are shorting costs and transaction costs. Following Daniel, Klos, and Rottke (2023), I identify stocks as short-sale constrained, a proxy for high shorting costs, if they have high short interest ratios and low institutional ownership (IO). I find these stocks exhibit stronger downward drift after negative surprises, particularly among Buy-rated firms, providing a channel for the estab-

[4]Microcap stocks are defined as those below the NYSE 20th-percentile market capitalization.

lished negative link between IO and PEAD (e.g., Bartov, Radhakrishnan, and Krinsky, 2000; Chen, Huang, and Jiang, 2017).[5] Nevertheless, the results show PEAD still exists in stocks that are not short-sale constrained. For transaction costs, the analysis reveals earnings surprises are poitively linked to bid-ask spreads consistent with prior work (e.g., Ng, Rusticus, and Verdi, 2008; Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009). However, the wedge in PEAD induced by confirmation bias does not exhbit any significant relationship with bid-ask spreads. This suggests confirmation bias effects are more persistent and additional arbitrage constraints (e.g., insufficient arbitrage capital, noise-trader risk) are needed to explain its existence.

Several psychological biases could potentially explain differing responses to positive and negative surprises based on analysts' recommendations, including representativeness (Kahneman and Tversky, 1972, 1973), anchoring (Rottenstreich and Tversky, 1997; Tversky and Kahneman, 1974), and overconfidence (Daniel, Hirshleifer, and Subrahmanyam, 1998; Odean, 1998). However, confirmation bias stands out for two reasons: its attentional nature aligns with PEAD's established attention link, and it uniquely predicts response polarization to ambiguous evidence (Lord, Ross, and Lepper, 1979). Pouget, Sauvagnat, and Villeneuve (2017) demonstrated confirmation bias in analyst behavior by showing polarization in their forecast revisions based on firm-level priors. Building on this, I analyze analyst-level priors (Buy and Hold/Sell recommendations) and find analysts are significantly more likely to revise forecasts in directions consistent with their priors. This resulting polarization provides evidence that confirmation bias is the primary mechanism driving these patterns.

My results contribute to several strands of literature. First, this paper advances the extensive research on the PEAD, which has been linked to factors such as limited attention (Hirshleifer and Teoh, 2003; Hirshleifer, Lim, and Teoh, 2009; DellaVigna and Pollet, 2009), firm size (Bernard and Thomas, 1989), information uncertainty (Jiang, Lee, and Zhang, 2005; Bird, Choi, and Yeung, 2014), transaction costs (Ng, Rusticus, and Verdi, 2008; Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009), and institutional ownership (Bartov, Radhakrishnan, and Krinsky, 2000; Chen, Huang, and

[5]The negative drift being more pronounced among buy firms is also consistent with the mechanism in Daniel, Klos, and Rottke (2023), in which optimists take control of short-sale constrained stocks severely limiting abirtrageurs ability to correct the mispiricng.

Jiang, 2017), among others. I show that PEAD is driven not just by whether investors allocate attention, but how they do so. Specifically, I provide evidence that limited attention (the whether) and confirmation bias (the how) are key drivers of the PEAD. Additionally, I contribute to the debate on the decline of the PEAD (Richardson, Tuna, and Wysocki, 2010; Martineau, 2021b) by showing that, since at least 1994, it remains robust for prior-inconsistent surprises. However, for prior-consistent surprises, the evidence suggests it has disappeared since 2006.

Second, this paper contributes to the risk-factor literature. The Fama and French (1993) three-factor model and its extensions - including momentum (Chordia and Shivakumar, 2006), the APT risk factors of Chen, Roll, and Ross (1986), and future inflation risk (Chordia and Shivakumar, 2005) - fail to account for the PEAD. Instead, Daniel, Hirshleifer, and Sun (2020) demonstrate that a three-factor behavioral model, incorporating the market factor, the PEAD, and a net-share-issuance factor, explains the cross-section of average realized returns at least as well as the five-factor model of Fama and French (2015). Building on Daniel, Hirshleifer, and Sun (2020), I provide further evidence that the PEAD represents a behavioral mispricing factor rather than a risk factor.

Third, this paper adds to the debate on investor underreaction and overreaction (Daniel, Hirshleifer, and Subrahmanyam, 1998; Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999; Rabin, 2002). The primary explanations for underreaction include conservatism (Barberis, Shleifer, and Vishny, 1998), overconfidence in private signals (Daniel, Hirshleifer, and Subrahmanyam, 1998), the law of small numbers (Rabin, 2002), and limited attention (Hong and Stein, 1999; Hirshleifer, Lim, and Teoh, 2011). Building on this work, I provide evidence that the PEAD - a key component of underreaction in financial markets - is best explained by a combination of limited attention and confirmation bias. In fact, accounting for limited attention, I show confirmation bias leads to underreaction to prior-inconsistent signals and overreaction to prior-consistent signals.

Finally, this paper contributes to both the behavioral economics and finance literature. Attention is increasingly recognized as a key driver of decision-making across various domains (Gabaix, 2019; Bordalo, Gennaioli, and Shleifer, 2022). In finance, attentional constraints help explain various asset-pricing anomalies, including gradual information diffusion (Brennan, Jegadeesh, and Swaminathan, 1993; Hong and Stein, 1999), media and salience effects on asset prices (Dyck and

Zingales, 2003; Bordalo, Gennaioli, and Shleifer, 2013), and return comovement (Peng and Xiong, 2006). Consistent with this literature, I show attentional mechanisms are central to understanding the underreaction to earnings announcements. While confirmation bias is a well-established psychological bias (Lord, Ross, and Lepper, 1979; Hart, Albarracín, Eagly, Brechan, Lindberg, and Merrill, 2009; Charness and Dave, 2017),[6] its impact on financial markets remains underexplored. Existing research, such as Pouget, Sauvagnat, and Villeneuve (2017) and Kapons and Kelly (2023), document confirmation bias in analyst forecast revisions. I extend this work by demonstrating that confirmation bias also drives asset prices movements underlying the PEAD. Additionally, this paper contributes to the nascent literature on belief polarization in financial decision-making (Bonaparte, Kumar, and Page, 2017; Meeuwis, Parker, Schoar, and Simester, 2022).[7] My findings suggest that this polarization may, in part, be driven by confirmation bias, further highlighting its role in shaping investor behavior.

The rest of the paper is organized as follows. Section 2 presents the theoretical model. Section 3 describes the data. Sections 4 and 5 discuss the main empirical results and robustness checks. Section 6 examines limits to arbitrage, and Section 7 addresses the claim that PEAD is declining. Section 8 distinguishes confirmation bias from alternative biases, and Section 9 concludes.

II Simple Representative Agent Model

A. Dividend Process

I assume a risk-neutral representative agent who values firm i, where the total dividend at $t = 2$ consists of three components. The first is a known base dividend at $t = 0$, denoted D_0. The second is a short-run dividend shock, d_{i2}, realized at $t = 2$. The third is a long-run dividend shock, δ_{i2}, also revealed at $t = 2$. Formally,

$$D_{i2} = D_0 + \delta_{i2} + d_{i2}, \tag{1}$$

[6] A meta-analysis by Hart, Albarracín, Eagly, Brechan, Lindberg, and Merrill (2009), covering 91 studies and over 8,000 participants, found that individuals strongly favor belief-confirming information.

[7] For example, Meeuwis, Parker, Schoar, and Simester (2022) finds that after the 2016 Republican election, likely-Republicans increased their equity share, while likely-Democrats shifted into safer assets.

where $d_{i2} \sim \mathcal{N}(0, \sigma^2)$. Intuitively, D_0 represents the average long-run dividend level across firms, while $\delta_{i2} > 0$ (< 0) indicates that firm i has above-average (below-average) long-run dividend levels.

The agent's prior belief about δ_{i2} is modeled as:

$$\delta_{i2} = \delta_{i,\text{prior}} + \rho\, d_{i2} + \epsilon_{i2}, \tag{2}$$

where $\delta_{i,\text{prior}}$ is a known, fixed prior belief, and $\rho > 0$. I define the agent as *optimistic* if the agent's prior belief about the long-run dividend level for firm i is positive ($\delta_{i,prior} > 0$) and *pessimistic* if it's negative ($\delta_{i,prior} < 0$). For simplicity, I also assume the prior is rational. This set-up incorporates the kernel of truth property since the agent is optimistic (pessimistic) about companies that generally have higher long-run dividend growth (lower long-run dividend growth, respectively).[8] The key uncertainty about δ_{i2} arises because its link with the short-run dividend shock, d_{i2}, reflecting the agent's understanding that positive short-run shocks persistently increase long-run dividends. Mispricing arises from how the agent processes new information.

At $t = 1$, the short-run dividend shock d_{i2} is not directly observable. Instead, the agent observes a noisy signal, x_{i1}, defined as:

$$x_{i1} = d_{i2} + \nu_{i1}, \quad \nu_{i1} \sim \mathcal{N}(0, \sigma_\nu^2). \tag{3}$$

B. Rational Bayesian Updating

For a risk-neutral agent, the price at $t = 1$ equals the subjective expectation of the final dividend D_{i2}. Under rational Bayesian updating, the posterior expectation of d_{i2} is:

$$\mathbb{E}^{\text{rational}}[d_{i2} \mid x_{i1}] = \frac{\sigma^2}{\sigma^2 + \sigma_\nu^2}\, x_{i1}. \tag{4}$$

[8]The model can easily extended for irrational priors since this assumption does not impact the key item of interest - namely, the interaction effect between news and agents' priors.

If the signal variance is low relative to the fundamental uncertainty σ^2, the agent places more weight on the signal. The $t = 1$ price is then:

$$p_{i1}^{\text{rational}} = D_0 + \delta_{i,\text{prior}} + (1+\rho)\frac{\sigma^2}{\sigma^2 + \sigma_v^2}\, x_{i1}. \tag{5}$$

Here, $D_0 + \delta_{i,\text{prior}}$ is the $t = 0$ price, $\frac{\sigma^2}{\sigma^2+\sigma_v^2}\, x_{i1}$ reflects the updated expectation of d_{i2}, and $\rho\frac{\sigma^2}{\sigma^2+\sigma_v^2}\, x_{i1}$ accounts for the revised long-run dividend expectation. This can be restated more simply as

$$p_{i1}^{\text{rational}} = p_{i0} + w_r x_{i1}, \tag{6}$$

where $p_{i0} = D_0 + \delta_{i,\text{prior}}$ and $w_r = (1+\rho)\frac{\sigma^2}{\sigma^2+\sigma_v^2}$.

C. Limited Attention and Confirmation Bias

Suppose, instead the agent is not rational but is subject to two biases. First, reflecting the large literature that has documented underreaction to earnings surprises and shown strong evidence this underreaction is linked to limited attention (DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009), the agent has limited attention. Second, the agent has confirmation bias implying he overweights (underweights) signals that confirm his prior (diconfirm his prior, respectively). Formally, the agent's t=1 price is given by

$$p_{i1}^{\text{agent}} = p_{i0} + w_r x_{i1}\left[\beta + \alpha \mathbf{1}_{\{\text{sgn}(\delta_{i,\text{prior}})=\text{sgn}(x_{i1})\}} - \alpha \mathbf{1}_{\{\text{sgn}(\delta_{i,\text{prior}})\neq\text{sgn}(x_{i1})\}}\right], \tag{7}$$

where $\beta < 1$ reflects limited attention, $0 < \alpha < 1 - \beta$ captures confirmation bias, $\mathbf{1}_{\{\text{sgn}(\delta_{i,prior})=\text{sgn}(x)\}}$ is an indicator is the sign of the surprise equals the sign of the agent's prior and $\mathbf{1}_{\{\text{sgn}(\delta_{i,prior})=\text{sgn}(x)\}}$ is an indicator if the signs differ. Agents overweight signals that confirm their priors ($+\alpha$) and underweight disconfirming signals ($-\alpha$). I assume $\alpha \leq 1 - \beta$, ensuring that even when an agent receives a confirming signal, the overreaction induced by confirmation bias remains insufficient to fully counteract the effects of limited attention, so that underreaction still dominates.

I can restate equation (7) as:

$$p_{i1}^{\text{agent}} = p_{i0} + \beta w_r x_{i1} + \alpha |x_{i1}| \left[\mathbf{1}_{\{\delta_{i,\text{prior}} > 0\}} - \mathbf{1}_{\{\delta_{i,\text{prior}} < 0\}} \right]. \tag{8}$$

Define the *Announcement Return Response* (ARR) as the return of the company at t=1 after the news, x_{i1}, is released. Then

$$\text{ARR}_i = \frac{p_{1i}^{(\text{agent})} - p_{0i}}{p_{0i}} = \frac{\beta w_r x_{i1} + \alpha |x_{i1}| \left[\mathbf{1}_{\{\delta_{i,prior} > 0\}} - \mathbf{1}_{\{\delta_{i,prior} < 0\}} \right]}{p_{oi}} \tag{9}$$

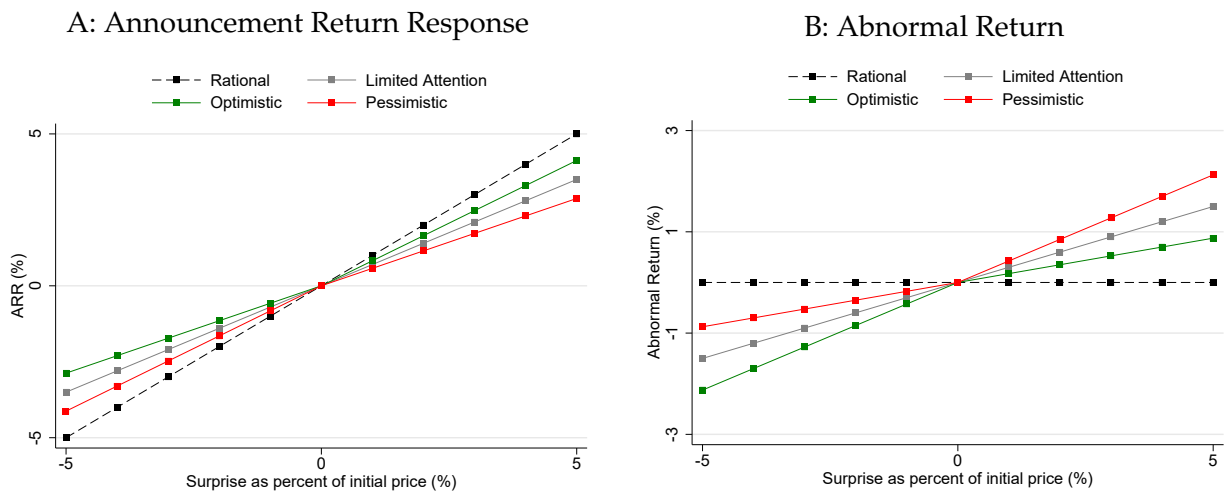
Similarly, define *Abnormal Return* as the difference between the rational price and the agent's price after the news is released, normalized by the original price p_{oi}. Then

$$\text{Abnormal Return}_i = \frac{p_{1i}^{(\text{rational})} - p_{1i}^{(\text{agent})}}{p_0 i} = \frac{[1-\beta] w_r \; x_{i1} - \alpha |x_{i1}| \left[\mathbf{1}_{\{\delta_{i,prior} > 0\}} - \mathbf{1}_{\{\delta_{i,prior} < 0\}} \right]}{p_{0i}} \tag{10}$$

Figure 1 depicts the announcement return response (Panel A) and the resulting abnormal return (Panel B) under four scenarios: rational expectations, limited attention, and confirmation bias with either an optimistic or pessimistic prior. Under rational expectations (dashed black line) and the parametrization chosen, the announcement return is a 45-degree line, reflecting a one-to-one response between the scaled surprise and the return; consequently, abnormal returns are flat (zero). With limited attention (gray line), the announcement return slope is flatter - indicating underreaction - leading to a positively sloped abnormal return.

When confirmation bias is added, each positive or negative surprise x introduces an additional wedge of size $\alpha \, w_r \, |x|$, which shifts the announcement return away from the limited attention case (where $\alpha = 0$). Specifically, an optimistic agent (green line) overweights positive surprises, yielding a steeper slope in Panel A and reducing the corresponding abnormal returns in Panel B. Conversely, a pessimistic agent (red line) underweights positive surprises, leading to a flatter slope in Panel A but more positive abnormal returns in Panel B. Negative surprises have analogous effects in the opposite direction. Thus, Panels A and B highlights the announcement

Figure 1



Panel A plots the announcement return response (i.e., the initial return of the firm) for positive and negative information shocks, when the agent suffers from both limited attention and confirmation bias, and has an optimistic prior (green) and a pessimistic prior (red) for the firm. The dash black line represents the rational expectations response. The gray line represents the response when the agent only suffers from limited attention. Panel B plots the resultant firm abnormal returns, defined as the difference between the rational expectations price and the agent's price, scaled by the initial price. See the Appendix for the details of the model and the parametrization that generates these beliefs and price paths.

return response and resulting abnormal returns under both limited attention and confirmation bias relative to the rational expectations benchmark.

III Data

The data on quarterly earnings announcements comes from the CRSP-Compustat-IBES merged database. When earnings announcement dates are available in both Compustat and IBES, I adopt the earlier date, as recommended by DellaVigna and Pollet (2009), who find that it is typically the more accurate of the two.

Earnings surprises (ES) are defined as the difference between reported earnings and the consensus forecast, scaled by the stock price at the time of the forecast:

$$ES_{iq} = \frac{e_{iq} - F_{iq}}{P_{iq}} \tag{11}$$

Here, e_{iq} denotes reported earnings, F_{iq} represents the consensus forecast, and P_{iq} is the stock price. The consensus forecast is based on the median of analysts' estimates from the IBES summary statistics file. To ensure forecasts are timely, only one- or two quarter ahead forecasts issued or reviewed within 60 calendar days of the earnings announcement date are included (Hirshleifer, Lim, and Teoh, 2009).

Cumulative abnormal returns (CAR) around earnings announcements are calculated over the interval $[t, T]$, relative to the announcement date a. The computation involves subtracting the returns of a size- and book-to-market (BM)-matched portfolio from the announcing firm's returns:

$$CAR[t, T]_{iq} = \prod_{k=a+t}^{k=a+T} (1 + R_{ik}) - \prod_{k=a+t}^{k=a+T} (1 + R_{pk}) \tag{12}$$

where R_{ik} is the return of the firm i and R_{pk} is the return of the matching size-BM portfolio on day k and a is the announcement date of quarter q's earnings. Each quarter, each stock is matched with 1 of 25 size-BM portfolios whre the matching is based on firm's size and BM characteristics as of the prior June, with BM ratios computed using book equity at the fiscal year-end and market capitalization at the prior December (Fama and French, 1993). The portfolio return data of the 25 size-BM portfolios are from Kenneth French's online libary. I focus on post-announcement windows up to 90 trading days, as most price drift occurs within the first one or two quarters

Figure 2:
Histogram of IBES Analyst Ratings

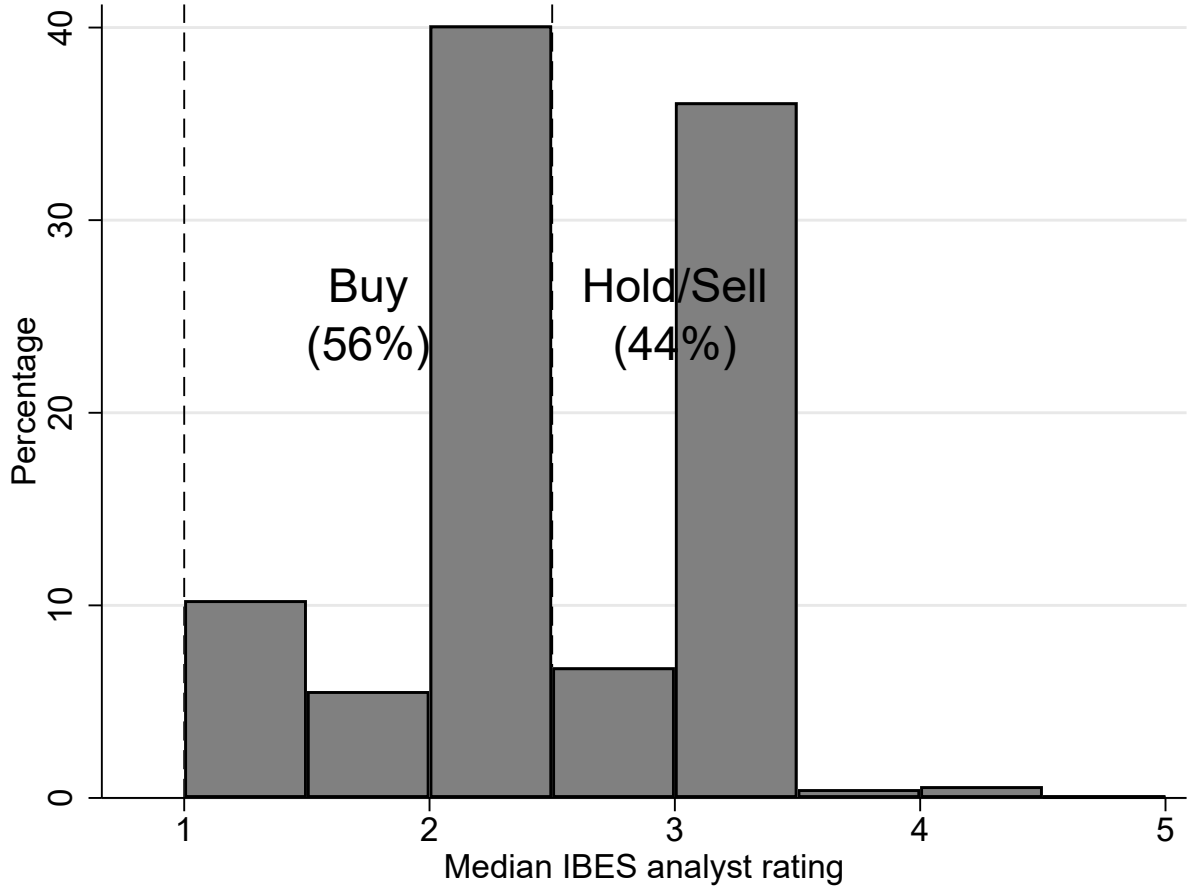


Figure 2 illustrates the distribution of the consensus median IBES analyst ratings for firms in the sample. Analyst ratings are sourced from the IBES recommendations summary file, which provides the consensus median rating for each firm. This consensus median is derived from individual analyst ratings, measured on a five-point scale (1 : Strong Buy, 2 : Buy, 3 : Hold, 4 : Underperform, 5 : Sell). The median consensus rating is calculated at the end of the quarter preceding earnings announcements. Firms are classified into two categories: "Buy" (median rating ≤ 2) and "Hold/Sell" (median rating > 2). The histogram displays the percentage of firms in each rating category, with 56% of firms classified as "Buy" and 44% as "Hold/Sell." The sample spans from 1994Q1 to 2022Q4.

following announcement (Bernard and Thomas, 1989, 1990). I also drop firms that have a stock price less than $1 at the end of the quarter.

I use analyst consensus median recommendations from the IBES rcommendations summary file as the overall measure of investors' priors. IBES analysts rank firms on a scale of one to five,

where {1: Strong Buy, 2: Buy, 3:Hold, 4: Underperform, 5: Sell }. I use the last conensus recommendation at the end of the quarter prior to any earnings announcements being made, to ensure investors priors are formed before the arrival of any news. Figure 2 plots the histogram distribution of the consensus median rating of our sample. In the main analysis, I classify investors' as having a "Buy" prior if the median consensus rating is less than or equal to to two, while investors have a "Hold/Sell' prior otherwise. This classification splits the data into roughly equal samples, with 56% (44%) of firms in our sample being classified as Buy (Hold/Sell, respectively). In subsequent analyses, I leverage the full distribution of analyst ratings, to assess whether the patterns are stronger as the strength of investors' overall optimism or pessimism varies.

A. Descriptive Statistics

Table 6 Panel A, outlines key characteristics of the sample firms across the Buy and Hold/Sell groups. The size and BM ratios are computed annually at the end of June where market capitalization and book equity are constructed following Fama and French (1993). *Momentum* is calculated as the firm's cumulative return from month t-12 to month t-2, in line with Carhart (1997). *Volatility* (σ) is the standard deviation of monthly returns over the past year (minimum nine observations required) computed annually at the end of June. *Reporting Lag* is the number of days from quarter-end until the announcement date, # *Analysts* is the number of analysts following the firm during the most recent calendar quarter, *Earnings Persistence* is the AR(1) autocorrelation coefficient of quarterly earnings per share during the past 4 year (split adjusted; minimum four observations required) and # *Earnings announcement* is the number of firms announcing earnings on that announcement date (Hirshleifer, Lim, and Teoh, 2009). *Institutional ownership* (IO) is calculated as the proportion of total shares outstanding (from CRSP) held by institutions at the end of the most recent quarter following (Daniel, Hirshleifer, and Subrahmanyam, 1998). Institutional ownership data is sourced from Thomson-Reuters Institutional 13-F filings (up to June 2013) and SEC filings through WRDS (post-June 2013). Finally, *Bid-Ask Spread* is calculated as the spread between the ask-price and bid-price as percentage of the average of the two at the end of the most recent quarter.

Table 1:
Summary Statistics

Analyst consensus median recommendations are obtained from the IBES recommendations summary file. Analysts rate firms on a five-point scale $\{1 : \text{Strong Buy}, 2 : \text{Buy}, 3 : \text{Hold}, 4 : \text{Underperform}, 5 : \text{Sell}\}$, and I classify investors as having a "Buy" prior for the firm if the median consensus rating is less than or equal to 2, and a "Hold/Sell" prior otherwise. I use the last consensus recommendation at the end of the prior-quarter, before any announcements are made. The sample is from the CRSP-Compustat-IBES merged database and spans from 1994Q1 to 2022Q4. In Panel A, the variables include Earnings Surprise, Log(Size), Log(BM) , Momentum, Volatility, Reporting Lag, the number of analysts covering the firm (# Analysts), the AR(1) autocorrelation coefficient of quarterly earnings earnings per share (Earnings Persistence), the number of earnings announcements on the same day (# Earnings Announcements), Institutional Ownership (IO)and Bid-Ask Spread. See Section 3 for detailed variable definitions. Panel B provides standardized regression results with "Buy" as the dependent variable, and where all independent variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are adjusted for heteroskedasticity and clustered by announcement date. All variables are winsorized at the 0.5% and 99.5% levels. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sample Characteristics

	Earnings Surprise (%)	Log(Size) std.	Log(BM)	Momentum (%)	Volatitlity std.	Reporting Lag	# Analysts	Earnings Persistence	# Earnings Announcements	IO (%)	Bid-Ask Spread (%)
Buy	-0.037	0.372	0.522	202.361	0.129	35.592	8.519	0.432	221.105	64.460	0.832
Hold/Sell	-0.120	0.414	0.675	6.940	0.114	34.011	8.869	0.368	209.836	63.672	0.759
Hold/Sell - Buy	-0.083***	0.042***	0.153***	-15.421***	-0.015***	-1.582***	0.350***	-0.065***	-11.269***	-0.788***	-0.073***

Panel B: Regression Analysis

	Dependent variable: Buy
Earnings Surprise	0.009***
	(0.001)
Log(Size) std.	-0.005***
	(0.002)
Log(BM)	-0.061***
	(0.002)
Momentum	0.063***
	(0.002)
Volatility	0.034***
	(0.002)
Reporting Lag	0.036***
	(0.002)
# Analysts	-0.013***
	(0.002)
Earnings Persistence	0.032***
	(0.001)
# Earnings announcements	0.029***
	(0.002)
IO	0.022***
	(0.001)
Bid-Ask Spread	0.029***
	(0.001)
Constant	0.559***
	(0.002)
Observations	262,030
R^2	5.2 %

Panel A highlights notable differences between Buy and Hold/Sell firms. One concern with using analyst Buy and Hold/Sell ratings as optimism and pessimism proxies, respectively, is that they may reflect the exact opposite of the marginal investors' expectations - namely, analysts tend to be optimistic (pessimistic) about firms that are undervalued (overvalued, respectively) precisely becuase marginal investors are too pessimistic (optimistic, respectively) about those firms. Nevertheless, consistent with Jegadeesh, Kim, Krische, and Lee (2004) I find that Buy firms exhibit characteristics associated with "glamour" stocks. Specifically, they tend to be high momentum growth

stocks, providing support for the assumption that analyst ratings are aligning with marginal investors' expectations and capturing investor optimism. Buy firms tend to also be smaller with higher bid-ask spreads, consistent with the relationship between smaller firm size and higher transaction costs. Panel B extends this analysis using a multivariate regression of Buy on standardized firm characteristics (mean of 0 and standard deviation of 1). The results align with the univariate analysis, reinforcing the observed patterns.

IV Main Empirical Results

A. Post-Announcement Abnormal Returns

My theoretical model (Section 2) posits that the post-announcement abnormal return are driven by two biases: limited attention (β) and confirmation bias (α). Specifically, the model equation (10) for post-announcement abnormal returns is given by

$$\text{Abormal Return}_i = [1-\beta] w_r Surprise_i - \alpha w_r |Surprise_i| \left[\mathbf{1}_{\{\delta_{i,prior}>0\}} - \mathbf{1}_{\{\delta_{i,prior}<0\}} \right] \tag{13}$$

where $Surprise_i = \frac{x_i}{p_{oi}}$. Thus, the equation yields two key predictions for the cross-section of post-announcement returns: (i) underreaction to earnings surprises, captured by the term $\left[1-\beta\right] w_r \, Surprise_i$ yielding an upward (a downward) drift to positive news (negative news, respectively) and (ii) and an additional downward (upward) adjustment to this initial drift direction if the agent is optimistic (pessimistic, respectively) that depends on the size of the surprise, as captured by the term $\pm\, \alpha \, |Surprise_i|$. Motivated by this equation, I run regressions of the form

$$\begin{aligned} \text{CAR[2,61]}_i = {} & a_0 + a_1(\text{ES}_i - \text{Median ES}) + a_2|\text{ES}_i - \text{Median ES}| \times [\text{Buy}_i - \text{Hold/Sell}_i] \\ & + a_3[\text{Buy}_i - \text{Hold/Sell}_i] + \sum_{i=1}^{n} b_i X_i + \sum_i c_i \left[X_i \times (\text{ES}_i - \text{Median ES})\right] + \epsilon_i \end{aligned} \tag{14}$$

where CAR[2,61]_i is the 60-day post-announcement cumulative abnormal return for firm i, (ES-Median ES) is the earnings surprise decile relative to it's median value (ES-Median ES=-4.5 most negative; ES-Median=4.5 most positive), and Buy_i and Hold/Sell_i are indicators if the concensus

analyst recommendation at the end of the previous quarter prior to any announcements is a Buy and Hold/Sell , respectively. Following past literature, since the relation between announcement abnormal returns and earnings surprises are nonlinear (Kothari, 2001), I use the decile rank of forecast error as opposed to the forecast error itself yielding an almost linear relationship between the dependant and independent variables.

Figure 3 shows the 60-day cumulative abnormal returns (CAR) by earnings surprise deciles, both unconditionally and split by analysts' priors. Unconditionally, the most positive (ES=10) and most negative (ES=1) deciles yield 60-day abnormal returns of 2.3% and -1.2%, respectively, resulting in a PEAD of 3.5% in line with the prior literature (Bernard and Thomas, 1989, 1990; Fink, 2021)[9] For firms with prior-inconsistent news, those in the highest decile with Hold/Sell ratings achieve a 60-day abnormal return of 2.9%, while firms in the lowest decile with Buy ratings experience a return of -1.8%. This results in a PEAD of 4.7%. In contrast, for firms with prior-consistent news, the PEAD is only 2.3%. Thus, the 60-day PEAD for prior-inconsistent news is more than twice as large as that for prior-consistent news.

Table 2 columns (1)-(3) assesess the statisical significance of these patterns by presenting the empirical results of running regression equation (14). Standard errors are adjusted for heteroskedasticity and clustered by announcement date. Under the limited attention and confirmation bias hypothesis we expect $a_1 > 0$ and $a_2 < 0$. I find direct support for this hypothesis. In column (1), $a_1 = 0.31 > 0$ confirms investor underreaction to news, consistent with PEAD and limited attention (Hirshleifer, Lim, and Teoh, 2009; DellaVigna and Pollet, 2009). Additionally, $a_2 = -0.11 < 0$ supports the confirmation bias hypothesis, as prior-inconsistent news leads to significantly stronger PEAD than prior-consistent news. Column (2) adds controls for variables linked to PEAD including size, book-to-market, momentum deciles, as well as reporting lag, earnings persistence, bid-ask spread, institutional ownership, number of earnings announcement, day of week dummies (e.g., Jiang, Lee, and Zhang, 2005; Ng, Rusticus, and Verdi, 2008; DellaVigna and Pollet, 2009, etc.), with results remaining robust. In column (3) I further restrict the sample to

[9]Prior literature finds quarterly abnormal returns between 2% and 4% depending on the sample period and the measure of abnormal returns - see Fink (2021) for an excellent overview.

Figure 3:
Post-Announcement Abnormal Returns by Analysts' Priors

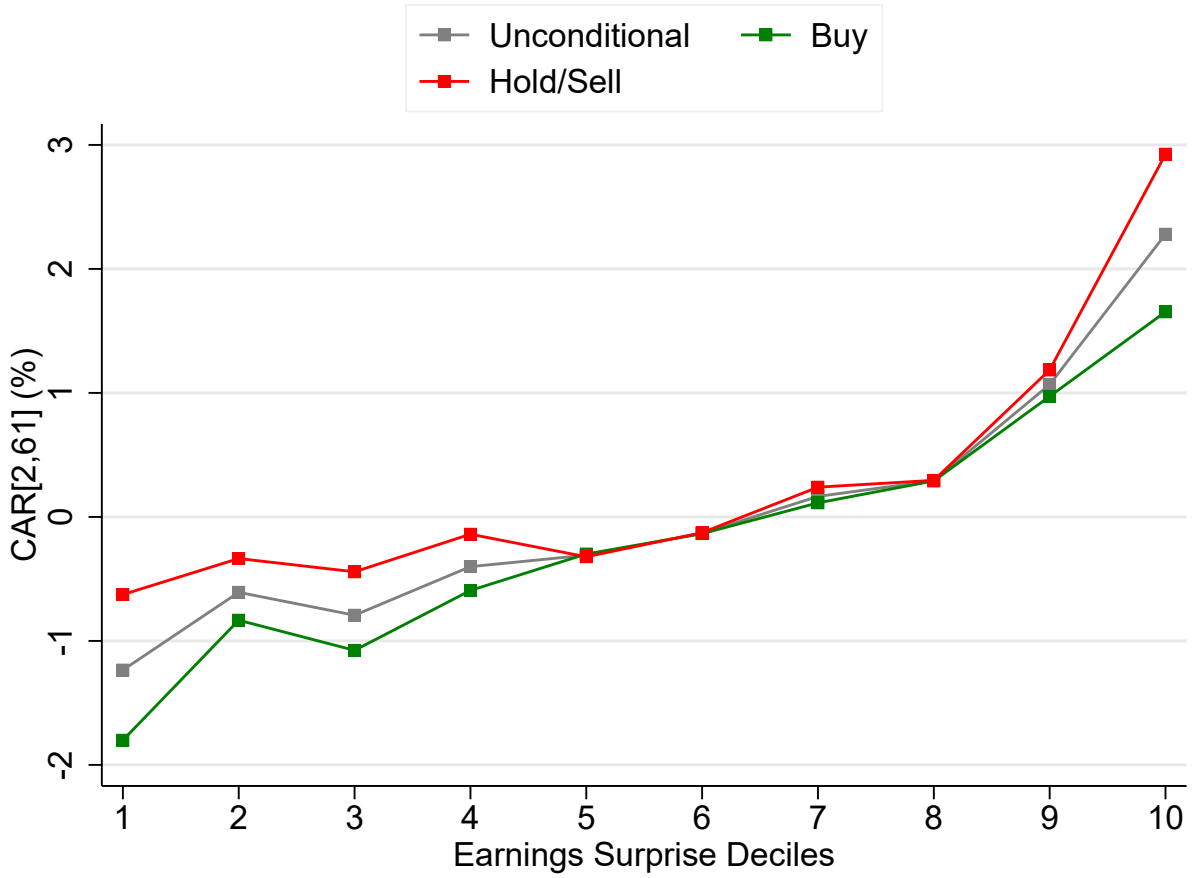


Figure 3 displays the mean 60-day post-announcement cumulative abnormal returns (CAR) by earnings surprise decile (ES = 1 for the most negative surprises; ES = 10 for the most positive surprises). The figure includes results for firms unconditionally (Unconditional), firms with a Buy rating, and firms with a Hold/Sell rating. Earnings surprise deciles are derived from IBES analyst forecast errors, calculated as the actual reported earnings minus the median consensus forecast, scaled by the stock price. Firms are categorized as having a Buy rating if the median IBES consensus rating at the end of the prior quarter is less than or equal to 2, and as Hold/Sell otherwise. Additional information on analyst ratings is provided in Figure 2.

the bottom two and top deciles and find the results are stronger, indicating confirmation bias is more pronounced among extreme surprises.

Interestingly, after controlling for the "earnings surprise x analyst ratings" channel, I observe no evidence that analyst ratings have unconditional predictive power for future returns. This

Table 2:
Market Reaction to Earnings News: Regression Analysis

Table 2 reports regressions relating 60-day post-announcement cumulative abnormal returns ($CAR[2,61]$) and 3-day announcement abnormal returns (CAR[-1,1]) to earnings-surprise deciles relative to it's median value (ES-Median ES=-4.5 most negative; ES-Median ES=4.5 most positive), as well as it's absolute value , |ES-Median ES|, interacted with analyst consensus recommendations for the firm before any announcements are made (Buy-Hold/Sell=1 if the recommendation is Buy; Buy -Hold/Sell=-1 if the recommendation is Hold/Sell). The dependent variable $CAR[t,T]$ is measured relative to size- and book-to-market–matched portfolios. Control variables include deciles of size, book-to-market, and momentum along with return volatility, reporting lag, analyst coverage, earnings persistence, the number of earnings announcements, institutional ownership, bid-ask spread, 20-day cumulative abnormal returns before the announcemnt date and day-of-week, quarter, and year dummies. All controls are interacted with ES-Median ES. Variable definitions appear in Section 3. Standard errors are heteroskedasticity-robust and clustered by announcement date. All variables are winsorized at the 0.5% and 99.5% levels. *, **, *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	Post-Annouenement Abnormal Returns			Announcement Abnornmal Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[2,61]	CAR[2,61]	CAR[2,61]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]
[Buy - Hold/Sell]	0.04	0.08	1.06*	0.09***	-0.01	-0.41**
	(0.08)	(0.08)	(0.55)	(0.03)	(0.03)	(0.18)
ES-Median ES	0.31***	0.51***	0.55***	0.83***	0.46***	0.51***
	(0.02)	(0.10)	(0.12)	(0.01)	(0.03)	(0.04)
|ES-Median ES| x [Buy - Hold/Sell]	-0.11***	-0.12***	-0.35**	-0.03**	0.02**	0.11***
	(0.03)	(0.03)	(0.14)	(0.01)	(0.01)	(0.05)
Controls Interacted with, ES-Median ES		X	X		X	X
Top & Bottom 2 Groups			X			X
Constant	0.07	0.36	0.23	0.26***	0.60***	0.54***
	(0.06)	(0.39)	(0.55)	(0.02)	(0.12)	(0.18)
Observations	262,030	262,030	109,753	262,030	262,030	109,753
R^2	0.2%	1.0%	2.1%	8.7%	35.5%	38.1%

provides evidence against the analyst fixed effect channel (e.g., firms with Buy ratings being systematically overvalued and those with Hold/Sell ratings being systematically undervalued). Prior research has produced mixed findings on the relationship between analyst ratings and future returns. For example, Jegadeesh, Kim, Krische, and Lee (2004) find that stocks with favorable analyst ratings (e.g., buy) and strong characteristics (e.g., momentum) tend to perform well, whereas those with unfavorable characteristics (e.g., high growth) underperform. However, after controlling for momentum, they conclude that analyst ratings have no unconditional predictive power for returns, a result consistent with my findings. In contrast, my study examines how the predictive component of firms' earnings news interacts with analyst ratings before the news arrives and finds that stocks with favorable ratings underperform those with unfavorable ratings.

B. Announcement Abnromal Returns

The theoretical model provides specific predictions for the announcement response. Through the confirmation bias mechanism, investors react more strongly to prior-consistent news than prior-inconsistent news. The announcement return response is expressed in equation (10) as:

$$\text{Announcement Response}_i = \beta w_r Surprise_i + \alpha w_r |Surprise_i| \left[\mathbf{1}_{\{\delta_{i,prior}>0\}} - \mathbf{1}_{\{\delta_{i,prior}<0\}}\right] \tag{15}$$

where $Surprise_i = \frac{x_i}{p_{oi}}$. Without knowing the rational response (w_r), I cannot test whether $\beta < 1$, consistent with limited attention. However, I can test whether $\alpha > 0$ to determine if announcement return responses align with confirmation bias. Motivated by this equation, I estimate the following regression:

$$\begin{aligned} \text{CAR[-1,1]}_i = a_0 + a_1(\text{ES}_i - \text{Median ES}) + a_2|\text{ES}_i - \text{Median ES}| \times [\text{Buy}_i - \text{Hold/Sell}_i] \\ + a_3[\text{Buy}_i - \text{Hold/Sell}_i] + \sum_{i=1}^{n} b_i X_i + \sum_i c_i \left[X_i \times (\text{ES}_i - \text{Median ES})\right] + \epsilon_i \end{aligned} \tag{16}$$

where CAR[-1,1]$_i$ is the 3-day announcement cumulative abnormal return for firm i centered on the reported announcement day (t=0).

Table 2 (columns (4)-(6)) presents the regression results. Under the confirmation bias hypothesis, I expect $a_2 > 0$. In column (4), without controlling for additional variables, I do not find support for this hypothesis. However, there is an extensive literature on measuring the size of the announcement return response to earnings surprises - commonly referred to as the "Earnings Response Coefficient" (ERC) - showing the ERC is affected by many factors (Kothari, 2001). Notably, prior research highlights that the ERC is significantly affected by pre-announcement returns driven by information released between earnings announcements. Importantly, I find that firms with prior-inconsistent earnings surprises exhibit significantly larger pre-announcement abnormal returns (see Table A.1). Once I control for firm-level characteristics, including pre-announcement returns, column (5) shows that $a_2 = 0.02$, consistent with the confirmation bias hypothesis. Moreover, when including only pre-announcement abnormal returns as a control,

the coefficient remains at $a_2 = 0.02 > 0$. Appendix Table A.1 further examines this relationship, showing that analysts' 1-year revisions leading up to the announcement are significantly larger for prior-inconsistent surprises. This suggests that the larger pre-announcement returns observed for prior-inconsistent surprises stem from their greater persistence - i.e., these surprises trigger a more substantial re-rating of earnings expectations along the term structure. In column (6), I further restrict the sample to the extreme deciles of earnings surprises and find that the coefficient increases to $a_2 = 0.11$. This implies that, for extreme surprises, the abnormal return response is 0.99% stronger for prior-consistent surprises.

V Robustness

This section shows the results are robust to various concerns including: (i) portfolio sorts, (ii) different post-announcement periods, (iii) analyzing positive and negative suprises, seperately and (iv) varying the degree of investor optimism or pessimism.

A. Portfolio Sorts

Portfolio sorts offer a straightforward, non-parametric approach to studying PEAD. Unlike multivariate regressions, which impose assumptions about functional forms and linearity, this method avoids potential misspecification and inference risks inherent in regression-based analyses, particularly when firms experience extreme performance (Barber and Lyon, 1996, 1997).

For this analysis, I sort firms into quintiles at the end of each quarter based on their earnings surprise quintiles (Q1-Q5) and further classify them by whether they had a "Buy" or "Hold/Sell" prior. To focus on the strongest PEAD effects, I restrict the sample to firms reporting earnings within 60 days of quarter-end, as PEAD is most pronounced in the first few months following an announcement (Bernard and Thomas, 1990).

Table 3:
Risk-Adjusted Portfolio Returns: Portfolio Sorts

Table 3 reports average monthly abnormal returns for quintile portfolios formed based on earnings surprises quintiles and split into firms with a Buy or Hold/Sell prior, where I restrict the sample to firms that report earnings within 60 days of the end of the quarter. Firms are classified as having a Buy prior if the median consensus analyst recommendation from the IBES recommendations summary file is less than or equal to 2; otherwise, they are classified as Hold/Sell. For detailed variable definitions, see Section 3. Portfolios are rebalanced at the end of each quarter. Panels A, B, and C present risk-adjusted alphas from CAPM, Fama and French (1993) three-factor, and Carhart (1997) four-factor models, respectively. The long-short portfolio (High-Low) is constructed by taking a long position in the highest quintile ("High" quintile) and a short position in the lowest quintile ("Low" quintile). The sample spans 1994m1 to 2022m12. Standard errors, shown in parentheses, are adjusted for heteroskedasticity. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Low		Neutral		High			High -Low
	Q1	Q2	Q3	Q4	Q5	Q3–Q1	Q5–Q3	Q5–Q1
Panel A: CAPM								
Buy	-0.89***	-0.37**	0.06	-0.13	-0.16	0.95***	-0.22	0.72***
	(0.22)	(0.15)	(0.13)	(0.14)	(0.20)	(0.18)	(0.16)	(0.11)
Hold/Sell	-0.36	0.06	0.05	0.14	0.26	0.41**	0.21	0.62***
	(0.23)	(0.16)	(0.13)	(0.15)	(0.22)	(0.20)	(0.20)	(0.13)
Hold/Sell-Buy	0.52***	0.43***	-0.02	0.28**	0.42***	0.54***	0.44***	-0.10
	(0.14)	(0.12)	(0.14)	(0.13)	(0.15)	(0.15)	(0.17)	(0.14)
Panel B: FF1993								
Buy	-0.87***	-0.36***	0.10	-0.13	-0.14	0.97***	-0.24*	0.73***
	(0.15)	(0.10)	(0.09)	(0.09)	(0.13)	(0.16)	(0.14)	(0.11)
Hold/Sell	-0.44***	0.02	0.01	0.08	0.21	0.45**	0.20	0.65***
	(0.16)	(0.11)	(0.11)	(0.11)	(0.15)	(0.19)	(0.19)	(0.13)
Hold/Sell - Buy	0.43***	0.38***	-0.09	0.21*	0.35***	-0.52***	0.44**	-0.08
	(0.11)	(0.11)	(0.12)	(0.11)	(0.13)	(0.15)	(0.17)	(0.14)
Panel D: Carhart								
Buy	-0.63***	-0.26***	0.09	-0.07	-0.03	0.72***	-0.12	0.61***
	(0.15)	(0.09)	(0.09)	(0.09)	(0.13)	(0.16)	(0.15)	(0.10)
Hold/Sell	-0.15	0.12	0.03	0.13	0.42***	0.18	0.38*	0.56***
	(0.15)	(0.11)	(0.12)	(0.11)	(0.15)	(0.19)	(0.20)	(0.12)
Hold/Sell-Buy	0.49***	0.37***	-0.06	0.20*	0.44***	-0.54***	0.50***	-0.04
	(0.12)	(0.12)	(0.12)	(0.11)	(0.13)	(0.14)	(0.17)	(0.14)

Figure 4:
Three Post-Earnings Announcement Drift (PEAD) Long-Short Strategies: Conditioning on Analysts' Priors

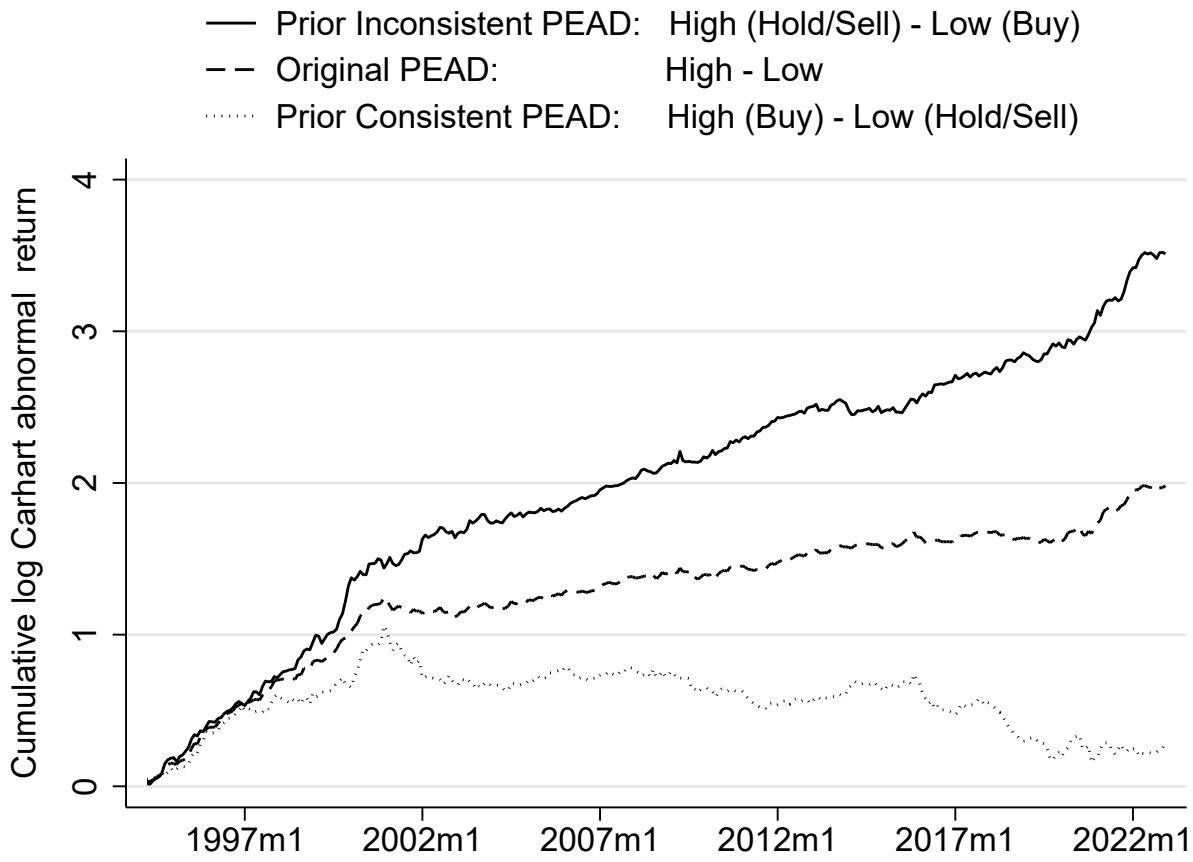


Figure 4 plots cumulative log Carhart (1997) FF-4 abnormal returns for the three PEAD strategies: Original PEAD (dashed line), Prior-Inconsistent PEAD (solid line), and Prior-Consistent PEAD (dotted line). Portfolios are constructed based on analyst earnings surprise quintiles and split into firms with a "Buy" or "Hold/Sell" prior, where I restrict the sample to firms that report earnings within 60 days of the end of the quarter. Firms are classified as having a Buy prior if the median consensus analyst recommendation from the IBES recommendations summary file is less than or equal to 2; otherwise, they are classified as Hold/Sell. The Original PEAD strategy goes long the top earnings surprise quintile ("High" quintile) and short the bottom quintile ("Low" quintile). The Prior-Inconsistent PEAD strategy goes long (short) the top quintile (bottom quintile, respectively) for firms with a Hold/Sell prior (Buy prior, respectively). The Prior-Consistent PEAD strategy goes goes long (short) the top quintile (bottom quintile, respectively) for firms with a Buy prior (Hold/Sell prior, respectively). Portfolios are rebalanced at the end of each quarter. Abnormal returns are computed using the Carhart (1997) four-factor model, and cumulative log returns are calculated by compounding these monthly abnormal returns. The sample spans 1994m1 to 2022m12.

Table 3 reports equal-weighted monthly average returns for these portfolios, adjusted for different risk models, with quarterly rebalancing. Panels A, B, and D present CAPM, Fama and French (1993) three-factor, and Carhart (1997) four-factor alphas, respectively. Each specification also includes a long-short portfolio, which takes a long position in the highest quintile ("High") and a short position in the lowest quintile ("Low").

The confirmation bias hypothesis posits that negative drift should be stronger for firms with a Buy prior, while positive drift should be stronger for firms with a Hold/Sell prior. Table 3 supports this hypothesis, with heteroskedasticity-adjusted errors.

Panel A, which adjusts for CAPM, reveals strong evidence of PEAD across both groups. The long-short portfolio (High-Low) delivers monthly abnormal returns of 72 basis points (bps) for Buy firms and 62 bps for Hold/Sell firms, both statistically significant at the 1% level. However, there are notable asymmetries in the High and Low legs. Consistent with confirmation bias, the CAPM abnormal return for the Low leg is significantly stronger for Buy firms (-89 bps) than for Hold/Sell firms (-36 bps). Conversely, for the High leg, Hold/Sell firms exhibit significantly stronger abnormal returns (26 bps) than Buy firms (-16 bps). Additionally, for the neutral (Q3) news leg, there is no significant difference between Buy and Hold/Sell firms, supporting the idea that the effect operates through the news-prior interaction channel, consistent with confirmation bias. Panels B and D extend the analysis to the Fama and French (1993) and Carhart (1997) factor-models, confirming the robustness of these patterns.

The original post-earnings announcement drift strategy ("The Original PEAD Strategy") involves buying the top quintile and shorting the bottom quintile without conditioning on priors. Table 3 suggests that incorporating the effect of confirmation bias can enhance or dampen these returns, motivating two alternative strategies:

The Prior-Inconcistent PEAD Strategy This strategy exploits underreaction to news that contradicts prior beliefs. It takes a long position in the top quintile for Hold/Sell firms and a short position in the bottom quintile for Buy firms.

The Prior-Consistent PEAD Strategy This strategy exploits underreaction to news that confirms prior beliefs. It takes a long position in the top quintile for Buy firms and a short position in the bottom quintile for Hold/Sell firms.

Results of the three PEAD Strategies Figure 4 plots cumulative log Carhart (1997) abnormal returns for the three strategies. The Prior-Inconsistent (solid line) and Prior-Consistent (dotted) PEAD Strategies deliver Carhart (1997) alphas of 105 bps per month and 12bps per month, respectively, compared to the Original (dashed line) PEAD Strategy's alpha of 59 bps. In other words, nearly all of the PEAD's portfolio abnormal return is concentrated in the prior-inconsistent surprises. Appendix Table A.2 confirms that these results are also robust to the CAPM and Fama and French (1993) factor models.

B. Different Post-Announcement Windows

Figure 5 plots CARs over different post-announcement windows for extreme earnings surprises. Panel A shows negative surprises ($ES = 1$), and Panel B shows positive surprises ($ES = 10$), further split by analysts' priors. A key pattern emerges: the positive drift following good news is significantly stronger for firms with a Hold/Sell prior than for those with a Buy prior. As a result, the CAR wedge between these two groups increases as time since the announcement progresses. Similarly, for negative surprises, the drift is more pronounced for firms with a Buy prior compared to those with a Hold/Sell prior, leading to a widening CAR gap over time. Interestingly, while the CAR for positive surprises stabilizes around 60 trading days post-announcement, the negative drift exhibits more persistence. This suggests that downward price adjustments following bad news take longer to fully correct, possibly due to shorting constraints.[10]

These visual patterns align closely with the regression results in Table 4. The coefficient on $|ES - \text{Median ES}| \times [\text{Buy - Hold/Sell}]$ is consistently negative across all post-announcement windows, indicating that PEAD is stronger when news contradicts investor priors. The coefficient is not statistically significant over the shorter 30-day window (column (1)), likely because mispric-

[10]Consistent with this interpretation, Section 6 shows negative drift patterns are more pronounced for stocks with high shorting costs.

Figure 5:
Evolution of Post-Announcement Cumulative Abnormal Returns

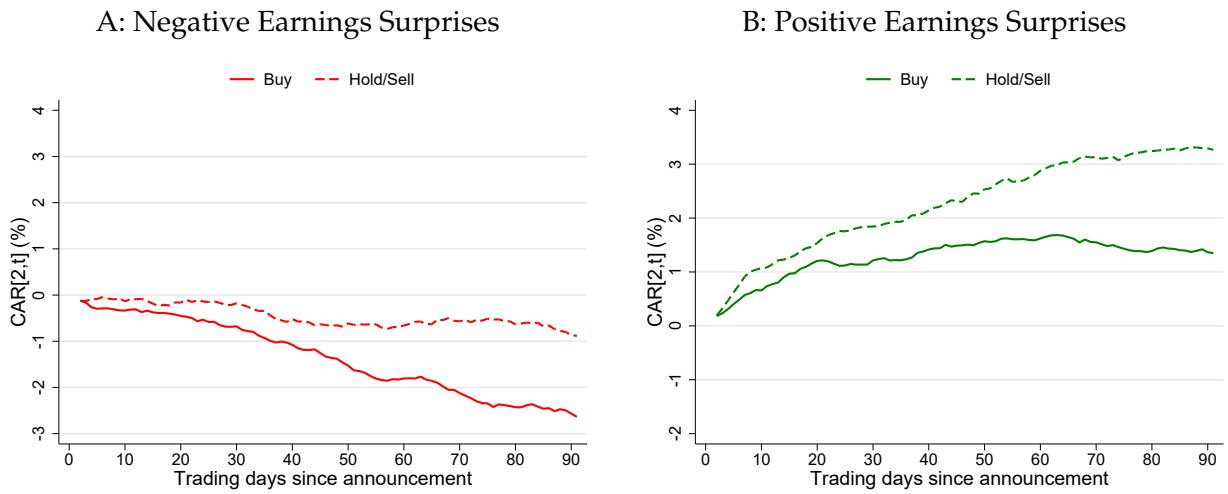


Figure 5 shows the mean post-announcement cumulative abnormal returns (CAR[2, t]) up to trading day t, plotted against trading days since the announcement ($t = 2, 3, \ldots, 91$). Panels A and B display this series for the most negative decile of earnings surprises (ES = 1, labeled as "Negative Earnings Surprises") and the most positive decile of earnings surprises (ES = 10, labeled as "Positive Earnings Surprises"), respectively. Earnings surprise deciles are based on IBES analyst forecast errors, calculated as actual reported earnings minus the median consensus forecast, scaled by the stock price. Each panel further separates these series based on firms' prior recommendations, categorizing them as either Buy or Hold/Sell. Firms are classified as Buy if the median consensus rating (from the IBES summary recommendatins file) at the end of the prior quarter is less than or equal to 2, and as Hold/Sell otherwise.

ing has not yet fully corrected. However, as the window extends, the coefficient grows in both magnitude and significance, suggesting a gradual correction of mispricing over time - consistent with the gradual diffusion of information documented in the literature (Hong and Stein, 1999; Ramnath, 2002; Hou, 2007). Together, Figure 5 and Table 4 confirm that the findings hold across different post-announcement horizons.

C. Positive and Negative Surprises

To further explore how investors react to good versus bad news, I partition the sample based on the sign of the earnings surprise and re-estimate the main regression. Table 5 presents the results. Columns (1)-(2) focus on negative surprises, while Columns (3)-(4) analyze positive surprises.

The results reinforce my main findings. Over the 60-day window, the interaction term, $|\text{ES} - \text{Median ES}| \times [\text{Buy - Hold/Sell}]$, is identical for negative and positive surprises (both -0.16), con-

Table 4:
Different Post-Announcement Periods: Regression Analysis

Table 4 reports regressions relating different post-announcement cumulative abnormal returns ($CAR[2,t]$) to earnings-surprise deciles relative to it's median value (ES-Median ES=-4.5 most negative; ES-Median ES=4.5 most positive), as well as it's absolute value , |ES-Median ES|, interacted with analyst consensus recommendations for the firm before any announcements are made (Buy-Hold/Sell=1 if the recommendation is Buy; Buy -Hold/Sell=-1 if the recommendation is Hold/Sell). The dependent variable $CAR[t,T]$ is measured relative to size- and book-to-market–matched portfolios. Control variables include deciles of size, book-to-market, and momentum along with return volatility, reporting lag, analyst coverage, earnings persistence, the number of earnings announcements, institutional ownership, bid-ask spread, 20-day cumulative abnormal returns before the announcemnt date and day-of-week, quarter, and year dummies. All controls are interacted with ES-Median ES. Variable definitions appear in Section 3. Standard errors are heteroskedasticity-robust and clustered by announcement date. All variables are winsorized at the 0.5% and 99.5% levels. *, **, *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	(1) CAR[2,31]	(2) CAR[2,41]	(3) CAR[2,51]	(4) CAR[2,71]	(5) CAR[2,81]	(6) CAR[2,91]
[Buy - Hold/Sell]	-0.04	0.00	0.05	0.13	0.18**	0.20**
	(0.05)	(0.06)	(0.07)	(0.08)	(0.09)	(0.10)
ES-Median ES	0.43***	0.47***	0.49***	0.55***	0.58***	0.63***
	(0.07)	(0.08)	(0.09)	(0.11)	(0.12)	(0.13)
|ES-Median ES| x [Buy - Hold/Sell]	-0.02	-0.05**	-0.09***	-0.15***	-0.18***	-0.19***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Controls Interacted with, ES-Median ES	X	X	X	X	X	X
Constant	0.17	0.23	0.19	1.08**	1.52***	1.39***
	(0.27)	(0.31)	(0.35)	(0.43)	(0.45)	(0.48)
Observations	262030	262030	262030	262030	262030	262030
R^2	0.7%	0.8%	0.9%	1.0%	1.0%	1.0%

sistent with agent's confirmation bias being equivalently strong for negative and positive surprises, as posited in the model in Section 2. Turning to the announcement window $\big(\text{CAR}[-1,1]\big)$, I see a similar pattern of stronger reactions for prior-consistent news. Looking at negative surprises in Column (2), the interaction coefficient is $+0.03$ ($p < 0.05$) while the direct effect [Buy - Hold/Sell] is insignificant. Interpreted together, investors react more strongly to bad news when they hold a Hold/Sell prior, and that difference in response grows with the severity of the negative news. Conversely, for positive surprises in Column (4), the interaction coefficient is -0.02 and the direct effect on [Buy - Hold/Sell] is $+0.08$. In combination, these results imply that investors with a Buy prior respond more sharply to good news in general, but, interestingly, that the incremental reaction moderates for extremely positive surprises.

Table 5:
Market Reaction to Negative and Positive Surprises

Table 5 repeats the main regression results (see Table 2) but for positive and negative surprises, seperately. This table relates 60-day post-announcement cumulative abnormal returns ($CAR[2,61]$) and 3-day announcement abnormal returns (CAR[-1,1]) to earnings-surprise deciles relative to it's median value (ES-Median ES=-4.5 most negative; ES-Median ES=4.5 most positive), as well as it's absolute value , |ES-Median ES|, interacted with analyst consensus recommendations for the firm before any announcements are made (Buy-Hold/Sell=1 if the recommendation is Buy; Buy -Hold/Sell=-1 if the recommendation is Hold/Sell). Positive and negative surprises are surprises which are above the median surprise decile (i.e., $ES - MedianES > 0$) and below the median surprise decile, respectively. The dependent variable $CAR[t,T]$ is measured relative to size- and book-to-market–matched portfolios. See Table 2 for more information on this regression specification and the control variables used. Standard errors are heteroskedasticity-robust and clustered by announcement date. All variables are winsorized at the 0.5% and 99.5% levels. *, **, *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	Negative Surprises		Positive Surprises	
	(1)	(2)	(3)	(4)
	CAR[2,61]	CAR[-1,1]	CAR[2,61]	CAR[-1,1]
[Buy - Hold/Sell]	0.19*	-0.01	0.23**	0.08**
	(0.11)	(0.04)	(0.10)	(0.04)
ES-Median ES	0.69**	0.69***	0.40	0.40***
	(0.31)	(0.09)	(0.30)	(0.09)
|ES-Median ES| x [Buy - Hold/Sell]	-0.16***	0.03**	-0.16***	-0.02*
	(0.04)	(0.01)	(0.04)	(0.01)
Controls Interacted with, ES-Median ES	X	X	X	X
Constant	1.09	1.33***	0.79	0.82***
	(0.91)	(0.27)	(0.82)	(0.26)
Observations	131,068	131,068	130,962	130,962
R^2	1.2%	29.9%	1.1%	32.4%

Overall, separating positive and negative surprises reinforce our main conclusion. The consistent theme is that prior-inconsistent news generally elicits a weaker immediate response, leading to a stronger PEAD.

D. Varying the Degree of Inevstor Optimism

In the main analysis, firms are categorized into two binry groups: those with a consensus median rating $\leq$ 2 as Buy and those above 2 as Hold/Sell. A natural question arises: do the results strengthen when varying degree of analyst optimism or pessimism?

Table 6:
Varying the Degree of Inevstor Optimism

Table 6 reports regressions relating 60-day post-announcement cumulative abnormal returns ($CAR[2,61]$) and 3-day announcement abnormal returns (CAR[-1,1]) to earnings-surprise deciles relative to it's median value (ES-Median ES=-4.5 most negative; ES-Median ES=4.5 most positive), as well as it's absolute value , |ES-Median ES|, interacted with analyst IBES rankings for the firm before any announcements are made [IBES Ranking - Median IBES Ranking]. IBES rankings corresponds to re-ranked IBES consensus analyst ratings from the IBES summary file so that higher ranking values correspond to stronger consensus ratings. See Section 5.4 for more detail on the contstruction of this variable. Control variables include deciles of size, book-to-market, and momentum along with return volatility, reporting lag, analyst coverage, earnings persistence, the number of earnings announcements, institutional ownership, bid-ask spread, 20-day cumulative abnormal returns before the announcemnt date and day-of-week, quarter, and year dummies. All controls are interacted with ES-Median ES. Variable definitions appear in Section 3. Standard errors are heteroskedasticity-robust and clustered by announcement date. All variables are winsorized at the 0.5% and 99.5% levels. *, **, *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	(1) CAR[2,61]	(2) CAR[2,61]	(3) CAR[2,61]	(4) CAR[-1,1]	(5) CAR[-1,1]
[IBES Ranking - Median IBES Ranking]	-0.10	-0.06	1.34*	-0.11***	-0.69***
	(0.13)	(0.12)	(0.79)	(0.04)	(0.26)
ES - Median ES	0.31***	0.51***	0.55***	0.46***	0.51***
	(0.02)	(0.10)	(0.12)	(0.03)	(0.04)
|ES - Median ES| x [IBES Ranking - Median IBES Ranking]	-0.10**	-0.11**	-0.46**	0.06***	0.18***
	(0.04)	(0.04)	(0.20)	(0.01)	(0.06)
Controls Interacted with, ES-Median ES		X	X	X	X
Top & Bottom 2 Groups			X		X
Constant	0.12**	0.43	0.34	0.58***	0.54***
	(0.06)	(0.39)	(0.55)	(0.12)	(0.18)
Observations	262,030	262,030	109,753	262,030	109,753
R^2	0.2%	1.0%	2.1%	35.5%	38.1%

Two extreme interpretations support this possibility. First, stronger analyst ratings might indicate stronger priors, amplifying confirmation bias. Second, a firm's price may reflect the weighted beliefs of optimistic and pessimistic investors, with the overall strength of confirmation bias increasing with the absolute difference between the proportions of optimists (μ_o) and pessimists (μ_p) (i.e., $|\mu_o - \mu_p|$). Both interpretations motivate the regression model:

$$\begin{aligned} \text{CAR}[t,\tau]_i = {} & a_0 + a_1(\text{ES}_i - \text{Median ES}) + a_2[\text{IBES Ranking}_i - \text{Median IBES Ranking}_i] \\ & + a_3|\text{ES}_i - \text{Median ES}| \times [\text{IBES Ranking}_i - \text{Median IBES Ranking}_i] \\ & + \sum_{i=1}^{n} b_i X_i + \sum_i c_i \left[X_i \times (\text{ES}_i - \text{Median ES})\right] + \epsilon_i \end{aligned} \tag{17}$$

IBES Ranking represents re-ranked IBES consensus median analyst ratings, where higher values indicate stronger ratings. I transform the original IBES consensus ratings into seven categories to better reflect the uneven distribution of ratings: {1: 4, 1.5: 3.5, 2: 3, 2.5: 2.5, 3: 2, $\geq$4: 1.5}. This adjustment accounts for the fact that "Buy" or "Outperform" ratings (54% of observations) are split into three levels of optimism, "Neutral" (rating = 2.5) serves as the median, and the remaining ratings (35%) are divided into three levels of pessimism.

Table 6 presents the results. Columns (1)-(3) examine 60-day post-announcement returns (CAR$[2, 61]$), while Columns (4)-(5) analyze 3-day announcement-window returns (CAR$[-1, 1]$). For post-announcement returns, the interaction term (a_3) is negative and significant, suggesting that greater optimism or pessimism amplifies the drift for prior-inconsistent news. For announcement-window returns, the interaction term is significantly positive, indicating stronger immediate responses when surprises align with analyst priors, particularly at extreme levels of optimism or pessimism. Though standard errors increase due to finer IBES groupings, the results both indicate the degree of confirmation bias increases the more extreme the analyst consensus rating.

VI Limits to Arbitrage

Despite the mispricings documented in Sections 4 and 5, several constraints may prevent arbitrageurs from fully correcting these inefficiencies. Two primary limitations are shorting constraints and transaction costs. This section examines their roles and implications for the PEAD.

A. Shorting Costs

Shorting costs can significantly hinder arbitrage, especially for negative earnings surprises, as they restrict the ability of arbitrageurs to drive down overpriced stocks. Following Daniel, Klos, and Rottke (2023), I classify stocks as *short-sale constrained* if they fall in the top tercile of short-interest ratio (indicating high shorting demand) and the bottom tercile of institutional ownership (indicating limited share availability for borrowing). Unconstrained stocks fall outside these thresholds.[11] Short interest ratio is computed as short interest divided by shares outstanding from CRSP, with

[11] If short-interest data is missing ($\sim$ 8.5% of observations), I classify the stock as unconstrained.

Table 7:
PEAD and Shorting Constraints

This table repeats the post-announcement abnormal return regression analysis of Table 2 for different sub-samples. In colums (1)-(2) and columns (3)-(4) I consisder stocks which are unconstrained and short-sales constrained, respectively. Stocks are classified as short-sale constrained if they are in the top tercile of the short-interest ratio and the bottom tercile of institutional ownership (Daniel, Klos, and Rottke, 2023); otherwise stocks are classified as unconstrained. Short-interest ratio is calculated as short interest scaled by shares outstanding from CRSP. In columns (1) and (3) I restrict the sample of stocks to those who experienced negative earnings surprises (i.e., ES-Median ES<0), and in columns (2) and (4) I restrict the sample of stocks to those who experienced positive earnings surprises (i.e., ES-Median ES>0). See Table 2 and Section 3 for more detail on the construction of the earnings surprise decile (ES), Buy and Hold/Sell variables, as well as the control variables. *, **, *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	Unconstrained		**Short-Sale constrained**	
	Negative Surprises	Positive Surprises	Negative Surprises	Positive Surprises
	(1)	(2)	(3)	(4)
	CAR[2,61]	CAR[2,61]	CAR[2,61]	CAR[2,61]
[Buy-Hold/Sell]	0.12	0.22**	0.40	0.06
	(0.11)	(0.11)	(0.51)	(0.51)
ES-Median ES	0.53	0.46	2.38**	0.61
	(0.32)	(0.31)	(1.02)	(1.13)
|ES-Median ES| x [Buy - Hold/Sell]	-0.12***	-0.14***	-0.35**	-0.19
	(0.05)	(0.04)	(0.17)	(0.17)
Controls Interacted with, ES-Median ES	X	X	X	X
Constant	0.71	0.95	6.54**	-1.41
	(0.94)	(0.85)	(3.18)	(3.33)
Observations	117,096	119,011	13,972	11,951
R^2	1.2%	1.2%	2.8%	2.9%

short interest data sourced from Compustat (April 1980-May 1988 and post-June 2003) and directly from NYSE, AMEX, and NASDAQ (June 1988-June 2003).[12]

Prior research links low institutional ownership (IO) to PEAD (Bartov, Radhakrishnan, and Krinsky, 2000; Doyle, Lundholm, and Soliman, 2006; Chen, Huang, and Jiang, 2017), but the underlying cause remains unclear. Low IO may proxy for higher shorting costs or reflect biases among non-institutional investors who process earnings information less efficiently. By constructing a clean measure of short-sale constraints, I help distinguish the impact of shorting costs from investor behavior.

I hypothesize that negative surprises in short-sale constrained stocks experience a stronger downward drift in abnormal returns and, consistent with research by Daniel, Klos, and Rottke

[12]I thank Kent Daniel for providing the short-interest data.

(2023), this effect is most pronounced among stocks dominated by optimistic investors.[13] In contrast, positive surprises should be less affected, as the resulting undervaluation encourages arbitrageurs to go long, eliminating the need to incur shorting costs.

Table 7 provides some support for this hypothesis. Among short-sale constrained stocks, PEAD is stronger for negative surprises, and even stronger when optimists dominate. The slope on the unconditional term, ES-Median ES, is 2.38 for stocks which are short-sale constrained compared to 0.53 for unconstrained stocks indicating stronger negative drift when stocks are constrained (the difference is statistically significant - see Table A.3). Additionally, the slope on the interaction term, ES-Median ES $\times$ [Buy-Hold/Sell], is -0.35 for stocks which are short-sale constrained compared to -0.12 for unconstrained (although the difference is not statistically significant - see Table A.3). Importantly, PEAD still persists in unconstrained stocks, suggesting that shorting constraints alone do not fully explain the mispricings.

B. Transaction Costs

Prior research indicates that transaction costs may represent another barrier to exploiting PEAD (Ng, Rusticus, and Verdi, 2008; Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009). To distinguish direct transaction costs (e.g., bid-ask spreads) from shorting costs, this analysis focuses on unconstrained stocks. Specifically, firms are sorted into terciles based on their bid-ask spreads at the end of the prior quarter, using NYSE breakpoints to define low-, medium-, and high- bid-ask spread groups and only unconstrained firms are analyzed.

Table 8 shows that, unconditionally, PEAD increases monotonically with bid-ask spreads and the difference between the High BA spread group and the rest is statistically significant (see Table A.4), consistent with prior work (e.g, Ng, Rusticus, and Verdi, 2008). However, conditioning on the prior-consistency of surprises, I find there is no significant relationship between bid-ask spreads and PEAD. Concretely, I find that the slope on | ES-Median ES|$\times$ [Buy-Hold/Sell] among the lowest two teciles are not significantly different to the slope on the highest tercile (see Table A.4 for

[13] Concretely, per Daniel, Klos, and Rottke (2023), high shorting costs allow optimists to take control of these stocks severely limiting abirtrageurs ability to correct mispricings.

Table 8:
PEAD and Bid-Ask Spreads

This table extends the post-announcement abnormal return regression analysis from Table 2 to different sub-samples. All columns focus on stocks that are not short-sale constrained (i.e., unconstrained) to isolate the impact of bid-ask spreads from shorting costs. For the definition of short-sale constrained stocks, see Table 7. Columns (1)–(3) and (4)–(6) analyze stocks from the full sample period and the post-2004 period, respectively. Within each group, columns (1)–(3) (and columns (4)–(6)) restrict the analysis to stocks in the bottom tercile (Low BA), middle tercile (Med BA), and top tercile (High BA) of bid-ask spreads, based on NYSE breakpoints. Control variables include momentum, earnings persistence, numbers of announcements and reporting lag, as well as day-of-week and year-quarter dummies. For details on the construction of the earnings surprise decile (ES), Buy, Hold/Sell, and control variables, refer to Table 2 and Section 3. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Unconstrained: Full-Sample			**Unconstrained: Post-2004**		
	Low BA	Med BA	High BA	Low BA	Med BA	High BA
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[2,61]	CAR[2,61]	CAR[2,61]	CAR[2,61]	CAR[2,61]	CAR[2,61]
[Buy-Hold/Sell]	0.02	-0.14	0.15	0.09	0.03	0.21
	(0.11)	(0.13)	(0.16)	(0.11)	(0.14)	(0.18)
ES-Median ES	-0.02	0.10	0.46***	0.13	0.28**	0.45***
	(0.13)	(0.12)	(0.10)	(0.14)	(0.14)	(0.12)
|ES-Median ES| x [Buy - Hold/Sell]	-0.13***	-0.02	-0.09*	-0.11**	-0.04	-0.13**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Controls Interacted with, ES-Median ES	X	X	X	X	X	X
Constant	-0.06	-0.53*	-0.83**	0.42	0.03	-0.55
	(0.35)	(0.32)	(0.35)	(0.34)	(0.36)	(0.41)
Observations	74579	69991	91537	42974	45926	63934
R^2	0.8%	1.4%	1.6%	0.9%	0.9%	1.2%

slope difference estimates). Furthermore, these results are robust even after 2004, when average bid-ask spreads declined significantly from an average of 1.83% to only 0.28% (see Figure A.1).

Overall, my results suggest that while shorting constraints and transaction costs are barriers to arbitrage, they do not entirely account for the prior-consistency component of PEAD. This suggests that other factors - including noise-trader risk, systematic risk, and limited arbitrage capital - may also play significant roles in sustaining these inefficiencies.

VII PEAD is Not Dead

This section builds on Martineau (2021a), who documents a decline in PEAD over time. Using data through 2019, he finds that PEAD becomes insignificant for All-but-microcap stocks after

Table 9:
PEAD is Not Dead: Subsample Regression Analyses

Table 9 replicates Table 3, Panel A of Martineau (2021a) for different sub-samples. It reports regression coefficients for firms' 59-day post-announcement abnormal returns (CAR[2,60]) on the analyst earnings surprise decile rank (ES rank), including firm and year-quarter fixed effects. See Martineau (2021a) for details on variable construction. Panel A shows results for firms with non-missing recommendations from the IBES summary recommendations file. Panels B and C restrict the sample to prior-inconsistent and prior-consistent earnings surprises, respectively. I define a prior-inconsistent surprises as (i) a positive surprise accompanied by a pessimistic (Hold/Sell) consensus rating, or (ii) a negative surprise accompanied by an optimistic (Buy) rating. Prior-consistent surprises are defined analogously. See Section 3 for the definition of Buy and Hold/Sell ratings. Results are shown separately for all-but-microcap and microcap stocks, with microcaps defined as those with a market capitalization below the NYSE 20th percentile. Standard errors are clustered by firm and year-quarter. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: CAR[2,60]					
	(1)	(2)	(3)	(4)	(5)	(6)
	1994-2000	2001-2005	2006-2010	2011-2015	2016-2019	2020-2022
Panel A: Full Sample						
A1: All-but-microcap						
ES rank	0.30***	0.18***	0.00	0.03	-0.08**	0.22**
	(0.07)	(0.06)	(0.08)	(0.03)	(0.04)	(0.09)
A2: Microcap						
ES rank	0.34***	0.42***	0.31***	0.21***	0.12	0.23**
	(0.06)	(0.06)	(0.07)	(0.05)	(0.07)	(0.09)
Panel B: Prior-Inconsistent Surprises						
B1: All-but-microcap						
ES rank	0.40***	0.57***	0.26***	0.18**	0.13*	0.33***
	(0.06)	(0.09)	(0.07)	(0.06)	(0.06)	(0.12)
B2: Microcap						
ES rank	0.60***	0.76***	0.52***	0.48***	0.35**	0.56**
	(0.10)	(0.13)	(0.09)	(0.11)	(0.14)	(0.24)
Panel C: Prior-Consistent Surprises						
C1: All-but-microcap						
ES rank	0.15	-0.16	-0.26	-0.06	-0.33***	-0.06
	(0.11)	(0.10)	(0.17)	(0.09)	(0.09)	(0.14)
C2: Microcap						
ES rank	0.26***	0.39**	0.11	0.12	-0.01	0.15
	(0.09)	(0.16)	(0.12)	(0.09)	(0.15)	(0.23)

2006 and for Microcap stocks after 2016.[14] I extend this analysis and show that (1) PEAD reemerges in the out of sample period (2020-2022) and (2) for prior-inconsistent surprises, PEAD has been robustly alive since at least 1994 in both Microcap and All-but-microcap groups.

To ensure comparability with Martineau (2021a), I estimate the following regression:

$$\text{CAR}[2,60]_{i,j} = b_0 + b_1 \text{ES Rank}_{i,j} + \alpha_i + \alpha_q + \epsilon_{i,j} \tag{18}$$

where CAR$[2,60]i,j$ corresponds to stock i's cumulative abnormal return following announcement j, ES Ranki,j is the earnings surprise decile rank, and α_i and α_q are firm and year-quarter fixed effects, respectively.

Table 9 presents subsample regression results replicating Table 3, Panel A of Martineau (2021a). Panel A confirms Martineau's main conclusion: PEAD is statistically insignificant for All-but-Microcap stocks after 2006 and for Microcap stocks after 2016. However, in the out-of-sample period (2020–2022), PEAD returns, with significantly positive coefficients across both stock groups, challenging the notion that PEAD has disappeared. Next, I test whether this time variation is driven by an overlooked factor: the consistency of earnings surprises with investors' prior beliefs. Panel B of Table 9 shows that PEAD remains consistently strong for prior-inconsistent surprises across all periods, with statistically significant coefficients from 1994 to 2022 for both All-but-Microcap and Microcap stocks. In contrast, Panel C reveals that prior-consistent surprises exhibit little to no PEAD: for All-but-Microcap stocks, the anomaly has been largely absent since 1994, while for Microcap stocks, it disappears entirely after 2006. Overall, these results underscore the nuanced nature of the PEAD: it remains robust for prior-inconsistent surprises, but the evidence suggests it has effectively disappeared for prior-consistent ones since 2006.

[14]Microcap stocks are defined as those with market capitalizations below the NYSE 20th percentile.

VIII Distinguishing Between Biases

A. Psychology Literature and Confirmation Bias

Many psychological biases could explain why investors respond differently to positive versus negative earnings surprises depending on analysts' recommendations. For example, representativeness (Kahneman and Tversky, 1972, 1973) implies that when investors already view a firm favorably, they might view good news as represenative of a firm's potential and bad news as unrepresentative. Anchoring (Rottenstreich and Tversky, 1997; Tversky and Kahneman, 1974) could lead investors to cling to initial optimistic beliefs, underreacting to negative news. Since Buy stocks often have a history of strong performance, overconfidence (Langer and Roth, 1975; Fischhoff, 1982) might causes investors to attribute positive outcomes to personal skill, making them overweight positive signals and dismiss negative signals as in Daniel, Hirshleifer, and Subrahmanyam (1998). While any of these biases could help explain the observed asymmetric responses, confirmation bias (Lord, Ross, and Lepper, 1979; Nickerson, 1998) stands out for two key reasons. First, its attentional nature directly aligns with PEAD's established link to limited attention: investors pay more attention to belief-consistent information and pay less attention to disconfirming signals. Second, it uniquely predicts polarization in ambiguous settings, where individuals interpret the same evidence in ways that reinforce their prior beliefs.

In a seminal study, Lord, Ross, and Lepper (1979) demonstrated polarization among attitudes toward the death penalty. Participants with opposing initial stances on the death penalty were shown two purpoted studies (one positive and one negative) relating to the death penalty. Remarkably, each group became more convinced of their initial stance after reviewing the same information, leading to polarization. Pouget, Sauvagnat, and Villeneuve (2017) subsequently demonstrated polarization among analysts forecast revisions by showing that, when a new earnings surprise contradicted their prior outlook, analysts were significantly more likely to revise their forecasts in the opposite direction. Building on that idea, in the subsequent section, I incorporate analyst-level recommendations (Buy vs. Hold/Sell) as a measure of investors' priors and find a similar polarization effect: analysts overwhelmingly adjust their forecasts in ways that confirm

their initial stance. This pattern provides direct evidence that confirmation bias is the primary driver of the observed asymmetric responses.

B. Confirmation Bias: Polarization in Analyst Revisions

I obtain quarterly earnings announcements and firm-level accounting data from the CRSP-Compustat merged database and analysts' annual earnings forecasts (one- or two-fiscal periods ahead) from the Institutional Brokers' Estimates System (IBES) database (available from 1982). I merge this with the IBES detailed recommendations file, which contains individual analyst recommendations (available from 1994). I also exclude stocks with prices below \$5 and adjust earnings forecasts for stock splits using CRSP's shares outstanding data. Since individual IBES recommendations are updated less frequently than earnings forecasts (Ljungqvist, Marston, and Wilhelm Jr, 2006), I fill in missing recommendations with the most recent one from the same fiscal year, if available.[15]

Following Pouget, Sauvagnat, and Villeneuve (2017), I measure earnings surprises using the standardized unexpected earnings (SUE) metric:

$$\text{SUE} = \frac{E_{i,Q} - E_{i,Q-4} - \mu_{i,Q}}{\sigma_{i,Q}}, \tag{19}$$

where $E_{i,Q}$ is firm i's quarterly earnings per share (EPS) in year-quarter Q, $E_{i,Q-4}$ is EPS from four quarters prior, and $\mu_{i,Q}$ and $\sigma_{i,Q}$ are the mean and standard deviation of the past eight quarters' one-year EPS changes. As in Section 3, an analyst's prior is classified as a Buy if their rating is ≤ 2 and Hold/Sell otherwise. Analyst j's forecast revision is defined as their one fiscal-year (or, if missing, two fiscal-year) forecast change for firm i between the end of quarter $Q-1$ and quarter

[15] Results are robust to using the original recommendation or extending the lookback window to two years.

Q. To ensure meaningful updates, zero revisions are excluded. To test for polarization in analyst forecasts, I estimate the following linear probability model:

$$\begin{aligned}
&\text{Same-Direction-Revision}_{i,j,Q} = a_0 + a_1 \text{SUE Sign Change}_{i,(Q,Q-1)} + a_2 |\text{SUE}_{i,Q}| \\
&+ a_3 (\text{Prior-Consistent SUE}_{i,Q} - \text{Prior-Inconsistent SUE}_{i,Q}) \\
&+ a_4 |\text{SUE}_{i,Q}| \times (\text{Prior-Consistent SUE}_{i,Q} - \text{Prior-Inconsistent SUE}_{i,Q}) \\
&+ \gamma \text{Controls}_{i,j,Q} + \delta_Q + \eta_j + \epsilon_{i,j,Q}
\end{aligned} \tag{20}$$

where Same-Direction-Revision is a dummy equal to 1 if analyst j revises their forecast in the same direction as the earnings surprise. SUE Sign Change equals 1 if the firm's earnings surprise changes sign between Q and $Q-1$. Prior-Consistent SUE equals 1 if the surprise is positive and the analyst has a Buy rating, or if the surprise is negative and the analyst has a Hold/Sell rating. Prior-Inconsistent SUE is defined analogously. Controls include the number of analysts, log market capitalization, log book-to-market ratio, return volatility, and return on assets (ROA, defined as operating income after depreciation divided by total assets at the fiscal year-end). Other variables are defined in Section 3.

Figure 6 shows the relationship between earnings surprise magnitude (SUE deciles on the x-axis) and the likelihood of a same-direction revision. The pattern follows a U-shape: extreme surprises, whether positive or negative, are more likely to elicit revisions in the same direction, as clearer news prompts stronger responses. Splitting the sample by analysts' priors (Buy vs. Hold/Sell) reveals shifts consistent with confirmation bias. Buy analysts are more likely to revise upward after positive surprises but less likely to revise downward after negative surprises, reinforcing prior optimism and creating polarization.

Table 10 presents the regression results. The coefficient on SUE Sign Change$_{i,(Q,Q-1)}$ (a_1) is negative and significant, consistent with Pouget, Sauvagnat, and Villeneuve (2017), who argue that a prior positive surprise fosters optimism, making a subsequent negative surprise less likely to prompt a downward revision (and vice-versa). The coefficient on a_3 is positive and significant, confirming that analysts revise forecasts in the direction of surprises when they align with their prior rating but are significantly less likely to do so when surprises contradict their priors. Inter-

Figure 6:
Polarization in Analyst Earnings Forecast Revisions

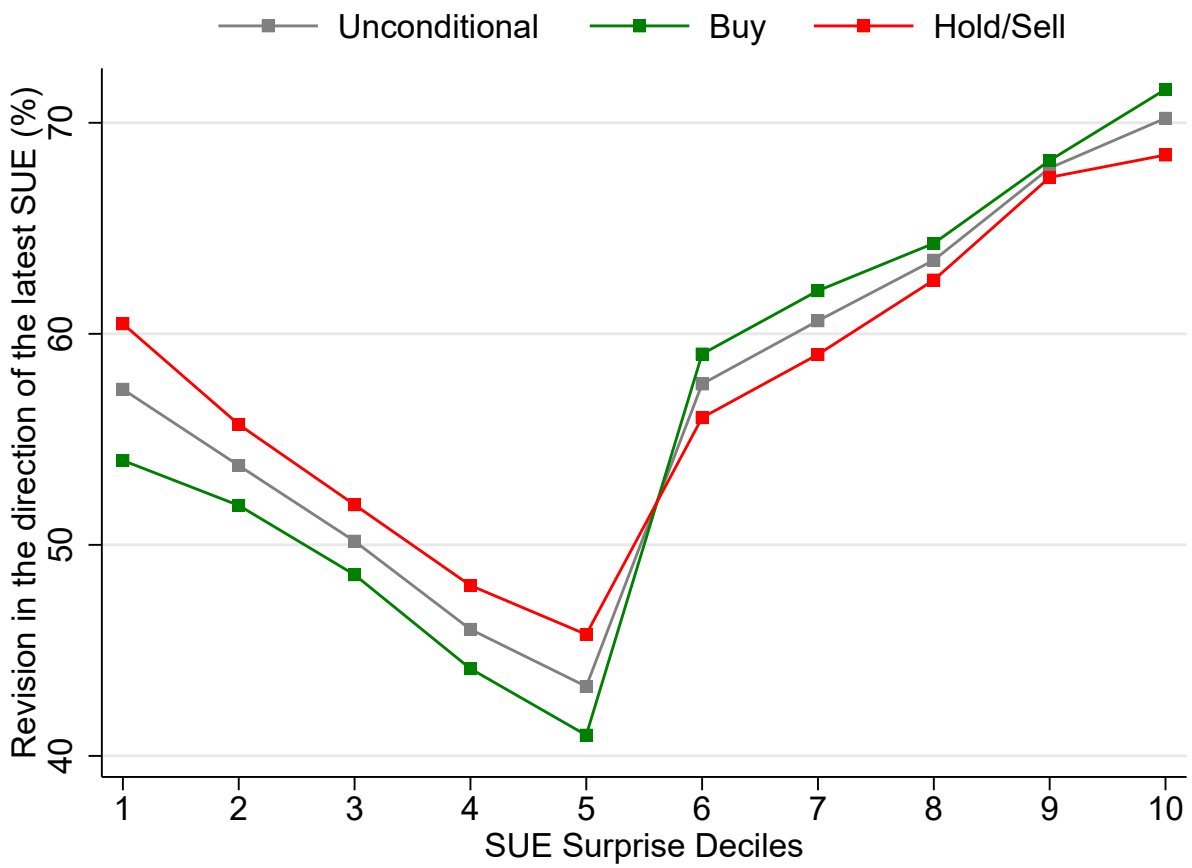


Figure 6 displays the percentage of analysts who revise their annual earnings forecasts between end of quarters Q-1 and @ in the same direction as the standardized unexpected earnings measure (SUE) in quarter Q. SUE is calculated as $E_{i,Q} - E_{i,Q-4} - \mu_{i,Q}) \ / \ \sigma_{i,Q}$, where $E_{i,Q}$ is the quarterly earnings per share for firm i in year-quarter Q, $E_{i,Q-4}$ is quarterly earnings per share four quarters ago, and $\mu_{i,Q}$ and $\sigma_{i,Q}$ are the mean and standard deviation, respectively, of the one-year change in quarterly earnings per share $\left(E_{i,Q} - E_{i,Q-4}\right)$ over the previous eight quarters. The figure includes results for analysts unconditionally ("Unconditional"), analysts with a "Buy" rating, and analysts with a "Hold/Sell" rating. Analysts are categorized as having a "Buy" rating if their rating at the end of the prior quarter is less than or equal to 2, and as "Hold/Sell" otherwise. Additional information on analyst ratings is provided in Section 8.

estingly, a_4 is insignificant, possibly due to offsetting forces. For example, smaller surprises may be less salient, reducing confirmation bias, but precisely because the surprise is close to zero, less of a "mind-change" is needed for analysts to revise their forecast in the opposite direction.

Table 10:
Polarization in Analyst Forecast Revisions: Regression Analysis

This Table estimates from a linear probability model where the dependent variable is a dummy (in %) indicating whether an analyst's annual earnings forecast revision for a given stock made between the end of quarter $Q-1$ and Q quarterly, has the same sign as the most recent standardized unexpected earnings (SUE) within quarter Q. SUE Sign Change (Q,Q-1) is a dummy that equals 1 if there is a change in the sign of SUE between quarters $Q-1$ and Q. [Prior-Consistent SUE − Prior-Inconsistent SUE] is an indicator taking the value 1 if the sign of SUE aligns with the analyst's prior rating (*Buy* for positive SUE, *Hold/Sell* for negative SUE) and -1 otherwise. |SUE| is the absolute value of the standardized unexpected earnings. Controls include # *Analysts*, (log) *size*, the (log) BM ratio, *Volatility* and return on assets (*ROA*). ROA is defined as operating income after depreciation over total assets computed at the end of the current fiscal year and all other variables are defined as in 3. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Revision in the direction of the latest SUE (%)			
	(1)	(2)	(3)	(4)
SUE Sign Change (Q,Q-1)	-1.028***		-0.954***	-0.695**
	(0.281)		(0.281)	(0.292)
[Prior-Consistent SUE - Prior-Inconsistent SUE]		1.820***	1.814***	1.695***
		(0.215)	(0.215)	(0.220)
|SUE|	7.160***	7.172***	7.087***	6.676***
	(0.218)	(0.217)	(0.218)	(0.227)
|SUE| x [Prior-Consistent SUE - Prior-Inconsistent SUE]		0.168	0.165	0.157
		(0.213)	(0.213)	(0.218)
Controls	X	X	X	X
Constant	52.890***	52.496***	52.890***	51.339***
	(0.821)	(0.812)	(0.820)	(1.234)
Observations	151,096	151,096	151,096	151,096
R^2	7.3%	7.4%	7.4%	14.2%
Year-Quarter FE	yes	yes	yes	yes
Analyst FE	yes	yes	yes	yes
Stock FE				yes

These findings reinforce the conclusions of Lord, Ross, and Lepper (1979); Pouget, Sauvagnat, and Villeneuve (2017) by demonstrating polarization in analyst forecasts using analyst-level priors. Since polarization in the face of ambiguous evidence is a defining feature of confirmation bias it provides evidence that confirmation bias - rather than alternative psychological biases - drives the asymmetric responses to earnings news.

IX Conclusion

This paper provides evidence that confirmation bias plays a crucial role in the PEAD. While prior work attributes the PEAD to limited attention, I show this explanation is incomplete, and that, selective attention to belief-consistent surprises helps resolve the anomaly. Concretely, using analysts' recommendations as a proxy for investor priors, I demonstrate that the immediate reaction to prior-inconsistent surprises are weaker, but the resulting PEAD is more than double.

The implications for future research are stark. First, understanding investors' priors is key to understanding asset price movements as investors process information through the lens of their priors. Second, if investors' priors are heterogeneous then it suggests asset pricing models may need to account for this heterogeneity (McCarthy and Hillenbrand, 2021). Future work should explore how investors' priors evolve and interact with other biases to refine models of investor behavior.

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APPENDIX

I Appendix

A. Model Simulation

This appendix outlines the simulation process used to generate Figure 1. The simulation follows the theoretical framework described in Section 2. Specifically, Panel A is constructed using Equation (13) for announcement returns:

$$\text{Announcement Response}_i = \beta w_r Surprise_i + \alpha w_r |Surprise_i| \left[\mathbf{1}_{\{\delta_{i,prior}>0\}} - \mathbf{1}_{\{\delta_{i,prior}<0\}}\right] \quad \text{(A.1)}$$

where Surprise represents the signal surprise (x) scaled by the initial price, which corresponds to the x-axis in Figure 1 Panels A and B. Similarly, Panel B is constructed using Equation (13) for abnormal returns:

$$\text{Abormal Return}_i = [1-\beta] w_r Surprise_i - \alpha w_r |Surprise_i| \left[\mathbf{1}_{\{\delta_{i,prior}>0\}} - \mathbf{1}_{\{\delta_{i,prior}<0\}}\right] \quad \text{(A.2)}$$

To generate the graphs, the following parameter values are used for each agent:

- *Rational agent:* $w_r = 1, \beta = 1, \alpha = 0$
- *Limited attention agent:* $w_r = 1, \beta = 0.7, \alpha = 0$
- *Optimistic agent:* $w_r = 1, \beta = 0.7, \alpha = 0.125$ and $\delta_{prior} > 0$
- *Pessimistic agent:* $w_r = 1, \beta = 0.7, \alpha = 0.125$ and $\delta_{prior} < 0$

The graph is constructed by plotting the Announcement Response (Panel A) and the Abnormal Return (Panel B) on the y-axis, against surprise values on the x-axis, which range from -5 to 5 in 0.5 intervals for each of the agents.

B. Tables

Table A.1:
Analyst 1yr Revisions to Earnings Surprises

This table reports coefficients from regressions based on equation (14) using different dependent variables. Column (1) uses analyst 1-year revisions occurring from one calendar month before the announcement to two trading days before the announcement (REV[-1m,0m]). Columns (2) and (3) use analyst 1-year revisions from one trading day before the announcement to three months after (REV[0m,3m]) and six months after (REV[0m,6m]), respectively. Columns (4) and (5) use 20-day pre-announcement abnormal returns (CAR[-21,-2]) and 60-day post-announcement abnormal returns (CAR[2,61]), respectively. Analyst 1-year revisions for firm i in quarter q between months m and $t+m$ are calculated as Analyst 1yr Revisions$_{i,m} = \frac{\mathbb{F}_{i,t+m}[e_{1yr}] - \mathbb{F}_{i,m}[e_{1yr}]}{p_{i,q-1}}$ where $\mathbb{F}_{i,m}[e_{1yr}]$ is the IBES analyst median 1-year forecast for firm i in month m, obtained from the IBES summary file. IBES 1-year forecasts are constructed following McCarthy and Hillenbrand (2021). All regressions include the same set of control variables as in Table 2, except for column (4), which excludes the 20-day pre-announcement abnormal returns as a control. See Table 2 for details on control variables and variable definitions. Standard errors are heteroskedasticity-robust and clustered by announcement date. All variables are winsorized at the 0.5% and 99.5% levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Analyst 1yr revisions			Pre- and post-announcement returns	
	(1)	(2)	(3)	(4)	(5)
	REV[-1m,0m]	REV[0m,3m]	REV[0m,6m]	CAR[-21,-2]	CAR[2,61]
Panel A: Full-Sample					
[Buy - Hold/Sell]	0.03***	0.04***	0.08***	0.35***	0.08
	(0.00)	(0.01)	(0.01)	(0.05)	(0.08)
ES-Median ES	-0.01**	0.13***	0.15***	1.10***	0.51***
	(0.00)	(0.01)	(0.02)	(0.01)	(0.10)
ES-Median ES x [Buy - Hold/Sell]	-0.01***	-0.01***	-0.04***	-0.15***	-0.12***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.03)
Constant	0.02	-0.18***	-0.31***	2.33***	0.36
	(0.01)	(0.04)	(0.05)	(0.28)	(0.39)
Observations	262,030	262,030	262,030	262,030	262,030
Panel B: Non Missing Analyst 1yr Revisions					
[Buy - Hold/Sell]	0.03***	0.05***	0.09***	0.36***	0.01
	(0.00)	(0.01)	(0.01)	(0.05)	(0.08)
ES-Median ES	-0.01*	0.10***	0.13***	1.12***	0.43***
	(0.01)	(0.02)	(0.03)	(0.01)	(0.11)
ES-Median ES x [Buy - Hold/Sell]	-0.01***	-0.02***	-0.05***	-0.15***	-0.09***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.03)
Constant	0.02	-0.25***	-0.46***	2.55***	0.31
	(0.02)	(0.04)	(0.06)	(0.30)	(0.41)
Observations	224,095	224,095	224,095	224,095	224,095

Table A.2:
Three Post-Earnings Announcement Drift (PEAD) Long-Short Strategies: Risk-Adjusted Portfolio Returns

Table A.2 reports average monthly abnormal returns and factor loadings for three PEAD strategies: (1) the Original PEAD strategy, (2) the New PEAD Strategy and (3) the Anti-PEAD Strategy. Refer to Figure 4 for more detail on the construction of these strategies. For each strategy, the table reports the risk-adjusted alphas and factor loadings from CAPM, Fama-French (1993) three-factor, and Carhart (1997) four-factor models, respectively. The sample spans 1994m1 to 2022m12. Standard errors, shown in parentheses, are adjusted for heteroskedasticity. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Original PEAD Strategy			New PEAD Strategy			Anti-Pead Strategy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Positive -Negative			Positive (Hold/Sell) -Negative (Buy)			Positive (Buy) -Negative (Hold/Sell)	
Mkt-RF	-0.00	-0.00	0.05**	-0.06*	-0.02	-0.01	0.05	0.02	0.11***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)
SMB		-0.04	-0.05		-0.07	-0.08		0.00	-0.0
		(0.04)	(0.03)		(0.05)	(0.05)		(0.08)	(0.06)
HML		-0.07**	-0.02		0.29***	0.30***		-0.45***	-0.36***
		(0.04)	(0.04)		(0.05)	(0.05)		(0.06)	(0.06)
MOM			0.15***			0.05			0.24***
			(0.03)			(0.04)			(0.04)
α	0.69***	0.70***	0.59***	1.15***	1.08***	1.05***	0.20	0.30*	0.12
	(0.09)	(0.09)	(0.09)	(0.14)	(0.13)	(0.13)	(0.17)	(0.15)	(0.15)
Observations	345	345	345	345	345	345	345	345	345
R^2	0.0%	2.0%	16.6%	1.0%	16.7%	17.4%	0.6%	21.4%	32.3%

Table A.3:
PEAD and Shorting Constraints

This table repeats the results of Table 7 for negative and positive earnings surprises, seperately, by interacting all variables with an indicator if firms are short-sale constrained (SSC). Stocks are classified as short-sale constrained if they are in the top tercile of the short-interest ratio and the bottom tercile of institutional ownership (Daniel, Klos, and Rottke, 2023); otherwise stocks are classified unconstrained. Short-interest ratio is calculated as short interest scaled by shares outstanding from CRSP. In columns (1) and (2) we restricts the sample of stocks to those who experienced negative earnings surprises (i.e., ES-Median ES<0) and positive earnings surprises (i.e., ES-Median ES>0), respectively. See Table 8 for more detail on the construction of the earnings surprise decile (ES), Buy and Hold/Sell variables, as well as the control variables. *, **, *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	Negative Surprises	Positive Surprises
	(1)	(2)
	CAR[2,61]	CAR[2,61]
ES-Median ES	0.53	0.46
	(0.32)	(0.31)
ES-Median ES x SSC	1.85*	0.15
	(1.05)	(1.15)
|ES-Median ES| x [Buy - Hold/Sell]	-0.12***	-0.14***
	(0.05)	(0.04)
|ES-Median ES| x [Buy-Hold/Sell] x SSC	-0.22	-0.05
	(0.17)	(0.17)
[Buy - Hold/Sell]	0.12	0.22**
	(0.11)	(0.11)
SSC	-1.40	-6.64*
	(4.07)	(3.92)
[Buy-Hold/Sell] x SSC	0.28	-0.16
	(0.52)	(0.51)
Controls Interacted with, ES-Median ES and SSC	X	X
Constant	1.09	0.45
	(1.10)	(1.04)
Observations	131,068	130,962
R^2	1.5%	1.5%

Table A.4:
PEAD and Bid-Ask Spreads

This table repeats the results of Table 8 by interacting all variables with an indicator if firms are in the middle tercile (Med BA) and top tercile (High BA) of bid-ask spreads, based on NYSE breakpoints. All columns focus on stocks that are not short-sale constrained (i.e., unconstrained) to isolate the impact of bid-ask spreads from shorting costs. For the definition of short-sale constrained stocks, see Table 7. Columns (1) and (2) analyze stocks from the full sample period and the post-2004 period, respectively. Control variables include momentum, earnings persistence, numbers of announcements and reporting lag, as well as day-of-week and year-quarter dummies. All controls variables are interacted with the earnings surprise decile relative to the median decile (ES - Median ES), as well as medium- and top-tercile bid-ask spread indicators. For details on the construction of the earnings surprise decile (ES), Buy, Hold/Sell, and control variables, refer to Table 2 and Section 3. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Unconstrained: Full-Sample	**Unconstrained: Post-2004**
	(1)	(2)
	CAR[2,61]	CAR[2,61]
ES-Median ES	-0.02	0.13
	(0.13)	(0.14)
ES-Median ES x Med BA	0.12	0.15
	(0.18)	(0.19)
ES-Median ES x High BA	0.48***	0.33*
	(0.16)	(0.18)
ES-Median ES x [Buy - Hold/Sell]	-0.13***	-0.11**
	(0.05)	(0.05)
ES-Median ES x [Buy - Hold/Sell] x Med BA	0.12	0.08
	(0.07)	(0.08)
ES-Median ES x [Buy - Hold/Sell] x High BA	0.04	-0.02
	(0.07)	(0.08)
	(0.17)	(0.18)
Controls Interacted with, ES-Median ES, Med BA and High BA	X	X
Constant	0.25	0.35
	(0.73)	(0.64)
Observations	236,107	152,834
R^2	1.4%	1.1%

C. *Figures*

Figure A.1: Evolution of Bid-Ask Spreads

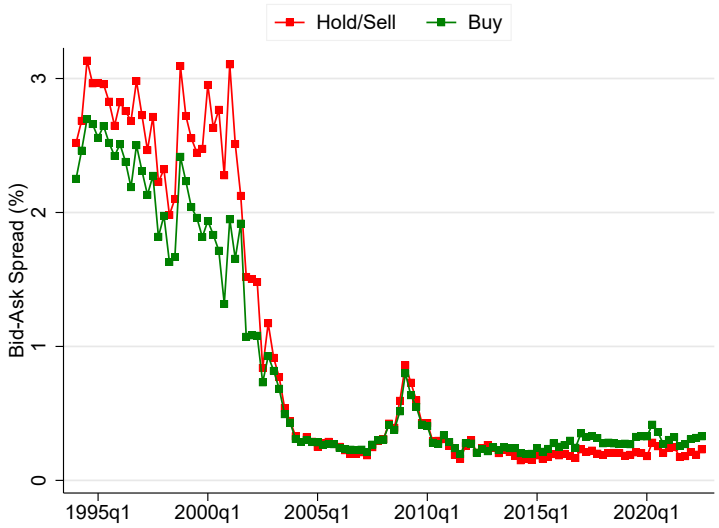


Figure A.1 plots the average bid-ask spread each quarter for firms with Buy and Hold/Sell recommendations. The bid-ask spread is calculated as the difference between the ask and bid prices, expressed as a percentage of their average, at the end of the most recent quarter. Firms are classified as Buy if their median consensus analyst recommendation from the IBES summary file is ≤ 2; otherwise, they are classified as Hold/Sell. The sample covers 1994:Q1 to 2022:Q4.