Disagreement and Bond PEAD*

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Abstract

This paper documents post-earnings announcement drift (PEAD) in corporate bond prices using transaction data. We find a counterintuitive relationship between the drift and trading volume: PEAD is more pronounced for more heavily traded bonds than for less frequently traded bonds. Across markets, PEAD is observed for credit default swaps but not for stocks. We explain these findings using a unified model that incorporates both debt and equity trading, where investors possess private information about the underlying firm's cash flows and may hold differing opinions. Our empirical evidence supports the model's prediction that payoff structures and investor disagreement account for the distinct price dynamics across asset classes.

JEL Classification: G12, G14, G13

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1 Introduction

Post-earnings announcement drift (PEAD) of stock returns has been one of the most widely debated research topics in the literature since Ball and Brown (1968). While a drift can be observed in any security issued by a firm, the role of payoff structure – downside risk and upside potential – in shaping the drift has not been explored. Empirically, a few papers study downside risk-driven corporate bond returns (e.g., Easton et al. 2009; Wei et al. 2012; Jenkins et al. 2016) around earnings announcements. However, the existence of bond PEAD, that is, the tendency of a bond price to move in the same direction as the news after the announcement, has not been documented based on factor investment analysis with no look-ahead bias. Moreover, the literature is silent on how PEAD differs across securities for a given firm.

Against this backdrop, we present empirical evidence of persistent PEAD in corporate bonds, using Enhanced TRACE data from 2002 through 2022 and a standard factor-investing framework. In our analysis, two robust empirical patterns emerge: First, in our sample period, PEAD exists for corporate bonds and credit default swaps (CDS) but not for stocks. Second, PEAD is more pronounced among bonds with higher proxies for investor disagreement and higher trading volume than others. We explain these findings based on a model featuring investor disagreement and different payoff structures between stocks and bonds.

Specifically, we present a model in which investors hold differing views on the value of a firm's cash flows and engage in trading both the firm's bonds and equities. The disagreement arises because they assess the firm based on their subjective interpretation of news while ignoring potential information contained in the trades of others (Harris and Raviv 1993; Kandel and Pearson 1995). When investors are collectively subject to this bias, heightened disagreement among them impedes the timely aggregation of their opinions, thus delaying the market's response to earnings announcements.

In our model, the magnitude of PEAD is determined by two factors. First, when investor disagreement intensifies, security prices are more likely to exhibit a price drift. Second, the payoff structure of securities also matters. Specifically, under reasonably calibrated model parameters, we show that bond prices are more likely to exhibit drift than equity prices. When investors' posterior beliefs about the firm's underlying cash flows are relatively pessimistic – corresponding to unfavorable public news or weak past returns – the firm is effectively insolvent, and expected equity returns remain close to zero, exhibiting neither drift nor reversal. In this region, however, bond returns can respond either positively or negatively to changes in posterior beliefs. By contrast, when posterior beliefs are sufficiently optimistic, bond returns converge to zero due to the capped payoff of debt, whereas equity returns can be unbounded, reflecting the convex nature of the equity payoff. Ultimately, price drift arises when the ex-ante expectation of security returns, taken over the distribution of posterior beliefs, is positive, which holds under our calibration.

Our disagreement-based theory also predicts that greater disagreement among investors leads to an increase in trading volume. As both optimistic and pessimistic investors become more confident in their own interpretations of the announcement, they tend to take more aggressive positions. Consequently, when prices exhibit drift, our model predicts a positive relationship between price drift and trading volume.

We next empirically examine the implications of our model. First, we show that PEAD exists in the corporate bond market. To this end, we sort bonds into portfolios according to their issuer's most recent earnings surprise and compute portfolio returns for the following month. We find that, on average, bonds in the highest earnings surprise decile have monthly returns 28 basis points (bps) higher than those in the lowest decile. This suggests an underreaction of bond prices to the firm's earnings announcements.

Figure 1 shows the price reactions to earnings announcements using the event study approach based on different measures of earnings surprises and subsamples. The figure reveals that the cumulative bond return slowly increases after positive earnings news and decreases after negative news up to 60 business days. Thus, the bond PEAD is visually evident, indicating that investors, on average, trade at the "wrong" prices following announcements.

Bond PEAD is not accounted for by risk exposures. To show this, we apply an 8-factor model that combines six factors of Fama and French (2018) and two bond factors of van Binsbergen, Nozawa, and Schwert (2025). We observe that the difference in risk-adjusted returns between the highest and lowest earnings surprise deciles is highly significant at 33 bps. The associated information ratio is 1.04 (annualized), which is higher than those of commonly used asset pricing factors, suggesting the economic significance of bond PEAD.

Second, we investigate PEAD in the CDS and equity markets to provide a comprehensive description of price drifts across various asset classes. As with the corporate bond market, we find a strong PEAD effect in the CDS market: A strategy that sells CDS protection on a firm after a positive earnings surprise and buys CDS protection after a negative surprise has an information ratio of 1.03, which is comparable to that of corporate bonds.

In contrast, we find no evidence of stock PEAD in our sample from 2002 to 2022. When we sort the stocks of bond-issuing firms into quintiles based on their earnings surprises, the return difference between high- and low-surprise firms is largely insignificant. There are two reasons for this insignificance: First, our sample period is matched to that of the bond sample and is thus relatively recent. Second, the bond issuers are large firms. Thus, we observe interesting differences in PEAD across assets: PEAD exists for bonds and CDS but not for stocks, which is consistent with the prediction of the model.

Third, we investigate more directly whether disagreement generates the bond PEAD. If this is true, then the profits from PEAD should be higher for bonds with a higher level of investor disagreement than for those with a lower level. To test this hypothesis, we use three proxies to measure disagreement: 1) dispersion in analysts' earnings forecasts (*DISP*), 2) idiosyncratic volatility of the issuer's stock returns, and 3) reaching-for-yield proxies (i.e., the difference between the yield of a bond and those of its peers with the same credit rating). We find evidence consistent with disagreement being a key driver of PEAD. Across all three proxies, a long-short PEAD strategy generates higher profits from bonds with greater disagreement than from those with lower disagreement. For instance, a PEAD strategy can deliver 52 bps of risk-adjusted profits for bonds in the highest quintile for *DISP*, but -13 bps for bonds in the lowest quintile.

Disagreement helps explain not only PEAD but also trading volume. We find that bonds with high disagreement exhibit higher trading volumes on earnings announcement days than those with low disagreement. This finding is intriguing because it contradicts the intuition that infrequent transactions of bonds would result in delayed price reactions to news. However, the positive relationship between volume and PEAD is exactly what our disagreement model predicts. Thus, investor disagreement accounts for both the price and the quantity of corporate bond transactions around earnings release dates.

To confirm that the correlation between disagreement and PEAD is not caused by other firm characteristics that influence both, we conduct a series of multivariate analyses to disentangle the relationship between disagreement and other variables. The set of exercises includes time-series factor regressions with eight factors, panel regressions with five sets of fixed effects and eleven firm- and bond-level characteristics, and non-parametric triple sort analysis. All results confirm that disagreement is not merely a proxy for other characteristics, such as uncertainty and liquidity.

Finally, we show that the magnitude of disagreement helps reconcile the empirical disparity between bond and stock PEAD. To this end, we present evidence that analyst forecast dispersion is greater for downside risk than for upside potential. This suggests that disagreement for bond and CDS cash flows, which are sensitive to downside risk, is greater than that for equity cash flows. In addition, the volume of bond trading on announcement days increases relative to normal days more than stock trading does. Therefore, the available evidence indicates that bond and CDS markets are more susceptible to investor disagreement than equity markets.

In summary, we contribute to the extant literature by documenting the reactions of bond prices and volumes to earnings announcements. These findings allow us to compare PEAD across asset classes and identify the best theory that explains PEAD in *all* three assets related to earnings surprises.

Our paper contributes to the literature on slow-moving prices in the bond market, including Hotchkiss and Ronen (2002), Gebhardt et al. (2005), Jostova et al. (2013), Chordia et al. (2017), Bali et al. (2021), and Li and Galvani (2021). Wei et al. (2012) examine PEAD over a 30-day period following earnings announcement dates in the corporate bond market. However, their findings cannot always be applied in actual trading strategies because they estimate price drifts by aggregating panel data. By contrast, we examine bond PEAD by using an approach that is not subject to look-ahead bias and provide a unified explanation for this phenomenon.

Our research is related to the rapidly growing literature that evaluates (and re-evaluates) the performance of factor investing in the corporate bond market (e.g., Bali et al. 2020; Dickerson et al. 2023; Kelly et al. 2023; Dick-Nielsen et al. 2023; van Binsbergen et al. 2025). These papers do not explicitly study PEAD. The exception is a follow-up paper by Dickerson, Julliard, and Mueller (2026a), who study the joint pricing kernel across stocks and corporate bonds and find that both equity PEAD and bond PEAD are important for pricing. A related strand of literature examines the role of information and market structure on bond prices, including studies by Bao et al. (2011), Feldhütter (2012), Bao et al. (2018), Bessembinder et al. (2018), Wei and Zhou (2016), Berndt and Zhu (2019), and Ivashchenko (2024). In contrast to these papers, we focus on disagreement as the key mechanism behind price drifts.

This study further contributes to previous research that documents PEAD in the stock market (e.g., Ball and Brown 1968; Bernard and Thomas 1989; Lee and Swaminathan 2000; Chordia and Shivakumar 2006; Luo et al. 2022) and on its source. Proposed explanations include arbitrage risk (Mendenhall 2004), the disposition effect (Frazzini 2006), limited attention (Hirshleifer and Teoh 2003; Ben-Rephael et al. 2017), illiquidity (Bhushan 1994; Ng et al. 2008; Chordia et al. 2009), and overconfidence (Liang 2003; Luo et al. 2021). We test these competing explanations comprehensively in the bond market and provide empirical evidence for investor disagreement as the key driver behind bond PEAD. Closely related to our disagreement explanation, Garfinkel and Sokobin (2006) show that increased disagreement around the earnings announcement date is associated with more positive stock returns. However, they acknowledge that their results do not explain negative price drifts following bad news.[1] Since both PEAD and momentum represent return continuation, our paper complements Hong and Stein (2007) and Verardo (2009) in providing evidence that disagreement contributes to return continuation.[2]

The remainder of the paper is organized as follows: in Section 2, we describe our data and provide evidence for PEAD; in Section 3, we present a unified model to explain our empirical findings; in Section 4, we empirically examine the link between PEAD and disagreement measures; and in Section 5, we offer concluding remarks.

[1]Although Anderson et al. (2007) argue that divergent opinions contribute to PEAD, their approach is not implementable in actual trading strategies and is largely confined to the short-period proprietary Nasdaq trading data.

[2]Papers that study the role of disagreement over asset prices include Chen et al. 2002; Diether et al. 2002; Goetzmann and Massa 2005; Avramov et al. 2009; Xiong and Yan 2009; Banerjee 2011; Yu 2011; Carlin et al. 2014; Atmaz and Basak 2018; Cookson and Niessner 2020; Buraschi et al. 2022; Golez and Goyenko 2022. However, few studies investigate the effect of disagreement risk on corporate bonds. Exceptions include Güntay and Hackbarth (2010); Buraschi et al. (2014); Gao et al. (2019).

2 Evidence of PEAD in the Bond and Stock Markets

2.1 Data

We use Enhanced TRACE data to obtain corporate bond prices from July 2002 to December 2022 and Mergent FISD to collect information on bond characteristics such as amount outstanding, credit rating,[3] and time to maturity.

Following Dick-Nielsen (2014), we clean the TRACE data, remove canceled transaction records, and adjust records that are subsequently corrected or reversed. Next, following the recent literature (e.g., Dickerson et al. 2023; Dick-Nielsen et al. 2023), we apply additional filters to eliminate (1) bonds that are not listed or traded in the U.S. public market; (2) bonds that are U.S. Government, private placements, mortgage-backed, asset-backed, agency-backed, or equity-linked;[4] (3) convertible bonds or bonds with a floating coupon rate or an odd frequency of coupon payments; (4) bonds that have less than one year to maturity; (5) bond transactions that are labeled as when-issued, locked-in, or have special sales conditions; (6) transaction records with volumes less than \$10,000; and (7) bonds that do not have a principal value of \$1,000. We also follow Bessembinder et al. (2009) to correct potential data errors and remove observations in enhanced TRACE data with large return reversals, defined as a 20% or greater return followed by a 20% or greater return of the opposite sign.[5]

Using the collected and screened transaction data, we construct monthly bond returns for the main results as follows. First, to reduce potential market microstructure noise in bond returns, following Bessembinder et al. (2009), we calculate a bond's volume-weighted average price on a day to estimate its mid-price. Then, we employ the mid-price to construct monthly returns as:

$$R_{t+1} = \frac{P_{t+1} + AI_{t+1} + C_{t+1}}{P_t + AI_t} - 1, \tag{1}$$

where P_t is the average price on the last day with non-zero transactions in the last five business

[3] When both Moody's and Standard & Poor's credit ratings are available, we take the average of the two numerical values.

[4] Following Dick-Nielsen et al. (2023), we define equity-linked bonds, as bonds whose field "issue name" contains any of the strings "`EQUITYLINKED`", "`EQUITY LINKED`", and "`INDEX-LINKED`".

[5] Our results are not sensitive to this data filter. Panel E of the Internet Appendix Table A2 reports that the main results reproduced without the filter are almost identical to our main results.

days of month t, AI_{t+1} is accrued interest at the end of month $t+1$, and C_{t+1} is the coupon paid in month $t+1$. If there are no trades in the last five business days of a month, we treat the price as missing. As a result, our monthly bond return sample starts from August 2002.

Because we use volume-weighted average prices excluding small transactions, a return in (1) is less likely to be affected by a bid-ask bounce in transaction prices. Still, in the next section, we examine the fraction of bid transactions in calculating average prices and verify that a bid-ask bounce does not artificially generate the main results of this study.

We obtain data on analysts' earnings forecasts from the Institutional Brokers Estimate System (I/B/E/S). We use quarterly forecasts in unadjusted detailed files to measure forecast errors and annual year-end forecasts to compute *DISP*. To calculate forecast errors, we follow Livnat and Mendenhall (2006) and require an earnings announcement to have at least one analyst's forecast. Moreover, we require that for the announcement quarter, the price per share must be available in Compustat and be greater than \$1. In addition, we require at least two analysts' forecasts when constructing *DISP*.

To confirm evidence outside of the corporate bond market, we obtain five-year CDS contracts for the U.S. dollar-denominated, senior unsecured debt of 737 U.S.-based corporate obligors from Markit, covering the period from August 2002 to December 2022. We set this sample's beginning month to August 2002 so that it starts at the same time as the corporate bond return sample. We focus on five-year, on-the-run CDS contracts with available credit ratings because they are the most liquid contracts.[6] Furthermore, we only use contracts that adopt modified restructuring documentation clauses before April 2009 (when the CDS Big Bang occurred) and those with no restructuring clauses afterward. We also obtain stock price and return data from CRSP and firm fundamentals from Compustat.

To correctly identify earnings announcement dates, following Dellavigna and Pollet (2009), we compare announcement dates in Compustat with those in I/B/E/S and assign the earlier date as the "correct" date. Following Johnson and So (2018), we eliminate instances in which Compustat's

[6]We follow the convention that single-name CDS contracts move to new on-the-run contracts each quarter on the 20th of March, June, September, and December until December 2015. In December 2015, the ISDA Credit Steering Committee adopted a new standard schedule on a semi-annual frequency, in which contracts roll over in March and September. We follow this new schedule to find on-the-run contracts since January 2016.

and I/B/E/S's announcement dates are more than two calendar days apart. According to the time stamp of I/B/E/S, if the announcement occurs after market closure, we adjust the announcement date one trading day forward.

Using these data, we construct three measures of an earnings surprise. First, following Livnat and Mendenhall (2006), we calculate the difference between the announced earnings per share and the median of analysts' forecasts scaled by price per share at the quarter end (CE). Second, following Chiang et al. (2019), we calculate the fraction of forecasts that miss on the same side (FOM), defined as $K/N - M/N$ where K (M) is the number of analysts who predicted lower (higher) earnings than what was announced, and N is the total number of forecasts. Finally, following Chan et al. (1996), Frazzini (2006), Brandt et al. (2008), and Daniel et al. (2020), we measure earnings surprises using the cumulative abnormal stock return (CAR) from day $d-1$ to $d+1$ around the earnings-announcement date d.[7] The first two proxies directly measure the surprise in announced earnings per share relative to analyst forecasts, whereas CAR reflects the surprise in the overall announcement, including soft information (e.g., press releases and conference calls) disseminated by the firm relative to investors' expectations. We further require the three earnings surprise measures to be non-missing.

Table 1 presents the summary statistics of panel data on bond returns and characteristics. After filtering data and matching bonds to earnings announcements, we obtain 960,990 bond-month observations on bond returns for 28,851 bonds issued by 1,806 firms. In our sample, the average bond has a monthly return of 0.43%, a credit rating of BBB (which corresponds to a numerical value of 8.2), a time to maturity of 9.9 years, an amount outstanding of $653 million, and a return volatility of 2.19%.

2.2 Bond Market Reactions to Earnings News

We first investigate bond price reactions to earnings announcements. By examining the link between announcement-day bond returns and various proxies for earnings surprises, we identify a valid measure for earnings surprises. If a proxy accurately captures earnings surprises experienced by

[7] To calculate abnormal returns, we use daily stock returns on 150 trading days up to $d-7$ and estimate factor exposures by using the three-factor model of Fama and French (1993). A similar approach is employed by Daniel et al. (2020) to construct an equity-based PEAD factor.

corporate bond investors, bond returns should jump in response to the surprises.

Specifically, we run a pooled ordinary least squares (OLS) regression of three-day bond abnormal returns on earnings surprise measures and control variables,

$$R_{i,d-1\rightarrow d+1} - R_{MKT,d-1\rightarrow d+1} = a + bSurprise_{i,d} + cCtrl_{i,d} + FE_q + \varepsilon_{i,d-1\rightarrow d+1}, \qquad (2)$$

where $R_{MKT,d-1\rightarrow d+1}$ is a return on corporate bond indices,[8] $Ctrl_{i,d}$ is a vector of control variables, including the bond age, time to maturity, numerical credit ratings, and bond size (i.e., the market value of the amount outstanding), and FE_q is year-quarter fixed effects. We standardize the three earnings surprise measures to compare the economic significance of the coefficient estimates.

Table 2 presents the estimated slope coefficients, associated t-statistics, and adjusted R-squared of the regressions in (2). We find that corporate bond returns strongly react to all three earnings surprise measures upon announcement. When each measure is separately included in regressions, a one-standard-deviation increase in *CAR*, *CE*, and *FOM* leads to a 0.29, 0.06, and 0.07 percentage-point increase, respectively, in bond returns over a three-day window. Given that the standard deviation of three-day abnormal bond returns is 1.77%, these reactions are economically meaningful. This finding implies that bond investors update their valuations rapidly in response to announced news, consistent with the findings reported by the previous literature, including Easton, Monahan, and Vasvari (2009), Shivakumar et al. (2011), and Defond and Zhang (2014). Overall, these results confirm that the surprise measures used in this study are valid proxies for news relevant to corporate bond investors and, thus, provide a foundation on which to study PEAD.

Columns 4 to 6 of Table 2 present the results of horse races that compare *CAR*, *CE*, and *FOM* in explaining contemporaneous bond returns. We observe that, for bond investors, *CAR* is the strongest measure of earnings surprises. In multivariate regressions including *CAR* and another measure in (2), the estimated slope coefficient on *CE* remains stable at 0.06% and that on *FOM* decreases to -0.008%. In contrast, the loading on *CAR* barely changes when put together with *CE* or *FOM*. These results suggest that it is important to consider information other than earnings per share in understanding how bond investors react to earnings-related news. Because a strong initial

[8] We use the Bloomberg Barclays US Corporate Total Return Index (LUACTRUU) for IG bonds and the Bloomberg Barclays US Corporate High Yield Total Return Index (LF98TRUU) for HY bonds.

price reaction to news will work against finding PEAD, in the following analysis we use CAR as our main measure of earnings surprises to be conservative and the other two measures for robustness testing.

2.3 Bond PEAD: Portfolio Analysis

In this section, we provide evidence for the presence of bond PEAD based on a calendar-month portfolio approach using monthly bond returns.[9] At the end of month t, we sort bonds into deciles based on the latest available observation for announcement-day stock CAR. Then, we take the value-weighted average across bonds in a given portfolio and calculate month $t+1$ portfolio returns. For example, at the end of April 2019, we rank all bonds in terms of CAR on the latest earnings announcement dates, some of which may be as of February 2019 while others may be as of March or April 2019. Regardless of the announcement's exact timing, we rank all bonds and form portfolios at the end of April and calculate portfolio returns in May.[10] This method avoids forward-looking biases in calculating portfolio returns and prevents the seasonality inherent to earnings announcements from affecting our sample size.[11]

Panel A of Table 3 presents the average value-weighted portfolio returns in excess of the T-bill rate. The average excess returns increase from the lowest CAR decile (0.24%) to the highest (0.52%), with a difference of 0.28% and a t-statistic of 3.47. Due to the low volatility of the hedge portfolio, its annualized Sharpe ratio is 0.85, which is higher than that of the corporate bond market portfolio (0.54) over the same period, proxied by the Bloomberg US Corporate Total Return index. Thus, corporate bonds exhibit economically significant PEAD, suggesting that some investors trade at a month-t price that is too low after positive news and too high after negative news.

Panel B of Table 3 reports the average bond characteristics for each portfolio. The average bond size (i.e., market value of the amount outstanding), credit rating, time to maturity, Roll measure of illiquidity ($ACOV$), and bond age are all similar between the lowest and highest deciles, suggesting

[9]Figure 1 provides evidence for PEAD by using the event-time approach, which is described in detail in Internet Appendix A.

[10]If there is no earnings announcement for a firm in the past four months, we exclude its bonds from the PEAD portfolio.

[11]Chan et al. (1996); Frazzini (2006); and Daniel et al. (2020), among others, use a similar approach to study the stock market.

that we capture firm-specific news regarding earnings, independent of the other determinants of bond returns.

In Panel B, we also report the fraction of the dollar bid (i.e., dealer buys) volume relative to the total volume on a given day. Because of bid-ask spreads, the volume-weighted average bond price on a given day would be lower than the mid-price if transactions in which dealers buy dominate those in which dealers sell. In contrast, the volume-weighted average price would be higher than the mid-price if dealer sales dominate. We find that the average bid fraction is similar between the lowest and highest CAR deciles: The fraction of bids for P_t is 34.17% for the first decile and 34.37% for the tenth decile. In addition, bid-ask spreads tend to be higher for small transactions (e.g. Edwards et al. 2007) and we therefore report the proportion of small transactions, with a size of less than $1 million, used to calculate daily prices for each decile. The ratio is very similar across deciles, around 85%. Thus, the observed return difference between the portfolios is unlikely to be due to a bid-ask bounce.

Now, we examine whether risk exposure can explain the difference in average excess returns on CAR-sorted portfolios. To this end, we run a time-series regression of portfolio excess returns on several sets of factors,

$$R^e_{p,t} = \alpha_p + \beta_p' F_t + u_{p,t}, \tag{3}$$

where F_t represents the two duration-adjusted bond CAPM factors of van Binsbergen, Nozawa, and Schwert (2025), or the six stock factors of Fama and French (2018), namely stock market, size, value, investment, profitability, and momentum factors. In addition, we combine the two sets to create an 8-factor model.

Panel A of Table 3 reports the intercept of Equation (3). We find that controlling for risk factors tends to increase returns on the long-short portfolio, implying that bonds with a high CAR tend to have lower betas than do those with a low CAR. For example, the 8-factor alpha for the high-minus-low strategy is 33 bps per month (t = 3.48), which is roughly 4% per year. The annualized information ratio also increases to 1.04 after adjustment for risk exposure. Similar results are obtained when we use the equal-weighted portfolios of bonds (as reported in Panel C) or the firm-level data (Panel D). In the latter, we create a firm-level bond return by value-weighting its bonds' returns using prior-month bond market capitalization and form portfolios of firms using equity market capitalization.

The alphas reported in Table 3 indicate whether profits generated by the bond PEAD strategy result from its short or long leg. The 8-factor alpha of value-weighted portfolios is -0.12% for the lowest CAR decile and 0.21% for the highest. Although the short leg contributes to approximately one-third of the profits, the long leg generates the remaining nontrivial fraction. Thus, bond PEAD is not a simple reflection of short-sale constraints in the bond market.[12]

The subsample analysis reveals a pattern consistent with the disagreement-based explanation. Hong and Sraer (2013) find that bonds that are closer to default are more sensitive to investor disagreement. We also find that the PEAD effect is more pronounced for bonds with higher default risk (Table 3, Panel E). Moreover, it is more significant for bonds with higher transaction costs (Panel G). In Section 3, we explain this pattern using our model based on disagreement.

In the Internet Appendix, we provide further robustness tests. Specifically, we confirm that the bond PEAD effects are not driven by stale announcements in month $t-2$ (Table A2, Panel A), are robust to alternative definitions of earnings surprises, including bond CAR and analyst forecast errors (CE) (Table A2, Panel B), and exist after excluding the Global Financial Crisis period (Table A2, Panel C). Finally, we verify the results using alternative bond return datasets sourced from Dick-Nielsen et al. (2023) and the WRDS Bond Returns database (Table A2, Panel D). Figure A1 visualizes the robustness of bond PEAD across these various databases, plotting the estimated 8-factor alphas and their corresponding two-standard-error confidence intervals.[13]

To examine the time-series pattern in bond PEAD profitability, Figure 2 plots the cumulative returns on the long-short portfolio together with those on the bond market portfolio and the term and default factors, each scaled to match the monthly volatility of the PEAD portfolio. Panel A shows that the strategy accumulates gains over much of the sample period up to 2021.[14] This is because, as shown in Panel B, the long and short legs of the strategy largely offset market

[12] Asquith et al. (2013) report that the cost of shorting corporate bonds is comparable to that of shorting stocks.

[13] The PEAD effect remains significant when extending the holding period beyond one month, as detailed in the Internet Appendix B. Finally, we show that the PEAD exists in the quote-price based bond database provided by ICE, presented in the Internet Appendix C.

[14] Whether the decline in 2022 reflects a structural change or not is unclear. Forces that potentially improve market efficiency, such as increased TRACE dissemination, growth in electronic bond trading, and greater mutual fund ownership, had already been underway well before 2022.

exposure.[15] Another notable fact is that the correlation between the bond market portfolio and the PEAD hedge portfolio is -0.15 in the whole sample period. The low correlation between cumulative returns and the business cycle suggests that bond PEAD is not a reflection of omitted risk factors. Considering the high Sharpe ratio and the non-systematic nature of PEAD returns, a seemingly small premium from the bond PEAD strategy is economically significant.[16]

2.4 Comparing Earnings Announcements to Other News

To evaluate the uniqueness of earnings announcements, we compare earnings surprises to other forms of market news. To this end, we examine changes in bonds' credit ratings and more general news reflected in past stock returns. Gebhardt et al. (2005) report that the previous six-month equity returns predict bond returns in the following month, suggesting the underreaction of the bond market to news. Thus, we compare the performance of our earnings announcement measure (i.e., stock returns on earnings announcement dates) with stock returns on non-announcement days.

Using these variables, we run monthly cross-sectional regressions of Fama and MacBeth (1973). Every month, we regress bond excess returns on proxies for news released in the past and control variables:

$$R^e_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} News_{i,t} + \lambda_t Ctrl_{i,t} + \eta_{i,t+1}, \tag{4}$$

where $News_{i,t}$ includes our earnings surprise measure (i.e., CAR), dummy variables for changes in credit ratings in the previous three months (one dummy for upgrade and another for downgrade),[17] equity momentum (i.e., cumulative market-adjusted equity returns from month $t-5$ to t), and cu-

[15] A notable dip in early 2020 is not directly due to the pandemic-driven recession. The return in January and February 2020 was -1.03% and -0.71%, respectively. However, in March, when the pandemic hit the market hardest, the return was positive at 1.19%.

[16] To evaluate whether incorporating the bond PEAD effect meaningfully expands a representative investor's mean-variance efficient frontier, we define a bond PEAD factor as the long-short decile portfolio sorted on CAR. We augment the bond market factor with the bond PEAD factor, constructing a simple two-factor model. We benchmark this augmented model against several alternative bond pricing models, including a single-factor bond market model, the duration-adjusted bond CAPM proposed by van Binsbergen et al. (2025), and the TERM and DEF factors of Fama and French (1993). Following the methodology of Barillas et al. (2020), we compute the bias-adjusted squared Sharpe ratios for these competing models. As detailed in Table A3 of the Internet Appendix, the combination of bond market factor and bond PEAD factor yields the highest adjusted squared Sharpe ratio of 0.087. For further verification, we conduct pairwise model comparison tests, the results of which are also presented in Table A3. These tests confirm that the augmented two-factor model consistently outperforms other competing models.

[17] We set the dummy to one if there is at least one rating upgrade/downgrade by any rating agency in the period from month $t-2$ to t, and zero otherwise.

mulative market-adjusted three-day equity returns on non-announcement days that are randomly selected from the previous six months ($NoAnnCAR$) conditional on the absolute value of the return being over 2.12 times its volatility. We establish a cutoff of 2.12, which equals the ratio of the standard deviation of three-day announcement returns to the standard deviation of three-day returns on non-announcement days. By using this cutoff, we select dates with non-trivial news other than earnings announcements. For the equity momentum variable, we construct two versions including and excluding earnings announcement returns, denoted as *SRet6mAll* and *SRet6m*, respectively. We subtract returns on the stock market portfolio over the corresponding period from the past stock returns to obtain the market-adjusted momentum variables. The set of control variables comprises bond size, credit rating, time to maturity, downside risks, the Roll measure of illiquidity, past short- and medium-term bond returns (in month t and from months $t-11$ to $t-1$), bond and stock return volatility, the fraction of bids in month t and $t+1$ prices, and industry-fixed effects defined by Fama and French's 30 industry classifications. Excluding dummy variables, we standardize right-hand-side variables for ease of interpretation.

Table 4 presents the estimated average slope coefficient of the Fama-MacBeth regression in (4). For brevity, we report estimates for control variables in Internet Appendix Table A4. Before comparing earnings surprises with other forms of news, we examine bond PEAD in the regression setup. When CAR is used independently (Column 1), its one-standard-deviation increase predicts a 9.3 bps ($t = 3.21$) increase in bond returns in the following month. The PEAD effect remains invariant to the inclusion of control variables, such as past bond returns, liquidity, and market microstructure controls (Column 2). These results suggest that bond PEAD is not merely a reflection of differences in the risks associated with bonds or measurement errors in the data.

Turning to other forms of news, the coefficient for *SRet6m* is 12.6 bps (Column 3), indicating that past equity returns predict bond returns even when limited to non-announcement days. To examine the role of earnings announcements on an equal footing, we use three-day abnormal stock returns on non-announcement days (i.e., $NoAnnCAR$) as another regressor. As reported in Column 4, the loading on $NoAnnCAR$ is close to zero and statistically insignificant. Therefore, earnings announcements are special in predicting bond returns in the following month.

As another reference point, the regression in Column 5 includes dummies for upgrades or downgrades in credit ratings. We find that the loading on the upgrade dummy is 10.9 bps ($t = 2.39$), whereas that on the downgrade dummy is -10.0 bps ($t = -1.18$). The significantly positive loading on the upgrade dummy suggests that bond prices tend to underreact to positive rating changes. The degree of underreaction is similar to a one-standard-deviation change in earnings surprises.

Next, we run horse races among these news variables in generating drifts in bond prices. The regression reported in Column 6 includes *CAR*, *SRet6m*, other news measures, and control variables. The estimated slope coefficient for earnings surprises remains roughly unchanged at 9.6 bps, even after controlling for a host of other news variables, including *SRet6m*, bond momentum, and rating changes. The predictive power of *CAR* is remarkable, considering that its information is typically more outdated than the information in *SRet6m*, which depends on the stock price at the end of month t (i.e., when we form portfolios). Moreover, the significance of earnings surprises in the multivariate regression suggests that PEAD is not an artifact arising from news disseminated in the period between announcement dates and portfolio formation dates. If this were the case, controlling for the past stock and bond returns would eliminate bond PEAD; however, we obtain contrasting results.

Finally, in Column 7, we replace *SRet6m* with *SRet6mAll*. The slope estimate for *CAR* is then 6 bps ($t = 2.68$), which is significant even after controlling for equity momentum that includes announcement-date stock returns. In Internet Appendix Table A5, we report that the median analyst forecast error (*CE*) significantly predicts bond returns after controlling for equity momentum and other bond characteristics. However, *FOM* loses its significance. Overall, our findings are consistent with Chan et al. (1996), who show that, in the stock market, momentum and PEAD carry independent information. Moreover, we confirm that earnings surprises are unique and provide information that predicts bond returns above and beyond other forms of market news reflected in the momentum variables.

2.5 PEAD in the CDS Market

In this section, we examine PEAD in the CDS market. Oehmke and Zawadowski (2017) point out that CDS contracts are more standardized than corporate bonds and thus are likely to be more liquid. If illiquidity in corporate bonds is the cause of slow price movements, then PEAD would not exist in the CDS market. With this in mind, we examine five-year, on-the-run, single-name CDS contracts and estimate the trading profits of a strategy that sells CDS protection according to past earnings surprises.

To measure the return on CDS contracts, following Augustin et al. (2020), we calculate the approximate present value of cash flows. Specifically, the price of a protection seller's position is

$$P_t^{CDS} = \frac{c - s_t}{r_t + \frac{s_t}{1-\mathcal{R}}} \left(1 - e^{-\left(r_t + \frac{s_t}{1-\mathcal{R}}\right)(T-t)}\right), \tag{5}$$

where c is a coupon rate set at 1% for IG firms and 5% for HY firms; s_t is the breakeven CDS spread; r_t is the $(T-t)$-year risk-free rate; and $\mathcal{R}$ is the recovery rate.[18] An excess return on a strategy to sell protection in month t and unwind the position in $t+1$ is:

$$R_{t+1}^{e,CDS} = \frac{P_{t+1}^{CDS} - P_t^{CDS}}{\Phi}, \tag{6}$$

where the fraction of the notional collateralized, Φ, is set to 1 following Loon and Zhong (2014). $\Phi = 1$ implies that investors fully collateralize the CDS notional amount; however, our results remain invariant to the choice of Φ as long as it is constant.[19]

Using the CDS returns in (6), we form quintile portfolios of firms based on their latest earnings surprises and calculate the value-weighted average excess returns, where weights are obtained from a firm's stock market capitalization. In addition, we calculate equal-weighted average returns and find that the results are more pronounced for equal-weighted averages than for value-weighted averages. Thus, we report value-weighted returns to be conservative. Additionally, we regress portfolio excess returns on the same set of factors as our main results and estimate the alphas. These results are reported in Panel A of Table 5.

Consistent with our findings for corporate bonds, CDS contracts exhibit PEAD. For example, the average excess CDS return is -0.03% for firms in the lowest earnings surprise quintile and 0.05% for those in the highest quintile; this results in an average return difference of 0.08% ($t = 3.24$).[20]

[18] We use Markit's "Real Recovery Rate" if it is available and the "Assumed Recovery Rate" if not. If neither value is available, we assume $\mathcal{R} = 0.4$.

[19] Kang et al. (2023) recently proposed an alternative methodology for calculating CDS returns.

[20] We find that the average excess return on the strategy of selling CDS protection is negative because the definition of excess return in Equation (6), as used in the literature, does not include coupons received by CDS protection sellers.

Because CDS returns are less volatile than corporate bond returns, even this difference of 8 bps in average excess returns translates into a sizable annualized Sharpe ratio of 0.81, which is comparable to that for corporate bonds. Furthermore, after controlling for the 8-factor risk exposure, the alpha and information ratio increase to 9 bps and 1.03, respectively.[21]

Since the calculation of CDS returns involves some approximation, we also examine results using changes in the natural logarithms of CDS spreads in place of CDS returns. Because an increase in CDS spreads reduces the return for CDS protection sellers, the sign of the difference between the high and low earnings-surprise quintiles is reversed: Panel B of Table 5 indicates that a firm in the highest quintile tends to have significantly lower CDS spreads in the month after portfolio construction than a firm in the lowest quintile. These findings are qualitatively consistent with those obtained for CDS and corporate bond returns.

2.6 No PEAD in the Stock Market

We compare bond and CDS PEAD with PEAD in the equity market. We adopt the same set of earnings surprise measures as we do for the bond market and study the subset of firms that issue corporate bonds as well as the entire universe of firms. More specifically, for every month, we sort firms based on their latest earnings surprises to form five equal- and value-weighted portfolios of stocks. Then, we calculate hedge returns for a strategy that goes long on firms in the top earnings surprise quintile and short on firms in the bottom quintile. Finally, we regress the returns on the six stock factors of Fama and French (2018) and estimate the regression intercepts. Panel A of Table 6 reports the estimated alphas of the stock PEAD strategy for bond issuers. When the sample period is matched to that of bonds (i.e., August 2002 to December 2022), we find weak evidence for stock PEAD: The average hedge returns based on value-weighted portfolios are 0.17%, 0.11% and 0.08% when using *CAR*, *CE* and *FOM*, respectively, as the measure of earnings surprises. These estimates are statistically indistinguishable from zero.

Adding 1/12% coupons to IG contracts and 5/12% coupons to HY contracts leads to positive average excess returns but does not affect the cross-sectional difference that we focus on.

[21] Jenkins, Kimbrough, and Wang (2016) report weak evidence for PEAD in the CDS market. The difference arises because i) they use seasonal changes in quarterly earnings as the measure of earnings surprises, which is valid only under the assumption that earnings follow a random walk; and ii) our data sets cover more firms over a longer sample period.

The absence of stock PEAD in our sample can be attributed to two reasons. First, as Nozawa (2017) documents, bond-issuing firms tend to be large, and their stocks are less likely to be affected by anomalies. As presented in Table 1, the fraction of bond observations corresponding to "big" firms (i.e., firms with a market capitalization above the 50th percentile of NYSE stocks) is as large as 93%. By contrast, only 2% of bond return observations correspond to "micro" stocks (i.e., those below the 20th percentile). When we use the stocks of all firms and repeat the exercise, the alphas for stock PEAD strategies increase. As shown in Panel B of Table 6, most of the alphas for value- and equal-weighted portfolios are significant from August 2002 to December 2022 and are larger for equal-weighted portfolios than value-weighted portfolios. This finding indicates that stock PEAD profits are concentrated among small firms, whereas most bond issuers are large firms for which stock PEAD is weak or absent.

Second, our sample period is relatively recent, when the profitability of stock PEAD is known to be low (Martineau 2022).[22] In Panel C of Table 6, we repeat the same exercise by using all firms in the sample period from January 1984 to July 2002. We find that, regardless of earnings surprise measures, PEAD during this period is significant, with six-factor alphas ranging from 36 to 56 bps when firms are value-weighted, and from 74 to 132 bps when they are equally weighted. Thus, our finding for bond PEAD contrasts with that for stock PEAD: Although bond issuers tend to be large firms, we obtain evidence for bond PEAD but not for stock PEAD. We explain this difference in the following sections.

3 A Model of Payoff Structure, Disagreement, and PEAD

In this section, we study how payoff structures and investor disagreement affect PEAD in debt and stock markets within a unified framework. Our model is based on Banerjee et al. (2025), which extends Hellwig (1980) to allow the firm to be leveraged and to allow investors to potentially ignore the information in prices. We modify their model to account for potentially different degrees of disagreement across bond and stock markets. This framework enables us to conduct a novel analysis

[22] Our evidence is related but distinct: Martineau (2022) studies the time-series decay of aggregate equity PEAD, whereas we document that a cross-sectional long-short portfolio sorted on CAR generates no significant alpha for bond-issuing firms in 2002–2022. Both findings point to the weakness of exploitable equity PEAD in the recent period, but through different empirical lenses.

of the differences in PEAD between securities for the same underlying firm.

3.1 Model Setup

Consider an economy with three dates ($t \in \{0, 1, 2\}$). On date 1, a public announcement regarding a firm's earnings is made. During this period, investors trade the firm's risky debt ("bonds") and equity, alongside a risk-free security. Date 0 represents the moment immediately before the earnings announcement, while date 2 is the payoff date when all asset values are realized and investors consume.

Assets. In this economy, there are three assets: a risk-free asset, and the firm's risky debt and equity. The gross return on the risk-free security is normalized to 1. The firm's total cash flows per share (i.e., the sum of cash flows per share/unit that accrue to equity and debt holders) are $\tilde{\mathcal{V}} = m + \tilde{\theta}$. The per capita supply of the firm's securities is $\kappa \geq 0$; that is, there are κ units of debt and equity shares outstanding per capita. As argued in Banerjee et al. (2025), setting per capita supply equal in the debt and equity securities ensures that changes in the firm's capital structure do not mechanically change the total cash flows paid to investors.

To ensure that the payoffs on both debt and equity satisfy limited liability, we assume that the total cash flows $\tilde{\mathcal{V}}$ follow a truncated normal distribution $N(m, \sigma_\theta^2)$, truncated below at zero. Specifically, the unconditional density of $\tilde{\mathcal{V}}$ is $f_{\tilde{\mathcal{V}}}(\nu) = \frac{\mathbf{1}_{\nu \geq 0} \frac{1}{\sqrt{2\pi}\sigma_\theta} \exp\{-\frac{1}{2}\frac{(\nu - m)^2}{\sigma_\theta^2}\}}{1 - \Phi\left(\frac{-m}{\sigma_\theta}\right)}$. The firm has a debt with a face value of K per unit. That is, the payoffs to equity and debt per share are respectively

$$\tilde{V}_E = \max(\tilde{\mathcal{V}} - K, 0) \text{ and } \tilde{V}_D = \min(\tilde{\mathcal{V}}, K), \tag{7}$$

so that $\tilde{\mathcal{V}} = \tilde{V}_E + \tilde{V}_D$. These payoffs are realized on date 2, while on date 1, they trade at prices $\tilde{P}_{E,1}$ and $\tilde{P}_{D,1}$, which are determined endogenously.

We denote the prices of debt and equity on date 0 as $\tilde{P}_{E,0}$ and $\tilde{P}_{D,0}$. As will be introduced later, on this date, all investors are ex-ante identical and share the same prior beliefs. Consequently, the prices are determined by the unconditional expected values of the payoffs:

$$\tilde{P}_{E,0} = E[\tilde{V}_E] \text{ and } \tilde{P}_{D,0} = E[\tilde{V}_D]. \tag{8}$$

Similarly, the prices of the risky assets on date 2 are denoted as $\tilde{P}_{E,2}$ and $\tilde{P}_{D,2}$. Since all uncertainties are resolved by this date, the prices are the realized asset values:

$$\tilde{P}_{E,2} = \tilde{V}_E \text{ and } \tilde{P}_{D,2} = \tilde{V}_D. \tag{9}$$

Investors and Information. There is a unit mass of investors indexed by $i \in [0, 1]$. Each investor is endowed with κ shares of equity and bond, and exhibits Constant Absolute Risk Aversion (CARA) utility with a common risk-aversion coefficient γ. We denote $x_{E,i}$ and $x_{D,i}$ as investor i's demands for equity and debt, respectively (so that her net trades are $x_{E,i} - \kappa$ and $x_{D,i} - \kappa$). Thus, the terminal wealth of investor i is

$$W_i = \kappa(\tilde{P}_{D,1} + \tilde{P}_{E,1}) + x_{E,i}(\tilde{V}_E - \tilde{P}_{E,1}) + x_{D,i}(\tilde{V}_D - \tilde{P}_{D,1}). \tag{10}$$

On date 1, the firm announces its earnings, revealing a public signal: $\tilde{y} = \tilde{\theta} + \tilde{\eta}$, with $\tilde{\eta} \sim N(0, \tau_\eta^{-1})$. Meanwhile, investor i develops their own interpretation and produces the following private signal regarding the firm's fundamentals:

$$\tilde{s}_i = \tilde{\theta} + \tilde{\varepsilon}_i, \text{ with } \tilde{\varepsilon}_i \sim N(0, \tau_\varepsilon^{-1}). \tag{11}$$

The error terms $\tilde{\eta}$ and $\tilde{\varepsilon}_i$ are independent of each other and of all other random variables.

After observing the public information $\tilde{y}$ and their own private information $\tilde{s}_i$, investor i chooses the optimal demands of equity and debt, $x_{E,i}$ and $x_{D,i}$, to maximize their CARA utility:

$$\max_{x_{D,i}, x_{E,i}} E\left[-\exp\left(-\frac{1}{\gamma} W_i\right) \mid \tilde{y}, \tilde{s}_i, \tilde{P}_{D,1}, \tilde{P}_{E,1}\right], \tag{12}$$

where the terminal wealth W_i is given by Equation (10).

In addition to these rational investors, liquidity traders submit demands $\tilde{z}_D \sim N(0, \sigma_{zD}^2)$ and $\tilde{z}_E \sim N(0, \sigma_{zE}^2)$ in the equity and debt markets, respectively. We denote $\tilde{z} \equiv (\tilde{z}_D, \tilde{z}_E)'$ and assume that noise trading in the two markets is independent; that is, $\tilde{z}_D$ and $\tilde{z}_E$ are independent of each other and of all other random variables.

Heterogeneous Beliefs. We follow Banerjee et al. (2025) to consider a flexible specification of subjective beliefs about the private information of others, while allowing for potentially different degrees of disagreement between the equity and bond markets.

Specifically, investor i's belief about her own signal is defined by Equation (11). However, when assessing the bond market, she believes that another investor j's signal is represented as $\tilde{s}_j =_i \rho_D \tilde{\theta} + \sqrt{1-\rho_D^2}\tilde{\xi}_i + \tilde{\varepsilon}_j$, whereas in the equity market, her belief regarding investor j's signal is given by $\tilde{s}_j =_i \rho_E \tilde{\theta} + \sqrt{1-\rho_E^2}\tilde{\xi}_i + \tilde{\varepsilon}_j$. Here, $\tilde{\xi}_i \sim_i N(0, \sigma_\theta^2)$ and $\tilde{\varepsilon}_j \sim_i N(0, \sigma_\varepsilon^2)$, and are independent of all other random variables.

The two parameters $\rho_D \in [0,1]$ and $\rho_E \in [0,1]$ capture the degree of disagreement regarding the firm's fundamentals in the debt and equity markets, respectively. When $\rho_k = 1$ (for $k \in \{D, E\}$), all investors are in agreement, sharing common priors about the joint distribution of fundamentals and exhibiting rational expectations. Conversely, when $\rho_k = 0$ ($k \in \{D, E\}$), investors experience maximum disagreement, believing that no other investor possesses payoff-relevant information, leading to prices that are not incrementally informative about payoffs.

Equilibrium. In our setting, $(\tilde{\theta}, \{\tilde{\xi}_i\}_i, \{\tilde{\varepsilon}_i\}_i, \tilde{z}_D, \tilde{z}_E, \tilde{\eta})$ are the underlying random variables that characterize the economy. They are mutually independent. The tuple $\mathcal{E} \equiv \{m, K, \rho_D, \rho_E, \gamma, \kappa, \sigma_\theta, \sigma_\eta, \sigma_\varepsilon, \sigma_{zD}, \sigma_{zE}\}$ defines an economy. Given an economy, we have shown that the bond and equity prices in equilibrium on dates 0 and 2 are specified by (8) and (9), respectively. On date 1, the equilibrium consists of investor demands $\{x_{D,i}, x_{E,i}\}_{i\in[0,1]}$ and asset prices $(\tilde{P}_{D,1}, \tilde{P}_{E,1})$ such that (i) the demands $(x_{D,i}, x_{E,i})$ maximize investor i's expected utility, conditional on her information set and the subjective belief formation mechanism described above, as given by (12), and (ii) the equilibrium prices $(\tilde{P}_{D,1}, \tilde{P}_{E,1})$ are determined by market-clearing conditions:

$$\int x_{k,i}di + \tilde{z}_k = \kappa, \text{ for } k \in \{D, E\}. \tag{13}$$

3.2 Equilibrium Characterization

In this section, we characterize the equilibrium on date 1. Following Breon-Drish (2015) and Banerjee et al. (2025), we focus on a generalized linear equilibrium in which the information in prices $(\tilde{P}_{D,1}, \tilde{P}_{E,1})$ reduces to two linear statistics:

$$\tilde{s}_{pD} = \bar{s}_D + b_D\tilde{z}_D \text{ and } \tilde{s}_{pE} = \bar{s}_E + b_E\tilde{z}_E, \tag{14}$$

where $\bar{s}_D = \rho_D\tilde{\theta} + \sqrt{1-\rho_D^2}\xi_i$ and $\bar{s}_E = \rho_E\tilde{\theta} + \sqrt{1-\rho_E^2}\xi_i$ represent the subjective average private signals in the bond and equity markets, respectively. The constants b_D and b_E are endogenously determined in equilibrium. There exists a function $(\tilde{P}_D(\cdot), \tilde{P}_E(\cdot))$ that maps $\mathbb{R}^2$ into $\mathbb{R}^2$ such that the equilibrium debt and equity prices are given by $\tilde{P}_D(\tilde{s}_{pD}, \tilde{s}_{pE})$ and $\tilde{P}_E(\tilde{s}_{pD}, \tilde{s}_{pE})$.

Given the public signal $\tilde{y}$, private signal $\tilde{s}_i$, and the price information $\tilde{s}_{pD}$ and $\tilde{s}_{pE}$, investor i's beliefs about the firm's cash flows follow a truncated normal distribution. We define the mean and variance of the normal distribution as μ_i and σ_s^2 respectively; that is,

$$\mu_i \equiv E[\tilde{\mathcal{V}} \mid \tilde{y}, \tilde{s}_i, \tilde{s}_p] \text{ and } \sigma_s^2 \equiv Var[\tilde{\mathcal{V}} \mid \tilde{y}, \tilde{s}_i, \tilde{s}_p], \tag{15}$$

given by (D3) and (D4) in Internet Appendix D, respectively. Thus, investor i's conditional expected utility in (12) can be expressed as (see Internet Appendix D for the detailed derivation):

$$\begin{aligned}\mathcal{U} &\equiv E\left[-\exp\left(-\gamma W_i\right) \mid \tilde{y}, \tilde{s}_i, \tilde{s}_p\right] \\ &= -\exp\left(-\gamma(\mathbf{1}\kappa - x_i)'\tilde{P}) + g\left(-\gamma x_i + \mathbf{1}\frac{\mu_i}{\sigma_s^2}\right) - g\left(\mathbf{1}\frac{\mu_i}{\sigma_s^2}\right)\right),\end{aligned}$$

where $\tilde{s}_p \equiv (\tilde{s}_{pD}, \tilde{s}_{pE})'$, $x_i \equiv (x_{D,i}, x_{E,i})'$, and $\tilde{P} \equiv (\tilde{P}_D, \tilde{P}_E)$. The function $g : \mathbb{R}^2 \to \mathbb{R}$ is defined by Equation (D7) in the Internet Appendix. Maximizing $\mathcal{U}$ with respect to the demands

$x_i \equiv (x_{D,i}, x_{E,i})'$ yields the demand function of investor i as:

$$x_i = \frac{1}{\gamma}\left(\mathbf{1}\frac{\mu_i}{\sigma_s^2} - \left(g'\right)^{-1}(\tilde{P})\right). \tag{16}$$

Imposing the market-clearing conditions (13) and rearranging yields the equilibrium price vector:

$$\tilde{P} = g'\left(\mathbf{1}\frac{\int \mu_j d_j}{\sigma_s^2} + \gamma(\tilde{z} - \mathbf{1}\kappa)\right). \tag{17}$$

Plugging in the expression for μ_i from Equation (D3), grouping terms, and imposing the generalized linear price conjecture (14), we find that there is a unique solution $b_D = b_E = \gamma\sigma_\varepsilon^2$ for the price signal coefficient. We thus characterize the equilibrium prices on date 1 in this economy. Investors' equilibrium demands can then be derived by inserting these equilibrium prices, $\tilde{P}$, into the demand function specified in Equation (16).

3.3 Calibration Analysis

In this section, we conduct a calibration exercise to evaluate price drift/reversal and trading volume in the bond and equity markets for empirically plausible parameters.

We start with formal definitions of our two objects of interest, price drift/reversal and trading volume. Following Banerjee et al. (2020), we consider price drift/reversal based on public information $\tilde{y}$ and refer to it as SUE PEAD. Specifically, SUE PEAD exists if

$$\frac{\partial E[\tilde{P}_{k,2} - \tilde{P}_{k,1}|\tilde{y}]}{\partial\, \tilde{y}} > 0, \text{ where } k \in \{D, E\}; \tag{18}$$

otherwise if $\frac{\partial E[\tilde{P}_{k,2} - \tilde{P}_{k,1}|\tilde{y}]}{\partial\, \tilde{y}} < 0$, it exhibits a reversal. In addition, following Banerjee et al. (2009), we define the price drift (CAR PEAD) or reversal as follows. If

$$\frac{\partial E[\tilde{P}_{k,2} - \tilde{P}_{k,1}|\tilde{P}_{k,1} - \tilde{P}_{k,0}]}{\partial(\tilde{P}_{k,1} - \tilde{P}_{k,0})} > 0, \text{ where } k \in \{D, E\}, \tag{19}$$

prices exhibit a drift. Otherwise, if $\frac{\partial E[\tilde{P}_{k,2} - \tilde{P}_{k,1}|\tilde{P}_{k,1} - \tilde{P}_{k,0}]}{\partial(\tilde{P}_{k,1} - \tilde{P}_{k,0})} < 0$, prices exhibit a reversal.

Furthermore, following Vives (2010), we measure trading volume on date 1 as the expected aggregate volume traded by investors

$$TV_k \equiv E\left[\int_0^1 |x_{k,i}| di\right] \text{ for } k \in \{D, E\}. \tag{20}$$

3.3.1 Parameter Values

We calibrate our model on a quarterly basis, aligning with the frequency of earnings announcements made by firms. That is, the interval between date 1 and date 2 is interpreted as one quarter. Table 7 presents the parameter values used in our calibration analysis and we explain how these parameter values are chosen below.

We follow Feldhütter and Schaefer (2018) to estimate the annual return on firms' asset values during our sample period, which is approximately 10.05%. For BBB-rated firms, the asset volatility ranges from the 10th percentile at 11% to the 90th percentile at 52%, with a median of 26%. Given that our truncated normal distribution framework is designed to capture tail events and ensure limited liability constraints, we set the volatility parameter to 34%, which falls between the median and 90th percentile values. Therefore, for a quarterly period, we set the mean asset value to $m = 1 + 10.05\%/4 = 1.0251$ (noting that the risk-free gross return is normalized to one) and the volatility to $\sigma_\theta = \sqrt{0.34^2/4} = 0.17$.

Given that the unconditional leverage ranges between 20% and 40%, we set the debt value to $K = 0.4$. The numerical analysis remains similar if we set the debt value between 0.37 and 0.48, ensuring that the leverage aligns with empirical values. Consequently, with parameters $m = 1.0251, \sigma_\theta = 0.17$, and $K = 0.4$, the average leverage ratio is 39%.

As estimated by Dávila and Parlatore (2023), the average information signal-to-payoff ratio for a typical U.S. stock in the recent decade is around 0.07 (i.e., $\frac{\sigma_\varepsilon^{-2}}{\sigma_\theta^{-2}} \approx 0.07$). To match this ratio for informed investors' private information, we set $\sigma_\varepsilon = \sqrt{\frac{\sigma_\theta^2}{0.07}} = 0.6425$. There is little guidance about the precision of public information, and we simply set the same signal-to-payoff ratio $\sigma_\eta = \sigma_\varepsilon$ but also note that our results remain robust to σ_η with a similar magnitude of σ_ε. In addition, following Farboodi and Veldkamp (2020), we set the risk aversion coefficient to $\gamma = 0.05$. Note that the investors in our economy can invest across the bond and equity markets and thus are considered to have low risk aversion.

We normalize the per capita supply κ of the firm's securities to be 10; that is, there are 10 units of debt and 10 shares of equity outstanding per capita. In our model, noise trader demand is measured in the number of shares. Following Peress and Schmidt (2021), we estimate that the intensity of noise trading in the bond and equity markets lies within the range $[2, 5]$. We simply set the noise–trading intensities in the two markets to $\sigma_{zD} = \sigma_{zE} = 3$, and our calibration results remain robust within this range. Finally, there is limited guidance regarding the degree of disagreement among investors. We thus allow the disagreement to vary between 0 and 1.

3.3.2 Implications

Disagreement, Price Drifts, and Trading Volume. Figure 3 illustrates the impact of investor disagreement on price drifts in both bond and equity markets, as well as on trading volume in these markets. In this analysis, we assume a uniform degree of investor disagreement (i.e., $\rho_D = \rho_E \equiv \rho$). However, we will relax this assumption later to better reflect real-world conditions.

Panel (a) of Figure 3 explores how investor disagreement ρ about firm cash flows affects price drift in bond and equity markets, measured by SUE as defined in (18). The shaded area highlights the regions where prices exhibit drift. Our findings indicate that significant investor disagreement (i.e., low ρ) is likely to result in observable price drift in both bond and equity markets. This result emphasizes the essential role of investor disagreement in generating price drifts.

The underlying intuition is as follows: when investors have differences in their opinions, they emphasize their own private information and believe that no other investor holds information of any incremental value to their private signal. Thus, investors place more weight on their individual private signals and less on the information held by others, which is reflected in the price. Information is thus slowly incorporated into prices, resulting in a price drift.[23]

[23]Our disagreement-based theory can be connected to classic noise trader models in behavioral finance (e.g., De Long, Shleifer, Summers, and Waldmann 1990; Shleifer 2000). In these frameworks, noise traders' misperceptions create undiversifiable risk that limits arbitrage and generates persistent price deviations. Our model shows how disagreement delays information aggregation in bonds, paralleling how noise trader sentiment creates systematic risk. The higher transaction costs and lower liquidity in bond markets amplify these effects relative to equities, motivating our construction of a bond PEAD factor, as noted in Footnote 16.

Panel (b) of Figure 3 analyzes price drift as measured by CAR, as defined in (19). Similar to the SUE measure, prices exhibit drift in bond markets when investor disagreement is substantial, while equity markets show no price drift across various levels of disagreement. Once again, investor disagreement proves essential for the presence of price drifts.

The first part of Implication 1 summarizes these results.

Implication 1 (Price drift: Bond and stock markets) *When there is significant disagreement among investors, price drift is likely to occur in bond/equity markets. Moreover, it is more prevalent in bond markets than in equity markets.*

In addition to investor disagreement, the incidence of drift/reversal also depends on the security's payoff structure. The second part of Implication 1 suggests that, given investor disagreement regarding firm cash flows, price drifts are more likely to occur in the bond market than in the equity market, as illustrated in Panels (a) and (b) of Figure 3 by the larger shaded area in the bond market. This result aligns with our empirical findings presented in Section 2, where we demonstrate the presence of bond drift and the absence of equity drift.

What accounts for the greater likelihood of price drift in bonds relative to equities? Since both debt and equity claims are written on the same underlying cash flows and are subject to the same level of investor disagreement, the difference must arise from the distinct payoff structures of bonds and equities. To build intuition, we decompose the drift by examining how information affects equilibrium security prices and expected value, as implied by definitions (18) and (19). Specifically, Panel (a) of Figure 4 plots the bond price, $\tilde{P}_{D,1}$ (dashed lines), and its expected value, $E[\min(\tilde{\mathcal{V}}, K)|\mu]$ (dotted lines), as functions of the state variable – investors' average posterior belief about the firm's cash flows, $\mu \equiv \int_0^1 \mu_i di$, where μ_i is given by Equation (15). Similarly, Panel (b) of Figure 4 plots the equity price, $\tilde{P}_{E,1}$ (dashed lines), and its expected payoff, $E[\max(\tilde{\mathcal{V}} - K, 0)|\mu]$ (dotted lines), against μ.[24] Note that in both the SUE-based PEAD measure (18) and the CAR-based PEAD measure (19), public information $\tilde{y}$ or past security returns affect expected returns through their impact on the average posterior belief about the firm's cash flows, μ.

[24] In this analysis, we shut down noise trading, which allows us to use the average posterior mean, μ, as the state variable. It is worth noting that our main results, presented in Figure 3, remain robust even when noise–trading intensities approach zero. Furthermore, we set investor disagreement to relatively high levels — for example, $\rho_D = \rho_E = 0.15$ — to highlight the key role of investor disagreement in driving the results.

In the bond market as shown in Panel (a), both the bond price and its expected value are increasing and concave functions of the posterior mean μ, bounded above by the face value K. This concavity implies that following positive information—reflected in a higher μ—such as favorable public news or strong past returns, both the bond price and its expected value increase but eventually plateau as μ becomes sufficiently large. In contrast, Panel (b) shows that the equity price and its expected value are increasing and convex functions of μ, with a lower bound at zero. Unlike in the bond market, these variables are unbounded above as the average posterior beliefs become highly positive.

The conditional returns – defined as the difference between the expected value and the security price – are plotted in Panel (c) of Figure 4. When investors' average posterior belief, μ, increases from zero, bond returns initially rise. As μ continues to increase and approaches the level consistent with the bond's face value, bond returns begin to decline, though they remain positive, and eventually converge to zero for sufficiently high μ. In contrast, when μ is very low and the firm remains effectively insolvent, equity returns are close to zero and largely unresponsive. As posterior beliefs become more optimistic, equity returns initially increase because the expected equity value rises more sharply than the market price. However, for higher levels of μ, this pattern reverses: the equity price reacts more strongly to the positive news than the expected payoff, causing conditional equity returns to decline.[25]

Then, whether prices exhibit drift or reversal depends on whether expected returns are, on average, positively or negatively associated with information, that is, on the ex-ante expectation of the conditional returns over the distribution of μ under the calibrated parameters. The bounded nature of bond returns combined with the unbounded nature of equity returns (particularly given that equity returns eventually decline for sufficiently high values of μ under this set of parameters) implies a greater propensity for bond-price drift and a lower propensity for equity-price drift.

We further investigate the impact of investor disagreement on trading volume. Panel (c) of Figure 3 illustrates that as investor disagreement about the underlying firm cash flows increases (i.e., ρ decreases), trading volume rises in both the bond and equity markets. This heightened disagreement indicates that investors are placing greater emphasis on their private information to

[25]This general non-monotonicity is consistent with Albagli et al. (2024).

update their beliefs regarding the firm's cash flows and thus the associated payoffs of the securities. Consequently, increased disagreement leads to more trading activity among investors, resulting in higher trading volume.

Furthermore, Panels (a) and (b) of Figure 3 demonstrate that the magnitude of price drifts, when they occur, increases with greater investor disagreement. Alongside the previously discussed trading volume results, this indicates a positive relationship among the three variables: disagreement, price drift, and trading volume. This finding is a significant empirical implication of our disagreement-based explanation, which we will empirically test in Section 4. The following implication summarizes this result.

Implication 2 (Price drift, disagreement, and trading volume) *When disagreement exists in the bond (or equity) market, greater investor disagreement is associated with stronger price drift and higher trading volume.*

More Disagreement in Bond Markets. Thus far, we have assumed equal levels of investor disagreement across bond and equity markets. Consequently, the only distinction between the two securities has been their differing payoff structures. We observe that this payoff structure alone has suggested a higher likelihood of price drift in bonds compared to equities. Despite this, we relax the equal disagreement assumption to better align with empirically plausible conditions. As will be shown in Section 4.2, we find evidence of greater disagreement regarding downside risk than upside potential, suggesting that investor disagreement is stronger in bond markets than in equity markets — that is, $\rho_D < \rho_E$.

As shown in Figure 3, price drift is more likely to be observed using the SUE PEAD measure compared to the CAR PEAD measure; therefore, we focus on the former. To examine the implications of different investor disagreement, in Figure 5, we hold equity market disagreement constant while varying bond market disagreement (fixing ρ_E and adjusting ρ_D). Given that there is limited guidance on the level of disagreement in equity markets, we simply set $\rho_E = 0.5$ (but note that our results remain robust for other choices of ρ_E). In the empirically relevant region $\rho_D < \rho_E$, our model predicts that bond prices consistently show drift, whereas equity prices do not exhibit any drift. Furthermore, as disagreement in the bond market further intensifies compared to the equity market, it is more likely to observe bond drift. This finding reinforces our disagreement-based explanation for the existence of bond drift and the absence of equity drift.

4 Disagreement-Based Explanation of PEAD

4.1 Empirical Evidence in the Bond Market

In this section, we provide evidence to support the disagreement-based explanation of bond and stock PEAD. Because we do not directly observe disagreement, we construct proxies that capture the variation in investor beliefs on bond values.

Specifically, we use three proxies for disagreement. First, we construct the analyst forecast dispersion, *DISP*, which is calculated as the standard deviation of each firm's annual earnings forecasts by analysts scaled by the absolute mean forecast value, as proposed by Diether, Malloy, and Scherbina (2002).[26] This measure of disagreement reflects equity analysts' opinions on a firm's profit in the coming year and incorporates revisions following the release of said firm's quarterly earnings.[27]

Second, we follow Goulding et al. (2023) and use idiosyncratic stock volatility (*IVOL*) as a disagreement proxy. Every month, we regress bond issuing firms' daily stock returns on the six factors of Fama and French (2018), including market, size, value, investment, profitability, and momentum, and calculate the standard deviation of regression residuals. This gives an estimate of the size of the firm's idiosyncratic risk, which is correlated with how investors perceive the uncertainty facing the firm.[28]

Finally, we use another proxy for disagreement based on bond prices. Becker and Ivashina (2015), Choi and Kronlund (2018), and Chen and Choi (2024) provide compelling evidence for

[26]We use the annual year-end analyst forecast and remove excluded and stopped estimates. To alleviate the staleness of forecasts, analyst forecasts for a given firm-year pair are carried forward until either the date of the same firm-year pair's consecutive estimates released by the same analyst or the date that is 105 days ahead of the earnings announcement date, whichever comes earlier. The decision to carry the forecast forward for up to 105 days aligns with I/B/E/S rules: If an estimate has not been updated for 105 days, it is supposed to be filtered, footnoted, and excluded from the consensus calculation.

[27]We also construct a disagreement proxy using only below-median analyst forecasts and find that the relationship between PEAD and disagreement is even stronger. However, we use *DISP* in the following analysis to be consistent with the previous literature.

[28]Goulding et al. (2023) provides a theoretical justification as to why *IVOL* is generated by investor disagreement.

bond institutional investors' reaching-for-yield behavior. On the one hand, some insurance firms and bond mutual funds tilt their portfolios toward bonds with higher yields relative to other bonds with the same rating. On the other hand, because these bonds have higher yields, other investors must correctly anticipate rare, tail events that may occur when their marginal utility is high, and their view is reflected in the bond's low price. This observation implies that bonds with yields higher than the benchmark are subject to a higher level of disagreement regarding their values between optimists (i.e., those who tilt their portfolio toward those bonds) and pessimists (i.e., those who recognize the possibility of tail events). Thus, we use the difference between a bond's yield and the cross-sectional average yields of bonds with the same credit rating (RFY) as the third measure of disagreement.

Using these proxies for disagreement, we identify the driver behind bond PEAD. Specifically, every month, we independently double-sort bonds into 25 value-weighted portfolios based on their earnings surprises (CAR) and a disagreement measure. Then, we calculate the difference between the highest and lowest CAR quintiles for each disagreement quintile separately.

Table 8 reports the 8-factor alphas of the bond PEAD strategy per the disagreement quintile. In Panel A, we use *DISP* as a measure of disagreement and find that bonds with a higher level of disagreement generate greater alphas under the bond PEAD strategy than those with a lower level of disagreement do. Specifically, the alpha of the strategy is 0.52% using the 8-factor model for the highest *DISP* quintile but -0.13% for the lowest *DISP* quintile. The difference between the two values is 0.65% and statistically significant, with a t-statistic of 3.32.

Panel A also reports the characteristics of bonds included in each *DISP* quintile. We observe that *DISP* is positively correlated with the daily turnover rate (i.e., the transaction volume scaled by the amount outstanding) on the earnings announcement date ($d = 0$) and in the announcement month (month $t = 0$). For instance, the average turnover on the announcement date is 0.47% for the lowest *DISP* quintile and 0.93% for the highest quintile. This finding is important because a key feature of disagreement models is their ability to explain transaction volume (e.g., Hong and Stein 2007). The dispersion in analysts' earnings forecasts captures not only the disagreement among analysts, but also among bond investors about bond value, which leads to greater transaction volumes. The relationship between the disagreement proxies and transaction volume refutes the alternative interpretation of the proxy, such as information asymmetry, because greater asymmetry would lead to lower volume.

Examining other bond characteristics, we also find that bonds with higher *DISP* tend to have lower credit quality and higher bid-ask spreads than do bonds with lower *DISP*. Although the 8-factor model should capture the risk exposure associated with these characteristics, in the panel regression below, we directly control for this exposure and examine if disagreement is subsumed by those risk proxies.

Panel B of Table 8 repeats the analysis by using stock idiosyncratic volatility, $IVOL$. We observe that the PEAD strategy generates 0.56% alpha for the highest $IVOL$ quintile but only 0.02% for the lowest $IVOL$ quintile; the difference is 0.52% (t = 3.41). In Panel C, we observe a similar pattern in PEAD profits when we use reaching-for-yield as a disagreement measure. Notably, when we measure disagreement using RFY, the average credit rating for bonds in the high and low disagreement quintiles is approximately the same. This finding suggests that the difference in alpha is not driven by variation in credit quality. In sum, although our disagreement proxies are derived from different data sets (analysts' forecasts, stock idiosyncratic volatility, and bond prices), they point to the same conclusion: Disagreement among investors leads to a greater drift in bond prices and higher transaction volumes.

To separate the effect of disagreement from those of other potentially confounding characteristics of bond returns, we run panel regressions of bond excess returns on earnings surprises (i.e., CAR), disagreement, and their interactions:

$$\begin{aligned} R^e_{i,t+1} = {} & \gamma_0 + \gamma_1 CAR_{i,t} + \gamma_2 Disagreement_{i,t} \\ & + \gamma_3 CAR_{i,t} \times Disagreement_{i,t} + \lambda Ctrl_{i,t} + \eta_{i,t+1}, \end{aligned} \tag{21}$$

where *Disagreement* is a vector of four dummies corresponding to the second through fifth quintiles of the disagreement measures (i.e., *DISP*, $IVOL$, or RFY); and $Ctrl_{i,t}$ is a vector of control variables, including bonds size, credit rating, time to maturity, downside risk, illiquidity, past one-month bond returns, bond momentum (i.e., cumulative eleven-month returns from month $t-11$ to $t-1$), bond return volatility, stock return volatility, and fractions of bids in month t and $t+1$ prices, and industry fixed effects. In addition, depending on the specification, we add year-month fixed effects or rating $\times$ year-month fixed effects, or replace industry fixed effects with industry $\times$ year-month fixed effects.

Table 9 presents the estimated slope coefficients for *Disagreement* and CAR in (21). We report estimates for CAR and the interaction between CAR and the fifth disagreement quintile dummy, which measures the difference in the PEAD effect between the fifth (high) and first (low) disagreement quintiles. The estimates on the other variables are reported in the Internet Appendix, Table A6. In Panel A, we report estimates for the regression only with CAR for reference. In Panel B, we add an interaction term between CAR and *DISP* and find that the coefficient is highly significant, ranging from 13 to 18 bps. Thus, the effect of bond PEAD nearly doubles for bonds in the highest disagreement quintile from the average in Panel A. In specifications (3), (5), and (6), we include month $t+1$ stock returns as additional controls; however, they do not change the estimated effect of disagreement on bonds.

In Panels C and D, the interaction terms between CAR and other disagreement measures are also significantly positive, suggesting that bond PEAD strengthens with disagreement even after controlling for bond characteristics such as bond size, credit rating, maturity, illiquidity, and uncertainty.

Next, we conduct an additional non-parametric analysis to further address the potential concerns about the correlation between the disagreement proxies and other determinants of PEAD, such as default risk, information asymmetry, uncertainty, and illiquidity. In particular, properly controlling for volatility is essential since uncertainty may generate both disagreement and PEAD. To this end, we perform a triple sorting of bonds based on bond characteristics first, then on disagreement, and finally on CAR. Within each characteristic tercile, we calculate the difference in PEAD returns between the high and low disagreement terciles. If the disagreement effect is subsumed by the characteristics of bonds, then we should observe no difference in PEAD profits across disagreement terciles. For this exercise, we create a composite measure of disagreement (*CDIS*) by averaging the rankings in *DISP*, *IVOL*, and RFY.

In Table 10, we observe that, even when bond characteristics, such as bid-ask spreads, credit ratings, downside risk, uncertainty, and size are held constant, changes in the composite disagreement index generate significant variation in PEAD profits (Panel A). In contrast, when we perform a triple sorting of bonds based on disagreement first, then on bond characteristics, and finally on CAR, most characteristics do not generate significant variation in PEAD profits (Panel B). Thus, regardless of the statistical methods used (i.e., factor risk adjustment in Table 8, multivariate regression in Table 9, and triple conditional sorts in Table 10), the effect of disagreement is not explained by the correlation with other bond characteristics, including bond and stock volatility.

4.2 Difference in Disagreement Between Bonds and Stocks

To further reconcile the presence of bond PEAD and the absence of equity PEAD as implied in Section 3.3.2, we compare proxies for bond and equity disagreement. First, inspired by $DISP$, we consider the negative and positive semivariance of analyst forecasts as proxies for disagreement about downside prospects, a risk relevant to bonds, and upside prospects, a risk relevant to stocks.

For each firm in each quarter, we compute the semivariance as the variance of the analyst forecast separately from the forecasts below and above the median. We require at least three forecasts for this exercise. We then compute the difference between negative and positive semivariance and report the average over the panel data.

Panel A of Table 11 reports estimates for the intercept of panel regressions of the difference in semivariance, with and without control variables. Specification (1) shows the regression without controls, where the intercept coefficient is equal to the sample average. The mean difference is estimated to be 4.56, suggesting that analysts tend to disagree more on the downside potential of firms' earnings than on the upside potential. Specifications (2) to (7) include a host of fixed effects and firm-level control variables, but we see that the estimated mean remains positive and highly significant. The greater disagreement on downside risk than about upside potential is consistent with the difference in PEAD between bonds and stocks.

Second, we compare the disagreement between bond and stock investors by examining the trading volume around the earnings announcement. Specifically, for each firm, we compute the total daily transaction volume for bonds and stocks on the three days surrounding the announcement (i.e., day [-1,1]), scaled by the volume (per day) on days [-21,-2]. If trading volume is higher around earnings announcements, then the ratio is higher than 100%. This measure of disagreement follows the spirit of Garfinkel (2009), except that we do not subtract the market average from the firm-level variable because our aim is to compare the abnormal volume across two markets. We examine the mean difference in this ratio between bonds and stocks, with and without firm-level controls.

Panel B of Table 11 reports the regression of the difference in the volume ratio between bonds and stocks on the intercept. Specification (1), which includes no control variables, shows that the average difference is 56%, suggesting that bond trading increases significantly more than stock trading around announcement dates. Specifically, the average bond volume increases by 84% due to earnings news while the average stock volume increases by 28% (not reported in the table), leading to a difference of 56%. Specifications (2) to (7) show that these estimates are unaffected by firm-level characteristics.

In sum, the available proxies for bond and stock disagreement suggest that bond investors disagree more in forecasting and interpreting earnings news than stock investors, supporting the underlying disagreement mechanism of the model.

4.3 Alternative Explanations for PEAD

In this section, we briefly discuss alternative explanations for bond PEAD. The first alternative is investors' limited attention. According to this explanation, investors do not pay attention to earnings announcements, leading to the drift. In Internet Appendix E, we use proxies for investors' attention and inattention proposed in the literature (e.g., Dellavigna and Pollet 2009, Hirshleifer et al. 2009, and Ben-Rephael et al. 2017) and show that PEAD is not pronounced when investors' attention is low.

The next alternative is the disposition effect proposed by Frazzini (2006). Following his argument, in Internet Appendix F, we examine whether bonds with a higher capital gain exhibit stronger PEAD after positive news and bonds with a capital loss do so after negative news. We do not find evidence supporting this theory, confirming that disagreement is the most likely explanation for bond PEAD.[29]

[29] In Internet Appendix Table A7, we run a panel regression of Table 9 using both inattention measures and capital gains as controls and find that the disagreement effect is significant after controlling for these competing explanations.

Finally, to study the role of transaction costs, we plot the bid-ask spreads of corporate bonds, CDS, and stocks in Figure A2 of the Internet Appendix. As expected, the spreads of bonds and CDS are higher than those of stocks. Consistent with this observation, Table 12 shows that the trading profits from bond PEAD are largely dominated by transaction costs.[30] While these results help explain why PEAD is not arbitraged away in the bond and CDS markets, they do not explain why it exists in the first place. As emphasized in Ke, Kelly, and Xiu (2019), the assessment of predictability provides economic context and magnitude to predictive signals, even when net returns after costs are modest or zero. In our case, the predictability highlights the role of investor disagreement, offering insights beyond mere tradability.

5 Conclusion

In this paper, we provide compelling empirical evidence for PEAD in the corporate bond market, in stark contrast to the declining PEAD observed in the stock market. Bonds issued by a firm with positive earnings surprises in the previous quarter tend to appreciate relative to bonds issued by a firm with negative surprises. This finding indicates the bond market's slow price reaction to prominent news that affects the value of the bond. Moreover, this result suggests that investors trade bonds at prices that are too low after positive news and too high after negative news.

We develop a unified framework that jointly models equity and bond trading for the same issuing firm and incorporates investor disagreement about the firm's underlying cash flows. We show that disagreement slows down information aggregation, thereby generating price drifts. Moreover, under reasonably calibrated parameters, the distinct payoff structures of debt and equity imply that bond prices are more prone to drift than equity prices. This explanation – grounded in investor disagreement and payoff asymmetry – is compelling because it explains several empirical findings under the unified framework, including i) why bonds with higher volume exhibit more pronounced PEAD and ii) why bond and CDS PEAD remain robust over time while equity PEAD decays.

[30]To measure the impact of transaction costs, we follow Bartram et al. (2025) and calculate the transaction costs of implementing the bond PEAD strategy, taking into account portfolio turnover and half spreads. The details of these calculations are provided in Internet Appendix G.

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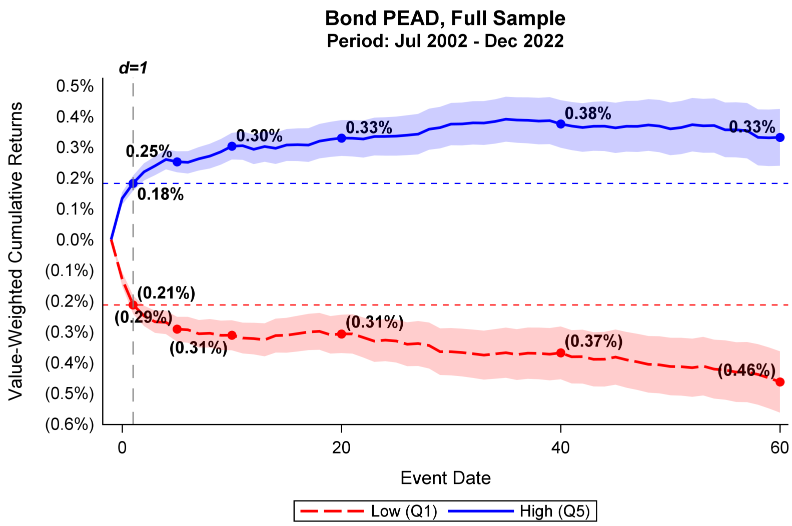
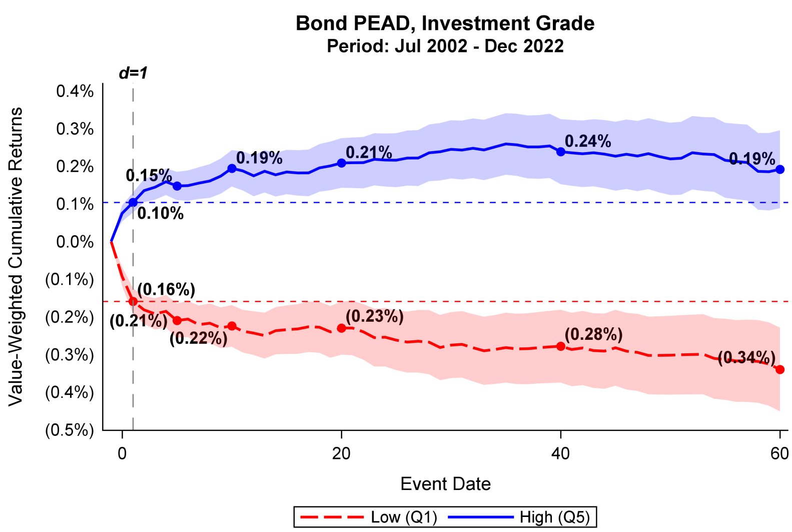
Figure 1: Event Time Plot of the PEAD Strategy

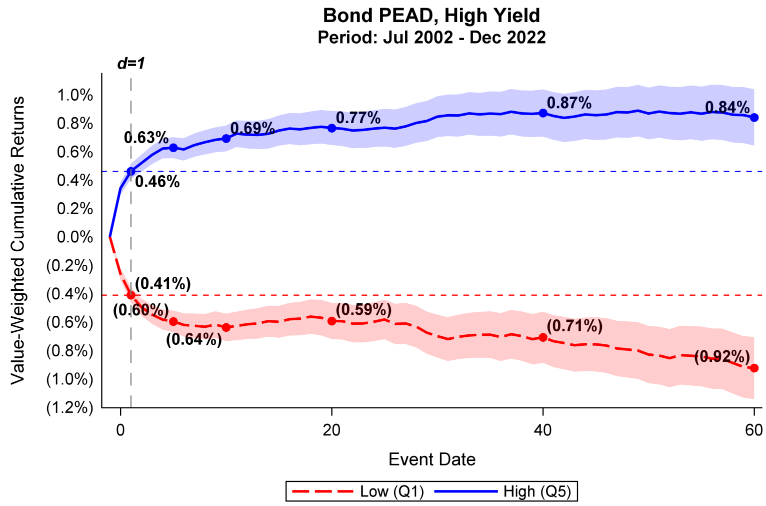
This figure plots the cumulative average abnormal returns (CAARs) on bonds with the highest earnings surprise (Q5) and those with the lowest earnings surprise (Q1) from one trading day before and 60 trading days after the earnings announcement dates. *CAR* is cumulative abnormal stock returns adjusted by the Fama-French three-factor model from trading day $d-1$ to $d+1$. *CE* is analyst forecast errors based on median consensus. *FOM* is the fraction of forecasts that miss on the same side. We use consecutive price observations to compute daily bond returns. We deduct from bond returns the return on the rating and maturity benchmark portfolios. The shaded area represents the pointwise 95% confidence bands around CAARs. The vertical line corresponds to the day on which earnings surprises are observed (i.e., $d = 1$ for *CAR* and $d = 0$ for *CE* and *FOM*). The two horizontal lines refer to the (cumulative) abnormal bond returns for Q1 (red dashed line) and Q5 (blue dashed line) portfolios at date $d = 1$ (Panel A–C) or $d = 0$ (Panel D–E). For this figure, the sample is limited to bonds that have at least 15 daily returns during the window from $d-1$ to $d+60$. For more details and analysis, see Internet Appendix A.



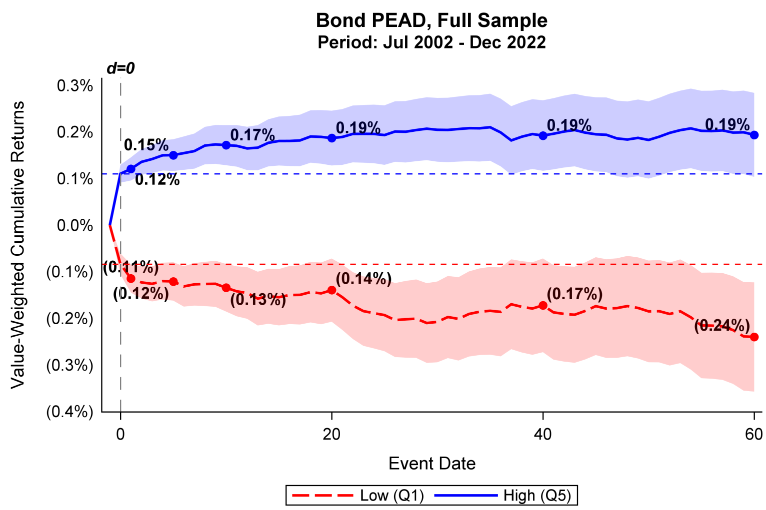
Panel A: Sorted by CAR, All



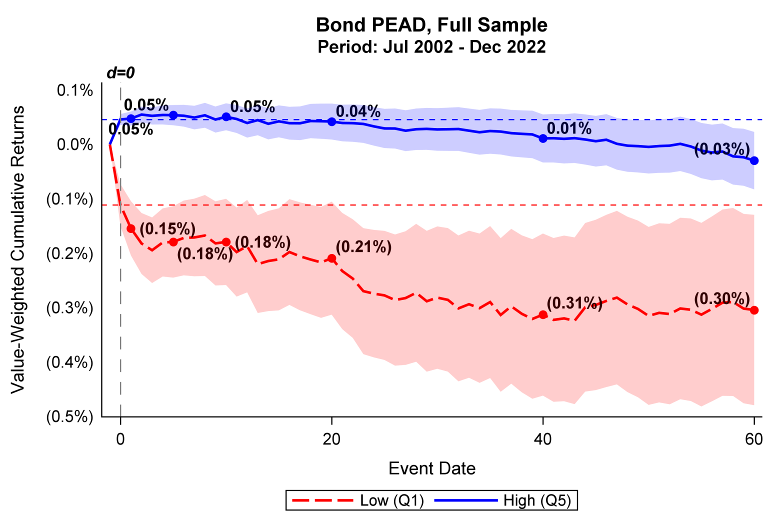
Panel B: Sorted by CAR, IG



Panel C: Sorted by CAR, HY



Panel D: Sorted by CE, All



Panel E: Sorted by FOM, All

Figure 2: Time Series Plot of the PEAD Strategy

This figure presents the time series of cumulative PEAD portfolio returns, the default factor (*DEF*), the term factor (*TERM*), as well as excess bond market returns (*MKT*) from August 2002 through December 2022. The PEAD portfolio is formed each month by long bonds with the highest earnings surprises (High *CAR*) and short bonds with the lowest earnings surprises (Low *CAR*). We use the Bloomberg US Corporate Total Return index as a proxy for the market return. *DEF* is the return difference between long-term investment-grade bonds and long-term government bonds. *TERM* is the return difference between the long-term government bond return and the one-month T-bill rate. *DEF* and *TERM* are obtained from Amit Goyal's website. *MKT*, *DEF*, and *TERM* are re-scaled to have the same volatility as the PEAD strategy over the sample period. The gray area is the NBER-dated recessions in our sample period (Jan 2008 - Jun 2009; Mar 2020 - Apr 2020).

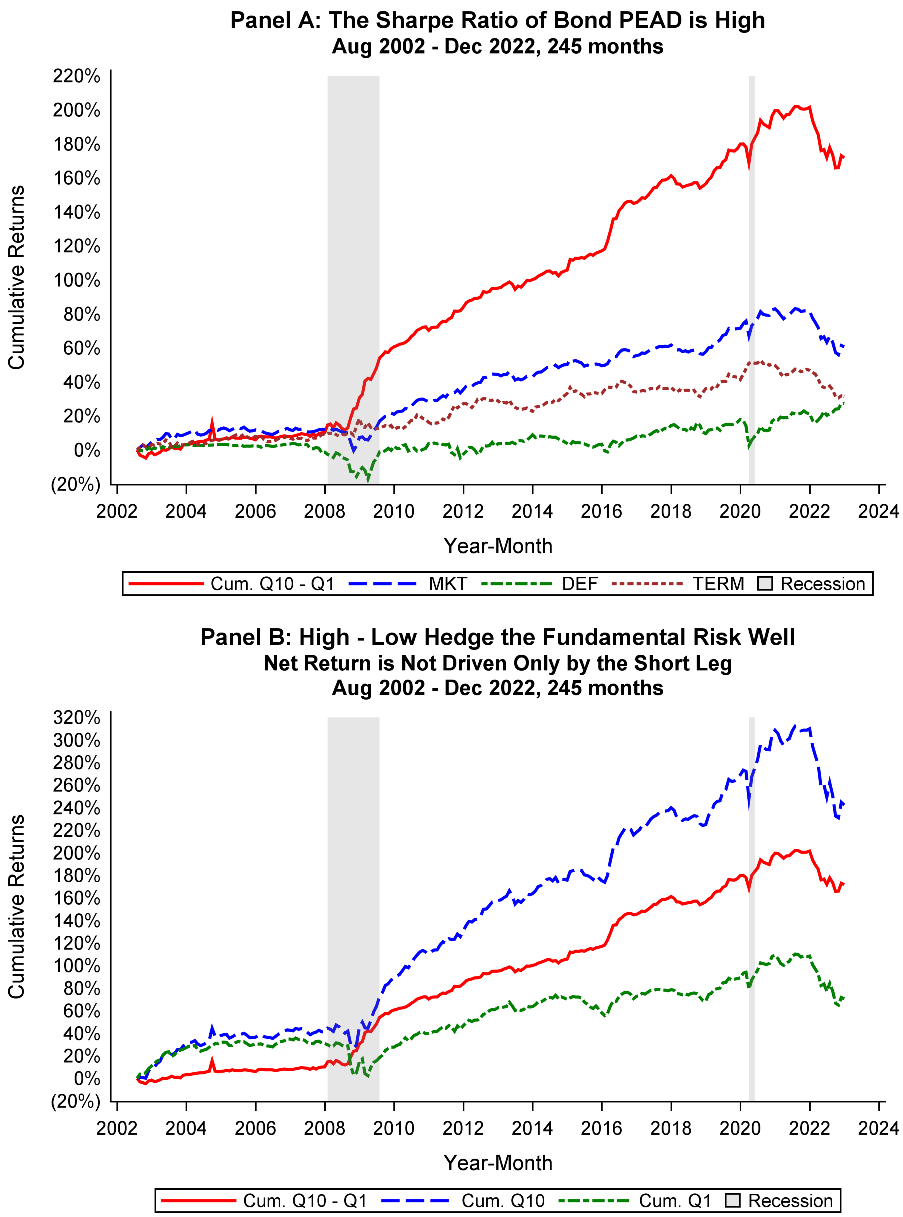
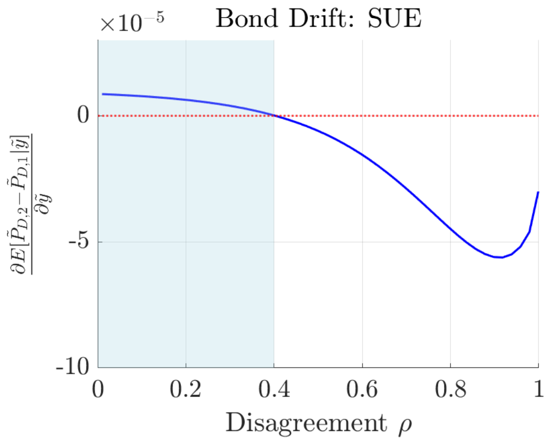
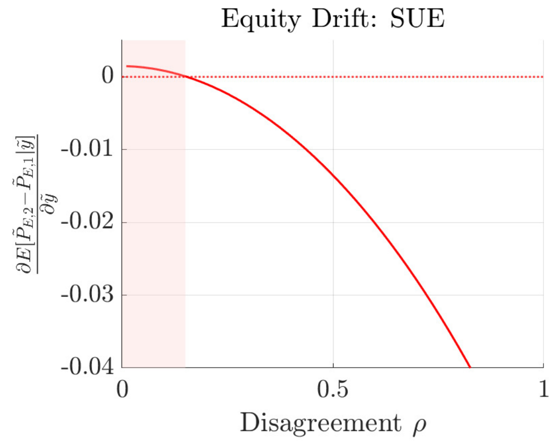


Figure 3: Price Drift, Disagreement, and Trading Volume

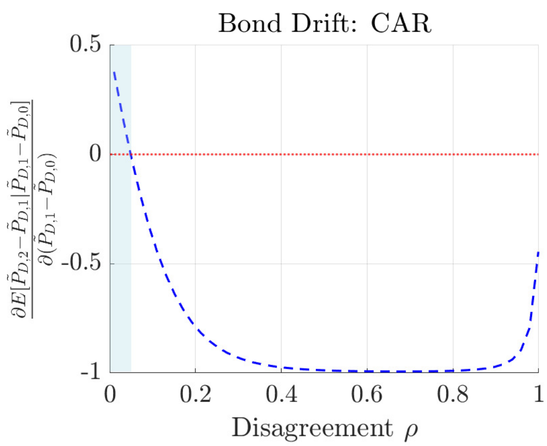
Panels (a) and (b) of this figure illustrate the impact of investor disagreement on price drift in the bond and equity markets. The shaded area highlights the region where drift occurs. Panel (c) examines the influence of disagreement on trading volume in both markets. The parameters are $m = 1.0251, K = 0.4, \sigma_\theta = 0.17, \sigma_\epsilon = \sigma_\eta = 0.6425, \gamma = 0.05, \kappa = 10$, and $\sigma_{zD} = \sigma_{zE} = 3$.



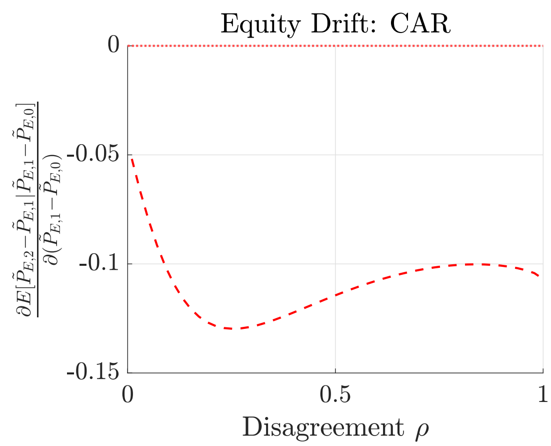
(a1) Bond Drift: SUE



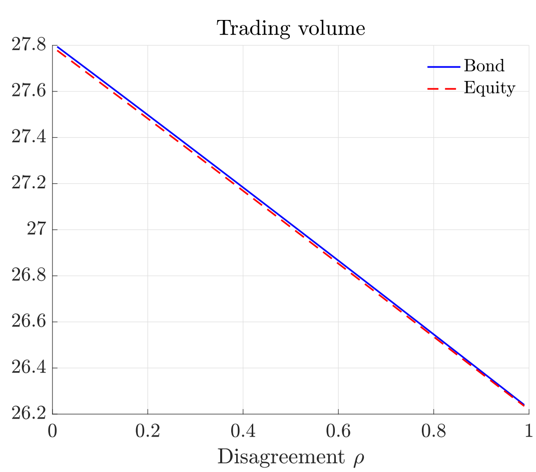
(a2) Equity Drift: SUE



(b1) Bond Drift: CAR



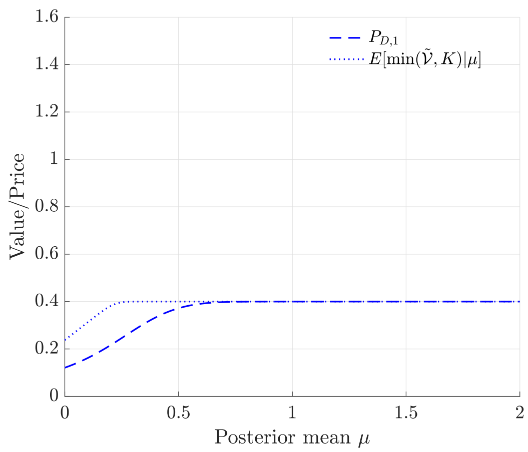
(b2) Equity Drift: CAR



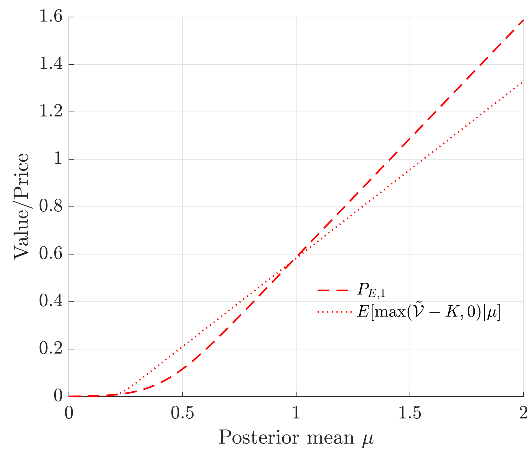
(c) Trading Volume

Figure 4: Prices, Expected Value, and Conditional Returns – An Illustration

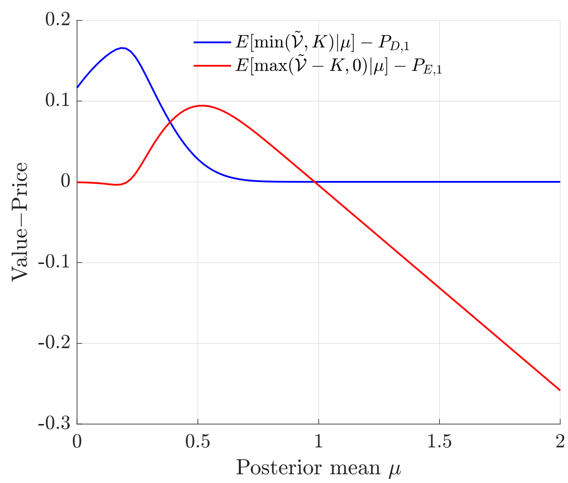
This figure plots the expected values and prices of the bond and equity against investors' average posterior belief about the firm's cash flows in Panels (a) and (b), and the expected returns of the two securities in Panel (c). The parameters are: $m = 1.0251, \sigma_\theta = 0.17, \sigma_\epsilon = \sigma_\eta = 0.6425, \gamma = 0.05, \kappa = 10$, $\sigma_{zD} = \sigma_{zE} \approx 0$, and $\rho_D = \rho_E = 0.15$.



(a) Bond: Concave Payoffs



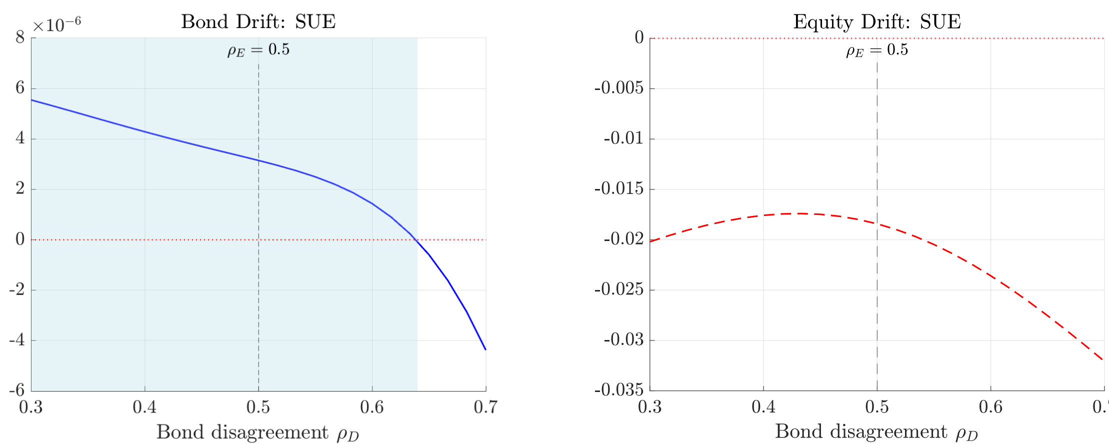
(b) Equity: Convex Payoffs



(c) Conditional Returns

Figure 5: Comparative Statics with respect to Bond Disagreement

This figure plots the effect of bond investor disagreement on price drift in the bond and equity markets. The parameters are set the same as in Figure 3 except that $\rho_E = 0.5$. The shaded area highlights the region where drift occurs.



(a) Bond Drift

(b) Equity Drift

Table 1: Descriptive Statistics

This table reports summary statistics for key variables at the bond-month level. Variable definitions are provided in Table A1. Raw and excess bond returns are not winsorized. All other continuous variables are winsorized at the 1st and 99th percentiles each month. The sample period spans August 2002 to December 2022.

Variables	*N*	Mean	SD	Min	P25	Median	P75	Max
Return (%)	960,990	0.429	5.699	-97.158	-0.547	0.327	1.420	3,450.125
Excess Return (%)	960,990	0.344	5.701	-97.268	-0.636	0.242	1.338	3,450.015
Rating	960,990	8.178	3.243	1.000	6.000	8.000	9.500	20.000
Maturity (years)	960,990	9.901	8.468	1.118	3.781	6.715	13.271	38.852
Size ($, mil)	960,990	653	634	0	271	495	817	4,291
DOWN (5% VaR)	448,998	3.609	3.446	0.219	1.503	2.639	4.501	34.115
BAS (bps)	855,613	95.688	116.458	-226.384	25.750	54.121	123.990	2,292.730
ACOV	691,328	0.635	4.496	-18.546	0.012	0.074	0.342	330.746
Age (years)	960,990	4.538	4.300	0.008	1.537	3.340	6.200	25.825
Duration	960,962	6.824	4.420	1.086	3.437	5.642	9.110	21.336
STR (%)	849,178	0.404	3.260	-49.462	-0.541	0.326	1.410	69.852
MOM (%)	694,589	4.750	12.275	-69.719	0.660	4.071	8.305	395.019
Vol (%)	802,539	2.186	2.619	0.069	0.800	1.487	2.653	45.500
SRVol (%)	960,987	1.870	1.511	0.261	1.057	1.476	2.153	30.834
$Frac(Bid)_t$ *(%)*	960,990	34.675	36.662	0.000	0.000	25.000	54.545	100.000
$Frac(Bid)_{t+1}$ *(%)*	960,990	34.500	36.706	0.000	0.000	24.891	54.286	100.000
Stock CAR (%)	960,990	-0.098	5.371	-44.435	-2.754	-0.082	2.662	40.887
Bond CAR (%)	457,894	0.032	1.605	-23.068	-0.408	-0.013	0.403	50.256
CE	960,990	-0.002	0.129	-8.631	0.000	0.001	0.002	0.780
FOM	960,990	0.388	0.706	-1.000	-0.100	0.714	1.000	1.000
DISP	911,284	0.135	0.451	0.000	0.013	0.031	0.083	10.923
IVOL (%)	960,987	1.087	0.889	0.157	0.614	0.857	1.255	21.823
RFY (%)	942,195	-0.150	1.366	-7.246	-0.964	-0.211	0.689	9.439
CGO (%)	815,949	0.413	10.882	-263.835	-2.407	0.959	4.985	43.361
SRet1m (%)	960,985	-0.015	7.736	-86.105	-3.732	-0.166	3.471	166.663
SRet6m (%)	960,985	0.092	18.921	-94.761	-9.243	-0.701	8.271	338.242
$Trade^{Small}$*(%)*	960,990	85.471	17.357	0.000	78.571	91.429	100.000	100.000
Micro	960,985	0.015	0.122	0.000	0.000	0.000	0.000	1.000
Small	960,985	0.054	0.226	0.000	0.000	0.000	0.000	1.000
Big	960,985	0.931	0.253	0.000	1.000	1.000	1.000	1.000

Table 2: Contemporaneous Bond Return Reaction to Earnings Surprises

This table presents the results of the earnings announcement event study regression. The dependent variable is cumulative abnormal bond returns from trading day $d-1$ to $d+1$, where $d=0$ is the earnings announcement date. We use the Bloomberg Barclays bond indices as benchmarks to adjust raw bond returns. Stock CAR is three-day cumulative abnormal stock returns adjusted by the Fama-French three-factor model around earnings announcement dates. CE is analyst forecast errors based on median consensus. FOM is calculated as $K/N - M/N$, where $K(M)$ is the number of forecasts strictly lower (higher) than actual earnings, and N is the total number of analyst forecasts. The control variables are a bond's credit rating, age, remaining time to maturity, and size. All continuous independent variables are standardized to have a mean of zero and a standard deviation of one. Year-quarter fixed effects are included in each regression. We double cluster standard errors by firm and year-quarter, and t-statistics are in parentheses. The asterisks represent the significance level of 1% (***), 5% (**), and 10% (*), respectively. The sample period is from July 2002 to December 2022.

Left-Hand Side Variable: 3-Day Bond CAR Around Earnings Announcement						
	(1)	(2)	(3)	(4)	(5)	(6)
Stock CAR	0.291***			0.291***	0.294***	0.295***
	(4.65)			(4.65)	(4.45)	(4.45)
CE		0.055***		0.055***		0.056***
		(3.11)		(2.87)		(2.94)
FOM			0.071**		-0.008	-0.012
			(2.59)		(-0.28)	(-0.41)
Rating	0.042**	0.044**	0.053**	0.042**	0.041*	0.041*
	(2.03)	(2.14)	(2.40)	(2.08)	(1.81)	(1.83)
Age	0.016	0.014	0.014	0.016	0.016	0.016
	(1.54)	(1.22)	(1.23)	(1.51)	(1.55)	(1.53)
Maturity	-0.005	-0.007	-0.006	-0.005	-0.005	-0.006
	(-0.27)	(-0.38)	(-0.34)	(-0.29)	(-0.27)	(-0.29)
Size	-0.067***	-0.068***	-0.070***	-0.067***	-0.066***	-0.067***
	(-4.55)	(-4.68)	(-4.89)	(-4.60)	(-4.66)	(-4.69)
Intercept	0.056***	0.056***	0.056***	0.056***	0.056***	0.056***
	(4.99)	(5.21)	(5.20)	(4.99)	(4.99)	(4.98)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	167,056	167,056	167,056	167,056	167,056	167,056
Adjusted R^2	0.009	0.003	0.003	0.009	0.009	0.009

Table 3: Univariate Portfolios of Bonds Sorted on Earnings Surprises

At the beginning of each month from August 2002 to December 2022, decile portfolios are formed by sorting corporate bonds based on the corresponding firm's most recent earnings surprises at the end of the previous month. We use stock CAR as an earnings surprise measure. Decile 1 ("Low") is the portfolio with the lowest earnings surprises, and Decile 10 ("High") is the portfolio with the highest earnings surprises. The portfolios are held for one month and rebalanced monthly. Portfolios are value-weighted using the prior month's market value of the amount outstanding as weights. Panel A reports the average excess returns and alphas of decile portfolios. Alphas are calculated from a bond factor model, a stock factor model, and a bond+stock model. The bond factor model uses two duration-adjusted bond CAPM factors from van Binsbergen, Nozawa, and Schwert (2025). The stock factors are the six factors (market, size, value, investment, profitability, and momentum) from Fama and French (2018). The bond+stock model combines the two bond factors and the six stock factors. Panel B reports average bond characteristics for each decile portfolio sorted on stock CAR. In Panel C, we equally weight bonds instead of value-weighting. In Panel D, we value-weight bond returns within each firm using prior-month bond market value to obtain firm-level bond returns, and form value-weighted portfolios of firms using prior-month equity market capitalization. Panels E and F report 8-factor alphas of value-weighted portfolios sorted on stock CAR using subsamples by rating and maturity. Panel G reports 8-factor alphas of bond portfolios with low bid-ask spreads (bottom half) and high bid-ask spreads (top half). Details on the construction of these variables are provided in Table A1. Column "SR/IR" reports the annualized Sharpe ratios or information ratios for various bond PEAD strategies. All returns and alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are reported in parentheses below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Low	2	3	4	5	6	7	8	9	High	High - Low	SR/IR
Panel A: Value-Weighted Portfolios Sorted on Earnings Announcement Stock CAR												
Average Excess Return	0.24	0.25*	0.27**	0.25**	0.30**	0.32**	0.33***	0.32**	0.37***	0.52***	0.28***	0.85
	(1.59)	(1.76)	(2.17)	(2.07)	(2.47)	(2.26)	(2.77)	(2.58)	(2.88)	(3.39)	(3.47)	
2 Bond Factor Alpha	-0.10	-0.06	-0.04	-0.05	-0.00	-0.02	0.02	0.01	0.07**	0.20***	0.31***	0.95
	(-1.60)	(-1.31)	(-1.17)	(-1.56)	(-0.13)	(-0.30)	(0.86)	(0.19)	(2.25)	(3.28)	(3.40)	
6 Stock Factor Alpha	0.03	0.10	0.12	0.11	0.17	0.19	0.20*	0.17	0.23**	0.36***	0.33***	1.03
	(0.22)	(0.81)	(0.98)	(1.08)	(1.45)	(1.52)	(1.88)	(1.58)	(2.11)	(2.76)	(3.51)	
8 Factor Alpha	-0.12	-0.06	-0.05	-0.05	-0.01	-0.00	0.03	0.00	0.08**	0.21***	0.33***	1.04
	(-1.59)	(-1.02)	(-1.34)	(-1.51)	(-0.27)	(-0.03)	(0.93)	(0.18)	(2.43)	(3.65)	(3.48)	
Panel B: Average Portfolio Characteristics												
CAR (%)	-9.98	-4.54	-2.77	-1.53	-0.51	0.47	1.50	2.76	4.60	9.83	19.81	
$Frac(Bid)_t$ (%)	34.17	34.46	34.45	35.12	34.64	35.08	35.02	35.02	34.43	34.37	0.20	
$Frac(Bid)_{t+1}$ (%)	33.73	34.01	34.47	34.76	34.53	34.99	34.94	34.97	34.25	34.38	0.65	
$Trade^{Small}$ (%)	84.42	86.21	85.94	85.80	85.69	85.64	85.64	85.32	85.45	83.61	-0.81	
$Size$ ($, mil)	629.62	672.05	665.72	671.44	679.83	654.15	654.78	684.77	687.16	638.72	9.10	
$Rating$	9.56	8.05	7.83	7.71	7.50	7.62	7.75	7.95	8.24	9.67	0.11	
$Maturity$ (years)	9.17	9.86	10.38	10.50	10.44	10.49	10.26	10.07	9.84	9.07	-0.10	
$ACOV$	2.08	1.17	1.24	0.85	2.23	0.98	0.94	1.17	1.20	3.83	1.75	
Age (years)	4.67	4.61	4.57	4.53	4.60	4.48	4.60	4.52	4.57	4.55	-0.11	

Table 3, Continued.

	Low	2	3	4	5	6	7	8	9	High	High - Low	*SR/IR*
	8-Factor Alphas of Earnings-Surprise-Sorted Portfolios											
Panel C: Equal-Weighted Portfolios Sorted on Earnings Announcement Stock *CAR*												
Estimates	-0.03	0.02	0.04	-0.09	0.05**	0.12	0.12***	0.09***	0.16***	0.41***	0.44***	0.87
	(-0.23)	(0.24)	(1.25)	(-1.62)	(2.02)	(1.25)	(2.76)	(2.74)	(3.75)	(4.28)	(2.78)	
Panel D: Firm-Level Data, Sorted on Earnings Announcement Stock *CAR*												
Estimates	-0.07*	-0.03	-0.02	0.00	0.03	-0.00	0.02	0.02	0.08	0.17***	0.24***	1.19
	(-1.94)	(-0.96)	(-0.80)	(0.08)	(0.81)	(-0.03)	(0.81)	(0.86)	(1.64)	(3.91)	(5.00)	
Panel E: Sorted on Credit Rating and Earnings Announcement Stock *CAR*												
IG+ (AAA to A-)	-0.15	-0.13*	-0.06	-0.09**	-0.09***	-0.06**	-0.02	-0.07*	-0.03	0.09	0.24	0.57
	(-1.59)	(-1.90)	(-1.31)	(-2.16)	(-2.62)	(-2.56)	(-0.40)	(-1.72)	(-0.78)	(0.85)	(1.44)	
IG- (BBB+ to BBB-)	-0.06	-0.01	0.09*	-0.01	-0.03	0.07*	-0.01	0.01	0.11**	0.20*	0.26**	0.35
	(-0.76)	(-0.15)	(1.81)	(-0.33)	(-1.08)	(1.67)	(-0.21)	(0.34)	(2.16)	(1.94)	(2.60)	
HY (BB+ or lower)	0.05	-0.01	0.10	0.16	0.26**	-0.03	0.23**	0.23***	0.39***	0.46***	0.42***	0.54
	(0.33)	(-0.05)	(1.02)	(0.97)	(2.02)	(-0.31)	(2.57)	(3.42)	(4.26)	(3.35)	(2.86)	
Panel F: Sorted on Maturity and Earnings Announcement Stock *CAR*												
$<$ 5 years	-0.01	0.08	0.02	-0.00	0.08***	0.11*	0.09***	0.12***	0.15***	0.27***	0.28**	0.51
	(-0.12)	(1.48)	(0.46)	(-0.12)	(3.21)	(1.66)	(3.28)	(3.72)	(3.84)	(3.14)	(2.10)	
5 to 10 years	-0.12	-0.05	0.04	-0.01	0.05	-0.00	0.04	0.07**	0.10***	0.17***	0.29***	0.84
	(-1.47)	(-0.87)	(0.89)	(-0.20)	(0.92)	(-0.03)	(1.64)	(2.36)	(2.61)	(2.99)	(3.09)	
$\geq$ 10 years	-0.21	-0.20*	-0.10	-0.14**	-0.11	-0.12	-0.08	-0.03	-0.05	0.19***	0.40***	0.71
	(-1.44)	(-1.78)	(-1.45)	(-2.36)	(-1.43)	(-1.29)	(-1.14)	(-0.57)	(-0.79)	(2.66)	(2.76)	
Panel G: Sorted on Bid-Ask Spreads and Earnings Announcement Stock *CAR*												
Low BAS	-0.13**	-0.05	-0.01	-0.02	0.02	-0.03	0.01	0.01	0.04*	0.07	0.20**	0.65
	(-2.04)	(-1.17)	(-0.33)	(-0.75)	(0.54)	(-0.99)	(0.34)	(0.35)	(1.76)	(1.35)	(2.54)	
High BAS	-0.15	-0.05	0.03	-0.02	-0.02	0.07	0.06	0.04	0.23***	0.37**	0.51***	0.92
	(-1.16)	(-0.52)	(0.35)	(-0.29)	(-0.44)	(0.86)	(1.27)	(1.16)	(3.06)	(2.35)	(2.68)	

Table 4: Uniqueness of Earnings Surprises: Fama-MacBeth Regressions on Earnings Surprises, Past Stock Returns and Past Rating Changes

This table reports the average slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the earnings surprises and other measures of news with and without controls. Earnings surprise is proxied by the stock *CAR*. *SRet6m* (*SRet6mAll*) is past six-month stock return, calculated as the cumulative market-adjusted stock returns over the past six months, excluding (including) the earnings announcement returns. *NoAnnCAR* is the pseudo *CAR* without earnings surprises, calculated as the three-day cumulative abnormal returns around a date randomly picked from significant price movement days in the previous six months, excluding the earnings announcement windows. We use the ratio of the standard deviation of *CAR* to the standard deviation of non-earnings-announcement *CAR* as a threshold to filter out pools of *NoAnnCAR*. *Downgrade* (*Upgrade*) is a dummy variable for rating downgrade (upgrade) in the previous three months, which equals one if there is at least one downgrade (upgrade) by any rating agencies. Bond characteristics controls include bond size (*Size*), credit rating, maturity, downside risk (*DOWN*), illiquidity (*ACOV*), short-term bond return reversal (*STR*), bond return momentum (*MOM*), bond return volatility (*Vol*), stock return volatility (*SRVol*), and the fraction of bid in month t and t+1. All continuous independent variables are standardized to have a mean of zero and a standard deviation of one. All regressions include industry dummy variables based on 30 Fama and French industry classifications. Newey-West adjusted t-statistics (with six lags) are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from August 2002 to December 2022.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CAR	0.093***	0.096***				0.096***	0.060***
	(3.21)	(3.61)				(3.81)	(2.68)
SRet6m			0.126***			0.151***	
			(4.47)			(4.95)	
SRet6mAll							0.150***
							(5.06)
NoAnnCAR				-0.015		-0.037**	-0.032**
				(-1.00)		(-2.33)	(-2.05)
Dummy: *Downgrade*					-0.100	-0.086	-0.074
					(-1.18)	(-1.11)	(-0.92)
Dummy: *Upgrade*					0.109**	0.077**	0.083**
					(2.39)	(2.05)	(2.08)
Bond Controls	NO	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES	YES	YES	YES
Observations	369,464	369,464	369,464	369,464	369,464	369,464	369,464
Average R^2	0.106	0.396	0.395	0.396	0.397	0.410	0.410

Table 5: Univariate Portfolios of CDS Sorted on Earnings Surprises

We use the five-year CDS contracts for USD-denominated senior unsecured debt of 737 U.S.-based corporate obligors from Markit for the period from August 2002 to December 2022. We include contracts that adopt the modified restructuring documentation clause before April 2009 ("CDS Big Bang") and no restructuring clause afterward. At the beginning of each month, quintile portfolios are formed by sorting CDS contracts based on the corresponding firm's most recent earnings surprises at the end of the previous month. We use stock CAR as an earnings surprise measure. Quintile 1 ("Low") is the portfolio with the lowest earnings surprises, and Quintile 5 ("High") is the portfolio with the highest earnings surprises. The portfolios are held for one month and rebalanced monthly. Portfolios are value-weighted using the prior month's firm market capitalization as weights. We compute two versions of CDS price/premium changes. Panel A presents the collateralized CDS returns following Augustin et al. (2020). Panel B uses changes in the natural logarithms of CDS spreads. Alphas are calculated from a bond factor model, a stock factor model, and a bond+stock model. The bond factor model uses two duration-adjusted bond CAPM factors from van Binsbergen, Nozawa, and Schwert (2025). The stock factors are the six factors (market, size, value, investment, profitability, and momentum) from Fama and French (2018). The bond+stock model combines the two bond factors and the six stock factors. Column "SR/IR" reports the annualized Sharpe ratios or information ratios for the CDS PEAD strategy. All returns and alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are reported in parentheses below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Low	2	3	4	High	High - Low	SR/IR
Panel A: Collateralized CDS Returns							
Average Excess Return	-0.03	0.01	0.00	0.00	0.05	0.08***	0.81
	(-0.55)	(0.36)	(0.00)	(0.13)	(1.19)	(3.24)	
2 Bond Factor Alpha	-0.07**	-0.01	-0.03	-0.02	0.02	0.09***	1.01
	(-2.54)	(-0.56)	(-1.39)	(-0.97)	(0.69)	(3.64)	
6 Stock Factor Alpha	-0.08**	-0.02	-0.04	-0.03	0.01	0.09***	0.99
	(-2.34)	(-0.87)	(-1.22)	(-1.03)	(0.45)	(3.69)	
8 Factor Alpha	-0.07***	-0.02	-0.04	-0.03	0.02	0.09***	1.03
	(-2.91)	(-0.81)	(-1.50)	(-1.04)	(0.59)	(3.52)	
Panel B: Log CDS Spread Changes							
Average Spread Changes	0.52	-0.15	0.22	0.07	-0.80	-1.32***	
	(0.71)	(-0.19)	(0.27)	(0.09)	(-1.28)	(-4.47)	

Table 6: PEAD in Stock Returns: Six-Factor Alphas for Various Subsamples

This table presents the performance of the stock PEAD strategy. Quintile portfolios are formed by sorting stocks based on the corresponding firm's most recent earnings surprises at the end of the previous month. Quintile 1 is the portfolio with the lowest earnings surprises, and Quintile 5 is the portfolio with the highest earnings surprises. We consider three earnings surprise measures: *CAR*, *CE*, and *FOM*. Details on the construction of these variables are provided in Table A1. Since the values of FOM are between -1 and 1, we assign firms with $FOM = -1$ into Quintile 1 and firms with $FOM = 1$ into Quintile 5 unconditionally, and form tercile portfolios for the remaining firms ($-1 < FOM < 1$) each month for Quintile 2 to Quintile 4. All the portfolios are held for one month and rebalanced monthly. Portfolios are value-weighted using the prior month's firm market capitalization as weights (left panel) or equal-weighted (right panel). This table reports six-factor alphas for the high-minus-low hedge portfolios sorted on the earnings surprises. The six stock market factors (market, size, value, investment, profitability, and momentum) are from Fama and French (2018). We consider bond issuers (Panel A) as well as all common stocks in our sample period (Panel B) from August 2002 to December 2022. Also, we show earlier sub-period results for the stock PEAD from January 1984 to July 2002 (Panel C). All alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are reported in parentheses below alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

CAR	*CE*	*FOM*	*CAR*	*CE*	*FOM*
Value-Weighted Portfolios			Equal-Weighted Portfolios		
Panel A: Bond Issuers, Aug 2002 - Dec 2022					
0.17	0.11	0.08	0.19*	-0.07	-0.05
(1.46)	(0.70)	(0.52)	(1.95)	(-0.55)	(-0.49)
Panel B: All Firms, Aug 2002 - Dec 2022					
0.21*	0.39**	0.14	0.34***	0.40***	0.29***
(1.82)	(2.21)	(1.22)	(3.58)	(3.65)	(3.34)
Panel C: All Firms, Jan 1984 - Jul 2002					
0.53***	0.36*	0.56***	0.74***	1.32***	1.07***
(2.84)	(1.95)	(4.10)	(8.03)	(10.50)	(8.68)

Table 7: Parameter Values

This table summarizes the values of parameters used in our calibration analysis.

Parameter	Description	Value
K	Debt face value	0.4
m	Mean of firm asset value	1.0251
σ_θ	Volatility of firm asset value	0.17
σ_ε	Volatility of noises in investors' private information	0.6425
σ_η	Volatility of noises in public information	0.6425
σ_{zD}, σ_{zE}	Noise trading intensity in bond/equity markets	3
κ	Mean of asset supply	10
γ	Risk aversion coefficient	0.05
ρ_D, ρ_E	Disagreement in bond and equity markets	$[0, 1]$

Table 8: 8-Factor Alphas for PEAD Long-Short Strategies: Subsample by Disagreement Proxies

Every month from August 2002 to December 2022, 25 value-weighted portfolios are formed by independently sorting corporate bonds based on the issuer's most recent earnings surprises and disagreement proxies. Earnings surprise is proxied by the stock *CAR*. We use three disagreement proxies: *DISP*, *IVOL*, and *RFY*. *DISP* is analyst forecast dispersion, calculated as the standard deviation of analyst forecasts scaled by the absolute mean forecast value. *IVOL* is stock idiosyncratic volatility, defined as the standard deviation of the daily residuals estimated from the regression of excess stock returns on a constant and the six factors (market, size, value, investment, profitability, and momentum) from Fama and French (2018) at a monthly level. *RFY* is bond-level reaching for yield proxy, defined as the difference between a bond's yield and the cross-sectional average yield of bonds with the same credit rating, calculated following Choi and Kronlund (2018) and Chen and Choi (2024). We present the 8-factor alphas, where portfolios are value-weighted using the market value of the amount outstanding as weights. We also report the average daily bond turnover rate on earnings announcement day and month, as well as other bond characteristics for each disagreement quintile. Details on the construction of these variables are provided in Table A1. All returns and alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Low Disagreement	2	3	4	High Disagreement	High - Low
Panel A: Analyst Forecast Dispersion (*DISP*) As Disagreement Proxy						
PEAD 8 Factor Alpha	-0.13	-0.12	-0.02	-0.00	0.52***	0.65***
	(-0.96)	(-1.59)	(-0.13)	(-0.01)	(3.29)	(3.32)
DISP	0.008	0.018	0.035	0.076	0.617	
Turnover on Ann. Date	0.47	0.51	0.57	0.69	0.93	
Turnover on Ann. Month	0.50	0.52	0.56	0.61	0.68	
Size	674.38	667.90	720.19	678.99	616.51	
Rating	6.71	7.15	7.69	8.57	10.43	
Maturity	10.76	10.79	10.20	9.76	8.96	
BAS	80.81	88.57	88.31	101.68	111.69	
Panel B: Stock Idiosyncratic Volatility (*IVOL*) As Disagreement Proxy						
PEAD 8 Factor Alpha	0.02	0.03	0.10	0.03	0.56***	0.52***
	(0.20)	(0.30)	(0.81)	(0.27)	(3.36)	(3.41)
IVOL	0.52	0.72	0.91	1.19	2.20	
Turnover on Ann. Date	0.43	0.49	0.57	0.66	1.04	
Turnover on Ann. Month	0.49	0.52	0.54	0.58	0.72	
Size	739.15	698.44	658.18	646.93	573.32	
Rating	6.39	7.09	7.81	8.74	10.99	
Maturity	10.72	10.64	10.23	9.73	8.68	
BAS	91.21	89.04	88.57	92.82	110.02	
Panel C: Reaching For Yield (*RFY*) As Disagreement Proxy						
PEAD 8 Factor Alpha	0.25*	0.26*	0.31***	0.34***	0.70***	0.45***
	(1.66)	(1.70)	(2.78)	(3.24)	(3.52)	(3.90)
RFY	-1.84	-0.92	-0.24	0.55	1.73	
Turnover on Ann. Date	0.48	0.49	0.64	0.74	0.79	
Turnover on Ann. Month	0.48	0.51	0.61	0.65	0.64	
Size	677.89	732.21	717.56	650.29	566.43	
Rating	8.45	7.69	7.96	7.60	8.30	
Maturity	3.21	4.90	7.78	15.46	19.02	
BAS	50.08	63.74	78.99	116.09	163.26	

Table 9: Panel Regressions of Bond Returns on Earnings Surprises and Disagreement

This table reports the slope coefficients from panel regressions of one-month-ahead corporate bond excess returns on earnings surprise measures and disagreement proxies with control variables. Bond characteristics controls include bond size (*Size*), credit rating, maturity, downside risk (*DOWN*), illiquidity (*ACOV*), short-term bond return reversal (*STR*), bond return momentum (*MOM*), bond return volatility (*Vol*), stock return volatility (*SRVol*), and the fraction of bid in month t and t+1. We also include quintile dummies of three disagreement proxies (*DISP*, *IVOL*, and *RFY*), as well as interactions of these dummies with earnings surprises. *DISP* is analyst forecast dispersion, calculated as the standard deviation of analyst forecasts scaled by the absolute mean forecast value. *IVOL* is stock idiosyncratic volatility, defined as the standard deviation of the daily residuals estimated from the regression of excess stock returns on a constant and the six factors (market, size, value, investment, profitability, and momentum) from Fama and French (2018) at a monthly level. *RFY* is bond-level reaching for yield proxy, defined as the difference between a bond's yield and the cross-sectional average yield of bonds with the same credit rating, calculated following Choi and Kronlund (2018) and Chen and Choi (2024). All independent continuous variables are standardized to have a mean of zero and a standard deviation of one. We include industry dummies based on 30 Fama and French industry classifications, t+1 stock returns, year-month, rating × year-month, and industry × year-month fixed effects across different specifications. We double cluster standard errors by firm and time, and t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from August 2002 to December 2022.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline Results						
CAR	0.107***	0.091***	0.085***	0.091***	0.084***	0.079***
	(3.42)	(3.38)	(3.28)	(3.14)	(3.10)	(3.08)
Bond Controls	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	NO	NO	NO
Year-Month FE	YES	NO	NO	NO	NO	NO
Rating × Year-Month	NO	YES	YES	NO	NO	YES
Include $t+1$ Stock Returns?	NO	NO	YES	NO	YES	YES
Industry × Year-Month	NO	NO	NO	YES	YES	YES
Observations	369,920	369,920	369,915	369,588	369,583	369,583
Adjusted R^2	0.236	0.296	0.333	0.339	0.373	0.407
Panel B: *DISP* Quintiles						
CAR	0.021	0.017	0.021	0.013	0.015	0.011
	(1.03)	(0.70)	(0.91)	(0.73)	(0.90)	(0.51)
CAR × *DISP5*	0.180***	0.157***	0.131**	0.165***	0.139**	0.135**
	(2.76)	(2.61)	(2.25)	(2.71)	(2.31)	(2.42)
DISP Quintiles	YES	YES	YES	YES	YES	YES
Bond Controls	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	NO	NO	NO
Year-Month FE	YES	NO	NO	NO	NO	NO
Rating × Year-Month	NO	YES	YES	NO	NO	YES
Include $t+1$ Stock Returns?	NO	NO	YES	NO	YES	YES
Industry × Year-Month	NO	NO	NO	YES	YES	YES
Observations	351,866	351,866	351,861	351,511	351,506	351,506
Adjusted R^2	0.246	0.308	0.341	0.350	0.378	0.413

Table 9, Continued

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: *IVOL* Quintiles						
CAR	0.038*	0.035	0.034	0.014	0.021	0.036
	(1.92)	(1.53)	(1.64)	(0.48)	(0.76)	(1.53)
CAR × *IVOL5*	0.137**	0.125**	0.118**	0.131**	0.118*	0.101*
	(2.25)	(2.32)	(2.25)	(1.99)	(1.89)	(1.83)
IVOL Quintiles	YES	YES	YES	YES	YES	YES
Bond Controls	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	NO	NO	NO
Year-Month FE	YES	NO	NO	NO	NO	NO
Rating × Year-Month	NO	YES	YES	NO	NO	YES
Include $t+1$ Stock Returns?	NO	NO	YES	NO	YES	YES
Industry × Year-Month	NO	NO	NO	YES	YES	YES
Observations	369,920	369,920	369,915	369,588	369,583	369,583
Adjusted R^2	0.236	0.297	0.334	0.339	0.373	0.407
Panel D: *RFY* Quintiles						
CAR	0.018	0.014	0.008	0.019	0.012	0.014
	(1.60)	(1.21)	(0.80)	(1.63)	(1.11)	(1.18)
CAR × *RFY5*	0.178***	0.175***	0.180***	0.181***	0.185***	0.185***
	(2.74)	(2.91)	(2.98)	(2.76)	(2.91)	(3.07)
RFY Quintiles	YES	YES	YES	YES	YES	YES
Bond Controls	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	NO	NO	NO
Year-Month FE	YES	NO	NO	NO	NO	NO
Rating × Year-Month	NO	YES	YES	NO	NO	YES
Include $t+1$ Stock Returns?	NO	NO	YES	NO	YES	YES
Industry × Year-Month	NO	NO	NO	YES	YES	YES
Observations	360,918	360,918	360,913	360,571	360,566	360,566
Adjusted R^2	0.303	0.362	0.394	0.393	0.423	0.462

Table 10: 8-factor Alphas on Triple-Sorted Portfolios of Earnings Surprises, Disagreement, and Bond Characteristics

27 (3 × 3 × 3) portfolios are formed every month from August 2002 to December 2022 by conditionally sorting corporate bonds based on the corresponding firm's most recent earnings surprises, disagreement measures, and bond characteristics. Earnings surprise is proxied by the stock *CAR*. We use four disagreement proxies (*DISP*, *IVOL*, *RFY*, and *CDIS*) and eight bond characteristics. *CDIS* is a composite disagreement measure. Each month, we sort all bonds into ten buckets based on the three disagreement proxies (*DISP*, *IVOL*, and *RFY*) respectively, from the low to high disagreement, and compute an average rank for this bond as *CDIS*. Details on the construction of other variables are provided in Table 1. In Panel A, corporate bonds are sorted first on one of the eight bond characteristics, and then on one of the disagreement measures, and lastly on *CAR*. We compute the PEAD long-short portfolios for each characteristic/disagreement cell, where the bonds are value-weighted using the market value of the amount outstanding as weights. Then, within each characteristic tercile, we calculate the difference in PEAD profits between the highest and lowest disagreement terciles and take the simple average of the resulting three portfolio excess returns. We present 8-factor alpha (in percent per month). In Panel B, we switch the role of characteristics and disagreement, and repeat the exercise. Specifically, we first sort on disagreement, then on characteristics, and lastly on *CAR*, and report the alphas due to the variation in PEAD profits across characteristics within disagreement terciles. Newey-West adjusted t-statistics (with six lags) are reported in parentheses below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Bond Vol	*Stock Vol*	*Size*	*Rating*	*Maturity*	*Down*	*BAS*	*ACOV*
Panel A: Conditional Triple-Sort on Bond Characteristics, Disagreement, and *CAR* (PEAD Difference Between High and Low Disagreement Within Characteristic Terciles)								
DISP	0.31***	0.26***	0.37***	0.20**	0.39***	0.18**	0.42***	0.40***
	(3.47)	(2.78)	(3.17)	(2.48)	(3.54)	(2.07)	(3.15)	(3.23)
IVOL	0.34**	0.19***	0.30***	0.22***	0.32***	0.15	0.36***	0.30**
	(2.19)	(2.69)	(2.93)	(2.72)	(2.93)	(1.64)	(2.76)	(2.25)
RFY	0.06	0.08	0.38***	0.20**	0.33***	0.18**	0.20	0.29**
	(0.72)	(0.92)	(2.96)	(2.05)	(2.71)	(2.16)	(1.65)	(2.56)
CDIS	0.36**	0.23***	0.50***	0.40***	0.39***	0.36**	0.44**	0.48***
	(2.39)	(2.71)	(2.81)	(2.83)	(3.33)	(2.54)	(2.56)	(3.10)
Panel B: Conditional Triple-Sort on Disagreement, Bond Characteristics, and *CAR* (PEAD Difference Between High and Low Characteristics Within Disagreement Terciles)								
DISP	0.14**	0.11*	-0.13	0.09	0.04	0.14*	0.12	-0.11
	(2.31)	(1.73)	(-1.54)	(1.31)	(0.56)	(1.69)	(1.18)	(-1.27)
IVOL	0.05	0.14*	-0.01	0.12	0.13**	0.16	0.17	-0.00
	(0.56)	(1.66)	(-0.23)	(1.52)	(2.08)	(1.55)	(1.38)	(-0.04)
RFY	0.05	0.31**	-0.18	0.23***	-0.07	0.27***	0.09	0.01
	(0.68)	(2.23)	(-1.64)	(3.10)	(-0.85)	(3.12)	(1.51)	(0.24)
CDIS	0.00	0.08	-0.13	0.06	0.08	0.13	0.14	-0.05
	(0.03)	(0.73)	(-1.16)	(0.83)	(1.11)	(1.59)	(0.98)	(-0.53)

Table 11: Panel Regressions of Differences in Disagreement Between Bonds and Stocks on Intercepts

This table reports the intercepts from panel regressions of the disagreement differences between bonds and stocks on firm characteristics. The left-hand side variable (LHV) is the difference between negative and positive semivariance ($\times$ 100) in Panel A or the difference between bond and stock volume ratios (in percentages) in Panel B. Negative (positive) semivariance is calculated as an average of the squared deviations of each firm's annual earnings forecasts by analysts that are less (more) than the median analyst forecasts scaled by the absolute mean forecast value. Volume ratios are computed as the trading volume in the three-trading-day window [-1, 1] around earnings announcement dates divided by the trading volume in the pre-announcement 20-trading-day window [-21, -2] for both bonds and stocks. We take the value-weighted average of bond volume ratios at each firm-quarter level. The common firm-level controls include the logarithm of market capitalization, the logarithm of book-to-market ratio, past 11-month stock returns skipping the most recent month, operating profitability, investment, Amihud measure, and bid-ask spread. Panel A additionally controls for the logarithm of the number of analysts, while Panel B additionally controls for the value-weighted bond ratings, the value-weighted time to maturity, and the logarithm of the sum of the market value of the bond amount outstanding. We include industry dummies, time dummies, size $\times$ time, rating $\times$ time, and industry $\times$ time fixed effects across different specifications. We cluster standard errors by firm, and t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1984 to December 2022 for Panel A and July 2002 to December 2022 for Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: LHV = (Negative Semivariance − Positive Semivariance) $\times$ 100							
Intercept	4.563***	4.563***	4.563***	4.563***	4.563***	4.563***	4.563***
	(14.35)	(14.49)	(14.64)	(14.64)	(14.77)	(14.79)	(14.77)
Firm Controls	NO	NO	NO	NO	YES	YES	YES
Industry Controls	NO	YES	YES	NO	YES	YES	NO
Year-Month Dummies	NO	YES	NO	NO	YES	NO	NO
Size $\times$ Year-Month	NO	NO	YES	YES	NO	YES	YES
Industry $\times$ Year-Month	NO	NO	NO	YES	NO	NO	YES
Observations	708,576	708,576	708,576	708,576	708,576	708,576	708,576
Adjusted R^2	-0.000	0.005	0.009	0.013	0.009	0.012	0.015
Panel B: LHV = Bond Volume Ratio (%) − Stock Volume Ratio (%)							
Intercept	56.183***	56.183***	56.183***	56.183***	56.183***	56.183***	56.183***
	(24.07)	(26.32)	(26.96)	(26.60)	(27.98)	(28.54)	(28.19)
Firm Controls	NO	NO	NO	NO	YES	YES	YES
Industry Controls	NO	YES	YES	NO	YES	YES	NO
Year-Qtr Dummies	NO	YES	NO	NO	YES	NO	NO
Rating $\times$ Year-Qtr	NO	NO	YES	YES	NO	YES	YES
Industry $\times$ Year-Qtr	NO	NO	NO	YES	NO	NO	YES
Observations	43,299	43,299	43,299	43,299	43,299	43,299	43,299
Adjusted R^2	-0.000	0.021	0.025	0.027	0.025	0.029	0.031

Table 12: Transaction Costs and Net Performance of PEAD Strategy

This table shows monthly one-way turnover, transaction costs as well as the net performance of the value-weighted long-short investment strategy based on earnings surprises (PEAD strategy) with monthly rebalancing. The construction of one-way turnover and transaction costs follows Bartram et al. (2025). The daily bid-ask spread is computed as $(S-B)/0.5(S+B)$, where S (B) is the volume-weighted average sell (buy) price for a bond on a given day. We use the institutional-size trade with a volume larger than $100,000 to compute the bid-ask spread. If the bid-ask spread for a bond is missing for a month, we use the 90th percentile of the cross-sectional distribution for that month. All returns and alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are reported in parentheses below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Low CAR	CAR, 2	CAR, 3	CAR, 4	High CAR	High - Low
Panel A: Portfolio Turnover and Transaction Costs						
One-Way Turnover (%)	30.93	35.51	34.32	34.24	32.25	63.18
Transaction Costs (%)	0.09	0.10	0.09	0.09	0.09	0.18
Panel B: Net Performance: Univariate Sort on Earnings Surprise						
Average Excess Return	0.16	0.16	0.21*	0.23*	0.36***	0.02
	(1.09)	(1.38)	(1.75)	(1.97)	(2.66)	(0.28)
2 Bond Factor Alpha	-0.17***	-0.14***	-0.11***	-0.08***	0.05	0.05
	(-2.84)	(-5.73)	(-3.94)	(-3.75)	(1.33)	(0.74)
6 Stock Factor Alpha	-0.03	0.01	0.07	0.08	0.20*	0.04
	(-0.22)	(0.08)	(0.63)	(0.79)	(1.70)	(0.72)
8 Factor Alpha	-0.18***	-0.15***	-0.11***	-0.08***	0.05	0.05
	(-2.70)	(-6.26)	(-3.88)	(-3.72)	(1.48)	(0.75)

Internet Appendix to "Disagreement and Bond PEAD"

A Bond PEAD: Initial Look

In this section, we study the cumulative daily abnormal returns 60 trading days after earnings announcements. The use of daily returns provides us with the initial look at the bond PEAD and allows us to pin down when the drift arises.

To this end, we calculate a daily abnormal return on a bond as the difference in return between the bond and a benchmark. We use six value-weighted portfolios of bonds in our sample double sorted by credit rating (IG and HY) and time to maturity ($<$ 5 years, 5 to 10 years, $\geq$ 10 years) as the benchmark. Since bonds do not trade every day, we calculate a daily return only when the bond is traded on two consecutive trading days and use the subsample of relatively liquid corporate bonds that have at least 15 daily return observations over the event window $[d-1, d+60]$.[31] Then, we classify bonds into five groups based on earnings surprises. The threshold is set using the panel data of earnings surprises. We take the value-weighted average of abnormal returns on the bonds within each group and compound the daily average abnormal returns for the first and fifth earnings-surprise quintiles to obtain cumulative average abnormal returns. To value-weight bonds in a quintile, we use the bonds' market value as weights. Standard errors for the quintile-level abnormal returns are calculated by regressing bonds' daily abnormal returns on a constant (where each observation is weighted by a bond's lagged amount outstanding) and clustered by calendar dates to account for cross-sectional correlation in bond returns.

We plot bonds' cumulative abnormal returns in Figure 1. Panel A depicts the returns and their 95% confidence interval when we classify bonds based on CAR. We measure the drift using the difference in cumulative abnormal returns between 60 days and 1 day after the announcement. We use Day 1 rather than Day 0 as a reference point because the earnings surprise measure (CAR) includes the information on Day 1. We find that, for the bonds with the top 20% earnings surprise (Q5), the difference in the cumulative abnormal returns on Day 60 and Day 1 is 0.15%, while for those with the bottom 20% (Q1), the difference is -0.25%. These findings suggest that bond prices tend to drift in the same direction after earnings announcements as their initial reactions to the

[31] Daily bond returns and bond market values are winsorized at the 0.5th and 99.5th percentiles in the pooled bond-day panel before the rating $\times$ maturity benchmark averages and the quintile-level value-weighted averages are computed. The treatment limits the influence of extreme daily observations on the cumulative averages plotted in Figure 1 and does not affect the monthly-return sample used in the main tables.

news.

Panel A of Figure 1 also highlights the importance of downside risk in the bond market. On Day 1, the magnitude of the returns is greater for Q1 (-0.21%) than Q5 (0.18%), highlighting the key feature of corporate bonds that are exposed to downside risk but have limited upside potentials. Furthermore, the magnitude of the drift after the announcement for Q1 (0.25%) is greater than that for Q5 (0.15%), suggesting that PEAD is more pronounced after negative news than positive news.

This asymmetric response aligns with the perspective that corporate bonds are equivalent to holding the risk-free rate while shorting a put option on the underlying firm's value (e.g., Merton 1974). Given this capped payoff structure relative to equities, bonds naturally exhibit heightened sensitivity to negative information. Negative news, which increases perceived default risk, significantly reduces bond prices more than equivalent positive news can increase them. This asymmetry is clearly evident in Figure 1 Panel A, where the value-weighted cumulative return for Q1 (i.e., negative news) is notably lower (-0.46%) at Day 60 compared to Q5 (i.e., positive news) at 0.33%. This robust pattern consistently holds across various samples and alternative measures of earnings news presented in subsequent subplots.

Panels B and C of Figure 1 present the cumulative abnormal returns separately for IG and HY bonds. These figures show that there is PEAD both in IG and HY bonds, especially after bad news. However, PEAD is more pronounced for HY bonds than for IG bonds, consistent with Chordia et al. (2017) who find that anomalies are more pronounced for HY bonds than for IG bonds in the corporate bond market.

Finally, Panels D and E report the cumulative abnormal bond returns when earnings surprise is measured by *CE* and *FOM*. In this case, both the initial reactions to earnings news and the subsequent drifts are smaller in magnitude than the case with *CAR*. Still, the cumulative abnormal returns in 60 days are significantly different from Day-0 returns for the bonds with the bottom 20% earnings surprise, suggesting that bond prices exhibit drift after negative news regardless of the proxy we use for earnings surprises.

Akey, Gregoire, and Martineau (2022) and Meursault et al. (2022) show that stock *CAR* responds to soft information contained in press releases distributed upon announcement as well as the headline numbers. In addition, there is arguably more room for disagreement over the interpretation of soft information than earnings per share. This greater role of disagreement explains why bond prices exhibit greater drift after announcement using stock *CAR* than *CE* and *FOM*, which are both based on hard information. We formalize this argument in Section 3.

B PEAD Profits When Holding Period Is Longer Than One Month

In this section, we study the persistence of profits of the PEAD strategy. We follow Jegadeesh and Titman (1993) to buy and hold value-weighted portfolios for K months, and record their monthly returns. We then take the simple average of monthly returns across portfolios formed in months $t, \ldots, t-K+1$, and obtain returns on the quintile portfolios. Table A8 reports the strategy's average excess returns and 8-factor alphas. The profits of a bond PEAD strategy decay slowly within a year: For example, when the holding period is three months, the average excess returns and 8-factor alphas are 13 bps and 16 bps, respectively, which are more than a third of the main results where $K = 1$. However, the decay in profits for a longer horizon suggests that it is difficult to profit from a simple PEAD strategy with a lower rebalancing frequency.

C Bond PEAD Using Sample from 1997 to 2020

In this section, we use Merrill Lynch's quote data provided by ICE from 1997 to 2020 to examine bond PEAD. With this data, we create a bond PEAD strategy using subsamples before and after the introduction of TRACE, measure the potential impact of the introduction of TRACE, and observe the longer-term trend in bond PEAD profitability.

Table A9 shows the average excess returns and factor alphas for deciles sorted on stock CAR around earnings announcement dates. Similarly, we use the two duration-adjusted bond CAPM factors of van Binsbergen, Nozawa, and Schwert (2025) and the six stock factors of Fama and French (2018) to control for risks.

In Panel A, we study bond PEAD using the sample from January 1997 to June 2002. The average excess return on the long-short portfolio on earnings surprise is 6 bps, which is statistically indistinguishable from zero. Thus, we do not see evidence supporting bond PEAD during this (roughly) five-year period.

In Panel B, we study the subsample from July 2002 (when TRACE was introduced) to December 2020. In this period, the average excess return on the bond PEAD strategy is 29 bps, which is very similar to the main results based on TRACE in Table 3. These quote-based results are best viewed as complementary to the TRACE-based evidence in the main text. The similarity of results across the two data constructions suggests that the PEAD pattern is not specific to one pricing source. This finding also suggests that the introduction of TRACE does not necessarily make the bond market more efficient.

D Proofs

Details of Equilibrium Characterization

Section 3.2 has outlined how to characterize equilibrium in the model. Here, we provide additional details that were previously omitted in that section.

Below we derive the economy without public information, i.e., $\sigma_\eta = \infty$. To incorporate public information, we simply need to make the following adjustment. Denote the untruncated normal distribution as $\mathcal{V}'$. The characterized equilibrium prices and demands remain unchanged after replacing

$$E[\tilde{\mathcal{V}}'] = m \text{ with } E[\tilde{\mathcal{V}}' \mid \tilde{y}] = m + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\eta^2}\tilde{y}, \tag{D1}$$

$$Var[\tilde{\mathcal{V}}'] = \sigma_\theta^2 \text{ with } Var[\tilde{\mathcal{V}}' \mid \tilde{y}] = \frac{\sigma_\theta^2 \sigma_\eta^2}{\sigma_\theta^2 + \sigma_\eta^2}. \tag{D2}$$

Following Banerjee et al. (2025), we can show that the conditional cash flow distribution remains truncated normal, with the normal distribution having mean μ_i and variance σ_s^2. Given investor i's information set $\{\tilde{y}, \tilde{s}_i, \tilde{s}_p\}$, where $\tilde{s}_p = (\tilde{s}_{pD}, \tilde{s}_{pE})'$, we apply Bayes' rule and compute the conditional moments as follows:

$$\mu_i \equiv E[\tilde{\mathcal{V}}' \mid \tilde{s}_i, \tilde{s}_{pD}, \tilde{s}_{pE}] = m + \sigma_s^2(\frac{\tilde{s}_i}{\sigma_\varepsilon^2} + \beta_D \tilde{s}_{pD} + \beta_E \tilde{s}_{pE}), \tag{D3}$$

and

$$\begin{aligned}\sigma_s^2 \equiv Var[\tilde{\mathcal{V}}' \mid \tilde{s}_i, \tilde{s}_{pD}, \tilde{s}_{pE}] = \sigma_\theta^2\sigma_\varepsilon^2 \cdot \Big(b_D^2 b_E^2 \sigma_{zD}^2 \sigma_{zE}^2 + b_E^2(1-\rho_D^2)\sigma_{zE}^2\sigma_\theta^2 + b_D^2(1-\rho_E^2)\sigma_{zD}^2\sigma_\theta^2\Big) \times \\ \Big(b_D^2\sigma_{zD}^2(\sigma_\varepsilon^2 + (1-\rho_D^2)\sigma_\theta^2)\sigma_\theta^2 + b_E^2\sigma_{zE}^2(\sigma_\varepsilon^2 + (1-\rho_E^2)\sigma_\theta^2)\sigma_\theta^2 \\ + \left(\rho_E^2 + \rho_D^2 - 2\rho_D^2\rho_E^2 - 2\rho_D\rho_E\sqrt{1-\rho_D^2}\sqrt{1-\rho_E^2}\right)\sigma_\varepsilon^2\sigma_\theta^4 + b_D^2 b_E^2 \sigma_{zD}^2\sigma_{zE}^2(\sigma_\varepsilon^2 + \sigma_\theta^2)\Big)^{-1},\end{aligned} \tag{D4}$$

where the β coefficients are

$$\beta_D = \frac{b_E^2\rho_D\sigma_{zE}^2 + \rho_D(1-\rho_E^2)\sigma_\theta^2 - \rho_E\sqrt{1-\rho_D^2}\sqrt{1-\rho_E^2}\sigma_\theta^2}{b_D^2 b_E^2\sigma_{zD}^2\sigma_{zE}^2 + b_E^2(1-\rho_D^2)\sigma_{zD}^2\sigma_\theta^2 + b_D^2(1-\rho_E^2)\sigma_{zD}^2\sigma_\theta^2}, \tag{D5}$$

$$\beta_E = \frac{b_D^2\rho_E\sigma_{zD}^2 + \rho_E(1-\rho_D^2)\sigma_\theta^2 - \rho_D\sqrt{1-\rho_D^2}\sqrt{1-\rho_E^2}\sigma_\theta^2}{b_D^2 b_E^2\sigma_{zD}^2\sigma_{zE}^2 + b_E^2(1-\rho_D^2)\sigma_{zD}^2\sigma_\theta^2 + b_D^2(1-\rho_E^2)\sigma_{zD}^2\sigma_\theta^2}. \tag{D6}$$

(Note that $E[\tilde{\mathcal{V}}' \mid \tilde{y}, \tilde{s}_i, \tilde{s}_p]$ and $Var[\tilde{\mathcal{V}}' \mid \tilde{y}, \tilde{s}_i, \tilde{s}_p]$ take the same form as in Equations (D3) and (D4), but with the parameters $m + \frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_\eta^2}$ and $\frac{\sigma_\theta^2\sigma_\eta^2}{\sigma_\theta^2+\sigma_\eta^2}$ in place of m and σ_θ^2.)

Therefore, the posterior distribution of the firm's cash flows follows a truncated normal distribution, with the unconditional mean m replaced by the conditional mean μ_i and the unconditional variance σ_θ^2 replaced by the conditional variance σ_s^2.

We next derive investor i's conditional expected utility.

$$\begin{aligned}\mathcal{U} &\equiv E\left[-\exp\left(-\gamma W_i\right) \mid \tilde{s}_i, \tilde{s}_p\right] \\ &= E\left(-\exp\left(-\gamma\left(\kappa(P_D+P_E) + x_{E,i}(\tilde{V}_E - P_E) + x_{D,i}(\tilde{V}_D - P_D)\right)\right)\right) \\ &= -\exp\left(-\gamma\left((\kappa - x_{D,i})P_D + (\kappa - x_{E,i})P_E\right)\right) \times E\left[\exp\left(-\gamma\left(x_{D,i}\tilde{V}_D + x_{E,i}\tilde{V}_E\right)\right)\right].\end{aligned}$$

The expectation term can be simplified as follows:

$$
\begin{aligned}
&E\left[\exp\left(-\gamma\left(x_{D,i}\tilde{V}_D + x_{E,i}\tilde{V}_E\right)\right) \mid \tilde{s}_i, \tilde{s}_p\right] \\
&= \int_0^\infty \exp\left(-\gamma x_{D,i}\cdot \min\{t, K\} - \gamma x_{E,i}\cdot \max(t-K, 0)\right) dF_{\mathcal{V}}(t \mid \tilde{s}_i, \tilde{s}_p) \\
&= \int_0^K \exp\left(-\gamma t x_{D,i}\right) dF_{\mathcal{V}}(t \mid \tilde{s}_i, \tilde{s}_p) + \int_K^\infty \exp\left(-\gamma(K x_{D,i} + (t-K)x_{E,i})\right) dF_{\mathcal{V}}(t \mid \tilde{s}_i, \tilde{s}_p) \\
&= \int_0^K \exp\left(-\gamma t x_{D,i}\right) \frac{\frac{1}{\sqrt{2\pi}\sigma_s}\exp\{-\frac{1}{2}\frac{(t-\mu_i)^2}{\sigma_s^2}\}}{1-\Phi(-\frac{\mu_i}{\sigma_i})} dt \\
&\quad + \int_K^\infty \exp\left(-\gamma(K x_{D,i} + (t-K)x_{E,i})\right) \frac{\frac{1}{\sqrt{2\pi}\sigma_s}\exp\{-\frac{1}{2}\frac{(t-\mu_i)^2}{\sigma_s^2}\}}{1-\Phi(-\frac{\mu_i}{\sigma_i})} dt \\
&= \exp\left\{\frac{1}{2}\sigma_s^2\left(\frac{\mu_i}{\sigma_s^2} - \gamma x_{D,i}\right)^2 - \frac{1}{2}\sigma_s^2\left(\frac{\mu_i}{\sigma_s^2}\right)^2\right\} \frac{\Phi\left(\frac{K - \sigma_s^2\left(\frac{\mu_i}{\sigma_s^2} - \gamma x_{D,i}\right)}{\sigma_s}\right) - \Phi\left(\frac{-\sigma_s^2\left(\frac{\mu_i}{\sigma_s^2} - \gamma x_{D,i}\right)}{\sigma_s}\right)}{1-\Phi(-\frac{\mu_i}{\sigma_s})} \\
&\quad + \exp\left\{-\gamma(x_{D,i} - x_{E,i})K + \frac{1}{2}\sigma_s^2\left(\frac{\mu_i}{\sigma_s^2} - \gamma x_{E,i}\right)^2 - \frac{1}{2}\sigma_s^2\left(\frac{\mu_i}{\sigma_s^2}\right)^2\right\} \frac{1 - \Phi\left(\frac{K - \sigma_s^2\left(\frac{\mu_i}{\sigma_s^2} - \gamma x_{E,i}\right)}{\sigma_s}\right)}{1-\Phi(-\frac{\mu_i}{\sigma_s})} \\
&\equiv \exp\left\{g\left(-\gamma x_i + \mathbf{1}\frac{\mu_i}{\sigma_s^2}\right) - g\left(\mathbf{1}\frac{\mu_i}{\sigma_s^2}\right)\right\},
\end{aligned}
$$

where the function $g : \mathbb{R}^2 \to \mathbb{R}$ is defined as

$$
\begin{aligned}
g\begin{pmatrix} y_D \\ y_E \end{pmatrix} \equiv \log\Bigg(&\exp\{\frac{1}{2}\sigma_s^2 y_D^2\}\left(\Phi\left(\frac{K - \sigma_s^2 y_D}{\sigma_s}\right) - \Phi\left(\frac{-\sigma_s^2 y_D}{\sigma_s}\right)\right) \\
&+ \exp\{(y_D - y_E)K + \frac{1}{2}\sigma_s^2 y_E^2\}\left(1 - \Phi\left(\frac{K - \sigma_s^2 y_E}{\sigma_s}\right)\right)\Bigg). \quad \text{(D7)}
\end{aligned}
$$

Taken together, investor i's expected utility is

$$
\begin{aligned}
\mathcal{U} &\equiv E\left[-\exp\left(-\gamma W_i\right) \mid \tilde{s}_i, \tilde{s}_p\right] \\
&= -\exp\left(-\gamma\left((\kappa - x_{D,i})P_D + (\kappa - x_{E,i})P_E\right) + g\left(-\gamma x_i + \mathbf{1}\frac{\mu_i}{\sigma_s^2}\right) - g\left(\mathbf{1}\frac{\mu_i}{\sigma_s^2}\right)\right).
\end{aligned}
$$

E Limited Attention

In this section, we examine another potential explanation for bond PEAD, which is investors' limited attention. Limited attention provides a compelling intuition for PEAD; if bond investors do not pay attention to earnings announcements, then the bond's price will not immediately reflect the news, leading to a drift thereafter. The challenge in assessing a limited attention-based explanation is that researchers do not observe investors' attention directly and, instead, rely on noisy proxies.

Here we use two ideas proposed in the literature to measure limited attention. First, we compare announcements that investors are likely to be distracted from against those that engage their immediate attention. To this end, we follow Hirshleifer et al. (2009) and use the number of announcements that are made on the same day as a measure of distraction. We classify each announcement into ten groups based on the number of announcements made on that day. If more announcements are on a particular day, then investors are arguably more distracted and pay less attention, which would strengthen PEAD. Additionally, we follow Dellavigna and Pollet (2009) and Michaely et al. (2016) and compare announcements made on a Friday against those made on other days of the week. If investors are more distracted on Fridays than on other days, then we expect a more pronounced bond PEAD following Friday announcements.

The second idea is to examine investors' news searching and reading activities. If investors search for and read certain information on firms, then we interpret this action as investors paying attention to the news. To this end, we follow Ben-Rephael et al. (2017) and construct two measures related to abnormal institutional investor attention (AIA) using news readership scores downloaded from the Bloomberg terminal. AIA is a dummy variable that equals one if Bloomberg's readership score is 3 or 4,[32] and zero otherwise; meanwhile, $AIAC$ is a continuous value transformed from Bloomberg's raw readership scores using the conditional means of the truncated normal distribution.[33] A greater value of those variables means that investors are paying more attention to a firm's news on its earnings announcement date.

[32]Bloomberg assigns a score of 0 to 4 based on the count of a firm's news searches and readership. These values correspond to below 80%, between 80% and 90%, 90% and 94%, 94%, and 96%, and greater than 96% of the distribution over the previous 30 days.

[33]We convert the raw scores to -0.350, 1.045, 1.409, 1.647, and 2.154, assuming that the distribution for news searching activities over the previous 30-day follows a normal distribution.

In Panel A of Table A10, we run a Fama-MacBeth regression of monthly returns on earnings announcement CAR and its interaction with inattention measures. We find that the average slope coefficients on the interaction terms are economically small relative to the coefficients on CAR and statistically insignificant, aside from the number of competing announcements, which has a t-statistic of 1.65. The insignificant loading on the interaction between earnings surprises and AIA is particularly important since AIA measures the attention of institutional investors who are dominant in the bond market.

Next, we study whether the effect of investors' attention differs after positive and negative news. Given that corporate bonds have limited upside potentials but are exposed to downside risk, investors may pay more attention to negative news than to positive news. Thus, we create two dummy variables corresponding to positive and negative values of CAR and use them in Fama-MacBeth regressions. The results reported in Panel B of Table A10 show that the interactions between the news dummies and (in)attention measures are all insignificant. Taken together, we do not find compelling evidence for inattention in generating PEAD.

F Disposition Effect

Frazzini (2006) reports that investor disposition effects exacerbate sluggish movements in stock prices. The disposition effect refers to the psychological bias of wanting not to sell securities at a loss but, instead, wanting to sell securities that have appreciated in value since their purchase. In other words, if a bond is held with a capital gain, then the holder is more likely to sell it, which prevents good news from being quickly incorporated into the price. In contrast, if an investor carries a bond at a loss, then she is less likely to sell the bond, which prevents negative news from being reflected in the price. Consistent with this hypothesis, Frazzini (2006) finds that stocks that have higher earnings surprises and higher capital gains earn higher returns than stocks that have lower earnings surprises and lower capital gains.

To examine whether the disposition effect drives bond PEAD, we follow Frazzini (2006) and calculate capital gains overhangs (CGO) using eMAXX's bond holding data. First, we calculate the reference price for institutional investors' aggregate trade as

$$RP_{i,q} = \frac{1}{\bar{V}} \sum_{n=0}^{q} V_{i,q,q-n} P_{i,q-n}, \tag{D8}$$

where $V_{i,q,q-n}$ is the face value of bond i purchased in quarter $q-n$ and still held in quarter q, $P_{i,q-n}$ is the bond price in quarter $q-n$, and $\bar{V} = \sum_{n=0}^{q} V_{i,q,q-n}$. If a bond is purchased at different points in time and some of the holding is sold later, then we assume the first-in-first-out rule to calculate $V_{i,q,q-n}$.

We measure CGO for bond i as the ratio of the gap between a market price and a reference price to the market price,

$$CGO_{i,q} = \frac{P_{i,q} - RP_{i,q}}{P_{i,q}}. \tag{D9}$$

If $CGO_{i,q}$ is positive, then the average institutional investor carries bond i at a capital gain. If $CGO_{i,q}$ is negative, she carries the bond at a loss.

To construct CGO, we use institutional investors' bond holding data provided by eMAXX. These holdings data cover U.S. insurance firms, mutual funds, pension funds, and other investors from 2002Q1 to 2022Q4, accounting for 48% of our sample period's average ownership share. In addition, we use institutional stock ownership data provided by Thomson Reuters and the original Securities and Exchange Commission's 13F filings for the same period. We treat missing holding observations as zero holdings.

Using the CGO measure, we double-sort bonds every month based on the latest available values of the earnings surprises and $CGO_{i,q}$, and form 25 value-weighted portfolios. Table A11 reports each portfolio's 8-factor alphas. If the disposition effect explains bond PEAD, we expect significantly negative alphas for bonds with the lowest earnings surprises and lowest CGO. However, in the data, the 8-factor alpha is -12 bps with a t-statistic of -0.91. Furthermore, the alpha for the highest earnings surprise quintile with the highest CGO is 6 bps with a t-statistic of 0.73. Thus, we do not find evidence supporting the disposition effect as the primary driver behind bond PEAD.

G Transaction Costs

In this section, we provide details on how we calculate transaction costs. We directly measure the cost of implementing the bond PEAD strategy by accounting for portfolio turnover and bid-ask spreads. Specifically, we calculate a half spread for bond i on day d as

$$\text{half spread}_{i,d} = \frac{Sell_{i,d} - Buy_{i,d}}{Sell_{i,d} + Buy_{i,d}}, \tag{D10}$$

where $Sell_{i,d}$ is the volume-weighted average price at which a dealer sells to a customer (i.e., ask), and $Buy_{i,d}$ is the volume-weighted average price at which a dealer buys from a customer (i.e., bid). In calculating half spreads, we only use transactions with volumes exceeding \$100,000 (the cutoff value set following Bessembinder et al. 2009), and thus the estimated transaction costs are for institutional investors rather than retail investors. If the dealer sells and buys do not occur on the same day, we treat observations on the day as missing. Monthly half spreads are the simple average of daily half spreads in a month. We take the average of half spreads across bonds in each CAR-quintile in a month and assign the portfolio-level spreads to all bonds that belong to a given portfolio.

Assigning the same half spread to all bonds in each portfolio yields an unbiased estimate for bond-level half spreads if bonds with missing half spreads have the same transaction costs as those with non-missing half spreads. However, this assumption is clearly invalid in that illiquid bonds do not trade as frequently as liquid bonds do. Thus, bonds with missing half spreads would incur high costs were they to trade. To attenuate this bias, we, before taking the average across bonds at the portfolio level, assign the 90-th percentile value of half spreads in a month to all bonds with missing half spread data. We then take the average across bonds in each quintile to obtain conservative estimates of portfolio-level spreads.

H Additional Results

In this section, we report the additional results mentioned in the paper.

- Figure A1 plots the estimated 8-factor alphas for bond PEAD, along with their associated two-standard-error confidence intervals, across various bond return datasets.
- Figure A2 plots the bid-ask spreads of corporate bonds, CDS, and stocks over time.
- Table A1 provides definitions and constructions of the main variables used in the paper.
- Table A2 reports the 8-factor alphas of decile bond PEAD portfolios using different weighting schemes, subsamples, and alternative earnings surprises measures.
- Table A3 presents the squared Sharpe ratio and pairwise model comparisons among various bond pricing factor models.
- Table A4 displays the coefficient estimates associated with the control variables in Table 4.
- Table A5 reports the PEAD effects using *CE* and *FOM* controlling for other news variables.
- Table A6 reports the coefficient estimates for the control variables in Table 9.
- Table A7 presents the panel regression estimates of bond returns on earnings surprises, disagreement, investors' attention, and the disposition effect.

Figure A1: Bond PEAD Across Different Databases

This figure plots monthly alphas of the bond PEAD portfolios across different databases. Alphas are estimated using a bond+stock model that combines two duration-adjusted bond factors from van Binsbergen, Nozawa, and Schwert (2025) and six stock factors from Fama and French (2018). We present the baseline 8-factor alphas alongside alternative estimates using bond return datasets from Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023) (DFPS), Dickerson, Robotti, and Rossetti (2026b) (DRR), and the WRDS Bond Returns database (WRDS). To obtain firm-level bond returns, we compute value-weighted averages of individual bond returns within each firm-month and report alphas based on equal-weighted firm portfolios. All alphas are in percent per month. Error bars denote the two-standard-error confidence intervals, where standard errors are Newey-West adjusted with six lags. The sample spans from August 2002 through December 2022, except for the DFPS data, which ends in December 2021.

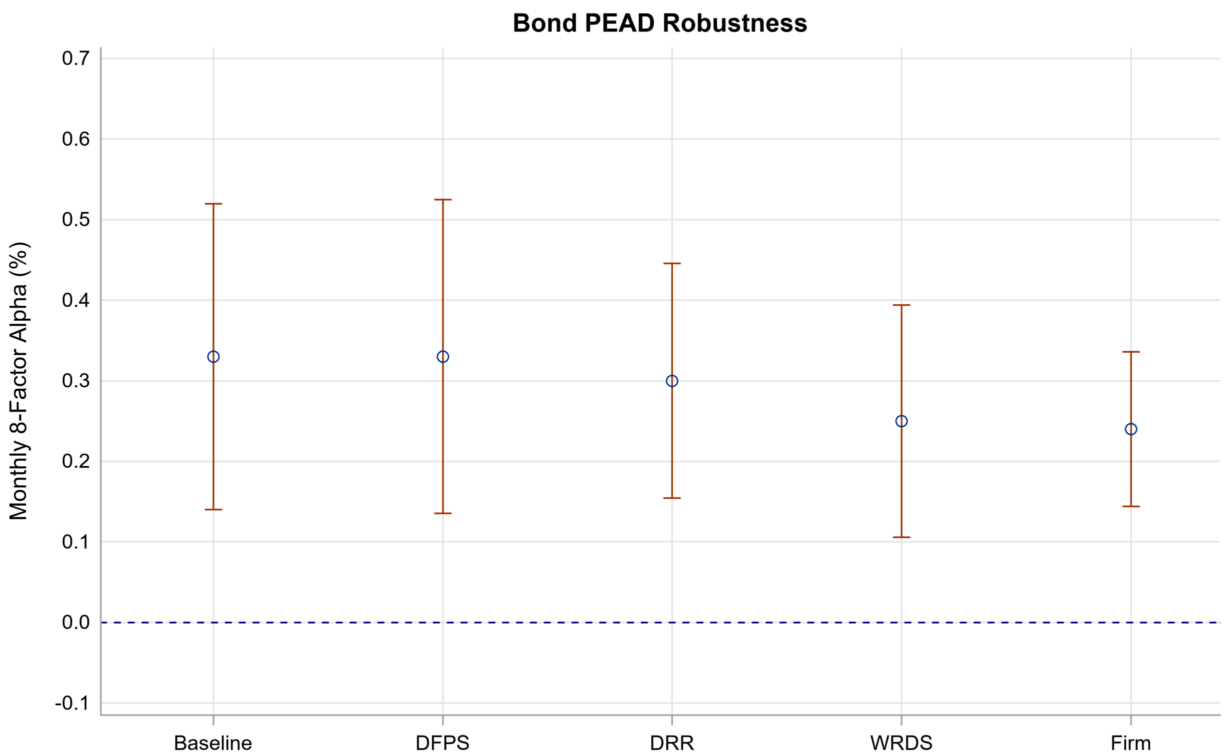


Figure A2: Time Series Plot of Bid-Ask Spreads

This figure presents the time series of average bid-ask spreads in the bond, CDS, and stock markets in our sample period from August 2002 to December 2022. We compute the bid-ask spreads as (ask price - bid price)/mid price for bonds and stocks, and as the absolute difference between the ask and bid prices for CDS. We take the weighted average of bid-ask spreads for each month, using the market value of the amount outstanding (for bonds) or firm market capitalization (for stocks and CDS) as weights. Bond bid-ask spreads are computed from TRACE. Stock bid-ask spreads are computed based on closing bid and ask prices from the CRSP daily stock file. CDS bid-ask spreads (only available after April 2010) are calculated from Markit. Panel A shows the level of bid-ask spreads. Panel B shows the natural logarithm of bid-ask spreads. The gray area is the NBER-dated recessions in our sample period (Jan 2008 - Jun 2009; Mar 2020 - Apr 2020).

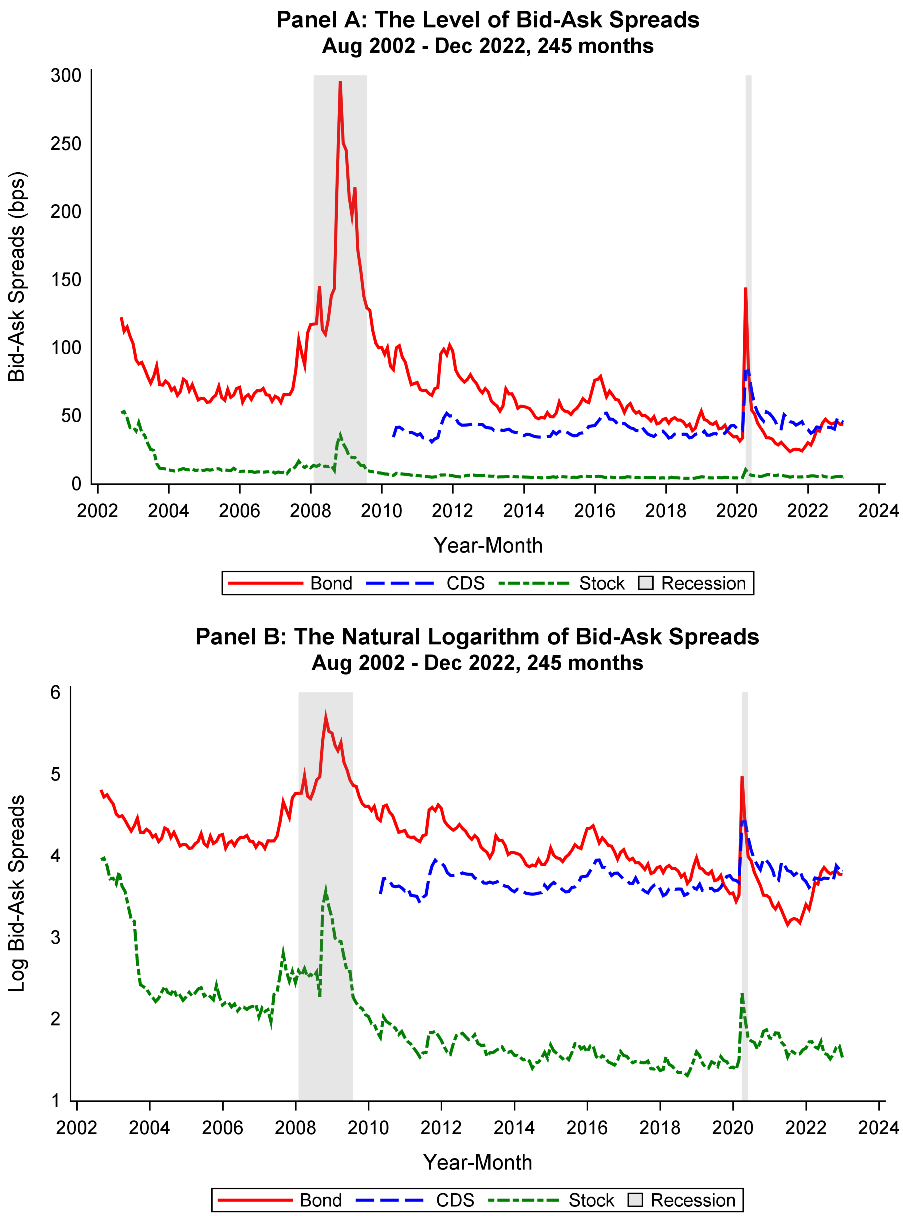


Table A1: Variable Definitions

Variables	Definitions
Return	Monthly bond return, reported in percent per month.
Excess Return	Bond return in excess of one-month Treasury bill rate, reported in percent per month.
Rating	Numerical rating score (1 for AAA, 21 for C rating by S&P and Moody's).
Maturity	Time-to-maturity of the bond in years.
Size	Market value of the amount outstanding of a bond.
DOWN	5% VaR of corporate bond return, defined as the second-lowest monthly return observation over the past 36 months.
BAS	Bid-ask spread, computed as $(S - B)/0.5(S + B)$, where S and B represent the volume-weighted average sell and buy prices, respectively, on a given day for a bond. The monthly average of daily bid-ask spreads is used.
ACOV	Autocovariance of the daily price changes within each month, multiplied by -1.
Age	Bond age, measured in years since the bond's issuance.
Duration	Bond's Macaulay duration.
STR	Short-term reversal, calculated as the previous month's bond return.
MOM	Past 11-month cumulative returns from month $t - 12$ to $t - 2$, skipping the short-term reversal month $t - 1$.
Vol	Bond return volatility estimated using bond returns over the past six months.
SRVol	Stock return volatility estimated using daily stock returns in month t.
$Frac(Bid)_t$	Fraction of dollar bid (dealer buy) volume relative to the total volume for a daily price in month t.
$Frac(Bid)_{t+1}$	Fraction of dollar bid (dealer buy) volume relative to the total volume for a daily price in month $t + 1$.
Stock CAR	Cumulative abnormal stock returns adjusted by the Fama-French three-factor model from trading day -1 to 1 around the earnings announcement date.
Bond CAR	Cumulative abnormal bond returns from trading day $t - 1$ to $t + 1$, where $t = 0$ is the earnings announcement date. The abnormal return is calculated using market-adjusted returns, with the Bloomberg US Corporate Total Return Index serving as the market return proxy.
CE	Analyst forecast errors based on median consensus.
FOM	Fraction of analyst forecasts that miss on the same side (Chiang et al. 2019), calculated as $K/N - M/N$, where K (M) represents the number of forecasts strictly lower (higher) than actual earnings, and N is the total number of analyst forecasts.

Table A1, Continued

Variables	Definitions
DISP	Analyst forecast dispersion, defined as the standard deviation of annual year-end analyst forecasts scaled by the absolute mean forecast value after removing excluded or stopped estimates.
IVOL	Stock idiosyncratic volatility, defined as the standard deviation of the daily residuals estimated from the regression of excess stock returns on a constant and six factors (market, size, value, investment, profitability, momentum) from Fama and French (2018).
RFY	Bond-level reaching for yield proxy, defined as the difference between a bond's yield and the cross-sectional average yield of bonds with the same credit rating, following Choi and Kronlund (2018) and Chen and Choi (2024).
CGO	Capital gains overhang, measured as the percentage deviation of the aggregate cost basis from the quarter-end bond price. The reference cost is calculated following the procedure in Frazzini (2006).
SRet1m	Past one-month stock return, calculated as cumulative market-adjusted stock returns over the past one month, excluding the earnings announcement returns.
SRet6m	Past six-month stock return, calculated as cumulative market-adjusted stock returns over the past six months, excluding the earnings announcement returns.
$Trade^{\text{Small}}$	Ratio of small-size trade, defined as the number of trades smaller than \$1 million divided by the total number of trades for each bond in a month.
Micro	A dummy variable that equals one if a firm belongs to the micro stock market capitalization group, defined as firms below the 20th percentile of NYSE market capitalization.
Small	A dummy variable that equals one if a firm belongs to the small stock market capitalization group, defined as firms between the 20th and 50th percentiles of NYSE market capitalization.
Big	A dummy variable that equals one if a firm belongs to the big stock market capitalization group, defined as firms with market capitalization above the NYSE median.

Table A2: Univariate Portfolios of Bonds Sorted on Earnings Surprises: Robustness

This table reports the 8-factor alphas of decile portfolios sorted on earnings surprises. Alphas are estimated using a bond+stock model that combines two duration-adjusted bond factors from van Binsbergen, Nozawa, and Schwert (2025) and six stock factors from Fama and French (2018). Panel A repeats the baseline analysis using a subsample of firms that announce earnings in months $t-1$ and t only. Panel B reports alphas for value-weighted portfolios sorted based on alternative measures of earnings surprises, namely, *Bond CAR*, *CE*, and *FOM*. Panel C presents alphas for value-weighted portfolios sorted by stock *CAR* excluding the Global Financial Crisis period (Jan 2008 - Jun 2009). Panel D reports alphas estimated using alternative bond return datasets from Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023) (DFPS), Dickerson, Robotti, and Rossetti (2026b) (DRR), and the WRDS Bond Returns database (WRDS). Panel E reports alphas estimated after excluding the Bessembinder, Kahle, Maxwell, and Xu (2009) intraday price reversal filter, which removes transactions involved in a 20% or greater price change followed by a 20% or greater price change of the opposite sign. Details on the construction of these variables are provided in Table A1. Column "SR/IR" reports the annualized Sharpe ratios or information ratios for various bond PEAD strategies. All returns and alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are reported in parentheses below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample spans from August 2002 through December 2022, except for the DFPS data, which ends in December 2021.

	Low	2	3	4	5	6	7	8	9	High	High - Low	SR/IR
	8-Factor Alphas of Earnings-Surprise-Sorted Portfolios											
Panel A: Subsample of Firms that Have Announcements at Months $t-1$ and t Only												
Estimates	-0.08	-0.07	-0.04	-0.01	-0.01	0.05	-0.05	0.06**	0.06**	0.24***	0.32***	0.81
	(-1.09)	(-1.30)	(-0.80)	(-0.41)	(-0.34)	(0.86)	(-1.29)	(2.17)	(2.05)	(3.31)	(3.18)	
Panel B: Alternative Measures for Earnings Surprises												
Bond CAR	-0.08	-0.03	-0.03	-0.01	-0.02	0.01	-0.01	0.05	0.04	0.26**	0.34***	0.93
	(-0.78)	(-0.65)	(-1.01)	(-0.41)	(-0.97)	(0.56)	(-0.29)	(1.55)	(0.85)	(2.56)	(3.76)	
CE	0.03	-0.06	-0.01	-0.00	-0.03	0.00	-0.03	0.03	0.03	0.18***	0.15**	0.33
	(0.44)	(-1.35)	(-0.19)	(-0.10)	(-1.25)	(0.10)	(-0.64)	(1.28)	(0.78)	(2.93)	(2.17)	
FOM	0.02	-0.08	-0.01	-0.04	0.09	0.04	-0.01	-0.01	0.01	0.03	0.01	0.03
	(0.51)	(-1.61)	(-0.41)	(-0.86)	(1.16)	(0.86)	(-0.33)	(-0.31)	(0.29)	(1.58)	(0.18)	
Panel C: Excluding Global Financial Crisis Period												
Estimates	-0.05	-0.02	-0.03	-0.07**	0.01	-0.04*	0.01	0.00	0.06**	0.16***	0.21***	0.81
	(-0.97)	(-0.43)	(-0.96)	(-2.22)	(0.50)	(-1.80)	(0.36)	(0.00)	(2.47)	(3.77)	(4.51)	
Panel D: Alternative Bond Return Datasets												
DFPS	-0.11	-0.06	-0.06	-0.08**	-0.06**	0.00	0.02	0.01	0.07*	0.22***	0.33***	1.29
	(-1.38)	(-0.78)	(-1.53)	(-2.07)	(-2.06)	(0.00)	(0.58)	(0.34)	(1.79)	(3.33)	(3.39)	
DRR	-0.11	-0.08	0.06	-0.06	-0.05*	0.05	0.04*	0.01	0.05	0.19***	0.30***	1.19
	(-1.46)	(-1.45)	(0.74)	(-1.48)	(-1.67)	(1.04)	(1.80)	(0.23)	(1.08)	(3.75)	(4.12)	
WRDS	-0.09	-0.03	-0.04	-0.04	-0.02	0.03	0.03	0.01	0.07**	0.16***	0.25***	0.88
	(-1.41)	(-0.69)	(-1.16)	(-1.25)	(-0.81)	(0.78)	(1.10)	(0.24)	(2.13)	(3.30)	(3.47)	
Panel E: Excluding Intraday Price Reversal Filter												
Estimates	-0.12	-0.06	-0.05	-0.05	-0.01	0.00	0.02	0.00	0.08**	0.21***	0.33***	1.02
	(-1.59)	(-1.02)	(-1.30)	(-1.51)	(-0.27)	(0.08)	(0.68)	(0.15)	(2.44)	(3.61)	(3.43)	

Table A3: Model Comparison

This table presents the squared Sharpe ratio and pairwise model comparisons for various bond pricing factors, including the bond market factor (MKTB), the bond market factor augmented with our PEAD factor (MKTB and PEAD), the duration-adjusted bond CAPM (BDDUR and BDRISK) proposed by van Binsbergen, Nozawa, and Schwert (2025), and the TERM and DEF factors of Fama and French (1993). For each model, we compute the adjusted maximum squared monthly Sharpe ratio following the methodology of Barillas, Kan, Robotti, and Shanken (2020). The values in brackets represent the p-values associated with the differences in the squared Sharpe ratios. The analysis is based on a sample of 245 monthly observations spanning from August 2002 to December 2022.

	MKTB	MKTB + PEAD	BDDUR + BDRISK	TERM + DEF
Adj. SP^2	0.020	0.087	0.025	0.011
Pairwise model comparison				
MKTB		-0.068	-0.006	0.008
		[0.067]	[0.479]	[0.453]
MKTB + PEAD			0.062	0.076
			[0.100]	[0.050]
BDDUR + BDRISK				0.014
				[0.424]

Table A4: Fama-MacBeth Regressions on Earnings Surprises, Past Stock Returns and Past Rating Changes, Detailed Estimates

This table reports the detailed estimates for Table 4, including those on control variables.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CAR	0.093***	0.096***				0.096***	0.060***
	(3.21)	(3.61)				(3.81)	(2.68)
SRet6m			0.126***			0.151***	
			(4.47)			(4.95)	
SRet6mAll							0.150***
							(5.06)
NoAnnCAR				-0.015		-0.037**	-0.032**
				(-1.00)		(-2.33)	(-2.05)
Dummy: *Downgrade*					-0.100	-0.086	-0.074
					(-1.18)	(-1.11)	(-0.92)
Dummy: *Upgrade*					0.109**	0.077**	0.083**
					(2.39)	(2.05)	(2.08)
Size		0.037**	0.031**	0.036**	0.032**	0.037**	0.038**
		(2.26)	(2.27)	(2.27)	(2.27)	(2.28)	(2.25)
Rating		0.049	0.036	0.034	0.038	0.042	0.041
		(1.03)	(0.69)	(0.65)	(0.70)	(0.87)	(0.86)
Maturity		0.017	0.008	0.010	0.010	0.006	0.009
		(0.27)	(0.13)	(0.17)	(0.17)	(0.10)	(0.14)
Down		0.104*	0.107*	0.104*	0.109*	0.110**	0.106*
		(1.83)	(1.88)	(1.87)	(1.95)	(1.98)	(1.92)
ACOV		0.272	0.287	0.269	0.268	0.288	0.283
		(1.45)	(1.48)	(1.43)	(1.44)	(1.50)	(1.49)
STR		-0.585***	-0.578***	-0.573***	-0.580***	-0.596***	-0.595***
		(-11.74)	(-11.87)	(-11.71)	(-11.53)	(-12.31)	(-12.17)
MOM		-0.264**	-0.308**	-0.262**	-0.276**	-0.335***	-0.339***
		(-2.08)	(-2.44)	(-2.06)	(-2.17)	(-2.63)	(-2.62)
Vol		0.097	0.096	0.104	0.107	0.112*	0.115*
		(1.35)	(1.37)	(1.47)	(1.52)	(1.66)	(1.69)
SRVol		-0.143***	-0.123***	-0.140***	-0.141***	-0.103***	-0.099**
		(-3.00)	(-2.81)	(-2.99)	(-2.92)	(-2.46)	(-2.44)
$Frac(Bid)_t$		0.208***	0.207***	0.211***	0.210***	0.205***	0.205***
		(6.78)	(6.74)	(6.57)	(6.46)	(6.69)	(6.63)
$Frac(Bid)_{t+1}$		-0.265***	-0.264***	-0.263***	-0.264***	-0.265***	-0.266***
		(-8.46)	(-8.67)	(-8.67)	(-8.82)	(-8.73)	(-8.73)
Intercept	0.261**	0.415***	0.362***	0.394***	0.399***	0.390***	0.392***
	(2.55)	(3.06)	(2.92)	(3.04)	(3.02)	(3.03)	(3.07)
Industry Controls	YES	YES	YES	YES	YES	YES	YES
Observations	369,464	369,464	369,464	369,464	369,464	369,464	369,464
Average R^2	0.106	0.396	0.395	0.396	0.397	0.410	0.410

Table A5: Uniqueness of Earnings Surprise: Fama-MacBeth Regressions on Alternative Earnings Surprises, Past Stock Returns and Past Rating Changes

This table reports the average slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on alternative earnings surprises and other measures of news with and without controls. Earnings surprise is proxied by *CE* and *FOM*. *CE* is the analyst forecast errors based on median consensus. *FOM* is calculated as $K/N - M/N$, where $K(M)$ is the number of forecasts strictly lower (higher) than actual earnings, and N is the total number of analyst forecasts. *SRet6m* (*SRet6mAll*) is past six-month stock return, calculated as the cumulative market-adjusted stock returns over the past six months, excluding (including) the earnings announcement returns. *NoAnnCAR* is the pseudo *CAR* without earnings surprises, calculated as the three-day cumulative abnormal returns around a date randomly picked from significant price movement days in the previous six months, excluding the earnings announcement windows. We use the ratio of the standard deviation of *CAR* to the standard deviation of non-earnings-announcement *CAR* as a threshold to filter out pools of *NoAnnCAR*. *Downgrade* (*Upgrade*) is a dummy variable for rating downgrade (upgrade) in the previous three months, which equals one if there is at least one downgrade (upgrade) by any rating agencies. Bond characteristics controls include bond size (*Size*), credit rating, maturity, downside risk (*DOWN*), illiquidity (*ACOV*), short-term bond return reversal (*STR*), bond return momentum (*MOM*), bond return volatility (*Vol*), stock return volatility (*SRVol*), and the fraction of bid in month t and t+1. All continuous independent variables are standardized to have a mean of zero and a standard deviation of one. All regressions include industry dummy variables based on 30 Fama and French industry classifications. Newey-West adjusted t-statistics (with six lags) are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from August 2002 to December 2022.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns						
	(1)	(2)	(3)	(4)	(5)	(6)
CE	1.746***		1.633***		1.422***	
	(3.43)		(3.15)		(2.74)	
FOM		0.042***		0.028**		0.009
		(3.03)		(1.99)		(0.53)
SRet6m			0.142***	0.138***		
			(5.24)	(5.01)		
SRet6mAll					0.166***	0.168***
					(4.89)	(4.90)
NoAnnCAR			-0.038**	-0.039**	-0.037**	-0.039**
			(-2.38)	(-2.37)	(-2.40)	(-2.43)
Dummy: *Downgrade*			-0.119	-0.096	-0.104	-0.078
			(-1.62)	(-1.26)	(-1.39)	(-0.99)
Dummy: *Upgrade*			0.087**	0.082**	0.086*	0.083*
			(2.06)	(1.97)	(1.92)	(1.86)
Bond Controls	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES	YES	YES
Observations	369,464	369,464	369,464	369,464	369,464	369,464
Average R^2	0.400	0.393	0.414	0.408	0.414	0.408

Table A6: Panel Regressions of Bond Returns on Earnings Surprise and Disagreement, Detailed Estimates

This table reports the detailed estimates for Table 9, including those on the interactions between earnings surprise and disagreement quintiles. We use the most restrictive specification, controlling bond characteristics, t+1 stock returns, rating × time, and industry × time fixed effects.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns				
	(1)	(2)	(3)	(4)
CAR	0.079***	0.011	0.036	0.014
	(3.08)	(0.51)	(1.53)	(1.18)
CAR × *DISP2*		0.008		
		(0.26)		
CAR × *DISP3*		-0.021		
		(-0.68)		
CAR × *DISP4*		0.028		
		(0.93)		
CAR × *DISP5*		0.135**		
		(2.42)		
CAR × *IVOL2*			-0.019	
			(-0.63)	
CAR × *IVOL3*			-0.044	
			(-1.06)	
CAR × *IVOL4*			-0.005	
			(-0.12)	
CAR × *IVOL5*			0.101*	
			(1.83)	
CAR × *RFY2*				0.001
				(0.10)
CAR × *RFY3*				0.065***
				(3.22)
CAR × *RFY4*				0.074*
				(1.91)
CAR × *RFY5*				0.185***
				(3.07)
Disagreement Quintiles	NO	YES	YES	YES
Bond Controls	YES	YES	YES	YES
Rating × Year-Month	YES	YES	YES	YES
Include $t+1$ Stock Returns?	YES	YES	YES	YES
Industry × Year-Month	YES	YES	YES	YES
Observations	369,583	351,506	369,583	360,566
Adjusted R^2	0.407	0.413	0.407	0.462

Table A7: Horse Race Tests: Panel Regressions of Bond Returns on Earnings Surprises, Disagreement, Investors' Attention, and Disposition Effect

This table reports the slope coefficients from panel regressions of one-month-ahead corporate bond excess returns on the earnings surprises, disagreement measures, investor attention proxies, and disposition effect. Earnings surprise (*CAR*) is cumulative abnormal stock returns adjusted by the Fama-French three-factor model from trading day *d-1* to *d+1* around the earnings announcement date. CAR^+ (CAR^-) is a dummy variable equals one if *CAR* is positive (negative), and zero otherwise. *NRank* is the number-of-announcements decile based on the quarterly sort of the number of announcements on the day of the announcement. *AIA* is a dummy variable that equals one if Bloomberg's score is 3 or 4, and zero otherwise. To account for the missing values of *AIA*, we define AIA^* equals *AIA* if not missing, and zero otherwise. Similarly, we define $AIA_{Missing}$ equals one if *AIA* is missing, and zero otherwise. *CGO* is capital gains overhang as defined in Table A11 and we use the top and bottom quintile dummies of *CGO* to proxy for the disposition effect. Details on the construction of the control variables are provided in Table A1. All continuous independent variables are standardized to have a mean of zero and a standard deviation of one. All regressions control for disagreement quintile dummies, t+1 stock returns, rating × year-month, and industry × year-month fixed effects. We double cluster standard errors by firm and time, and t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns			
	(1)	(2)	(3)
Panel A: *NRank* as Attention Proxy			
CAR	0.034	0.041	-0.005
	(0.81)	(1.28)	(-0.14)
CAR × *DISP5*	0.138**		
	(2.51)		
CAR × *IVOL5*		0.098*	
		(1.79)	
CAR × *RFY5*			0.186***
			(2.93)
NRank	-0.005	-0.004	0.001
	(-1.65)	(-0.93)	(0.24)
CGO1	-0.000	-0.002	-0.001
	(-0.00)	(-0.02)	(-0.01)
CGO5	-0.005	-0.001	0.007
	(-0.06)	(-0.01)	(0.09)
CAR × *NRank*	-0.005	-0.001	0.004
	(-0.75)	(-0.19)	(0.68)
CAR^- × *CGO1*	0.036	0.023	0.026
	(0.44)	(0.29)	(0.38)
CAR^+ × *CGO5*	0.025	0.009	-0.021
	(0.72)	(0.25)	(-0.52)
Disagreement Quintiles	YES	YES	YES
Bond Controls	YES	YES	YES
Rating × Year-Month	YES	YES	YES
Include $t+1$ Stock Returns?	YES	YES	YES
Industry × Year-Month	YES	YES	YES
CAR^+ × *CGO5* - CAR^- × *CGO1*	-0.011	-0.014	-0.047
p-value	0.895	0.862	0.580
Observations	346,644	364,662	355,692
Adjusted R^2	0.413	0.407	0.462

Table A7, Continued

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns			
	(1)	(2)	(3)
Panel B: *AIA* as Attention Proxy			
CAR	-0.100	-0.081	-0.132
	(-1.14)	(-0.95)	(-1.53)
CAR × *DISP5*	0.121**		
	(2.34)		
CAR × *IVOL5*		0.072	
		(1.45)	
CAR × *RFY5*			0.172***
			(2.86)
AIA^*	-0.029	-0.039	0.010
	(-0.46)	(-0.62)	(0.24)
$AIA_{Missing}$	-0.082	-0.097	-0.045
	(-1.19)	(-1.40)	(-0.96)
CGO1	0.001	-0.001	0.004
	(0.01)	(-0.01)	(0.05)
CGO5	-0.006	-0.005	0.002
	(-0.08)	(-0.06)	(0.02)
CAR × AIA^*	0.101	0.087	0.124
	(1.10)	(0.95)	(1.39)
CAR × $AIA_{Missing}$	0.145	0.193*	0.202**
	(1.41)	(1.83)	(2.01)
CAR^- × *CGO1*	0.034	0.022	0.018
	(0.42)	(0.27)	(0.25)
CAR^+ × *CGO5*	0.029	0.019	-0.009
	(0.80)	(0.53)	(-0.25)
Disagreement Quintiles	YES	YES	YES
Bond Controls	YES	YES	YES
Rating × Year-Month	YES	YES	YES
Include $t+1$ Stock Returns?	YES	YES	YES
Industry × Year-Month	YES	YES	YES
CAR^+ × *CGO5* - CAR^- × *CGO1*	-0.005	-0.004	-0.027
p-value	0.953	0.966	0.745
Observations	346,644	364,662	355,692
Adjusted R^2	0.413	0.407	0.463

Table A8: Bond PEAD Strategy Returns for Longer Holding Periods

At the beginning of each month from August 2002 to December 2022, decile portfolios are formed by sorting corporate bonds based on the corresponding firm's most recent earnings surprises at the end of the previous month. We use stock CAR as the earnings surprise measure. A PEAD investment strategy is to long bonds with the highest earnings surprises and to short bonds with the lowest earnings surprises. We use a rolling portfolio approach following Jegadeesh and Titman (1993) with a holding period of K months, where K is from 1 to 12. The resulting overlapping returns are calculated as the returns of a trading strategy that in any given month t holds an equal-weighted portfolio of CAR-sorted portfolios selected in the current month as well as in the previous *K-1* months. We report average excess returns and 8-factor alphas for the value-weighted portfolios. All returns and alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are reported in parentheses below returns/alphas. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Holding Period (month)	1	2	3	4	5	6	7	8	9	10	11	12
Average Excess Return	0.28***	0.20**	0.13*	0.08	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.03
	(3.47)	(2.50)	(1.87)	(1.48)	(0.93)	(0.92)	(1.10)	(1.25)	(1.22)	(1.07)	(0.92)	(0.82)
8 Factor Alpha	0.33***	0.24***	0.16**	0.10*	0.06	0.05	0.06	0.07*	0.07*	0.07	0.05	0.05
	(3.48)	(2.67)	(2.12)	(1.83)	(1.33)	(1.39)	(1.62)	(1.88)	(1.81)	(1.58)	(1.29)	(1.16)

Table A9: Average Returns and Alphas on Univariate Portfolios of Bonds Sorted by Earnings Surprises (1997-2020)

We use the Bank of America Merrill Lynch's bond pricing data. At the beginning of each month from January 1997 to December 2020, decile portfolios are formed by sorting corporate bonds based on the corresponding firm's most recent earnings surprises at the end of the previous month. We use stock *CAR* as our primary earnings surprises measure. Decile 1 is the portfolio with the lowest earnings surprises, and Decile 10 is the portfolio with the highest earnings surprises. The portfolios are held for one month and rebalanced monthly. Portfolios are value-weighted using the prior month's bond market value. This table reports the average excess return and alpha of the decile portfolios. Alphas are calculated from a bond factor model, a stock factor model, and a bond+stock model. The bond factor model uses two duration-adjusted bond CAPM factors from van Binsbergen, Nozawa, and Schwert (2025). The stock factors are the six factors (market, size, value, investment, profitability, and momentum) from Fama and French (2018). The bond+stock model combines the two bond factors and the six stock factors. Panel A reports the results in the period up to June 2002 while Panel B reports the period after. All returns and alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are reported in parentheses below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Low *CAR*	2	3	4	5	6	7	8	9	High *CAR*	High - Low
Panel A, Pre-TRACE: Jan 1997 - Jun 2002 (66 months)											
Average Excess Return	-0.07	0.16	0.18	0.18	0.22	0.22	0.24	0.27	0.23	-0.01	0.06
	(-0.45)	(1.14)	(1.06)	(1.06)	(1.31)	(1.33)	(1.47)	(1.64)	(1.57)	(-0.06)	(0.32)
2 Bond Factor Alpha	-0.15***	0.02	0.02	0.03	0.06	0.06	0.08	0.14**	0.09**	-0.04	0.11
	(-2.77)	(0.66)	(0.29)	(0.47)	(1.05)	(1.02)	(1.53)	(2.18)	(2.13)	(-0.38)	(0.83)
6 Stock Factor Alpha	-0.12	0.08	0.04	0.13	0.10	0.11	0.10	0.18	0.13	-0.01	0.11
	(-0.65)	(0.50)	(0.20)	(0.65)	(0.58)	(0.61)	(0.58)	(0.92)	(0.82)	(-0.04)	(0.82)
8 Factor Alpha	-0.13**	0.02	-0.03	0.06	0.03	0.03	0.03	0.13	0.07*	0.03	0.16
	(-2.55)	(0.62)	(-0.45)	(1.02)	(0.63)	(0.52)	(0.47)	(1.62)	(1.91)	(0.38)	(1.45)
Panel B, Post-TRACE: Jul 2002 - Dec 2020 (222 months)											
Average Excess Return	0.35**	0.41***	0.41***	0.37***	0.41***	0.43***	0.43***	0.41***	0.48***	0.64***	0.29***
	(2.35)	(2.91)	(3.31)	(3.31)	(3.41)	(3.58)	(3.93)	(3.65)	(3.97)	(4.28)	(4.54)
2 Bond Factor Alpha	-0.11**	-0.05	-0.03	-0.07**	-0.06**	-0.05	-0.01	-0.04	0.06	0.20***	0.31***
	(-2.31)	(-1.31)	(-1.39)	(-2.36)	(-2.08)	(-1.58)	(-0.37)	(-1.14)	(1.62)	(2.95)	(4.26)
6 Stock Factor Alpha	0.14	0.28*	0.29**	0.25**	0.27**	0.30**	0.30***	0.29**	0.35***	0.47***	0.33***
	(0.99)	(1.82)	(2.17)	(2.22)	(2.20)	(2.56)	(2.79)	(2.52)	(3.12)	(3.48)	(4.94)
8 Factor Alpha	-0.12**	-0.04	-0.02	-0.07**	-0.07**	-0.05	-0.01	-0.02	0.06	0.20***	0.32***
	(-2.41)	(-0.88)	(-0.84)	(-2.17)	(-2.05)	(-1.48)	(-0.32)	(-0.74)	(1.59)	(3.67)	(4.74)

Table A10: Limited Attention: Regressions of Bond Returns on Earnings Surprises and Investors' Attention

This table reports the average slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the earnings surprises, investor attention proxies, and their interactions. Earnings surprise (CAR) is cumulative abnormal stock returns adjusted by the Fama-French three-factor model from trading day *d-1* to *d+1* around the earnings announcement date. CAR^{+} (CAR^{-}) is a dummy variable equals one if CAR is positive (negative), and zero otherwise. We use four investor attention measures. *NRank* is the number-of-announcements decile based on the quarterly sort of the number of announcements on the day of the announcement. *Friday* is a dummy variable that equals one if the announcements were made on Friday. AIA and $AIAC$ are two abnormal institutional investor attention measures based on Bloomberg news readership data. AIA is a dummy variable that equals one if Bloomberg's score is 3 or 4, and zero otherwise. $AIAC$ is transformed continuous values from Bloomberg's 0, 1, 2, 3, and 4 scores using the conditional means of the truncated normal distribution. Details on the construction of the control variables are provided in Table A1. Continuous independent variables are standardized to have a mean of zero and a standard deviation of one. The Fama and French 30 industry effect is included in each regression and Newey-West adjusted t-statistics (with six lags) are given in parentheses. The asterisks represent the significance level of 1% (***), 5% (**), and 10% (*), respectively.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns				
	(1)	(2)	(3)	(4)
Panel A: Continuous CAR				
CAR	0.046**	0.096***	0.024	0.058
	(2.19)	(3.46)	(0.17)	(0.69)
NRank	0.003			
	(0.39)			
CAR × *NRank*	0.010*			
	(1.65)			
Friday		0.082*		
		(1.73)		
CAR × *Friday*		0.010		
		(0.30)		
AIA			-0.035	
			(-0.58)	
$CAR \times AIA$			0.024	
			(0.17)	
$AIAC$				0.000
				(0.02)
$CAR \times AIAC$				-0.006
				(-0.15)
Bond Controls	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES
Observations	369,920	369,920	241,370	241,370
Average R^2	0.401	0.400	0.439	0.439

Table A10, Continued

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns				
	(1)	(2)	(3)	(4)
Panel B: Positive and Negative *CAR* Dummies				
CAR^+	0.076**	0.086***	-0.031	0.051
	(2.22)	(2.63)	(-0.32)	(0.47)
CAR^-	-0.003	-0.031	0.046	0.090
	(-0.18)	(-1.19)	(1.06)	(0.98)
$NRank$	-0.001			
	(-0.11)			
$CAR^+ \times NRank$	0.007			
	(0.97)			
$CAR^- \times NRank$	-0.002			
	(-0.24)			
$Friday$		0.178		
		(1.53)		
$CAR^+ \times Friday$		-0.039		
		(-0.70)		
$CAR^- \times Friday$		-0.091		
		(-1.11)		
AIA			-0.086	
			(-1.42)	
$CAR^+ \times AIA$			0.132	
			(1.49)	
$CAR^- \times AIA$			-0.005	
			(-0.08)	
$AIAC$				-0.002
				(-0.22)
$CAR^+ \times AIAC$				0.006
				(0.13)
$CAR^- \times AIAC$				-0.038
				(-0.92)
Bond Controls	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES
Observations	369,920	369,920	241,370	241,370
Average R^2	0.396	0.396	0.437	0.438

Table A11: Disposition Effect: Bivariate Portfolios on Earnings Surprise and Capital Gains Overhang

25 portfolios are formed every month from August 2002 to December 2022 by independently sorting corporate bonds based on the capital gains overhang (CGO) and the corresponding firm's most recent earnings surprises. Earnings surprise is proxied by the stock CAR. We follow Frazzini (2006) and calculate (CGO) using eMAXX bond holding data. First, we calculate the reference price for the aggregate institutional investors' trade as, $RP_{i,q} = \frac{1}{\bar{V}} \sum_{n=0}^{q} V_{i,q,q-n} P_{i,q-n}$, where $V_{i,q,q-n}$ is the face values of bond i purchased in quarter $q-n$ and still held in quarter q, $P_{i,q-n}$ is the bond price in quarter $q-n$, and $\bar{V} = \sum_{n=0}^{q} V_{i,q,q-n}$. If a bond is purchased at different points in time and then some of the holdings are sold later, then we assume First-In-First-Out (FIFO) rule to calculate $V_{i,q,q-n}$. We measure capital gain overhang for bond i as the ratio of the gap between a market price and a reference price to the market price, $CGO_{i,q} = \frac{P_{i,q} - RP_{i,q}}{P_{i,q}}$. We present the 8-factor alphas, where portfolios are value-weighted using the market value of the amount outstanding as weights with a holding period of one month. All returns and alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Low CAR	CAR, 2	CAR, 3	CAR, 4	High CAR	High - Low
Low Capital Gains	-0.05	0.10	0.21*	0.10	0.31***	0.36***
	(-0.41)	(0.86)	(1.84)	(1.04)	(2.61)	(3.08)
CGO, 2	-0.07	0.01	-0.02	0.06	0.08*	0.16**
	(-1.10)	(0.13)	(-0.38)	(1.37)	(1.69)	(2.25)
CGO, 3	-0.12*	-0.02	-0.03	0.04	0.09**	0.22**
	(-1.79)	(-0.94)	(-0.89)	(1.46)	(2.32)	(2.36)
CGO, 4	-0.07	-0.02	-0.01	0.01	0.06*	0.13***
	(-1.40)	(-0.42)	(-0.25)	(0.36)	(1.71)	(2.72)
High Capital Gains	-0.17*	-0.04	-0.03	-0.03	0.05	0.22***
	(-1.83)	(-0.52)	(-0.29)	(-0.41)	(0.66)	(4.33)
High - Low	-0.12	-0.15	-0.24	-0.13	-0.26	-0.13
	(-0.64)	(-0.80)	(-1.32)	(-0.84)	(-1.53)	(-1.19)