Disagreement, Liquidity, and Price Drifts in the Corporate Bond Market*

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Abstract

We document empirical evidence for post-earnings announcement drift in corporate bond prices using transaction data. The drift is more pronounced for bonds that trade more frequently, and also exists in the credit default swap market, rejecting the idea that illiquidity generates the drift. We explain this puzzling positive link between the drift and liquidity using a stylized model where investors agree to disagree. Empirical evidence supports the hypothesis that disagreement explains both the observed price drift and trading volume.

JEL Classification: G12, G13

Keywords: Disagreement, Liquidity, Informational Efficiency, Corporate Bonds, Post Earnings Announcement Drift

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1 Introduction

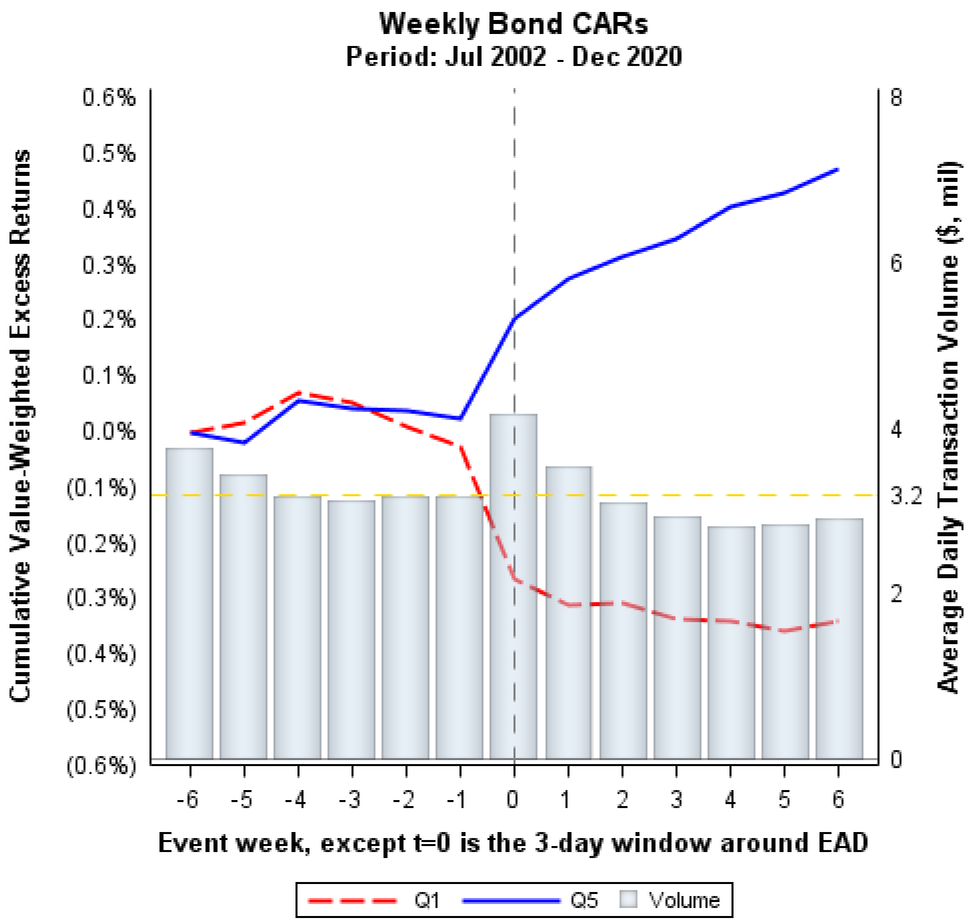
Slow market price reactions to news are the key issue in assessing market efficiency. In an efficient market, asset prices immediately reflect investor's information and thus should not exhibit drift after news release. The literature on the stock market provides ample evidence against this thesis, but the reason behind the slow price movement is not well understood. In this paper, we document evidence for sluggish price reactions to earnings announcement in the corporate bond market, and examine the link between liquidity and post-earnings announcement drift (PEAD) using the framework where investors agree to disagree on bond values.

The corporate bond market offers a unique setup for researchers, in which the role of liquidity and disagreement among investors play crucial roles in determining prices. As well known in the literature, corporate bonds trade less frequently than stocks do, and there is ample evidence of corporate bond liquidity premiums (e.g. Bao, Pan, and Wang 2011). The role of disagreement is also important as cash flow shocks to corporate bonds are less frequently observed than those for stocks, which makes it challenging for investors to correctly assess the riskiness of bonds. This provides rooms for disagreement among investors on the likelihood of defaults. Widely documented reaching-for-yield behavior of bond investors corroborates the importance of disagreement: on the one hand, rational investors recognize the risk of rare, tail events and push up bonds' yield; on the other hand, investors who are oblivious of tail risk prefer to purchase such bonds. This phenomenon highlights the prominence of disagreement among bond investors which affects how they deferentially interpret news and trade, and how the market price is formed after the news. Therefore, the corporate bond market is an ideal place to study the link between disagreement, liquidity and slow price movements.

In this article, we report three empirical findings that appear puzzling at first sight, and offer a unified explanation based on a stylized model. Specifically, we show that i) there is PEAD in the corporate bond market, ii) PEAD is more pronounced for bonds that trade more frequently than those that trade less often, iii) both the PEAD effect and bonds' turnover are greater when investors disagree on bonds' values. Then, based on the model, we explain why PEAD is more pronounced when investors disagree and when the bonds' trading volume is high.

We begin by presenting empirical evidence for bond PEAD using transaction data from 2002 to 2020. Specifically, we sort bonds into portfolios based on an issuing firm's most recent earnings surprise (measured by 3-day stock returns around quarterly earnings announcement

Figure 1: Post Earnings Announcement Drift in Corporate Bonds



This figure plots the cumulative abnormal returns on bonds with high earnings surprise (Q5) and those with low earnings surprise (Q1) around the earnings announcement week. Volume is the average transaction volume across bonds in the sample. For this figure, the sample is limited to bonds that trade every week during the event window.

dates), and calculate portfolio returns in the following month. We find that bonds in the highest earnings surprise quintile earn 17 bps higher returns on average than those in the lowest quintile, suggesting that bond prices underreact to the news. Figure 1 visualizes the drift after the news: though bond prices jump up (down) after good (bad) news, they seem to follow the same trajectory in the following six weeks. Since we use actual transactions to estimate a mid price and ensure that they accurately reflect investors' valuation, PEAD documented in the paper is not a reflection of dealers' stale quotes. Rather, it shows that investors on average trade at a "wrong" price after the news.

The average return difference is not accounted for by risk exposures such as liquidity risk: we apply an 11-factor model which combines the six stock factors of Fama and French

(2018) and the five bond factors of Bai, Bali, and Wen (2019), including bond market, credit risk, liquidity risk, downside risk and reversal risk, and find that the difference in alphas is significant at 22 bps. Although a 22 bps difference in alphas does not look striking, bond PEAD is economically significant because risks involving bond PEAD strategy are largely idiosyncratic, leading to low volatility of the long-short strategy. As a result, the annualized Sharpe ratio of the strategy is 0.73, which is comparable to that of the bond market portfolio. Furthermore, the profitability of the strategy is stable over our sample period and not related to the business cycle; in fact, the strategy logs profits even during the financial crisis in 2008 or the Covid-19 shock in March 2020.

Bond PEAD is pervasive across different types of corporate bonds: we double sort bonds based on earnings surprise and various bond characteristics, and find that PEAD exists both in investment-grade (IG) bonds and high-yield (HY) bonds, and in all maturity quintiles. Moreover, the earnings announcement is unique among other news: earnings surprise predicts bond returns after controlling for news on credit rating changes and the past 6-month equity returns which capture all other news relevant for bonds' value. The last finding is important as it shows that bond PEAD is not a simple reflection of equity-bond momentum spillover documented in Gebhardt, Hvidkjaer, and Swaminathan (2005).

Since the bond market is notoriously illiquid, one might think that bond PEAD is an obvious outcome of illiquidity. However, as implied by the classic inventory model (e.g., Grossman and Miller 1988), inventory frictions in the dealer-driven market tend to generate return reversal rather than drift. Thus, illiquidity may not be the origin of bond PEAD. To test this hypothesis, we double sort bonds based on earnings surprise and seven illiquidity measures: i) the Amihud (2002) measure, ii) the Roll measure (Bao, Pan, and Wang 2011), iii) bid-ask spreads, iv) imputed round-trip costs of Feldhütter (2010), v) turnover, vi) the fraction of days with no trades, and vii) the composite index of the six measures. We find that bond PEAD exists for all illiquidity-based quintiles, and there is little difference in trading profits between high illiquidity bonds and low illiquidity bonds. If anything, there is a positive link between bonds' trading volume and the magnitude of drifts. Furthermore, we find that PEAD exists for credit default swap (CDS) as well. In fact, the Sharpe ratio for a strategy that sells CDS protection for a firm after a positive earnings surprise and buys protection after a negative surprise is 0.94, even higher than that for corporate bonds. This finding is surprising and goes against the intuition that infrequent transactions, or more generally, illiquidity, in the corporate bond market generate PEAD. This puzzling pattern in the data begs another explanation for PEAD which is consistent with the evidence on trading volume and liquidity.

We then turn to investors' disagreement as a potential explanation for PEAD and liquidity. To test this explanation, we double sort bonds into 25 portfolios based on earnings surprise and three measures of disagreement: (i) the dispersion in analysts' earnings forecasts, (ii) the dispersion in institutional investors' portfolio weights, and (iii) reaching for yield proxies (a difference in a bond's yield and its peer with the same credit rating). We find that the long-short strategy on PEAD earns greater 11-factor alphas among bonds with higher disagreement than those with lower disagreement. For example, PEAD strategy delivers 43 bps 11-factor alphas for bonds in the highest analyst forecast dispersion quintile, while the same strategy yields 10 bps for bonds in the lowest quintile. Double-sorting bonds based on dispersion in investor portfolio weights or the reaching-for-yield proxy yields similar results.

Importantly, disagreement appears to explain the link between liquidity and slow price movements. We find that the bonds with high disagreement exhibit higher trading volume on earnings announcement days than low disagreement bonds do. Thus, if disagreement is the source for bond PEAD, then the puzzling positive relationship between trading volume and PEAD is no longer a puzzle, because generally investors trade securities more when they disagree on the value.

Having presented strong evidence for disagreement as the origin of bond PEAD, we build a stylized model in which investors exhibit difference of opinions to formalize the mechanism and offer a unified explanation for the positive relationship between PEAD and trading volume. In our model, investors can disagree on the bond value because they have different valuation models and thus different interpretations of the same public earnings announcement (Harris and Raviv 1993; Kandel and Pearson 1995). Consistent with Banerjee, Kaniel, and Kremer (2009), we find that in the presence of different opinions, prices can exhibit drift (or PEAD in the earnings announcement context). Intuitively, as investors hold different opinions about the public signal, they place high weight on their own private interpretation when updating beliefs, ignoring the potential information from the trades of others. This in turn results in slow aggregation of investor opinions, giving rise to price underreaction to the public signal and hence drift.

We then derive two empirical implications for the disagreement mechanism. First, bonds with high disagreement should be associated with more pronounced PEAD and higher trading volume. The implication on trading volume is important because we need to ensure that disagreement explains not only the above-documented patterns in prices but also quantities. Second, our model predicts that to the extent that disagreement drives PEAD, more pronounced PEAD can be associated with *higher* liquidity. This surprising result is unique to the disagreement mechanism; only when the asset is liquid can investors express different opinions through trade, which slows aggregation of information into prices. Specifically, even if illiquidity exacerbates bond PEAD by limiting arbitrage activities, as long as disagreement is the dominant driver, the relation between illiquidity and PEAD can be negative or insignificant, which is consistent with the empirical findings. Therefore, our model explains the observed patterns in disagreement, PEAD and illiquidity in a parsimonious way.

To bolster our argument for the disagreement-based explanation, we conduct more empirical tests to explore other alternative explanations for bond PEAD. First, we examine whether limited attention explains bond PEAD. Specifically, we examine subsample of earnings announcements when investors pay less attention to news, such as those occurring on Friday, those occurring on days when other firms also announce earnings,[1] or those with a low level of the investor attention measure proposed by Ben-Rephael, Da, and Israelsen (2017). We find that bond PEAD is not pronounced for bonds when investors pay less attention, suggesting that limited attention is unlikely to be the reason for the bond market PEAD.

Next, Frazzini (2006) proposes another explanation for PEAD based on another psychological bias of institutional investors. Specifically, he asserts that the disposition effect affects institutional investors' trading behavior, and therefore they are less likely to sell securities with capital loss and more likely to sell securities with capital gain. We construct his measure of the disposition effect, but find no evidence that capital gain or loss for the aggregate institutional investors affects bond PEAD.

The link between bond PEAD and disagreement is consistent with the findings in the stock market. To assess the role of disagreement, we regress stock returns on lagged earnings surprises, disagreement measures, and an interaction term between the two. We find that the coefficient on the interaction term is positive, which suggests that disagreement contributes to stock PEAD as well. However, the average stock PEAD effect is not strong in our sample. When we ignore the level of disagreement and sort stocks of bond issuing firms into earnings-surprise-based quintiles, we find that the return difference between high-surprise firms and low-surprise firms is mostly insignificant in the recent sample of 2002 to 2020. This insignificance arises because bond issuing firms are mostly large-cap stocks that exhibit less pronounced anomalies (e.g., Fama and French 2008), and stock PEAD strategy becomes less profitable over time (e.g. Chordia, Subrahmanyam, and Tong 2014; Martineau 2021).[2]

[1]Hirshleifer and Teoh (2003), Hirshleifer, Lim, and Teoh (2009, 2011), Dellavigna and Pollet (2009), and Michaely, Rubin, and Vedrashko (2016) explore the link between these inattention measures and PEAD in the equity market.

[2]McLean and Pontiff (2016) examine dozens of stock market anomalies and find a decline in return predictability in the recent sample period or post publication.

For those large-cap stocks, a rise of uninformed, algorithm-based traders eliminates trading profits from PEAD in recent years.[3] In contrast, due to large transaction costs, bond PEAD is not arbitraged away, which makes the bond market a unique testing ground for alternative theories for slow price movements and trading volume. Consistent with this claim, we find that unconditionally, the bond PEAD strategy yields near-zero profits after transaction costs. However, the strategy yields positive profits net of costs if we focus on subsample of bonds with high disagreement.

In sum, we contribute to the literature by providing a new insight into the relationship among disagreement, slow price reactions to news, and liquidity. We do not only document robust evidence that bonds' transaction prices react slowly to earnings surprise, but provide a unified explanation for the link between PEAD and liquidity.

Our paper relates to a strand of literature that documents slow-moving prices in the bond market, including Hotchkiss and Ronen (2002), Gebhardt, Hvidkjaer, and Swaminathan (2005), Jostova et al. (2013), Chordia et al. (2017), and Bali, Subrahmanyam, and Wen (2019). The paper closest to ours is Gebhardt, Hvidkjaer, and Swaminathan (2005) who document equity-bond momentum spillover. Our paper differs as we use transaction data rather than a dealer's quotes and thus our results reflects investors' actual trading behavior not affected by how quickly dealers update their quotes. Another closely-related paper is Wei, Truong, and Veeraraghavan (2012), who document post-earnings announcement drift over the 30-day period following earnings announcement dates in the corporate bond market. They compute average abnormal returns using panel data, and thus it may not be possible to exploit the drift in actual trading strategy. We verify bond PEAD using an approach which does not suffer from look-ahead bias, and explore the potential explanations for bond PEAD.

We also contribute to the literature that studies the bond market structure and its effect on bond returns. Wei and Zhou (2016) study corporate bond transactions before earnings announcements, and find that institutional trades predict earnings surprises and bond returns. Berndt and Zhu (2019) show the link between the inventory cost of dealers and information efficiency in the bond market. Ivashchenko (2019) argues that bond investors trade for both liquidity needs and information motivations, and documents that bonds with

[3]A recent work by Luo, Subrahmanyam, and Titman (2020) posits these high-frequency traders as noise traders and explores the implication on market efficiency. It is worth noting that our stylized model helps reconcile the strong (weak) PEAD phenomenon in the bond (stock) markets. Specifically, as in many standard information-based models (e.g., Grossman and Stiglitz 1980; Grossman and Miller 1988), noise trading tends to generate mean reversions in returns, thereby attenuating price drift. As such, to the extent that noise trading is lower for bonds than for equities (e.g., bond investors tend to buy and hold), we should be more likely to observe PEAD in bond markets than in stock markets.

high information asymmetry exhibit stronger short-term price reversals than those with low information asymmetry.[4]

This paper contributes to previous research that studies the source of slow price movements in the stock market. The proposed explanations vary across papers including disagreement (Hong and Stein 2007; Verardo 2009; Garfinkel and Sokobin 2006), the disposition effect (Frazzini 2006), limited attention (Hirshleifer and Teoh 2003; Ben-Rephael, Da, and Israelsen 2017), and overconfidence (Luo, Subrahmanyam, and Titman 2020). We test these competing explanations comprehensively in the bond market, and provide empirical evidence for disagreement as a key driver.[5]

Finally, this paper relates to the literature on the role of disagreement on asset prices (e.g., Diether, Malloy, and Scherbina 2002; Chen, Hong, and Stein 2002; Goetzmann and Massa 2005; Avramov, Chordia, Jostova, and Philipov 2009; Banerjee 2011; Yu 2011; Carlin, Longstaff, and Matoba 2014; Atmaz and Basak 2018; Golez and Goyenko 2019; Cookson and Niessner 2020). These papers focus on predicting stock returns using various disagreement proxies and document mixed evidence on the effects of investors' dispersion of beliefs on expected returns. In contrast, we focus on the bond market and use disagreement to explain sluggish price reaction to earnings announcement.

The rest of the paper is organized as follows; in Section 2, we describe our data and present evidence for bond PEAD; in Section 3, we empirically study the link between PEAD, liquidity and disagreement measures; in Section 4, we present a stylized model to explain the empirical findings; in Section 5, we provide extensions of the main analysis including explorations of alternative explanations for bond PEAD, transaction cost analysis, and comparison with equity PEAD; and in Section 6, we provide concluding remarks.

2 Evidence of Bond PEAD

2.1 Data

We use enhanced TRACE data for corporate bond prices from July 2002 to December 2020, and Mergent FISD for bond characteristics such as amount outstanding, credit rating and

[4]In the equity market, Kaniel et al. (2012) show evidence for informed individual investors trading on private information.

[5]Our paper is different from Garfinkel and Sokobin (2006) as we study bonds, use more direct measure of disagreement, and present a stylized model to explain the link between liquidity, disagreement, and PEAD. In addition, Garfinkel and Sokobin (2006) document earnings announcement premiums rather than PEAD.

time to maturity.

We clean TRACE data and remove transaction records that are canceled, and adjust records that are subsequently corrected or reversed following Dick-Nielsen (2014). We further adopt the additional filters using FISD data following Bai, Bali, and Wen (2019): (1) remove bonds that are not listed or traded in the U.S. public market; (2) drop bonds that are structured notes, mortgage-backed, asset-backed, agency-backed, or equity-linked; (3) delete convertible bonds or bonds with floating coupon rate or odd frequency of coupon payments; (4) exclude a transaction price under \$5 or above \$1000; (5) remove bonds that have less than one year to maturity; (6) eliminate bond transactions that are labeled as when-issued, locked-in, or have special sales conditions, that have more than a two-day settlement; (7) drop transaction records with volume less than \$10,000.[6]

We construct monthly bond returns from transaction data as follows; first, in order to reduce potential market microstructure noise in bond returns, we follow Bessembinder et al. (2008) and calculate the volume-weighted average price in a day; second, we construct monthly returns from the daily price data as

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

where P_{t+1} is the average price on the last day with non-zero transactions in the last five business days in month $t+1$, AI_t is accrued interest at the end of month $t+1$, C_{t+1} is coupon paid in month $t+1$. For P_t, we first look for the last day with non-zero transactions in the last five business days in month t, and use it if such an observation is available. If we do not find such an observation, we use the average price on the first date with non-zero transactions in the first five business days in month $t+1$ for P_t.

Since we use volume-weighted average prices excluding small transactions, a return in (1) is less likely to be affected by bid-ask bounce in transaction prices. Still, we verify whether or not the remaining potential measurement errors affect our results below by examining the fraction of bids in calculating the prices, and confirm that bid-ask bounce does not artificially generate our main results.

In order to construct measures of disagreement and disposition effect, we use institutional investors' bond holding data provided by eMAXX. The holding data covers the U.S. insurance firms, mutual funds, pension funds and other investors from 2002Q1 to 2020Q4, totalling 48% of the average ownership share in our sample period. We obtain stock price and return

[6] Our main results are robust to this volume threshold. The results are similar if we only use transactions with volume no less than \$100,000 following Bessembinder et al. (2008).

data from CRSP and firm fundamentals from Compustat. The data on analysts' earnings forecasts are taken from the Institutional Brokers Estimate System (I/B/E/S). We use the Unadjusted Detailed files and focus on the quarterly forecasts for our analysis.[7] Following Livnat and Mendenhall (2006), we require an earnings announcement to have at least one analyst forecast, and the price per share is available from Compustat as of the announcement quarter and is greater than $1.

To confirm the evidence outside of the corporate bond market, we obtain the five-year CDS contracts for U.S. dollar-denominated senior unsecured debt of 929 U.S.-based corporate obligors from Markit over the period from July 2002 to December 2020. We set the sample beginning month so they start at the same time as the corporate bond sample. We focus on on-the-run five-year CDS contracts as they are the most liquid tenor.[8] We include contracts that adopt the modified restructuring documentation clause before April 2009 (when the CDS Big Bang occurred) and no restructuring clause afterwards.

To correctly identify the announcement dates, we follow Dellavigna and Pollet (2009), compare Compustat and I/B/E/S announcement dates and assign the earlier date as being correct. Following Johnson and So (2018), we further remove observations where the Compustat and I/B/E/S announcement dates are more than two trading days apart from each other. If the announcement, based on the I/B/E/S time stamp, occurred after the market close, we adjust the announcement date one trading day forward.

Using those data, we construct three measures of earnings surprise. First, following Livnat and Mendenhall (2006), we calculate the difference between announced earnings per share and median analyst forecast scaled by price per share at quarter end, *CE*. Second, we follow Chiang et al. (2019) and calculate the fraction of forecasts that miss on the same side (FOM), defined as $J/N - M/N$ where J (M) is the number of analyst who predicted lower (higher) earnings than announced, and N is the total number of forecast. Lastly, we follow Frazzini (2006) and Brandt et al. (2008) and use cumulative abnormal stock returns (CAR) from day $d-1$ to $d+1$ around earnings announcement date d as a measure of surprise. The first two proxies directly measure the surprise in announced earnings per share relative to analyst's forecast, while CAR contains the surprise in overall announcement including earnings figure and other information (e.g., detailed components of earnings and

[7] We also use the annual year-end forecast to compute analyst forecast dispersion later.

[8] 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. Since December 2015, ISDA Credit Steering Committee has recommended a new standard schedule with an amendment from a quarterly frequency to a semi-annual frequency. The new schedule is to only roll to new contracts in March and September, following the current convention for Credit Indices.

conference calls) disseminated by the firm. Furthermore, CAR is a surprise relative to stock investors' expectation instead of analyst forecast. Thus, CAR contains broader information than analysts' forecast errors, which may or may not be relevant for bond prices.

Table 1 reports the summary statistics of the panel data on bond returns and characteristics. After the data filtering and matching bonds to earnings announcement data, we have 563,859 bond-month observations on bond returns for 14,394 bonds issued by 1,741 firms. In our sample, the average bond has a monthly return of 0.56%, credit rating of BBB (which corresponds to the numerical value of 8.8), time to maturity of 9.8 years, amount outstanding of $709 million with return volatility of 2.1%.

2.2 Bond Market Reactions to Earnings News

As a warm-up exercise, we investigate bond price reactions to earnings announcement. By studying the link between announcement-day bond returns and various proxies for earnings surprise, we aim to identify a valid earnings surprise measure. If a proxy truly captures earnings surprise for corporate bond investors, then bond returns should jump in response to the surprise.

Specifically, we run a pooled OLS regression of 3-day bond abnormal returns on earnings surprise measures and control variables,

$$R_{i,d-1\to d+1} - R_{MKT,d-1\to d+1} = a + bSurprise_{i,d} + cCtrl_{i,d} + FE_q + \varepsilon_{i,d-1\to d+1}, \tag{2}$$

where $R_{MKT,d-1\to d+1}$ is a return on corporate bond indices,[9] $Ctrl_{i,d}$ is a vector of control variables including time to maturity and numerical credit rating, and FE_q is year-quarter fixed effects. We standardize the three earnings surprise measures so we can compare the economic significance of bond market reactions to these surprise measures.

Table 2 reports the estimated slope coefficients, associated t-statistics and adjusted R-squared of regressions in (2). We find that corporate bond returns strongly react to all three measures of earnings surprise upon announcement. When each measure is included separately in regressions, a one-standard deviation increase in CAR, CE and FOM leads to a 0.39, 0.13 and 0.10 percentage point increase in bond returns over the three-day window. These reactions are significant given that standard deviation of three-day abnormal bond returns is 1.55%. The significant bond price reaction to earnings surprise implies that bond

[9] Specifically, 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.

investors update their valuation quickly in response to news, confirming the earlier results in Hotchkiss and Ronen (2002). Given the strong reaction to news, it is far from clear whether we should observe PEAD in the corporate bond market despite the large transaction costs. However, these results confirm that the surprise measures we use are valid proxies for news relevant to corporate bond investors, and thus they provide a foundation to study post announcement drifts.

Columns 4 to 6 of Table 2 report the results of horse races, comparing CAR, CE and FOM in explaining contemporaneous bond returns. We find that CAR is by far the strongest measure of earnings surprise for bond investors; in multivariate regression including CAR and another measure in (2), the estimated slope coefficient on CE decreases from 0.13% to 0.03%, while that on FOM decreases to -0.003%. In contrast, the loading on CAR barely changes when it is put together with CE or FOM. These results suggest that, in understanding how bond investors react to earnings-related news, it is important to account for information other than earnings per share, such as managerial discussion during conference calls and sales projection for the future. Thus, in the following analysis, we use CAR as our main measure of earnings surprise, and other two measures for robustness tests.[10]

2.3 Bond PEAD: Univariate Portfolio Sort

Now we turn to the first main empirical results, which is post-earnings announcement drift in the bond market. To this end, at the end of month t, we sort bonds into quintiles based on the latest available observation for announcement-day stock CAR, and calculate subsequent portfolio returns by taking the value-weighted average across bonds in the portfolio.[11] 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. Regardless of the exact timing of announcement, we rank all bonds and form portfolios at the end of April and calculate the portfolio return in May.[12] This method avoids forward-looking biases in calculating portfolio returns and prevents the seasonality inherent in earnings announcements from affecting the sample size.[13] Thus, our estimates for PEAD reflect returns on a tradable strategy.

[10]Interestingly, Even-Tov (2017) finds that bond returns upon earnings announcement predict stock returns beyond standard measures of earnings surprise.

[11]Following Bai, Bali, and Wen (2019), we use the amount outstanding of a bond as portfolio weights.

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

[13]Chan, Jegadeesh, and Lakonishok (1996), Frazzini (2006), and Daniel, Hirshleifer, and Sun (2020), among others, use a similar approach in the stock market.

Panel A of Table 3 reports the average value-weighted portfolio returns in excess of T-bill rates. The average excess returns increase nearly monotonically from the lowest CAR quintile (0.40%) to the highest (0.57%), and the difference is 0.17% with a t-statistic of 3.63. Thus, bonds with positive earnings surprise continue to earn higher returns than those with negative surprise. The monthly returns used in the analysis are based on actual transactions rather than stale quotes, and thus the evidence suggests that despite large transaction costs, some investors implement a trade at 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 amount outstanding, credit rating, time to maturity, the Roll measure of illiquidity ($ACOV$), and bonds' age are similar between the lowest and highest quintiles, suggesting that we are capturing firm-specific news on earnings independent of other determinants of bond returns.

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

$$R^e_{q,t} = \alpha_q + \beta_q' F_t + u_{q,t}, \tag{3}$$

where F_t is five bond factors of Bai, Bali, and Wen (2019) including bond market, downside risk, credit risk, liquidity risk and reversal factors, or six stock factors of Fama and French (2018) including stock market, size, value, investment, profitability and momentum factors. We also combine the two sets to create the 11-factor model.

Panel A of Table 3 reports the intercept of equation (3). We find that controlling for risk factors generally increases returns on the long-short portfolio, implying that bonds with high CAR tend to have lower betas than those with low CAR do.[14] For example, the 11-factor alpha on the high-minus-low strategy is 22 bps per month ($t = 4.52$), roughly 2.5% per year. Since the difference in alpha is greater than that in average excess returns, high CAR bonds are less risky than low CAR bonds, leading to more pronounced difference in alphas.

The alphas reported in Table 3 show whether bond PEAD comes from the short- or long-leg of the strategy. The 11-factor alpha of value-weighted portfolios is -0.14% for the lowest CAR quintile and 0.07% for the highest CAR quintile. These values suggest that the long-leg of transactions contributes roughly one third of the profits to the bond PEAD strategy, and the short-leg generates the remaining two thirds. Thus, even though the drift

[14] In the untabulated results, we find that the highest CAR quintile loads significantly less on the bond illiquidity factor than the lowest CAR quintile does.

is more pronounced after negative news, bond PEAD is not a simple reflection of short sale constraints in the bond market.[15]

In Table 4, we show that bond PEAD effect exists both for investment-grade (IG) and high-yield (HY) bonds, as well as various subsamples by maturities. The 11-factor alpha for the long-short strategy is higher for HY bonds (33 bps, $t = 4.37$) than for IG bonds (10 bps, $t = 2.85$), while it is similar across quintiles defined by maturity. These results suggest that PEAD is a pervasive phenomenon across different segments of corporate bonds.

To examine the time-series pattern in the profitability of buying high CAR bonds and shorting low CAR bonds, we plot cumulative returns on the long-short portfolio together with those on the bond market portfolio, the term and default factors in Figure 2, Panel A. Other factors are scaled to have the same monthly volatility as the PEAD portfolio. We find that the cumulative returns on the PEAD strategy are not volatile and increasing steadily over time. Due to low volatility, the annualized Sharpe ratio of the portfolio is 0.73, which is comparable to 1.02 of the corporate bond market portfolio over the same period, and higher than the term and default factors.[16] Furthermore, Panel B shows that the long-short portfolio cancels the market exposure of each leg well. For example, the long-short strategy avoids the market crush in 2008 and in early 2016, but grows strongly as the market recovers. In early 2020, there is a notable dip in the cumulative returns, but this is not directly due to the pandemic-driven recession. The worst return on the PEAD strategy in 2020 is in fact in January (-0.98%), and the return in March 2020 when the pandemic hit the market the hardest is positive at 0.44%. The low correlation between the cumulative returns and business cycle suggests that the bond PEAD is not a reflection of omitted risk factors. Considering the non-systemic nature of PEAD returns, a seemingly small premium on the bond PEAD strategy is economically significant.

Better availability of information on market prices may reduce asset price drifts after announcements. Analysis on the effect of information environment requires a comparison between the PEAD before and after the introduction of TRACE. Since our sample starts with TRACE, it is not possible for us to analyze the effect of the increased transparency on the price drift. Thus, in Appendix A, we study the extended sample from 1997 to 2016 using Merrill Lynch's quote data, and compare the profitability of bond PEAD strategies before and after the introduction of TRACE in 2002. We confirm that alphas from the bond PEAD strategy are about the same as the main results using TRACE, and that bond PEAD

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

[16] The plot cumulates the long- and short-leg separately, and thus the cumulative profit for PEAD turns out to be higher than that on the bond market despite the lower Sharpe ratio.

is not more pronounced in the earlier sample than in the latter sample.[17] Therefore, better information environment does not reduce the efficacy of the PEAD strategy. Furthermore, the quote data do not suffer from missing observations on no-trade dates and thus the existence of the bond PEAD effect in both samples provides comfort to our main findings.

In order to check if PEAD is an artifact of market microstructure noise in the data, we calculate the fraction of dollar bid (i.e. dealer buy) volume relative to the total volume on a day. Due to bid-ask spreads, the volume-weighted average bond price on a day would be lower than the true mid price if transactions with dealer buy dominate those with dealer sell, and higher than the true mid if dealer sell dominates. Thus, if the fraction of bids in month-t price or month-$(t+1)$ price were correlated with CAR, then PEAD could be artificially generated from measurement errors. However, we find that the average bid fraction is similar between the lowest and highest CAR quintiles. For example, in Table 3 Panel B, the fraction of bids for P_t is 36.07% for the first quintile, while it is 35.96% for the fifth quintile. Thus, the observed return difference among the portfolios is unlikely to be generated by bid-ask bounce. Below, we verify this finding further using Fama-MacBeth regressions including the fraction of bids as control variables.

Even though we do not have data on which investor sets a price after announcement at the "wrong" level, we can see whether or not institutional investors as a whole take advantage of the PEAD effect from the fraction of bids in Table 3. If institutional investors exploit the PEAD effect, we should observe more customer buys after positive news than we do after negative one. However, Panel B shows that the fraction of bids (customer sell) is the same across all quintiles, suggesting that the average institutional investor does not trade to profit from the drift.

We next test if bond PEAD exists with alternative measures of earnings surprise including 3-day abnormal bond returns around earnings announcement (Bond CAR), CE and FOM, and verify the results with Stock CAR. Panel C of Table 3 reports the 11 factor alphas on value-weighted bond portfolios sorted on Bond CAR, CE and FOM. The difference between the highest and lowest earnings surprise quintiles is 30 bps using Bond CAR ($t = 4.53$), 12 bps using CE ($t = 2.38$) while it is 10 bps using FOM ($t = 1.82$). Thus, bond prices exhibit PEAD regardless of the measures of earnings surprise. However, Stock CAR contains more

[17]The literature finds that the mandatory dissemination of TRACE has mixed effects on the pricing efficiency of corporate bond market. On the one hand, the increased transparency decreases transaction costs, improves the efficiency of information aggregation and transmission, and thus reduces the market reaction to third-party information release, such as rating agencies (Asquith, Covert, and Pathak 2013b; Chen and Lu 2017; Badoer and Demiroglu 2019). On the other hand, post-trade transparency would reduce dealer' profits and informed traders' incentives to participate in the over-the-counter market, leading to attenuated price informativeness (Lewis and Schwert 2018).

value-relevant information for corporate bonds than *CE* and *FOM*. Not only bond returns react more to Stock CAR upon announcement than to the deviation from analysts' forecast, but they exhibit a greater drift after announcement using Stock CAR than *CE* or *FOM*. We also find that bond PEAD using Bond CAR as earnings surprise is even stronger than that using Stock CAR. However, as shown in Table 1, the sample size using Bond CAR is nearly 50% smaller than the main sample because we have to limit the sample to bonds that trade two days before and a day after the announcement. Thus, we use stock CAR in the main results as it provides wider coverage of bonds.

2.4 Comparing Earnings Announcement with Other News

To assess the uniqueness of earnings announcement, it is useful to compare earnings surprise with other news. To this end, we use credit rating changes and more general news reflected in stock returns for reference. Importantly, Gebhardt, Hvidkjaer, and Swaminathan (2005) find that previous 6-month equity returns predict bond returns in the following month, and interpret the finding as bond market underreacting to news. Thus, we contrast the performance of our earnings announcement measure (stock returns on earnings announcement days) with stock returns on non-announcement days.

We run monthly Fama and MacBeth (1973) cross-sectional regressions of bond returns on our earnings surprise measure (CAR), dummy variables for credit rating changes in the previous 3 months (one for upgrade and the other for downgrade),[18] equity momentum (cumulative market-adjusted equity returns from month $t-5$ to t, *SRet6m*), cumulative market-adjusted 3-day equity returns on non-announcement days that are randomly selected from the previous 6 months ($NoAnnCar$), and bond characteristic controls. The set of control variables comprises of bond's amount outstanding, credit rating, time to maturity, downside risk, the Roll measure, past short-term and medium term bond returns (in month t and from months $t-6$ to $t-1$), bond and stock return volatility, and the fraction of bids in month t and $t+1$ prices, and industry fixed effects (defined by Fama-French 30 industry classifications). Except for dummy variables, we winsorize the right-hand side variables at the 1% level, and standardize them for ease of interpretation. In constructing *SRet6m*, we cumulate daily stock returns excluding day $d-1$ to $d+1$ (i.e. the three-day period around earnings announcement dates), and subtract returns on the stock market portfolio over the corresponding period to obtain market adjusted stock returns. If bond PEAD is subsumed by stock-bond momentum spillover, then our proxy for earnings surprise should not predict

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

bond returns once we control for *SRet6m*.

Table 5 reports the estimated average slope coefficients from the Fama-MacBeth regressions. Before comparing earnings surprise with other news, we start by assessing the bond PEAD in the regression setup. When used independently (Column 1), we find that a one-standard deviation increase in earnings surprise (CAR) predicts a 7 bps (t=3.32) increase in bond returns next month. The PEAD effect is 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 a mere reflection of difference in risks of the bonds or measurement errors in the data.

Turning to other news, the coefficient for *SRet6m* is 12 bps (Column 3), which is larger than that for earnings surprise. To see the role of earnings announcement on an equal footing, we use 3-day abnormal stock returns on non-announcement days ($NoAnnCar$) as another regressor. The loading on $NoAnnCar$ (reported in Column 4) is close to zero and statistically insignificant. Therefore, even though the point estimate is smaller than that on the past 6-month returns, earnings announcement is indeed special in predicting bond returns in the following month.

As another reference point, regressions in Column (5) include dummies for credit rating upgrades or downgrades. We find that the loading on the upgrade dummy is close to zero, while that for the downgrade dummy is -13 bps (t=-2.10). The significantly negative loading on the downgrade dummy suggests that a bond price tends to underreact to downgrade news. The degree of underreaction is similar to a two-standard deviation change in earnings surprise.

Finally, we run horse races among these news variables in generating drifts in bond prices. The regression reported in Column 6 includes all of the above measures and control variables. The estimated slope coefficient for earnings surprise is about unchanged at 7 bps even after controlling for a host of other news variables. This predictive power of CAR is impressive, given that its information is typically more dated than the information in *SRet6m* which depends on the stock price at the end of month t (i.e., when we form portfolios). These findings are consistent with Chan, Jegadeesh, and Lakonishok (1996) who find that in the equity market, momentum and PEAD carry independent information. Overall, we confirm that earnings surprise is unique, and it carries information that predicts bond returns above and beyond other news reflected in non-announcement-day stock returns.

3 Disagreement and Liquidity as Potential Sources of Bond PEAD

We have presented novel empirical evidence that bond prices exhibit slow reaction to earnings announcements. In this section, we dissect the source of bond PEAD. It is intuitive to conjecture illiquidity – dealers' inventory frictions, infrequent transactions of corporate bonds and the over-the-counter market structure etc. – do not only prevent arbitragers from arbitraging away the drift, but are also the *origin* of the slow price movements. Surely, if investors trade infrequently, information travels slowly and this must give rise to a drift. But is this intuition really correct? We first test this thesis using the data. We then turn to an alternative explanation based on investors' disagreement on bond values as the origin for the drift.

3.1 Liquidity

To test the intuition that the illiquidity gives rise to PEAD, we conduct independent bivariate sorts of bonds based on CAR and various measures of illiquidity, and examine if PEAD is more pronounced for illiquid bonds. For illiquidity measures, we employ six proxies including the Amihud (2002) measure of illiquidity, the negative autocovariance proposed by Bao, Pan, and Wang (2011), bid-ask spreads (BAS), imputed round-trip costs of Feldhütter (2010), average daily turnover rate (daily trading volume divided by amount outstanding, averaged within a month), and the fraction of no trading days in a month. We use negative of turnover so all the variables are illiquidity (rather than liquidity) measures. Furthermore, we create a composite measure by sorting bonds into ten buckets each month based on each of the six proxies from the most liquid to least liquid, and calculate the average of the rank. By averaging rankings, we normalize these measures and create an aggregate illiquidity index.

Table 6 reports the 11-factor alphas on 25 value-weighted portfolios sorted on CAR and each of the seven illiquidity measures. We only report the difference between high CAR and low CAR quintiles for each illiquidity quintile for brevity. The table shows the relationship between PEAD profits and illiquidity is mixed. Double-sorting on bid-ask spreads and CAR shows that the PEAD profits are higher by 20 bps for high BAS bonds than low BAS bonds. However, other variables show the opposite sign. More liquid bonds (low Amihud measure, low Roll measure, high turnover, low zero trading days) earn higher PEAD profits than less liquid bonds (high Amihud measure, high Roll measure, low turnover, high zero trading days). As a result, the composite illiquidity index is weakly negatively associated with

PEAD profits. Thus, overall, we do not find strong evidence that PEAD profits concentrate on illiquid bonds. If anything, bonds that trade more frequently exhibit a stronger drift than bonds that trade less. For example, bonds with the highest turnover (lowest illiquidity, Q1) generate 0.30% for the PEAD strategy, while those with the lowest turnover (highest illiquidity, Q5) earn 0.14%. Therefore, the evidence thus far does not support the hypothesis that illiquidity generates corporate bond PEAD.

Still, the findings above are based on proxies for illiquidity, which may or may not be accurately capturing the reality. To bolster our argument, we examine CDS and study if PEAD exists or not. As Oehmke and Zawadowski (2016) point out, CDS contracts are more standardized than corporate bonds, and thus they are likely to be more liquid. If illiquidity in corporate bonds is the cause of slow price movements, then we should not expect the PEAD to exist in the CDS market. Thus, we examine 5-year on-the-run single-name CDS contracts and estimate the trading profits of a strategy which sells CDS protections based on past earnings surprise.

To measure a return on CDS contract, we calculate an approximate present value of cash flows following Augustin, Saleh, and Xu (2020). Specifically, the price of the position for a protection seller is:

$$P_t = \frac{c - s_t}{r_t + \frac{s_t}{1-\mathcal{R}}} \left(1 - e^{-(r_t + \frac{s_t}{1-\mathcal{R}})(T-t)}\right), \tag{4}$$

where c is a coupon rate set at 1% for IG and 5% for HY firms, s_t is the breakeven CDS spreads, r_t is $(T-t)$-year risk-free rate, and $\mathcal{R}$ is a recovery rate.[19] An excess return on a strategy to sell protection in month t and unwind the position in $t+1$ is,

$$R_{t+1}^{e,CDS} = \frac{P_{t+1}^{CDS} - P_t^{CDS}}{\Phi}, \tag{5}$$

where the fraction of notional collateralized, Φ, is set to 1 following Loon and Zhong (2014). $\Phi = 1$ implies that investors fully collateralize the CDS notional, but our results are invariant to the choice of Φ as long as they are a constant.

Using CDS returns in (5), we form quintile portfolios of firms based on the latest earnings surprise and calculate the value-weighted excess returns, where weights are given by the firm's stock market capitalization. We regress portfolio excess returns on the set of factors to estimate alphas as well. These results are reported in Panel A of Table 7.

We find that CDS contracts exhibit PEAD, consistent with our findings for corporate

[19] We use Markit's "Real Recovery Rate" if it is available, and "Assumed Recovery Rate" if not. If neither values are available, we set $\mathcal{R} = 0.4$.

bonds. For example, the average excess CDS returns for firms in the lowest earnings surprise quintile are -0.14%, while those in the highest quintile are -0.07%, resulting in the average return difference of 0.07% (t=3.61). Since CDS returns are less volatile than corporate bond returns, even the 7 bps difference in average excess returns is translated into a sizable annualized Sharpe ratio of 0.94, higher than the corporate bond counterpart. Furthermore, after controlling for the 11-factor risk exposure, the alpha and the Sharpe ratio rise to 11 bps and 1.65, respectively.[20]

Since the calculation of CDS returns involves some approximation, we also check the results using the differences of the natural logarithms of CDS spreads instead of CDS returns. The advantage of changes in CDS spreads is its simplicity and transparency though they have a drawback of being unable to capture the investment value for CDS investors. In Panel B, we replace CDS returns in Panel A with log credit spread changes, and repeat the exercise. Since an increase in CDS spreads reduces a return for CDS protection seller, the sign of the difference between the high and low earnings surprise quintiles reverses: Panel B shows that a firm in the highest quintile tends to have significantly lower CDS spreads in the month following portfolio construction than a firm in the lowest quintile. These findings are qualitatively consistent with the results using CDS and corporate bond returns.

Overall, we observe strong evidence for PEAD for CDS despite its higher liquidity. The drift in CDS market also suggests that we need to take a step deeper to explore the cause of the corporate bond PEAD.

3.2 Empirical Evidence for Disagreement

As an alternative explanation to illiquidity, we empirically study whether bond PEAD is more pronounced for bonds when there is greater disagreement on bond values. Since we do not directly observe disagreement, we construct proxies for disagreement capturing the variation in investors' belief on bond values.

Specifically, we use three proxies for disagreement. First, we construct analysts' forecast dispersion, *DISP*, which is standard deviation of analysts' earnings forecast for each firm scaled by the average stock price, as proposed by Diether, Malloy, and Scherbina (2002).[21]

[20] Jenkins, Kimbrough, and Wang (2016) report weak evidence for PEAD in the CDS market. The difference between our results and theirs likely come from the measure of earnings surprises: we use announcement-day stock returns while they use a less powerful measure of surprise based on the seasonal changes in quarterly earnings. Seasonally differenced earnings can be interpreted as earnings surprise only under the assumption of random walk earnings, and thus a noisy measure of a surprise. Moreover, we use a different data source from theirs and cover more firms in a longer sample period.

[21] We use the annual year-end analyst forecast and remove excluded and stopped estimates. To alleviate

This measure of disagreement is based on equity analysts' opinion of firm's profit in the coming year and incorporates revisions following the release of quarterly earnings. We also created a disagreement proxy using only below-median analyst forecasts to capture downside risk, but the results were similar to overall dispersion in forecast, and thus we only use *DISP* in the following analysis.

To measure bond investors' disagreement more directly, we construct our own measure of disagreement. Specifically, we use institutional investors' bond holdings and examine how they differ from each other. By focusing on bond holding, we aim to capture disagreement on the longer-term prospects for the bond. To this end, we calculate the coefficient of variation of portfolio weights across investors for borrower k,

$$CV_{k,q} = \frac{\sigma_{k,q}[w_{k,j,q}]}{E_{k,q}[w_{k,j,q}]}, \tag{6}$$

where $w_{k,j,q}$ is investor j's portfolio weights on bonds issued by firm k's in quarter q. To measure disagreement based on bond holding, we focus on portfolio weights rather than dollar value of bond holding because dollar value will be affected by the variation in investor size. We scale standard deviation of portfolio weights by its average to control for the size of the bond. If investors hold the market portfolio of bonds, then their portfolio weights are equalized, leading to CV=0. In reality, CV is generally not zero because investors deviate from the market portfolio.[22]

the staleness of forecasts, the analyst forecast for a given firm-year pair is carried forward till either the date of the consecutive estimate release for the same firm-year pair by the same analyst, or the date which is 105 days ahead of the earnings announcement date, whichever comes sooner. The decision to carry the forecast forward for up to 105 days is based on the 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. We scale the standard deviation using the average price in month $t-1$ and t.

[22] As suggested by Goetzmann and Massa (2005) and Cookson and Niessner (2020), the difference in portfolio weights may reflect investors' investment style rather than her opinion on the specific bond. To address this concern, we conduct a robustness test using an alternative measure of disagreement based on portfolio weights after controlling for investor style. We first run a cross-sectional regression for each bond across investors,

$$w_{k,j,q} = b_0 + b_1 AvgRating_{j,q} + b_2 AvgMaturity_{j,q} + b_3 AvgIlliq_{j,q} + u_{k,j,q}, \tag{7}$$

where *Avg* denotes the average of characteristics across bonds held by investor j. By averaging across bonds, the right-hand side variables in (7) capture an investor's style, and the residual captures the deviation in portfolio weights from similar bonds held by the investor, which should reflect her opinion on bonds issued by firm k. We then create an alternative holding-based disagreement measure as,

$$CV2_{k,q} = \frac{\sigma_{k,q}[u_{k,j,q}]}{E_{k,q}[w_{k,j,q}]}. \tag{8}$$

We report the results using this alternative measure in Appendix Tables A2 and A3, and confirm that the results are similar.

Lastly, we use another proxy for bond investors' disagreement based on bond prices. Choi and Kronlund (2017) and Choi and Chen (2021) report compelling evidence of reaching-for-yield behavior of bond institutional investors. In particular, some corporate bond mutual funds tilt their portfolio 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 a rare, tail event that may occur when their marginal utility is high, and their view is reflected in the bond's prices as they are lower than the peer. This observation implies that bonds that have high yield relative to the benchmark are subject to greater disagreement on their values between optimists (who tilt their portfolio toward those bonds) and pessimists (who recognize the possibility of tail events). Thus, we use the difference between bonds' yield and the average yield of the bonds with the same credit rating (RFY) as the third measure of disagreement.

Armed with the proxies for disagreement, we study the driver of bond PEAD. Specifically, every month, we independently double-sort bonds into 25 value-weighted portfolios based on earnings surprise (CAR) and a disagreement measure. We then calculate the difference between the highest and lowest CAR quintiles separately for each disagreement quintile.

Table 8 reports our second main results, which are the 11-factor alphas on the bond PEAD strategy for each disagreement quintile. In Panel A, we use *DISP* as a measure of disagreement, and find that bonds with higher disagreement generate greater average excess returns on bond PEAD strategy than those with low disagreement. Specifically, the strategy earns 0.43% alphas using the 11-factor model for the highest *DISP* quintile, but earns only 0.10% for the lowest *DISP* quintile. The difference between the two is statistically significant with a t-statistic of 2.25.

Panel A also reports the characteristics of bonds for each *DISP* quintile. We find that *DISP* is correlated with the daily turnover rate (transaction volume scaled by amount outstanding) on the earnings announcement date (d=0) and in the announcement month (month t=0). For example, the average turnover on the announcement date for the lowest *DISP* quintile is 0.48%, while it is 1.14% for the highest quintile. This finding is important, because the key feature of disagreement models is its ability to explain transaction volume (see, for example, Hong and Stein 2007). The analysts' earnings forecast dispersion captures not only disagreement among analysts, but also disagreement among bond investors on the value of the bond, which leads to greater transaction volume.

Looking at other bond characteristics, we also find that bond volatility (estimated using monthly returns over the past six months) and stock volatility (estimated using daily returns over the past one month) are positively correlated with *DISP*, suggesting that trading activities might lead to higher return volatility. Finally, we find that bonds with high *DISP* tend to have lower credit quality (as measured by high numerical values of credit rating), higher downside risk and higher illiquidity. Though the 11-factor model should have captured risk exposures regarding those characteristics, in the analysis below, we directly control for those characteristics and examine if disagreement is subsumed by those risk proxies.

Panel B of Table 8 repeats the analysis using portfolio weight dispersion (CV). We find that the PEAD strategy generates 0.36% alpha for the highest CV quintile while it yields -0.02% for the lowest CV quintile, and the difference is 0.37% (t = 2.67). In Panel C, we show that we obtain a similar pattern in PEAD profits when we use reaching-for-yield as a disagreement measure. It is notable that when we measure disagreement using RFY, the average credit rating for bonds in the high and low disagreement quintiles is about the same. This suggests that the difference in alpha is not driven by variation in credit quality. In sum, even though our disagreement proxies come from various data sets with different nature (one from analysts' forest, the other from bond investors' positions and the last from bond prices), they point to the same conclusion; disagreement among investors leads to a greater drift in bond prices.

To separate the effect of disagreement from other potentially confounding characteristics of bond returns, we run monthly cross-sectional regressions of Fama and MacBeth (1973). Every month, we regress bond excess returns on earnings surprise (CAR), disagreement, and their interactions:

$$\begin{aligned} R^e_{i,t+1} = {} & \gamma_{0,t} + \gamma_{1,t} CAR_{i,t} + \gamma_{2,t} DisAgreement_{i,t} \\ & + \gamma_{3,t} CAR_{i,t} \cdot DisAgreement_{i,t} + \lambda_t Ctrl_{i,t} + \eta_{i,t+1} \end{aligned} \tag{9}$$

where *DisAgreement* is a measure of disagreement, including *DISP*, CV or RFY, and $Ctrl_{i,t}$ is a vector of control variables including bond's amount outstanding, credit rating, time to maturity, downside risk, illiquidity, past one-month bond returns, bond momentum (cumulative 6-month returns from month $t-6$ to $t-1$), bond return volatility, stock return volatility, fractions of bids in month t and $t+1$ prices, and industry fixed effects.

Table 9 reports the time-series averages of the estimated slope coefficients in (9). In Column 1, we repeat the estimates for the regression only with CAR for reference. In Column 2, we add an interaction term between CAR and *DISP*, and find that the coefficient is estimated at 3.9 bps, and thus the effect of bond PEAD increases nearly 50% if a bond has a one-standard deviation increase in *DISP*. In Columns 3 and 4, the interaction term between CAR and other disagreement measures is also significant in positively predicting bond returns, suggesting that bond PEAD strengthens with disagreement even after controlling for bond characteristics, such as a bond's size, credit rating, maturity and illiquidity.[23]

The proxies for disagreement used in the analysis above can be driven by other frictions and biases that give rise to differences in forecast or portfolio weights. For example, information asymmetry among analysts can create forecast dispersion, and investors' preference (e.g. preference for green bonds) can create variation in portfolio weights. While it is difficult to fully address this concern,[24] we further argue for disagreement as the source of bond PEAD based on the non-decaying PEAD profits shown in Figure 2. If information asymmetry is the source of PEAD, then the profits should decay over time as market participants learn from each other. This is particularly true due to the introduction of TRACE, which improved the post-trade transparency and reduced information asymmetry. Furthermore, Figure 2 also shows that the PEAD profits are high right after market downturns with high volatility. Hong and Sraer (2013) show that disagreement on bond value is positively related to the level of asset prices. When a firm is closer to default with a lower asset value, its bond becomes more sensitive to underlying value (and disagreement on it), just like at-the-money options are more sensitive to underlying assets than out-of-the-money options are. Following this logic, disagreement on bonds rises when firm values are lower, consistent with the observation that the PEAD profits are high in 2009 and 2016. The link between asset values and disagreement also explains why the PEAD profits are higher for HY bonds than for IG bonds. In sum, evidence from the cross-sectional and time-series variation in PEAD supports our argument that disagreement is the source of bond PEAD.

Finally, since past 6-month stock returns (*SRet6m*) also predict bond returns independent of bond PEAD, we use *SRet6m* as an alternative testing ground for our hypothesis that disagreement generates slow price movements. Specifically, we replace CAR in regression (9) with *SRet6m*, and study the interaction between *SRet6m* and the disagreement proxies. Table 10 reports the estimates for the regression. The interaction term with equity momentum and the three disagreement measures turn out to be all positive and significantly different from zero. These findings suggest that disagreement does not only generate bond PEAD but also affects bond market's underreaction to news in a broader setup, lending support to our hypothesis on the mechanism behind slow bond price movements.

[23]In Appendix Table A4, we use bid-ask spreads instead of the Roll measure as a control variable for illiquidity. We find that the results are highly similar to Table 9. Thus, even though the disagreement proxies positively correlate with bid-ask spreads, their explanatory power is not subsumed by the spreads.

[24]Bollerslev, Li, and Xue (2018) propose a clean measure of disagreement based on the elasticity of volume with respect to volatility motivated by a theory. However, their measures require high-frequency data, which is not available in the corporate bond market.

4 A Stylized Model of Disagreement and PEAD

We have documented robust evidence that disagreement, rather than liquidity, is more likely to drive bond PEAD. In this section, we present a stylized model to formalize the underlying mechanism that disagreement leads to PEAD and offer a unified explanation for the documented evidence. We intentionally keep our model stylized (abstracting away from institutional details in corporate bond markets such as dealer intermediation, dealer inventory costs and asymmetric bond payoffs) so that we can focus on the pricing implications.

4.1 Model Setup

Consider an economy with three dates ($t \in \{0, 1, 2\}$) and a public announcement is made on date 1. There are two assets: one risk-free asset with the constant return normalized to zero and one risky asset (a corporate bond) with the payoff $\tilde{v}$ realized on date 2, where $\tilde{v} \sim N(0, \tau_v^{-1})$ and $\tau_v \in (0, +\infty)$. The supply of the risky asset is assumed to be 1, and it trades at price $\tilde{p}_t$ on date t, which will be endogenously determined. There is a continuum of investors, indexed by $i \in [0, 1]$, who derive expected utility over their terminal wealth according to a constant absolute risk aversion (CARA) utility with a common risk-aversion coefficient γ, where $\gamma \in (0, +\infty)$. There is noisy demand $\tilde{u}$ for the risky asset on date 1, where $\tilde{u} \sim N(0, \tau_u^{-1})$, $\tau_u \in (0, +\infty)$, and $\tilde{u}$ is independent of all other random variables in the economy. For example, noisy demand can arise when investors suffer from a liquidity shock (fire sales by mutual funds, and investors' sales for liquidity needs during economic downturns, etc) and have to trade the risky asset to hedge that shock.

At the beginning of date 1, there is a firm earnings announcement and a public signal $\tilde{y}$ is revealed:

$$\tilde{y} = \tilde{v} + \tilde{\eta}, \text{ where } \tilde{\eta} \sim N(0, \tau_\eta^{-1}), \tau_\eta \in (0, +\infty),$$

and $\tilde{\eta}$ is independent of the fundamental $\tilde{v}$. After observing the public signal, investor i has her own interpretation and produces the following private signal about the firm fundamental:[25]

$$\tilde{s}_i = \tilde{y} + \tilde{\varepsilon}_i, \text{ where } \tilde{\varepsilon}_i \sim N(0, \tau_\varepsilon^{-1}), \tau_\varepsilon \in (0, +\infty),$$

and $(\tilde{v}, \{\tilde{\varepsilon}_i\})$ are mutually independent.

Further, we follow Banerjee, Kaniel, and Kremer (2009) and model investors' difference

[25] Blankespoor, deHaan, and Marinovic (2020) emphasize that it is often unrealistic to assume that firms' disclosures are "public." In fact, it can be highly costly to acquire and understand firms' disclosures and firms' disclosures should be a form of private information to each individual investor.

of opinions as follows: investors agree to disagree and each investor conditions *only* on her private signal $\tilde{s}_i$ to update her beliefs about the firm fundamental and trades accordingly. This notion of disagreement is standard in the literature (e.g., Harrison and Kreps 1978).

4.2 Price Drift, Trading Volume, Disagreement, and Illiquidity

We now characterize the equilibrium in the economy and derive empirical predictions based on the relation between return-volume characteristics and investor disagreement, which one could proxy empirically.

Date 2 is the payoff date, so the price of the risky asset is exogenously given as the realized value, i.e., $\tilde{p}_2 = \tilde{v}$. Date 0 is interpreted as the time immediately before the public earnings announcement. Since all investors are ex ante identical and have a prior of zero for the value of the risky asset, $\tilde{p}_0 = 0$ is the price that will prevail if investors trade at $t = 0$. Our focus is on the date-1 asset price since all meaningful interactions happen on the earnings announcement day. Maximizing investor i's conditional expected utility yields her optimal demand for the risky asset: $x_i = \frac{E[\tilde{v}|\tilde{s}_i]-\tilde{p}_1}{\gamma Var[\tilde{v}|\tilde{s}_i]}$. Inserting the demand functions into the market-clearing condition $\int_0^1 x_i di + \tilde{u} = 1$, we obtain the equilibrium price on date 1 as follows:

$$\tilde{p}_1 = \frac{\tau_\varepsilon \tau_\eta (\tilde{v} + \tilde{\eta}) + \gamma(\tau_\varepsilon + \tau_\eta)\tilde{u} - \gamma(\tau_\varepsilon + \tau_\eta)}{\tau_\varepsilon \tau_\eta + \tau_v(\tau_\varepsilon + \tau_\eta)}.$$

Obviously, the asset price on date 1 aggregates the dispersed opinions among investors and contains noise as well.

We then follow Banerjee, Kaniel, and Kremer (2009) and define price drift as follows: if $E[\tilde{p}_2 - \tilde{p}_1|\tilde{p}_1 - \tilde{p}_0] = k(\tilde{p}_1 - \tilde{p}_0)$ for some positive k, then prices exhibit drift. Otherwise if $k < 0$, prices exhibit reversals.[26] This definition of price drift is ex ante in the sense that it is conditional only on information available to investors at the time they make investment decisions, which corresponds to our tradable investment strategies in the empirical design.

[26] In Banerjee, Breon-Drish, and Engelberg (2020)'s terminology, our defined PEAD is *CAR* PEAD, rather than *SUE* PEAD. This definition is more consistent with our use of *CAR* as the main measure of earnings surprise.

We can express k as follows:[27]

$$k = \underbrace{-\frac{\gamma^2\tau_v(\tau_\varepsilon+\tau_\eta)^2\sigma_u^2}{\tau_\varepsilon^2\tau_\eta(\tau_v+\tau_\eta)+\gamma^2\sigma_u^2\tau_v(\tau_\varepsilon+\tau_\eta)^2}}_{\text{Noise trading}} + \underbrace{\frac{\tau_v\tau_\varepsilon\tau_\eta^2}{\tau_\varepsilon^2\tau_\eta(\tau_v+\tau_\eta)+\gamma^2\sigma_u^2\tau_v(\tau_\varepsilon+\tau_\eta)^2}}_{\text{Disagreement}}. \tag{10}$$

As shown by equation (10), there are two forces that determine whether or not prices exhibit drift. First, as common in the information-based models (e.g., Grossman and Stiglitz 1980; Kyle 1985; Grossman and Miller 1988), noise induces negative correlation in prices. This is because a temporary noisy demand shock can push the asset price away from the fundamental, which drives returns in adjacent periods towards opposite directions and thus leads to price reversals. Moreover, the more volatile the noisy demand (i.e., high σ_u^2), the more likely the price reversals. Second, prices tend to present drift when investors exhibit difference of opinions. Specifically, each investor sticks to her own interpretation of the public announcement and believes that no other investor holds information of any incremental value to her private signal. Investors then put more weight on their private signal and less on information held by others, which is reflected in the price. Therefore, information is slowly incorporated into prices, giving rise to a price drift. Taken together, when noise trading is low, the latter effect prevails and prices can exhibit a drift. That is, $k > 0$ when $\sigma_u^2 < \frac{\tau_\varepsilon\tau_\eta^2}{\gamma^2(\tau_\varepsilon+\tau_\eta)^2}$. And the lower the noise trading, the more likely to observe the price drift. The following summarizes the implication of this finding in the PEAD setting.

Implication 1 *It is likely to observe PEAD when the variance of noise trading is low.*

Implication 1 also suggests a unified explanation for the existence of bond PEAD and weak-existence of stock PEAD, as will be shown in Section 5.4. Specifically, bond investors tend to buy and hold, which implies lower noise trading in the bond market compared with that in the stock market. Furthermore, Choi et al. (2020) find no evidence of fire sale by corporate bond mutual funds (which is the second largest class of bond investors), while equity mutual funds fire sell their holdings, supporting our argument. All else equal, equation (10) shows that it is more likely to observe price drift when the variance of noise trading (σ_u^2) is lower. Therefore, to the extent that disagreement drives slow price reactions in both the bond market and the stock market, bond PEAD should be more likely to arise. Moreover, Luo, Subrahmanyam, and Titman (2020) interpret the recent rise of quantitative

[27] Without difference of opinions, the model becomes a standard rational expectations equilibrium (REE) model (e.g., Grossman and Stiglitz 1980; Hellwig 1980). In Appendix B, we show that under an REE model, prices always exhibit reversal; that is, $k < 0$. This demonstrates disagreement as a necessary component in generating drift.

investors in the stock market as an increase in the variance of noise trading and argue that this trend leads to an attenuation and even reversal of momentum profits. Consistently, in our framework, the increasing noise trading in the stock market implies a decreasing likelihood of stock PEAD. This helps understand why stock PEAD decays over time but bond PEAD persists.

Furthermore, we find that the higher the precision of the public announcement, the more pronounced is the price drift, namely, $\frac{\partial k}{\partial \tau_\eta} > 0$. The intuition is as follows. When the public news is more precise, investors' private information becomes more accurate accordingly, and they thus trade more on their private information, ignoring the other investors' information. This leads to a slower price reaction to the public news and hence greater price drift. This finding offers a unified explanation for the existence of price drift on the earnings announcement days (bond PEAD) and its non(weak)-existence on non-announcement days. Specifically, while there can always be public news $\tilde{y}$ about the firm fundamental $\tilde{v}$, on the earnings announcement days the public information is more specific to the particular firm and contains more accurate information. Therefore, to the extent that disagreement drives slow price reactions in the bond market, prices on the earnings announcement days should be more likely to exhibit drift relative to those on the non-announcement days. We summarize this finding in the following implication.

Implication 2 *It is more likely to observe price drift on earnings announcement days.*

Next, to derive testable implications, we follow Banerjee (2011) to conduct comparative statics with respect to the precision of investors' private information τ_ε. However, τ_ε is not empirically observable and we must derive empirical predictions based on observable variables. We thus derive expressions for trading volume, disagreement, and illiquidity and develop testable empirical prediction for our disagreement explanation. Furthermore, we emphasize that we focus on the parameter region where τ_ε is low. This is because for low τ_ε investors' realized information significantly differs from each other's, and in this way we highlight our disagreement mechanism.

Following Vives (2010), we measure trading volume at $t = 1$ as the expected aggregate volume traded by informed investors

$$TV \equiv E\left[\int_0^1 |x_i| di\right]. \tag{11}$$

Following Banerjee (2011), investor disagreement $DISP$ is defined as the cross-sectional variance in investors' posterior expectations about the fundamental value, and is given by

$$DISP \equiv Var\left[E\left[\tilde{v}|\tilde{s}_i\right] - \int_0^1 E\left[\tilde{v}|\tilde{s}_i\right] di\right], \tag{12}$$

which is also closely tied to our empirical proxy. Illquidity measures the ease of selling an asset in the market and following the literature (e.g., Vives, 2010; Goldstein and Yang, 2017), we define it as follows,

$$ILLIQ \equiv \frac{\partial \tilde{p}_1}{\partial \tilde{u}}. \tag{13}$$

First, an examination of the magnitude of price drift (10), trading volume (11), and disagreement (11) shows that as the precision τ_ε of investors' private information increases, investors disagree more with each other, trading volume increases, and price drift becomes more pronounced; that is, *DISP*, TV, and k move in the same direction. The intuition is as follows. Recall private information is the source of disagreement among investors. When investors' private information becomes more precise, they place more weight on the private information to update their beliefs about the asset fundamental, thereby creating more investor disagreement. The more pronounced disagreement generates more trading activities among investors, increasing trading volume. Further, as the dispersion of investor valuations rises, prices exhibit a stronger drift. This is because with more precise private information, the investors have even more confidence in their own private interpretations and further attempt not to draw inferences from the trades of others. As a result, prices become even slower to aggregate investor opinions. The following summarizes this testable empirical prediction and the results in Section 3.2 corroborate it.

Implication 3 (Price drift, disagreement, and trading volume) *Consider two assets that differ only in the precision level of investors' private information τ_ε and τ_ε is low. The asset with higher investor disagreement will have higher trading volume and a stronger price drift.*

Second, we explore the relation between market illiquidity and price drift under the disagreement framework. We find as the precision τ_ε of investors' private information increases, while price drift becomes more significant, market illquidity decreases. In other words, the magnitude of price drift can be negatively associated with illquidity (k and ILLIQ move in the opposite direction). The following summarizes this implication.

Implication 4 (Price drift and illiquidity) *Consider two assets that differ only in the precision level of investors' private information* τ_ε *and* τ_ε *is low. The asset with lower illiquidity can have a stronger price drift.*

This result appears surprising as the common illiquidity explanation suggests that PEAD should concentrate in illiquid assets (e.g., Chordia et al., 2009). How can we generate the opposite prediction under disagreement framework? The intuition is as follows. To the extent that disagreement drives PEAD, only when the asset is liquid can investors fully express their different opinions through trade, thereby leading to slow aggregation of information into prices. As such, more pronounced price drift can be associated with lower illiquidity.

Importantly, this result helps reconcile the mixed illiquidity evidence presented in Section 3.1. Specifically, while illquidity may intuitively contribute to bond PEAD, due to the other force presented under the disagreement framework, the relation between illiquidity and PEAD can be mixed or even negative. This theoretical prediction reinforces our argument that disagreement is the dominant source of bond PEAD.

Finally, it is worth mentioning that when τ_ε is so high that our disagreement mechanism weakens, while Implication 3 remains valid, Implication 4 is reversed; that is, the asset with higher illiquidity has a stronger price drift. This result helps explain the difference between our finding and that in Chordia et al. (2009). Specifically, because disagreement plays a less important role in determining the stock PEAD, illiquidity and stock PEAD are positively correlated.

5 Alternative Explanations for Bond PEAD and Extensions

In this section, we explore several alternative explanations for bond PEAD, including limited attention and the disposition effect. Furthermore, we assess the profitability of the PEAD strategies for real time investors who pay transaction costs to implement transactions. Finally, we revisit the equity market to show that the PEAD has become weaker in the recent sample.

5.1 Limited Attention

We examine another potential explanation for bond PEAD, which is investors' limited attention. Limited attention provides compelling intuition for PEAD; if bond investors do not pay attention to earnings announcement, then the price does not fully reflect news immediately, leading to price drift after the announcement. The challenge for limited attention-based explanation is that researchers do not observe investors' attention directly and rely on noisy proxies.

Here we use two ideas to measure limited attention proposed in the literature. The first is to compare announcements when investors are more likely to be distracted than those when investors pay attention. To this end, we follow Hirshleifer, Lim, and Teoh (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 there are more announcements on a day, then investors are arguably more distracted and pay less attention, which would strengthen PEAD. Furthermore, we follow Dellavigna and Pollet (2009) and Michaely, Rubin, and Vedrashko (2016) and compare announcement on Friday and that on other days of a week. We use a dummy variable which equals one if an announcement day is Friday, and zero otherwise. If investors are more distracted on Fridays than on other days, then we expect more pronounced bond PEAD for Friday announcements.

The second idea is to examine investor's news searching and reading activity. If investors search for and read certain information on firms, then we interpret the fact as investors paying attention to the news. To this end, we follow Ben-Rephael, Da, and Israelsen (2017) and construct two measures related with abnormal institutional inattention (AIA) using the news readership score downloaded from Bloomberg terminal. Specifically, AIA is a dummy variable which equals one if Bloomberg's readership score is 3 or 4,[28] and zero otherwise, while $AIAC$ is a continuous value transformed from Bloomberg's raw readership scores using the conditional means of the truncated normal distribution.[29] A greater value of those variables means that investors are paying more attention to news of the firm on earnings announcement days.

In Table 11, we run Fama-MacBeth regressions of monthly returns on earnings announce-

[28]Bloomberg assigns a score of 0 to 4 based on the count of news search and readership for a firm. 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.

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

ment 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 except for the number of competing announcements, which has a t-statistic of 1.69. Thus, we do not find compelling evidence for inattention attenuating bond price reactions to news or generating PEAD. The insignificant loading on the interaction between earnings surprise and AIA is particularly important, as AIA measures attention of institutional investors who are dominant in the bond market. Therefore, we conclude that limited attention is not the driver of bond PEAD.

5.2 Disposition Effect

Frazzini (2006) reports that the disposition effect on investors exacerbates sluggish movements in stock prices. The disposition effect refers to investors' psychological bias to not sell securities at a loss but to sell securities that have appreciated in value since purchase. Thus, if a bond is held with capital gain, then the holder is more likely to sell it, which prevents good news from being impounded into prices quickly. 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 the hypothesis, Frazzini (2006) finds that stocks that have higher earnings surprise and higher capital gain earn higher returns than stocks that have lower earnings surprise and lower capital gain.

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

$$RP_{i,q} = \frac{1}{\bar{V}} \sum_{n=0}^{q} V_{i,q,q-n} P_{i,q-n} \tag{14}$$

where $V_{q,q-n}$ 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 in different points in time and then some of the holding is 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,

$$CGO_{i,q} = \frac{P_{i,q} - RP_{i,q}}{P_{i,q}}. \tag{15}$$

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

Using the capital gains overhang measure, we double-sort bonds every month based on the latest available values of earnings surprise and $CGO_{i,q}$, and form 25 value-weighted portfolios. Table 12 reports the 11 factor alphas for each portfolio. If the disposition effect explains bond PEAD, we expect significantly negative alphas for the lowest earnings surprise quintile and the lowest capital gains overhang quintile. In the data, we find that the alphas against the factor models are not significantly negative: for example, the 11-factor alpha is -3 bps with a t-statistic of -0.25. We also examine if bonds in the highest earnings surprise quintile with the highest overhang have positive alphas or not. Table 12 shows that the 11-factor alpha for the portfolio is in fact negative, estimated at -8 bps. Thus, in our sample, the capital gains overhang does not strengthen bond PEAD. If anything, the results are the opposite. For example, bonds in the highest earnings surprise quintile and the lowest overhang quintile earn 16 bps alphas against the 11-factor model, while those in the lowest earnings surprise quintile and the highest overhang quintile earn -33 bps alphas. Thus, bond PEAD is more pronounced for bonds that are unlikely to exhibit a drift according to the disposition effect.

In summary, we do not find evidence supporting the disposition effect as the primary driver of bond PEAD. The abnormal returns on earnings surprise strategies are significant regardless of capital gains overhang, and we need a different explanation for the price drift in corporate bonds.

5.3 Is the PEAD Strategy Profitable After Transaction Costs?

To understand the impact of transaction costs on the bond PEAD strategy, we evaluate whether arbitragers can profit from the PEAD after transaction costs. The answer to this question depends on whether the signal is persistent or not, and on the relative size of profits to bid-ask spreads for bonds.

To this end, we directly measure the cost of implementing our strategy by accounting for portfolio turnover and bid-ask spreads. Specifically, we calculate a half spread for bond i on day d as

$$\text{half spread}_{i,d} = \frac{Sell_{i,d} - Buy_{i,d}}{Sell_{i,d} + Buy_{i,d}}, \tag{16}$$

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). If dealer sells and buys do not occur on the same day, then we treat the observation 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 the portfolio. In calculating the half spread, we only use transactions with volume no less than \$100,000, and thus the estimated transaction costs are for institutional investors rather than retail investors.

Assigning the same half spread to all bonds in each portfolio yields an unbiased estimate for the 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 as illiquid bonds do not trade as frequently as liquid bonds do. Thus, bonds with missing half spreads would incur high costs should they trade. To attenuate this bias, before we take the average across bonds at the portfolio level, we 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 for each quintile to obtain the portfolio-level spreads.

Following Bartram, Grinblatt, and Nozawa (2020), we calculate the transaction costs to implement the trading strategy based on CAR, accounting for portfolio turnover and half spreads. Panel A, Table 13 reports the average excess returns net of transaction costs on value-weighted portfolios sorted on CAR. We find that transaction costs largely eliminate profits from trades, as Panel B shows that the average excess returns and 11-factor alphas shrink to -2 bps ($t = -0.39$) and 5 bps ($t = 1.07$) after accounting for transaction costs, respectively. The existence of large costs prevents bond PEAD from being arbitraged away, and helps explain why we observe bond PEAD, while (as we show below) PEAD in the equity market becomes weaker in the recent sample.

One of the reasons why the profits do not survive after transaction cost is the high portfolio turnover rate for this trading strategy. If the signal is persistent, we may be able to employ strategies with a lower rebalancing frequency to attenuate the cost. To examine this possibility, we study the persistence of the profits from the trading strategy based on PEAD. We follow Jegadeesh and Titman (1993), and buy and hold value-weighted portfolios for K month, and record monthly returns of the strategy. We then take the simple average of monthly returns across portfolios formed in months $t, \ldots, t-K+1$, and obtain returns on quintile portfolios. Table 14 reports the excess returns on the long-short strategy, as well as 11-factor alphas. The results show that profits on bond PEAD strategy decay significantly within a year: for example, when the holding period is 6 months, the average excess returns and 11-factor alphas are 7 bps and 10 bps, about half of the main results with $K = 1$.

Though there is some predictability in returns beyond $K = 3$ (despite the fact that our signal is updated quarterly), the relatively fast decay in profits suggests that it is difficult to profit from the simple PEAD strategy after accounting for portfolio turnover and bid-ask spreads.

Since the results in the previous section suggest that the PEAD is more pronounced for bonds with greater disagreement, we test whether investors profit from PEAD if they focus on bonds with high disagreement. To this end, we create the composite measure of disagreement by taking the average across ranking in *DISP*, *CV* and *RFY*, and double sort bonds into 25 portfolios on earnings surprise and the disagreement index. In Panel C, Table 13, we show that for the bonds in the highest disagreement quintile, the 11-factor alphas net of transaction costs is as large as 35 bps (t=2.80). Therefore, even though transaction costs make it impossible for arbitragers to profit from the univariate PEAD strategy, it is possible to earn net profits by focusing on bonds on which investors disagree the most.

5.4 Equity PEAD

To contrast with the bond PEAD, we revisit 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. Specifically, every month, we sort firms based on their latest earnings surprise to form five equal- and value-weighted portfolios of stocks. We then calculate the hedge returns on the strategy where we go long on firms in the top earnings-surprise quintile and short firms in the bottom quintile. Lastly, we regress those returns on the six stock factors of Fama and French (2018) and estimate regression intercepts. Panel A of Table 15 reports the estimated alphas of the stock PEAD strategy based on value-weighted portfolios. With the sample period matched to that for bonds (i.e. 2002 to 2020), we find that the evidence for stock PEAD is weak: the average hedge returns based on the value-weighted portfolios are 0.19%, -0.08% and 0.13% using *CAR*, *CE* and *FOM* as measures of earnings surprise, respectively, and these estimates are statistically indistinguishable from zero.

There are two reasons why we do not find stock PEAD in our sample. First, as Nozawa (2017) documents, bond issuing firms tend to be large and their stocks are less likely to be affected by anomalies (Fama and French 2008). As Table 1 shows, the fraction of bond observations corresponding to "Big" firms (i.e. firms with market capitalization above the 50th percentile of NYSE stocks) is as large as 91%, while only 2% of bond return observations correspond to "micro" stocks (those below the 20th percentile). Indeed, when we instead use stocks of all firms and repeat the exercise, alphas on stock PEAD strategies increase. As shown in Panels B and E of Table 15, alphas on value- and equal-weighted portfolios are mostly significant from 2002 to 2020, and they are larger for equal-weighted portfolios than for value-weighted portfolios. This finding shows that the PEAD strategy is profitable using small firms than large firms to which most bond issuers belong.

Second, as Martineau (2021) points out, profitability of stock PEAD decays over time as uninformed traders using algorithmic trading technology participate in the stock market and arbitrage away mispricing.[30] In Panel C of Table 15, we repeat the same exercise using all firms in the earlier sample period from 1984 to 2001. We find that the evidence for PEAD during this period is very strong regardless of earnings surprise measures, with six-factor alphas ranging from 37 bps to 65 bps when firms are value weighted, and 72 bps to 131 bps when equally weighted.

Thus, our finding for bond PEAD presents an interesting contrast with stock PEAD. Although bond issuers tend to be large firms, we see evidence for bond PEAD but no evidence on stock PEAD. According to our model in Section 4, the existence of noise trading weakens the drift, which explains the difference in PEAD between bonds and stocks.

Still, it is interesting to study whether disagreement explains stock PEAD in the past or not. Therefore, we run Fama-MacBeth regressions of stock returns on the earnings surprise measure (CAR), analysts' disagreement ($DISP$) as well as institutional (equity) investors' portfolio weight dispersion (CV_{Stock}). If disagreement contributes to stock PEAD, then interaction terms between earnings surprise and disagreement proxies should be positive. Furthermore, we include firm size, the book-to-market ratio, momentum, operating profitability, investment as well as illiquidity measures (the Amihud measure and bid-ask spreads), and industry dummies as control variables. Since Table 15 points to a difference between small and large firms, we run FM regressions with "value-weights" to reduce the effect of small firms on the slope coefficients. Specifically, for each observation, we multiply month-$(t+1)$ returns and month-t controls with square root of the market value of the firm in month t. By scaling both left-hand side and right-hand side variables, the slope coefficients (which are returns on tradable strategies) become value-weighted.

Table 16 presents the estimated slope coefficients of the Fama-MacBeth regressions of

[30]According to Heitz, Narayanamoorthy, and Zekhnini (2020), high-frequency trading accounted for fewer than 10% of equity orders in the early 2000s, but grew more than 100% in the late 2000s. Beaver, McNichols, and Wang (2020) additionally documents an increased stock market response to earnings announcements in the recent two decades and attribute this change to the increase in concurrent information along with earnings announcements, e.g., management guidance, analyst forecasts, and detailed financial statement line items.

stock returns. The first two columns report the results using the full sample period (1984-2020). Consistent with the portfolio sort results in Table 15, we find the PEAD effect in stock returns as the loading on earnings surprise is positive at 21 bps (when controlling for *DISP*) and 29 bps (when controlling for CV_{Stock}). The interaction term between earnings surprise and *DISP* is 8 bps ($t = 1.90$), while the interaction with CV_{Stock} is 10 bps ($t = 3.16$), which are significant at the 10% and 1% level, respectively. The next four columns show the results using two sub-periods (1984-2001 and 2002-2020); they suggest that *DISP* is a more important driver for PEAD in the later period (2002-2020) while CV_{Stock} is more significant in the earlier sample. Overall, the results in Table 16 show that, even though stock PEAD becomes weaker over time, stocks with greater disagreement exhibit more pronounced drift after earnings announcement than those with lower disagreement.

6 Conclusion

In this paper, we document compelling empirical evidence for PEAD in the corporate bond market. Bonds issued by a firm that had positive earnings surprise in the previous quarter tend to appreciate relative to bonds issued by a firm who had bad news. This evidence points to slow bond market price reaction to prominent news that affects the value of the firm. Because we use bond transaction prices rather than quotes, the findings suggest that some investors trade at prices that are too low after positive news, and too high after negative news. Taking advantage of this drift yields an attractive Sharpe ratio of 0.73, and the returns on this strategy has little exposure to systemic risk.

We further show that bond PEAD is more pronounced for bonds that trade more frequently. Because of the positive association between trading volume and PEAD, illiquidity of corporate bonds is unlikely to be the source of PEAD. This argument is further bolstered by the existence of PEAD in CDS contracts. Therefore, we turn to disagreement as a potential source of PEAD in the bond market. We present a stylized model that abstracts away from the institutional details of the bond market, and show that disagreement can generate PEAD and higher bond turnover which explains the puzzling empirical pattern in price and liquidity. We empirically support model's prediction by using various measures of disagreement.

Our explanation of PEAD based on disagreement extends to the stock market. We find supporting evidence that stock PEAD is greater when disagreement on firms' value is higher. However, the average PEAD effect in the stock market becomes weaker over time, as high-frequency traders arbitrage any mispricing away. This makes the bond market a suitable place to study why a market price appears to react to news slowly, and how liquidity and PEAD are related.

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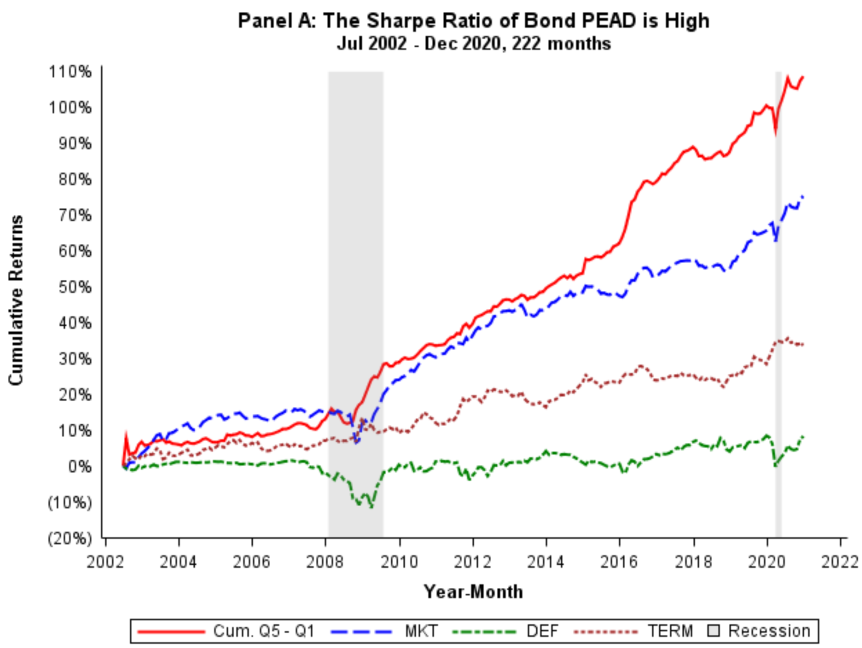
Figure 2: Time Series Plot of the PEAD Strategy

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 July 2002 through December 2020. 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*). *DEF* is the return difference between the long-term investment-grade bonds and the 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).



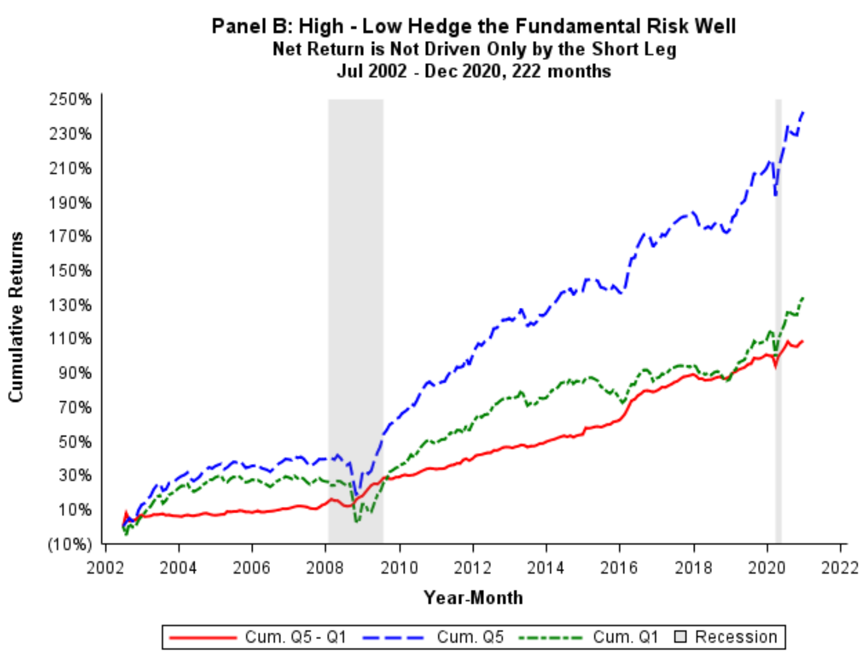


Table 1: Descriptive Statistics

This table reports the summary statistics of the main variables at the bond-month level. *Return* is monthly bond return and *Excess Return* is the bond return in excess of one-month Treasury bill rate. Both are reported in percent per month. *Rating* is the numerical rating score, where 1 refers to a AAA rating by S&P and Aaa by Moody's, 21 refers to a C rating for both S&P and Moody's. *Maturity* is the time-to-maturity of the bond in years. *Size* is the dollar value of amount outstanding of a bond. *DOWN* is the 5% VaR of corporate bond return, defined as the second lowest monthly return observation over the past 36 months. *BAS* is the bid-ask spread, computed as $(S-B)/0.5(S+B)$, where S (B) is the volume-weighted average sell (buy) price on a day for a bond. *ACOV* is the autocovariance of the daily price changes within each month, multiplied by -1. *Age* is expressed in years since bond issuance. *Duration* is a bond's MacCauley duration. *STR* is the short-term reversal, calculated as the previous month bond return. *MOM* is the past 11-month cumulative returns from month t-12 to t-2, skipping the short-term reversal month t-1. *Vol* is volatility estimated using bond returns over the past six months. *SRVol* is stock return volatility estimated using daily stock returns in month t-1.. *Frac_Bid t* (*Frac_Bid t+1*) is the fraction of dollar bid (i.e. dealer buy) volume relative to the total volume for a daily price in month t (month t+1). *DISP* is the analyst forecast dispersion, defined as the standard deviation of the annual year-end analyst forecasts scaled by the average monthly price, after removing excluded or stopped estimates. *CV* (CV_{Stock}) is the coefficient of variation of investor's portfolio weight in a firm, calculated as the standard deviation of a firm's bond (stock) portfolio weight across institutional investors divided by the average weight, based on the eMAXX (Thomson-Reuters 13F) holding data. *CV2* ($CV2_{Stock}$) is the coefficient of variation of residual portfolio weight, where the residual weight is the residual in the cross-sectional regression of portfolio weight on the investor-level rating, maturity and illiquidity (size, book-to-market, momentum) at each quarter. *RFY* is the bond-level reaching for yield proxy, defined as the difference between a bond's yield and the average yield of bonds with the same rating. Following Chen and Choi (2021), we use 16 rating categories: AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-. *CGO* is the capital gains overhang, defined as the percentage deviation of the aggregate cost basis from the quarter-end bond price, where the reference cost calculation follows the procedure in Frazzini (2006). *Stock CAR* is the cumulative abnormal stock returns adjusted by Fama-French three-factor model from trading day -1 to 1 around the earnings announcement date. *Bond CAR* is the excess bond returns from trading day t-1 to t+1, where $t=0$ is the earnings announcement date. We use the Bloomberg Barclays bond indices as benchmarks to adjust raw bond returns. *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. *SRet1m* (*SRet6m*) is the past one-month (six-month) stock return, calculated as the cumulative market-adjusted stock returns over the past one (six) months, excluding the earnings announcement returns. *Micro*, *Small*, and *Big* are dummies that equal to one if a firm belongs to the respective stock market capitalization group. We follow Fama and French (2008) and assign firms to size groups at the end of June each year. *Micro* firms are below the 20^{th} percentile of NYSE market cap at the end of June, *Small* firms are between the 20^{th} and 50^{th} percentiles, and *Big* firms are above the NYSE median. The sample period is from July 2002 to December 2020.

Variables	N	Mean	SD	P1	P25	Median	P75	P99
Return (%)	563,859	0.556	3.313	-8.066	-0.360	0.405	1.476	9.546
Excess Return (%)	563,859	0.477	3.318	-8.127	-0.445	0.322	1.398	9.496
Rating	562,364	8.839	3.219	2.000	6.500	8.500	10.000	17.000
Maturity (years)	563,859	9.832	8.554	1.252	3.962	6.627	9.942	29.858
Size ($, mil)	563,859	708.795	586.100	55.222	343.168	525.060	849.407	3198.811
DOWN (5% VaR)	303,188	3.472	3.348	0.503	1.480	2.554	4.298	18.416
BAS (bps)	517,969	80.884	88.107	-9.062	26.466	50.891	101.633	427.693
ACOV	454,461	1.159	3.563	-0.457	0.072	0.279	0.902	16.256
Age (years)	563,859	3.823	3.321	0.134	1.397	2.984	5.332	16.479
Duration	563,841	6.766	4.374	1.211	3.581	5.547	8.223	17.733
STR (%)	563,859	0.565	3.110	-7.629	-0.367	0.414	1.499	9.288
MOM (%)	415,387	5.972	10.618	-17.178	1.416	4.745	9.085	38.211
Vol (%)	528,610	2.150	2.592	0.175	0.800	1.457	2.571	12.779
SRVol (%)	563,850	1.824	1.415	0.525	1.019	1.427	2.111	7.618
Frac_Bid t (%)	563,859	35.793	37.733	0.000	0.000	25.000	61.733	100.000
Frac_Bid t+1 (%)	563,859	35.895	37.801	0.000	0.000	25.000	62.180	100.000
DISP	529,127	0.007	0.022	0.000	0.001	0.002	0.005	0.082
CV	551,798	1.395	0.288	0.894	1.199	1.348	1.547	2.306
RFY (%)	548,720	-0.078	1.359	-2.917	-0.893	-0.196	0.688	3.825
CV2	551,773	1.652	0.307	1.083	1.424	1.631	1.844	2.493
CV_{Stock}	504,330	2.156	0.851	0.761	1.531	2.065	2.651	4.701
$CV2_{Stock}$	504,330	2.131	1.040	0.710	1.450	1.983	2.590	5.357
CGO (%)	512,576	1.131	9.748	-27.390	-1.904	1.158	5.052	20.340
Stock CAR (%)	562,532	0.002	5.716	-17.040	-2.650	-0.001	2.758	15.918
Bond CAR (%)	291,637	0.013	1.551	-3.938	-0.397	-0.012	0.391	4.065
CE	563,859	0.000	0.015	-0.027	0.000	0.001	0.002	0.022
FOM	563,859	0.359	0.720	-1.000	-0.182	0.667	1.000	1.000
SRet1m (%)	563,444	-0.143	7.301	-19.518	-3.704	-0.160	3.348	19.589
SRet6m (%)	562,658	-0.713	17.923	-46.471	-9.695	-0.940	7.802	46.913
Micro	560,611	0.019	0.137	0.000	0.000	0.000	0.000	1.000
Small	560,611	0.071	0.256	0.000	0.000	0.000	0.000	1.000
Big	560,611	0.910	0.286	0.000	1.000	1.000	1.000	1.000

Table 2: Contemporaneous Bond Return Reaction to Earnings Surprises

This table presents the results for the earnings announcement event study regression. The dependent variable is the excess 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 Fama-French three-factor model around earnings announcement dates. *Rank (CE)* is the cross-sectional rank score from 1 to 10 transformed from *CE*, where *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. The control variables are a bond's credit rating and time to maturity. Observations for Bond *CAR*, Stock *CAR*, *CE*, and *FOM* are winsorized at 0.5% and 99.5%. Continuous independent variables are standardized to have a mean of zero and a standard deviation of one. Year-Quarter fixed effect is included in each regression. All standard errors are clustered by firm and year-quarter. t-statistics are in parentheses. The asterisks represent the significance level of 1% (***), 5% (**), and 10% (*), respectively.

Left-Hand Side Variable: 3-Day Bond *CAR* Around Earnings Announcement						
	(1)	(2)	(3)	(4)	(5)	(6)
Stock CAR $[-1, +1]$	0.391***			0.382***	0.391***	0.385***
	(6.41)			(5.93)	(6.08)	(5.96)
Rank (CE)		0.134***		0.033*		0.113***
		(7.95)		(1.67)		(3.62)
FOM			0.100***		-0.003	-0.098***
			(9.03)		(-0.15)	(-3.64)
Rating	0.017***	0.016***	0.021***	0.017***	0.017***	0.012***
	(3.15)	(2.74)	(3.49)	(3.15)	(3.13)	(2.67)
Maturity	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.35)	(-0.50)	(-0.43)	(-0.36)	(-0.35)	(-0.42)
Intercept	-0.131**	-0.118**	-0.167***	-0.130**	-0.130**	-0.084*
	(-2.57)	(-2.16)	(-2.95)	(-2.55)	(-2.57)	(-1.95)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Obs	103,199	103,199	103,199	103,199	103,199	103,199
Adj. R^2	0.070	0.014	0.011	0.071	0.070	0.072

Table 3: Univariate Portfolios of Bonds Sorted on Earnings Surprises

At the beginning of each month from July 2002 to December 2020, quintile portfolios are formed by sorting corporate bonds based on the corresponding firm's most recent earnings surprises at the end of previous month. We use stock *CAR* $[-1, +1]$ as an earnings surprise measure in Panels A and B. Quintile 1 is the portfolios with the lowest earnings surprises and Quintile 5 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 dollar value amount outstanding as weights (Panel A). This table reports the next-month average excess return as well as portfolio alphas. Alphas are calculated from a bond factor model, a stock factor model, and a bond+stock model. The bond factor model uses five factors (bond market, downside risk, credit risk, liquidity risk, and reversal) from Bai, Bali, and Wen (2019). 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 five bond factors and the six stock factors. We also report average bond characteristics for each quintile in Panel B and 11-factor alphas of value-weighted portfolios sorted on alternative earnings surprises measures, *Bond CAR*, *CE*, and *FOM*, in Panel C. Details on construction of these variables are provided in Table 1. Column "*SR*" reports the annualized Sharpe 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 parenthesis below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Low	2	3	4	High	High - Low	*SR*
Panel A: Value-Weighted Portfolios Sorted on Earnings Announcement Stock *CAR*							
Average Excess Return	0.40***	0.44***	0.45***	0.45***	0.57***	0.17***	0.73
	(2.88)	(3.64)	(3.88)	(4.12)	(4.21)	(3.63)	
5 Bond Factor Alpha	-0.14***	-0.04	-0.03	0.01	0.06***	0.21***	1.54
	(-3.99)	(-1.37)	(-1.52)	(0.69)	(2.72)	(4.44)	
6 Stock Factor Alpha	0.21	0.30**	0.31***	0.31***	0.40***	0.20***	0.93
	(1.58)	(2.42)	(2.73)	(2.90)	(3.28)	(4.32)	
11 Factor Alpha	-0.14***	-0.04	-0.02	0.01	0.07***	0.22***	1.68
	(-3.84)	(-1.14)	(-1.11)	(0.53)	(3.15)	(4.52)	
Panel B: Average Portfolio Characteristics							
CAR (%)	-7.40	-2.05	0.06	2.20	7.39	14.80	
Frac_Bid t (%)	36.07	36.77	36.88	36.95	35.96	-0.12	
Frac_Bid t+1 (%)	35.38	36.24	36.33	36.45	35.69	0.32	
Size ($, mil)	669.73	696.97	677.06	700.86	678.74	9.01	
Rating	9.66	8.41	8.17	8.29	9.60	-0.06	
Maturity (years)	9.51	10.46	10.59	10.40	9.40	-0.10	
ACOV	1.46	1.06	1.06	1.04	1.24	-0.22	
Age (years)	4.06	4.03	4.02	4.00	3.92	-0.14	
Pane C: Alternative Measures for Earnings Surprises (11-Factor Alpha)							
Bond CAR	-0.22***	-0.02	0.01	0.02	0.07	0.30***	1.53
	(-4.98)	(-0.97)	(0.74)	(0.97)	(1.55)	(4.53)	
CE	-0.14***	-0.04	0.05**	0.00	-0.01	0.12**	1.02
	(-3.79)	(-1.65)	(2.30)	(0.15)	(-0.38)	(2.38)	
FOM	-0.07	-0.10***	-0.03	-0.00	0.03**	0.10*	0.76
	(-1.27)	(-3.00)	(-1.28)	(-0.19)	(2.59)	(1.82)	

Table 4: 11-Factor Alphas on Bivariate Portfolios of Earnings Surprise and Credit Rating/Maturity

25 portfolios are formed every month from July 2002 to December 2020 by independently sorting corporate bonds based on the corresponding firm's most recent earnings surprises and two bond characteristics: *Rating* and *Maturity*. Earnings surprise is proxied by the stock CAR $[-1, +1]$. *Rating* is the numerical rating score, where 1 refers to a AAA rating by S&P and Aaa by Moody's, 21 refers to a C rating for both S&P and Moody's. We group *Rating* into five rating buckets: IG (1-10), AAA/AA (1-4), A (4-7), BBB (7-10), HY ($>$ 10). *Maturity* is the time-to-maturity of the bond in years. We present the 11-factor alphas, where portfolios are value-weighted using the dollar value 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
Panel A: Double Sort on Earnings Surprise (CAR) and Credit Rating						
IG	-0.07	-0.02	-0.01	0.01	0.03	0.10***
	(-2.15)	(-1.10)	(-0.65)	(0.21)	(1.55)	(2.85)
AAA/AA	-0.12	0.09	0.12	0.15	0.13	0.25***
	(-1.00)	(1.55)	(2.47)	(3.05)	(1.51)	(3.07)
A	0.01	0.00	0.01	0.00	0.03	0.02
	(0.26)	(0.26)	(0.41)	(0.02)	(0.77)	(0.26)
BBB	-0.12	-0.03	-0.08	-0.04	-0.00	0.12***
	(-2.83)	(-0.96)	(-2.10)	(-0.92)	(-0.01)	(2.78)
HY	-0.26	-0.29	-0.16	-0.03	0.08	0.33***
	(-4.01)	(-1.88)	(-1.59)	(-0.37)	(1.33)	(4.37)
HY - IG	-0.19***	-0.27*	-0.15	-0.03	0.04	0.23***
	(-3.02)	(-1.78)	(-1.58)	(-0.41)	(0.77)	(3.12)
Panel B: Double Sort on Earnings Surprise (CAR) and Time to Maturity						
Low	-0.03	0.00	0.01	0.08	0.08	0.11***
	(-0.78)	(0.07)	(0.39)	(3.25)	(2.79)	(2.96)
Maturity, 2	-0.12	-0.04	-0.02	0.02	0.08	0.21***
	(-2.97)	(-0.88)	(-0.61)	(0.96)	(1.85)	(3.28)
Maturity, 3	-0.24	-0.05	-0.02	-0.01	0.05	0.29***
	(-3.94)	(-1.22)	(-0.55)	(-0.27)	(1.32)	(3.96)
Maturity, 4	-0.18	-0.05	-0.08	-0.03	0.02	0.19***
	(-3.78)	(-1.14)	(-2.75)	(-0.98)	(0.44)	(2.65)
High	-0.17	-0.04	-0.01	0.01	0.09	0.26***
	(-2.34)	(-0.85)	(-0.35)	(0.18)	(1.26)	(3.61)
High - Low	-0.14**	-0.04	-0.02	-0.07	0.01	0.15*
	(-2.30)	(-0.76)	(-0.45)	(-1.05)	(0.07)	(1.91)

Table 5: Uniqueness of Earnings Surprise: Fama-MacBeth Regressions on Earnings Surprises, Past Stock Returns and Past Rating Changes

This table reports the average intercept and 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* $[-1, +1]$. *SRet6m* is the past six-month stock return, calculated as the cumulative market-adjusted stock returns over the past six months, excluding the earnings announcement returns. *NoAnnCAR* is the pseudo *CAR* $[-1, +1]$ without earnings surprises, calculated as the three-day cumulative abnormal returns around a date randomly picked from the previous six months, excluding the earnings announcement windows. *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 winsorized each month at the 1% level and 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 July 2002 to December 2020.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns						
	(1)	(2)	(3)	(4)	(5)	(6)
Past News Variables (Continuous Variables Are Standardized):						
CAR	0.070***	0.066***				0.074***
	(3.32)	(5.11)				(5.33)
SRet6m			0.120***			0.125***
			(6.96)			(7.28)
NoAnnCAR				-0.010		-0.014
				(-0.78)		(-1.13)
Dummy: *Downgrade*					-0.130**	-0.119**
					(-2.10)	(-2.07)
Dummy: *Upgrade*					-0.004	-0.011
					(-0.13)	(-0.34)
Control Variables:						
Size		0.007	0.005	0.006	0.007	0.005
		(0.50)	(0.42)	(0.43)	(0.51)	(0.42)
Rating		0.052	0.047	0.048	0.049	0.050
		(1.15)	(1.05)	(1.06)	(1.08)	(1.14)
Maturity		0.122**	0.121**	0.121**	0.123**	0.121**
		(2.20)	(2.19)	(2.19)	(2.20)	(2.18)
Down		0.104**	0.099**	0.101**	0.104**	0.102**
		(2.59)	(2.47)	(2.48)	(2.54)	(2.54)
ACOV		-0.004	-0.000	-0.002	-0.004	0.004
		(-0.13)	(-0.01)	(-0.06)	(-0.12)	(0.11)
STR		-0.548***	-0.554***	-0.540***	-0.547***	-0.576***
		(-10.54)	(-10.85)	(-10.37)	(-10.45)	(-11.47)
MOM		-0.212*	-0.249**	-0.211*	-0.230**	-0.275**
		(-1.92)	(-2.30)	(-1.92)	(-2.08)	(-2.52)
Vol		0.059	0.066	0.066	0.072	0.076
		(0.98)	(1.11)	(1.10)	(1.20)	(1.28)
SRVol		-0.051	-0.041	-0.056	-0.049	-0.040
		(-1.30)	(-1.16)	(-1.41)	(-1.26)	(-1.15)
Frac_Bid t		0.219***	0.218***	0.220***	0.221***	0.217***
		(6.16)	(6.21)	(6.20)	(6.14)	(6.12)
Frac_Bid t+1		-0.266***	-0.268***	-0.266***	-0.267***	-0.268***
		(-9.32)	(-9.32)	(-9.41)	(-9.38)	(-9.48)
Intercept	0.347***	0.453***	0.427***	0.453***	0.461***	0.446***
	(3.98)	(3.83)	(3.68)	(3.82)	(3.88)	(3.68)
Industry Controls	YES	YES	YES	YES	YES	YES
Obs	250,817	250,817	250,817	250,817	250,817	250,817
R^2	0.120	0.433	0.433	0.432	0.435	0.445

Table 6: 11-Factor Alphas for PEAD Long-Short Strategies: Subsamples by Illiquidity Measures

25 portfolios are formed every month from July 2002 to December 2020 by independently sorting corporate bonds based on the corresponding firm's most recent earnings surprises and various bond illiquidity measures. Earnings surprise is proxied by the stock CAR $[-1, +1]$. We use seven bond liquidity proxies. *Amihud* is the Amihud liquidity measure, calculated as the daily average of absolute returns divided by the trade size of consecutive transactions. $ACOV$ is the autocovariance of the daily price changes within each month, multiplied by -1. BAS is the bid-ask spread, computed as $(S - B)/0.5(S + B)$, where S (B) is the volume-weighted average sell (buy) price on a day for a bond. *IRC* is the imputed roundtrip cost, computed as the highest price minus the lowest price and scaled by the highest price within an roundtrip trade, where two or three trades in a given bond with the same trade size take place within 15 minutes. *NegTurn* is the negative turnover ratio, calculated as the (negative of) total trading volume scaled by the amount outstanding. For *Amihud*, *BAS*, *IRC*, and *NegTurn*, we define a monthly measure by taking an average of daily estimates within a month. *Zero* is the zero trading ratio, calculated as the percentage of days during a month where the bond did not trade. *AILLIQ* is the aggregate illiquidity measure. Each month, we sort all bonds into ten buckets based on the six illiquidity proxies (*Amihud*, $ACOV$, *BAS*, *IRC*, *NegTurn*, and *Zero*) respectively, from most liquid (low) to most illiquid (high), and compute an average rank for this bond requiring at least four valid ranks. We present 11-factor alphas of the PEAD long-short strategy for each illiquidity quintile, where portfolios are value-weighted using the dollar value amount outstanding as weights with 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.

Illiquidity Rank	*Amihud*	*ACOV*	*BAS*	*IRC*	*NegTurn*	*Zero*	*AILLIQ*
Liquid	0.22***	0.27***	0.18**	0.18***	0.30***	0.26***	0.19***
	(3.21)	(3.04)	(2.57)	(3.63)	(3.12)	(3.42)	(2.86)
2	0.22***	0.13***	0.17**	0.22***	0.27***	0.18***	0.25***
	(3.31)	(3.13)	(2.56)	(3.70)	(4.16)	(2.84)	(3.19)
3	0.26***	0.23***	0.21***	0.12**	0.14**	0.21***	0.23***
	(4.22)	(3.46)	(3.94)	(2.23)	(2.28)	(4.45)	(4.70)
4	0.18***	0.25***	0.14**	0.37***	0.15***	0.19***	0.20***
	(4.09)	(4.63)	(2.41)	(4.02)	(2.79)	(4.23)	(3.92)
Illiquid	0.12**	0.21**	0.38***	0.27***	0.14**	0.10*	0.17**
	(2.07)	(2.20)	(4.00)	(3.46)	(2.50)	(1.95)	(2.54)
Illiquid - Liquid	-0.10	-0.06	0.20**	0.09	-0.16**	-0.16**	-0.03
	(-1.43)	(-0.54)	(2.54)	(1.29)	(-2.01)	(-2.12)	(-0.40)

Table 7: Univariate Portfolios of CDS Sorted on Earnings Surprises

We use the five-year CDS contracts for USD-denominated senior unsecured debt of 929 U.S.-based corporate obligors from Markit for the period from July 2002 to December 2020. 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 previous month. We use stock CAR $[-1, +1]$ as an earnings surprise measure. Quintile 1 ("Low") is the portfolios 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 five factors (bond market, downside risk, credit risk, liquidity risk, and reversal) from Bai, Bali, and Wen (2019). 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 five bond factors and the six stock factors. Column "*SR*" reports the annualized Sharpe 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 parenthesis below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Low	2	3	4	High	High - Low	*SR*
Pane A: Value-Weighted Portfolios, Collateralized CDS Returns							
Average Excess Return	-0.14***	-0.12***	-0.12***	-0.11***	-0.07	0.07***	0.94
	(-2.74)	(-2.89)	(-2.82)	(-2.69)	(-1.51)	(3.61)	
5 Bond Factor Alpha	-0.24***	-0.18***	-0.19***	-0.17***	-0.13***	0.11***	1.56
	(-6.85)	(-5.86)	(-5.78)	(-5.23)	(-3.76)	(5.06)	
6 Stock Factor Alpha	-0.20***	-0.16***	-0.16***	-0.15***	-0.11***	0.09***	1.27
	(-5.72)	(-5.28)	(-4.92)	(-4.92)	(-3.65)	(4.45)	
11 Factor Alpha	-0.24***	-0.18***	-0.19***	-0.16***	-0.13***	0.11***	1.65
	(-7.31)	(-5.93)	(-5.71)	(-5.14)	(-3.69)	(5.09)	
Panel B: Value-Weighted Portfolios, Log CDS Spread Changes							
Average Spread Changes	0.38	-0.19	0.02	-0.16	-0.92	-1.30***	
	(0.48)	(-0.24)	(0.03)	(-0.22)	(-1.39)	(-4.34)	

Table 8: 11-Factor Alphas for PEAD Long-Short Strategies: Subsample by Disagreement Proxies

Every month from July 2002 to December 2020, 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 $[-1, +1]$. We use three disagreement proxies: *DISP*, *CV*, and *RFY*. *DISP* is analyst forecast dispersion, calculated as the standard deviation of analyst forecasts scaled by the average stock price. *CV* is the bond portfolio weight dispersion, calculated as the standard deviation of a firm's bond portfolio weight across institutional investors divided by the average weight. *RFY* is the bond-level reaching for yield proxy, defined as the difference between a bond's yield and the average yield of bonds with the same rating, calculated following Chen and Choi (2021). We present the 11-factor alphas, where portfolios are value-weighted using the dollar value 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 construction of these variables are provided in Table 1. 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.

Disagreement Quintiles	Average Dis-agreement	PEAD 11-Factor Alpha	Turnover (%) on Announcement Day	Turnover (%) on Announcement Month	Average Portfolio Characteristics: *Bond Vol*	*Stock Vol*	*Size*	*Rating*	*Maturity*	*Down*	*BAS*	*ACOV*
Panel A: Analyst Forecast Dispersion (*DISP*) As Disagreement Proxy												
Low	0.0005	0.10**	0.48	0.41	1.73	1.36	660.70	7.27	10.59	2.60	69.86	0.77
		(2.01)										
2	0.0011	0.11***	0.55	0.44	1.80	1.47	687.87	7.69	11.07	2.80	75.56	0.92
		(2.91)										
3	0.0022	0.16***	0.60	0.46	1.89	1.65	713.00	8.31	10.52	2.95	80.33	1.02
		(3.12)										
4	0.0048	0.10*	0.75	0.54	2.09	1.93	748.85	9.14	9.86	3.29	81.15	1.12
		(1.69)										
High	0.0306	0.43***	1.14	0.68	3.31	2.69	659.50	11.29	8.76	5.52	96.48	1.83
		(3.31)										
High - Low		0.33**										
		(2.25)										

Disagreement Quintiles	Average Dis-agreement	PEAD 11-Factor Alpha	Turnover (%) on Announcement Day	Month	Average Portfolio Characteristics *Bond Vol*	*Stock Vol*	*Size*	*Rating*	*Maturity*	*Down*	*BAS*	*ACOV*
Panel B: Portfolio Weight Dispersion (CV) As Disagreement Proxy												
Low	1.07	-0.02	0.62	0.48	1.93	1.61	1,034.21	7.99	11.17	3.12	69.30	0.83
		(-0.17)										
2	1.25	0.14*	0.60	0.45	1.87	1.61	773.68	7.72	10.68	3.06	72.06	0.83
		(1.80)										
3	1.37	0.21**	0.68	0.48	2.01	1.73	632.92	8.43	10.32	3.26	77.28	0.98
		(2.50)										
4	1.53	0.37***	0.75	0.51	2.25	1.89	538.31	9.33	9.47	3.61	86.84	1.25
		(3.73)										
High	1.89	0.36***	0.94	0.61	2.88	2.24	466.61	10.63	8.69	4.54	97.21	1.76
		(4.56)										
High - Low		0.37***										
		(2.67)										
Panel C: Reaching For Yield (RFY) As Disagreement Proxy												
Low	-1.75	0.11***	0.48	0.42	1.00	1.66	656.61	8.88	3.09	1.83	46.54	0.44
		(3.52)										
2	-0.83	0.08**	0.54	0.44	1.37	1.66	704.27	8.39	5.00	2.35	60.15	0.62
		(2.24)										
3	-0.18	0.08**	0.66	0.51	1.83	1.70	706.68	8.56	7.62	2.91	71.35	0.82
		(2.34)										
4	0.56	0.29***	0.83	0.56	2.57	1.76	698.06	8.49	14.95	4.17	91.97	1.27
		(4.77)										
High	1.91	0.48***	0.98	0.57	3.70	2.15	696.04	8.73	20.23	5.41	134.20	2.52
		(4.44)										
High - Low		0.37***										
		(3.65)										

Table 9: Fama-MacBeth Regressions of Bond Returns on Earnings Surprise and Disagreement

This table reports the average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional 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 three disagreement proxies (*DISP*, *CV*, and *RFY*), as well as interactions of these variables with earnings surprises. *DISP* is the analyst forecast dispersion, calculated as the standard deviation of analyst forecasts scaled by the average stock price. *CV* is the bond portfolio weight dispersion, calculated as the standard deviation of a firm's bond portfolio weight across institutional investors divided by the average weight, based on the eMAXX holding data. *RFY* is the bond-level reaching for yield proxy, defined as the difference between a bond's yield and the average yield of bonds with the same rating, calculated following Chen and Choi (2021). All independent variables are winsorized each month at the 1% level and 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 July 2002 to December 2020.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns				
	(1)	(2)	(3)	(4)
CAR	0.066***	0.063***	0.057***	0.059***
	(5.11)	(4.85)	(5.21)	(5.88)
DISP		-0.083*		
		(-1.78)		
CAR × *DISP*		0.039**		
		(2.42)		
CV			-0.035*	
			(-1.88)	
CAR × *CV*			0.025**	
			(2.34)	
RFY				0.187***
				(4.39)
CAR × *RFY*				0.032**
				(2.22)
Size	0.007	0.008	0.001	0.014
	(0.50)	(0.58)	(0.09)	(1.07)
Rating	0.052	0.057	0.056	0.069
	(1.16)	(1.34)	(1.32)	(1.63)
Maturity	0.122**	0.115**	0.120**	0.030
	(2.20)	(2.10)	(2.15)	(0.53)
Down	0.104**	0.146***	0.104**	0.076**
	(2.60)	(3.70)	(2.54)	(2.19)
ACOV	-0.004	0.002	-0.007	-0.029
	(-0.13)	(0.06)	(-0.20)	(-0.97)
STR	-0.548***	-0.593***	-0.555***	-0.627***
	(-10.55)	(-11.68)	(-10.58)	(-15.97)
MOM	-0.213*	-0.247**	-0.233**	-0.205**
	(-1.93)	(-2.14)	(-2.09)	(-2.03)
Vol	0.058	0.083	0.060	0.004
	(0.97)	(1.41)	(1.01)	(0.10)
SRVol	-0.051	-0.045	-0.052	-0.094**
	(-1.30)	(-1.22)	(-1.31)	(-2.43)
Frac_Bid t	0.219***	0.203***	0.218***	0.204***
	(6.16)	(7.95)	(6.18)	(6.66)
Frac_Bid t+1	-0.266***	-0.269***	-0.267***	-0.259***
	(-9.32)	(-9.14)	(-9.23)	(-9.30)
Intercept	0.453***	0.486***	0.464***	0.539***
	(3.83)	(3.89)	(3.86)	(3.40)
Industry Controls	YES	YES	YES	YES
Obs	250,845	236,048	250,721	243,627
R^2	0.433	0.458	0.439	0.460

Table 10: Fama-MacBeth Regressions of Bond Returns on Past Stock Returns and Disagreement

This table reports the average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on past six-month stock returns and disagreement proxies with control variables. *SRet6m* is the past six-month stock return, calculated as the cumulative market-adjusted stock returns over the past six months, excluding the earnings announcement returns. 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 for a daily price in month t and t+1. We also include three disagreement proxies (*DISP*, CV, and RFY), as well as interactions of these variables with earnings surprises. *DISP* is the analyst forecast dispersion, calculated as the standard deviation of analyst forecasts scaled by the average stock price. CV is the bond portfolio weight dispersion, calculated as the standard deviation of a firm's bond portfolio weight across institutional investors divided by the average weight, based on the eMAXX holding data. RFY is the bond-level reaching for yield proxy, defined as the difference between a bond's yield and the average yield of bonds with the same rating, calculated following Chen and Choi (2021). All independent variables are winsorized each month at the 1% level and 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 July 2002 to December 2020.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns				
	(1)	(2)	(3)	(4)
SRet6m	0.120***	0.103***	0.104***	0.125***
	(6.96)	(5.91)	(6.09)	(8.22)
DISP		-0.008		
		(-0.22)		
SRet6m × *DISP*		0.081***		
		(2.75)		
CV			-0.035*	
			(-1.96)	
SRet6m × CV			0.042***	
			(2.93)	
RFY				0.207***
				(4.93)
SRet6m × RFY				0.086***
				(4.84)
Bond-level Controls	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES
Obs	250,911	236,065	250,787	243,693
R^2	0.433	0.460	0.440	0.463

Table 11: Limited Attention: Regression of Bond Returns on Earnings Surprises and Investors' Attention

This table reports the average intercept and 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 the cumulative abnormal stock returns adjusted by Fama-French three-factor model from trading day *d-1* to *d+1* around the earnings announcement date. 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 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 construction of the control variables are provided in Table 1. Continuous independent variables are winsorized at the 1% level and standardized to have a mean of zero and a standard deviation of one. Fama and French 30 industry effect in 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)
CAR	0.036**	0.062***	0.051	0.028
	(2.04)	(4.74)	(0.61)	(0.34)
NRank	0.004			
	(0.94)			
CAR × *NRank*	0.006*			
	(1.69)			
Friday		0.064		
		(1.47)		
CAR × *Friday*		0.028		
		(1.00)		
AIA			0.003	
			(0.06)	
$CAR \times AIA$			0.006	
			(0.07)	
$AIAC$				0.014
				(0.55)
$CAR \times AIAC$				0.013
				(0.34)
Bond-level Controls	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES
Obs	251,117	251,117	158,483	158,483
R^2	0.437	0.436	0.472	0.472

Table 12: Disposition Effect: Bivariate Portfolios on Earnings Surprise and Capital Gains Overhang

25 portfolios are formed every month from July 2002 to December 2020 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 $[-1, +1]$. 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, $RP_{i,q} = \frac{1}{V} \sum_{n=0}^{q} V_{i,q,q-n} P_{i,q-n}$, where $V_{q,q-n}$ 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 in different points in time and then some of the holding is 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 11-factor alphas, where portfolios are value-weighted using the dollar value amount outstanding as weights with 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	-0.03	0.02	0.21	0.11	0.16	0.19**
	(-0.25)	(0.26)	(1.67)	(1.04)	(1.62)	(2.14)
CGO, 2	-0.07	0.02	0.01	0.08	0.10	0.17***
	(-1.23)	(0.72)	(0.22)	(1.67)	(2.80)	(3.92)
CGO, 3	-0.12	-0.02	-0.02	0.01	0.04	0.16***
	(-2.34)	(-0.71)	(-0.75)	(0.59)	(1.70)	(3.11)
CGO, 4	-0.14	-0.06	-0.05	-0.04	-0.03	0.12***
	(-2.99)	(-1.29)	(-0.86)	(-1.18)	(-0.97)	(2.63)
High Capital Gains	-0.33	-0.05	-0.15	-0.08	-0.08	0.26***
	(-4.28)	(-0.81)	(-1.93)	(-1.19)	(-1.35)	(4.59)
High - Low	-0.30*	-0.08	-0.36*	-0.19	-0.24	0.06
	(-1.73)	(-0.62)	(-1.90)	(-1.23)	(-1.63)	(0.60)

Table 13: 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, Grinblatt, and Nozawa (2020). 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 on a day for a bond. We use the institutional-size trade with volume no less than \$100,000 to compute the bid-ask spread. If the bid-ask spread in a month is missing for a bond, we use the 90-percentile of the cross-section distribution in that month for the bond. Panel C presents the net performance of PEAD strategy across composite disagreement (*CDIS*) quintiles. Each month, we sort all bonds into ten buckets based on the three disagreement proxies (*DISP*, *CV*, and *RFY*) respectively, from the low to high disagreement, and compute an average rank for this bond. All returns and alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are reported in parenthesis 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 (%)	30.57	33.55	33.51	33.14	31.46	62.03
Transaction Costs (%)	0.09	0.10	0.10	0.10	0.09	0.19
Panel B: Univariate Sort on Earnings Surprise						
Average Excess Return	0.31**	0.33***	0.35***	0.34***	0.48***	-0.02
	(2.21)	(2.80)	(3.07)	(3.18)	(3.53)	(-0.39)
11 Factor Alpha	-0.23***	-0.13***	-0.11***	-0.08***	-0.02	0.05
	(-5.60)	(-3.90)	(-6.78)	(-3.27)	(-0.71)	(1.07)
Panel C: Bivariate Sort on Earnings Surprise and Disagreement (11-Factor Alpha)						
Low Disagreement	-0.18	-0.09	-0.13	-0.09	-0.07	-0.06*
	(-6.36)	(-4.25)	(-4.06)	(-4.32)	(-2.99)	(-1.75)
CDIS, 2	-0.19	-0.04	-0.10	-0.04	-0.02	-0.00
	(-3.69)	(-1.15)	(-2.87)	(-1.56)	(-0.64)	(-0.07)
CDIS, 3	-0.11	-0.12	-0.04	-0.07	-0.01	-0.07
	(-3.22)	(-3.66)	(-1.03)	(-1.55)	(-0.29)	(-1.32)
CDIS, 4	-0.08	-0.13	0.04	-0.16	0.01	-0.07
	(-1.36)	(-1.61)	(0.64)	(-1.82)	(0.28)	(-0.92)
High Disagreement	-0.53	-0.37	-0.40	-0.17	-0.01	0.35***
	(-5.15)	(-2.85)	(-4.86)	(-1.63)	(-0.12)	(2.80)

Table 14: Bond PEAD Strategy Returns for Longer Holding Periods

At the beginning of each month from July 2002 to December 2020, quintile portfolios are formed by sorting corporate bonds based on the corresponding firm's most recent earnings surprises at the end of previous month. We use stock CAR $[-1, +1]$ 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 a 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 11-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 parenthesis 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	0.17***	0.15***	0.12**	0.10**	0.08**	0.07**	0.06*	0.06*	0.06	0.05	0.05	0.04
	(3.57)	(2.84)	(2.51)	(2.37)	(2.09)	(2.04)	(1.72)	(1.68)	(1.65)	(1.53)	(1.37)	(1.24)
11 Factor Alpha	0.21***	0.18***	0.14***	0.11***	0.10***	0.10***	0.09***	0.09***	0.09***	0.09***	0.08***	0.07***
	(4.37)	(3.78)	(3.29)	(2.98)	(3.02)	(3.50)	(3.85)	(4.32)	(4.73)	(4.50)	(4.10)	(3.81)

Table 15: PEAD in Stock Returns 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 previous month. Qunitile 1 is the portfolios with the lowest earnings surprises and Quintile 5 is the portfolio with the highest earnings surprises. We consider three earnings surprises measures: *CAR*, *CE*, and *FOM*. Details on the construction of these variables are provided in Table 1. 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. "VW" denotes value-weighted (Panel A, Panel B, and Panel C) and "EW" denotes equal-weighted (Panel D, Panel E, and Panel F). 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 and Panel D) as well as all stocks in our sample. Also, we show sub-period results for the stock PEAD: 2002 - 2020 and 1984 - 2011 (Panel C and Panel F). All alphas are in percent per month. Newey-West adjusted t-statistics (with six lags) are reported in parenthesis below alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bond Issuers, 2002 − 2020, VW			
	CAR	*CE*	*FOM*
Six Factor Alpha	0.19	-0.08	0.13
	(1.33)	(-0.48)	(0.98)

Panel B: All Firms, 2002 − 2020, VW			
	CAR	*CE*	*FOM*
Six Factor Alpha	0.22*	0.31*	0.16
	(1.65)	(1.94)	(1.45)

Panel C: All Firms, 1984 − 2001, VW			
	CAR	*CE*	*FOM*
Six Factor Alpha	0.65***	0.37**	0.56***
	(3.63)	(2.00)	(4.16)

Panel D: Bond Issuers, 2002 − 2020, EW			
	CAR	*CE*	*FOM*
Six Factor Alpha	0.23**	-0.16	0.02
	(2.49)	(-1.15)	(0.13)

Panel E: All Firms, 2002 − 2020, EW			
	CAR	*CE*	*FOM*
Six Factor Alpha	0.42***	0.32***	0.24***
	(4.30)	(3.23)	(3.11)

Panel F: All Firms, 1984 − 2001, EW			
	CAR	*CE*	*FOM*
Six Factor Alpha	0.72***	1.31***	1.06***
	(7.71)	(10.38)	(8.23)

Table 16: Fama-MacBeth Regressions of Stock Returns on Earnings Surprise and Disagreement

This table reports the average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead excess stock returns on the earnings surprise measures, two stock-level disagreement proxies (*DISP* and CV_{Stock}), as well as interactions of these variables with earnings surprises. We use the "value-weighted" Fama-MacBeth regression using the square root of lagged market capitalization as weights to mitigate the influence of small stocks. Stock characteristics controls include the logarithm of market capitalization (*Ln(ME)*), the logarithm of book-to-market ratio (*Ln(BE/ME)*), past 11-month stock returns skipping the most recent month (*MOM*), operating profitability (*OP*), investment (*INV*), Amihud measure (*Amihud*), and bid-ask spread (*BAS*). Following Ball, Gerakos, Linnainmaa, and Nikolaev (2016), we define operating profitability as sales minus cost of goods sold minus sales, general, and administrative expenses (excluding research and development expenditures), and then scaled by total assets to obtain *OP*. *INV* is calculated as a change in total assets divided by the previous-year total assets. *Amihud* is the monthly average ratio of the daily absolute return to the dollar trading volume. *BAS* is the monthly average of daily bid-ask spread. *DISP* is the analyst forecast dispersion, calculated as the standard deviation of analyst forecasts scaled by the average stock price. CV_{Stock} is the coefficient of variation of investor's stock portfolio weight in a firm, calculated as the standard deviation of a firm's stock portfolio weight across institutional investors divided by the average weight, based on the Thomson-Reuters 13F holding data. All independent variables are winsorized each month at the 1% level and 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.

Left-Hand Side Variable: One-Month-Ahead Excess Stock Returns						
	1984 − 2020		1984 − 2001		2002 − 2020	
	(1)	(2)	(3)	(4)	(5)	(6)
CAR	0.212***	0.289***	0.346***	0.500***	0.085***	0.090***
	(6.26)	(7.25)	(6.28)	(8.61)	(3.36)	(3.85)
DISP	-0.024		0.096		-0.137*	
	(-0.40)		(1.07)		(-1.87)	
CAR × *DISP*	0.081*		0.066		0.095**	
	(1.93)		(0.91)		(2.14)	
CV_{Stock}		0.001		-0.070		0.068**
		(0.03)		(-1.62)		(2.43)
CAR × CV_{Stock}		0.098***		0.188***		0.014
		(3.35)		(3.64)		(0.68)
Stock-level Controls	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES	YES	YES
Obs	724,514	963,061	285,249	427,463	439,265	535,598
R^2	0.195	0.175	0.213	0.187	0.178	0.164

Appendices

A Bond PEAD Using Sample from 1997 to 2016

In this section, we use Merrill Lynch's quote data from 1997 to 2016 to examine bond PEAD. With this data, we create bond PEAD strategy using subsamples before and after introduction of TRACE, measure the potential impact of the introduction of TRACE and observe the longer-term trend in bond PEAD profitability.

Table A1 shows the average excess returns and factor alphas for quintiles sorted on stock CAR around earnings announcement dates. Since bond factors do not date back before the introduction of TRACE, we use the stock factor models of Fama and French (1993, 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 4 bps which is statistically indistinguishable from zero. Thus, we do not see evidence supporting bond PEAD during this (roughly) 5-year period.

In Panel B, we study the subsample from June 2002 (when TRACE is introduced) to December 2016. In this period, the average excess return on bond PEAD strategy is 18 bps, which is very similar to the main results based on TRACE in Table 3. We should treat the results based on quote data with a caveat because we cannot distinguish dealers' sluggish updates on their quotes from true drift in investor's bond valuation. However, this exercise shows no evidence for weakening bond PEAD in two subperiods we study. This finding also suggests that introduction of TRACE does not necessarily make the bond market more efficient.

Table A1: Average Returns and Alphas on Univariate Portfolios of Bonds Sorted by Earnings Surprises (1997-2016)

We use the Bank of America Merrill Lynch's bond pricing data. At the beginning of each month from January 1997 to December 2016, quintile portfolios are formed by sorting corporate bonds based on the corresponding firm's most recent earnings surprises at the end of previous month. We use stock *CAR* [-1, +1] as our primary earnings surprises measure. Qunitile 1 is the portfolios with the lowest earnings surprises and Quintile 5 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 capitalization as weights. This table reports the next-month average excess return as well as portfolio alphas. Alphas are calculated from various combinations of stock factors, default spread, and term spread. The stock market factors are the six factors (market, size, value, investment, profitability, and momentum) from Fama and French (2018). The default spread (*DEF*) and the term spread (*TERM*) are obtained from Amit Goyal's website. 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 parenthesis below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Low *CAR*	2	3	4	High *CAR*	High-Low
Panel A, Pre-TRACE: Jan 1997 - Jun 2002 (66 months)						
Average Excess Return	0.38***	0.50***	0.55***	0.58***	0.42***	0.04
	(3.11)	(3.92)	(4.31)	(4.63)	(2.75)	(0.48)
FF3+DEF+TERM Alpha	0.25***	0.35***	0.41***	0.44***	0.30**	0.04
	(2.93)	(4.09)	(4.93)	(5.71)	(2.55)	(0.56)
FF5+DEF+TERM Alpha	0.25***	0.33***	0.36***	0.41***	0.34***	0.08
	(3.72)	(4.90)	(5.97)	(7.50)	(3.95)	(1.31)
FF6+DEF+TERM Alpha	0.12***	0.16***	0.18***	0.20***	0.17***	0.04
	(3.68)	(5.03)	(6.07)	(7.25)	(3.94)	(1.31)
Panel B, Post-TRACE: Jul 2002 - Dec 2016 (174 months)						
Average Excess Return	0.52***	0.52***	0.55***	0.57***	0.70***	0.18***
	(2.86)	(3.70)	(3.91)	(4.13)	(4.30)	(3.16)
FF3+DEF+TERM Alpha	0.23**	0.26***	0.25***	0.32***	0.44***	0.21***
	(2.21)	(2.76)	(3.13)	(3.20)	(5.17)	(3.40)
FF5+DEF+TERM Alpha	0.26**	0.29***	0.27***	0.33***	0.46***	0.20***
	(2.44)	(3.16)	(3.40)	(3.37)	(5.24)	(3.37)
FF6+DEF+TERM Alpha	0.13**	0.14***	0.13***	0.17***	0.23***	0.10***
	(2.59)	(3.35)	(3.82)	(3.69)	(6.13)	(3.43)

Table A2: Bivariate Portfolios of Earnings Surprise and Alternative Disagreement Measures

25 portfolios are formed every month from July 2002 to December 2020 by independently sorting corporate bonds based on the corresponding firm's most recent earnings surprises and disagreement proxies. Earnings surprise is proxied by the stock CAR $[-1, +1]$. We use three disagreement proxies: $CV2$, CV_{Stock}, and $CV2_{Stock}$. $CV2$ is residual bond portfolio weight dispersion, where the residual weight is the residual in the cross-sectional regression of portfolio weights on the investor-level rating, maturity and illiquidity at each quarter. CV_{Stock} is the coefficient of variation of investor's stock portfolio weight in a firm, calculated as the standard deviation of a firm's stock portfolio weight across institutional investors divided by the average weight, based on the Thomson-Reuters 13F holding data. $CV2_{Stock}$ is the coefficient of variation of residual stock portfolio weight, where the residual weight is the residual in the cross-sectional regression of portfolio weight on the investor-level size, book-to-market, momentum at each quarter. We present the 11-factor alphas, where portfolios are value-weighted using the dollar value amount outstanding as weights with holding period of one month. 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 construction of these variables are provided in Table 1. 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.

Disagreement	Average	PEAD	Turnover (%) on		Average Portfolio Characteristics							
Quintiles	Dis-agreement	11-Factor Alpha	Announcement Day	Month	*Bond Vol*	*Stock Vol*	*Size*	*Rating*	*Maturity*	*Down*	*BAS*	*ACOV*
Panel A: Bond Residual Portfolio Weight Dispersion As Disagreement Proxy												
Low	1.25	0.02	0.61	0.46	1.82	1.73	1119.64	7.78	9.49	3.10	72.71	0.85
		(0.26)										
2	1.47	0.13	0.65	0.47	1.94	1.79	743.35	8.49	9.50	3.21	74.89	0.92
		(1.35)										
3	1.64	0.34***	0.70	0.49	2.10	1.79	606.90	9.05	9.99	3.44	81.85	1.06
		(3.84)										
4	1.80	0.15	0.74	0.50	2.25	1.80	527.25	9.14	10.40	3.61	84.44	1.23
		(0.94)										
High	2.16	0.40***	0.92	0.60	2.85	1.97	448.61	9.62	10.98	4.26	89.56	1.68
		(3.81)										
High - Low		0.38***										
		(2.79)										

Disagreement Quintiles	Average Dis-agreement	PEAD 11-Factor Alpha	Turnover (%) on Announcement Day	Month	Average Portfolio Characteristics *Bond Vol*	*Stock Vol*	*Size*	*Rating*	*Maturity*	*Down*	*BAS*	*ACOV*
Panel B: Stock Portfolio Weight Dispersion As Disagreement Proxy												
Low	1.14	0.08**	0.48	0.39	1.71	1.45	1109.35	5.81	11.74	2.87	73.83	0.84
		(2.07)										
2	1.68	0.09	0.60	0.45	1.85	1.57	774.85	7.48	11.45	2.90	73.36	0.87
		(1.42)										
3	2.11	0.19***	0.69	0.50	2.01	1.69	601.42	8.73	10.81	3.11	80.50	1.07
		(2.61)										
4	2.56	0.14*	0.81	0.56	2.20	1.88	526.11	9.82	9.53	3.49	84.24	1.28
		(1.69)										
High	3.45	0.39***	1.17	0.69	3.31	2.64	452.69	12.05	7.82	5.38	100.16	2.04
		(3.54)										
High - Low		0.30***										
		(2.84)										
Panel C: Stock Residual Portfolio Weight Dispersion As Disagreement Proxy												
Low	1.09	0.09**	0.47	0.39	1.69	1.44	1103.61	5.75	11.62	2.82	72.87	0.82
		(2.38)										
2	1.60	0.10**	0.60	0.45	1.83	1.56	776.00	7.49	11.42	2.89	73.05	0.86
		(2.25)										
3	2.03	0.16***	0.68	0.50	2.01	1.71	594.73	8.73	10.84	3.08	81.46	1.08
		(2.62)										
4	2.50	0.24***	0.80	0.56	2.20	1.87	527.71	9.87	9.59	3.48	84.25	1.27
		(2.65)										
High	8.90	0.33***	1.19	0.69	3.35	2.66	462.04	12.05	7.89	5.49	100.55	2.08
		(3.21)										
High - Low		0.24**										
		(2.38)										

Table A3: Fama-MacBeth Regressions of Bond Returns on Earnings Surprise and Stock CV

This table reports the average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the earnings surprise measures, portfolio weight dispersion, and their interaction terms. *CV2* is residual bond portfolio weight dispersion, where the residual weight is the residual in the cross-sectional regression of portfolio weight on the investor-level rating, maturity and illiquidity at each quarter. CV_{Stock} is the coefficient of variation of investor's stock portfolio weight in a firm, calculated as the standard deviation of a firm's stock portfolio weight across institutional investors divided by the average weight, based on the Thomson-Reuters 13F holding data. $CV2_{Stock}$ is the coefficient of variation of residual stock portfolio weight, where the residual weight is the residual in the cross-sectional regression of portfolio weight on the investor-level size, book-to-market, momentum at each quarter. The control variables are the same as in Table 9. All independent variables are winsorized each month at the 1% level and 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 July 2002 to December 2020.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns			
	(1)	(2)	(3)
CAR	0.064***	0.051***	0.057***
	(5.30)	(4.16)	(4.51)
CV2	-0.025*		
	(-1.89)		
CAR × *CV2*	0.042***		
	(3.74)		
CV_{Stock}		0.003	
		(0.15)	
CAR × CV_{Stock}		0.028***	
		(2.63)	
$CV2_{Stock}$			0.003
			(0.13)
CAR × $CV2_{Stock}$			0.025**
			(2.00)
Size	0.002	0.004	0.004
	(0.13)	(0.31)	(0.34)
Rating	0.055	0.055	0.055
	(1.22)	(1.36)	(1.34)
Maturity	0.123**	0.114**	0.114**
	(2.22)	(2.08)	(2.07)
Down	0.100**	0.118***	0.117***
	(2.47)	(2.90)	(2.87)
ACOV	-0.007	-0.010	-0.012
	(-0.21)	(-0.33)	(-0.40)
STR	-0.554***	-0.564***	-0.564***
	(-10.58)	(-11.30)	(-11.28)
MOM	-0.229**	-0.198*	-0.203*
	(-2.06)	(-1.79)	(-1.82)
Vol	0.060	0.061	0.064
	(1.02)	(1.04)	(1.10)
SRVol	-0.053	-0.046	-0.048
	(-1.33)	(-1.19)	(-1.24)
Frac_Bid t	0.218***	0.215***	0.215***
	(6.16)	(6.42)	(6.49)
Frac_Bid t+1	-0.267***	-0.267***	-0.266***
	(-9.20)	(-9.81)	(-9.88)
Intercept	0.448***	0.457***	0.445***
	(3.76)	(3.75)	(3.64)
Industry Controls	Yes	YES	YES
Obs	250,721	227,557	227,557
R^2	0.439	0.443	0.445

Table A4: Fama-MacBeth Regressions of Bond Returns on Earnings Surprise and Disagreement, Controlling for Bid-ask Spread

This table reports the average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the earnings surprise measures and disagreement proxies with control variables. Bond characteristics controls include bond size (*Size*), credit rating, maturity, downside risk (*DOWN*), bid-ask spread (*BAS*), 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 three disagreement proxies (*DISP*, *CV*, and *RFY*), as well as interactions of these variables with earnings surprises. *DISP* is the analyst forecast dispersion, calculated as the standard deviation of analyst forecasts scaled by the average stock price. *CV* is the bond portfolio weight dispersion, calculated as the standard deviation of a firm's bond portfolio weight across institutional investors divided by the average weight, based on the eMAXX holding data. *RFY* is the bond-level reaching for yield proxy, defined as the difference between a bond's yield and the average yield of bonds with the same rating, calculated following Chen and Choi (2021). All independent variables are winsorized each month at the 1% level and 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 July 2002 to December 2020.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns				
	(1)	(2)	(3)	(4)
CAR	0.063***	0.057***	0.054***	0.057***
	(5.48)	(5.42)	(5.31)	(6.21)
DISP		-0.079*		
		(-1.74)		
CAR × *DISP*		0.045***		
		(2.69)		
CV			-0.032*	
			(-1.81)	
CAR × *CV*			0.019*	
			(1.93)	
RFY				0.191***
				(4.45)
CAR × *RFY*				0.029**
				(2.25)
Size	0.008	0.010	0.004	0.011
	(0.63)	(0.73)	(0.31)	(0.89)
Rating	0.047	0.051	0.050	0.064
	(1.00)	(1.13)	(1.11)	(1.43)
Maturity	0.124**	0.115**	0.121**	0.028
	(2.23)	(2.11)	(2.18)	(0.50)
Down	0.106**	0.149***	0.106**	0.080**
	(2.57)	(3.51)	(2.58)	(2.22)
BAS	-0.005	-0.001	-0.005	-0.031*
	(-0.24)	(-0.05)	(-0.21)	(-1.97)
STR	-0.591***	-0.634***	-0.596***	-0.667***
	(-11.33)	(-12.57)	(-11.36)	(-16.82)
MOM	-0.210*	-0.255**	-0.226**	-0.212**
	(-1.92)	(-2.24)	(-2.05)	(-2.24)
Vol	0.039	0.066	0.041	-0.006
	(0.63)	(1.13)	(0.69)	(-0.15)
SRVol	-0.050	-0.047	-0.052	-0.092**
	(-1.34)	(-1.35)	(-1.38)	(-2.50)
Frac_Bid t	0.218***	0.203***	0.217***	0.200***
	(6.96)	(8.90)	(6.92)	(7.41)
Frac_Bid t+1	-0.274***	-0.276***	-0.275***	-0.269***
	(-8.79)	(-8.67)	(-8.73)	(-8.82)
Intercept	0.444***	0.463***	0.452***	0.525***
	(3.71)	(3.68)	(3.77)	(3.33)
Industry Controls	YES	YES	YES	YES
Obs	272,801	256,691	272,667	265,081
R^2	0.425	0.449	0.431	0.452

B Proofs

Derivation of an REE model

As a benchmark, we develop an REE model to show the effect of difference of opinions on the price drift. In the REE model, assume that investor i condition not only on her private signal $\tilde{s}_i$ but also the public price $\tilde{p}_1$ to update her beliefs about the firm fundamental. All other setups are the same as in the main model.

We conjecture that a linear price at date 1 as follows:

$$\tilde{p}_1 = \alpha_0 + \alpha_v(\tilde{v} + \tilde{\eta}) + \alpha_u \tilde{u}, \tag{B1}$$

which is equivalent to the following signal in predicting the firm fundamental:

$$\tilde{s}_p \equiv \frac{\tilde{p}_1 - \alpha_0}{\alpha_v} = \tilde{v} + \tilde{\eta} + \frac{1}{a}\tilde{u},$$

where $a \equiv \frac{\alpha_v}{\alpha_u}$ is positively related to price informativeness.

Then, investor i's optimal demand of the risky asset becomes:

$$\begin{aligned}
\tilde{x}_i &= \frac{E[\tilde{v}|\tilde{s}_i, \tilde{p}_1] - \tilde{p}_1}{\gamma Var[\tilde{v}|\tilde{s}_i, \tilde{p}_1]} \\
&= \frac{1}{\gamma} \frac{\frac{\tau_\eta}{\tau_v + \tau_\eta} \frac{\tau_\varepsilon \tilde{s}_i + \tau_u a^2 \frac{\tilde{p}_1 - \alpha_0}{\alpha_v}}{\frac{\tau_v \tau_\eta}{\tau_v + \tau_\eta} + \tau_\varepsilon + \tau_u a^2} - \tilde{p}_1}{\frac{1}{\tau_v + \tau_\eta} + \left(\frac{\tau_\eta}{\tau_v + \tau_\eta}\right)^2 \frac{1}{\frac{\tau_v \tau_\eta}{\tau_v + \tau_\eta} + \tau_\varepsilon + \tau_u a^2}},
\end{aligned}$$

where $\tau_u = \frac{1}{\sigma_u^2}$. Inserting the demand function into the market-clearing condition $\int_0^1 \tilde{x}_i di + \tilde{u} = 1$ and matching the solved price with the conjectured form (B1) we obtain that the equilibrium price at date 1 is given by equation (B1), where the coefficients are

$$\begin{aligned}
\alpha_v &= \frac{\tau_\eta}{\tau_v + \tau_\eta} \frac{\tau_\varepsilon + \tau_u a^2}{\frac{\tau_v \tau_\eta}{\tau_v + \tau_\eta} + \tau_\varepsilon + \tau_u a^2}, \\
\alpha_u &= \frac{\alpha_v}{a}, \\
\alpha_0 &= -\frac{\gamma}{\tau_v + \tau_\eta} - \left(\frac{\tau_\eta}{\tau_v + \tau_\eta}\right)^2 \frac{\gamma}{\frac{\tau_v \tau_\eta}{\tau_v + \tau_\eta} + \tau_\varepsilon + \tau_u a^2},
\end{aligned}$$

where a is the unique positive root of the following equation:

$$a^3\gamma\tau_u + a\gamma\left(\tau_\eta + \tau_\varepsilon\right) - \tau_\eta\tau_\varepsilon = 0.$$

Finally, we can compute the magnitude of return autocorrelation in the REE model as follows: $E[\tilde{p}_2 - \tilde{p}_1|\tilde{p}_1 - \tilde{p}_0] = k(\tilde{p}_1 - \tilde{p}_0)$, where

$$k = -\frac{\tau_\eta\tau_v\tau_\varepsilon\sigma_u^4}{\left(a^2 + \sigma_u^2\tau_\varepsilon\right)\left(a^2\tau_\eta + \tau_v\left(a^2 + \tau_\eta\sigma_u^2\right)\right)} < 0. \tag{B2}$$

Compared with equation (10), it is obvious that in the REE model, only the first "noise-trading" force shows up and it always generates price reversals.

Proof of Implication 1

Based on equation (10), prices exhibit drift when $\tau_\varepsilon\tau_\eta^2 > \gamma^2(\tau_\varepsilon + \tau_\eta)\sigma_u^2$. Thus, when σ_u^2 is low, the inequality is more likely to hold.

Proof of Implication 2

We focus on the case in which prices exhibit drift, namely, $k > 0$. Taking derivative of the magnitude of price drift k in equation (10) with respect to τ_η yields the following:

$$\frac{\partial k}{\partial\tau_\eta} = \tau_v\tau_\varepsilon^2\frac{\gamma^2\sigma_u^2\left(\tau_\eta + \tau_\varepsilon\right)\left(\tau_v\left(\tau_\eta + \tau_\varepsilon\right) + 2\tau_\eta\tau_\varepsilon\right) + \tau_\eta^2\tau_v\tau_\varepsilon}{\left(\gamma^2\sigma_u^2\tau_v\left(\tau_\eta + \tau_\varepsilon\right)^2 + \tau_\eta\tau_\varepsilon^2\left(\tau_\eta + \tau_v\right)\right)^2} > 0.$$

Proof of Implication 3

We focus on the case in which prices exhibit drift, namely, $k > 0$. Taking derivative of the magnitude of price drift k in equation (10) with respect to τ_ε yields the following:

$$\frac{\partial k}{\partial\tau_\varepsilon} = \tau_\eta^2\tau_v\frac{\gamma^2\sigma_u^2\left(\tau_\eta + \tau_\varepsilon\right)\left(\tau_v\left(\tau_\eta + \tau_\varepsilon\right) + 2\tau_\eta\tau_\varepsilon\right) - \tau_\eta\tau_\varepsilon^2\left(\tau_\eta + \tau_v\right)}{\left(\gamma^2\sigma_u^2\tau_v\left(\tau_\eta + \tau_\varepsilon\right)^2 + \tau_\eta\tau_\varepsilon^2\left(\tau_\eta + \tau_v\right)\right)^2}, \tag{B3}$$

which is positive when $f(\tau_\varepsilon) > 0$, where

$$f(\tau_\varepsilon) = \left(\gamma^2\sigma_u^2(\tau_v + 2\tau_\eta) - \tau_\eta(\tau_v + \tau_\eta)\right)\tau_\varepsilon^2 + 2\gamma^2\sigma_u^2\tau_\eta(\tau_v + \tau_\eta)\tau_\varepsilon + \gamma^2\sigma_u^2\tau_v\tau_\eta^2. \tag{B4}$$

As we focus on low σ_u^2 and low τ_ε, the condition for $\frac{\partial k}{\partial \tau_\varepsilon} > 0$ can be rewritten as follows:

$$\sigma_u^2 < \{\frac{\tau_\varepsilon \tau_\eta^2}{\gamma^2(\tau_\varepsilon + \tau_\eta)^2}, \frac{\tau_\eta(\tau_v + \tau_\eta)}{\gamma^2(\tau_v + 2\tau_\eta)}\} \text{ and } \tau_\varepsilon < \bar{\tau}_\varepsilon, \tag{B5}$$

where

$$\bar{\tau}_\varepsilon = \frac{\gamma^2 \sigma_u^2 \tau_\eta(\tau_v + \tau_\eta) + \gamma \sigma_u \tau_\eta \sqrt{\tau_\eta(\tau_v^2 + \gamma^2 \sigma_u^2 \tau_\eta + \tau_v \tau_\eta)}}{\tau_\eta(\tau_v + \tau_\eta) - \gamma^2 \sigma_u^2 (\tau_v + 2\tau_\eta)}.$$

Note that $\sigma_u^2 < \frac{\tau_\varepsilon \tau_\eta^2}{\gamma^2(\tau_\varepsilon + \tau_\eta)^2}$ ensures that we can observe price drift. Furthermore, $\sigma_u^2 < \frac{\tau_\eta(\tau_v + \tau_\eta)}{\gamma^2(\tau_v + 2\tau_\eta)}$ makes the quadratic function $f(\tau_\varepsilon)$ open downward; coupled with the fact that $f(\tau_\varepsilon)$ has a positive intercept, a low τ_ε can lead to $\frac{\partial k}{\partial \tau_\varepsilon} > 0$.

Based on the definition of trading volume in (11), we can derive

$$TV = \sigma \sqrt{\frac{2}{\pi}} \exp\left(-\frac{1}{2\sigma^2}\right) + \operatorname{erf}\left(\frac{1}{\sqrt{2\sigma^2}}\right),$$

where $\sigma^2 = \frac{\tau_\varepsilon \tau_\eta^2}{\gamma^2(\tau_\varepsilon + \tau_\eta)^2} + \sigma_u^2$. Taking derivative of TV with respect to τ_ε yields that

$$\frac{\partial TV}{\partial \tau_\varepsilon} = \frac{\tau_\eta^2 \left(\tau_\eta - \tau_\varepsilon\right) \exp\left(-\frac{\gamma^2(\tau_\eta + \tau_\varepsilon)^2}{2\left(\gamma^2 \sigma_u^2 (\tau_\eta + \tau_\varepsilon)^2 + \tau_\eta^2 \tau_\varepsilon\right)}\right)}{\sqrt{2\pi} \gamma^2 \left(\tau_\eta + \tau_\varepsilon\right)^3 \sqrt{\frac{\gamma^2 \sigma_u^2 (\tau_\eta + \tau_\varepsilon)^2 + \tau_\eta^2 \tau_\varepsilon}{\gamma^2 (\tau_\eta + \tau_\varepsilon)^2}}},$$

which is positive when

$$\tau_\varepsilon < \tau_\eta. \tag{B6}$$

Next, we can derive disagreement defined in (12) as follows:

$$DISP = \frac{\tau_\eta^2 \tau_\varepsilon}{\left(\tau_v \left(\tau_\eta + \tau_\varepsilon\right) + \tau_\eta \tau_\varepsilon\right)^2}.$$

Taking derivative with respect to τ_ε yields

$$\frac{\partial DISP}{\partial \tau_\varepsilon} = \tau_\eta^2 \frac{\tau_v \tau_\eta - \tau_\varepsilon(\tau_v + \tau_\eta)}{\left(\tau_v \left(\tau_\eta + \tau_\varepsilon\right) + \tau_\eta \tau_\varepsilon\right)^3},$$

which is positive if

$$\tau_\varepsilon < \frac{\tau_v \tau_\eta}{\tau_v + \tau_\eta}. \tag{B7}$$

To sum, we can observe that $\frac{\partial k}{\partial \tau_\varepsilon} > 0$, $\frac{\partial TV}{\partial \tau_\varepsilon} > 0$, and $\frac{\partial DISP}{\partial \tau_\varepsilon} > 0$ when the three conditions (B5), (B6), and (B7) simultaneously hold, which features low σ_u^2 and low τ_ε.

Proof of Implication 4

The illiquidity defined in (12) can be expressed as follows:

$$ILLIQ = \frac{\gamma(\tau_\varepsilon + \tau_\eta)}{\tau_\varepsilon \tau_\eta + \tau_v(\tau_\varepsilon + \tau_\eta)}.$$

Taking its derivative with respect to τ_ε yields

$$\frac{\partial ILLIQ}{\partial \tau_\varepsilon} = -\frac{\gamma \tau_\eta^2}{(\tau_\varepsilon \tau_\eta + \tau_v(\tau_\varepsilon + \tau_\eta))^2} < 0.$$

Therefore, coupled with (B3), we know that when τ_ε is low, k and ILLIQ can be negatively correlated.