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

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Abstract

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

JEL Classification: G12, G13

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

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1 Introduction

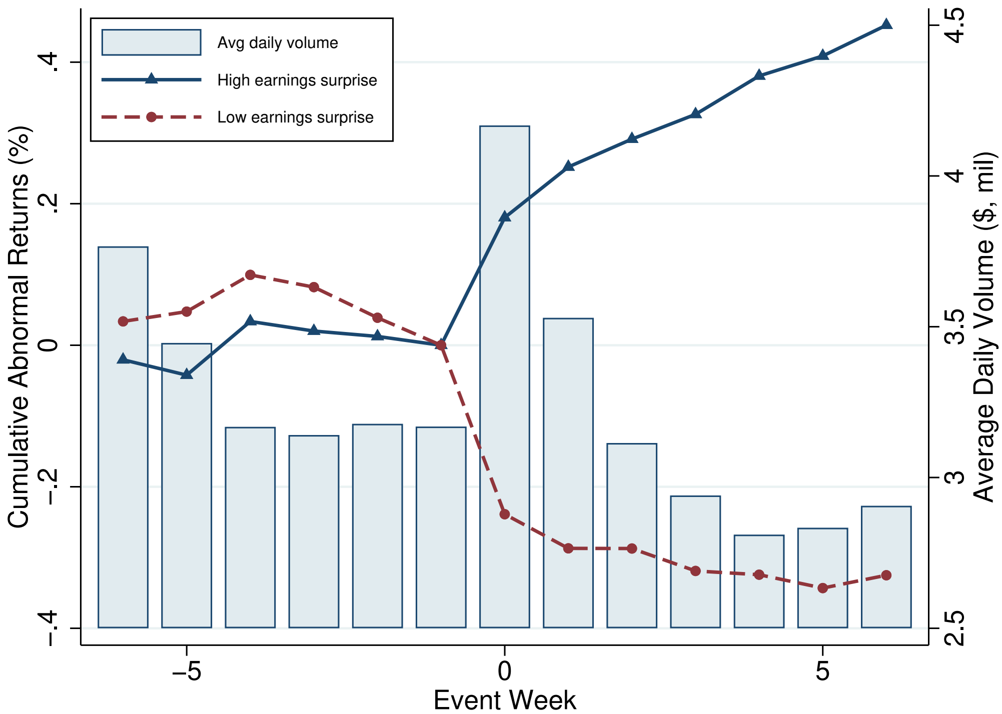
Slow price reactions to market news, such as the announcement of a firm's earnings, are vital to assessing market efficiency. In an efficient market, asset prices immediately reflect investors' information on a given firm's value and, thus, should not exhibit drift after the news release. Literature on the stock market provides ample evidence against this theoretical assumption, but no consensus has been reached on the driving mechanism behind slow price reactions to news. This paper explores post-earnings announcement drift (PEAD) in the corporate bond market, and examines how liquidity and disagreement among investors affect PEAD.

The corporate bond market offers a unique research setting in which the role of liquidity and disagreement among investors is crucial in determining prices. As is well established in the literature, corporate bonds trade less frequently than stocks do and exhibit liquidity premiums (e.g., Bao, Pan, and Wang 2011). In addition to liquidity, the role of disagreement is key since shocks to corporate bonds' cash flows are less frequently observed than to stocks, challenging investors to correctly assess the riskiness of bond cash flows based on historical data. This creates room for disagreement over the likelihood of default. Bond investors' widely documented reaching-for-yield behavior corroborates the influence of disagreement. Rational investors recognize the default risk of a borrowing firm and push up bonds' yield; meanwhile, optimistic investors ignore this tail risk and purchase these bonds. This difference in default risk assessment leads to disagreement on the bonds' value. As such, the corporate bond market is an ideal place to study the joint effects of disagreement and liquidity on price formation.

In this paper, we report three empirical findings that appear puzzling at first: i) PEAD exists in the corporate bond market, ii) PEAD is more pronounced for bonds that trade more frequently than those that trade less often, and iii) both PEAD and bond turnover are greater when investors disagree more strongly on bonds' value. We then offer a unified explanation for these findings using a stylized model in which investors agree to disagree.

We begin by presenting empirical evidence for the existence of bond PEAD using transaction data from 2002 to 2020. We sort the bonds into portfolios according to an issuing firm's most recent earnings surprise, which is measured by three-day stock returns surrounding the announcement date of the firm's quarterly earnings, and calculate portfolio returns for the month that follows. We find that bonds in the highest earnings surprise quintile gain on average 17 basis points (bps) more than those in the lowest quintile, suggesting that bond prices have underreacted to the firm's earnings announcements. Figure 1 visualizes the drift

Figure 1: Post-Earnings Announcement Drift in Corporate Bonds



This figure plots the weekly cumulative abnormal returns (left scale, in percent) on bonds with high earnings surprise (Q5) and those with low earnings surprise (Q1) six week before and after the earnings announcement. We rescale the cumulative abnormal return in week $t = -1$ to be zero. Volume is the average transaction volume across bonds in the sample (right scale, in millions). For this figure, the sample is limited to bonds that trade every week during the event window.

after an earnings surprise: Although bond prices spike up (down) after positive (negative) news, they appear to follow the same trajectory in the following six weeks. Because we employ actual transactions to estimate a mid-price and ensure that they accurately reflect investors' valuations, PEAD documented in this paper is not a reflection of dealers' stale quotes. Rather, it shows that investors, on average, trade at the "wrong" prices following announcements.

Bond PEAD is robust when we use alternative measures of earnings surprise such as median analyst forecast errors, and the drift is not accounted for by risk exposures. To show this, we apply an 11-factor model that combines the six stock factors of Fama and French (2018) and the five bond factors of Bai, Bali, and Wen (2019), including the bond market, credit risk, liquidity risk, downside risk, and reversal risk and find that the difference in alpha between the highest and lowest earnings surprise quintiles is significant at 22 bps. While a 22 bps difference in alpha may not seem striking, bond PEAD is economically significant because the risks of the bonds in each portfolio are largely idiosyncratic, leading to the low volatility of the PEAD strategy that goes long on the highest quintile and short on the lowest. As a result, the strategy's annualized Sharpe ratio is 0.73, higher than commonly-used bond factors. Furthermore, its profitability is stable over our sample period, remaining unaffected by the business cycle. In fact, this strategy logged profits even during the global financial crisis of 2008 and the shock of the covid-19 pandemic in March 2020.

Bond PEAD is pervasive across different types of corporate bonds: We double-sort bonds by earning surprise and various bond characteristics and find that PEAD exists both in investment-grade (IG) and high-yield (HY) bonds, as well as in all maturity quintiles. Moreover, earnings announcements are unique from other types of market news: We find that earnings surprises predict bond returns after controlling for changes in credit ratings and equity returns for the previous six months, which capture all other news relevant to bond value. This last finding regarding equity returns is important in that bond PEAD is not a simple reflection of the momentum spillover from equity to bonds, as documented in Gebhardt, Hvidkjaer, and Swaminathan (2005).

Since the bond market is notoriously illiquid, one might believe that bond PEAD is an obvious outcome of illiquidity. To test this hypothesis, we double-sort bonds by 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 (Feldhütter 2010), v) turnover, vi) the fraction of days with no trade, and vii) the composite index of the six measures. We find that bond PEAD exists for all illiquidity-based quintiles, and that there is a weakly negative relationship between the composite illiquidity index and the PEAD profits. This negative link is partly driven by a positive relationship between the measures of bonds' trade frequency and the magnitude of drift. Furthermore, we find that PEAD also exists for credit default swaps (CDS) as well. In fact, the Sharpe ratio of a strategy that sells CDS protection of a firm after its positive earnings surprise and buys protection following a negative surprise is 0.94, even higher than that of corporate bonds. Thus, even though large transaction costs should, in principle, prevent mispricing from being arbitraged away, the other aspects of illiquidity, such as price impact or infrequent transactions, do not seem to be the source of PEAD. This surprising pattern in the data begs another explanation for PEAD that is consistent with the evidence on trading volume and liquidity.

Eliminating illiquidity, we now turn to investors' disagreement as a potential explanation for PEAD and liquidity. To test this explanation, we double sort bonds into 25 portfolios by earnings surprise and three measures of disagreement: i) the dispersion in analysts' earnings forecasts (*DISP*), ii) the dispersion in institutional investors' portfolio weights, and

iii) reaching for yield proxies (i.e., the difference between a bond's yield and those of its peers with the same credit rating). We find that a long-short PEAD strategy earns greater 11-factor alphas among bonds with higher disagreement than those with lower disagreement. For example, the PEAD strategy delivers 43 bps 11-factor alphas for bonds in the highest quintile for *DISP* while the same strategy yields 10 bps for bonds in the lowest quintile. The results using dispersion in investor portfolio weights or reaching-for-yield proxies as a measure of disagreement are similar.

Perhaps most importantly, disagreement appears to explain the link between liquidity and slow price movements. We find that bonds with high disagreement exhibit higher trading volumes on earning announcement dates than low disagreement bonds do. Thus, if disagreement is the source of bond PEAD, the puzzling positive relationship between trading volume and PEAD is no longer a puzzle because generally, investors trade securities more when they disagree on asset value (Banerjee and Kremer, 2010).

Having established a robust case for disagreement as the source of bond PEAD, we build a stylized model in which investors exhibit differences in opinions, thus formalizing the mechanism. In our model, investors disagree on a bond's value since they employ different valuation models and, thus, hold different interpretations of the same 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, bond prices exhibit drift (PEAD in the earnings announcement context) when noise trading is low. Because investors hold varying opinions regarding the announcement, they place high weight on their own private interpretation when updating their beliefs, ignoring potential information contained in the trades of others. This results in the slow aggregation of investor opinions, causing a price underreaction to the public announcement and, hence, drift.

We then derive two relevant empirical implications for our disagreement mechanism. First, bonds with high disagreement are associated with more pronounced PEAD and higher trading volume. This implication on trading volume is especially crucial since we must ensure that disagreement explains the patterns documented thus far in prices as well as quantities. Second, more pronounced PEAD is associated with higher liquidity. This surprising finding is unique to the disagreement mechanism: Only when an asset is liquid can investors express different opinions through trade, which slows the aggregation of information into prices. The weak negative link between the composite illiquidity index and the PEAD profits provides some suggestive evidence for this second implication.

The link between bond PEAD and disagreement is consistent with findings within 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, suggesting that disagreement also 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 the stocks of bond-issuing firms into earnings-surprise-based quintiles, the return difference between high and low-surprise firms is mostly insignificant in the sample from 2002 to 2020. This lack of drift arises because bond-issuing firms are mostly large-cap stocks that exhibit less pronounced anomalies (e.g., Fama and French 2008), and the stock PEAD strategy becomes less profitable over time (Chordia, Subrahmanyam, and Tong 2014; McLean and Pontiff 2016; Martineau 2021). This is an expected outcome of our model: First, due to a higher fraction of retail investors, noise trading in the stock market is greater than the institution-dominated bond market, which attenuates price drift in the stock market as suggested by our model and other standard information-based models (e.g., Grossman and Miller, 1988; Banerjee, Kaniel, and Kremer, 2009); second, in the disagreement-based model, PEAD reflects mispricing caused by investors overvaluing their own signals, and thus the drift should be arbitraged away in the absence of large transaction costs. This is one of the reasons why, in recent years, a rise in algorithm-based traders has eliminated stock PEAD, especially for large-cap stocks (Luo, Subrahmanyam, and Titman, 2020). In contrast, due to low noise trading and large transaction costs, the disagreement effect on bond PEAD remains dominant, which makes the bond market a unique testing ground to study the drivers for slow price movements. Consistent with this claim, we find that the bond PEAD strategy unconditionally yields near-zero profits after transaction costs. However, if we focus on a subsample of bonds with high disagreement, the strategy yields a positive profit net of costs.

To bolster our argument for the disagreement-based explanation of bond PEAD, we conduct several more empirical tests that explore alternative explanations, including investors' limited attention and the disposition effect. However, we find that bond PEAD is not pronounced for bonds when investors pay less attention or when dealing with bonds that have large capital gains or losses, suggesting that these alternative psychological biases are unlikely to be the driving force behind bond PEAD.

In sum, we contribute to extant literature by providing new insights into the relationships among disagreement, slow price reactions to news, and liquidity. In addition to documenting robust evidence for bond PEAD, we provide a unified explanation for the link between PEAD and liquidity.

Our paper relates to a stream 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), Bali, Subrahmanyam, and Wen (2019), and Li and Galvani (2021). Wei, Truong, and Veeraraghavan (2012) document PEAD over a 30-day period following earnings announcement dates in the corporate bond market. They estimate price drifts by aggregating panel data, and thus one cannot always exploit their findings in actual trading strategies. We verify bond PEAD using an approach that does not suffer from look-ahead bias and explore the potential explanations for this phenomenon.

We also contribute to the literature on the role of information and market structure on bond returns, which includes works by Wei and Zhou (2016), Berndt and Zhu (2019), and Ivashchenko (2019). In contrast to those papers, we focus on disagreement as the key mechanism behind price drifts.

As may be expected, this paper further contributes to previous research that documents PEAD in the stock market (e.g., Ball and Brown 1968; Bernard and Thomas 1989; Chordia and Shivakumar 2006) and studies its source. Proposed explanations vary across papers but include arbitrage risk (Mendenhall 2004), 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), liquidity (Bhushan 1994; Ng, Rusticus, and Verdi 2008; Chordia et al. 2009), and overconfidence (Luo, Subrahmanyam, and Titman 2020). We test these competing explanations comprehensively in the bond market and provide empirical evidence for disagreement as the key driver of PEAD.

Finally, this paper relates to the breadth of literature on the role of disagreement over asset prices (e.g., Diether, Malloy, and Scherbina 2002; Chen, Hong, and Stein 2002; Goetzmann and Massa 2005; Avramov et al. 2009; Banerjee 2011; Yu 2011; Xiong 2013; Carlin, Longstaff, and Matoba 2014; Atmaz and Basak 2018; Golez and Goyenko 2019; Cookson and Niessner 2020; Buraschi, Piatti, and Whelan 2021). These papers mostly focus on predicting stock returns using various disagreement proxies and document mixed evidence for the effects of investors' dispersion of beliefs on expected returns. In contrast, we focus on the corporate bond market and use disagreement to explain slow price reactions to earnings announcements.

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 explore alternative explanations for bond PEAD, analyze transaction costs, and compare bond PEAD to equity PEAD; and in Section 6, we offer 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 ratings, and time to maturity.

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

Using the collected and screened transaction data, we construct monthly bond returns as follows. First, to reduce potential market microstructure noise in bond returns, we follow Bessembinder et al. (2008) and calculate a bond's volume-weighted average price in a day to estimate the mid-price. We then employ it to construct monthly returns as

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

where P_{t+1} is the average price on the last day with non-zero transactions in the last five business days of month $t+1$, AI_t is accrued interest at the end of month $t+1$, and C_{t+1} is coupon paid in month $t+1$. For P_t, we first identify and use the last day with non-zero transactions in the last five business days of month t 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 of 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 a bid-ask bounce in transaction prices. Still, in the next section, we examine the fraction of bid transactions in calculating the average prices, and verify that a bid-ask bounce does not artificially generate this paper's main results.

To construct measures of disagreement and the disposition effect, we use institutional investors' bond holding data provided by eMAXX. This holding data covers U.S. insurance firms, mutual funds, pension funds, and other investors from 2002Q1 to 2020Q4, totaling 48% of our sample period's average ownership share. We also use institutional stock ownership data from the same period, as provided by Thomson Reuters and the original Securities and Exchange Commission's 13F filings. We obtain stock price and return data from CRSP and firm fundamentals from Compustat. Additionally, we obtain data on analysts' earnings forecasts from the Institutional Brokers Estimate System (I/B/E/S), using quarterly forecasts in unadjusted detailed files to measure forecast errors, and annual year-end forecasts to compute *DISP*. Following Livnat and Mendenhall (2006), we require an earnings announcement to have at least one analyst forecast, and as of the announcement quarter, the price per share must be available from Compustat and be greater than $1.

To confirm evidence outside of the corporate bond market, we obtain from Markit five-year CDS contracts for the U.S. dollar-denominated, senior unsecured debt of 929 U.S.-based corporate obligors from July 2002 to December 2020. We set this sample's beginning month to July 2002 so that they start at the same time as the corporate bond sample. We focus on on-the-run, five-year CDS contracts, given that they are the most liquid tenor.[1] We only use contracts that adopt modified restructuring documentation clauses before April 2009 (when the CDS Big Bang occurred) and those with no restructuring clauses afterward.

To correctly identify earnings announcement dates, we follow Dellavigna and Pollet (2009), comparing Compustat's and I/B/E/S's announcement dates and assigning the earlier date as the "correct" date. Following Johnson and So (2018), we eliminate stances in which Compustat's and I/B/E/S's announcement dates are more than two trading days apart from one another. If the announcement, based on I/B/E/S's time stamp, occurred after market close, we adjust the announcement date one trading day forward.

Using this data, we construct three measures of an earnings surprise. First, following Livnat and Mendenhall (2006), we calculate the difference between the announced earnings per share and the median of analyst forecasts 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 analysts who predicted lower (higher) earnings than what was announced, and N is the total number of forecasts. Lastly, we follow Frazzini (2006) and Brandt et al. (2008) and use cumulative abnormal stock returns (CAR) from day $d-1$ to $d+1$ surrounding earnings-announcement

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

date d as a measure of surprise.[2] The first two proxies directly measure the surprise in announced earnings per share relative to analyst forecasts, while CAR reflects the surprise in the overall announcement, including soft information (e.g., press releases and conference calls) disseminated by the firm relative to investors' expectations.

Table 1 reports summary statistics of the panel data on bond returns and characteristics. After filtering data and matching bonds to earnings announcements, we end up with 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%, a credit rating of BBB (which corresponds to a numerical value of 8.8), time to maturity of 9.8 years, an amount outstanding of $709 million, and 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 announcements. By studying the link between announcement-day bond returns and various proxies for earnings surprises, we aim to identify a valid measure for earnings surprises. If a proxy truly captures the earnings surprises that corporate bond investors experience, then bond returns should jump in response to the surprise.

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

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

where $R_{MKT,d-1\to d+1}$ is a return on corporate bond indices,[3] $Ctrl_{i,d}$ is a vector of control variables including time to maturity and numerical credit ratings, and FE_q is year-quarter fixed effects. We standardize the three earnings surprise measures to compare the economic significance of the bond market reactions they generate.

Table 2 reports the estimated slope coefficients, associated t-statistics, and adjusted R-squared of the regressions in (2). We find that corporate bond returns strongly react to all three measures of earnings surprises 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, respectively, in bond returns over a three-day

[2] To calculate abnormal returns, we use daily stock returns on 150 trading days up to $d-7$ and estimate factor exposures using the three-factor model of Fama and French (1993).

[3] 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.

window. Given that the standard deviation of three-day abnormal bond returns is 1.55%, these reactions are significant. This implies that bond investors update their valuation quickly in response to announced news, confirming Hotchkiss and Ronen (2002)'s results. Given the strong reactions to news, we are still far from confirming PEAD in the corporate bond market. However, these results do confirm that the surprise measures we use are valid proxies for news relevant to corporate bond investors and, thus, provide a foundation on which to study PEAD.

Columns 4 to 6 of Table 2 report the results of horse races that compare CAR, CE, and FOM in explaining contemporaneous bond returns. We find that, for bond investors, CAR is by far the strongest measure of earnings surprise; in the multivariate regressions 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 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. Thus, in the following analysis, we use CAR as our main measure of earnings surprises, and the other two measures for robustness testing.

2.3 Bond PEAD: Univariate Portfolio Sort

Now we turn to our first main empirical result, which is the existence of PEAD in the bond market. At the end of month t, we sort bonds into quintiles based on the latest available observation for announcement-day stock CAR. Then we take the value-weighted average across bonds in a given portfolio and calculate subsequent portfolio returns. For example, at the end of April 2019, we rank all bonds in terms of CAR on the latest earnings announcement dates, some of which may be as of February 2019 while others may be as of March or April 2019. Regardless of the announcement's exact timing, we rank all bonds and form portfolios at the end of April, and calculate portfolio returns in May.[4] This method avoids forward-looking biases in calculating portfolio returns and prevents the seasonality inherent to earnings announcements from affecting our sample size.[5] To value-weight bonds, we follow Bai, Bali, and Wen (2019) and use bonds' outstanding amounts as our portfolio weights.

Panel A of Table 3 reports the average value-weighted portfolio returns in excess of the

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

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

T-bill rate. 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. Due to the low volatility of the hedge portfolio, its annualized Sharpe ratio is high at 0.73, which is less than 1.02 of the corporate bond market portfolio over the same period, but higher than the stock market portfolio (0.64), term (0.55) and default (0.09) factors of Fama and French (1993). Thus, bonds with positive earnings surprises continue to earn higher returns than those with negative surprises. As mentioned before, the monthly returns used in our analysis are based on actual transactions rather than stale quotes; thus, evidence suggests that some investors implement a trade at a month-t price that is too low after positive news, and too high after negative news.

Panel B of Table 3 reports average bond characteristics for each portfolio. The average amount outstanding, credit rating, time to maturity, Roll measure of illiquidity ($ACOV$), and bond age are all similar between the lowest and highest quintiles, suggesting that we are capturing firm-specific news regarding 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 several sets of factors,

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

where F_t is the five bond factors of Bai, Bali, and Wen (2019) (i.e., including bond market, downside risk, credit risk, liquidity risk, and reversal factors), or the six stock factors of Fama and French (2018) (i.e., including stock market, size, value, investment, profitability and momentum factors). We also combine the two sets to create an 11-factor model. Given the availability of the factor data, the sample period for our results based on these bond factors starts in July 2004.

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. 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. The annualized Sharpe ratio also rises to 1.68 after adjusting for risk exposures.

The alphas reported in Table 3 show whether the bond PEAD strategy's profits come from its short or long leg. The 11-factor alpha of value-weighted portfolios is -0.14% for the lowest CAR quintile and 0.07% for the highest. These values suggest that the long leg of transactions contributes to roughly one-third of the profits while the short leg generates the remaining two-thirds. Thus, even though the drift is more pronounced after negative news, bond PEAD is not a simple reflection of short sale constraints within the bond market.[6]

In Table 4, we show that the bond PEAD effect exists both for IG and HY bonds as well as across various subsamples by maturity. 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, and the term and default factors in Figure 2, Panel A. These factors are scaled to have the same monthly volatility as the PEAD portfolio.[7] We find that cumulative returns on the PEAD strategy increase steadily over time. Furthermore, Panel B shows that the long-short portfolio effectively cancels out market exposure for each leg of the strategy. For example, the strategy avoids the market crash in 2008 and in early 2016 and grows strongly as the market recovers. In early 2020, there is a notable dip in cumulative returns, but this is not directly due to the pandemic-driven recession. In fact, the worst return in 2020 occurs in January at -0.98%, but later in March when the pandemic hit the market hardest, the return is positive at 0.44%. The correlation between the bond market portfolio and the PEAD hedge portfolio is -0.24. The low correlation between cumulative returns and the business cycle suggests that bond PEAD is not a reflection of omitted risk factors. Considering the high Sharpe ratio and the non-systematic nature of PEAD returns, a seemingly small premium from the bond PEAD strategy is economically significant.

Enhanced availability of information on market prices may reduce asset price drifts after announcement. To analyze the effect of the information environment on PEAD , we must compare 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 increased transparency on price drifts. However, in Internet Appendix A, we study an extended sample that covers the period 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 the alphas from the bond PEAD strategy are approximately the same as our main results using TRACE and that the bond PEAD is not more pronounced in the earlier sample than

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

[7] 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.

in the latter. Therefore, a better information environment does not reduce bond PEAD. Furthermore, the quote data does not suffer from missing observations on no-trade dates and thus the existence of the bond PEAD effect in both samples bolsters our main findings.

To check if PEAD is an artifact of market microstructure noise in our data, we calculate the fraction of the dollar bid (i.e., dealer buys) volume relative to the total volume on a given 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 in which dealers buy dominate those in which dealers sell, and higher than the true mid-price if dealer sells dominate. Thus, if the fraction of bids in month-t's price or month-$(t+1)$'s price is 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. In Table 3 Panel B, the fraction of bids for P_t is 36.07% for the first quintile and 35.96% for the fifth quintile. Thus, the observed return difference among the portfolios is unlikely to be generated by a bid-ask bounce. Below, we further verify this finding using a Fama-MacBeth regression that includes the fraction of bids as control variables.

Although we lack data on which investors set prices at the "wrong" level after an announcement, 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 news. However, Panel B shows that the fraction of bids (i.e., customer sells) is the same across all quintiles, suggesting that the average institutional investor does not trade to profit from price drifts.

Lastly, we test if bond PEAD exists with alternative measures of earnings surprises, including three-day abnormal bond returns around earnings announcement (i.e., bond CAR), *CE*, and *FOM*, and verify our main results. Panel C of Table 3 reports the 11-factor alphas on value-weighted bond portfolios sorted by 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), and 10 bps using *FOM* (t = 1.82). Thus, bond prices exhibit PEAD regardless of the earning-surprise measure employed, though *FOM* is significant only at the 10% level. Akey, Gregoire, and Martineau (2021) show that stock CAR responds to soft information contained in press releases distributed upon announcement as well as the headline numbers. In addition, there is arguably more room for disagreement over the interpretation of soft information than earnings per share. This explains why bond prices exhibit greater drift after announcement using stock CAR than *CE* and *FOM*, which are both based on hard information. We also find that bond PEAD using bond CAR as the earnings-surprise measure is even more pronounced 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 must limit the sample to bonds that trade two days before and a day after the announcement. Since it provides wider coverage of bonds, we use stock *CAR* to earn our main results.

2.4 Comparing Earnings Announcements Against Other News

To assess the uniqueness of earnings announcements, we compare earnings surprises against other forms of market news. To this end, we reference changes in bonds' credit ratings and more general news reflected in past stock returns. Gebhardt, Hvidkjaer, and Swaminathan (2005) find that previous six-month equity returns predict bond returns in the month that follows, and interpret this finding as the bond market underreacting to news. Thus, we contrast the performance of our earnings announcement measure (i.e., stock returns on earnings announcement dates) with stock returns on non-announcement days.

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

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

where $News_{i,t}$ includes our earnings surprise measure (i.e., *CAR*), dummy variables for changes in credit ratings in the previous three months (one dummy for upgrade and another for downgrade),[8] equity momentum (i.e., cumulative market-adjusted equity returns from month $t-5$ to t), and cumulative market-adjusted three-day equity returns on non-announcement days that are randomly selected from the previous six months (*NoAnnCar*) conditional on the absolute value of the return being above 2.07 times as high as its volatility. We establish a cutoff of 2.07 as the ratio of the volatility of three-day announcement returns to the overall three-day return volatility. With this cutoff, we select dates with non-trivial news other than earnings announcements. For the equity momentum variable, we construct two versions including and excluding earnings announcement returns, denoted as *SRet6mAll* and *SRet6m* respectively. We subtract returns on the stock market portfolio over the corresponding period from those to obtain market-adjusted stock returns. The set of control variables is comprised of amount outstanding, credit rating, time to maturity, downside risks,

[8] 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.

the Roll measure of illiquidity, past short-term and medium-term bond returns (in month t and from months $t-11$ to $t-1$), bond and stock return volatility, the fraction of bids in month t and $t+1$ prices, and industry-fixed effects defined by Fama and French's 30 industry classifications. Leaving aside dummy variables, we winsorize the right-hand-side variables at the 1% level and standardize them for ease of interpretation.

Table 5 reports the estimated average slope coefficients from the Fama-MacBeth regression in (4). For brevity, we report the estimates for the control variables in Internet Appendix Table A2. Before comparing earnings surprises with other forms of news, we assess the bond PEAD in the regression setup. When used independently (Column 1), a one-standard-deviation increase in *CAR* predicts a 6.9 bps ($t = 3.30$) increase in bond returns in the following 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 the difference in risks associated with the bonds or measurement errors in the data.

Turning to other forms of news, the coefficient for *SRet6m* is 12 bps (Column 3), indicating that the equity momentum predicts bond returns even after being restricted to non-announcement days. To see the role of earnings announcements on an equal footing, we use three-day abnormal stock returns on non-announcement days (i.e., *NoAnnCar*) as another regressor. As reported in Column 4, the loading on *NoAnnCar* is close to zero and statistically insignificant. The point estimate is smaller than what it is for the past six-month returns, but earnings announcements are, indeed, special in predicting bond returns in the month that follows.

As another reference point, regressions in Column 5 include dummies for upgrades or downgrades in credit ratings. We find that the loading on the upgrade dummy is close to zero while the loading on the downgrade dummy is -12.3 bps ($t = -2.07$). The significantly negative loading on the downgrade dummy suggests that a bond price tends to underreact to negative rating changes. The degree of underreaction is similar to a two-standard-deviation change in earnings surprises.

We next run horse races among these news variables in generating drifts in bond prices. The regression reported in Column 6 includes *CAR*, *SRet6m*, other news measures, and control variables. The estimated slope coefficient for earnings surprises is roughly unchanged at 7 bps, even after controlling for a host of other news variables including *SRet6m* and bond momentum. *CAR*'s predictive power 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). Finally, in Column 7, we replace *SRet6m* with

SRet6mAll. The slope estimate for *CAR* is then 3.7 bps ($t = 2.61$), which is significant even after controlling for equity momentum that include announcement-date returns. In Internet Appendix Table A3, we report that median analyst forecast error (*CE*) also significantly predicts bond returns after controlling for equity momentum and other bond characteristics; meanwhile, *FOM* loses its significance. Overall, our findings are consistent with Chan, Jegadeesh, and Lakonishok (1996), who show that, in the stock market, momentum and PEAD carry independent information. We also confirm that earnings surprises are unique and carry information that predicts bond returns above and beyond other forms of market news reflected in the momentum variables.

3 Disagreement and Liquidity as Potential Sources of Bond PEAD

We have presented novel, empirical evidence for bond prices exhibiting slow reactions to earnings announcements. In this section, we dissect the source of bond PEAD. It is intuitive to conjecture that illiquidity (e.g., dealers' inventory frictions, infrequent transactions of corporate bonds, and the over-the-counter market structure) not only prevents arbitragers from arbitraging away price drifts but is also the *origin* of slow price movements. Surely, if investors trade infrequently, information travels just as slowly and this must give rise to price drifts. However, is this intuition really correct? We first test this theory using the data. We then turn to an alternative explanation for bond PEAD: investors' disagreement over bond values.

3.1 Liquidity

To test the intuition that 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. As 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 posited by Feldhütter (2010); average daily turnover rates (i.e., daily trading volume divided by the bond's amount outstanding, averaged within a month); and the fraction of no trading days in a month. We convert the turnover rate by adding a negative sign, so all variables measure illiquidity (rather than liquidity). Furthermore, we create a composite measure by sorting bonds into ten buckets each month based on each of the six proxies from most to least liquid and calculate the average of the ranks. By averaging the rankings, we normalize these measures and create an aggregate illiquidity index.

Table 6 reports the 11-factor alphas on 25 value-weighted portfolios sorted by CAR and each of the seven illiquidity measures. For brevity, we only report the difference between high CAR and low CAR quintiles for each illiquidity quintile. The table shows that the relationship between PEAD profit and illiquidity is mixed. The Amihud measure, the Roll measure, turnover rates, and the fraction of zero trading days all indicate that more liquid bonds earn higher PEAD profits than less liquid bonds. However, bid-ask spreads and imputed round-trip costs suggest that more liquid bonds earn lower PEAD profits than less liquid bonds. Only bid-ask spreads, turnover rates, and the fraction of zero trading days are statistically significant. The composite illiquidity index, which averages these six proxies, is weakly negatively associated with PEAD profits. Thus, 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 do. For example, bonds with the highest turnover (i.e., lowest illiquidity, Q1) generate 0.30% under the PEAD strategy while those with the lowest turnover (i.e., highest illiquidity, Q5) earn 0.14%. Furthermore, in Section 3.2, we show that the effect of bid-ask spreads disappears once we control for disagreement. Therefore, the evidence thus far does not support the hypothesis that illiquidity generates corporate bond PEAD.

Still, these initial findings rely on proxies for illiquidity, which may or may not be accurately capturing true states. To bolster our argument, we examine CDS and study whether PEAD exists or not. As Oehmke and Zawadowski (2016) point out, CDS contracts are more standardized than corporate bonds and, thus, are likely to be more liquid. If illiquidity in corporate bonds is the cause of slow price movements, then we should not expect PEAD to exist in the CDS market. With this in mind, we examine five-year, on-the-run, single-name CDS contracts and estimate the trading profits of a strategy that sells CDS protection according to past earnings surprises.

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

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

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 the $(T-t)$-year risk-free rate; and $\mathcal{R}$ is a recovery rate.[9] An excess return on a strategy to sell protection in month t and unwind the position in $t+1$ is

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

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

Using CDS returns in (6), we form quintile portfolios of firms based on their latest earnings surprises and calculate the value-weighted excess returns, where the weights are given by a firm's stock market capitalization. Additionally, we regress the portfolio excess returns on the set of factors and estimate alphas. These results are reported in Panel A of Table 7.

We find that, consistent with our findings for corporate bonds, CDS contracts exhibit PEAD. 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 an average return difference of 0.07% (t = 3.61). Since CDS returns are less volatile than corporate bond returns, even this 7 bps difference in average excess returns translates 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.[10]

Since the calculation of CDS returns involves some approximation, we also check out the results using differences in the natural logarithms of CDS spreads in place of CDS returns. The advantage of employing changes in CDS spreads is in their simplicity and transparency, though they have the drawback of being unable to capture the investment value for CDS investors. In Panel B, we replace CDS returns in Panel A with changes in log credit spreads and repeat the exercise. Since an increase in CDS spreads reduces a return for CDS protection sellers, the sign of the difference between the high and low earnings-surprise quintiles reverses: In Panel B, 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 those results using CDS and corporate bond

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

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

returns.

Overall, we observe strong evidence for PEAD in CDS despite its higher liquidity. These findings suggest that we must take a step deeper to explore the cause of bond PEAD.

3.2 Empirical Evidence for Disagreement

As an alternative explanation to illiquidity, we empirically study whether PEAD is more pronounced for bonds when investors disagree more strongly over their values. Since we do not directly observe disagreement, we construct proxies that capture the variation in investor beliefs on bond values.

More specifically, we use three proxies for disagreement. First, we construct the analysts' forecast dispersion, *DISP*, which is the standard deviation of each firm's annual analyst earnings forecasts scaled by the average stock price, as proposed by Diether, Malloy, and Scherbina (2002).[11] This measure of disagreement reflects equity analysts' opinions on a firm's profit in the coming year and incorporates revisions following the release of said firm's quarterly earnings. To calculate downside risk, we also created a disagreement proxy using only below-median analyst forecasts, but the results were similar to the overall dispersion in the forecast. As such, we only use *DISP* in the following analysis.

To measure bond investors' disagreement more directly, we construct our own measures using institutional investors' bond holdings and examine how they differ from one another. By focusing on bond holdings, we aim to capture disagreement over the longer-term prospects of the bond. To this end, we calculate the coefficient of variation in portfolio weights across investors for borrower k as

$$CV_{k,q} = \frac{\sigma_{k,q}[w_{k,j,q}]}{E_{k,q}[w_{k,j,q}]}, \tag{7}$$

where $w_{k,j,q}$ is investor j's portfolio weights on bonds issued by firm k in quarter q. To measure disagreement using bond holdings, we focus on portfolio weights rather than the dollar value of bond holdings because the dollar value will be affected by variations in investor size. We then scale the 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

[11] We use the annual year-end analyst forecast and remove excluded and stopped estimates. To alleviate the staleness of forecasts, analyst forecasts for a given firm-year pair are carried forward until either the date of the same firm-year pair's consecutive estimate release by the same analyst or the date that is 105 days ahead of the earnings announcement date, whichever comes sooner. The decision to carry the forecast forward for up to 105 days aligns with I/B/E/S rules: If an estimate has not been updated for 105 days, it is supposed to be filtered, footnoted, and excluded from the consensus calculation. We scale the standard deviation using the average price in months $t-1$ and t.

weights are equalized, leading to $CV = 0$. In reality, CV is generally not zero because investors deviate from the market portfolio.[12]

Lastly, we use another proxy for disagreement based on bond prices. Becker and Ivashina (2015) and Choi and Kronlund (2017) report compelling evidence of bond institutional investors' reaching-for-yield behavior. Some insurance firms and bond mutual funds tilt their portfolios toward bonds with higher yields relative to other bonds with the same rating. On the other hand, because these bonds have higher yields, other investors must correctly anticipate rare, tail events that may occur when their marginal utility is high, and their view is reflected in the bond's low price. This observation implies that bonds with yields higher than the benchmark are subject to greater disagreement regarding their values between optimists (i.e., those who tilt their portfolio toward those bonds) and pessimists (i.e., those who recognize the possibility of tail events). Thus, we use the difference between bond yields and the average yield of bonds with the same credit rating (RFY) as the third measure of disagreement.

Prepared with the proxies for disagreement, we now study the driver behind bond PEAD. Specifically, every month, we independently double-sort bonds into 25 value-weighted portfolios based on earnings surprises (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 set of main results, which are the bond PEAD strategy's 11-factor alphas per disagreement quintile. In Panel A, we use $DISP$ as a measure of disagreement and find that bonds with higher disagreement generate greater alphas under the bond PEAD strategy than those with low disagreement. Specifically, the strategy earns

[12] As suggested by Goetzmann and Massa (2005) and Cookson and Niessner (2020), the difference in portfolio weights may reflect investors' investment style rather than their 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,

$$w_{k,j,q} = b_0 + b_1 AvgRating_{j,q} + b_2 AvgMaturity_{j,q} + b_3 AvgIlliq_{j,q} + u_{k,j,q}, \tag{8}$$

where Avg denotes the average of characteristics across bonds held by investor j. By averaging across bonds, the right-hand-side variables in (8) 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 in the form of

$$CV2_{k,q} = \frac{\sigma_{k,q}[u_{k,j,q}]}{E_{k,q}[w_{k,j,q}]}. \tag{9}$$

We report results using this alternative measure in Internet Appendix, Tables A4 and A6, and confirm that findings are similar.

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 included in each *DISP* quintile. We find that *DISP* is positively correlated with the daily turnover rate (i.e., transaction volume scaled by the amount outstanding) on the earnings announcement date ($d = 0$) and in the announcement month (month $t = 0$). For instance, the average turnover on the announcement date is 0.48% for the lowest *DISP* quintile and 1.14% for the highest quintile. This finding is important in that a key feature of disagreement models is their 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 a bond, which leads to greater transaction volumes.

Examining 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. Additionally, we find that bonds with high *DISP* tend to have lower credit quality, higher downside risk, and higher illiquidity than low-*DISP* bonds do. Although the 11-factor model should have captured risk exposures associated with these characteristics, in the analysis below, we directly control for them 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 obtain a similar pattern in PEAD profits when we use reaching-for-yield as a disagreement measure. Notably, when we measure disagreement using RFY, the average credit rating for bonds in the high and low disagreement quintiles is approximately the same. This suggests that the difference in alpha is not driven by variation in credit quality. In sum, though our disagreement proxies are derived from differing data sets (one from analysts' forecast, 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 and higher transaction volume.

To separate the effect of disagreement from other potentially confounding characteristics of bond returns, we run the Fama and MacBeth (1973) regression of bond excess returns on earnings surprises (i.e., CAR), disagreement, and their interactions,

$$R^e_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}CAR_{i,t} + \gamma_{2,t}Disagreement_{i,t} + \gamma_{3,t}CAR_{i,t} \cdot Disagreement_{i,t} + \lambda_t Ctrl_{i,t} + \eta_{i,t+1}, \tag{10}$$

where *Disagreement* is a measure of disagreement (i.e., *DISP*, CV or RFY); and $Ctrl_{i,t}$ is a vector of control variables, including bonds' amount outstanding, credit rating, time to maturity, downside risk, illiquidity, past one-month bond returns, bond momentum (i.e., cumulative eleven-month returns from month $t-11$ to $t-1$), bond return volatility, stock return volatility, fractions of bids in month t and $t+1$ prices, and industry fixed effects.

Table 9 reports the time-series average of the estimated slope coefficients on *Disagreement* and CAR in (10). The estimates on the control variables are relegated to Internet Appendix, Table A5. In Column 1, we report 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; thus, the effect of bond PEAD increases nearly 50% if a bond experiences a one-standard-deviation increase in *DISP*. In Columns 3 and 4, the interaction term between CAR and other disagreement measures is also significantly positive, suggesting that bond PEAD strengthens with disagreement even after controlling for bond characteristics such as a bond's size, credit rating, maturity, and illiquidity. To bolster this finding, we present the results of triple-sorted portfolios on each of the eight bond characteristics, the disagreement proxies, and CAR in Internet Appendix C and Table A7. We find that, even when bond characteristics are held constant, changes in the disagreement proxies generate significant variation in PEAD profits. In contrast, when we control for the disagreement proxies, the bid-ask spreads do not generate significant variations in PEAD profits. Thus, regardless of the statistical methods we employ, the disagreement effect is not subsumed by other bond characteristics.

Although the statistical results for the role of disagreement are robust, the interpretation of the evidence presented above may appear insufficient for two reasons: First, the disagreement proxies used in the analysis may be affected by other frictions and biases. For example, information asymmetry among analysts can create forecast dispersion while investors' preferences (e.g., preference for green bonds) can create variation in portfolio weights. We argue, however, that these proxies are at least partially driven by disagreement because of their ability to explain trading volume. If, instead, they are driven by other frictions, why these proxies are positively related to the bonds' turnover rate remains unclear. Furthermore, if information asymmetry generates PEAD, then we should see a decline in the profitability of the PEAD strategy over time as investors learn from each other – this should be true especially after the introduction of TRACE. However, the evidence in Figure 2 does not support this argument.

The second concern is that our disagreement proxies are correlated with other risk characteristics, for which the statistical procedures employed above (factor-risk adjustment, multivariate regression, and triple conditional sort) may have failed to fully account. We argue that this is a feature, rather than a bug, of the hypothesis that disagreement generates PEAD. Hong and Sraer (2013) show that the disagreement over bond value is negatively related to the underlying firm value. When firm value is low and the firm is close to default, its bond becomes sensitive to the underlying value, translating a given level of disagreement over firms' assets into a greater bond-level disagreement. Therefore, disagreement over bonds *must* be positively correlated with other measures of bonds' risk. This link also explains why the PEAD profits are larger for HY bonds than for IG bonds in Table 4. However, the risk per se is unlikely to explain why the trading volume is higher[13] while disagreement can explain both price and quantity simultaneously.

Finally, since the past six-month stock returns (*SRet6m*) also predict bond returns independent of bond PEAD, we use it as an alternative testing ground for our hypothesis that disagreement generates slow price movements. To this end, we replace CAR in regression (10) with *SRet6m* and study the interaction between it and our disagreement proxies. Table 10 reports the estimates for the regression: The interaction term between equity momentum and the three disagreement measures turns out to all be positive and significantly different from zero. These findings suggest that disagreement not only generates bond PEAD but also affects the bond market's underreaction to news unrelated to earnings announcements, lending support to our hypothesis on the mechanism driving slow bond price movements.

4 A Stylized Model of Disagreement and PEAD

Thus far, we have documented that investor disagreement, rather than illiquidity, is likely to drive bond PEAD. In this section, we present a stylized model to formalize the underlying mechanism that disagreement leads to bond PEAD and offer a unified explanation for the documented evidence. To transparently illustrate how the disagreement mechanism

[13]Consistent with our argument, Hong and Stein (2007) remarked "In conventional rational asset-pricing models with common priors (...) the volume of trade is approximately pinned down by the unanticipated liquidity and portfolio rebalancing needs of investors. However, these motives would seem to be far too small to account for the tens of trillions of dollars of trade observed in the real world".

functions, we intentionally keep our model stylized, abstracting away institutional details in the corporate bond market, such as dealer intermediation, dealer inventory costs, and asymmetric bond payoffs.

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. A continuum of investors, indexed by $i \in [0, 1]$, 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 $\tilde{u} \sim N(0, \sigma_u^2)$, $\sigma_u^2 \in (0, +\infty)$, and $\tilde{u}$ is independent of all other random variables in the economy. For instance, noisy demand can arise when investors suffer from a liquidity shock (e.g., fire sales driven by idiosyncratic fund flows, regulatory constraints, and inventory frictions) and must trade the risky asset to hedge that shock.

At the beginning of date 1, a firm announces its earnings 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 develops her own interpretation and produces the following private signal regarding the firm's fundamentals:[14]

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

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

We follow Banerjee, Kaniel, and Kremer (2009) to model investors' difference of opinions as follows. Investors agree to disagree, and each investor conditions *only* on her private signal $\tilde{s}_i$ to update her beliefs regarding the firm's fundamentals and trades accordingly. This notion of disagreement is standard in the literature (e.g., Harrison and Kreps 1978).

[14]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.

4.2 Price Drift, Trading Volume, Disagreement, and Illiquidity

We now characterize the equilibrium in the economy and seek empirical predictions based on the relationship between return-volume characteristics and investor disagreement, which we can 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 preceding the firm's earnings announcement. Since all investors are ex-ante identical and have a prior of zero for the risky asset's value, $\tilde{p}_0 = 0$ is the price that will prevail if investors trade at $t = 0$. Our focus is on date-1's asset price since all meaningful interactions happen on the earnings-announcement date. 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 $\tilde{p}_1 = \frac{\tau_\varepsilon\tau_\eta(\tilde{v}+\tilde{\eta})+\gamma(\tau_\varepsilon+\tau_\eta)\tilde{u}-\gamma(\tau_\varepsilon+\tau_\eta)}{\tau_\varepsilon\tau_\eta+\tau_v(\tau_\varepsilon+\tau_\eta)}$. As expected, the asset price on date 1 aggregates all the dispersed opinions among investors and also contains noise.

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.[15] 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 their investment decisions, which corresponds to our tradable investment strategy in the empirical design. We can express k as follows:[16]

$$k = \underbrace{-\frac{\gamma^2\tau_v(\tau_\varepsilon+\tau_\eta)^2\sigma_u^2}{\tau_\varepsilon^2\tau_\eta(\tau_v+\tau_\eta)+\gamma^2\sigma_u^2\tau_v(\tau_\varepsilon+\tau_\eta)^2}}_{\text{Noise trading}} + \underbrace{\frac{\tau_v\tau_\varepsilon\tau_\eta^2}{\tau_\varepsilon^2\tau_\eta(\tau_v+\tau_\eta)+\gamma^2\sigma_u^2\tau_v(\tau_\varepsilon+\tau_\eta)^2}}_{\text{Disagreement}}. \tag{11}$$

As shown by equation (11), two forces determine whether or not prices exhibit drift. First, as common in information-based models (e.g., Grossman and Stiglitz 1980; Kyle 1985; Grossman and Miller 1988), noise induces negative correlations 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, in turn, leads to price rever-

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

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

sals. Moreover, the more volatile the noisy demand (i.e., high σ_u^2), the more likely the price reversals. Second, prices tend to drift when investors have differences in opinions. That is, each investor sticks to her own interpretation of a public announcement and believes that no other investor holds information of any incremental value to her private signal. As a result, investors place more weight on their individual, private signal and less on the information held by others, which is reflected in the price. Information is then slowly incorporated into prices, giving rise to a price drift. Taken together, when noise trading is low, the latter effect prevails, and prices can drift. That is, $k > 0$ when $\sigma_u^2 < \hat{\sigma}_u^2 \equiv \frac{\tau_\varepsilon \tau_\eta^2}{\gamma^2(\tau_\varepsilon+\tau_\eta)^2}$. And, the lower the noise trading, the more likely to observe the price drift. The following summarizes this finding's implication in the PEAD setting (note that all proofs are relegated to Internet Appendix D):

Implication 1 *It is likely to observe PEAD when the variance of noise trading is low (i.e., $\sigma_u^2 < \hat{\sigma}_u^2$).*

Implication 1 follows from equation (11), which shows that all else equal, it is more likely to observe price drifts when the variance of noise trading (σ_u^2) is lower. This suggests a unified explanation for the existence of bond PEAD and the weak existence of stock PEAD, as will be shown in Section 5.4. Noise trading in the bond market is low since bond investors tend to buy and hold. Choi et al. (2020) find no evidence of fire sales by corporate bond mutual funds, which is the second-largest class of bond investors; meanwhile, equity mutual funds fire sell their holdings. Furthermore, we estimate the noise trading intensity (σ_u^2) for bonds in Internet Appendix E and show that it is indeed lower than the previous estimates in the equity market. Therefore, to the extent that disagreement drives slow price reactions in both the bond and stock markets, bond PEAD is more likely to arise. Moreover, Luo, Subrahmanyam, and Titman (2020) interpret the recent rise of quantitative investors in the stock market as an increase in the variance of noise trading and argue that this trend leads to the attenuation and even reversal of momentum profits. Consistent with this argument, our framework shows that the increasing noise trading in the stock market implies a decreasing likelihood of stock PEAD. Overall, in addition to the cost of arbitrage argument, this difference in noise trading between the two markets helps explain why stock PEAD decays over time but bond PEAD persists.

Next, we derive expressions for trading volume, disagreement, and illiquidity, and develop testable, empirical predictions for our explanation on disagreement. Following Vives (2010), we measure trading volume at $t = 1$ as the expected aggregate volume traded by informed investors

$$TV \equiv E\left[\int_0^1 |x_i| di\right]. \tag{12}$$

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

$$DISP \equiv Var\left[E\left[\tilde{v}|\tilde{s}_i\right] - \int_0^1 E\left[\tilde{v}|\tilde{s}_i\right] di\right], \tag{13}$$

which proxies our measures for disagreement. Following Vives (2010) and Goldstein and Yang (2017), we define illiquidity as follows:

$$ILLIQ \equiv \frac{\partial \tilde{p}_1}{\partial \tilde{u}}. \tag{14}$$

This measure is often referred to as Kyle's (1985) lambda: a higher $ILLIQ$ means that liquidity trading $\tilde{u}$ has a larger price impact, and thus the market is less liquid. It captures the ease of selling an asset in the market, which can be proxied by our composite illiquidity index that aggregates various illiquidity measures. If we take it literally, the closest proxy to the measure in our empirical setting is the Amihud measure.

To derive testable implications, we follow Banerjee (2011) to conduct comparative statics of each observable variable with respect to the precision of investors' private information τ_ε and then develop empirical predictions based on the observable variables. We also focus on the parameter region where both σ_u^2 and τ_ε are low.[17] Low σ_u^2 enables us to observe price drifts, as shown in Implication 1, and low τ_ε implies that investors' realized information significantly differs among each individual so that our disagreement mechanism is highlighted.

First, an examination of the magnitude of price drift (11), trading volume (12), and disagreement (13) shows that, as the precision τ_ε of investors' private information increases, investors disagree more, trading volume increases, and price drift becomes more pronounced; that is, $DISP$, TV, and k move in the same direction. Panels (a) through (c) of Figure 3 graphically illustrate these patterns. The intuition is as follows. Recall that private information is the source of disagreement among investors. When investors' private information becomes more precise, they place more weight on it to update their beliefs regarding the asset value, thereby creating more investor disagreement. The more pronounced the disagreement

[17]On the other hand, τ_ε cannot be too close to zero; otherwise, investors' private information becomes pure noise.

generated, the more trading activity that takes place amongst investors, which increases the trading volume. Furthermore, as investor valuations become increasingly dispersed, prices drift more significantly; this is because with more precise private information, investors gain confidence in their individual, private interpretations and further neglect to draw inferences from the trades of others. As a result, prices react more slowly to aggregate investor opinions. The following implication summarizes this key, testable, empirical prediction and it is corroborated by the results in Section 3.2:

Implication 2 (Price drift, disagreement, and trading volume) *Consider two assets that differ only in the precision level of investors' private information τ_ε and both σ_u^2 and τ_ε are low (i.e., $\sigma_u^2 < \bar{\sigma}_u^2$ and $\tau_\varepsilon < \bar{\tau}_\varepsilon$, where $\bar{\sigma}_u^2$ and $\bar{\tau}_\varepsilon$ are given by (B6) and (B7), respectively). The asset that generates more investor disagreement has a higher trading volume and a stronger price drift.*

Second, we explore the relationship between market illiquidity and price drift under the disagreement framework. We find that, while the price drift becomes more significant as the precision τ_ε of investors' private information increases, market illiquidity decreases; see Panel (d) of Figure 3. In other words, the magnitude of the price drift can be negatively associated with illiquidity (i.e., k and $ILLIQ$ move in the opposite direction). The following summarizes this implication:

Implication 3 (Price drift and illiquidity) *Consider two assets that differ only in the precision level of investors' private information τ_ε and both σ_u^2 and τ_ε are low (i.e., $\sigma_u^2 < \bar{\sigma}_u^2$ and $\tau_\varepsilon < \bar{\tau}_\varepsilon$, where $\bar{\sigma}_u^2$ and $\bar{\tau}_\varepsilon$ are given by (B6) and (B7), respectively). The asset with lower illiquidity generates a stronger price drift.*

This result seems surprising, given that typical explanations of illiquidity suggest that PEAD should concentrate in illiquid assets (e.g., Chordia et al., 2009). How can we generate the opposite prediction under the disagreement framework? To the extent that disagreement drives PEAD, only when the asset is liquid can investors fully express their differing opinions through trade, thereby leading to the slow aggregation of information into prices. As such, a more pronounced price drift can be associated with higher liquidity. The empirical result in Section 3.1 provides suggestive evidence for this implication: The composite illiquidity index and the Amihud measure are weakly negatively associated with PEAD profits in Table 6.

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 strategy for real-time investors who pay costs to implement transactions. Finally, we revisit PEAD in the equity market.

5.1 Limited Attention

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

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

The second idea is to examine investors' news searching and reading activities. If investors search for and read certain information on firms, then we interpret this action as investors paying attention to the news. To this end, we follow Ben-Rephael, Da, and Israelsen (2017) and construct two measures related to abnormal institutional investor attention (AIA) using news readership scores downloaded from the Bloomberg terminal. AIA is a dummy variable that equals one if Bloomberg's readership score is 3 or 4,[18] and zero otherwise; meanwhile,

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

$AIAC$ is a continuous value transformed from Bloomberg's raw readership scores using the conditional means of truncated normal distribution.[19] A greater value of those variables means that investors are paying more attention to a firm's news on its earnings announcement date.

In Table 11, we run a Fama-MacBeth regression of monthly returns on earnings announcement CAR and its interaction with inattention measures. We find that the average slope coefficients on the interaction terms are economically small relative to the coefficients on CAR and statistically insignificant, aside from the number of competing announcements, which has a t-statistic of 1.69. The insignificant loading on the interaction between earnings surprises and AIA is particularly important since AIA measures the attention of institutional investors who are dominant in the bond market. Thus, we do not find compelling evidence for inattention in generating 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 the psychological bias of wanting not to sell securities at a loss but, instead, wanting to sell securities that have appreciated in value since their purchase. In other words, if a bond is held with a capital gain, then the holder is more likely to sell it, which prevents good news from being quickly impounded into the price. In contrast, if an investor carries a bond at a loss, then she is less likely to sell the bond, which prevents negative news from being reflected in the price. Consistent with this hypothesis, Frazzini (2006) finds that stocks that have higher earnings surprises and higher capital gains earn higher returns than stocks that have lower earnings surprises and lower capital gains.

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

$$RP_{i,q} = \frac{1}{\bar{V}} \sum_{n=0}^{q} V_{i,q,q-n} P_{i,q-n}, \tag{15}$$

where $V_{q,q-n}$ is the face value of bond i purchased in quarter $q-n$ and still held in quarter

96% of the distribution over the previous 30 days.

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

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

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

$$CGO_{i,q} = \frac{P_{i,q} - RP_{i,q}}{P_{i,q}}. \tag{16}$$

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

Using the CGO measure, we double-sort bonds every month based on the latest available values of the earnings surprises and $CGO_{i,q}$, and form 25 value-weighted portfolios. Table 12 reports each portfolio's 11-factor alphas. If the disposition effect explains bond PEAD, we expect significantly negative alphas for bonds with the lowest earnings surprises and lowest CGO. However, in the data, the 11-factor alpha is -3 bps with a t-statistic of -0.25. Furthermore, despite the disposition effect predicting positive alphas, the alpha for the highest earnings surprise quintile with the highest CGO is -8 bps. Thus, we do not find evidence supporting the disposition effect as the primary driver behind bond PEAD.

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 PEAD even after transaction costs. The answer to this question depends on if the signal is persistent, as well as on the size of profits relative to bonds' bid-ask spreads.

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

$$\text{half spread}_{i,d} = \frac{Sell_{i,d} - Buy_{i,d}}{Sell_{i,d} + Buy_{i,d}}, \tag{17}$$

where $Sell_{i,d}$ is the volume-weighted average price at which a dealer sells to a customer (i.e., ask), and $Buy_{i,d}$ is the volume-weighted average price at which a dealer buys from a customer (i.e., bid). In calculating half spreads, we only use transactions with volumes no less than \$100,000 (the cutoff value set following Bessembinder et al. 2008), and thus the estimated transaction costs are for institutional investors rather than retail investors. If the dealer sells and buys do not occur on the same day, we treat observations on the day as missing. Monthly half spreads are the simple average of daily half spreads in a month. We take the average of half spreads across bonds in each CAR-quintile in a month and assign the portfolio-level spreads to all bonds that belong to a given portfolio.

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

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

One of the reasons why profits do not survive after transaction costs is the high portfolio turnover rate that this trading strategy demands. 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 profits under the PEAD strategy. We follow Jegadeesh and Titman (1993) to buy and hold value-weighted portfolios for K month, and record their monthly returns. We then take the simple average of monthly returns across portfolios formed in months $t, \ldots, t-K+1$, and obtain returns on the quintile portfolios. Table 14 reports the strategy's average excess returns and 11-factor alphas. The profits of a bond PEAD strategy decay significantly within a year: For example, when the holding period is six months, the average excess returns and 11-factor alphas are 7 bps and 10 bps, respectively, which are approximately half of the main results where $K = 1$. Although our signal is updated quarterly, there is some predictability in returns beyond $K = 3$. However, the relatively fast decay in profits suggests that it is difficult to profit from a simple PEAD strategy with a lower rebalancing frequency.

Since the results in Section 3.2 suggest that 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 a composite measure of disagreement (*CDIS*) by taking the average of rankings in *DISP*, *CV*, and *RFY*, and double sort bonds into 25 portfolios based on earnings surprises and the composite disagreement index. In Panel C, Table 13, we show that for bonds in the highest disagreement quintile, the 11-factor alpha 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 a univariate PEAD strategy, it is possible to earn net profits by focusing on bonds over which investors disagree the most. This finding confirms the economic significance of bond PEAD for real-time investors.

5.4 Equity PEAD

To contrast with 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. More specifically, for every month, we sort firms based on their latest earnings surprises to form five equal- and value-weighted portfolios of stocks. We then calculate the hedge returns for a strategy that goes long on firms in the top earnings surprise quintile and short on firms in the bottom quintile. Finally, we regress those returns on the six stock factors of Fama and French (2018) and estimate the regression intercepts. Panel A of Table 15 reports the estimated alphas of the stock PEAD strategy for bond issuers. Under the sample period matched to that of bonds (i.e., 2002 to 2020), we find that 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*, respectively, as measures of earnings surprises. 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. 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 (i.e., those below the 20th percentile). When we instead use stocks of all firms and repeat the exercise, the alphas on stock PEAD strategies increase. As shown in Panel B of Table 15, most of the alphas on value- and equal-weighted portfolios are significant from 2002 to 2020 and are larger for equal-weighted portfolios than for value-weighted portfolios. This finding shows that the PEAD strategy is profitable using small firms rather than large firms to which most bond issuers belong.

Second, as Martineau (2021) points out, stock PEAD's profitability decays over time as high-frequency traders participate in the stock market and arbitrage away mispricing. In Panel C of Table 15, we repeat the same exercise using all firms in the sample period from 1984 to 2001. We find that, regardless of earnings surprise measures, evidence of PEAD during this period is very strong, with six-factor alphas ranging from 37 bps to 65 bps when firms are value-weighted, and 72 bps to 131 bps when they are 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 for stock PEAD. Lower costs of arbitrage and higher noise trading in the stock market (as discussed in Implication 1 of our model and in Internet Appendix E) weaken drifts, which explains the difference in PEAD between bonds and stocks.

Still, it is interesting to study whether disagreement explains stock PEAD in the past. Therefore, we run a Fama-MacBeth regression of stock returns on the earnings surprise measure (CAR), analysts' disagreement ($DISP$), and institutional equity investors' portfolio weight dispersion (CV_{Stock}). If disagreement contributes to stock PEAD, then the interaction terms between earnings surprises and disagreement proxies should be positive. Furthermore, we include a firm's market capitalization, the book-to-market ratio, momentum, operating profitability, investment, 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 the regression 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 the square root of a firm's market value in month t. By scaling both the left- and right-hand variables, the slope coefficients (which are returns on tradable strategies) become value-weighted.

Table 16 presents the estimated slope coefficients on the Fama-MacBeth regression of stock returns. The first two columns report the results using the full sample period (i.e., 1984 to 2020). Consistent with the portfolio-level results in Table 15, we find the stock PEAD effect: The loading on earnings surprises is positive at 21 bps when controlling for $DISP$ and 29 bps when controlling for CV_{Stock}. The interaction term between earnings surprises and $DISP$ is 8 bps ($t = 1.93$) while the interaction between earnings surprises and CV_{Stock} is 10 bps ($t = 3.35$), which are significant at the 10% and 1% levels, respectively. The next four columns show the results using two sub-periods (i.e., 1984 to 2001 and 2002 to 2020). They suggest that $DISP$ is a more significant driver for PEAD in the later period (2002 to

2020) while CV_{Stock} is more significant in the earlier sample. Overall, Table 16 shows that, though stock PEAD becomes weaker over time, stocks with more disagreement exhibit more pronounced drift after earnings announcements than those with low 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 surprises in the previous quarter tend to appreciate relative to bonds issued by a firm that had negative surprises. This evidence points to the bond market's slow price reaction to prominent news that affects the value of the bond. 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 return on the bond PEAD strategy has little exposure to systematic risk.

We hypothesize that disagreement is the source of bond PEAD and verify this hypothesis both empirically and theoretically. Using a stylized model, we show disagreement slows information aggregation down and thus generates the drift. This explanation is attractive because it explains several empirical findings under the unified framework, including i) why bonds with higher volume exhibit more pronounced PEAD, ii) why the link between bond illiquidity and PEAD is weakly negative, iii) why bond PEAD remains robust over time while equity PEAD decays, and iv) why HY bonds exhibit more pronounced PEAD than IG bonds do. Furthermore, we document supporting evidence that stock PEAD is greater when the disagreement on firms' value is higher. Taken together, we conclude that disagreement is the origin of bond PEAD, while illiquidity plays (at best) a secondary role by limiting arbitrage trades.

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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).

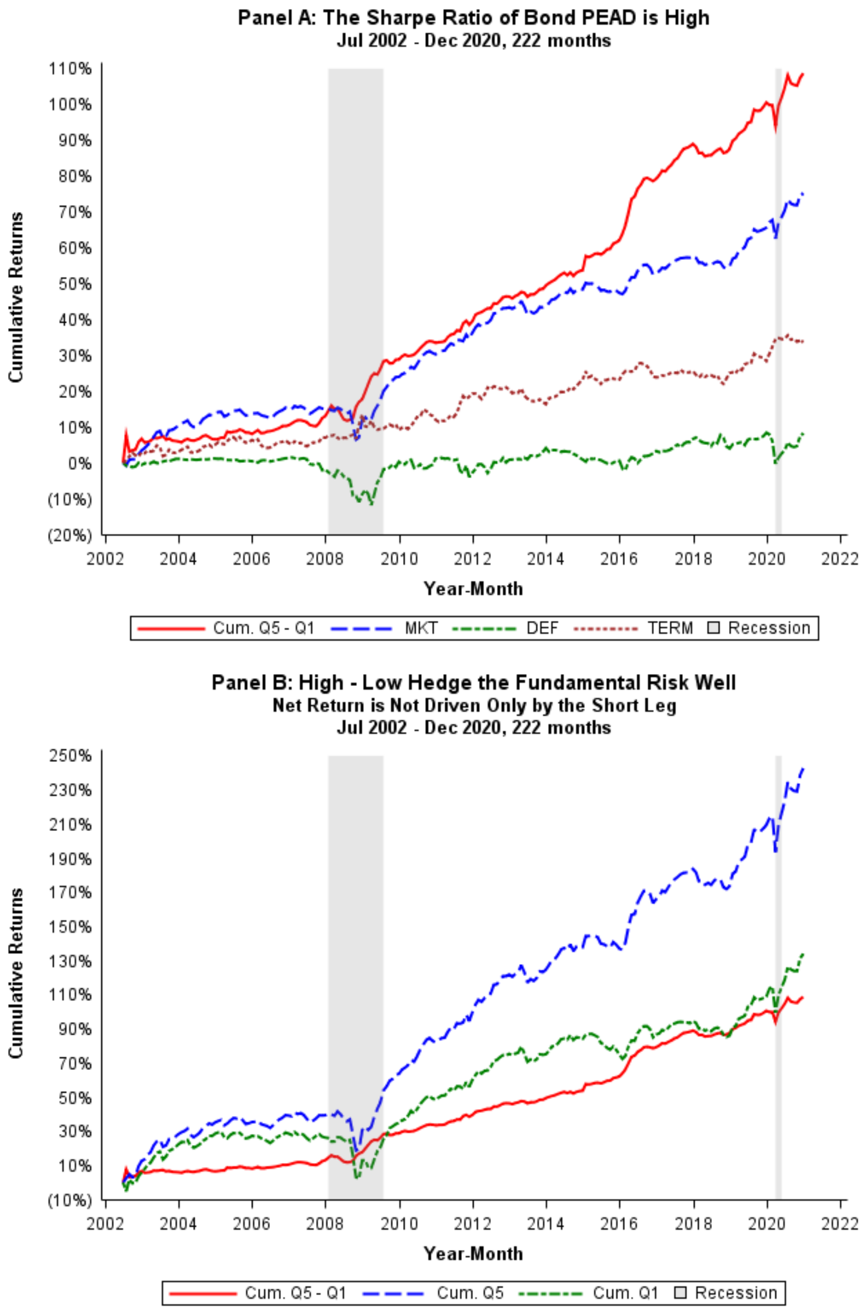
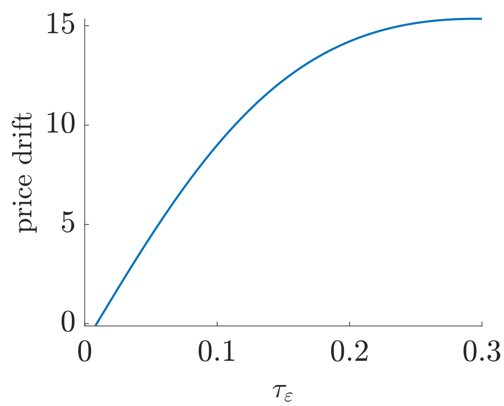
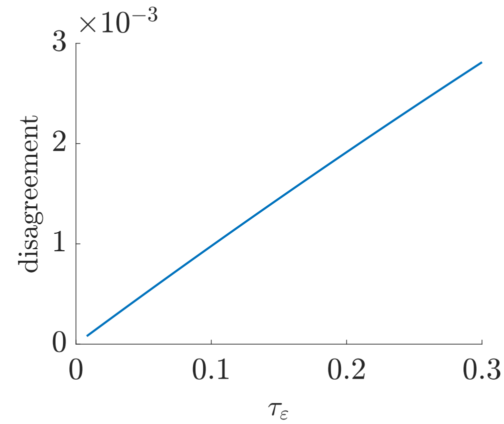


Figure 3: Comparative Statics with respect to τ_ε

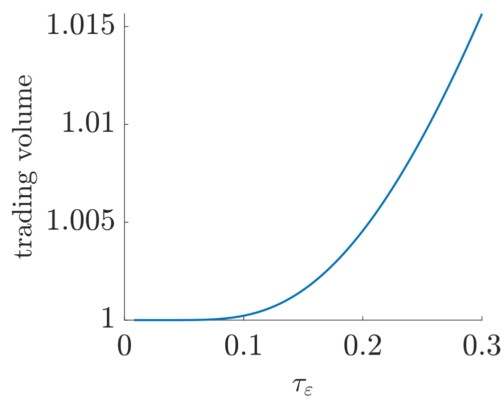
This figure plots comparative statics of price drift, disagreement, trading volume, and illiquidity with respect to τ_ε when (i) prices exhibit drift and (ii) τ_ε is low. The other parameters are $\tau_\eta = 100, \tau_v = 10, \gamma = 1$, and $\sigma_u = 0.3$.



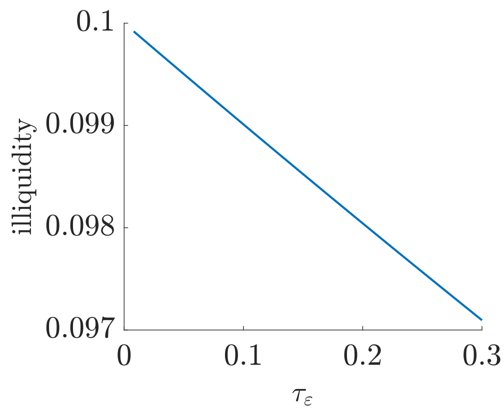
(a) Price drift



(b) Disagreement



(c) Trading volume



(d) Illiquidity

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 the 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's bond return. MOM is the past 11-month cumulative returns from month t-11 to t-1, skipping the short-term reversal month t. *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. *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 Choi and Kronlund (2017), 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 the previous month. We use stock *CAR* $[-1, +1]$ as an earnings surprise measure in Panels A and B. Quintile 1 is the portfolio 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 the 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* (*SRet6mAll*) is the past six-month stock return, calculated as the cumulative market-adjusted stock returns over the past six months, excluding (including) the earnings announcement returns. *NoAnnCAR* is the pseudo CAR $[-1, +1]$ without earnings surprises, calculated as the three-day cumulative abnormal returns around a date randomly picked from significant price movement days in the previous six months, excluding the earnings announcement windows. We use the ratio of standard deviation of CAR $[-1, +1]$ to standard deviation of non-earnings-announcement CAR $[-1, +1]$ as a threshold to filter out pools of *NoAnnCAR*. *Downgrade* (*Upgrade*) is a dummy variable for rating downgrade (upgrade) in the previous three months, which equals one if there is at least one downgrade (upgrade) by any rating agencies. Bond characteristics controls include bond size (*Size*), credit rating, maturity, downside risk ($DOWN$), illiquidity ($ACOV$), short-term bond return reversal (STR), bond return momentum (MOM), bond return volatility (*Vol*), stock return volatility (*SRVol*), and the fraction of bid in month t and t+1. All continuous independent variables are 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)	(7)
CAR	0.069***	0.065***				0.070***	0.037***
	(3.30)	(4.84)				(4.80)	(2.61)
SRet6m			0.120***			0.129***	
			(6.84)			(6.85)	
SRet6mAll							0.134***
							(6.10)
$NoAnnCAR$				0.015		-0.014	-0.009
				(1.15)		(-1.03)	(-0.69)
Dummy: *Downgrade*					-0.123**	-0.113**	-0.108**
					(-2.07)	(-2.04)	(-1.99)
Dummy: *Upgrade*					-0.005	-0.016	-0.022
					(-0.15)	(-0.47)	(-0.63)
Bond Characteristics Controls	NO	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES	YES	YES	YES
Obs	250,110	250,110	250,110	250,110	250,110	250,110	250,110
R^2	0.120	0.428	0.429	0.429	0.430	0.442	0.442

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 a 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 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.

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 the previous month. We use stock $CAR\ [-1, +1]$ as an earnings surprise measure. Quintile 1 ("Low") is the portfolio with the lowest earnings surprises and Quintile 5 ("High") is the portfolio with the highest earnings surprises. The portfolios are held for one month and rebalanced monthly. Portfolios are value-weighted using the prior month's firm market capitalization as weights. We compute two versions of CDS price/premium changes. Panel A presents the collateralized CDS returns following Augustin et al. (2020). Panel B uses changes in the natural logarithms of CDS spreads. Alphas are calculated from a bond factor model, a stock factor model, and a bond+stock model. The bond factor model uses 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: 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: 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 Choi and Kronlund (2017). 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 the 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	*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	Turnover (%) on Announcement 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 Choi and Kronlund (2017). 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)
Bond Characteristics Controls	YES	YES	YES	YES
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 Choi and Kronlund (2017). 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 Characteristics 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 the announcement. *Friday* is a dummy variable that equals one if the announcements were made on Friday. AIA and $AIAC$ are two abnormal institutional investor attention measures based on Bloomberg news readership data. AIA is a dummy variable that equals one if Bloomberg's score is 3 or 4, and zero otherwise. $AIAC$ is transformed continuous values from Bloomberg's 0, 1, 2, 3, and 4 scores using the conditional means of the truncated normal distribution. Details on the construction of the control variables are provided in Table 1. Continuous independent variables are winsorized at the 1% level and standardized to have a mean of zero and a standard deviation of one. The Fama and French 30 industry effect is included in each regression and Newey-West adjusted t-statistics (with six lags) are given in parentheses. The asterisks represent the significance level of 1% (***), 5% (**), and 10% (*), respectively.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns				
	(1)	(2)	(3)	(4)
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 Characteristics 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, $RP_{i,q} = \frac{1}{\bar{V}} \sum_{n=0}^{q} V_{i,q,q-n} P_{i,q-n}$, 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 at different points in time and then some of the holdings are sold later, then we assume First-In-First-Out (FIFO) rule to calculate $V_{i,q,q-n}$. We measure capital gain overhang for bond i as the ratio of the gap between a market price and a reference price to the market price, $CGO_{i,q} = \frac{P_{i,q} - RP_{i,q}}{P_{i,q}}$. We present the 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
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 a 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 the 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 an equal-weighted portfolio of CAR-sorted portfolios selected in the current month as well as in the previous *K-1* months. We report average excess returns and 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: Six-Factor Alphas for Various Subsamples

This table presents the performance of the stock PEAD strategy. Quintile portfolios are formed by sorting stocks based on the corresponding firm's most recent earnings surprises at the end of the previous month. Quintile 1 is the portfolio with the lowest earnings surprises and Quintile 5 is the portfolio with the highest earnings surprises. We consider three earnings 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. This table reports six-factor alphas for the high-minus-low hedge portfolios sorted on the earnings surprises. The six stock market factors (market, size, value, investment, profitability, and momentum) are from Fama and French (2018). We consider bond issuers (Panel A) as well as all stocks in our sample (Panels B and C). Also, we show sub-period results for the stock PEAD: 2002 - 2020 and 1984 - 2011 (Panel B and Panel C). 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.

CAR	*CE*	*FOM*	*CAR*	*CE*	*FOM*
Value-Weighted Portfolios			Equal-Weighted Portfolios		
Panel A: Bond Issuers, 2002 - 2020					
0.19	-0.08	0.13	0.23**	-0.16	0.02
(1.33)	(-0.48)	(0.98)	(2.49)	(-1.15)	(0.13)
Panel B: All Firms, 2002 - 2020					
0.22*	0.31*	0.16	0.42***	0.32***	0.24***
(1.65)	(1.94)	(1.45)	(4.30)	(3.23)	(3.11)
Panel C: All Firms, 1984 - 2001					
0.65***	0.37**	0.56***	0.72***	1.31***	1.06***
(3.63)	(2.00)	(4.16)	(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 the 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 Characteristics 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

Internet Appendix to “Disagreement, Liquidity, and Price Drifts in the Corporate Bond Market

Yoshio Nozawa, Yancheng Qiu and Yan Xiong

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 a bond PEAD strategy using subsamples before and after the introduction of TRACE, measure the potential impact of the introduction of TRACE, and observe the longer-term trend in bond PEAD profitability.

Table 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) five-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 the 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 to their quotes from the true drift in investors' bond valuation. However, this exercise shows no evidence for weakening the bond PEAD in the two subperiods we study. This finding also suggests that the introduction of TRACE does not necessarily make the bond market more efficient.

B Additional Results

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

- Table A2 reports the coefficient estimates for the control variables in Table 5.
- Table A3 reports the PEAD effects using *CE* and *FOM* controlling for other news variables.
- Table A4 reports the results of bivariate sort on earnings surprises and alternative measures of disagreement.
- Table A5 reports the coefficient estimates for the control variables in Table 9.

- Table A6 reports the results of Fama-MacBeth regressions on the alternative measures of disagreement.

C Triple Conditional Sort of Bonds

To separate the disagreement effect from potentially confounding effects from bonds' risk, we conduct a triple sort of bonds. Specifically, we classify corporate bonds into 3-by-3-by-3 value-weighted portfolios based first on one of the eight bond characteristics in Table 8, and then on one of the disagreement measures, and lastly on $CAR[-1,+1]$. Then, within each characteristic tercile, we calculate the difference in PEAD profits between the highest and the lowest disagreement terciles. We report the simple average across the characteristics terciles in Panel A, Table A7. These values reflect the difference in PEAD profits due to variation in disagreement controlling for the characteristic, allowing us to assess the disagreement effect independent of the characteristic.

Looking across the three disagreement proxies used in the paper and the eight bond control variables, 23 out of 24 possible combinations exhibit a significant difference in PEAD profits between the highest and the lowest disagreement terciles. Using the composite disagreement proxy ($CDIS$), the disagreement effect ranges from 19 bps to 43 bps, all statistically significant. Therefore, the disagreement effect is not subsumed by bonds' characteristics, including volatility, size, credit rating, maturity, downside risk, bid-ask spreads, or the Roll measure, confirming the regression results in Table 9.

In Panel B, Table A7, we switch the role of bonds' characteristics and disagreement, and examine the effect of bonds' characteristics on PEAD independent of disagreement. Using the composite disagreement measure as a control variable, we find that stock volatility, credit rating, and downside risk generate variation in PEAD profits ranging from 12 to 28 bps. However, other characteristics, including bond volatility, maturity, bid-ask spreads, and the Roll illiquidity measure are insignificant once we control for disagreement. Therefore, those proxies do not generate PEAD beyond what is captured by disagreement.

D Proofs

Derivation of an REE model

As mentioned in footnote 16, we develop an REE model to show that differences of opinions are crucial to generate the price drift. In the REE model, assume that investor i conditions not only on her private signal $\tilde{s}_i$ but also on the public price $\tilde{p}_1$ to update her beliefs about the asset value. 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 asset value:

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

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 (11), 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 (11), prices exhibit drift when

$$\sigma_u^2 < \hat{\sigma}_u^2 \equiv \frac{\tau_\varepsilon\tau_\eta^2}{\gamma^2(\tau_\varepsilon + \tau_\eta)^2}. \tag{B3}$$

Proof of Implication 2

We focus on the case in which prices exhibit drift, namely, condition (B3) holds. Taking derivative of the magnitude of price drift k in equation (11) with respect to τ_ε yields the following:

$$\frac{\partial k}{\partial \tau_\varepsilon} = \tau_\eta^2\tau_v\frac{\gamma^2\sigma_u^2\left(\tau_\eta + \tau_\varepsilon\right)\left(\tau_v\left(\tau_\eta + \tau_\varepsilon\right) + 2\tau_\eta\tau_\varepsilon\right) - \tau_\eta\tau_\varepsilon^2\left(\tau_\eta + \tau_v\right)}{\left(\gamma^2\sigma_u^2\tau_v\left(\tau_\eta + \tau_\varepsilon\right)^2 + \tau_\eta\tau_\varepsilon^2\left(\tau_\eta + \tau_v\right)\right)^2}, \tag{B4}$$

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

$$f(\tau_\varepsilon) = \left(\gamma^2\sigma_u^2(\tau_v + 2\tau_\eta) - \tau_\eta(\tau_v + \tau_\eta)\right)\tau_\varepsilon^2 + 2\gamma^2\sigma_u^2\tau_\eta(\tau_v + \tau_\eta)\tau_\varepsilon + \gamma^2\sigma_u^2\tau_v\tau_\eta^2. \tag{B5}$$

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:

$$\sigma_u^2 < \bar{\sigma}_u^2 \equiv \min\left\{\hat{\sigma}_u^2, \frac{\tau_\eta(\tau_v + \tau_\eta)}{\gamma^2(\tau_v + 2\tau_\eta)}\right\} \text{ and } \tau_\varepsilon < \hat{\tau}_\varepsilon, \tag{B6}$$

where

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

Note that $\sigma_u^2 < \hat{\sigma}_u^2$ (i.e., condition (B3)) ensures that we can observe price drift. The condition $\sigma_u^2 < \frac{\tau_\eta(\tau_v+\tau_\eta)}{\gamma^2(\tau_v+2\tau_\eta)}$ 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 (12), 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 the derivative of TV with respect to τ_ε yields that

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

which is positive when $\tau_\varepsilon < \tau_\eta$.

Next, we can derive the disagreement defined in (13) as follows:

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

Taking the derivative with respect to τ_ε yields

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

which is positive if $\tau_\varepsilon < \frac{\tau_v \tau_\eta}{\tau_v + \tau_\eta}$. Since $\frac{\tau_v \tau_\eta}{\tau_v+\tau_\eta} < \tau_\eta$, if $\frac{\partial DISP}{\partial \tau_\varepsilon} > 0$, then $\frac{\partial TV}{\partial \tau_\varepsilon} > 0$ must hold.

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 $\sigma_u^2 < \bar{\sigma}_u^2$ and $\tau_\varepsilon < \bar{\tau}_\varepsilon$, where $\bar{\sigma}_u^2$ is given by (B6) and

$$\bar{\tau}_\varepsilon \equiv \min\left\{\hat{\tau}_\varepsilon, \frac{\tau_v \tau_\eta}{\tau_v + \tau_\eta}\right\}. \tag{B7}$$

Proof of Implication 3

The illiquidity defined in (13) 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 (B4), we know that when $\sigma_u^2 < \bar{\sigma}_u^2$ and $\tau_\varepsilon < \bar{\tau}_\varepsilon$, $\frac{\partial k}{\partial \tau_\varepsilon} > 0$ and $\frac{\partial ILLIQ}{\partial \tau_\varepsilon} < 0$ hold simultaneously; that is, k and ILLIQ are negatively correlated.

E Intensity of Noise Trading in the Bond Market

In this section, we estimate the noise trading intensity in the corporate bond market and show that the estimate is lower than what is reported in the equity market. Our estimation method closely follows Peress and Schmidt (2021) who show that one can estimate the noise trading volatility in the market by regressing market turnover rate on retail turnover rates. The key identifying assumptions are that retail trades reflect noise trading and account for a constant fraction $(1/b)$ of the total noise trades in the market. Since retail trades are positively correlated with rational trades, the OLS regression estimates provide an upper bound of the true fraction. However, they use leading market microstructure models to show that the lower bound is half of the upper bound.

Thus, we follow their methodology and regress retail turnover of corporate bonds on total turnover to estimate the fraction b. The product of the slope and the volatility of retail turnover provides the estimate of the intensity of noise trading. To define retail trades, we follow the literature to use the two cutoffs: i) dealer-customer trades with quantity no more than \$10,000 following Bai, Bali, and Wen (2019), and ii) dealer-customer trades with quantity no more than \$100,000 following Bessembinder et al. (2008). Table A8 reports the estimates for the slope coefficient and the volatility of noise trading in the bond market. We find that the percentage of noise trading volatility to total trading volatility is generally low: the lower bound is up to 6% and the upper bound is up to 13% depending on the data frequency and the definition of retail trades. These estimates are lower than the values in the stock market reported in Peress and Schmidt (2021). In their Table 3, the provided lower bound for the noise trading intensity ranges from 10% to 50% of the total volume intensity, while the upper bound ranges from 20% to 100%. Therefore, the regression-based estimates suggest that the noise trading intensity is lower in the bond market than in the stock market.

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 the previous month. We use stock *CAR* [-1, +1] as our primary earnings surprises measure. Quintile 1 is the portfolio 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: Fama-MacBeth Regressions on Earnings Surprises, Past Stock Returns and Past Rating Changes, Detailed Estimates

This table reports the detailed estimates for Table 5, including those on control variables.

Left-Hand Side Variable: One-Month-Ahead Corporate Bond Excess Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CAR	0.069***	0.065***				0.070***	0.037***
	(3.30)	(4.84)				(4.80)	(2.61)
SRet6m			0.120***			0.129***	
			(6.84)			(6.85)	
SRet6mAll							0.134***
							(6.10)
NoAnnCAR				0.015		-0.014	-0.009
				(1.15)		(-1.03)	(-0.69)
Dummy: *Downgrade*					-0.123**	-0.113**	-0.108**
					(-2.07)	(-2.04)	(-1.99)
Dummy: *Upgrade*					-0.005	-0.016	-0.022
					(-0.15)	(-0.47)	(-0.63)
Size		0.009	0.007	0.007	0.008	0.009	0.010
		(0.49)	(0.44)	(0.39)	(0.49)	(0.52)	(0.60)
Rating		0.050	0.044	0.046	0.048	0.051	0.052
		(1.06)	(0.94)	(0.98)	(0.99)	(1.09)	(1.14)
Maturity		0.134**	0.133**	0.137**	0.135**	0.135**	0.136**
		(2.45)	(2.43)	(2.50)	(2.46)	(2.47)	(2.48)
Down		0.105**	0.101**	0.097**	0.107**	0.103**	0.100**
		(2.42)	(2.33)	(2.17)	(2.42)	(2.34)	(2.30)
ACOV		-0.008	-0.005	-0.008	-0.008	-0.003	-0.003
		(-0.28)	(-0.19)	(-0.29)	(-0.31)	(-0.11)	(-0.13)
STR		-0.532***	-0.538***	-0.525***	-0.531***	-0.560***	-0.561***
		(-10.47)	(-10.71)	(-10.30)	(-10.40)	(-11.49)	(-11.51)
MOM		-0.223*	-0.261**	-0.221*	-0.242**	-0.284**	-0.289**
		(-1.91)	(-2.28)	(-1.92)	(-2.09)	(-2.50)	(-2.51)
Vol		0.025	0.032	0.023	0.030	0.035	0.036
		(0.47)	(0.62)	(0.42)	(0.58)	(0.69)	(0.72)
SRVol		-0.042	-0.033	-0.043	-0.041	-0.028	-0.021
		(-1.02)	(-0.88)	(-1.04)	(-1.00)	(-0.78)	(-0.59)
Frac_Bid t		0.218***	0.217***	0.217***	0.219***	0.216***	0.216***
		(6.31)	(6.38)	(6.50)	(6.32)	(6.36)	(6.36)
Frac_Bid t+1		-0.266***	-0.268***	-0.266***	-0.267***	-0.268***	-0.268***
		(-9.48)	(-9.50)	(-9.71)	(-9.60)	(-9.86)	(-9.83)
Intercept	0.348***	0.449***	0.420***	0.439***	0.451***	0.435***	0.427***
	(3.98)	(3.91)	(3.81)	(3.88)	(3.95)	(3.81)	(3.84)
Industry Controls	YES	YES	YES	YES	YES	YES	YES
Obs	250,110	250,110	250,110	250,110	250,110	250,110	250,110
R^2	0.120	0.428	0.429	0.429	0.430	0.442	0.442

Table A3: Uniqueness of Earnings Surprise: Fama-MacBeth Regressions on Alternative 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 alternative earnings surprises and other measures of news with and without controls. Earnings surprise is proxied by *CE* and *FOM*. *CE* is the analyst forecast errors based on median consensus. *FOM* is calculated as $K/N - M/N$, where $K(M)$ is the number of forecasts strictly lower (higher) than actual earnings, and N is the total number of analyst forecasts. *SRet6m* (*SRet6mAll*) is the past six-month stock return, calculated as the cumulative market-adjusted stock returns over the past six months, excluding (including) the earnings announcement returns. *NoAnnCAR* is the pseudo *CAR* $[-1, +1]$ without earnings surprises, calculated as the three-day cumulative abnormal returns around a date randomly picked from significant price movement days in the previous six months, excluding the earnings announcement windows. We use the ratio of standard deviation of *CAR* $[-1, +1]$ to standard deviation of non-earnings-announcement *CAR* $[-1, +1]$ as a threshold to filter out pools of *NoAnnCAR*. *Downgrade* (*Upgrade*) is a dummy variable for rating downgrade (upgrade) in the previous three months, which equals one if there is at least one downgrade (upgrade) by any rating agencies. Bond characteristics controls include bond size (*Size*), credit rating, maturity, downside risk (*DOWN*), illiquidity (*ACOV*), short-term bond return reversal (*STR*), bond return momentum (*MOM*), bond return volatility (*Vol*), stock return volatility (*SRVol*), and the fraction of bid in month t and t+1. All continuous independent variables are 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)
CE	0.130***		0.122**		0.105**	
	(2.76)		(2.60)		(2.22)	
FOM		0.027**		0.022**		0.008
		(2.43)		(2.10)		(0.75)
SRet6m			0.121***	0.118***		
			(6.71)	(6.48)		
SRet6mAll					0.138***	0.140***
					(6.51)	(6.58)
NoAnnCAR			-0.012	-0.014	-0.009	-0.012
			(-1.01)	(-1.06)	(-0.78)	(-0.93)
Dummy: *Downgrade*			-0.138***	-0.119**	-0.133**	-0.114**
			(-2.61)	(-2.17)	(-2.56)	(-2.16)
Dummy: *Upgrade*			-0.034	-0.022	-0.042	-0.032
			(-0.78)	(-0.63)	(-1.00)	(-0.94)
Bond Characteristics Controls	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES	YES	YES
Obs	250,187	250,187	250,187	250,187	250,187	250,187
R^2	0.433	0.427	0.446	0.440	0.447	0.441

Table A4: 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 a 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 the 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: 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	Turnover (%) on Announcement 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 A5: Fama-MacBeth Regressions of Bond Returns on Earnings Surprise and Disagreement, Detailed Estimates

This table reports the detailed estimates for Table 9, including those on control variables.

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 A6: Fama-MacBeth Regressions of Bond Returns on Earnings Surprise and Alternative Disagreement Measures

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)		
$CAR \times CV2$	0.042***		
	(3.74)		
CV_{Stock}		0.003	
		(0.15)	
$CAR \times CV_{Stock}$		0.028***	
		(2.63)	
$CV2_{Stock}$			0.003
			(0.13)
$CAR \times CV2_{Stock}$			0.025**
			(2.00)
Bond Characteristics Controls	Yes	YES	YES
Industry Controls	Yes	YES	YES
Obs	250,721	227,557	227,557
R^2	0.439	0.443	0.445

Table A7: 11-Factor Alphas on Triple-Sorted Portfolios of Earnings Surprise, Disagreement, and Bond Characteristics

27 ($3 \times 3 \times 3$) portfolios are formed every month from July 2002 to December 2020 by conditionally sorting corporate bonds based on the corresponding firm's most recent earnings surprises, disagreement measures, and bond characteristics. Earnings surprise is proxied by the stock *CAR* $[-1, +1]$. We use four disagreement proxies (*DISP*, *CV*, *RFY*, and *CDIS*) and eight bond characteristics from Table 8. *CDIS* is a composite disagreement measure. 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 as *CDIS*. Details on the construction of other variables are provided in Table 1. In Panel A, corporate bonds are sorted first on one of the eight bond characteristics, and then on one of the disagreement measures, and lastly on *CAR*$[-1,+1]$. We compute the PEAD long-short portfolios for each characteristic/disagreement cell, where the bonds are value-weighted using the dollar value amount outstanding as weights. Then, within each characteristic tercile, we calculate the difference in PEAD profits between the highest and lowest disagreement terciles and take the simple average of the resulting three portfolio excess returns. We present 11-factor alpha (in percent per month). In Panel B, we switch the role of characteristics and disagreement, and repeat the exercise. Specifically, we first sort on disagreement, then on characteristics, and lastly on *CAR*, and report the alphas due to the variation in PEAD profits across characteristics within disagreement terciles. Newey-West adjusted t-statistics (with six lags) are reported in parenthesis below returns/alphas. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Bond Vol	*Stock Vol*	*Size*	*Rating*	*Maturity*	*Down*	*BAS*	*ACOV*
Panel A: Conditional Triple-Sort on Bond Characteristics, Disagreement, and *CAR*								
DISP	0.25***	0.17**	0.29***	0.15*	0.25***	0.24***	0.30***	0.24**
	(3.52)	(2.17)	(3.27)	(1.92)	(2.74)	(3.38)	(3.07)	(2.33)
CV	0.21**	0.19***	0.32***	0.16**	0.30***	0.17*	0.35***	0.38***
	(2.60)	(2.67)	(4.63)	(1.98)	(3.62)	(1.93)	(3.17)	(3.21)
RFY	0.07	0.24***	0.27***	0.25***	0.26***	0.20***	0.30***	0.24***
	(1.08)	(3.67)	(4.38)	(2.82)	(4.19)	(3.25)	(4.17)	(3.68)
CDIS	0.31***	0.24***	0.40***	0.28***	0.41***	0.19**	0.43***	0.39***
	(4.36)	(3.44)	(5.12)	(3.63)	(3.90)	(2.24)	(4.08)	(3.51)
Panel B: Conditional Triple-Sort on Disagreement, Bond Characteristics, and *CAR*								
DISP	0.20***	0.14*	-0.09*	0.08*	0.08**	0.30***	0.12**	0.05
	(3.69)	(1.82)	(-1.67)	(1.67)	(2.04)	(3.69)	(2.14)	(0.94)
CV	0.33***	0.22***	-0.07	0.22***	0.09*	0.30***	0.06	0.06
	(5.81)	(3.31)	(-1.45)	(3.13)	(1.97)	(3.19)	(1.02)	(0.73)
RFY	0.19***	0.16***	-0.07	0.18**	-0.06	0.24***	-0.07	-0.01
	(3.31)	(3.24)	(-1.60)	(2.51)	(-1.01)	(3.05)	(-1.49)	(-0.19)
CDIS	0.12	0.23***	-0.01	0.12**	0.00	0.28***	0.09	0.00
	(1.59)	(3.32)	(-0.18)	(2.20)	(0.05)	(2.93)	(1.42)	(0.02)

Table A8: Estimates of the Intensity of Noise Trading in the Corporate Bond Market

We follow Peress and Schmidt (2021) and regress total turnover (trading volume divided by a bond's amount outstanding) on retail turnover (sum of retail customer buys and sells divided by the amount outstanding), where transactions no more than $10,000 (Panel A) or $100,000 (Panel B) are classified as retail trades. The daily turnover is first adjusted for seasonality and time trends by regressing it on dummy variables for day of the week, month of the year, and year and then taking residuals. The slope coefficient determines bounds on the fraction of noise turnover that is due to retail traders. The standard deviation of noise trading is bounded from below by the standard deviation of retail trades multiplied by the regression coefficient; it is bounded from above by twice that product. These bounds are displayed in terms of levels and also as a percentage of the standard deviation of total turnover in the market.

		Std. Dev. of				Std. Dev. of Noise Trading			
Frequency	Nobs	Total Turnover	Retail Turnover	Regression Coefficient	(s.e)	Lower Bound	(%)	Upper Bound	(%)
Panel A. Retail trade <= $10,000									
Daily	25,104,890	996.54	0.69	35.38	0.29	24.50	2.5%	49.01	4.9%
Weekly	9,202,910	1,647.22	1.56	28.99	0.35	45.21	2.7%	90.42	5.5%
Monthly	3,128,896	2,832.76	3.95	23.68	0.40	93.64	3.3%	187.29	6.6%
Quarterly	1,368,625	4,290.95	8.43	20.26	0.43	170.81	4.0%	341.63	8.0%
Panel B. Retail trade <= $100,000									
Daily	25,104,890	996.54	5.73	7.91	0.03	45.30	4.5%	90.61	9.1%
Weekly	9,202,910	1,647.22	10.71	7.60	0.05	81.36	4.9%	162.71	9.9%
Monthly	3,128,896	2,832.76	22.43	6.98	0.07	156.52	5.5%	313.05	11.1%
Quarterly	1,368,625	4,290.95	42.91	6.32	0.09	271.04	6.3%	542.07	12.6%