



Corporate bond price reversals

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ARTICLE INFO

JEL classification:

G12

G14

Keywords:

Corporate bonds

Trading volume

Reversal

Informed trading

Dealer inventory

ABSTRACT

I demonstrate empirically that corporate bond dealers mitigate adverse selection risk by passing potentially informed transactions to institutional investors. I contrast price reversals following days with abnormal trading volume across bonds with different information asymmetry. In informed trading, the part of reversal specific to high-volume days should increase with information asymmetry. In uninformed trading, there is no such effect. Following high-volume days when investors provide liquidity, the reversals are consistent with the former case. When dealers provide liquidity, I observe the latter. The results suggest that the informational content of bond prices is higher when dealers do not take inventory.

1. Introduction

Trading with a better-informed counterparty is a risky business. Indeed, liquidity providers in securities markets may incur losses when trading with informed traders and seek remuneration to offset such adverse selection risk. This raises the question of whether all liquidity providers are equal in avoiding transactions with better-informed investors. To address this, I consider the case of the over-the-counter (OTC) corporate bond market in the United States and two distinct liquidity providers: broker-dealers and institutional investors.

My results suggest that liquidity-providing institutional investors are more likely to be adversely selected than the dealers. That is to say, bond dealers avoid trading with informed investors. Consider a dealer who is approached by an investor willing to sell a bond. In such a scenario, the dealer must decide whether to provide liquidity for the transaction herself or to let another investor supply liquidity. In the first case, the dealer buys the bond and holds it as part of their inventory for an ex ante unknown period. In the second case, the dealer finds another investor willing to buy the bond. The dealer then uses her balance sheet to transfer the bond from the seller to the buyer based on prearranged terms, but the bond only stays on the dealer's book for a few minutes. The key question here is whether bond prices are equally likely to reveal private information in these two cases. I argue that the information content of prices is higher when investors rather than dealers themselves supply liquidity.

First, assume that there are only two trading motives: private information and liquidity needs. Observed trading volume is the mixture of volumes generated by each trading motive. Second, how can the prevalent motive from the history of transaction prices and volumes be inferred?² I use a theoretically grounded empirical methodology that links the trading motive to the cross-sectional dependence between bond information asymmetry and a particular component of the first-order bond return autocorrelation specific

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¹ Web: <https://ivasche.com>. I thank Michael Rockinger (doctoral advisor), Edith Hotchkiss (discussant), Quan Wen (discussant), Vincent Bogousslavsky, Pierre CollinDufresne, Robert Czech, Jakub Hajda, Robert Kosowski, Maureen O'Hara, Norman Schürhoff, and Johan Walden for their helpful suggestions. I also thank seminar participants at HEC Montreal, Frankfurt School of Finance & Management, WU Vienna, Nova SBE, VU Amsterdam, the Bank of England, the University of Lausanne, the University of Geneva, the University of St. Gallen, and the Microstructure Exchange seminar series for their insightful comments and feedback.

² Historical pre-trade price benchmarks (executable dealer quotes) are unavailable for U.S. corporate bonds, which renders classic microstructure methods to answer the question, like Hasbrouck (1991), inapplicable.

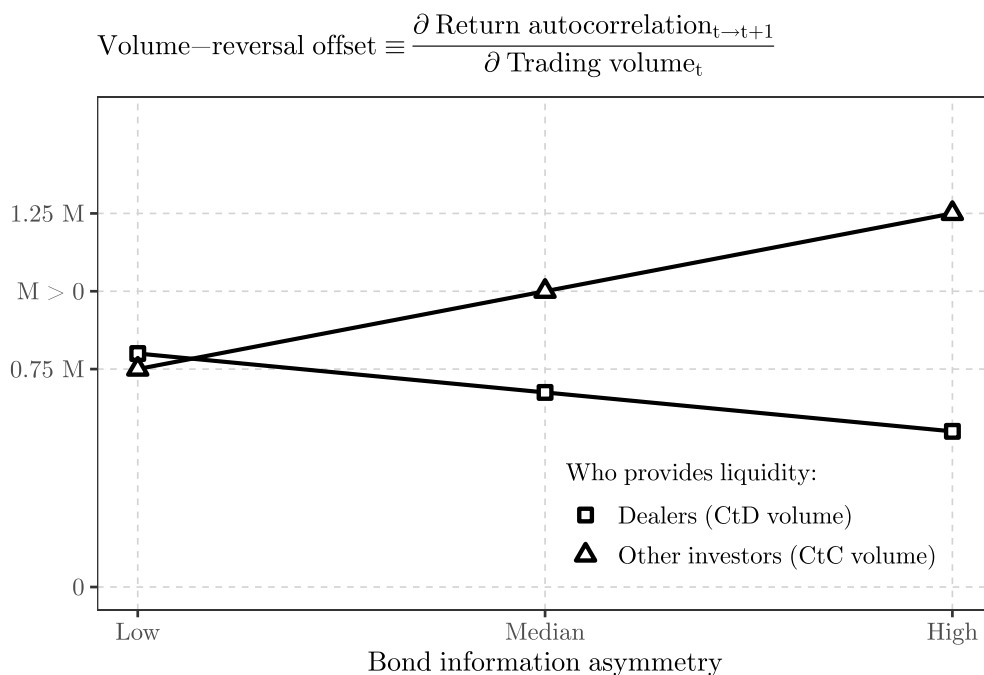


Fig. 1. Bond information asymmetry and the volume-reversal offset.

This figure is a stylized representation of the main empirical result: CtC volume-reversal offsets increase in line with bond information asymmetry, while CtD offsets do not. This is evidence of occasionally informed bond trading, specifically when customers (CtC) rather than dealers (CtD) provide liquidity.

to days with abnormal trading volume. I call such a component the volume-reversal offset. A positive volume-reversal offset means that return autocorrelation is higher (equivalently, the reversal is weaker) following days with high trading volume compared to days with average volume. I argue that, in the cross-section of bonds, the volume-reversal offset must increase with bond information asymmetry if trading is occasionally information-driven.³ If trading is only liquidity-driven, the cross-section of volume-reversal offsets is unrelated to information asymmetry.

I exploit this prediction to compare the prevalence of information-driven trading in two distinct types of corporate bond transactions. The first is liquidity provision by dealers. In such a case, dealers purchase bonds for their inventory and hold them at least until the next trading day or sell bonds that have been in their inventory at least since the previous trading day. The second type is liquidity provision by bond investors (also known as “customer liquidity provision”). Here, dealers facilitate transactions between buying and selling investors by holding the inventory only intraday. I call trading volumes attributed to these two liquidity provision regimes the client-to-dealer (CtD) and the client-to-client (CtC) volume, respectively. I hypothesize that these two types of trading volumes exhibit different informational content: the CtC volume is more likely to contain information about the fundamental value of the bond compared to the CtD volume, which is predominantly liquidity-driven. I test this hypothesis by comparing the cross-sectional dependence of the volume-reversal offset on bond information asymmetry between the CtC and CtD volumes.

My main empirical tests involve regressing the CtC and CtD volume-reversal offsets (estimated bond-by-bond) on information asymmetry in the cross-section of U.S. corporate bonds. I consider multiple bond- and issuer-specific information asymmetry proxies and compound information asymmetry indicators, which deliver similar results. I find that the CtC volume-reversal offset increases in line with information asymmetry in the cross-section of bonds (see Fig. 1). The effect is economically sizeable. For an average-asymmetry bond, a one standard deviation above-average daily CtC volume takes the expected *next day* price reversal from the average level of $-1/3$ to close to $-1/4$.⁴ For a bond from the top information asymmetry decile, the effect is 25% stronger. That is, the CtC offset is the strongest for those bonds in which information-driven trading is the most likely. In contrast, the CtD offset decreases with information asymmetry. Such a pattern is expected when informed volume loads onto customer liquidity provision while uninformed volumes are channeled into dealers’ inventory. Economic mechanisms beyond informational trading that link trading volume and reversal, such as search and bargaining functions, the “size discount” relation, and the bid–ask bounce, would not explain such results. I also demonstrate that the finding is robust to various definitions of bond returns, trading volumes, and alternative econometric specifications and that it holds in various bond subsamples. In addition, I derive implications for investment strategies that capitalize on corporate bond price reversals.

³ Lorente et al. (2002) generate such results in a stylized model of trading à-la Campbell et al. (1993), assuming that the volume of information-driven trading increases in the strength of the private information signal.

⁴ An average reversal of $-1/3$ means that a day with a 1% price increase is typically followed by a day with a 0.33% price drop.

I also explore the different types of information that can drive the volume-reversal relation. I find that the CtC volume-reversal offset grows twice as fast with information asymmetry immediately before the issuer's earnings announcements (i.e., when the informational motives for trading are the most acute) compared to other trading days. By contrast, CtD volumes appear even less informed before earnings announcements than in non-announcement periods. Moreover, for issuers with many bonds outstanding, I show that the link between information asymmetry and volume-reversal offsets exists even within the issuer's bonds. Hence, the informational content of the volume-reversal offset is both issuer- and issue-specific. Relatedly, I show that stock volume-reversal offsets have only limited explanatory power for bond volume-reversal offsets, emphasizing the role of bond-specific information in the analyzed relation.

My paper contributes to several streams of literature. Previous papers have documented that liquidity provision in the corporate bond market has been shifting from dealer banks, subject to stricter regulatory requirements, to less constrained bond investors, which has implications for corporate bond illiquidity, trading costs, and market quality.⁵ In my paper, however, I introduce a novel empirical link between adverse selection and non-dealer liquidity provision. In a related paper, [Goldstein and Hotchkiss \(2020\)](#) discuss how dealers' capital commitment varies in the cross-section of bonds; in doing so, they find that dealers tend to avoid holding inventory in riskier and less actively traded bonds. This finding is consistent with both the adverse selection concern and the search-and-bargaining cost motive for selecting bonds for inventory. I extend the finding of [Goldstein and Hotchkiss \(2020\)](#) by conducting an analysis of post-trade price patterns that contrasts the information channel with the impact of search frictions. I find that the realization of adverse selection risk is more likely following large trades in which dealers did not play an active intermediary role.

The terms of trade in the OTC market are often the outcome of bargaining between dealers and investors. In light of this, [Palleja \(2023\)](#) constructs a symmetric information OTC search model of bargaining between an investor and a dealer contemplating CtC and CtD transactions.⁶ In the model, investors prefer the immediacy of CtD trades over the uncertain delay associated with CtC trades, although the former is more expensive because of the dealer's inventory holding cost. Generally, investors make trading decisions based on their pre-trade preferences and asset holdings; however, as inventory costs rise, CtC trading becomes more popular, all else being equal. What would happen in a model like that of [Palleja \(2023\)](#) under asymmetric information? I conjecture that a higher inventory cost due to the adverse selection risk would force dealers to post wider bid-offers, making CtD trading more expensive for informed investors (given the duration of the private information signal) and pushing the bargaining outcomes towards CtC rather than CtD trading compared to the symmetric information case. Such a proposition aligns with my empirical findings.

By identifying price and volume patterns that are consistent with the footprint of private information, my paper contributes to the debate on the presence of information-driven trading in the corporate bond market. [Asquith et al. \(2013\)](#) analyze the relation between bond short interest and returns and find no evidence of information-based trading either in investment-grade or in high-yield bonds. [Hendershott et al. \(2020\)](#) use similar data on loaned bonds and conclude that information-driven trading is present in high-yield bonds but not in the investment-grade universe. In my paper, high information asymmetry bonds are not necessarily high-yield ones. My sample consists primarily of investment-grade bonds, yet information asymmetry proxies vary significantly in the sample. Therefore, I find evidence of information-based trading in investment-grade bonds. Meanwhile, [Ronen and Zhou \(2013\)](#) and [Kedia and Zhou \(2014\)](#) discuss the informational efficiency of the corporate bond markets around corporate announcements and merger deals. Like [Ronen and Zhou \(2013\)](#), I find the footprint of informed trading in bond transaction prices around earnings announcements and further link it to customer liquidity provision. Finally, [Li and Galvani \(2021\)](#) highlight bond-specific informational content of bond return persistence at the monthly frequency. My results, from a different angle, point to bond-specific information as a driver of higher-frequency bond price fluctuations.

My results also have implications for corporate bond portfolio construction. [Chordia et al. \(2017\)](#) show that a lagged return is a strong return predictor in the cross-section of bonds. However, corporate bond reversal portfolios have zero or negative Sharpe ratios after trading cost adjustment ([Chordia et al., 2017](#)). I obtain the same result for reversal portfolios constructed on low information asymmetry bonds. However, I show that reversal portfolios of high asymmetry bonds survive the trading cost adjustment even under conservative assumptions about transaction costs.

Methodologically, my analysis follows the tradition of [Campbell et al. \(1993\)](#). In a related work, [Llorente et al. \(2002\)](#) investigate the volume-reversal offset of U.S. stocks. I extend and adapt their motivating theoretical model to apply an empirical framework to the OTC corporate bond market and make inferences about the exposure of different OTC liquidity providers to adverse selection risk. I also find that stock and bond volume-return offsets are almost unrelated in the cross-section of firms issuing both stocks and bonds.

The paper is organized as follows. In Section 2, I lay out my empirical strategy. In Section 3, I discuss the bond sample and the estimation of the volume-reversal offset, while I discuss the estimates in Section 4. In Section 5, I investigate the key cross-sectional relation between volume-reversal offsets and information asymmetry. In Section 6, I explore how the results change over time, around earnings announcements, and among bonds issued by the same firm. In Section 7, I discuss several robustness checks. In Section 8, I discuss the implications of my results for reversal investment strategies. Concluding remarks are in Section 9.

⁵ A non-exhaustive list of relevant literature includes [Adrian et al. \(2017\)](#), [Bessembinder et al. \(2018\)](#), [Dick-Nielsen and Rossi \(2018\)](#), [Berndt and Zhu \(2019\)](#), and [Choi et al. \(2023\)](#).

⁶ [Duffie et al. \(2005\)](#) pioneered the literature that analyzes OTC market frictions as the driver of asset illiquidity and prices. [Feldhütter \(2012\)](#) and [Friewald and Nagler \(2019\)](#), among others, quantify the impact of search and bargaining frictions on corporate bond prices.

2. Empirical framework

My empirical framework is inspired by the trading model of [Llorente et al. \(2002\)](#), which establishes the cross-sectional link between information asymmetry and the volume-reversal offset. An extension of such a model, which I present in Section A of the Internet Appendix, allows me to further distinguish between volume-reversal offsets arising from occasionally-informed and never-informed trading volume. The latter, unlike the former, generates offsets that are virtually unrelated to information asymmetry. I test empirically for such effects. In Section B of the Internet Appendix, I summarize the intuition in a non-technical way.

My analysis proceeds in two steps. In the first step, I estimate the relation between trading volume and subsequent price reversal for individual corporate bonds:

$$R_{t+1} = \beta_0 + \underbrace{(\beta_1 + \beta_2 \text{CtC volume}_t + \beta_3 \text{CtD volume}_t)}_{\text{Conditional return autocorrelation}} R_t + \epsilon_{t+1}. \quad (1)$$

In Eq. (1), R_t and R_{t+1} denote total corporate bond returns on trading days t and $t+1$, respectively. CtC and CtD volumes measure dealer and client liquidity provision. Eq. (1) estimates the price reversal (conditional return autocorrelation) between trading days t and $t+1$ as a linear function of the CtC and the CtD trading volume on day t . I standardize CtC and CtD volumes for individual bonds so that $\hat{\beta}_1$ is the average volume-day reversal. Following a trading day t with one standard deviation above-average CtC volume (and keeping the CtD volume at the average level), the reversal is $\hat{\beta}_1 + \hat{\beta}_2$. Hence, $\hat{\beta}_2$ is a measure of the CtC volume-reversal offset, that is, the difference in reversal between days with different CtC trading volumes. Likewise, $\hat{\beta}_3$ is the CtD volume-reversal offset.⁷ I estimate Eq. (1) only for bonds that are traded sufficiently often (Section 3 provides the details).

In the second step, I estimate the dependence between first-step estimates $\hat{\beta}_n$ and proxies of information asymmetry in the cross-section of individual bonds. The impact of information asymmetry on volume-reversal offsets $\hat{\beta}_2$ and $\hat{\beta}_3$ is of primary interest. If private information is more likely to drive CtC rather than CtD volumes, then $\hat{\beta}_2$ should exhibit a stronger cross-sectional relationship with information asymmetry than $\hat{\beta}_3$. This is a key empirical test. A $\hat{\beta}_2$ growing with information asymmetry in the cross-section of bonds, unlike $\hat{\beta}_3$, would identify CtC volumes as more information-rich than CtD volumes.

It should also be noted that economic mechanisms beyond information-driven trading might affect the relation between trading volume and price reversal; hence, the above identification. The question remains, though, as to whether CtC volumes are uninformed in practice and if the search and bargaining cost of liquidity provision specific to OTC markets ([Duffie et al., 2005](#)) drives the results. As a hypothetical, a liquidity provider contemplates taking a corporate bond position. Search and bargaining costs would make it expensive to offset such a position in the future, even more so if the original position is sizeable and the bond is infrequently traded. Hence, the cost of liquidity provision should increase in trade size and bond trading infrequency (which correlates with typical measures of information asymmetry). The post-trade price reversal (representing the remuneration of a liquidity provider) should then also be stronger for high-asymmetry bonds and following high-volume days. This prediction is the opposite of the private information channel prediction: the post-trade price reversal is less pronounced following the revelation of private information. Hence, search and bargaining costs likely generate a negative relation between information asymmetry and volume-reversal offsets, while the adverse selection risk channel implies a positive one.

Moreover, the relation between non-anonymous dealers and investors in OTC markets affects trading costs. In particular, clients generating a large amount of trading volume and, hence, revenue for liquidity providers tend to receive tighter bid-offers than clients trading infrequently and in smaller amounts. Such “size discounts” in OTC trading have been widely discussed in the literature.⁸ Size discounts translate into positive volume-reversal offsets in (1). Hence, positive values of $\hat{\beta}_2$ and $\hat{\beta}_3$ (which are positive for U.S. corporate bonds, on average) might be an indication of the relation motives in liquidity provision even in the absence of information-driven trading. However, there is no obvious or documented link between client-dealer relationship concerns and the dependence of the volume-reversal offset on information asymmetry in the cross-section of bonds. It is unlikely that liquidity suppliers would give the largest size discounts precisely in the riskiest of bonds.

A random arrival of buying and selling investors trading at given bid and offer prices also generates a price reversal even when trading is purely liquidity-driven. This phenomenon is known as the bid–ask bounce. A bond with wider bid–ask spreads would exhibit stronger price reversals due to the bid–ask bounce. In my setup, this translates into a more negative $\hat{\beta}_1$ for higher asymmetry bonds (as reported herein in the sample of TRACE bonds). However, a mechanism linking the bid–ask bounce to the cross-section of volume-reversal offsets has not been documented, and there is no obvious candidate for such a mechanism. In addition, my second-stage cross-sectional results on the dependence of $\hat{\beta}_2$ and $\hat{\beta}_3$ on information asymmetry hold qualitatively even for information asymmetry proxies that exhibit the lowest correlation with bond bid-offers.

⁷ I introduce the notion of a CtC/CtD volume-reversal offset for brevity because the “difference in reversals between high- and low-CtC/CtD-volume days” is a cumbersome notation.

⁸ For instance, [Green et al. \(2007\)](#) and [Edwards et al. \(2007\)](#) quantify size discounts in municipal and corporate bond markets, respectively. Plus, more recently, [Pintér et al. \(2022\)](#) demonstrated that the size discount disappears in the U.K. government bond transaction records after controlling for both dealer and client identities.

Table 1
Summary statistics of the bond-day panel.

	Mean	Median	S.D.	Min	5th	25th	75th	95th	Max	N.Obs.
Issue size, mln \$	992	750	802	9	150	500	1250	2500	15 000	4570902
Maturity, years	8.09	5.50	7.68	1.08	1.50	3.25	9.00	27.08	87.17	4570902
Coupon rate, %	4.94	5.01	1.85	0.45	1.95	3.50	6.12	7.90	15.00	4570902
Rating	7.49	7.00	3.36	1.00	3.00	5.00	9.00	14.00	21.00	4570902
Age, years	4.06	3.08	3.79	0.08	0.33	1.42	5.50	11.25	28.92	4570902
CtC volume, % of size	0.55	0.02	1.98	0.00	0.00	0.00	0.17	2.85	15.70	4570902
–ΔInventory, % of size	0.02	0.02	3.51	–19.40	–4.42	–0.19	0.36	4.21	18.48	4570902
CtD volume, % of size	1.50	0.28	3.17	0.00	0.01	0.06	1.24	7.85	19.40	4570902
Realized bond bid–ask, %	1.03	0.64	1.07	0.00	0.09	0.30	1.39	3.39	4.93	2795698
No. mutual fund owners	47.3	40.0	42.2	0.0	0.0	15.0	67.0	129.0	402.0	4570902
No. dealers	37.2	33.0	17.7	1.0	17.0	25.0	45.0	70.0	289.0	4570902
Issuer equity value, bln \$	88.3	49.3	108.4	0.0	2.6	16.3	135.0	258.1	1103.5	4203170
Stock bid–ask, %	0.05	0.03	0.10	0.00	0.01	0.02	0.05	0.16	1.99	4203164
Days to earnings announcement	44.4	44.0	26.3	0.0	4.0	22.0	67.0	85.0	92.0	3450335

The sample period runs from Jan. 4, 2005 to Dec. 31, 2018. Only active trading periods are retained. The issue size is the outstanding notional amount. Rating is conducted on a conventional numerical scale from 1 (AAA) to 21 (C). The total bond return consists of the change in the clean price and the accrued interest. The CtC (client-to-client) trading volume is the minimum between total client purchases and total client sales per bond per day. –ΔInventory is the difference between client purchases and client sales. Its absolute value is the CtD (client-to-dealer) trading volume. All trading volumes are expressed in percentages of the outstanding notional amount. The realized bond bid–ask spread is the difference between volume-weighted average client buy and sell prices, expressed as a percentage of the daily average price. “No. mutual fund owners” is the number of individual funds that hold the bond as of the bond trading date. “No. dealers” is the number of unique dealers who intermediated trades in the bond in a given month. “Stock bid–ask” is the difference between the closing bid and ask stock prices of the issuer, in % of the closing mid-price. In Section 6.1, bond trading days that are more than 92 days before the next earnings announcement are excluded from consideration.

3. Data and measurements

3.1. Data sources

I construct the dataset of corporate bond prices and volumes from Enhanced TRACE tick-by-tick data. The sample is restricted to USD-denominated, fixed-coupon, not asset-backed, non-convertible corporate bonds. I apply the filters of [Dick-Nielsen \(2014\)](#) to clean the TRACE data. I calculate daily corporate bond prices as volume-weighted transaction prices within a given day. Bond characteristics are from Mergent FISD, issuer characteristics—from CRSP and IBES, bond holdings of mutual funds—from CRSP Mutual Funds, and the data on intermediating dealers—from the academic version of the TRACE dataset.⁹ I talk in more detail about the sample in Section C of the Internet Appendix.

3.2. Sample filtering and “active periods”

To estimate Eq. (1) for each bond separately, I require a sufficiently long time series of returns and volumes for every bond. Moreover, to avoid over-fitting, I require at least 60 daily observations per bond. These are the days with at least one dealer-to-client transaction reported in TRACE; zero-trading days are removed from the sample. However, corporate bonds experience waves of trading activity, as documented in [Ivashchenko and Neklyudov \(2018\)](#), so the intervals between trading days with non-zero trading volume might be quite long. Therefore, asking for at least 60 consecutive business days is too restrictive, as very few bonds satisfy this criterion. Instead, I ask for more than 60 daily observations where every two successive observations are at most three business days apart.¹⁰

For some bonds, more than one sequence of trading days satisfies the criterion above. I call every such sequence an “active period” and retain all active periods in the sample. I also remove all days in between the active periods from the sample. Estimation of the volume–return relation is carried out per bond per active period.

Furthermore, I remove from the sample all active periods when a bond was either upgraded from high-yield (HY) to investment-grade (IG) or downgraded in the opposite direction. [Bao et al. \(2018\)](#) analyze the corporate bond market liquidity around downgrades and find abnormal price and volume patterns associated with insurance companies selling bonds due to regulatory constraints. To ensure that downgrade anomalies do not drive my results, I remove all such periods from my sample. I also remove bonds with less than one year to maturity from the sample. Such bonds are excluded from major bond market indices, which leads to substantial institutional rebalancing and creates abnormal price patterns that are not my primary focus.

⁹ The Academic Corporate Bond TRACE Data set has been obtained directly from FINRA under the standard data agreement. It contains masked identifying information about corporate bond dealers. Such information is missing in the Enhanced TRACE dataset available through WRDS. In this paper, the information on masked dealer identities only feeds into the calculation of bond-specific information asymmetry proxies in Section 3.4.

¹⁰ Here, I follow the approach of [Bao et al. \(2011\)](#), who study the illiquidity of corporate bonds on the daily data and allow consecutive observations to be several days apart.

Table 1 presents summary statistics of the bond-day panel where only active periods are retained in the sample. My filtered sample includes around 4.6 million bond-day observations that cover almost 16,000 distinct active periods between 2005 and 2018 and 7000 different bonds issued by more than 1000 firms. An average bond in the sample is an investment-grade bond with an outstanding notional amount of around 1 billion USD and a 5% coupon rate, observed four years since issuance and eight years prior to maturity. Its average daily total return is 2 bps, and the realized bid–ask spread is approximately 1% (in line with the magnitude of the effective spread estimated in Harris (2015) using proprietary bond transaction data). The bond is held by 47 mutual funds and is traded by 37 unique dealers. The sample of active trading periods constitutes around 20% of the entire TRACE corporate bond records. The excluded bonds are less liquid, riskier, and have smaller outstanding amounts than the sampled bonds.

3.3. Volume measures

Each transaction record in TRACE is a report by a bond dealer about an individual bond transaction. The dealer indicates whether a trading counterparty is a client or another bond dealer. To measure two types of aggregate trading volume per bond per day, I use only TRACE transactions between dealers and clients. A dealer also reports whether she was a buyer or a seller in each such transaction. To measure the CtC trading volume, I first compute total daily client purchases from dealers and client sales to dealers; call it V_{it}^{buy} and V_{it}^{sell} , respectively, for bond i on day t . The minimum of the two is my measure of the CtC trading volume:

$$\text{CtC volume}_{it} = V_{it}^{(c)} = \min \left\{ V_{it}^{\text{buy}}, V_{it}^{\text{sell}} \right\}.$$

CtC volume_{it} denotes a trading volume that has no impact on aggregate dealers' inventory in bond i at the end of the trading day t as compared to day $t - 1$. CtC volume_{it} is zero on the days when either V_{it}^{buy} or V_{it}^{sell} is zero; otherwise it is greater than zero.¹¹

The difference between client purchases and client sales is a negative change in dealers' inventory:

$$-\text{Change in aggregate inventory}_{it} = V_{it}^{(s)} = V_{it}^{\text{buy}} - V_{it}^{\text{sell}}.$$

$V_{it}^{(s)}$ can be either positive or negative. Positive values represent net purchases by clients from dealers and correspond to a decrease in total broker-dealers' inventory in bond i on day t . Conversely, negative values of $V_{it}^{(s)}$ are increases in dealers' inventory. In Eq. (1), I consider the absolute value of $V_{it}^{(s)}$, which I call the CtD trading volume¹²:

$$\text{CtD volume}_{it} = |-\text{Change in inventory}_{it}| = |V_{it}^{(s)}|.$$

Table 1 shows that the CtD volume is, on average, several times higher than the CtC volume. Notice that a traditional measure of daily trading volume (excluding inter-dealer transactions), $V^{\text{buy}} + V^{\text{sell}}$, is equal to CtD volume + 2 · CtC volume.

CtC volume_{it} and CtD volume_{it}, as defined above, treat bonds dealers in their entirety. Assume that on the day t , clients sold \$10 million worth of bond i to dealers and purchased \$8 million from dealers. Assume further that these trading volumes represent, respectively, 1% and 0.8% of the total outstanding amount in bond i . Then, CtC volume_{it} = 0.8%, and CtD volume_{it} = 0.2%. The latter figure indicates that dealers' inventory in bond i , aggregated across all dealers, increased by 0.2% of the outstanding amount on day t . It could be that \$10 million and \$8 million were sold to and bought from different dealers, but it is important to note that I do not construct and analyze individual dealer inventory. My focus instead is on the use of aggregate dealers' balance sheet space as opposed to client liquidity provision and how both relate to the underlying trading motives.¹³ On a practical level, this means that I evaluate CtC volume_{it} and CtD volume_{it} with a standard academic version of the (Enhanced) TRACE dataset without relying on individual dealer identities.

3.4. Proxies for information asymmetry

I next use individual issue- and issuer-specific variables and the principal components of different groups of variables to proxy for the extent of information asymmetry in the cross-section of bonds. Some variables are bond-level proxies: realized bond bid–ask spread, bond outstanding notional amount, the number of mutual funds that hold the bond, and the number of dealers who intermediate trades in the bond. Other variables are issuer-level information asymmetry proxies: issuer market capitalization and stock bid–ask spread. The last two proxies are calculated only for traded companies. I assume that informed trading is more likely in bonds with wider (stock or bond) bid–ask spreads, fewer mutual fund holders and intermediating dealers, lower outstanding

¹¹ When I estimate Eq. (1), I further standardize CtC and CtD volumes separately for each bond and each active trading period when I estimate Eq. (1). Hence, a zero-CtC-volume observation translates into $(-1) \times$ the average CtC volume scaled by the standard deviation of the CtC volume for that bond and that active trading period.

¹² Such an imposed symmetry of return autocorrelation conditional on increases and decreases in dealers' inventory is a simplification. However, it does not undermine an alleged dependence of volume-reversal offsets on information asymmetry. An investigation of the asymmetries in conditional price reversals, though, is beyond the scope of this paper.

¹³ Trades offsetting within the same day may still represent risky principal transactions. Indeed, in the event that buying and selling clients happen to transact on the same day with different dealers, I mis-attribute a part of the CtD volume to the CtC one. If within-day offsetting trades are less informed than the rest of the CtC volume, the mismeasurement reduces the information content of my measure of the CtC volume relative to the (unobserved) true one. Nonetheless, I find strong support for the higher information content of the CtC volume. Choi et al. (2023) elaborate on the difficulties of evaluating client liquidity provision in TRACE.

amounts, and that are issued by smaller firms. Below, I justify in more detail the use of these variables as proxies for information asymmetry.

The number of mutual funds that own the bond is related to the number of buy-side analysts scrutinizing bond valuations and the credit quality of the issuer. As in the equity literature, I assume that analyst coverage is negatively related to information asymmetry between investors. Similarly, **the number of broker-dealers** intermediating trades in the bond is positively related to sell-side analyst coverage and, hence, negatively related to information asymmetry. The number of active broker-dealers also measures the competition among them in a given bond. The lack of competition likely affects an average-volume day reversal, β_1 in Eq. (1), similarly to high information asymmetry: prices of bonds traded in a less competitive market should revert more on average. However, there is no straightforward explanation as to why bonds with lower dealer competition should exhibit higher volume-reversal offsets unless low competition among dealers is caused by high information asymmetry in the first place.

Issuer and issue sizes are typical proxies for trade informativeness in the literature. Both are related to a broader investor base and, again, more in-depth analyst coverage, which supposedly leads to a higher number of investors who are ready to arbitrage out bond misvaluations. As Table A4 in the Internet Appendix shows, issue and issuer sizes are indeed positively correlated with the numbers of intermediating dealers and mutual funds that own the bond.

Stock and bond bid-ask spreads are also classic measures of information asymmetry. In [Glosten and Milgrom \(1985\)](#), the bid-ask spread is positively related to the extent of informed trading. A dealer wants to be compensated ex ante for the risk of being adversely selected and charges wider spreads to trade riskier securities. There is a confounding non-informational effect of bid-ask spreads on conditional price reversals. The mere existence of bid-ask spreads implies price reversals as in [Roll \(1984\)](#), i.e., the “bid-ask bounce” effect. Additionally, it implies stronger reversals for bonds with wider spreads (even when, ex post, it transpires that there is only liquidity trading). Hence, the impact of the bid-ask bounce on the average-day return autocorrelation, β_1 in Eq. (1), is similar to the expected effect of information asymmetry. The impact of the bid-ask bounce on β_2 and β_3 in Eq. (1) is unclear because it depends on whether the effect becomes stronger or weaker with higher trading volumes. Compounding information asymmetry indicators constructed later in this section utilize sets of proxies with and without bond bid-ask spreads to address these concerns. Furthermore, in Section 5.2, I discuss the effect of individual proxies on β_i and demonstrate that it goes beyond what is typically captured by realized bid-ask spreads, while in Section 7 I establish the robustness of results when I calculate bond returns for a simple average of volume-weighted client buy and sell prices. This approach helps to mitigate the effect of the bid-ask bounce, at least on the days when both buy and sell client trades take place.

My set of information proxies is not exhaustive. In unreported results, I extended it by including additional characteristics at both the bond level (bond return volatility, yield spread) and issuer level (availability of a single-name CDS contract on the issuer, equity analyst disagreement, stock return volatility). Notably, though, these additions did not change the key quantitative or qualitative results. Thus, rather than extending the list of individual proxies (all of which are imperfect measures of information asymmetry), I blend the bond and stock characteristics into a single compound information asymmetry index.

3.5. Compound information asymmetry indicators (indices)

A compound cross-sectional information asymmetry characteristic serves a dual purpose. First, it mitigates the confounding impact of non-information components in individual bond and issuer characteristics on the volume-return coefficients $\hat{\beta}_n$ in the second-stage cross-sectional regressions. Second, it streamlines the presentation of results. I test for the impact of information asymmetry on the volume-reversal offsets. It is easier to interpret such a test when information asymmetry is a scalar metric in the cross-section of bonds.

I construct information asymmetry indices by extracting, in the cross-section of bonds, the first principal components from the groups of bond-average values of individual asymmetry proxies discussed above.¹⁴ In the cross-section, each individual proxy is standardized (de-measured and divided by a cross-sectional standard deviation) before the extraction of the principal components. The indices and respective groups are as follows:

- PC_{all} : stock and bond bid-ask spreads, (negative) issuer and issue sizes, (negative) numbers of mutual fund holders and intermediating dealers.
- PC_{bond} : Same as PC_{all} , but issuer-level characteristics (stock bid-ask, issuer size) are excluded.
- $PC_{bond-ex-ba}$: Same as PC_{bond} , but the bond bid-ask spread is excluded.

Issuer and issue size, as well as the numbers of fund holders and intermediating dealers, are assigned a negative sign to facilitate the interpretation of extracted principal components. The first principal component loads positively on all (scaled) individual characteristics in all three considered sets. For instance, PC_{bond} increases with the average bond realized bid-ask spread and decreases with issue size, number of mutual funds, and dealers. Table A3 in the Internet Appendix presents the loadings of principal components on individual characteristics. The table shows that issuer-level characteristics, while having the lowest loadings, remain substantial. For instance, PC_{all} has a loading of 0.24 (the lowest) on a standardized stock bid-ask spread and a loading of 0.55 (the

¹⁴ In the baseline specification, individual proxies are averaged for each bond in the same active trading periods in which volume-return coefficients are estimated. To address a possible confounding effect of the measurement error in the second stage of the empirical analysis, I run multiple robustness checks in Section 7. Most notably, I demonstrate that the main results of the paper hold when the principal components are extracted from the initial values of individual information asymmetry proxies (the values at the beginning of the first active trading period for each bond).

Table 2
Summary statistics of the estimated volume-return coefficients.

	Mean	Med.	No. > 0	No. < 0	No. > 0*	No. < 0*	No. Obs.
$\hat{\beta}_1$	−0.3345	−0.3489	179	15702	6	14277	15881
$\hat{\beta}_2$	0.0687	0.0587	11146	4735	2651	518	15881
$\hat{\beta}_3$	0.0531	0.0519	10780	5101	3206	773	15881

The estimation equation is (2). Each estimated coefficient is per bond per active period. There are at most fifteen active periods per bond. Returns are total returns between t and $t + 1$. Trading volumes are de-meaned and standardized per bond per active period. Mean and Med. are, respectively, sample average and sample median. “No. > (<) 0” is the number of positive (negative) coefficients. “No. > (<) 0*” is the number of positive (negative) coefficients significant at a 10% confidence level. The number of observations is the number of bond-active periods. The sample of estimated volume-return coefficients is truncated at the 1% and the 99% levels.

highest) on a (negative) standardized issue size. Issue size, meanwhile, has the highest loading across all indices. These first principal components explain a substantial portion of the variance, ranging from 42% (PC_{all}) to 70% ($PC_{bond-ex-ba}$). The intuitively interpretable loadings and the high portion of explained variance discussed above highlight the validity of constructed indicators as compound cross-sectional information asymmetry proxies.

4. Volume-return relation

4.1. Baseline volume-return coefficients for corporate bonds

I estimate Eq. (1) separately for every bond and every active period, rescaling trading volumes such that β_1 measures the first return autocorrelation on the average volume days:

$$R_{t+1} = \beta_0 + \beta_1 R_t + \beta_2 R_t \tilde{V}_t^{(c)} + \beta_3 R_t \tilde{V}_t^{(s)} + \epsilon_{t+1}, \quad (2)$$

where R_{t+1} denotes the total bond return between day t and day $t + 1$; $\tilde{V}_t^{(c)}$ is the CtC trading volume on day t , standardized¹⁵ for every active period separately; and $\tilde{V}_t^{(s)}$ denotes the CtD trading volume (the absolute value of inventory change) on day t , also standardized.

On the days when both the CtC and the CtD trading volumes are at the average level for a given bond in a considered active period, the first return autocorrelation is β_1 . On the days when the CtC volume is one standard deviation above the mean ($\tilde{V}_t^{(c)} = 1$) and the change in inventory is at the average level ($\tilde{V}_t^{(s)} = 0$), the first return autocorrelation is $\beta_1 + \beta_2$. Conversely, when only the CtD volume is one standard deviation above the average, the return autocorrelation equals $\beta_1 + \beta_3$. Negative values of β_1 would mean that prices revert following average volume days, while positive values of β_2 and β_3 would mean that prices tend to revert less following high volume days. In this section, I present and discuss the estimated volume-return coefficients $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$. Then, in the next section, I investigate the relation between the coefficients and information asymmetry proxies, the main focus of this study.

Table 2 provides a snapshot of $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ estimated for each bond in every active period. To mitigate the impact of extreme estimates on the second-stage regression, I truncate estimated volume-return coefficients in the sample of active trading periods at the 1% and the 99% levels. The average bond-active period has a first return autocorrelation of approximately −0.33. In practical terms, this means that if the price drops today by 100 bps, with both trading volumes at their average levels, the price tends to increase by 33 bps on the next trading day. Moreover, the average $\hat{\beta}_2$ of 0.07 suggests that, following high CtC volume days, prices tend to revert less. For instance, if the initial 100 bps price decrease was accompanied by one standard deviation above-average CtC trading volume, then the next day reversal would be close to one-fourth rather than one-third. Similarly, the average $\hat{\beta}_3$ of around 0.05 suggests that prices also revert following high-CtD-volume days either. Notably, though, the difference between the average $\hat{\beta}_2$ and $\hat{\beta}_3$ is not statistically significant.

At this stage, I cannot infer much from estimated volume-return coefficients $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$. Strongly negative $\hat{\beta}_1$ is a reflection of the high illiquidity of the corporate bond market, be it due to informational or non-informational frictions. The values of $\hat{\beta}_2$ and $\hat{\beta}_3$ are close; hence, both types of trading volume contribute similarly to price reversals. Positive $\hat{\beta}_2$ and $\hat{\beta}_3$ can be consistent with the presence of informed trading but can also reflect relation size discounts (Green et al., 2007).

4.2. Comparison with volume-return coefficients for stocks

Stocks and bonds issued by the same issuer are equally exposed to that issuer’s assets value shocks (Merton, 1974). In other words, if private information about the issuer is revealed in the stock market, it will be revealed at the same time in the bond market. Thus, in the absence of other sources of uncertainty, volume-return coefficients for stocks and bonds should exhibit significant commonality. By contrast, bond-specific uncertainty as a prevailing trading motive should result in bond volume-return coefficients

¹⁵ De-meaned and divided by the sample standard deviation so that $\tilde{V}_t^{(c)}$ has a zero mean and a unit variance for each bond and each active period.

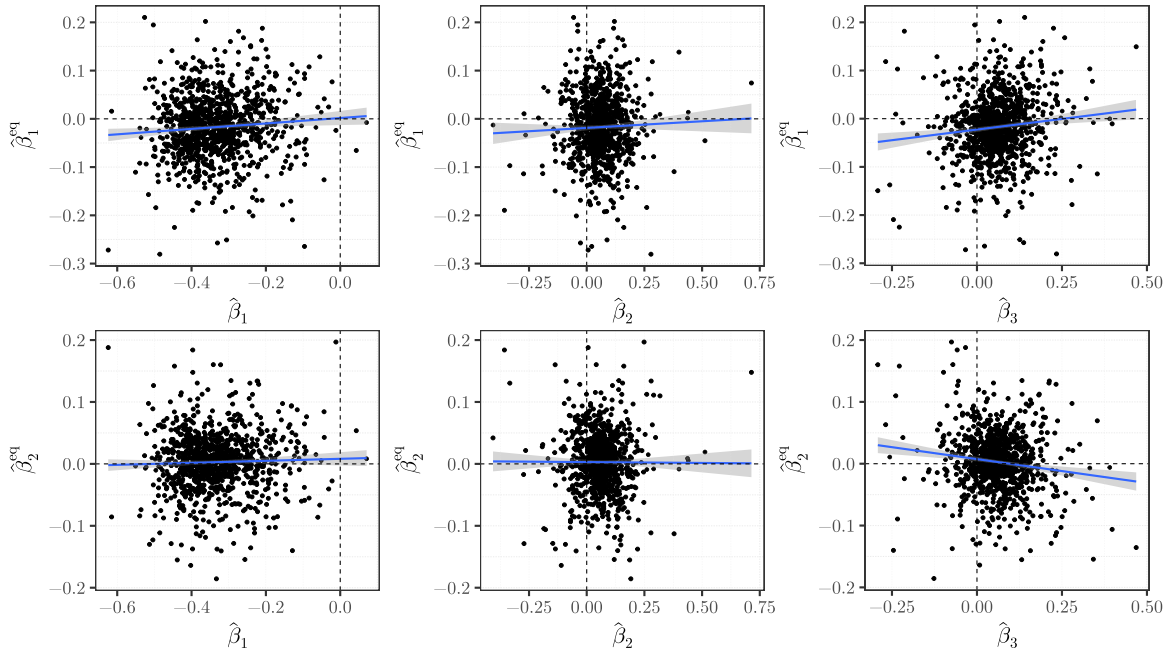


Fig. 2. Volume-return coefficients for corporate bonds and their issuers' stocks.

$\hat{\beta}_1^{eq}$ is the average daily stock price reversal, while $\hat{\beta}_2^{eq}$ is the stock volume-reversal offset. Both are estimated within the same (bond) active trading periods. Daily stock returns and trading volumes are from CRSP. $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ are corporate bond volume-return coefficients estimated in Eq. (2), averaged across all bonds and all active trading periods of the issuer. Each dot on the scatterplots is a unique issuer. Regression lines are OLS estimates.

that are distinguishable from those of stocks. To explore which of these scenarios aligns better with the data, I estimate volume-return coefficients for common stocks issued by the same issuers included in the bond sample.

To do this, I estimate stock volume-return coefficients within previously defined bond active trading periods. I use daily stock trading data from CRSP. Volume-return coefficients $\hat{\beta}_1^{eq}$ and $\hat{\beta}_2^{eq}$, per stock per trading period, come from the following OLS model:

$$R_{t+1}^{eq} = \beta_0^{eq} + \beta_1^{eq} R_t^{eq} + \beta_2^{eq} R_t^{eq} \tilde{V}_t^{eq} + u_{t+1}, \quad (3)$$

where R^{eq} denotes the daily (dividend-adjusted) stock return and \tilde{V}^{eq} denotes the standardized daily stock trading volume (turnover).¹⁶ For each issuer, it is possible that there are multiple bonds with multiple active trading periods in the sample. In this section, I average stock and bond volume-return coefficients across all bonds and all active trading periods for each issuer and compare two sets of volume-return coefficients in the cross-section of issuers (1017 public firms, most of which are large caps).

I find that the average stock price reversal $\hat{\beta}_1^{eq}$ and the volume-reversal offset $\hat{\beta}_2^{eq}$ are orders of magnitude smaller than their corporate bond counterparts. More specifically, the average $\hat{\beta}_1^{eq}$ in the cross-section of issuers is -1.7 bps (and significantly different from zero), which is 20 times smaller than the average bond price reversal. This confirms a well-known empirical fact that trading a corporate bond is, on average, considerably more expensive than trading stocks issued by the same issuer. Furthermore, the average volume-reversal offset $\hat{\beta}_2^{eq}$ is approximately 0.27 bps. Following one standard deviation above-average stock turnover day, the reversal is around $0.27/1.7 = 16\%$ less pronounced than following an average-volume day. The respective magnitudes for bonds are 21% for the CtC volume and the same (16%) for the CtD volume.

Fig. 2 shows that there is little commonality between the cross-sections of same-issuer stock and bond volume-return coefficients. There is a small positive correlation between $\hat{\beta}_1$ and $\hat{\beta}_1^{eq}$, which implies that if stock A is on average more expensive to trade than stock B, then the same applies to the bonds of the same issuer. Crucially, there is no dependence between $\hat{\beta}_2$ and either $\hat{\beta}_1^{eq}$ and $\hat{\beta}_2^{eq}$. In other words, stock reversal characteristics do not explain the cross-sectional variation in bond CtC volume-reversal offsets. There is, however, a slight positive dependence between $\hat{\beta}_3$ and $\hat{\beta}_1^{eq}$, suggesting that bonds that are relatively cheap to trade with dealers in high volumes are the ones with less pronounced corresponding stock price reversals.

The findings suggest that stock reversal characteristics have only limited explanatory power for respective bond reversal parameters. One possible explanation for this limited cross-sectional relation is the presence of credit market frictions, which could result in a lack of significant integration between equity and credit markets (e.g., Sandulescu, 2022; Collin-Dufresne et al., 2023). In Section 6.2, I provide evidence that bond-specific, on top of stock-specific information, is one of the key driving forces of corporate bond trading.

¹⁶ Since stocks are traded anonymously on exchanges, dividing \tilde{V}^{eq} into the dealer and non-dealer liquidity provision is impossible without additional strong assumptions.

Table 3
Summary statistics of the cross-section of volume-return coefficients and their predictors.

	Mean	Median	S.D.	Min	5th	25th	75th	95th	Max	N.Obs.
$\hat{\beta}_1$	−0.32	−0.34	0.12	−0.63	−0.48	−0.40	−0.25	−0.10	0.07	7212
$\hat{\beta}_2$	0.06	0.06	0.12	−0.52	−0.12	0.00	0.12	0.27	0.85	7212
$\hat{\beta}_3$	0.05	0.05	0.10	−0.38	−0.12	−0.01	0.11	0.22	0.51	7212
Credit rating	7.78	8.00	3.33	1.00	3.00	6.00	9.00	14.00	21.00	7212
Bond bid–ask, %	1.08	0.77	0.85	0.07	0.22	0.45	1.48	2.91	4.61	7212
No. mutual fund owners	40.6	34.3	38.2	0.0	0.0	8.5	59.2	114.9	381.8	7212
Issue size, bln \$	0.77	0.58	0.69	0.01	0.05	0.35	1.00	2.00	9.00	7212
No. dealers	32.1	28.7	13.0	7.7	17.4	23.3	37.4	58.0	120.7	7212
Issuer size, bln \$	75.4	37.3	105.8	0.0	2.2	12.4	102.6	235.8	930.8	6676
Stock bid–ask, %	0.05	0.03	0.07	0.01	0.01	0.02	0.06	0.16	1.33	6676
PC_{all}	0.00	0.22	1.60	−12.54	−3.09	−0.72	0.99	2.19	6.16	6676
PC_{bond}	0.00	0.21	1.52	−13.81	−2.86	−0.68	0.95	2.16	3.33	7212
$PC_{bond-ex-ba}$	0.00	0.36	1.45	−14.44	−2.83	−0.51	0.94	1.57	2.27	7212

The sample contains bond averages computed across all active periods in case there is more than one for a given bond. PC_{all} , PC_{bond} , and $PC_{bond-ex-ba}$ are the first principal components of (standardized) information asymmetry proxies (issuer and issue sizes, as well as numbers of dealers and mutual funds, are assigned a negative sign, so that higher covariate readings are associated with more information asymmetry). PC_{all} is extracted from the set of all six information asymmetry proxies. PC_{bond} is the first principal component of four bond-specific information asymmetry proxies. $PC_{bond-ex-ba}$ further excludes realized bond bid–ask from the list of factors.

5. Determinants of volume-return coefficients

5.1. Methodology

In this section, I study how the volume-return coefficients β_1 , β_2 , and β_3 vary with information asymmetry in the cross-section of bonds. The estimates $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ discussed in the previous section are per bond and per active period. While there is more than one active period for every bond in the sample, there are at most 14 active periods per bond. To create the cross-section of coefficients, I calculate bond averages. Then, I use these averages to fit explanatory linear models. Call $\hat{\beta}_{n,i}(k)$ a column-vector of estimates ($n = 1, 2$, or 3) for individual bonds $i \in \{1, \dots, N\}$ with credit ratings $k \in \{1, \dots, 21\}$. As the baseline, I fit the following model for each n (i.e., the cross-section of each volume-return coefficient) separately:

$$\hat{\beta}_{n,i}(k) = c_n \cdot \text{Info asymmetry proxy (-ies)}_{n,i} + \text{Rating } k \text{ FE}_n + \epsilon_{n,i}, \quad (4)$$

where, for every n , $\epsilon_{n,i}$ is distributed as a zero-mean normal variable, and rating fixed effects (FE) are used as control variables in the baseline specification (4).¹⁷

Table 3 presents summary statistics of the cross-section of estimated volume-return coefficients alongside their potential explanatory factors. There are approximately 7,000 individual bonds issued by 1000 firms in the cross-section, more than 90% of which are issued by public firms. There is substantial variation in both the left-hand side and the right-hand side variables of regression (4), as Table 3 shows.¹⁸

5.2. Main results

Table 4 presents estimated regressions (4) of volume-return coefficients on individual information asymmetry proxies. Issuer and issue sizes, as well as the numbers of mutual fund owners and intermediating dealers, are assigned a negative sign so that higher values of all right-hand side variables are associated with higher information asymmetry. Panel A in Table 4 presents the results for $\hat{\beta}_1$. Note that all information asymmetry proxies have a significantly negative impact on $\hat{\beta}_1$ if included in the regression separately. In a joint model 7, bond-specific information asymmetry proxies maintain significantly negative loadings. However, in a joint model 8 for public issuers, only the issuer's stock bid–ask spread flips the sign to positive. These results suggest that, on average, price reversals become more pronounced ($\hat{\beta}_1$ becomes more negative) for bonds characterized by higher information asymmetry (i.e., bonds with fewer fund owners and intermediating dealers, lower issue and issuer size, and higher bid–ask spread). However, it is important to note that the results concerning $\hat{\beta}_1$ are also consistent with explanations beyond the private information channel.

Panel B in Table 4 presents the results for $\hat{\beta}_2$. Recall that a higher β_2 indicates a stronger volume-reversal offset following days characterized by substantial trading among investors where dealers do not hold any additional inventory by the end of the trading day. In Panel B in Table 4, all bond-specific information asymmetry proxies enter the models for $\hat{\beta}_2$ significantly positively

¹⁷ The model in the Internet Appendix A shows that a tested cross-sectional relation between volume-return coefficients and information asymmetry holds when bond riskiness remains constant. Rating fixed effects in this second-stage model control for bond riskiness. The results are quantitatively similar when credit ratings are replaced in the second-stage regression with realized bond return volatility (unreported).

¹⁸ Table A4 in the Internet Appendix presents cross-sectional correlations of information asymmetry proxies.

Table 4
Cross-sectional regressions of $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ on individual information asymmetry proxies.

(A) Models for $\hat{\beta}_1$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bond bid–ask	−0.038*** (0.002)						−0.011*** (0.002)	−0.016*** (0.002)
–No. funds		−0.062*** (0.002)					−0.032*** (0.003)	−0.035*** (0.003)
–Issue size			−0.063*** (0.002)				−0.029*** (0.003)	−0.025*** (0.004)
–No. dealers				−0.039*** (0.002)			−0.009** (0.003)	−0.008** (0.004)
–Issuer size					−0.037*** (0.006)			−0.009*** (0.002)
Stock bid–ask						−0.009** (0.004)		0.009*** (0.002)
Rating FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,212	7,212	7,212	7,212	6,676	6,676	7,212	6,676
R ²	0.128	0.301	0.299	0.139	0.080	0.035	0.347	0.371

(B) Models for $\hat{\beta}_2$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bond bid–ask	0.009*** (0.002)						0.007*** (0.002)	0.004 (0.002)
–No. funds		0.011*** (0.002)					0.001 (0.002)	0.002 (0.002)
–Issue size			0.013*** (0.002)				0.005** (0.002)	0.005** (0.002)
–No. dealers				0.012*** (0.001)			0.008*** (0.002)	0.008*** (0.002)
–Issuer size					0.001 (0.002)			−0.005 (0.003)
Stock bid–ask						−0.002 (0.002)		−0.004** (0.002)
Rating FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,212	7,212	7,212	7,212	6,676	6,676	7,212	6,676
R ²	0.010	0.013	0.015	0.014	0.004	0.005	0.020	0.017

(C) Models for $\hat{\beta}_3$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bond bid–ask	−0.026*** (0.002)						−0.029*** (0.002)	−0.025*** (0.002)
–No. funds		−0.005** (0.002)					0.011*** (0.002)	0.009*** (0.003)
–Issue size			−0.004** (0.002)				−0.006** (0.002)	−0.007** (0.003)
–No. dealers				0.007*** (0.002)			0.007*** (0.002)	0.007*** (0.002)
–Issuer size					0.010*** (0.002)			0.011*** (0.002)
Stock bid–ask						−0.008** (0.004)		−0.001 (0.004)
Rating FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,212	7,212	7,212	7,212	6,676	6,676	7,212	6,676
R ²	0.072	0.018	0.017	0.020	0.026	0.025	0.081	0.075

Each model uses a fixed-effects estimator with rating-clustered standard errors (in parentheses). The regressors are standardized in the cross-section. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

when included separately (models 1 to 4). By contrast, the loadings on issuer-specific proxies (issuer size and stock bid–ask) are insignificant (models 5 and 6). In joint models 7 and 8, only the stock bid–ask spread becomes significantly negative. Otherwise, the results suggest that higher-asymmetry bonds exhibit stronger CtC volume-reversal offsets. Also of note is that, as shown in models 7 and 8, the effects of the issue size and the number of intermediating dealers on $\hat{\beta}_2$ extend beyond the impact of the realized bond bid–ask, which would likely not be the case if the variation in the cross-section of $\hat{\beta}_2$ is solely due to the bid–ask bounce.

Panel C in Table 4 presents the regression results for $\hat{\beta}_3$. The interpretation of β_3 is analogous to β_2 , but now the focus is shifted to the CtD volume-reversal offset. Unlike for β_2 , I do not expect to find any particular dependence of β_3 on information

Table 5
Cross-sectional regressions of $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ on information asymmetry indices.

	$\hat{\beta}_1$			$\hat{\beta}_2$			$\hat{\beta}_3$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PC_{all}	−0.043*** (0.001)			0.007*** (0.002)			−0.003* (0.001)		
PC_{bond}		−0.044*** (0.001)			0.010*** (0.001)			−0.005*** (0.001)	
$PC_{bond-ex-ba}$			−0.044*** (0.001)			0.010*** (0.001)			−0.001 (0.001)
Rating FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,676	7,212	7,212	6,676	7,212	7,212	6,676	7,212	7,212
R ²	0.348	0.342	0.322	0.012	0.018	0.017	0.022	0.021	0.016

Models (1)–(3) are for $\hat{\beta}_1$, models (4)–(6) are for $\hat{\beta}_2$, and models (7)–(9) are for $\hat{\beta}_3$. Each model uses a fixed-effect estimator with rating-clustered standard errors (in parentheses). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

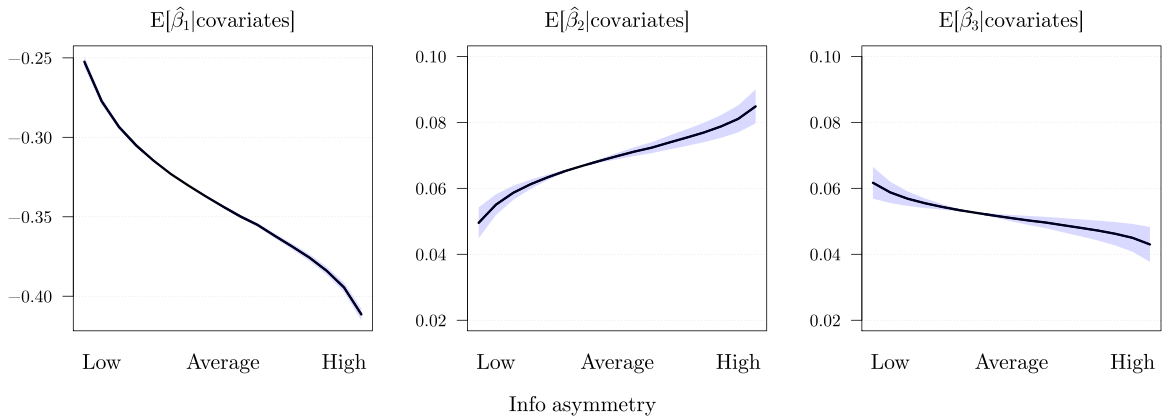


Fig. 3. Expected values of volume-return coefficients.

The calculations are based on models with PC_{bond} from Table 5. On the x-axes, from left to right, are the percentiles of PC_{bond} , from the 10th (“Low” information asymmetry) to the 90th (“High” information asymmetry). The credit rating remains fixed at the BBB level. The solid lines are point estimates, while the shaded areas around them are 95% confidence bands.

asymmetry because dealers would rather pass high-asymmetry bonds to other investors and not hold excess inventory in bonds with less transparent valuations.

Panel C in Table 4 shows that there is indeed no clear-cut dependence of $\hat{\beta}_3$ on information asymmetry. For instance, bond bid–ask spread, the (negative) number of mutual fund bond owners, and the (negative) issue size have significantly negative loadings in models 1–3 (which is the opposite to what I find for $\hat{\beta}_2$), while the (negative) number of dealers has a significantly positive loading (as for $\hat{\beta}_2$). In joint models 7 and 8 as well, there are both positive and negative loadings on the variables of interest.

Individual right-hand side variables in Table 4 are noisy measures of information asymmetry. The interpretation of the resulting effect on volume-return coefficients is ambiguous when all individual proxies are included in the regressions, as in models 7 and 8. To better summarize the relation between information asymmetry and volume-return coefficients, I regress $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ on compound information asymmetry indicators (indices). These are the first principal components extracted from different sets of information asymmetry proxies in the cross-section of bonds. The regression models resemble those in (4).

Table 5 presents the estimates. In models 1–3, I regress $\hat{\beta}_1$ on three information asymmetry indices PC_{all} , PC_{bond} , and $PC_{bond-ex-ba}$. In all three regressions, the coefficients of interest are close to −0.04 and are significant. Models 4–6, meanwhile, confirm that $\hat{\beta}_2$ increases in line with information asymmetry. Bonds with greater information asymmetry tend to have larger CtC volume-reversal offsets. The size of this effect is relatively consistent across different information asymmetry indices. Finally, models 7–9 suggest that the relation between $\hat{\beta}_3$ and information asymmetry is either negative or absent.¹⁹

In Fig. 3, I plot the relations between $\hat{\beta}_n$ and PC_{bond} , as reported in Table 5. The left panel of the figure displays the average values of $\hat{\beta}_1$ across percentiles of PC_{bond} . These values indicate a monotonic decrease, ranging from −0.25 for the bonds with little

¹⁹ Table A6 in the Internet Appendix shows that the negative relation between $\hat{\beta}_3$ and PC_{bond} pertains to both inventory-decreasing and inventory-increasing CtD volumes. For the former, the relationship is stronger, suggesting that the cost of dealer liquidity provision is higher when investors purchase rather than sell bonds. One explanation for this is that it is necessary to search for a required bond (if the dealer does not have one), which comes at an extra cost.

information asymmetry (10th percentile of PC_{bond}) to almost -0.4 for the bonds with high asymmetry (90th percentile of PC_{bond}). Moreover, the middle panel in the figure reveals an additional impact of high CtC volumes on next-day reversals. The average values of $\hat{\beta}_2$ exhibit a monotonic increase, ranging from 0.05 for low-asymmetry to almost 0.09 for high-asymmetry bonds. Finally, the right panel demonstrates that the predicted $\hat{\beta}_3$ is less sensitive to the degree of information asymmetry than $\hat{\beta}_2$ and that it decreases from 0.06 to 0.04 as the degree of information asymmetry rises. This pattern of results, where the relation between $\hat{\beta}_2$ and information asymmetry is positive and that between $\hat{\beta}_3$ and information asymmetry is negative, corroborates the hypothesis that the information content of bond prices on high-CtC-volume days differs from that on high-CtD-volume days.

6. Announcement, issuer, and time effects in volume-return coefficients

In this section, I extend the empirical evidence along several dimensions. I modify my baseline methodology to study how volume-return coefficients vary across time, within the issuer, and around corporate announcements.

6.1. Pre-announcement effects

Information trading is not constant over time and is likely to be more intense around earnings announcements (Dechow et al., 2014). Therefore, one should expect to find a stronger dependence between the CtC volume-reversal offset and information asymmetry immediately before earnings announcements. I test for such an effect using the following modification of my baseline methodology. I modify the volume-return relationship (2) to separate days close to quarterly earnings announcements from all other trading days:

$$R_{t+1} = \beta_0 + \beta_1 R_t + \beta_2 R_t \tilde{V}_t^{(c)} + \beta_3 R_t \tilde{V}_t^{(s)} + \beta_4 R_t \tilde{V}_t^{(c)} \mathbb{1}_t^{\text{EA}} + \beta_5 R_t \tilde{V}_t^{(s)} \mathbb{1}_t^{\text{EA}} + \epsilon_{t+1}. \quad (5)$$

In Eq. (5), $\mathbb{1}_t^{\text{EA}}$ is a dummy variable that takes the value of 1 if, starting from day t , there is at least one and at most ten days before the following quarterly earnings announcement for a given bond issuer (otherwise, the dummy is zero). This adjustment changes the interpretation of the volume-return coefficients. In this context, $\beta_1 + \beta_2$ is the average reversal following a far-from-announcement trading day t with the CtC volume one standard deviation above average for that bond and that active period. For a close-to-announcement trading day t with the same CtC volume, the average reversal is $\beta_1 + \beta_2 + \beta_4$. Similarly, following a CtD volume one standard deviation above average, the value β_5 measures the difference in average reversals between days close to and distant from earnings announcements.

I estimate Eq. (5) for the same subset of individual bonds issued by public firms and the same active trading periods as those used in Section 5. As before, the distributions of estimated volume-return coefficients (including $\hat{\beta}_4$ and $\hat{\beta}_5$ here) across bonds and active trading periods are truncated at the 1st and 99th percentiles to limit the impact of extreme observations on the second-stage results. In Table A7 in the Internet Appendix, I summarize the cross-section for the second-stage analysis of this section. The table shows that there is little difference compared to the cross-section in Section 5. More specifically, the cross-sectional averages of $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ are -0.31 , 0.06 , and 0.05 , respectively (virtually unchanged from the baseline analysis). The average values of $\hat{\beta}_4$ and $\hat{\beta}_5$ are, respectively, 0.03 and 0.02 . For the second stage, I use the same regression model (4) as that used in the previous analysis.

Panel A in Table 6 presents the results of the regressions of volume-return coefficients $\hat{\beta}_1$ – $\hat{\beta}_5$ on the information asymmetry index PC_{bond} with credit rating fixed effects. In the interest of clarity, I omit the results for other information asymmetry indices, but they are quantitatively similar. For $\hat{\beta}_1$, I find almost the same negative loading on PC_{bond} as in the baseline case in Table 5. The higher the information asymmetry, the stronger the average bond price reversal is. For $\hat{\beta}_2$ and $\hat{\beta}_4$, these coefficients offer insights into the information content of CtC volume-reversal offsets on days that are distant from ($\hat{\beta}_2$) and close to ($\hat{\beta}_4$) quarterly earnings announcements. The results reveal significantly positive loadings on PC_{bond} for both $\hat{\beta}_2$ and $\hat{\beta}_4$. However, $\hat{\beta}_4$ exhibits a loading nearly two and a half times greater than that of $\hat{\beta}_2$. This indicates that the information content of CtC trades is the highest near earnings announcements, as I expected. Note too that the respective estimate in Table 5 is 0.01, which is between 0.007 and 0.018 (info asymmetry loadings for $\hat{\beta}_2$ and $\hat{\beta}_4$, respectively) in Panel A of Table 6.

Similar to the results for $\hat{\beta}_2$ and $\hat{\beta}_4$, there is a stark difference between the CtD volume-reversal offset during periods far from ($\hat{\beta}_3$) and close to ($\hat{\beta}_5$) earnings announcements. Panel A in Table 6 shows that $\hat{\beta}_3$ is unrelated to PC_{bond} : there is no evidence of information-driven client-to-dealer trading even far from earnings announcements. In regard to near announcements, the table shows that $\hat{\beta}_5$ is negatively related to PC_{bond} . This contradicts the expectation that information-driven trading in client-to-dealer transactions would lead to an increase in $\hat{\beta}_5$ with rising information asymmetry. Instead, the observed negative relation aligns with the absence of informed client-to-dealer trading in the run-up to earnings announcements.

In Panel B of Table 6, I explore how $\hat{\beta}_1$ – $\hat{\beta}_5$ differ across positive and negative earnings announcements. I start from the same cross-section of volume-return coefficients as in Panel A but separate active trading periods with only positive or negative announcements as guided by the IBES Standardized Unexpected Earnings (SUE). This leaves me with slightly less than half of the cross-section, with the majority of observations corresponding to trading periods with positive-only announcements. The regressions for $\hat{\beta}_2$ and $\hat{\beta}_4$ yield quantitatively similar loadings on PC_{bond} , but the effect is slightly stronger and more significant for positive announcements. This result suggests that CtC volumes are more likely to be informed prior to unexpectedly positive than negative announcements. A possible explanation for this is that there is a lower cost of taking a long rather than a short corporate bond position for an informed investor. For the CtD volume-reversal offsets, $\hat{\beta}_3$ and $\hat{\beta}_5$, the (negative) relation with PC_{bond} appears to be stronger prior to negative than positive announcements. This suggests that client-to-dealer volumes are least informative before negative information disclosures.

Table 6

Cross-sectional regressions of extended volume-return coefficients on information asymmetry indices.

(A) All active trading periods with announcements										
	$\hat{\beta}_1$		$\hat{\beta}_2$		$\hat{\beta}_3$		$\hat{\beta}_4$		$\hat{\beta}_5$	
PC_{bond}	−0.046*** (0.001)		0.007*** (0.001)		−0.001 (0.001)		0.018*** (0.006)		−0.012*** (0.004)	
Rating FE	YES		YES		YES		YES		YES	
Observations	5,054		5,054		5,054		5,054		5,054	
R ²	0.356		0.011		0.016		0.005		0.006	

(B) Trading periods with only positive or negative announcements										
	$\hat{\beta}_1$		$\hat{\beta}_2$		$\hat{\beta}_3$		$\hat{\beta}_4$		$\hat{\beta}_5$	
	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg
PC_{bond}	−0.048*** (0.001)	−0.044*** (0.012)	0.008* (0.004)	0.007 (0.014)	−0.002 (0.003)	−0.024*** (0.007)	0.040** (0.015)	0.030 (0.059)	−0.019** (0.008)	−0.045 (0.035)
Rating FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,041	245	2,041	245	2,041	245	2,041	245	2,041	245
R ²	0.282	0.218	0.017	0.059	0.016	0.095	0.012	0.108	0.010	0.074

Volume-return coefficients $\hat{\beta}_1$ – $\hat{\beta}_5$ are estimated as in (5). Panel A presents the results for all active trading periods with earnings announcements. Panel B excludes active periods characterized by both positive and negative earnings surprises, focusing on the periods with solely positive or negative announcements. PC_{bond} is the first principal component extracted from the cross-section of standardized bond-specific information asymmetry proxies (the number of fund owners, intermediating dealers, and the issue size are assigned a negative sign). Higher values of PC_{bond} are associated with higher information asymmetry. Each model uses a fixed-effect estimator with rating-clustered standard errors (in parentheses). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7Cross-sectional regressions of $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ on information asymmetry for issuers with many bonds outstanding.

	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$
PC_{bond}	−0.038*** (0.001)	0.013*** (0.002)	−0.006*** (0.002)
Rating, Issuer FE	YES	YES	YES
Issuer-clustered SE	YES	YES	YES
Observations	3,516	3,516	3,516
R ²	0.440	0.121	0.123

The cross-section of bonds is restricted to issuers with at least 15 outstanding bonds. Each model uses a fixed effects estimator with rating and issuer fixed effects. Standard errors (in parentheses) are issuer-clustered. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2. Within-issuer effects

Some firms have many outstanding bonds at any given point in time. These bonds may differ in terms of coupon rates, maturity, embedded options, and other characteristics. I investigate how volume-return coefficients differ across bonds of the same issuer. In Table 7, I present the estimates produced by a modification of model (4) only for firms with more than 15 outstanding bonds. On top of credit rating fixed effects, I include issuer fixed effects in the regression models. Thus, Table 7 shows the within-firm dependence of volume-return coefficients on information asymmetry.

I find that the signs of the impact of information asymmetry on $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ hold for the bonds of the same issuer. In the cross-section of bonds, $\hat{\beta}_1$ and $\hat{\beta}_3$ decrease in information asymmetry while $\hat{\beta}_2$ increases. The loadings on PC_{bond} in Table 7 are similar in size to those in Table 5 (without issuer fixed effects).

These results suggest that private information held by some investors extends beyond both the issuer level (which is most likely private news about the issuer's credit quality) and the bond level.²⁰ The bond-level information can be, for instance, private knowledge about the liquidity trades of other investors, which yields a better estimate of price pressures and subsequent price reversals. It can also be private knowledge about the exercise probability of embedded options. Most bonds in my sample are callable, meaning that issuers have a right to redeem them at pre-specified dates before they reach maturity. The decision to exercise this call option can impact a bond's duration and, consequently, its risk profile. Therefore, possessing superior knowledge about the likelihood of an early call can provide an advantage in predicting bond returns ahead of call announcements.

²⁰ Addressing this point, Table A5 in the Internet Appendix presents the results of the regressions of the cross-section of $\hat{\beta}_1^{eq}$ and $\hat{\beta}_2^{eq}$ of Fig. 2 on the issuer-level information asymmetry. I find little evidence of information-driven trading in common stocks of bond issuers within bond-specific active trading periods.

Table 8
Regressions of $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ on information asymmetry indices in a bond-quarter panel.

(A) Full sample						
	$\hat{\beta}_1$		$\hat{\beta}_2$		$\hat{\beta}_3$	
PC _{bond}	−0.049*** (0.002)		0.008*** (0.001)		−0.007** (0.003)	
Rating FE	YES		YES		YES	
Time FE	YES		YES		YES	
Observations	78,332		78,332		78,332	
R ²	0.179		0.006		0.014	

(B) Pre- and post-GFC subsamples						
	$\hat{\beta}_1$		$\hat{\beta}_2$		$\hat{\beta}_3$	
	Pre-GFC	Post-GFC	Pre-GFC	Post-GFC	Pre-GFC	Post-GFC
PC _{bond}	−0.063*** (0.004)	−0.048*** (0.003)	0.010** (0.004)	0.008*** (0.001)	−0.018** (0.007)	−0.005** (0.002)
Rating FE	YES	YES	YES	YES	YES	YES
Observations	12,263	59,610	12,263	59,610	12,263	59,610
R ²	0.148	0.187	0.009	0.005	0.029	0.011

In Panel A, the sample runs from Jan. 2005 to Dec. 2018. In Panel B, the pre-GFC subsample runs from Jan. 2005 to Jun. 2008, and the post-GFC sample—from Jan. 2010 to Dec. 2018. Each model is a fixed-effect estimator with rating-quarter double-clustered standard errors (in parentheses). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

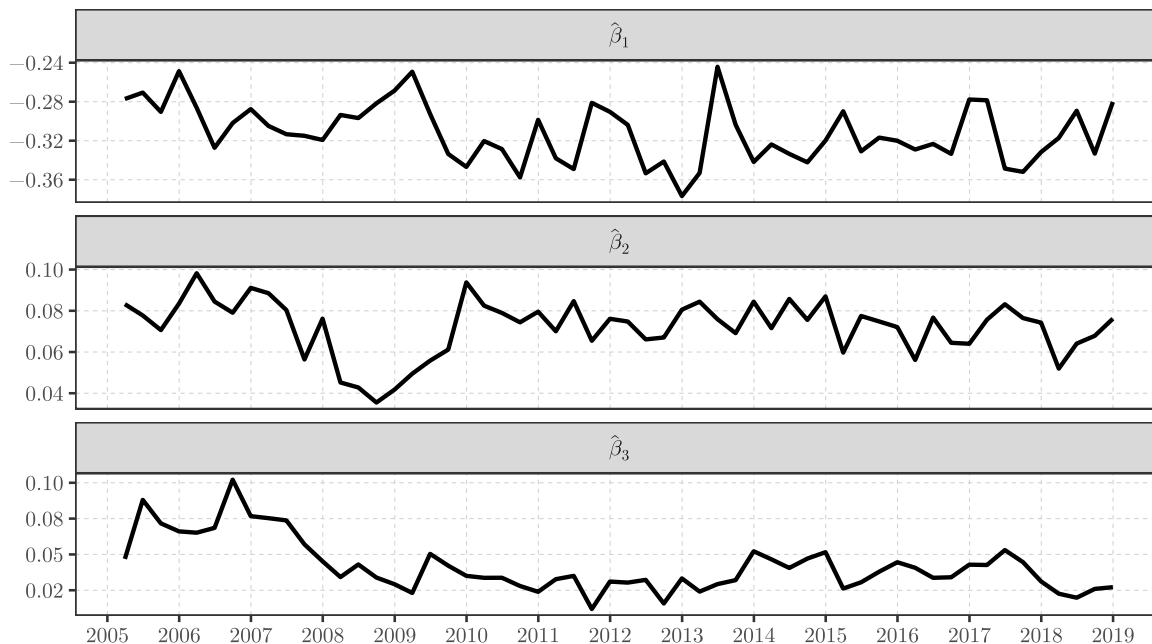


Fig. 4. Time fixed effects for volume-return coefficients.
The fixed effects are extracted from the models presented in Panel A of Table 8.

6.3. Time-varying volume-return coefficients

The evidence thus far is based on a dataset spanning from 2005 to 2018. However, the volume-return coefficients may not be persistent over time. Thus, I re-estimate Eq. (2) for individual bonds within each calendar year-quarter. In this section, I define an active period as a sequence of at least 40 trading days (days with non-zero trading volume) within a calendar quarter where every two consecutive trading days are at most three business days apart. This ensures that there is a unique active trading period (if any) per bond per calendar quarter. Therefore, I obtain bond i – year-quarter q panels of volume-return coefficients $\hat{\beta}_{1,i,q}$, $\hat{\beta}_{2,i,q}$, and $\hat{\beta}_{3,i,q}$. I then explain the panels of volume-return coefficients with the fixed effects models that are analogous to (4) up to the inclusion of year-quarter fixed effects.

Table 8 presents the second-stage estimates. Panel A shows the results of fitting rating-year-quarter fixed-effects models. The loadings on PC_{bond} have the same signs as in the cross-sectional estimation ($\hat{\beta}_1$ and $\hat{\beta}_3$ decrease with information asymmetry, while $\hat{\beta}_2$ increases). The point estimates are also close to the previously obtained values. Fig. 4 presents time fixed effects extracted from the models in Panel A. It transpires that $\hat{\beta}_1$ and $\hat{\beta}_2$ are stable over time (the time series of both variables do not contain a unit root according to conventional tests), while the level of $\hat{\beta}_3$ drops considerably around the GFC, from 0.08 to 0.03 on average. This result is in line with the evidence of a reduced risk-bearing capacity of dealer banks post-GFC (e.g., Adrian et al., 2017). Pre-GFC, bond dealers were more willing to accept the risk of being adversely selected and bond prices were more likely to move against dealers following large CtD trades than post-GFC. Panel B presents the estimates from the second-stage regression for pre- and post-GFC periods separately. I find that the dependence of $\hat{\beta}_2$ on information asymmetry does not differ much in these two subsets.

7. Robustness

I conduct several robustness tests to validate the main empirical findings about the dependence of $\hat{\beta}_2$ and $\hat{\beta}_3$ on information asymmetry. Below, I summarize the modifications made to the baseline methodology and provide the results of these robustness tests.

- *Log-clean-price return in the first-stage model.* I use the log-return based on the clean bond transaction price (without accrued interest) instead of the total return as the left-hand side variable in Eq. (2). The return is thus unaffected by additional accrued interest when an active trading period consists of non-consecutive days.
- *Log-volumes in the first-stage model.* I apply a $\log(x + \text{small constant})$ transformation to trading volumes before standardizing them per bond per active period. Therefore, $\tilde{V}^{(c)}$ and $\tilde{V}^{(s)}$ in Eq. (2) become standardized log-volumes. This helps to mitigate the impact of the largest trades on $\hat{\beta}_2$ and $\hat{\beta}_3$.
- *One-hour roundtrip volumes.* I alternatively evaluate the CtC volume $\tilde{V}^{(c)}$ as a total daily volume of transactions of equal size that were offset within one hour. Such a metric avoids counting transactions that could have been offset from the natural order flow later in the day. However, such a metric might be an underestimation of the CtC volume (as, for instance, in the case when a dealer offsets a \$1 million buy order with two \$0.5 million sell orders).
- *The simple average of the volume-weighted buy and sell prices instead of the VWAP.* To make the time series of individual bond prices less exposed to the bid-ask bounce, I take a simple average of the volume-weighted buy and sell prices rather than VWAPs (whenever the CtD volume is above zero).
- *Exclusion of retail-sized trades.* Small trades in corporate bonds are priced unfavorably (Edwards et al., 2007). Thus, the reversal in bond prices may be due to the prevalence of retail-sized transactions on certain days. To control for such an effect, I remove all trades smaller than either \$10,000 or \$100,000 in notional value. With either cut-off, the sample gets smaller and concentrates on more liquid bonds.
- *Exclusion of retail notes.* About 7% of the sample is retail notes. To assess whether the presence of retail notes introduces a possible bias, I remove them from the sample and re-run the baseline model on the sample that does not contain retail notes.
- *Market return in the first-stage model.* I add the market return as a linear term to the right-hand side of Eq. (2):

$$R_{t+1} = \beta_0 + \beta_1 R_t + \beta_2 R_t \tilde{V}_t^{(c)} + \beta_3 R_t \tilde{V}_t^{(s)} + \beta^{\text{mkt}} R_t^{\text{mkt}} + \epsilon_{t+1}.$$

The market is a size-weighted basket of all corporate bonds in the sample. The inclusion of market returns corrects for a possible omitted-variable bias in $\hat{\beta}_n$.

- *Trading volumes in the first-stage model.* I add $\tilde{V}^{(c)}$ and $\tilde{V}^{(s)}$ as linear terms on the right-hand side of Eq. (2):

$$R_{t+1} = \beta_0 + \beta_1 R_t + \beta_2 R_t \tilde{V}_t^{(c)} + \beta_3 R_t \tilde{V}_t^{(s)} + \gamma \tilde{V}_t^{(c)} + \delta \tilde{V}_t^{(s)} + \epsilon_{t+1}.$$

This potentially corrects for an omitted-variable bias.

- *Proxy for the lagged inventory in the first-stage model.* Dealers' inventory might affect the relation between information asymmetry and volume-return coefficients. To control for such inventory-driven price pressure, I add a proxy for aggregate dealers' inventory $I_t = \sum_{j=1}^{10} (V_{t-j}^{\text{sell}} - V_{t-j}^{\text{buy}})$ to model (2):

$$R_{t+1} = \beta_0 + \beta_1 R_t + \beta_2 R_t \tilde{V}_t^{(c)} + \beta_3 R_t \tilde{V}_t^{(s)} + \xi R_t \tilde{I}_t + \epsilon_{t+1}.$$

- *Control for inter-dealer turnover in the first-stage model.* To ensure that the omission of inter-dealer volume (which is allegedly uninformative) from Eq. (2) does not affect my key result, I add standardized inter-dealer volume $\tilde{V}^{(d)}$ to the model:

$$R_{t+1} = \beta_0 + \beta_1 R_t + \beta_2 R_t \tilde{V}_t^{(c)} + \beta_3 R_t \tilde{V}_t^{(s)} + \kappa R_t \tilde{V}_t^{(d)} + \epsilon_{t+1}.$$

- *Information asymmetry indices extracted from initial bond characteristics.* The averaging of bond characteristics across active periods for individual bonds introduces some measurement error to the right-hand side of Eq. (4). To limit its impact on the second-stage estimates, I use observed initial values (i.e., values at the beginning of the first active trading period) of information asymmetry proxies rather than time series averages for individual bonds.
- *Weighted second-stage regression.* In the first-stage regression, volume-return coefficients are estimated with varying precision. I assign higher weights to more precise estimates to limit the impact of high-variance estimates of $\hat{\beta}_n$ on the second-stage results. The weights are the inverse variance of the first-stage estimates.

Table 9
Robustness tests for the regressions of volume-return coefficients on information asymmetry.

	$\hat{\beta}_1$ (1)	$\hat{\beta}_2$ (2)	$\hat{\beta}_3$ (3)
A. Different inputs in the 1st stage			
Log-clean-price return	−0.041*** (0.001)	0.010*** (0.001)	−0.006*** (0.001)
Log-volumes	−0.043*** (0.001)	0.008*** (0.001)	−0.006*** (0.002)
1-hour roundtrip volumes	−0.034*** (0.002)	0.009*** (0.001)	0.004** (0.002)
Avg. of VW buy and sell prices	−0.048*** (0.004)	0.049*** (0.011)	−0.001 (0.002)
Trades less than \$10k excluded	−0.046*** (0.002)	0.032*** (0.007)	0.007*** (0.001)
Trades less than \$100k excluded	−0.034*** (0.002)	0.009** (0.004)	0.005*** (0.001)
Retail notes excluded	−0.045*** (0.001)	0.004*** (0.001)	0.002 (0.001)
B. Different models in the 1st stage			
Market return added	−0.029*** (0.001)	0.011*** (0.001)	−0.005*** (0.001)
Volumes added linearly	−0.041*** (0.001)	0.017** (0.006)	−0.002 (0.002)
Lagged inventory added	−0.039*** (0.002)	0.014*** (0.003)	−0.021*** (0.002)
Inter-dealer turnover added	−0.043*** (0.001)	0.008*** (0.002)	−0.009*** (0.002)
C. Different 2nd stage			
PCs extracted from initial obs.	−0.042*** (0.002)	0.009*** (0.002)	−0.004** (0.002)
Weighted observations	−0.044*** (0.001)	0.006*** (0.001)	−0.001 (0.001)
Vlm. correlation controls	−0.042*** (0.001)	0.008*** (0.001)	−0.006*** (0.002)

Each line in the table shows loadings on the information asymmetry index PC_{bond} in fixed-effects models for the cross-section of volume-return coefficients $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$. Fixed effects are bond credit ratings. Standard errors (in parentheses) are rating-clustered. The details for each robustness test are presented in Section 7. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

- *Control for volume persistence in the second-stage model.* Time-series correlation in trading volume might lead to amplification of price impacts and generate a relation between volumes and future returns similar to one of the asymmetric information and returns.²¹ I control for this alternative explanation by including the first autocorrelations of $\tilde{V}_t^{(c)}$ and $\tilde{V}_t^{(s)}$ (averages for individual bonds) in the second-stage model.

Table 9 presents the results of these robustness tests. Each coefficient in the table represents the estimated loading on PC_{bond} within the fixed effects models for the respective $\hat{\beta}_i$. In column (1), it is evident that $\hat{\beta}_1$ remains significantly negative across all alternative specifications, with minimal changes in effect size, except when market returns are included in the first stage. The same applies to $\hat{\beta}_2$. Here, the effect size varies more across specifications (ranging from 0.004 to 0.049, compared to the baseline estimate of 0.010), but the loading on PC_{bond} remains significantly positive. The results in column (3) show that $\hat{\beta}_3$ either exhibits a negative dependence on information asymmetry or lacks a significant association, except in cases where either CtC volumes are proxied by short-window roundtrip trades or retail-sized trades are removed. In such cases, despite the sample zooming into the most liquid and actively traded bonds, $\hat{\beta}_2$ is several times more sensitive to the information asymmetry index than $\hat{\beta}_3$. This is also in line with the explanation that CtC volume is more likely to be informed. Overall, these robustness tests support the main finding.

Additionally, I re-estimate the baseline empirical model (Table 5 with PC_{bond}) across different sample splits. Table A9 in the Internet Appendix shows that the results hold both in the investment-grade (IG) and the high-yield (HY) subsamples. Notably, the effects appear to be stronger for HY bonds, which are likely more information-sensitive than the IG bonds. Furthermore, as shown in Table A10 in the Appendix, the results hold consistently across bonds issued by industrial companies and financial firms. This indicates that the findings are not driven by industry-specific effects.

²¹ The average autocorrelation of $\tilde{V}_t^{(c)}$ is relatively low in the data (Table A2 in the Internet Appendix).

Table 10
Performance of the long leg of the corporate bond reversal strategy.

	Before T-cost				After T-cost (avg. bid-ask)				After T-cost (roundtrip)			
	Mean	S.D.	SR	IR	Mean	S.D.	SR	IR	Mean	S.D.	SR	IR
(A) Reversal: univariate sort on month $t-1$ return												
Baseline	6.34	6.22	0.94	1.37	0.08	6.17	-0.04	-0.26	-0.31	6.11	-0.10	-0.39
Many funds	5.48	7.16	0.69	0.83	-1.06	7.14	-0.20	-0.44	-0.95	7.08	-0.18	-0.43
Few funds	7.32	5.54	1.23	1.97	1.16	5.45	0.15	0.07	0.27	5.37	-0.02	-0.26
Big issuers	6.14	6.15	0.93	1.13	-0.36	6.10	-0.12	-0.34	-0.52	6.00	-0.13	-0.39
Small issuers	7.40	7.07	0.99	1.32	1.17	6.96	0.14	0.05	0.55	6.91	0.04	-0.10
Inv. grade	7.22	5.60	1.23	1.72	0.87	5.49	0.11	-0.03	0.36	5.37	0.02	-0.21
High yield	6.96	10.40	0.65	0.63	0.58	10.34	0.06	-0.05	0.80	10.35	0.07	-0.02
(B) Reversal: bi-variate sort on month $t-1$ return and rating												
Baseline	7.43	6.11	1.15	1.77	1.06	6.03	0.14	0.03	0.60	5.93	0.06	-0.12
Many funds	6.71	7.06	0.90	1.16	0.11	6.96	-0.02	-0.20	0.05	6.86	-0.02	-0.22
Few funds	8.56	6.00	1.35	2.01	2.26	5.91	0.35	0.38	1.30	5.79	0.18	0.10
Big issuers	6.87	6.86	0.95	1.19	0.39	6.80	0.02	-0.13	0.08	6.69	-0.01	-0.21
Small issuers	8.32	6.12	1.30	1.91	1.98	6.00	0.29	0.30	1.35	5.92	0.19	0.11
Inv. grade	7.60	5.87	1.24	1.73	1.19	5.77	0.17	0.07	0.59	5.64	0.07	-0.12
High yield	8.01	10.06	0.78	0.79	1.67	10.01	0.18	0.09	1.91	10.02	0.19	0.12

The investment universe is restricted to bonds whose previous month's outstanding amount exceeds \$200 mn and whose previous month's realized bid-ask spread (12-month backward-looking moving average) is below 100 bps. The rebalancing is monthly. In Panel A, value-weighted portfolios consist of bonds from the bottom quintile of the month $t-1$ cross-sectional return distribution. In Panel B, reversal signals are extracted by independently double-sorting bonds on the month $t-1$ credit rating (terciles) and total return (quintiles). Within each of the 15 resulting bins, the value-weighted portfolio is constructed. The long leg of such a double-sorted reversal strategy is the equally-weighted (across three rating terciles) portfolio of the bottom-return-quintile portfolios. The first four columns are performance characteristics without transaction cost adjustment. The middle four columns assume that the transaction cost is half of the realized bid-ask spread. The last four columns employ the roundtrip cost measure of [Feldhütter \(2012\)](#) as the T-cost. In columns, the mean is a sample average of monthly returns, in % per annum. S.D. is the standard deviation of monthly returns, in % per annum. SR is the Sharpe ratio relative to the 3-month Treasury bill. IR is the information ratio relative to the market portfolio, which is the value-weighted return of the bonds in the universe. The sample runs from Jan. 2006 to Dec. 2018.

8. Implications for investment strategies

In this section, I show that the short-term reversal strategy earns more if the likelihood of information trading is taken into account in portfolio formation. I exploit my result that price reversals depend on the extent of bond information asymmetry.

I start by constructing reversal portfolios with univariate and bivariate sorts at a monthly rebalancing frequency. Adopting a similar approach to that of [Chordia et al. \(2017\)](#), I obtain the univariate reversal signal by sorting bonds on the previous month's total return (here, quintiles). Meanwhile, the bivariate reversal signal, which is obtained using a similar method to that of [Dickerson et al. \(2023\)](#) and the earlier literature, involves the double sorting of bonds on the previous month's credit rating and return (terciles and quintiles, respectively). The investment universe for this analysis encompasses all corporate bonds with an outstanding amount of at least \$200 million and a 12-month backward-looking average of the realized bid-ask spread of at most 100 bps. The latter helps to reduce the transaction cost of the reversal strategy, which is usually very high due to high portfolio turnover. Here, I do not restrict the bond sample to active periods and do not remove the crossing of the IG/HY threshold as above, as to do so would introduce a look-ahead bias.

In this analysis, I only consider the long leg of the reversal strategy. For the univariate sorting, this is the value-weighted portfolio of bonds in the bottom quintile of the month $t-1$ cross-sectional return distribution (i.e., the portfolio of past losers). For the bivariate sorting, the long leg is the union of value-weighted bottom-return-quintile portfolios across three rating terciles (i.e., the portfolio of past losers in which each credit rating tercile is represented equally). I do not consider a short leg of the reversal strategy here because, in my sample, shorting top-performing corporate bonds was not profitable. I investigate this matter in more detail in [Ivashchenko and Kosowski \(2023\)](#). Furthermore, there is little public historical information on the cost of shorting (borrowing) corporate bonds. Regarding the long leg, I account for the explicit part of the transaction cost at the backward-looking realized bid-ask spread level or with the [Feldhütter \(2012\)](#) imputed roundtrip cost (IRC). [Schestag et al. \(2016\)](#) suggest that these metrics, among many others, are effective at measuring explicit execution costs. Additionally, [Ivashchenko and Kosowski \(2023\)](#) propose a method to evaluate implicit bond trading cost (market impact) and further derive capacity limits for several systematic strategies, including the reversal portfolios considered here.

In addition to (the long legs of) baseline reversal portfolios, I consider a few of their sub-portfolios. The first split divides the portfolios into investment-grade and high-yield credit classes. The second split is based on the number of mutual fund bondholders (below- and above-median) six months before the sorting date. The third split, which applies only to bonds issued by public firms, is based on issuer market capitalization (also below- and above-median). Within these splits, the information asymmetry in the portfolios of high-yield bonds, bonds with fewer institutional investors, and bonds issued by smaller firms is supposedly higher than in the portfolios of, respectively, investment-grade bonds, bonds with more institutional investors, and bonds issued by large firms.

[Table 10](#) shows the performance of reversal portfolios. Between 2006 and 2018, the average return of the long leg of baseline reversal portfolios was 6.3% per year for the univariate reversal signal and 7.4% for the bivariate signal before accounting for

trading cost adjustment. Across all sub-portfolios, the bivariate signal performed better than the univariate one. Within pairs of sub-portfolios, the ones with more information asymmetry generally performed better.²² For instance, the bivariate reversal portfolio with many fund owners earned approximately 6.7% per year, while the portfolio with few fund owners earned around 8.5%. The volatility of the sub-portfolio with few fund owners was also lower, resulting in superior risk-adjusted performance for the reversal strategy, particularly in bonds with higher levels of information asymmetry. Before T-cost adjustment, reversal portfolios outperform the market on a risk-adjusted basis, as suggested by the information ratios.

Once I account for transaction costs, the performance of reversal portfolios becomes considerably worse because of high portfolio turnover. The reversal signal is short-lived: one must replace approximately 85% of portfolio holdings each month. For baseline portfolios in Table 10, transaction costs comprise around 6.3–6.6 p.p. of the average gross return. Between the two T-cost proxies, the IRC is a more conservative adjustment method across the board (except for HY sub-portfolios). Focusing on ex-IRC performance characteristics, I find that sub-portfolios with higher information asymmetry still earn positive risk-adjusted net returns. In a previously discussed pair of portfolios with few and many institutional investors, the former earns on average 1.25 p.p. more than the latter after IRC adjustment. The return on the reversal portfolio with many fund owners is effectively zero after trading cost adjustment. Remarkably, all sub-portfolios with higher information asymmetry yield very similar ex-cost Sharpe ratios of 0.18–0.19 and information ratios (relative to the market portfolio) of 0.10–0.12.

The evidence suggests that conditioning on ex-ante information asymmetry has a considerable impact on the performance of reversal strategies in practice. Reversals tend to be stronger for bonds with more information asymmetry. Long-only reversal portfolios of bonds with limited mutual fund ownership or consisting of bonds issued by smaller firms outperform the corporate bond market on a risk-adjusted basis even after trading costs are accounted for. Given these findings, one can further investigate different information asymmetry signals and improve the performance of a corporate bond reversal strategy.

9. Conclusion

In this paper, I estimate individual corporate bond return autocorrelation as a linear function of the trading volume and explore the determinants of the estimated relation in the cross-section of TRACE bonds. My analysis focuses on the impact of information asymmetry on the volume-reversal offset, which refers to the difference in bond price reversals between high- and low-volume days.

In the cross-section of bonds, I can expect the volume-reversal offset to increase with the underlying bond information asymmetry when trading is occasionally driven by private information. By contrast, when trades are uninformed, there should be no such dependence. I use this prediction to identify the informational content of trading volumes attributed to either dealer or client liquidity provision.

I find that bonds with higher information asymmetry exhibit more substantial volume-reversal offsets when dealers' inventory remains stable, client purchases equal client sales, and bond investors are, in fact, liquidity providers. However, the opposite becomes true when dealers supply liquidity and trading volumes mirror dealers' bond inventory changes. In this scenario, the volume-reversal offset either decreases in or does not depend on information asymmetry. Notably, this result becomes more pronounced when informational motives for trading are more acute, such as before earnings announcements.

These results suggest that the informational content of bond prices is higher when investors, rather than intermediating dealers, supply liquidity to the corporate bond market. Since OTC dealers typically know their clients well and might detect informed traders, the dealers let other investors supply liquidity for informed trades. As a result, dealers and non-dealer liquidity providers experience different levels of exposure to adverse selection risk in the U.S. corporate bond market. These insights also have implications for the development of investment strategies that aim to capitalize on corporate bond price reversals.

CRedit authorship contribution statement

Alexey Ivashchenko: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Data availability

The codes will be publicly available. The data is non-public but a representative sample can be provided.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.finmar.2023.100880>.

²² The exception is the pair of IG and HY univariate reversal portfolios. Here, the IG outperforms the HY. Note too that univariate IG and HY reversal portfolios have an average return that is higher than the baseline univariate reversal portfolio [sic]. Each month, the baseline return is between the IG and the HY components, as it must be. However, the relative weight of the HY portfolio in the baseline increases almost four times in the GFC period amid multiple bond downgrades, which occurs when the HY reversal portfolio suffers substantial losses. In other words, the baseline portfolio “overweights” the HY component at the worst possible time. As a result, the average baseline return is below the average returns of its two components. Post-GFC, there is no such phenomenon.

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