# Cross-Bond Momentum Spillovers*

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**Abstract**

Bond peer momentum (PM), the average return of economically linked bonds, strongly predicts one-month-ahead excess returns. Across firm linkages, the shared-analyst network is most informative and subsumes alternative PMs. A long–short strategy based on this signal earns 0.45% per month, with alphas unexplained by standard bond and stock factor models and robust across samples, characteristics, and return measures. The predictability is concentrated among co-held bonds and is stronger when trading frictions are high, supporting a flow-based limits-to-arbitrage channel rather than limited attention. Compared with stocks, bond PM delivers comparable Sharpe ratios, lower crash risk, and shorter persistence.

**Keywords:** corporate bonds; momentum spillovers; peer momentum; shared-analyst networks; institutional flows; limits to arbitrage

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# 1 Introduction

Equity and corporate bonds are claims on the same underlying cash flows, differing primarily in payoff structure and priority. Any economic linkage that transmits information about a firm's fundamentals should therefore, in principle, affect both its equity and its debt. Yet most empirical work on cross-firm return predictability has focused on equities. The leading interpretation in this literature is that information from peer firms diffuses gradually because investors are inattentive or face frictions that slow its incorporation into prices, giving rise to cross-firm momentum spillovers.

An important question is whether fundamental linkages at the level of underlying cash flows also generate momentum spillovers in corporate bonds and, if so, whether the underlying mechanism mirrors that in equities. Institutional investors dominate the corporate bond market (Cai et al., 2019; Bai et al., 2021). Because these investors are sophisticated, benchmarked, closely monitored, and typically specialize by sector, a pure limited-attention explanation appears less compelling ex ante than in equities. At the same time, corporate bonds trade infrequently in over-the-counter markets, and the resulting illiquidity raises arbitrage costs, which may slow the incorporation of predictive signals into prices. The corporate bond market therefore provides a useful setting in which to distinguish among competing explanations for peer momentum documented in equities.

Using data from the Wharton Research Data Services (WRDS) Bond Return Database, we document a strong cross-bond momentum spillover effect. We consider several firm-level linkages studied in the stock literature, and map them to the bond market via issuers.[1]

[1]These include the industry linkage (Moskowitz and Grinblatt, 1999), text-based industry linkage (Hoberg and Phillips, 2018), geographic linkage (Parsons et al., 2020), customer linkage (Cohen and Frazzini, 2008), the supplier and customer industry linkage (Menzly and Ozbas, 2010), the complicated firm linkage (Cohen

As established in prior literature, these linkages are effective proxies for the fundamental relatedness between firms. For each linkage, we construct a bond peer momentum signal (PM hereafter) as the average of peer bonds' past one-month returns, excluding bonds issued by the same firm. Individually, several bond PM measures significantly and positively predict one-month-ahead bond returns in the cross-section. In horse-race regressions, factor spanning tests, and factor model Sharpe ratio comparisons (Barillas et al., 2020), however, the shared-analyst bond PM emerges as the strongest predictor and subsumes the predictive power of all other linkages in the horse-race regressions, echoing the stock market findings in Ali and Hirshleifer (2020).[2] Economically, this result is plausible because shared-analyst coverage can capture multiple dimensions of firm relatedness at once. Analysts often follow sets of firms that are connected through common industry structure, supply-chain relationships, geographic proximity, or technological similarity, since information about one firm can help inform valuation of another. As a result, shared-analyst coverage may provide a broader summary measure of fundamental relatedness than any single linkage taken in isolation. Accordingly, we focus the subsequent analysis on shared-analyst specification.

The cross-bond momentum spillover captured by the shared-analyst PM signal is economically large. A long–short strategy that buys bonds in the highest shared-analyst PM decile and sells those in the lowest decile earns an average return spread of about 0.45% per month, or 5.4% annually. This spread is not explained by standard factor models, in-

and Lou, 2012), the technological linkage (Lee et al., 2019), and shared-analyst coverage (Ali and Hirshleifer, 2020).

[2]Shared-analyst coverage here refers to equity analysts. We do not construct a parallel linkage based on fixed-income analyst coverage because debt analyst data from the Investext database is less accessible and has substantially weaker cross-sectional coverage than IBES equity analyst data (Johnston et al., 2009; Gurun et al., 2016). This choice should still be informative for our purposes. Because equity and corporate bonds are claims on the same underlying firm fundamentals, shared equity analyst coverage should still provide an informative proxy for fundamental relatedness among bond issuers.

cluding the bond market model in Dickerson et al. (2023), the classic Fama–French bond factor model in Fama and French (1993), or their combination. The effect is strongest in BBB and junk bonds and remains positive across maturity buckets. The effect survives a rich set of controls: this signal continues to forecast returns after we condition on a bond's own past return (Bai et al., 2023), the issuer's past stock return (Gebhardt et al., 2005b), shared-analyst stock PM, bond characteristics (maturity, amount outstanding, and rating), and a battery of bond return predictors in the literature, including bond market beta, VIX beta (Chung et al., 2019), value-at-risk (Bai et al., 2023), idiosyncratic volatility (Bai et al., 2021), and bond illiquidity (Bao et al., 2011). A comprehensive set of robustness checks, using value-weighted portfolios, firm-level aggregation, alternative bond samples, and alternative bond return measures (including duration-adjusted bond returns and bond returns from the Open Source Bond Asset Pricing database), confirms the stability of the effect.

We next turn to its underlying mechanism. In the stock literature, momentum spillovers are typically interpreted as evidence of limited investor attention or gradual information diffusion (e.g., Ali and Hirshleifer, 2020). In the corporate bond market, however, large institutional investors dominate holdings, making pure inattention unlikely to be the primary driver. We nevertheless test this hypothesis directly. Using bond-level measures of institutional ownership and investor composition based on trading horizons (Li and Yu, 2021), as well as firm-level abnormal institutional news readership (Ben-Rephael et al., 2017) and abnormal Google search volume (Da et al., 2011), we examine whether the momentum spillover is stronger where limited attention should matter more. We find only weak evidence: the effect does not systematically strengthen among bonds with lower institutional ownership or more buy-and-hold investor bases, nor for firms with lower levels of institutional or retail attention. Limited attention may play some role at the margin, but it does not appear to be the main force behind cross-bond momentum spillovers.

We also test whether factor momentum can account for the effect. Burt and Hrdlicka (2021) and Yan and Yu (2023) show that cross-asset lead–lag return relationships can arise mechanically if assets share exposure to common factors that themselves exhibit momentum. To assess this channel, we decompose each bond's return into a component explained by common stock and bond factors and a residual component that primarily reflects firm-specific news, and then construct shared-analyst PM signals separately from the systematic and idiosyncratic parts. The idiosyncratic PM signal has much stronger predictive power than the systematic PM signal, suggesting that the effect is not driven by exposure to common factors alone.

Instead, our evidence points to a flow-based limits-to-arbitrage mechanism. We build on the delegated-portfolio framework of Vayanos and Woolley (2013), in which gradual and uncertain flows into and out of benchmarked active funds generate short-run momentum, co-movement, and lead–lag even when all agents are fully rational and attentive. In that setting, assets that are tilted in a similar direction by the same active manager move together as flows are absorbed only gradually, and high returns in one such asset tend to forecast high returns in another. We adapt this mechanism to corporate bonds by using the shared-analyst network as a proxy for similar institutional tilts. Crucially, this channel only generates return predictability between two bonds if the same institutions actually hold both, so that their portfolio flows move the two securities jointly. Consistent with this implication, we split shared-analyst peer bonds into those that share at least one institutional owner with the focal bond (co-held peers) and those with distinct owners (non-co-held peers), and construct separate PM from each group. The predictive content of shared-analyst bond PM comes almost entirely from co-held peers, whereas PM constructed from non-co-held peers is essentially uninformative. Because the institutions that co-hold the focal bond and its peers are exactly the investors most likely to observe and react to peer news, this pattern is difficult to reconcile with an inattention-based story but lines up closely with a flow-portfolio mechanism.

We then ask why the resulting return predictability is not arbitraged away. In the model of Vayanos and Woolley (2013), short-run predictability persists because the manager who absorbs flows is risk-averse and benchmarked, so fully eliminating the effect would require taking on additional flow risk that is not attractive. In the corporate bond market, high trading costs and illiquidity provide an additional, first-order friction. Using bond illiquidity and idiosyncratic volatility as proxies for arbitrage costs (Bao et al., 2011; Bai et al., 2021), we find that the effect is much stronger among illiquid bonds and bonds with high idiosyncratic volatility. For example, the strategy earns an average monthly return of 0.44% in illiquid bonds versus 0.26% in liquid bonds, and 0.66% in high–idiosyncratic-volatility bonds versus 0.10% in their low-volatility counterparts, with similar differences in alphas. In Fama–MacBeth regressions, interaction terms between shared-analyst PM signal and these arbitrage-cost proxies are strongly positive. Moreover, following Bartram et al. (2025) and Dickerson et al. (2024a), we show that a one-way trading cost of about 13.57 basis points is sufficient to eliminate the average profits of this strategy, a threshold that is below typical estimates of corporate bond trading costs (such as the 19 basis points used in Kelly et al., 2023). Together, these results indicate that flow-based cross-bond predictability is strongest precisely where arbitrage is most difficult and that realistic transaction costs are enough to deter even relatively risk-neutral arbitrageurs from fully exploiting the effect.

This mechanism also helps explain why momentum spillovers look different in bonds than in stocks. The shared-analyst bond PM strategy has similar risk-adjusted performance to the shared-analyst stock PM strategy, but with much lower crash risk: the bond strategy has a maximum drawdown of only 8.41%, compared with 28.34% for the stock strategy, even though their Sharpe ratios are nearly identical (0.206 versus 0.197). The cross-bond momentum spillover is also much less persistent. Beyond the most recent month, longer-lag bond PMs provide little additional predictive power, whereas stock PM decays much more slowly. This contrast is consistent with a flow-based mechanism in a market dominated by benchmarked institutional investors facing high trading costs. In such a setting, momentum spillovers should emerge over short horizons as flows are transmitted across related bonds, but fade once those flows are absorbed.

This paper contributes to several strands of literature. First, it adds to the literature on momentum and reversal in the corporate bond market. Bai et al. (2023) and Bali et al. (2021a) document return reversals at very short (one-month) and very long horizons (one to four years). At intermediate horizons (within one year), there is no clear pattern overall, but there is momentum among non-investment-grade bonds (Gebhardt et al., 2005b; Jostova et al., 2013). A significant challenge in this literature is that bond trading occurs over-the-counter, subjecting prices to substantial market microstructure noise that contaminates both the signal and the outcome and can generate spurious predictability (Dickerson et al., 2024b). Unlike these studies, we construct the bond PM signal from the past returns of peer bonds rather than from a bond's own return history, which inherently mitigates concerns about mechanical noise-induced patterns.

Second, this paper extends the momentum spillover literature to the corporate bond market. A long-standing literature has documented strong momentum spillovers in the stock market based on various firm linkages (e.g., Moskowitz and Grinblatt, 1999; Hoberg and Phillips, 2018; Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Cohen and Lou, 2012; Lee et al., 2019; Parsons et al., 2020; Ali and Hirshleifer, 2020), and Gebhardt et al. (2005b) show that stock momentum spills over to corporate bonds. Recent work further emphasizes that momentum spillovers depend not only on firm linkages but also on the trading process and investor composition; for example, Wang (2025) decomposes peer firms' stock returns into overnight and intraday components and finds evidence of asymmetric cross-firm price pressure. Despite this large equity literature and related evidence on stock-to-bond spillovers, relatively few papers examine momentum spillovers within corporate bonds. Chen et al. (2016) construct bond PM through supplier–customer industry linkages and find that it predicts future bond returns, whereas Feng et al. (2025b) use co-movement in bond credit ratings to identify firm links and construct PM, but find no predictive power for future bond returns. We provide a comprehensive analysis across multiple linkages and show that shared-analyst bond PM dominates, mirroring the stock-market result in Ali and Hirshleifer (2020). However, our results point to a different mechanism: we find only weak evidence for limited attention, but strong evidence for a flow-based limits-to-arbitrage channel operating through common institutional ownership and high trading costs. In this sense, corporate bonds offer a sharp out-of-sample test of stock-market interpretations: the same shared-analyst network that organizes information also organizes institutional tilts and flow transmission.

Finally, this paper contributes to the literature on corporate bond return predictability by proposing a new predictor based on inter-firm linkages. Existing bond return predictors are largely based on stock characteristics (e.g., Gebhardt et al., 2005b; Chordia et al., 2017), bond-specific features (e.g., Gebhardt et al., 2005a; Lin et al., 2011; Chung et al., 2019; Bai et al., 2021, 2023; Bali et al., 2021a,b; Huynh and Xia, 2021; Bartram et al., 2025), option information (Cao et al., 2023), or machine learning approaches (e.g., Bali et al., 2020; Feng et al., 2025a). In contrast, our bond PM measures are based on linkages among bonds induced by firm-level networks and institutional coverage.

The remainder of this paper is organized as follows. Section 2 describes the data and variable constructions. Section 3 identifies shared-analyst as the most informative bond PM specification. Section 4 studies the shared-analyst specification in more detail, including heterogeneity, robustness, and comparison with stocks. Section 5 investigates mechanisms. Section 6 concludes.

# 2 Data and Variables

## 2.1 Corporate Bond Return

We use corporate bond return data from the Wharton Research Data Services (WRDS) Bond Return Database, which is constructed by WRDS research teams using procedures consistent with recent fixed-income research. Due to its high quality, this dataset is increasingly used in recent corporate bond literature (e.g., Li, 2022; deHaan et al., 2023). In constructing return, WRDS follows Asquith et al. (2013) and Dick-Nielsen (2009, 2014) to clean the TRACE Enhanced data for issues related to cancellation, correction, reversal, and double counting, and imposes the following bond filters: (1) coupon type equals fixed or zero (not variable coupons); (2) not under Rule 144A; (3) bond type is equal to US Corporate Convertible (CCOV), US Corporate Debentures (CDEB), Medium Term Note (CMTN), US Corporate Medium Term Note Zero (CMTZ), or US Corporate Paper (CP). In addition to these WRDS filters, we follow the corporate bond literature to exclude convertible bonds and bonds with maturity less than one year at the end of each month.

From the WRDS Bond Return Database, we obtain monthly bond returns using the `RET_L5M` field, which is based on the last price falling within the last five trading days of a month. Although WRDS bond returns are available from July 2002, `RET_L5M` in July 2002 is valid for only a small number of bonds that defaulted. As a result, the sample starts from August 2002 and ends in December 2020. The monthly risk-free rate from Kenneth French's website is used to calculate bond excess returns. In the robustness section, we repeat the main empirical analysis with alternative bond samples and alternative bond returns.

## 2.2 Bond Peer Momentum

To construct bond peer momentum, we first establish economic linkages among issuing firms and then map those linkages to their bonds.

*Industry linkage:* Firms in the same industry are natural peers, as they share similar fundamentals. At the end of each month, for each bond, we obtain the issuer's four-digit SIC code from its corresponding stock, using data from the `crsp.msenames` file. We then transform the four-digit SIC code into Fama–French 48 industries (excluding the "Other" industry). Bonds from the same industry group are defined as industry peers.

*Text-based industry linkage:* Hoberg and Phillips (2016) show that TNIC industry classification has many advantages over the traditional SIC-code-based industry classification. The TNIC data provide annual firm linkages based on product market similarity in the 10-K reports. Following Hoberg and Phillips (2018), we employ the TNIC-3 granularity and assume that the TNIC linkage in year $T$ is available from the end of June in year $T + 1$. We also exclude self-links that connect a firm to itself. Bonds whose firms share the TNIC linkage are defined as text-based industry peers.

*Geographic linkage:* Parsons et al. (2020) use firms' headquarters locations at the zip-code level from Compustat and group locations into economic areas defined by the Bureau of Economic Analysis (BEA). The ZIP code to economic area mapping is downloaded from Riccardo Sabbatucci's website. Bonds whose firms are located in the same economic areas are defined as geographic peers.

*Customer linkage:* We obtain information about firms' principal customers from the supply chain data in WRDS (the "wrdsapps.seglink" file). Following Cohen and Frazzini (2008), we assume that the customer data in calendar year $T$ is available from the end of June in year $T + 1$. Bonds from customer firms are defined as customer peers of the focal firm's bonds.

*Supplier- and Customer-industry linkages:* To establish the supplier- and customer-industry linkages, we apply the open source asset pricing code provided by Chen and Zimmermann (2022) to process the input-output data from BEA. This procedure already accounts for the timing of BEA data releases, so the resulting linkage measures do not introduce look-ahead bias in return prediction. Following their code, we obtain the supplier and customer industries for each industry at the BEA summary level. Bonds from the supplier or customer industries are defined as the supplier- or customer-industry peers of the bonds in the focal industry.

*Complicated firm linkage:* We obtain firms' business segment information from WRDS (the "compsegd.wrds_segmerged" file). Following Cohen and Lou (2012), we classify business segments at the two-digit SIC level and keep only those firms whose total sales from all reported segments account for at least 80% of their annual sales reported in Compustat. Conglomerate (standalone) firms are firms operating in at least one (only one) industry. We assume that the segment information in calendar year $T$ is available from the end of June in year $T + 1$. For each conglomerate firm, those standalone firms operating in the same industry as its segments are defined as its peers.

*Technological linkage:* We obtain firms' patent information from the GitHub repository maintained by Kogan, Papanikolaou, Seru, and Stoffman (KPSS), which extends the original data of Kogan et al. (2017) through 2022. Following Lee et al. (2019), we first construct for each firm a patent vector based on the proportional shares of patents across technology classes over the past five years. Because the updated KPSS data use the CPC system rather than the USPTO system used in Lee et al. (2019), we group patents by the first three digits of the CPC code, which yields 127 patent classes in total. When a patent is associated with multiple CPC codes, we use its first CPC code. We then measure technological closeness between firms as the cosine similarity of their patent vectors. Technological closeness is calculated in each calendar year $T$ based on patent grant dates over the previous five years, and we assume that it becomes available at the end of June of year $T + 1$.

*Shared-analyst linkage:* Following Ali and Hirshleifer (2020), at the end of each month, we consider a stock to be covered by an analyst if that analyst issued at least one FY1 or FY2 earnings forecast for it during the past 12 months, and two stocks to be connected if they are covered by at least one common analyst. The analyst data come from the Institutional Brokers Estimate System (IBES) detail file (the `ibes.detu_epsus` file in WRDS). Bonds whose corresponding stocks are connected through shared-analyst coverage are defined as shared-analyst peers.

After establishing the linkages among bonds, we construct nine bond PMs based on these linkages. For the industry, text-based industry, geographic, and customer linkages, we construct PM as the equal-weighted average of the past one-month bond returns of a firm's peers. For supplier- and customer-industry linkages, we follow Menzly and Ozbas (2010) to first calculate industry momentum as an equal-weighted average of past one-month bond returns within each BEA industry, and then for each firm, we calculate its supplier- and customer-industry PM as the weighted average of industry momentum across all its supplier- and customer-industries. The weight is the flow of goods or services from and to related industries, respectively. For complicated-firm linkage, we follow Cohen and Lou (2012) to first compute industry momentum as the equal-weighted average of past one-month bond returns of all standalone firms within each industry, and then construct complicated-firm PM for each conglomerate firm as the weighted average of industry momentum across all of the conglomerate's industry segments. The weight is the percentage of sales contributed by each industry segment of the conglomerate. For the technological linkage, a firm's PM is the weighted average of other firms' past one-month bond returns, using their technological closeness to the firm as weights. For shared-analyst linkage, we follow Ali and Hirshleifer (2020) to compute the PM as the weighted average of past one-month bond returns of peer firms, with the number of co-covering analysts as the weight.

Note that in all the above bond PM calculations, we do not classify bonds from the same firm as peers. That is, we only use past bond returns of peer firms and focus on the information from outside the focal firm.

## 2.3 Benchmark Factor Returns

To examine if the returns of bond PM strategies can be explained by common risk factors, we use three types of factor models to calculate the alphas. The first one is the bond market model (MKTB hereafter) in Dickerson et al. (2023), who find that newly proposed factor models do not outperform the MKTB in explaining corporate bond returns. At the end of each month, we calculate the bond market excess return as the weighted average of bond excess returns in the sample, with bond amount outstanding at the previous month's end as the weight.

The second one is the classic Fama and French (1993) bond factor model (FFDT hereafter), including the Fama–French three stock market factors (MKT, SMB, HML), default return spread (DEF), and term spread (TERM). DEF is the return difference between long-term corporate bonds and long-term government bonds. TERM is the return difference between long-term government bonds and Treasury bills. The data for MKT, SMB, and HML are from Kenneth French's website, while the data for DEF and TERM are obtained from the "Bond Factor Zoo" of the Open Source Bond Asset Pricing website.

Finally, the third factor model (FFDTB) is the combination of the above two. All factor return series in these factor models range from August 2002 to December 2020.

## 2.4 Control Variables

To explore whether bond PM provides distinct information in predicting bond returns, we control for an extensive set of variables, as described below.

Return-related controls: bond PM may correlate with other return-related variables that predict future bond returns in the literature. To account for this, we control for (1) past one-month bond return $RET^{Bond}$ (Bai et al., 2023), (2) past one-month stock return $RET^{Stock}$ of the corresponding stock (Gebhardt et al., 2005b), and (3) past one-month stock PM based on the same linkage used to construct bond PM. When we study bond PM from different linkages, stock PM changes accordingly.

Bond characteristics: from the WRDS Bond Return Database, we obtain bond characteristics at the end of each month, including time to maturity in years ($Maturity$), the amount outstanding in billions ($AMT$), and the numerical bond rating (*Rating*). The *Rating* in WRDS follows the priority order of S&P, Moody's, and Fitch. A lower numerical rating means higher credit quality (1 for AAA, 2 for AA+/AA1, 3 for AA/AA2, 4 for AA-/AA3, etc.).

Other bond return predictors: (1) bond market beta $\beta$, calculated by regressing monthly bond excess returns on monthly bond market excess returns over the past 36 months, with at least 24 valid observations; (2) bond VIX beta $\beta^{VIX}$ as in Chung et al. (2019), estimated by regressing monthly bond excess returns on the monthly changes of VIX and its lagged value, while controlling for the FFDT factor returns in Section 2.3. The $\beta^{VIX}$ is the sum of the two coefficients on VIX changes. The regression is run with past 36-month data while requiring at least 24 observations; (3) the 5% value-at-risk $VaR$ in Bai et al. (2023). For each bond, $VaR$ is the negative of its second lowest monthly excess return during the past 36 months, with at least 24 valid observations; (4) the bond idiosyncratic volatility $IVOL$ as in Bai et al. (2021). For each bond, $IVOL$ is the standard deviation of the residuals when regressing monthly bond excess return on monthly bond market excess return over the past 36 months, with at least 24 valid observations; (5) the bond illiquidity $ILLIQ$ in Bao et al. (2011). For each bond, $ILLIQ$ is the negative of the covariance between its daily log price change and the lagged log price change within a month, with at least 5 valid pairs in the covariance calculation. Here, the daily bond price is the trading-volume-weighted average price within the day using cleaned TRACE enhanced data provided by WRDS (the "wrdsapps.trace_enhanced_clean" file).

## 2.5 Descriptive Statistics

The final sample contains the monthly bond PM and other control variables from August 2002 to November 2020, and the one-month-ahead bond excess return from September 2002 to December 2020. Some control variables begin only in July 2004 because their construction requires at least 24 valid monthly observations. We require the one-month-ahead bond excess return to be non-missing, resulting in a total of 1,082,017 observations across 220 months. Figure 1 plots the monthly time series of the number of bonds and the number of firms in our sample, and Table 1 reports the time-series average of the monthly cross-sectional statistics for all variables. Among the bond PM measures, those based on industry and shared-analyst linkages have the broadest cross-sectional coverage, with averages of about 4,100 bonds from 800 firms per month. By contrast, under the customer linkage, bond PM is available for only about 582 bonds from 154 firms on average. The mean and median bond PM are both around 0.60%. Among the control variables, the average bond maturity is about 9.4 years, and the average numerical rating is about 8.7, which is close to the BBB level.

# 3 Bond Peer Momentum and Future Bond Returns

## 3.1 Baseline Evidence

We first conduct a univariate portfolio analysis to establish the baseline relation between bond PM and future bond returns. At the end of each month $t$, we sort bonds into 10 portfolios (deciles) based on their bond PM from low to high. We then compute the month $t+1$ equal-weighted excess return for each portfolio, where excess returns are measured relative to the monthly risk-free rate from Kenneth French's website. Table 2 reports the time-series averages of each portfolio's month $t+1$ excess return, the month $t+1$ high–minus–low return, and the corresponding alphas from different factor models: the one-factor bond market model (MKTB), the classic Fama–French (1993) bond factor model (FFDT), and their combination (FFDTB). Throughout the paper, we report Newey and West (1987) t-statistics with 5 lags, where the choice of 5 follows the formula $4 \times (T/100)^{2/9}$ in Bali et al. (2016) with $T = 220$ months.

The rows of Table 2 correspond to bond PMs constructed from various linkages. All bond PMs generate significant high–minus–low return spreads and alphas, with the exception of the customer-industry PM. In terms of economic magnitude, the text-based industry and shared-analyst linkages produce the largest high–minus–low spreads and alphas, ranging from 0.45% to 0.61% per month, or roughly 5.4% to 7.32% per year. Figure 2 plots the log cumulative returns on the long-short portfolios sorted by bond PM from different linkages. Several of the cumulative return series display noticeable jumps around the 2008–2009 market crash, whereas the shared-analyst series appears comparatively steadier.

We then conduct dependent double sorts to assess whether the bond PM effect survives controls for alternative bond return predictors. At the end of each month $t$, we sort bonds into quintiles on a given control variable and, within each control quintile, into quintiles on bond PM. We then compute the month $t+1$ high–minus–low spread across the five PM-sorted portfolios within each control quintile and average these five spreads across control quintiles. Table 3 reports the time-series average of this average high–minus–low spread; for brevity, we report only the spread, as the alpha patterns are similar.

Industry, text-based industry, complicated firm, technology, and shared-analyst PM remain significant in every control-conditioned double sort. Geography and customer PM remain significant on average across controls but fail under some individual controls, whereas supplier-industry PM is not robust. The last row of Table 3 reports the average double-sort performance across all control variables. Because data availability differs across controls, with some series beginning in August 2002 and others in July 2004, this average is computed each month using all available double-sort estimates for that month. Among the linkages that survive the individual double sorts, the industry, text-based industry, and shared-analyst linkages deliver the strongest average performance.

We further estimate Fama and MacBeth (1973) regressions of one-month-ahead bond excess returns on bond PM, with and without controls. In these regressions, we winsorize all the independent variables at the 0.5% and 99.5% levels each month and compute Newey and West (1987) t-statistics with 5 lags. The results are reported in Table 4, with each column corresponding to a different linkage-based PM. The coefficients on bond PM are significantly positive for the industry, text-based industry, technology, and shared-analyst linkages, regardless of whether we include the full set of controls. In contrast, PMs based on other linkages do not show robustly significant predictive power.

Among the return-based control variables, the past one-month bond return $RET^{Bond}$ significantly and negatively predicts future bond returns, consistent with the one-month reversal documented in the bond literature. Past one-month stock return $RET^{Stock}$ significantly and positively predicts future bond returns, consistent with the momentum spillover from stock to bond in Gebhardt et al. (2005b). However, stock PM, constructed using the same linkages as bond PM, does not have significant predictive power for future bond returns.

Given that past bond and stock returns are the two most significant controls in the cross-sectional regressions, we further examine whether the alphas of the long–short PM strategy remain significant under a more stringent factor benchmark. Specifically, we augment the FFDTB model from Table 2 with two additional long–short bond factors sorted on past bond and stock returns, which we refer to as the FFDTB-Plus model. The results in Section 3.3 show that the main conclusions are robust to this stricter benchmark.

Combining the baseline evidence in Tables 2, 3, and 4, we conclude that, when considered individually, bond PMs based on industry, text-based industry, technology, and shared-analyst linkages are most consistently robust across all three baseline tests.

## 3.2 Horse Race among Different Linkages

To explore which PM measures provide distinct information for bond return prediction and which appear to be redundant, we run Fama–MacBeth regressions that include multiple bond PMs in a horse-race specification. We report results both with and without the full set of controls from Table 4. In the specifications with controls, we additionally include the corresponding stock peer momentum variables ($PM^{Stock}$) for the linkages being compared.

We use the shared-analyst PM signal as the benchmark because it is the strongest predictor in Tables 2, 3, and 4. To preserve sample size, we focus on one-to-one comparisons: each regression includes this benchmark signal together with one alternative bond PM. Table 5 shows that, without controls, the benchmark signal subsumes nearly all of the predictive power of the other bond PMs, leaving only text-based industry PM marginally significant. Once the full set of controls is introduced, no alternative bond PM remains statistically significant. In particular, industry, text-based industry, and technology PMs, which are significant when tested individually in Table 4, lose significance once the benchmark signal is included. The same conclusion holds in unreported tests using alternative industry definitions, including the 20-industry grouping in Moskowitz and Grinblatt (1999), three-digit SIC industries, and TNIC-2 text-based industries. These results indicate that the shared-analyst PM signal contains distinct information for bond return prediction and subsumes the predictive content of other linkage-based bond PMs, consistent with the stock-market evidence in Ali and Hirshleifer (2020).

### 3.3 Factor Spanning Tests and Sharpe Ratio Comparisons

The horse-race Fama–MacBeth regressions already suggest that the shared-analyst bond PM contains the most distinct return-predictive information. We now examine this conclusion from a factor-pricing perspective using factor spanning tests and Sharpe ratio comparisons.

Throughout this subsection, we use the FFDTB-Plus model as the benchmark factor specification. This model augments the FFDTB model with two additional long–short bond factors sorted on past one-month bond returns and past one-month stock returns. We choose these two factors because lagged bond and stock returns are the two strongest return-related controls in Table 4. By contrast, factors based on past stock PM are largely insignificant there and, being linkage-specific, would add substantial complexity without much benefit. Relative to FFDTB, the FFDTB-Plus model provides a stricter benchmark by absorbing generic short-horizon bond return reversal and stock-to-bond momentum spillovers.

We first construct nine bond PM factors as the high–minus–low return spreads associated with the nine linkage-based bond PM signals and examine whether any of them are spanned by the others. Table 6 reports the results. Columns (3) and (4) show the mean return and FFDTB-Plus alpha of each bond PM factor. Under this stricter benchmark, only six of the nine bond PM factors retain statistically significant alphas, compared with eight under the FFDTB model in Table 2. Columns (5) and (6) then report the spanning tests relative to the shared-analyst bond PM factor. When each alternative bond PM factor is regressed on this factor together with the FFDTB-Plus factors, its alpha is no longer significantly positive. In the reverse regressions, however, the shared-analyst bond PM factor continues to deliver a significant alpha after controlling for the FFDTB-Plus factors and each alternative bond PM factor in turn. Taken together, these results show that the shared-analyst bond PM factor subsumes the other linkage-based bond PM factors.

We next compare the nine augmented factor models using the framework of Barillas et al. (2020), which evaluates models through improvements in the squared Sharpe ratio. Specifically, each candidate model adds one bond PM factor to the FFDTB-Plus benchmark, and we test whether its squared Sharpe ratio is at least as large as those of the other eight candidate models. Table 7 reports the likelihood-ratio statistic and associated $p$-value for each comparison. For every model other than the shared-analyst one, the null is rejected at the 10% level. By contrast, the shared-analyst model yields a $p$-value of 0.773, far above conventional significance thresholds. This indicates that the shared-analyst bond PM factor is the only clear top performer in the model set.

Overall, the factor spanning tests and the Sharpe ratio comparisons lead to the same conclusion as the horse-race regressions: among the linkage-based bond PM measures, the shared-analyst specification is the most informative and largely subsumes the others. We therefore focus on shared-analyst bond PM in the remainder of the paper.

# 4 Additional Results on Shared-Analyst Bond PM

This section provides a detailed examination of the shared-analyst bond PM specification along several dimensions. We first study cross-sectional heterogeneity by bond rating and maturity, and then assess the stability of the effect across sub-periods. We further conduct a comprehensive set of robustness checks, including alternative portfolio constructions, firm-level aggregation, sample restrictions, and alternative return definitions, as well as tests addressing information availability. Finally, we compare the performance and persistence of bond PM with its stock-market counterpart. Throughout this section, unless otherwise noted, $PM^{Bond}$ refers to the shared-analyst bond peer momentum measure.

## 4.1 Different Rating and Maturity Groups

Given that rating and maturity are two of the most important characteristics of corporate bonds, we investigate how the effect varies across different rating and maturity groups. At the end of each month, we segment bonds into four rating categories — AAA/AA ($Rating \leq 4$), A ($4 < Rating \leq 7$), BBB ($7 < Rating \leq 10$), and junk ($Rating > 10$) — and into four maturity buckets: short-term ($Maturity \leq 3$ years), medium-term (3–5 years), long-term (5–10 years), and very long-term ($Maturity > 10$ years). Within each rating or maturity group, we conduct univariate portfolio sort by shared-analyst bond PM. Since the sample size drops once we condition on rating and maturity, we focus on quintile sorts rather than deciles.

The results are reported in Table 8. The bond PM effect is weak among high-credit-quality bonds (AAA/AA and A) but economically and statistically significant for riskier BBB and junk bonds. Along the maturity dimension, the effect is significant in all buckets but is notably stronger for long-maturity bonds.

## 4.2 Sub-period Analysis

We now examine the predictive power of bond PM during different sub-periods. We consider sub-periods defined along several dimensions: time (the first versus the second half of the sample), the business cycle (normal versus crisis periods), the median value of economic policy uncertainty in our sample (Baker et al., 2016), the median value of bond market excess return in our sample, and the median value of investor sentiment in our sample (Baker and Wurgler, 2006). For the business-cycle split, we follow the NBER definition and identify two crisis periods during our sample: December 2007 to June 2009 and February 2020 to April 2020 (both inclusive). Sub-periods are defined based on the formation month of the PM signal.

Table 9 reports the Fama–MacBeth estimates for the alternative sub-periods and the associated tests for differences in the bond PM coefficient. The coefficient on bond PM is statistically significant in nearly all sub-periods, indicating stable predictive power over time. The absence of significance during crisis periods is likely attributable to the limited number of observations. Consistent with this interpretation, the coefficient-difference tests in the final row indicate no meaningful variation in predictive strength across the alternative sample partitions.

## 4.3 Value-weighted Portfolio Return

In the main analysis, we construct the bond PM strategy using equal-weighted portfolio returns, but there might be a concern that the PM effect is driven by small bonds with extreme returns. To address this, we use bonds' amount outstanding as weights to recalculate the portfolio return.

Table 10 reports the returns and alphas of the bond PM strategy under different robustness tests. From Panel A, we see that the bond PM effect is robust to using value-weighted portfolio returns.

## 4.4 Firm-level Analysis

So far, we have performed the analysis at the bond level, under which the bond PM signal is the same for all bonds within the same firm since they share the same peer bonds outside of the firm. This means that firms with more bonds may be overrepresented in the cross-sectional analysis. For robustness, we examine the bond PM effect at the firm level. Specifically, we aggregate bond returns at firm level first, and then calculate the firm-level bond PM as the weighted average of peer firms' firm-level bond returns, with the number of co-covering analysts as the weight. We then reexamine the relation between firm-level bond PM and future firm-level bond returns.

We consider both equal-weighted and amount-outstanding-weighted methods when averaging bond returns within the same firm. Panel B in Table 10 shows that firm-level bond PM still generates significantly positive month $t + 1$ high–minus–low returns and alphas, regardless of how firm-level bond returns are calculated. This suggests that the bond PM effect also exists at the firm level.

## 4.5 Excluding Bonds with Embedded Options

The embedded options in corporate bonds have confounding effects on the bond return, which could potentially affect the bond PM effect. To explore its influence, we exclude from our original sample those bonds that are putable, callable, or sinking fund. These filters reduce the original bond sample observations from 1,082,017 to 248,974. Other popular filters in the bond literature, such as excluding convertible bonds, non-US dollar-denominated bonds, and bonds backed by mortgages or other assets, have no effect on our original sample.

The large drop in sample size is driven by the exclusion of callable bonds, which make up a large fraction of corporate bonds, especially in recent years. Therefore, we also consider adding callable bonds back to the filtered sample, resulting in 1,072,528 observations, which is close to the original sample size.

Panel C of Table 10 shows that the bond PM strategy continues to generate positive and statistically significant returns and alphas after excluding bonds with embedded options. When callable bonds are reintroduced, the estimated performance is similar to that in the baseline sample. Overall, these results indicate that the bond PM effect is robust to the exclusion of bonds with embedded options.

## 4.6 Alternative Bond Returns

In the baseline analysis, bond returns are measured using the WRDS field `RET_L5M`, which corresponds to the return based on the last observed price within the last five trading days of the month. Throughout this subsection, we denote this baseline return as $R^{\mathrm{L5M}}$. For alternative return specifications, we recompute both the bond PM signal and the prediction target using consistent return definitions.

We first consider two alternative return measures available in WRDS. Specifically, we use `RET_EOM`, which we denote as $R^{\mathrm{EOM}}$ and which is based on the last observed price within the month, and `RET_LDM`, denoted as $R^{\mathrm{LDM}}$, which uses the price on the last trading day of the month. These measures differ in the strictness of price availability: $R^{\mathrm{EOM}}$ is the least restrictive, $R^{\text{L5M}}$ is intermediate, and $R^{\text{LDM}}$ is the most restrictive. As the return definition becomes more stringent, the sample size declines accordingly. As reported in the first two rows of Panel D of Table 10, the bond PM strategy continues to generate significant returns and alphas under both $R^{\text{EOM}}$ and $R^{\text{LDM}}$, with slightly larger estimates under the most stringent definition $R^{\text{LDM}}$.

Second, we use the unadjusted bond return data from the Open Source Bond Asset Pricing (OSB) database. We denote these returns as $R^{\text{OSB}}$. The OSB data are constructed from the WRDS Bond Return Database but apply different filters and adjustments to address return truncation issues. To maintain comparability, we restrict the sample period to August 2002 through December 2020. Panel D of Table 10 shows that the bond PM effect remains robust under $R^{\text{OSB}}$.

Finally, we consider duration-adjusted bond returns. Following van Binsbergen et al. (2025), we denote this measure as $R^{\text{DurAdj}}$, defined as the baseline return $R^{\text{L5M}}$ (i.e., `RET_L5M`) minus the corresponding duration-matched Treasury return. The duration-matched Treasury return is obtained from Yoshio Nozawa's website. We then reconstruct the shared-analyst bond PM using these duration-adjusted peer returns and use it to predict one-month-ahead $R^{\text{DurAdj}}$. Panel D of Table 10 shows that the bond PM effect remains strong under $R^{\text{DurAdj}}$.[3]

## 4.7 Information Availability

Unlike stocks, corporate bonds are traded far less frequently, and prices are often unavailable on every trading day. As a result, the monthly bond return used in our tests does not

[3]In unreported tests, we also construct bond PM using $R^{\text{L5M}}$ to predict future $R^{\text{DurAdj}}$, and vice versa. The results are similarly strong.

always reflect the prices on the last trading day of each month. During the portfolio formation month, the price used to calculate a bond's one-month-ahead return may therefore correspond to a date earlier than the date at which the bond PM signal is measured.

To address this information availability concern, we use the one-month-ahead `RET_LDM` return in WRDS as the prediction target, while using `RET_EOM` or `RET_L5M` in WRDS to construct bond PM signal. Since `RET_LDM` is based on the bond price on the last trading day of a month, it ensures that bond PM is available at the time of portfolio formation. Meanwhile, using the less strict return definitions `RET_EOM` or `RET_L5M` to construct the bond PM signal helps increase cross-sectional coverage. The first two rows in Panel E of Table 10 show that the bond PM strategy is still profitable after accounting for this information-availability issue. In fact, both the economic magnitude and statistical significance are higher than those of the original bond PM strategy.

We also use the MMN-adjusted bond return from the OSB website to construct bond PM and use it to predict the one-month-ahead unadjusted bond excess return from OSB. To address the market microstructure noise (MMN) issue in corporate bond studies, Dickerson et al. (2024b) propose an MMN-adjusted bond return that uses prices at least one trading day before the end-of-the-month transaction price. Using their MMN-adjusted bond return to construct bond PM makes the PM more likely to be available at the time of portfolio formation, which partially addresses the information-availability concern. From the last row in Panel E of Table 10, we see that the bond PM strategy is robust to using MMN-adjusted bond return.

## 4.8 PM Strategy Performance in Bond and Stock Markets

Having established the robustness of the shared-analyst bond PM, we compare its properties with those of the analogous stock-market counterpart. To do so, we construct stock PM using the past returns of stocks linked through shared-analyst coverage and examine its ability to predict one-month-ahead stock returns. The stock sample includes all common stocks listed on the NYSE, AMEX, and NASDAQ over August 2002 through December 2020. We do not restrict the stock sample to firms with bond return data, because such a restriction would materially reduce the size of the stock cross section.

Panel A of Table 11 compares mean return, the corresponding t-statistic, standard deviation, Sharpe ratio, skewness, excess kurtosis, and maximum drawdown for the bond and stock PM strategies. The mean return of the bond PM strategy is about one-third of that of the stock PM strategy (0.45% vs. 1.31% per month). However, the standard deviation of the bond PM strategy is also about one-third as large, which makes its Sharpe ratio comparable to or even slightly higher than that of stock PM strategy (0.206 vs. 0.197). Moreover, the maximum drawdown of the bond PM strategy is only about 8.41%, much smaller than the 28.34% drawdown of the stock PM strategy. This suggests that the bond PM strategy carries much lower crash risk than the stock PM strategy, despite their very similar Sharpe ratios.

## 4.9 Persistence of PM Effect in Bond and Stock Markets

Finally, we compare the persistence of the PM effect in the bond and stock markets. We begin with the bond market. In addition to the baseline measure, $PM_{t-1}^{Bond}$, we construct alternative bond PM signals using peer bonds' past returns over longer horizons. Specifically, $PM^{Bond}_{t-3,t-2}$, $PM^{Bond}_{t-6,t-2}$, and $PM^{Bond}_{t-12,t-2}$ are formed from returns over the preceding 3-, 6-, and 12-month windows, respectively, each excluding the most recent month, while $PM^{Bond}_{t-36,t-13}$ is formed from a longer window that excludes the most recent 12 months. To mitigate the influence of extreme observations, we compute returns within each window as the simple average of monthly returns and require at least two-thirds of the underlying monthly observations to be available.

In the upper part of Panel B in Table 11, we run Fama–MacBeth regressions of month-$t$ bond excess returns on bond PMs constructed over different past return windows, using a full set of controls that includes return-related variables with matching windows, bond characteristics, and other bond return predictors. The coefficient on the original $PM^{Bond}_{t-1}$ is always significantly positive, whereas the coefficients on bond PMs based on longer windows are either insignificant or lose significance once $PM^{Bond}_{t-1}$ is included. Overall, bond PMs from alternative past windows do not provide additional predictive power beyond $PM^{Bond}_{t-1}$.

Next, we perform similar tests for the stock PM in the stock market. In particular, we run Fama–MacBeth regression of month-$t$ stock excess return on the stock PMs constructed over different past windows, while controlling for past stock returns with the same windows, the log of stock market capitalization, and the log of the book-to-market ratio. The choice of this set of controls follows Ali and Hirshleifer (2020).

The lower part of Panel B in Table 11 shows that the stock PM constructed from longer lags continues to have significant predictive power, even after controlling for $PM^{Stock}_{t-1}$. This pattern is generally consistent with Ali and Hirshleifer (2020), who find that the stock PM effect lasts for roughly one year. The main discrepancy concerns the significance of

$PM^{Stock}_{t-36,t-13}$, which is stronger in our sample, likely because we use a different sample period.

In short, the bond PM strategy has much lower crash risk, and the bond PM effect is much less persistent, than their stock counterparts. With this result in mind, we next examine how and why the bond PM effect arises and persists.

# 5 Mechanism

## 5.1 Limited Attention

In the stock market, momentum spillovers are often interpreted as evidence of limited investor attention or gradual information diffusion (e.g., Ali and Hirshleifer, 2020). The underlying idea is that investors do not immediately incorporate value-relevant news from connected firms, so the focal stock price adjusts only gradually and past returns of peer stocks predict future returns of the focal stock. We examine whether a similar limited-attention channel is present in the corporate bond market.

To do so, we construct two attention-related variables from bond institutional holdings in eMAXX. Because the holdings data end in 2018Q4, this analysis covers August 2002 through December 2018. Since eMAXX data is quarterly, we assign each quarter's holdings to all months within that quarter.

The first eMAXX-based variable is bond institutional ownership, $IOR$, defined as the fraction of the total amount outstanding held by institutional investors. We cap $IOR$ at 1 and set missing values to 0. Bonds with lower institutional ownership are more likely to have a larger retail investor base and may therefore be more susceptible to limited attention.

The other eMAXX-based variable, $INV\_COMP$, is a bond-level investor composition measure which captures heterogeneity in investors' trading horizons by aggregating turnover rates across a bond's institutional investors, following Li and Yu (2021). For each fund $k$ in quarter $t$, we compute the percentage net change in bond holdings as

$$\text{net\_transaction}_{k,t} = \frac{|\sum_i H_{k,i,t} - \sum_i H_{k,i,t-1}|}{\sum_i H_{k,i,t-1}} \tag{1}$$

where $H_{k,i,t-1}$ is the par amount of bond $i$ held by fund $k$ in quarter $t-1$. We then average this measure over the previous four quarters to capture the persistent component of a fund's trading behavior, $NT_{k,t} = \frac{1}{4}\sum_{\tau=t-3}^{t} \text{net\_transaction}_{k,\tau}$. Bond-level investor composition is defined as the value-weighted average of these net transaction measures across a bond's investors:

$$INV\_COMP_{i,t} = \frac{\sum_k H_{k,i,t} \times NT_{k,t}}{\sum_k H_{k,i,t}}. \tag{2}$$

Bonds with high $INV\_COMP$, meaning bonds held primarily by short-term, active traders, should be less prone to limited attention because their investors are more likely to monitor and respond to information from peer bonds.

In addition, we consider more direct proxies for investor attention: Bloomberg news readership (Ben-Rephael et al., 2017) as a proxy for institutional attention, and Google search volume (Da et al., 2011) as a proxy for retail attention. For institutional attention, we follow Ben-Rephael et al. (2017) and collect the firm-level daily maximum news readership from Bloomberg terminals. This measure is already abnormal by construction, because Bloomberg defines it relative to a firm's own historical readership patterns. Following Ben-Rephael et al.

(2017), we define a dummy variable equal to one when the daily maximum news readership is 3 or 4, and zero otherwise, and then construct abnormal institutional attention ($AIA$) as the monthly average of this indicator. The $AIA$ analysis covers February 2010, when Bloomberg news readership data first become available, through December 2020, excluding September and October 2011 because Bloomberg readership observations are missing in those months. For retail attention, we obtain the monthly Search Volume Index (SVI) from Google Trends for all firms in our sample. Following deHaan et al. (2025), we apply the transformation $\ln(1 + SVI)$ so that observations with zero search volume are retained. We then define abnormal search volume ($ASV$) as the monthly change in this transformed series, in the spirit of Da et al. (2011). Because Google Trends data are unavailable before 2004, the $ASV$ analysis spans January 2004 through December 2020.

If limited attention were an important driver, we would expect the bond PM effect to be stronger among bonds with lower values of $IOR$, $INV\_COMP$, $AIA$, and $ASV$. To test this, we divide bonds into two groups at the end of each month based on the cross-sectional median of each of these variables, and then perform a quintile portfolio sort by bond PM within each subsample. Panel A of Table 12 reports the returns and alphas of the bond PM strategy in each subsample. The bond PM strategy yields somewhat higher returns and alphas in the subsamples with lower $IOR$, $INV\_COMP$, $AIA$, or $ASV$, but the differences between the high and low subsamples are generally not statistically significant.

To test cross-sectional heterogeneity more rigorously, Panel B of Table 12 reports Fama–MacBeth regressions with interaction terms between bond PM and the attention-related variables, using the full set of controls from Table 4. Under the limited-attention hypothesis, all interaction coefficients should be significantly negative. The evidence does not support this prediction. Although the coefficients on $PM^{Bond} \times IOR$ and $PM^{Bond} \times AIA$ are negative, neither is statistically significant. More notably, the coefficient on $PM^{Bond} \times INV\_COMP$ is positive, and the coefficient on $PM^{Bond} \times ASV$ is significantly positive, directly contradicting the limited-attention interpretation. A plausible reason for the latter result is that abnormal retail investor attention may be a poor proxy for the attention of large institutional investors, who dominate the corporate bond market.

Taken together, the attention results are mixed and provide at best weak support for a limited attention channel. This contrasts with the stock momentum spillover literature, where limited attention is often the leading interpretation (e.g., Ali and Hirshleifer, 2020). The discrepancy is natural: the corporate bond market is dominated by large, sophisticated institutional investors, for whom pure inattention is unlikely to be first-order.

## 5.2 Factor Momentum

Next, we explore whether the bond PM effect can be explained by factor momentum. Recent studies by Burt and Hrdlicka (2021) and Yan and Yu (2023) demonstrate that cross-asset lead–lag relationships can arise mechanically if assets are exposed to common factors and those factors themselves exhibit momentum. In such a setting, cross-asset predictability reflects the persistence of factor realizations rather than slow diffusion of firm-specific information.

To test this explanation, we decompose each bond's return into systematic and idiosyncratic components. The systematic component captures exposures to common factors and is thus subject to factor momentum, whereas the idiosyncratic component reflects firm-specific news. If factor momentum were the primary driver, the bond PM signal constructed from the systematic component should exhibit stronger predictive power than the one constructed from the idiosyncratic component.

More specifically, at the end of each month $t$, for each bond we regress its monthly excess return on the bond-plus-stock six factors (the FFDTB model in the main text) over the past 36-month window, requiring at least 24 observations. We then decompose the month-$t$ bond excess return into a systematic part (the fitted value) and an idiosyncratic part (the regression residual). Finally, we calculate the month-$t$ systematic (idiosyncratic) bond PM as the shared-analyst-number weighted average of peer bonds' systematic (idiosyncratic) returns, and use these to predict month $t + 1$ bond returns.

Table 13 reports Fama–MacBeth regressions of one-month-ahead bond excess returns on the two bond PM measures, with the full control set from Table 4. Idiosyncratic bond PM exhibits much stronger predictive power than systematic bond PM. This suggests that factor momentum is not the main explanation for the bond PM effect.

## 5.3 Inertial Fund Flow and Common Ownership

The evidence above points away from inattention and factor momentum, and toward a mechanism in which firm-specific shocks propagate across bonds along institutional demand linkages. A natural benchmark for such a mechanism is the delegated-portfolio model of Vayanos and Woolley (2013), which provides a rational theory of momentum, reversal, comovement, and lead–lag based on *inertial fund flows* between an index fund and an active fund.

In their framework, the active manager chooses an $N$-dimensional portfolio $\theta$ of risky assets, and the index fund holds the benchmark portfolio $\eta$ (for example, a market-weighted index). A central object is the "flow portfolio" $p_f$, which captures the direction in the cross-section along which flows act. Formally, $p_f$ is the component of $\theta$ that is orthogonal to the index; equivalently, it is the residual from regressing $\theta$ on $\eta$:

$$p_f \equiv \theta - \frac{\eta' \Sigma \theta}{\eta' \Sigma \eta} \, \eta, \tag{3}$$

where $\Sigma$ is the covariance matrix of asset payoffs. When investors move capital between the index and the active fund, flows scale the active portfolio and therefore push prices along $p_f$.

If flows into or out of the active fund were instantaneous and perfectly anticipated, prices would jump to fully reflect all future flow pressure. In contrast, Vayanos and Woolley (2013) assume that flows exhibit inertia (e.g., because contracts or investor behavior slow down reallocation) and are uncertain, and that the manager who absorbs them is risk-averse and benchmarked. In equilibrium, expected returns and covariances acquire a non-fundamental component proportional to $\Sigma p_f p_f' \Sigma$, and the *lagged* covariance of returns across time is given by a decaying function of the horizon multiplied by the same matrix.[4] Prices under-react to expected future flows because fully arbitraging them away would require bearing flow risk that is costly for a risk-averse, benchmarked manager. As a result, assets with similar (same-sign) loadings on $p_f$ exhibit short-horizon momentum and lead–lag in equilibrium: past returns of one such asset forecast near-term returns of another, even though all agents

[4] See their Corollary 6, where the lagged cross-covariance between $dR_t$ and $dR_{t'}$ can be written as $[\chi_1 e^{-\kappa(t'-t)} + \chi_2 e^{-b_2(t'-t)}] \Sigma p_f p_f' \Sigma \, dt \, dt'$ for positive constants $\chi_1, \chi_2, \kappa, b_2$. The off-diagonal elements of this matrix generate cross-asset lead–lag whenever two assets have the same-sign loading on $p_f$.

are fully rational and attentive.

We interpret the corporate bond market through this lens. Large institutional investors (e.g., insurers, mutual funds, and other active credit managers) play the role of the active fund, and broad bond indices (or internal benchmark portfolios) play the role of the index. These institutions take cross-sectional tilts in issuer/sector/rating space relative to their benchmarks; given the covariance matrix of fundamental shocks, these tilts define a bond-level analogue of the flow portfolio $p_f$ in Vayanos and Woolley (2013). When investors gradually reallocate capital between different credit mandates, or when internal capital is reallocated across desks, flows operate along this flow portfolio: bonds with similar sign and magnitude of $p_f$-loadings move together in response to flow shocks. Because flows are inertial and the institutions absorbing them are risk-averse, benchmarked, and face trading costs, prices of bonds that share similar $p_f$-loadings adjust only gradually, generating short-run cross-bond momentum and lead–lag.

In our setting, we do not observe the true vector $p_f$ or the underlying tilt vector $\theta$ directly. We therefore need a way to proxy for bonds that are likely to load similarly on $p_f$. The shared-analyst network provides a useful proxy. In practice, active credit portfolios are organized around analyst coverage: a sector analyst covers a set of issuers and their bonds, forms views on their relative value, and recommends over- or underweights versus the benchmark. Bonds covered by the same analyst are thus natural candidates to receive similar recommended tilts, and hence to have similar sign and magnitude of $p_f$-loadings in the sense of Vayanos and Woolley (2013). This interpretation is consistent with our earlier horse-race results, which show that the shared-analyst linkage subsumes other linkage measures in explaining bond PM.

However, the flow-portfolio channel only operates where flows are actually transmitted at the portfolio level. For flows to propagate from one bond to another, the two bonds must be held in the same institutional portfolio. Shared-analyst coverage by itself does not guarantee that: two issuers may share an analyst but be held by disjoint sets of investors, in which case there is no portfolio along which flow-induced trades in one bond mechanically spill over into the other.

We test this implication directly. At the end of each month, for each focal bond we take its shared-analyst peers and use eMAXX holdings to divide them into two groups: peers that share at least one common institutional owner with the focal bond ("co-held peers") and peers with entirely distinct institutional owners ("non-co-held peers"). We then compute two peer-momentum measures, $PM^{Bond}$(analyst&co-held) and $PM^{Bond}$(analyst&non-co-held), as the shared-analyst-number weighted average of past one-month returns within each group, and compare their ability to predict next-month bond returns in Fama–MacBeth regressions.

Table 14 reveals a stark contrast. The bond PM constructed from co-held peers strongly predicts next-month bond returns, with economically large and highly significant coefficients, whereas the PM constructed from non-co-held peers is statistically insignificant and even slightly negative when both measures enter jointly. In other words, within the set of shared-analyst peers (our proxy for similar $p_f$-loadings), the predictive content of peer momentum comes almost entirely from those pairs that are also co-held by the same institutions. This pattern is difficult to reconcile with a pure limited-attention story: institutions that co-hold the focal bond and its peers are precisely the sophisticated investors most likely to observe and process peer-bond news. Instead, it fits naturally with the flow-portfolio mechanism of Vayanos and Woolley (2013): shared-analyst coverage identifies bonds that are likely to have similar loadings on the institutional flow portfolio $p_f$, and common institutional ownership selects the subset of those bonds that actually sit in the same portfolios, along which inertial flows generate the observed cross-bond lead–lag.

### 5.4 Co-Holding Linkage

The evidence above indicates that, within the shared-analyst network, the predictive content of bond PM is concentrated among peers that are also jointly held by the same institutions. This result motivates a further test of whether a PM signal constructed directly from co-holding links is as informative as the shared-analyst-based measure. If common institutional ownership were the sole relevant linkage, a PM signal based directly on co-holding should display comparable predictive power.

To examine this question, at the end of each month and for each focal bond, we use eMAXX holdings from the previous quarter to identify its co-held peers, defined as bonds that share at least one common institutional owner with the focal bond. Using previous-quarter holdings accounts for data release delays and is appropriate here because the co-holding-based PM is constructed for a real-time forecasting exercise. As in our other linkage constructions, we do not classify bonds issued by the same firm as peers.

Let $\mathcal{I}_{ij}$ denote the set of institutions that co-hold bonds $i$ and $j$, and let $N_{ij}^{\text{coh}} = |\mathcal{I}_{ij}|$ be the number of common institutional owners. To simplify notation, we suppress the time subscript $t$ for all co-holding variables in this subsection. We construct three versions of co-holding-based bond PM. The first, $PM^{Bond}$(co-held), is the equal-weighted average of past one-month returns of co-held peer bonds. The second, $PM^{Bond}$(co-held, count), weights peer returns by the number of common institutional owners $N_{ij}^{\text{coh}}$. The third measure, $PM^{Bond}$(co-held, int), weights peer returns by the co-holding intensity between bond pairs,

$$s_{ij}^{\text{coh}} = \frac{\sum_{k \in \mathcal{I}_{ij}} (H_{k,i} + H_{k,j})}{AMT_i + AMT_j}, \tag{4}$$

where $H_{k,i}$ and $H_{k,j}$ denote institution $k$'s holdings of bonds $i$ and $j$, respectively, and $AMT_i$ and $AMT_j$ are the corresponding amounts outstanding.

Table 15 reports the results. The evidence is weak for co-holding-based PM. Both $PM^{Bond}$(co-held) and $PM^{Bond}$(co-held, count) are insignificant, while $PM^{Bond}$(co-held, int) is at most marginally significant. By contrast, the shared-analyst bond PM remains strongly significant when included in the same specifications. Thus, although common institutional ownership matters within the shared-analyst network, a PM signal based on co-holding links alone does not match the predictive power of shared-analyst bond PM.

Taken together with the results in Table 14, these findings support a more precise interpretation of the mechanism. Common institutional ownership appears to be necessary for flow transmission, but it is not sufficient by itself. What matters is common institutional ownership among bonds that are also likely to receive similar portfolio tilts or relative-value views. Shared-analyst coverage provides a plausible proxy for this additional condition: analyst-linked bonds are not only more likely to be co-held, but are also more likely to be viewed and traded as related positions within institutional portfolios. This is why the shared-analyst PM signal is substantially more informative than a PM signal constructed from co-holding links alone.

## 5.5 Limits to Arbitrage

Finally, we study why the bond PM effect is not arbitraged away, even though the market is dominated by sophisticated institutions and the flow-based mechanism described above is in principle observable. In the model of Vayanos and Woolley (2013), momentum and lead–lag persist in equilibrium because the manager who absorbs flows is risk-averse and benchmarked: eliminating all short-run predictability would require taking on additional flow risk that is not compensated in utility terms. Our empirical setting adds another important ingredient that is outside the scope of their model but first-order in corporate bonds: high trading costs and illiquidity.

We use bond illiquidity $ILLIQ$ (Bao et al., 2011) and bond idiosyncratic volatility $IVOL$ (Bai et al., 2021) as proxies for bond-level arbitrage costs, and examine whether the bond PM effect is stronger among hard-to-arbitrage bonds. The variable definitions are in Section 2.4. Panel A of Table 16 shows that the bond PM strategy earns a monthly return of 0.44% (0.66%) for bonds with high $ILLIQ$ ($IVOL$), but only 0.26% (0.10%) for bonds with low $ILLIQ$ ($IVOL$). The differences are statistically significant, and the same pattern holds for the strategy's alphas. Panel B of Table 16 reports Fama–MacBeth regressions with interactions between bond PM and $ILLIQ$ or $IVOL$. The interaction terms are significantly positive, confirming that peer momentum is strongest precisely where trading and arbitrage are most costly.

We also examine whether the PM strategy remains profitable after accounting for realistic transaction costs. Following Bartram et al. (2025) and Dickerson et al. (2024a), we compute the net-of-cost return of long–short strategy by subtracting transaction costs incurred on both the long and short legs from the gross return:

$$r_{t+1}^{long-short} = \sum_{i \in long} w_{i,t}^{long} r_{i,t+1} - \sum_{i \in short} w_{i,t}^{short} r_{i,t+1} - TC_t^{long} - TC_t^{short} \tag{5}$$

$$TC_t^{long} = h \times \sum_{i \in long} \left| w_{i,t}^{long} - \frac{1 + r_{i,t}}{1 + \sum_{j \in long} w_{j,t-1}^{long} r_{j,t}} w_{i,t-1}^{long} \right| \tag{6}$$

$$TC_t^{short} = h \times \sum_{i \in short} \left| w_{i,t}^{short} - \frac{1 + r_{i,t}}{1 + \sum_{j \in short} w_{j,t-1}^{short} r_{j,t}} w_{i,t-1}^{short} \right| \tag{7}$$

where $r_{t+1}^{long-short}$ is the after-cost return of the PM strategy at month $t+1$, $w_{i,t}$ ($w_{i,t-1}$) is the portfolio weight of bond $i$ in the long or short portfolio by PM signal at month $t$ ($t-1$), $r_{i,t+1}$ ($r_{i,t}$) is the return of bond $i$ at month $t+1$ ($t$), and $h$ is the one-way cost. The transaction cost, $TC$, is calculated as the one-way cost $h$ multiplied by the portfolio turnover rate, which accounts for the endogenous changes in portfolio weights caused by changes in bond values.[5] The portfolio weights are defined as $w_{i,t}^{long} = 1/N_t^{long}$ for bonds in the long leg of the PM strategy and $w_{i,t}^{short} = 1/N_t^{short}$ for bonds in the short leg, where $N_t^{long}$ ($N_t^{short}$) is the number of bonds in the long (short) leg at month $t$.

Using equations (5) - (7), we solve for the break-even cost $h$ that reduces the average net-of-cost return of the PM strategy to zero. The critical value is about 13.57 basis points (bps), which is below typical estimates of trading costs in the corporate bond market (e.g., the 19 bps used by Kelly et al. (2023)). Thus, a standard cost adjustment is sufficient to eliminate all of the PM strategy's net profits. Combined with the illiquidity and volatility interactions, this indicates that even a relatively risk-neutral arbitrageur would find it difficult to exploit and fully arbitrage away the flow-based lead–lag we document.

[5]In equation (5), we subtract $TC_t$ from the long-short strategy return at month $t+1$. Our results remain qualitatively similar if $TC_{t+1}$ is used instead.

Taken together, our evidence suggests the following interpretation. The bond PM effect arises because firm-specific shocks are transmitted across bonds through gradual, benchmark-constrained institutional flows along the shared-analyst and common institutional ownership links, consistent with the flow-portfolio mechanism in Vayanos and Woolley (2013). High trading costs and illiquidity, especially in the segments where the effect is strongest, prevent even sophisticated investors from fully arbitraging away the resulting predictability.

# 6 Conclusion

This paper documents a robust cross-bond momentum spillover effect in the U.S. corporate bond market. Bond PM, constructed from the recent returns of economically linked peer bonds, strongly predicts next-month bond excess returns, and the shared-analyst signal subsumes the predictive content of PM constructed from industry, text-based industry, geographic, supply-chain, technological, and conglomerate linkages. A corresponding long–short strategy earns about 0.45% per month (5.4% annually), with alphas that survive standard bond and stock factor models, a wide range of controls, and numerous robustness checks including value weighting, firm-level aggregation, alternative bond samples, and alternative return constructions.

Mechanism tests distinguish among competing explanations for momentum spillovers. The evidence is inconsistent with limited attention and factor momentum, and instead supports a flow-based limits-to-arbitrage channel: the effect is concentrated among bonds that are co-held by the same institutions, is much stronger when illiquidity and idiosyncratic volatility are high, and is unlikely to survive realistic transaction costs.

Relative to the analogous stock-market momentum spillover effect, the bond PM strategy delivers a similar Sharpe ratio but much lower crash risk and far shorter persistence, consistent with an over-the-counter market dominated by benchmarked institutional investors facing high trading costs. These results extend the momentum spillover literature to corporate bonds, provide a new network-based predictor of bond returns, and highlight the central role of institutional flows and trading frictions in shaping price dynamics in credit markets.

# References


Usman Ali and David Hirshleifer. Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics*, 136(3):649–675, 2020.

Paul Asquith, Andrea S Au, Thomas Covert, and Parag A Pathak. The market for borrowing corporate bonds. *Journal of Financial Economics*, 107(1):155–182, 2013.

Jennie Bai, Turan G Bali, and Quan Wen. Is there a risk-return tradeoff in the corporate bond market? time-series and cross-sectional evidence. *Journal of Financial Economics*, 142(3):1017–1037, 2021.

Jennie Bai, Turan G Bali, and Quan Wen. Replication of BBW factors with WRDS data. Working paper, 2023.

Malcolm Baker and Jeffrey Wurgler. Investor sentiment and the cross-section of stock returns. *Journal of Finance*, 61(4):1645–1680, 2006.

Scott R Baker, Nicholas Bloom, and Steven J Davis. Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4):1593–1636, 2016.

Turan G Bali, Robert F Engle, and Scott Murray. *Empirical asset pricing: The cross section of stock returns*. John Wiley & Sons, 2016.

Turan G Bali, Amit Goyal, Dashan Huang, Fuwei Jiang, and Quan Wen. Predicting corporate bond returns: Merton meets machine learning. Working paper, 2020.

Turan G Bali, Avanidhar Subrahmanyam, and Quan Wen. Long-term reversals in the corporate bond market. *Journal of Financial Economics*, 139(2):656–677, 2021a.

Turan G Bali, Avanidhar Subrahmanyam, and Quan Wen. The macroeconomic uncertainty premium in the corporate bond market. *Journal of Financial and Quantitative Analysis*, 56(5):1653–1678, 2021b.

Jack Bao, Jun Pan, and Jiang Wang. The illiquidity of corporate bonds. *Journal of Finance*, 66(3):911–946, 2011.

Francisco Barillas, Raymond Kan, Cesare Robotti, and Jay Shanken. Model comparison with sharpe ratios. *Journal of Financial and Quantitative Analysis*, 55(6):1840–1874, 2020.

Söhnke M Bartram, Mark Grinblatt, and Yoshio Nozawa. Book-to-market, mispricing, and the cross section of corporate bond returns. *Journal of Financial and Quantitative Analysis*, 60(3):1185–1233, 2025.

Azi Ben-Rephael, Zhi Da, and Ryan D Israelsen. It depends on where you search: Institutional investor attention and underreaction to news. *Review of Financial Studies*, 30(9): 3009–3047, 2017.

Aaron Burt and Christopher Hrdlicka. Where does the predictability from sorting on returns of economically linked firms come from? *Journal of Financial and Quantitative Analysis*, 56(8):2634–2658, 2021.

Fang Cai, Song Han, Dan Li, and Yi Li. Institutional herding and its price impact: Evidence from the corporate bond market. *Journal of Financial Economics*, 131(1):139–167, 2019.

Jie Cao, Amit Goyal, Xiao Xiao, and Xintong Zhan. Implied volatility changes and corporate bond returns. *Management Science*, 69(3):1375–1397, 2023.

Andrew Y Chen and Tom Zimmermann. Open source cross-sectional asset pricing. *Critical Finance Review*, 11(2):207–264, 2022.

Long Chen, Gaiyan Zhang, and Weina Zhang. Return predictability in the corporate bond market along the supply chain. *Journal of Financial Markets*, 29:66–86, 2016.

Tarun Chordia, Amit Goyal, Yoshio Nozawa, Avanidhar Subrahmanyam, and Qing Tong. Are capital market anomalies common to equity and corporate bond markets? an empirical investigation. *Journal of Financial and Quantitative Analysis*, 52(4):1301–1342, 2017.

Kee H Chung, Junbo Wang, and Chunchi Wu. Volatility and the cross-section of corporate bond returns. *Journal of Financial Economics*, 133(2):397–417, 2019.

Lauren Cohen and Andrea Frazzini. Economic links and predictable returns. *Journal of Finance*, 63(4):1977–2011, 2008.

Lauren Cohen and Dong Lou. Complicated firms. *Journal of Financial Economics*, 104(2): 383–400, 2012.

Zhi Da, Joseph Engelberg, and Pengjie Gao. In search of attention. *Journal of Finance*, 66 (5):1461–1499, 2011.

Ed deHaan, Jiacui Li, and Edward M Watts. Retail bond investors and credit ratings. *Journal of Accounting and Economics*, 76(1):101587, 2023.

Ed deHaan, Alastair Lawrence, and Robin Litjens. Measuring investor attention using google search. *Management Science*, 71(7):6275–6297, 2025.

Jens Dick-Nielsen. Liquidity biases in trace. *Journal of Fixed Income*, 19(2):43, 2009.

Jens Dick-Nielsen. How to clean enhanced trace data. *Available at SSRN 2337908*, 2014.

Alexander Dickerson, Philippe Mueller, and Cesare Robotti. Priced risk in corporate bonds. *Journal of Financial Economics*, 150(2):103707, 2023.

Alexander Dickerson, Cesare Robotti, and Yoshio Nozawa. Factor investing with delays. *Available at SSRN 5074221*, 2024a.

Alexander Dickerson, Cesare Robotti, and Giulio Rossetti. Common pitfalls in the evaluation of corporate bond strategies. *Available at SSRN*, 4575879, 2024b.

Eugene F Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.

Eugene F Fama and James D MacBeth. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636, 1973.

Guanhao Feng, Xin He, Yanchu Wang, and Chunchi Wu. Predicting individual corporate bond returns. *Journal of Banking & Finance*, 171:107372, 2025a.

Jian Feng, Xiaolin Huo, Xin Liu, Yifei Mao, and Hong Xiang. Economic links from bonds and cross-stock return predictability. *Journal of Financial Economics*, 171:104110, 2025b.

William R Gebhardt, Soeren Hvidkjaer, and Bhaskaran Swaminathan. The cross-section of expected corporate bond returns: Betas or characteristics? *Journal of Financial Economics*, 75(1):85–114, 2005a.

William R Gebhardt, Soeren Hvidkjaer, and Bhaskaran Swaminathan. Stock and bond market interaction: Does momentum spill over? *Journal of Financial Economics*, 75(3): 651–690, 2005b.

Umit G Gurun, Rick Johnston, and Stanimir Markov. Sell-side debt analysts and debt market efficiency. *Management Science*, 62(3):682–703, 2016.

Gerard Hoberg and Gordon Phillips. Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5):1423–1465, 2016.

Gerard Hoberg and Gordon M Phillips. Text-based industry momentum. *Journal of Financial and Quantitative Analysis*, 53(6):2355–2388, 2018.

Thanh D Huynh and Ying Xia. Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis*, 56(6):1985–2009, 2021.

Rick Johnston, Stanimir Markov, and Sundaresh Ramnath. Sell-side debt analysts. *Journal of Accounting and Economics*, 47(1-2):91–107, 2009.

Gergana Jostova, Stanislava Nikolova, Alexander Philipov, and Christof W Stahel. Momentum in corporate bond returns. *Review of Financial Studies*, 26(7):1649–1693, 2013.

Bryan Kelly, Diogo Palhares, and Seth Pruitt. Modeling corporate bond returns. *Journal of Finance*, 78(4):1967–2008, 2023.

Leonid Kogan, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, 132(2):665–712, 2017.

Charles MC Lee, Stephen Teng Sun, Rongfei Wang, and Ran Zhang. Technological links and predictable returns. *Journal of Financial Economics*, 132(3):76–96, 2019.

Jiacui Li. Endogenous inattention and risk-specific price underreaction in corporate bonds. *Journal of Financial Economics*, 145(2):595–615, 2022.

Jian Li and Haiyue Yu. Investor composition and the liquidity component in the us corporate bond market. *Available at SSRN 3900261*, 2021.

Hai Lin, Junbo Wang, and Chunchi Wu. Liquidity risk and expected corporate bond returns. *Journal of Financial Economics*, 99(3):628–650, 2011.

Lior Menzly and Oguzhan Ozbas. Market segmentation and cross-predictability of returns. *Journal of Finance*, 65(4):1555–1580, 2010.

Tobias J Moskowitz and Mark Grinblatt. Do industries explain momentum? *Journal of Finance*, 54(4):1249–1290, 1999.

Whitney K Newey and Kenneth D West. A simple, positive semi-definite, heteroskedasticity and autocorrelation. *Econometrica*, 55(3):703–708, 1987.

Christopher A Parsons, Riccardo Sabbatucci, and Sheridan Titman. Geographic lead-lag effects. *Review of Financial Studies*, 33(10):4721–4770, 2020.

Jules H van Binsbergen, Yoshio Nozawa, and Michael Schwert. Duration-based valuation of corporate bonds. *Review of Financial Studies*, 38(1):158–191, 2025.

Dimitri Vayanos and Paul Woolley. An institutional theory of momentum and reversal. *Review of Financial Studies*, 26(5):1087–1145, 2013.

Huaixin Wang. Decoding momentum spillover effects. *Journal of Financial and Quantitative Analysis*, page 1–64, 2025. doi: 10.1017/S002210902510238X.

Jingda Yan and Jialin Yu. Cross-stock momentum and factor momentum. *Journal of Financial Economics*, 150(2):103716, 2023.

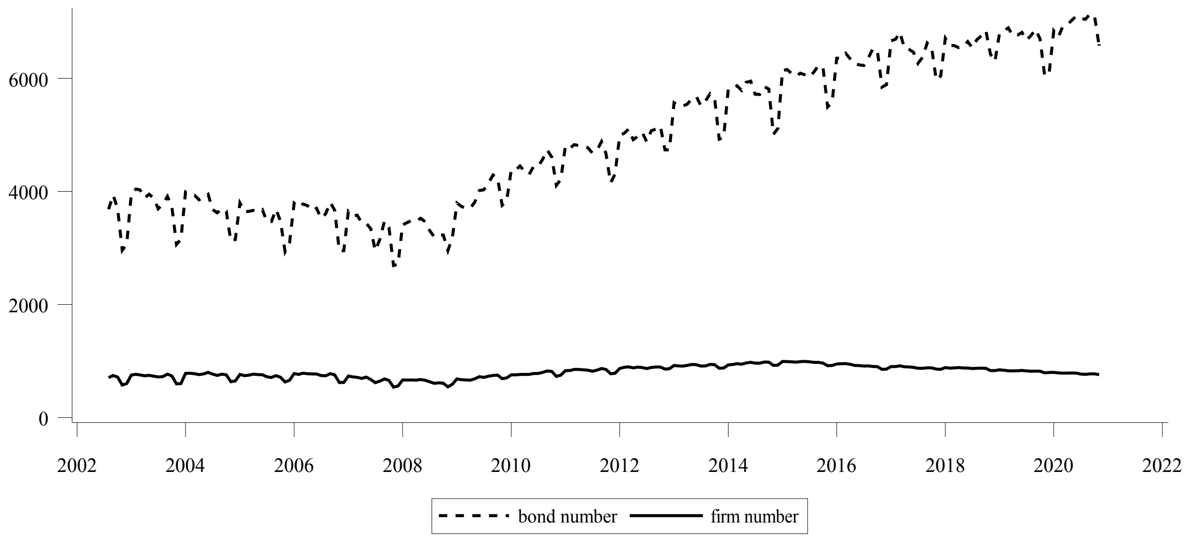
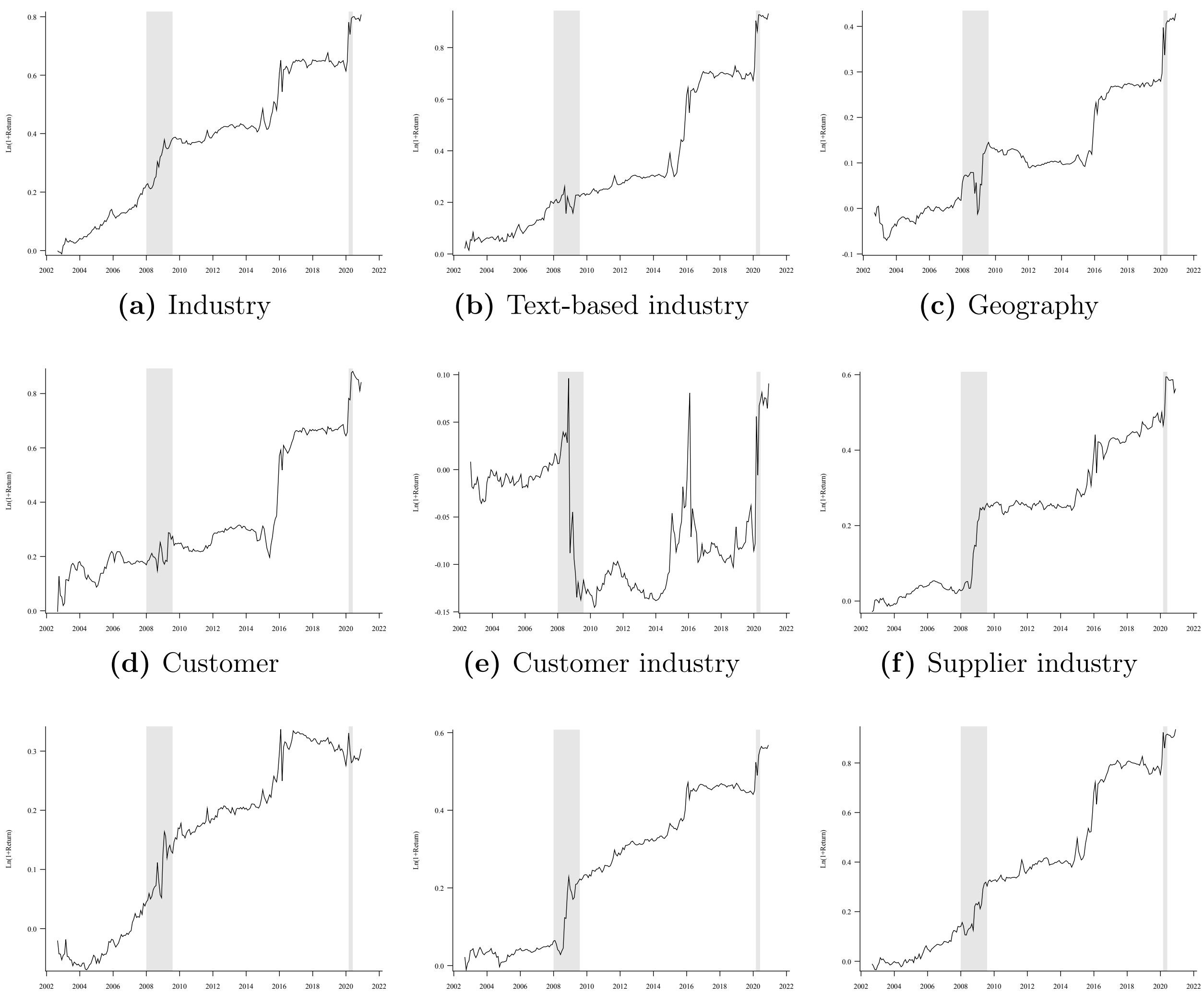



**Figure 1: Number of Bonds and Firms in the Sample.** This figure plots the monthly time series of bond number (dashed line) and firm number (solid line) in our sample.



**(a)** Industry **(b)** Text-based industry **(c)** Geography

**(d)** Customer **(e)** Customer industry **(f)** Supplier industry

**(g)** Complicated firm **(h)** Technology **(i)** Analyst

**Figure 2: Cumulative PM Strategy Returns.** This figure plots the log cumulative returns on the long-short portfolios sorted on different bond PMs. The shaded regions indicate NBER recession periods (December 2007 to June 2009 and February 2020 to April 2020). The y-axis represents the cumulative sum of ln(1 + high-minus-low return spread). The sample period ends in November 2020 and includes only those bond-month records with non-missing one-month-ahead bond returns; accordingly, the return series extends through December 2020.

## Table 1: Summary Statistics

This table reports the time-series averages of monthly cross-sectional mean, standard deviation, 10th percentile, median, and 90th percentile of bond PM and control variables. For bond PM, we also report its linkage-specific average number of focal bonds and focal firms. The sample ranges from August 2002 to November 2020 and includes only those bond-month records with non-missing one-month-ahead bond returns.

**Main variables: bond PM (%) from different linkages**

| | Mean | Std. | P10 | P50 | P90 | Avg. # focal bonds | Avg. # focal firms |
|---|---|---|---|---|---|---|---|
| $PM^{Bond}$(industry) | 0.60 | 0.96 | -0.36 | 0.59 | 1.61 | 4132 | 790 |
| $PM^{Bond}$(text-based industry) | 0.60 | 1.28 | -0.52 | 0.59 | 1.73 | 3403 | 640 |
| $PM^{Bond}$(geography) | 0.62 | 1.08 | -0.29 | 0.62 | 1.53 | 2993 | 606 |
| $PM^{Bond}$(customer) | 0.52 | 1.63 | -0.65 | 0.52 | 1.74 | 582 | 154 |
| $PM^{Bond}$(customer-industry) | 0.63 | 0.83 | -0.27 | 0.61 | 1.59 | 2763 | 573 |
| $PM^{Bond}$(supplier-industry) | 0.63 | 0.65 | 0.07 | 0.63 | 1.21 | 2768 | 582 |
| $PM^{Bond}$(complicated firm) | 0.64 | 1.40 | -0.67 | 0.61 | 1.97 | 1469 | 249 |
| $PM^{Bond}$(technology) | 0.58 | 0.38 | 0.18 | 0.57 | 0.99 | 2343 | 339 |
| $PM^{Bond}$(analyst) | 0.58 | 0.96 | -0.35 | 0.56 | 1.53 | 4100 | 774 |

**Control variables**

| Return-based controls (%) | | | | | | Other controls | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. | P10 | P50 | P90 | | Mean | Std. | P10 | P50 | P90 |
| $RET^{Bond}$ | 0.62 | 3.55 | -1.90 | 0.48 | 3.32 | $Maturity$ | 9.37 | 9.01 | 2.09 | 6.22 | 24.84 |
| $RET^{Stock}$ | 0.88 | 8.67 | -7.91 | 0.70 | 9.51 | $AMT$ | 0.64 | 0.62 | 0.18 | 0.45 | 1.28 |
| $PM^{Stock}$(industry) | 1.01 | 3.34 | -2.97 | 0.93 | 5.08 | $Rating$ | 8.71 | 3.63 | 4.85 | 8.08 | 14.01 |
| $PM^{Stock}$(text-based industry) | 1.06 | 4.82 | -4.01 | 0.93 | 6.24 | $\beta$ | 1.07 | 0.83 | 0.34 | 0.88 | 2.05 |
| $PM^{Stock}$(geography) | 1.07 | 2.73 | -1.77 | 1.00 | 3.89 | $\beta^{VIX} \times 100$ | -0.08 | 0.39 | -0.41 | -0.07 | 0.23 |
| $PM^{Stock}$(customer) | 0.87 | 6.78 | -6.41 | 0.69 | 8.10 | $VaR$ | 0.04 | 0.04 | 0.01 | 0.03 | 0.08 |
| $PM^{Stock}$(customer-industry) | 1.13 | 2.99 | -2.28 | 1.10 | 4.76 | $IVOL$ | 0.02 | 0.02 | 0.01 | 0.02 | 0.04 |
| $PM^{Stock}$(supplier-industry) | 1.13 | 2.17 | -0.87 | 1.10 | 3.14 | $ILLIQ \times 100$ | 0.06 | 2.06 | -0.00 | 0.00 | 0.03 |
| $PM^{Stock}$(complicated firm) | 1.14 | 4.01 | -2.71 | 1.09 | 5.11 | | | | | | |
| $PM^{Stock}$(technology) | 1.38 | 1.67 | -0.44 | 1.38 | 3.18 | | | | | | |
| $PM^{Stock}$(analyst) | 1.03 | 3.82 | -3.55 | 0.99 | 5.61 | | | | | | |

## Table 2: Univariate Portfolio Sort by bond PM

This table presents the results of univariate portfolio analysis for bond PM based on different linkages specified in the rows. At the end of each month $t$, bonds are sorted into 10 portfolios by ascending order of their bond PM. The table reports the time-series averages of each portfolio's equal-weighted month $t+1$ excess returns, the month $t+1$ high–minus–low return, as well as its alphas adjusted for different factor models, including the one-factor bond market model ($\alpha_{\text{MKTB}}$), the Fama and French (1993) model from Fama–French stock 3-factor plus default return spread and term spread ($\alpha_{\text{FFDT}}$), and their combination ($\alpha_{\text{FFDTB}}$). All returns and alphas are in percentages. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | High-Low | | $\alpha_{\text{MKTB}}$ | | $\alpha_{\text{FFDT}}$ | | $\alpha_{\text{FFDTB}}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| industry | 0.26 | 0.37 | 0.48 | 0.51 | 0.39 | 0.47 | 0.53 | 0.56 | 0.60 | 0.65 | 0.39*** | (3.49) | 0.54*** | (3.32) | 0.47*** | (3.92) | 0.51*** | (3.89) |
| text-based industry | 0.27 | 0.35 | 0.47 | 0.43 | 0.46 | 0.44 | 0.53 | 0.54 | 0.61 | 0.72 | 0.45*** | (2.91) | 0.61** | (2.33) | 0.48** | (2.13) | 0.54** | (2.12) |
| geography | 0.45 | 0.39 | 0.52 | 0.54 | 0.47 | 0.43 | 0.46 | 0.51 | 0.54 | 0.65 | 0.21** | (2.04) | 0.31** | (2.06) | 0.26* | (1.85) | 0.27* | (1.88) |
| customer | 0.34 | 0.37 | 0.25 | 0.31 | 0.31 | 0.61 | 0.44 | 0.65 | 0.74 | 0.76 | 0.42** | (2.27) | 0.55** | (2.33) | 0.47** | (2.14) | 0.56** | (2.52) |
| customer-industry | 0.46 | 0.55 | 0.51 | 0.41 | 0.48 | 0.59 | 0.35 | 0.60 | 0.45 | 0.53 | 0.07 | (0.59) | 0.15 | (0.69) | 0.00 | (0.01) | 0.04 | (0.15) |
| supplier-industry | 0.39 | 0.44 | 0.51 | 0.52 | 0.44 | 0.44 | 0.48 | 0.49 | 0.43 | 0.66 | 0.27** | (2.57) | 0.30** | (2.44) | 0.33*** | (2.61) | 0.30** | (2.26) |
| complicated firm | 0.42 | 0.44 | 0.36 | 0.48 | 0.48 | 0.59 | 0.54 | 0.49 | 0.62 | 0.57 | 0.15** | (2.35) | 0.24*** | (3.23) | 0.26*** | (3.03) | 0.24*** | (2.75) |
| technology | 0.30 | 0.38 | 0.57 | 0.43 | 0.53 | 0.48 | 0.48 | 0.50 | 0.45 | 0.57 | 0.27*** | (2.93) | 0.35*** | (2.92) | 0.32*** | (3.71) | 0.36*** | (4.21) |
| analyst | 0.32 | 0.38 | 0.36 | 0.40 | 0.47 | 0.50 | 0.49 | 0.52 | 0.60 | 0.77 | 0.45*** | (3.37) | 0.55*** | (2.94) | 0.49*** | (2.95) | 0.55*** | (3.16) |

## Table 3: Portfolio Sort by Bond Peer Momentum: Controlling for Other Return Predictors

This table presents the results of bivariate portfolio analysis for bond PM based on different linkages specified in the columns. At the end of each month $t$, bonds are first sorted into 5 groups based on a specific control variable in the rows, and within each control group, bonds are further sorted into 5 groups based on ascending order of bond PM. Next, we take the average value of the month $t+1$ bond-peer-momentum-sorted high–minus–low return spread across 5 control groups and report its time-series average in the table. The last row displays the average performance of double sorts across all controls listed above. All returns are in percentages. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| Control | Industry | | Text-based industry | | Geography | | Customer | | Customer industry | | Supplier industry | | Complicated firm | | Technology | | Analyst | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $RET^{Bond}$ | 0.33*** | (5.91) | 0.40*** | (4.78) | 0.14** | (2.07) | 0.31** | (2.59) | 0.03 | (0.43) | 0.04 | (0.83) | 0.22*** | (4.69) | 0.19*** | (3.42) | 0.43*** | (5.39) |
| $RET^{Stock}$ | 0.16*** | (3.18) | 0.22*** | (2.91) | 0.09 | (1.38) | 0.20 | (1.58) | 0.00 | (0.05) | 0.03 | (0.54) | 0.10** | (2.45) | 0.13** | (2.00) | 0.24*** | (3.03) |
| $PM^{Stock}$ | 0.16*** | (3.94) | 0.18*** | (2.84) | 0.02 | (0.32) | 0.21* | (1.78) | 0.14** | (2.38) | 0.03 | (0.63) | 0.08* | (1.91) | 0.11*** | (3.36) | 0.21*** | (2.98) |
| $Maturity$ | 0.31*** | (4.22) | 0.37*** | (3.58) | 0.17** | (2.17) | 0.40*** | (2.70) | 0.02 | (0.23) | 0.10 | (1.48) | 0.15*** | (2.99) | 0.18*** | (2.66) | 0.35*** | (3.57) |
| $AMT$ | 0.31*** | (4.27) | 0.34*** | (3.47) | 0.18** | (2.36) | 0.38** | (2.31) | 0.01 | (0.13) | 0.09 | (1.40) | 0.19*** | (3.25) | 0.18*** | (2.62) | 0.36*** | (3.76) |
| $Rating$ | 0.23*** | (3.80) | 0.23*** | (3.17) | 0.13* | (1.97) | 0.23** | (1.99) | 0.06 | (0.87) | 0.10* | (1.69) | 0.15*** | (3.53) | 0.13** | (2.55) | 0.25*** | (3.39) |
| $\beta$ | 0.31*** | (3.44) | 0.35*** | (2.81) | 0.22** | (2.39) | 0.48** | (2.55) | 0.14 | (1.41) | 0.12 | (1.61) | 0.16*** | (2.96) | 0.16** | (2.46) | 0.36*** | (3.38) |
| $\beta^{VIX}$ | 0.29*** | (3.32) | 0.37*** | (3.16) | 0.22** | (2.27) | 0.35** | (2.11) | 0.01 | (0.13) | 0.09 | (1.08) | 0.18*** | (3.06) | 0.19** | (2.59) | 0.38*** | (3.54) |
| $VaR$ | 0.26*** | (3.29) | 0.29*** | (2.82) | 0.18** | (2.11) | 0.32*** | (2.68) | 0.09 | (1.34) | 0.10 | (1.38) | 0.18*** | (2.82) | 0.15** | (2.05) | 0.31*** | (3.35) |
| $IVOL$ | 0.23*** | (3.06) | 0.23** | (2.53) | 0.18** | (2.01) | 0.28** | (2.50) | 0.09 | (1.07) | 0.14** | (2.25) | 0.14** | (2.55) | 0.14** | (2.13) | 0.31*** | (3.25) |
| $ILLIQ$ | 0.32*** | (4.12) | 0.32*** | (3.41) | 0.17** | (2.26) | 0.39*** | (2.86) | -0.00 | (-0.02) | 0.08 | (1.25) | 0.14** | (2.57) | 0.19*** | (3.15) | 0.34*** | (3.68) |
| $Average$ | 0.26*** | (4.30) | 0.30*** | (3.47) | 0.14** | (2.01) | 0.34*** | (2.70) | 0.05 | (0.71) | 0.08 | (1.39) | 0.14*** | (3.20) | 0.16*** | (2.85) | 0.31*** | (3.73) |

## Table 4: Fama–MacBeth Regression for Bond Peer Momentum

This table reports the Fama and MacBeth (1973) regression of one-month-ahead bond excess return on the bond PM based on different linkages specified in the columns, with and without control variables. We divide $Maturity$, $\ln(AMT)$, and $Rating$ by 100 to improve the readability of the regression coefficients. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Industry | | Text-based industry | | Geography | | Customer | | Customer industry | | Supplier industry | | Complicated firm | | Technology | | Analyst | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
| $PM^{Bond}$ | 0.135*** | 0.079*** | 0.121*** | 0.077*** | 0.048* | 0.006 | 0.074** | 0.011 | 0.043 | 0.008 | 0.051 | 0.012 | 0.054*** | 0.019 | 0.197** | 0.193*** | 0.178*** | 0.141*** |
| | (4.15) | (3.41) | (3.60) | (3.59) | (1.86) | (0.43) | (2.41) | (0.44) | (1.58) | (0.37) | (1.56) | (0.45) | (2.92) | (1.51) | (2.37) | (3.29) | (4.17) | (5.46) |
| $RET^{Bond}$ | | -0.167*** | | -0.174*** | | -0.173*** | | -0.136*** | | -0.170*** | | -0.171*** | | -0.212*** | | -0.209*** | | -0.172*** |
| | | (-7.96) | | (-7.91) | | (-7.84) | | (-4.52) | | (-6.47) | | (-7.27) | | (-10.90) | | (-10.85) | | (-8.53) |
| $RET^{Stock}$ | | 0.032*** | | 0.034*** | | 0.034*** | | 0.035*** | | 0.034*** | | 0.033*** | | 0.027*** | | 0.036*** | | 0.031*** |
| | | (9.05) | | (7.88) | | (7.33) | | (6.99) | | (7.14) | | (7.03) | | (5.98) | | (5.65) | | (8.25) |
| $PM^{Stock}$ | | 0.004 | | 0.001 | | 0.007* | | 0.005 | | 0.003 | | 0.004 | | -0.001 | | -0.007 | | 0.002 |
| | | (1.06) | | (0.38) | | (1.71) | | (0.84) | | (0.55) | | (0.46) | | (-0.17) | | (-0.77) | | (0.39) |
| $Maturity$ | | 0.012* | | 0.014** | | 0.013* | | 0.011 | | 0.014** | | 0.016** | | 0.012* | | 0.007 | | 0.013** |
| | | (1.90) | | (2.18) | | (1.88) | | (1.13) | | (2.06) | | (2.48) | | (1.82) | | (1.24) | | (2.01) |
| $\ln(AMT)$ | | -0.022 | | -0.034 | | -0.032* | | -0.010 | | -0.048* | | -0.051** | | -0.008 | | -0.020 | | -0.031 |
| | | (-1.10) | | (-1.48) | | (-1.69) | | (-0.23) | | (-1.78) | | (-2.10) | | (-0.40) | | (-1.03) | | (-1.46) |
| $Rating$ | | 0.006 | | 0.006 | | 0.011 | | -0.002 | | 0.003 | | 0.005 | | 0.009 | | 0.006 | | 0.006 |
| | | (0.35) | | (0.37) | | (0.70) | | (-0.12) | | (0.19) | | (0.25) | | (0.62) | | (0.36) | | (0.38) |
| $\beta$ | | 0.002 | | 0.002* | | 0.003* | | 0.003 | | 0.002 | | 0.001 | | 0.001* | | 0.003* | | 0.002* |
| | | (1.57) | | (1.67) | | (1.83) | | (1.61) | | (1.29) | | (1.17) | | (1.70) | | (1.84) | | (1.79) |
| $\beta^{VIX}$ | | -0.077 | | -0.155 | | -0.109 | | -0.050 | | -0.063 | | -0.060 | | 0.057 | | -0.088 | | -0.078 |
| | | (-0.46) | | (-0.76) | | (-0.56) | | (-0.16) | | (-0.30) | | (-0.31) | | (0.52) | | (-0.65) | | (-0.48) |
| $VaR$ | | 0.031 | | 0.020 | | 0.011 | | 0.063** | | 0.034 | | 0.036 | | 0.048** | | 0.027 | | 0.021 |
| | | (1.35) | | (0.89) | | (0.49) | | (2.41) | | (1.39) | | (1.48) | | (2.18) | | (1.09) | | (0.91) |
| $IVOL$ | | -0.070* | | -0.081** | | -0.066* | | -0.138* | | -0.090* | | -0.117** | | -0.027 | | -0.073 | | -0.070* |
| | | (-1.85) | | (-2.04) | | (-1.79) | | (-1.88) | | (-1.77) | | (-2.28) | | (-0.63) | | (-1.65) | | (-1.86) |
| $ILLIQ$ | | 0.011 | | -1.631 | | -0.278 | | 3.939 | | -0.948 | | 0.095 | | -0.255 | | 1.394 | | -0.935 |
| | | (0.00) | | (-0.71) | | (-0.12) | | (1.06) | | (-0.34) | | (0.04) | | (-0.08) | | (0.72) | | (-0.36) |
| $Adj.R^2$ | 1.4% | 26.8% | 1.8% | 27.8% | 0.6% | 27.5% | 1.2% | 38.7% | 0.7% | 28.8% | 0.7% | 29.1% | 0.9% | 34.1% | 0.7% | 31.4% | 2.4% | 27.4% |
| $Avg.\#bonds$ | 4132 | 2112 | 3403 | 1755 | 2993 | 1552 | 582 | 309 | 2763 | 1384 | 2768 | 1356 | 1469 | 745 | 2343 | 1246 | 4100 | 2103 |

## Table 5: Horse Race among Bond Peer Momentum

This table reports the Fama and MacBeth (1973) regression of one-month-ahead bond excess return on bond PM from different linkages specified in the rows, with or without a full set of controls used in Table 4. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | **Without Controls** | | | | | | | | **With Controls** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Analyst | 0.160*** | 0.164*** | 0.191*** | 0.208*** | 0.196*** | 0.175*** | 0.140*** | 0.169*** | 0.135*** | 0.142*** | 0.146*** | 0.154*** | 0.137*** | 0.127*** | 0.109*** | 0.152*** |
| | (3.67) | (3.91) | (4.32) | (3.13) | (4.12) | (3.64) | (4.27) | (3.91) | (5.05) | (4.19) | (4.91) | (2.79) | (5.24) | (4.58) | (3.71) | (4.33) |
| Industry | 0.033 | | | | | | | | -0.002 | | | | | | | |
| | (1.47) | | | | | | | | (-0.08) | | | | | | | |
| Text-based industry | | 0.038* | | | | | | | | 0.017 | | | | | | |
| | | (1.82) | | | | | | | | (0.86) | | | | | | |
| Geography | | | 0.013 | | | | | | | | -0.005 | | | | | |
| | | | (0.66) | | | | | | | | (-0.32) | | | | | |
| Customer | | | | 0.007 | | | | | | | | -0.007 | | | | |
| | | | | (0.34) | | | | | | | | (-0.24) | | | | |
| Customer industry | | | | | -0.016 | | | | | | | | -0.008 | | | |
| | | | | | (-0.72) | | | | | | | | (-0.37) | | | |
| Supplier industry | | | | | | -0.001 | | | | | | | | 0.013 | | |
| | | | | | | (-0.02) | | | | | | | | (0.54) | | |
| Complicated firm | | | | | | | 0.014 | | | | | | | | -0.002 | |
| | | | | | | | (0.79) | | | | | | | | (-0.15) | |
| Technology | | | | | | | | 0.010 | | | | | | | | 0.045 |
| | | | | | | | | (0.15) | | | | | | | | (0.73) |
| Controls | No | No | No | No | No | No | No | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Adj.*$R^2$ | 2.6% | 3.0% | 2.9% | 5.5% | 3.2% | 3.4% | 2.0% | 2.5% | 27.9% | 28.8% | 28.7% | 39.7% | 30.3% | 30.7% | 35.3% | 32.7% |
| *Avg.#bonds* | 4059 | 3373 | 2955 | 576 | 2733 | 2733 | 1444 | 2333 | 2083 | 1741 | 1535 | 307 | 1375 | 1347 | 734 | 1243 |

## Table 6: Factor Spanning Test

This table reports spanning tests for nine bond PM factors constructed from different economic linkages. Columns (1) and (2) list the alternative factor and the benchmark factor being compared. Columns (3) and (4) report the mean return and the alpha of the alternative factor relative to the FFDTB-Plus model. The FFDTB-Plus model augments the FFDTB model with two additional long–short bond factors sorted on past one-month bond returns and past one-month stock returns. Column (5) reports the alpha of the alternative factor after controlling for the FFDTB-Plus factors and the benchmark factor, while Column (6) reports the alpha of the benchmark factor after controlling for the FFDTB-Plus factors and the alternative factor. All returns and alphas are in percentages. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| Alternative factor | Benchmark factor | Mean return | Alpha vs. FFDTB-Plus | Alternative alpha given FFDTB-Plus + benchmark | Benchmark alpha given FFDTB-Plus + Alternative |
|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) |
| Analyst | | 0.45*** | 0.56*** | | |
| | | (3.37) | (6.32) | | |
| Industry | Analyst | 0.39*** | 0.42*** | -0.02 | 0.29*** |
| | | (3.49) | (3.74) | (-0.27) | (5.64) |
| Text-based industry | Analyst | 0.45*** | 0.56*** | 0.01 | 0.28*** |
| | | (2.91) | (4.21) | (0.10) | (4.90) |
| Geography | Analyst | 0.21** | 0.22* | 0.01 | 0.50*** |
| | | (2.04) | (1.70) | (0.09) | (6.03) |
| Customer | Analyst | 0.42** | 0.29 | -0.26 | 0.50*** |
| | | (2.27) | (1.37) | (-1.35) | (7.20) |
| Customer industry | Analyst | 0.07 | 0.14 | -0.10 | 0.54*** |
| | | (0.59) | (0.98) | (-0.58) | (6.33) |
| Supplier industry | Analyst | 0.27** | -0.07 | -0.37*** | 0.58*** |
| | | (2.57) | (-0.50) | (-2.62) | (6.86) |
| Complicated firm | Analyst | 0.15** | 0.28*** | 0.15 | 0.51*** |
| | | (2.35) | (3.55) | (1.51) | (5.68) |
| Technology | Analyst | 0.27*** | 0.22*** | 0.03 | 0.48*** |
| | | (2.93) | (2.65) | (0.40) | (6.24) |

## Table 7: Factor Model Sharpe Ratio Comparisons

This table reports multiple-model comparisons of squared Sharpe ratios for nine bond PM factor models, following Barillas et al. (2020). Each candidate model augments the FFDTB-Plus benchmark with one bond PM factor. The FFDTB-Plus model extends FFDTB by adding two long–short bond factors sorted on past one-month bond returns and past one-month stock returns. Column (1) lists the benchmark model in each comparison. Column (2) reports its bias-adjusted sample squared Sharpe ratio. Column (3) reports the number of alternative models in the comparison set. Columns (4) and (5) report the likelihood-ratio statistic and *p*-value for the null that the benchmark model performs at least as well as all alternatives. A lower LR statistic and a higher *p*-value indicate stronger relative performance of the benchmark model.

| Benchmark model | Bias-adj. $SR^2$ | # alt. models | LR stat. | *p*-value |
|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) |
| FFDTB-Plus+Analyst | 0.998 | 8 | 0.000 | 0.773 |
| FFDTB-Plus+Industry | 0.837 | 8 | 7.550 | 0.025 |
| FFDTB-Plus+Text-based industry | 0.854 | 8 | 5.228 | 0.078 |
| FFDTB-Plus+Geography | 0.737 | 8 | 10.882 | 0.007 |
| FFDTB-Plus+Customer | 0.719 | 8 | 10.644 | 0.011 |
| FFDTB-Plus+Customer industry | 0.710 | 8 | 14.581 | 0.005 |
| FFDTB-Plus+Supplier industry | 0.705 | 8 | 9.930 | 0.012 |
| FFDTB-Plus+Complicated firm | 0.768 | 8 | 7.153 | 0.023 |
| FFDTB-Plus+Technology | 0.751 | 8 | 8.540 | 0.016 |

### Table 8: Bond Peer Momentum Effect in Different Rating and Maturity Groups

This table examines the bond PM effect across subsample with different ratings and maturities. We focus on the shared-analyst PM. Within each rating or maturity group, we sort bonds into 5 portfolios by ascending order of their shared-analyst PM at the end of each month $t$. The table reports the time-series averages of each portfolio's equal-weighted month $t+1$ excess returns, the month $t+1$ high–minus–low return, and its alphas adjusted for different factor models. All returns and alphas are in percentages. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Different Rating Groups**

| | Low | 2 | 3 | 4 | High | High-Low | $\alpha_{\text{MKTB}}$ | $\alpha_{\text{FFDT}}$ | $\alpha_{\text{FFDTB}}$ |
|---|---|---|---|---|---|---|---|---|---|
| AAA/AA (Rating $\leq$ 4) | 0.29*** | 0.32*** | 0.33*** | 0.27*** | 0.35*** | 0.06 | 0.10* | 0.14** | 0.13** |
| | (3.45) | (3.80) | (3.55) | (3.18) | (4.15) | (1.29) | (1.66) | (2.28) | (2.17) |
| A (4<Rating $\leq$ 7) | 0.32*** | 0.36*** | 0.44*** | 0.39*** | 0.41*** | 0.09 | 0.16 | 0.15* | 0.16* |
| | (2.81) | (3.20) | (4.01) | (3.56) | (3.65) | (1.16) | (1.59) | (1.72) | (1.91) |
| BBB (7<Rating $\leq$ 10) | 0.38*** | 0.41*** | 0.48*** | 0.51*** | 0.64*** | 0.26*** | 0.31*** | 0.29*** | 0.32*** |
| | (2.62) | (3.47) | (3.88) | (4.00) | (4.12) | (2.82) | (2.73) | (2.63) | (2.77) |
| Junk (Rating>10) | 0.30 | 0.55** | 0.67*** | 0.87*** | 1.03*** | 0.73*** | 1.10*** | 0.94*** | 1.05*** |
| | (0.76) | (2.39) | (3.47) | (3.28) | (3.39) | (3.54) | (3.47) | (3.82) | (3.94) |

**Panel B: Different Maturity Groups**

| | Low | 2 | 3 | 4 | High | High-Low | $\alpha_{\text{MKTB}}$ | $\alpha_{\text{FFDT}}$ | $\alpha_{\text{FFDTB}}$ |
|---|---|---|---|---|---|---|---|---|---|
| Maturity $\leq 3$ | 0.23* | 0.22** | 0.24*** | 0.32*** | 0.42*** | 0.18** | 0.33*** | 0.24*** | 0.29*** |
| | (1.88) | (2.51) | (3.63) | (4.33) | (4.12) | (2.26) | (2.77) | (2.87) | (3.26) |
| $3 <$ Maturity $\leq 5$ | 0.23 | 0.29** | 0.39*** | 0.44*** | 0.62*** | 0.40*** | 0.52*** | 0.45*** | 0.50*** |
| | (1.41) | (2.44) | (4.54) | (4.47) | (4.24) | (3.56) | (3.71) | (3.48) | (3.70) |
| $5 <$ Maturity $\leq 10$ | 0.39** | 0.39** | 0.52*** | 0.56*** | 0.75*** | 0.36*** | 0.41*** | 0.36** | 0.39** |
| | (2.29) | (2.57) | (4.03) | (4.13) | (4.21) | (3.45) | (2.99) | (2.45) | (2.44) |
| Maturity $> 10$ | 0.41** | 0.65*** | 0.65*** | 0.69*** | 0.85*** | 0.44*** | 0.54*** | 0.52*** | 0.54*** |
| | (2.00) | (3.66) | (3.61) | (3.81) | (4.07) | (3.02) | (3.28) | (3.52) | (3.77) |

## Table 9: Fama–MacBeth Regression over Different Sub-Periods

This table reports Fama and MacBeth (1973) regressions of one-month-ahead bond excess returns on shared-analyst PM, $PM^{Bond}$, and the full set of control variables. The regressions are estimated separately across sub-periods defined by: (i) the first versus second half of the sample, (ii) normal versus crisis periods, (iii) low versus high economic policy uncertainty (EPU) following Baker et al. (2016), (iv) low versus high bond market excess returns, and (v) low versus high investor sentiment following Baker and Wurgler (2006). Sub-period classification is based on the cross-sectional median (or standard definitions where applicable) in the formation month. All independent variables are winsorized at the 0.5% and 99.5% levels on a monthly basis. The final row reports the difference in the $PM^{Bond}$ coefficient across paired sub-periods. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Time period | | Normal/Crisis | | EPU | | Bond market return | | BW sentiment | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1st half | 2nd half | Normal | Crisis | Low | High | Low | High | Low | High |
| $PM^{Bond}$ | 0.140*** | 0.142*** | 0.142*** | 0.139 | 0.168*** | 0.115*** | 0.135*** | 0.148*** | 0.126*** | 0.157*** |
| | (3.39) | (4.54) | (6.19) | (1.03) | (4.12) | (3.74) | (3.62) | (3.83) | (3.95) | (4.14) |
| $RET^{Bond}$ | -0.239*** | -0.105*** | -0.179*** | -0.120 | -0.191*** | -0.154*** | -0.147*** | -0.197*** | -0.179*** | -0.166*** |
| | (-13.53) | (-3.74) | (-9.52) | (-1.39) | (-6.59) | (-5.36) | (-4.49) | (-7.09) | (-9.55) | (-4.66) |
| $RET^{Stock}$ | 0.035*** | 0.026*** | 0.025*** | 0.075*** | 0.031*** | 0.030*** | 0.033*** | 0.029*** | 0.029*** | 0.032*** |
| | (5.26) | (8.97) | (9.67) | (4.89) | (7.80) | (5.14) | (6.59) | (6.68) | (5.04) | (7.95) |
| $PM^{Stock}$ | 0.004 | -0.000 | -0.001 | 0.026 | -0.001 | 0.004 | 0.007 | -0.003 | 0.001 | 0.003 |
| | (0.63) | (-0.07) | (-0.33) | (1.01) | (-0.12) | (0.63) | (1.24) | (-0.46) | (0.11) | (0.38) |
| $Maturity$ | 0.013 | 0.013 | 0.019*** | -0.032 | 0.012 | 0.013 | 0.012 | 0.014* | 0.013 | 0.012 |
| | (1.62) | (1.25) | (2.85) | (-1.47) | (1.36) | (1.36) | (1.22) | (1.90) | (1.53) | (1.45) |
| $\ln(AMT)$ | -0.026 | -0.036 | -0.028 | -0.055 | -0.074*** | 0.012 | -0.034 | -0.028 | -0.027 | -0.035 |
| | (-0.89) | (-1.16) | (-1.55) | (-0.46) | (-2.73) | (0.38) | (-1.08) | (-0.77) | (-1.04) | (-1.11) |
| $Rating$ | -0.004 | 0.016 | 0.021** | -0.117 | 0.000 | 0.012 | -0.030 | 0.041*** | 0.007 | 0.005 |
| | (-0.12) | (1.25) | (2.57) | (-1.07) | (0.01) | (0.37) | (-1.01) | (2.70) | (0.22) | (0.38) |
| $\beta$ | 0.001 | 0.004* | 0.001** | 0.011 | 0.000 | 0.004* | 0.003 | 0.002 | 0.002** | 0.003 |
| | (0.71) | (1.69) | (2.21) | (1.06) | (0.38) | (1.83) | (1.56) | (1.46) | (2.23) | (1.05) |
| $\beta^{VIX}$ | -0.023 | -0.133 | 0.062 | -1.194 | 0.131 | -0.285 | -0.030 | -0.126 | 0.141 | -0.295 |
| | (-0.23) | (-0.43) | (0.53) | (-1.40) | (1.47) | (-1.00) | (-0.16) | (-0.68) | (0.71) | (-1.18) |
| $VaR$ | 0.047* | -0.005 | 0.017 | 0.055 | -0.011 | 0.052* | -0.024 | 0.065** | 0.055** | -0.012 |
| | (1.78) | (-0.15) | (0.76) | (0.55) | (-0.32) | (1.82) | (-0.71) | (2.21) | (2.17) | (-0.35) |
| $IVOL$ | -0.050 | -0.089 | -0.032 | -0.373*** | -0.061 | -0.079 | -0.109** | -0.031 | -0.006 | -0.132*** |
| | (-1.18) | (-1.45) | (-1.10) | (-2.93) | (-1.40) | (-1.37) | (-2.13) | (-0.63) | (-0.15) | (-2.63) |
| $ILLIQ$ | 1.031 | -2.922 | -0.730 | -2.567 | -3.594* | 1.696 | -2.337 | 0.453 | -1.364 | -0.511 |
| | (0.61) | (-0.60) | (-0.25) | (-0.66) | (-1.67) | (0.37) | (-0.52) | (0.26) | (-0.38) | (-0.13) |
| $Adj.R^2$ | 26.1% | 28.8% | 27.4% | 27.7% | 26.2% | 28.6% | 27.7% | 27.2% | 26.6% | 28.3% |
| $Avg.\#bonds$ | 1403 | 2810 | 2182 | 1469 | 1765 | 2437 | 2140 | 2066 | 2183 | 2023 |
| | Coefficient difference on $PM^{Bond}$ between two sub-periods | | | | | | | | | |
| | Diff. | t-stats | Diff. | t-stats | Diff. | t-stats | Diff. | t-stats | Diff. | t-stats |
| | -0.002 | (-0.04) | 0.002 | (0.03) | 0.054 | (0.95) | -0.013 | (-0.23) | -0.031 | (-0.56) |

## Table 10: Robustness of Bond Peer Momentum Effect

This table examines the robustness of the shared-analyst PM effect. Panel A reports the results of the value-weighted shared-analyst PM strategy using bond amount outstanding as the weight. Panel B performs the firm-level analysis by aggregating bond returns within each firm, either through equal weight or value weight by bond amount outstanding. Panel C tests the influence of excluding bonds with embedded options. Panel D experiments with different kinds of bond returns. Panel E deals with the concern about the unavailable peer momentum signal at the time of portfolio formation. For each specification, the table reports the mean return and alphas of the long–short strategy, with the t-statistics in parentheses adjusted according to Newey and West (1987) with 5 lags. All returns and alphas are in percentages. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | High-Low | $\alpha_{\text{MKTB}}$ | $\alpha_{\text{FFDT}}$ | $\alpha_{\text{FFDTB}}$ |
|---|---|---|---|---|
| **Panel A: value-weighted strategy** | | | | |
| Portfolio return from bond-amount-outstanding-weighted average | 0.36*** | 0.47*** | 0.42*** | 0.49*** |
| | (2.92) | (3.03) | (2.74) | (3.10) |
| **Panel B: firm-level analysis** | | | | |
| Equal-weighted firm-level bond return | 0.76*** | 0.88*** | 0.79*** | 0.82*** |
| | (3.72) | (2.66) | (2.82) | (2.67) |
| Value-weighted firm-level bond return | 0.76*** | 0.90*** | 0.79*** | 0.84*** |
| | (3.71) | (2.66) | (2.81) | (2.70) |
| **Panel C: embedded options** | | | | |
| Excluding bonds with embedded options | 0.20** | 0.25** | 0.28*** | 0.29*** |
| | (2.04) | (2.56) | (2.63) | (2.78) |
| Excluding bonds with embedded options except callable bonds | 0.45*** | 0.55*** | 0.49*** | 0.55*** |
| | (3.39) | (2.95) | (2.96) | (3.16) |
| **Panel D: alternative bond returns** | | | | |
| Bond return based on the last price in a month ($R^{\text{EOM}}$) | 0.46*** | 0.59*** | 0.50*** | 0.57*** |
| | (3.49) | (3.12) | (3.19) | (3.38) |
| Bond return based on price in the last trading day of a month ($R^{\text{LDM}}$) | 0.49*** | 0.68*** | 0.55*** | 0.64*** |
| | (3.02) | (2.80) | (2.76) | (3.10) |
| Bond return from Open Source Bond Asset Pricing ($R^{\text{OSB}}$) | 0.55*** | 0.67*** | 0.58*** | 0.64*** |
| | (3.80) | (3.30) | (3.18) | (3.28) |
| Duration-adjusted bond return ($R^{\text{DurAdj}}$) | 0.43*** | 0.55*** | 0.47*** | 0.54*** |
| | (3.36) | (2.82) | (2.84) | (3.05) |
| **Panel E: available information at the time of portfolio formation** | | | | |
| Bond PM from $R^{\text{EOM}}$ predicts future $R^{\text{LDM}}$ | 0.50*** | 0.67*** | 0.57*** | 0.65*** |
| | (3.22) | (2.96) | (3.00) | (3.25) |
| Bond PM from $R^{\text{L5M}}$ predicts future $R^{\text{LDM}}$ | 0.55*** | 0.68*** | 0.61*** | 0.68*** |
| | (3.38) | (3.09) | (3.18) | (3.42) |
| Bond PM from MMN-adjusted $R^{\text{OSB}}_{\text{MMN}}$ predicts future $R^{\text{OSB}}$ | 0.53*** | 0.61*** | 0.54*** | 0.58*** |
| | (3.45) | (3.21) | (3.09) | (3.22) |

## Table 11: Comparing Peer Momentum Effects between Bond and Stock Markets

Panel A compares the performance of peer momentum strategies in the bond and stock markets over our sample period. The reported metrics are mean return, Newey and West (1987) t-statistics with 5 lags (in parentheses), standard deviation, Sharpe ratio (mean/standard deviation), skewness, excess kurtosis (kurtosis minus 3), and maximum drawdown (the largest decline in cumulative value from a prior peak). Panel B compares the persistence of the peer momentum effect across the two markets using Fama and MacBeth (1973) regressions of bond (stock) excess returns on lagged bond (stock) peer momentum. The subscript $(t-k, t-h)$ denotes the return window from month $t-k$ to month $t-h$, inclusive. In the bond regressions, we control for return-related variables measured over matching windows, bond characteristics, and other bond return predictors. In the stock regressions, following Ali and Hirshleifer (2020), we control for past stock returns over matching windows, log market capitalization, and log book-to-market ratio. All independent variables are winsorized at the 0.5% and 99.5% levels each month. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Performance metrics of peer momentum strategy**

| | Mean return (t-stats.) | Std. dev. | Sharpe ratio | Skewness | Excess kurtosis | Max drawdown |
|---|---|---|---|---|---|---|
| Bond PM | 0.45%*** (3.37) | 2.19% | 0.206 | 1.73 | 10.18 | 8.41% |
| Stock PM | 1.31%*** (3.66) | 6.65% | 0.197 | 0.34 | 5.44 | 28.34% |

**Panel B: Persistence of PM effects**

| | Bond excess returns on lagged PM | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $PM^{Bond}_{t-1}$ | 0.141*** | | 0.131*** | | 0.129*** | | 0.118*** | | 0.121*** |
| | (5.46) | | (4.66) | | (4.35) | | (4.54) | | (4.25) |
| $PM^{Bond}_{t-3,t-2}$ | | 0.027 | 0.066 | | | | | | |
| | | (0.42) | (1.50) | | | | | | |
| $PM^{Bond}_{t-6,t-2}$ | | | | 0.130* | 0.084 | | | | |
| | | | | (1.89) | (1.44) | | | | |
| $PM^{Bond}_{t-12,t-2}$ | | | | | | 0.091 | 0.019 | | -0.023 |
| | | | | | | (1.00) | (0.23) | | (-0.29) |
| $PM^{Bond}_{t-36,t-13}$ | | | | | | | | 0.011 | 0.159 |
| | | | | | | | | (0.05) | (0.94) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Adj.*$R^2$ | 27.4% | 25.3% | 30.1% | 25.6% | 30.6% | 25.7% | 30.5% | 24.3% | 32.2% |
| *Avg.#bonds* | 2103 | 2027 | 2027 | 1986 | 1959 | 2060 | 2028 | 1956 | 1846 |

| | Stock excess returns on lagged stock PM | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $PM^{Stock}_{t-1}$ | 0.093*** | | 0.102*** | | 0.109*** | | 0.103*** | | 0.099*** |
| | (4.47) | | (4.99) | | (5.82) | | (5.04) | | (4.69) |
| $PM^{Stock}_{t-3,t-2}$ | | 0.074** | 0.076*** | | | | | | |
| | | (2.36) | (2.85) | | | | | | |
| $PM^{Stock}_{t-6,t-2}$ | | | | 0.169*** | 0.177*** | | | | |
| | | | | (4.37) | (5.07) | | | | |
| $PM^{Stock}_{t-12,t-2}$ | | | | | | 0.197*** | 0.205*** | | 0.196*** |
| | | | | | | (3.28) | (3.54) | | (3.67) |
| $PM^{Stock}_{t-36,t-13}$ | | | | | | | | 0.240** | 0.175** |
| | | | | | | | | (2.37) | (2.41) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Adj.*$R^2$ | 2.8% | 2.5% | 3.6% | 2.7% | 3.7% | 2.9% | 3.9% | 2.1% | 4.5% |
| *Avg.#stocks* | 2764 | 2763 | 2763 | 2762 | 2762 | 2756 | 2755 | 2565 | 2565 |

### Table 12: Mechanism Test: Limited Attention

This table examines the limited attention channel for the bond PM effect, using variables related to investor attention. The attention-related variables include bond institutional ownership $IOR$, bond investor composition $INV\_COMP$ (Li and Yu, 2021), abnormal institutional attention $AIA$ from Bloomberg news readership (Ben-Rephael et al., 2017), and abnormal Google search volume $ASV$ (Da et al., 2011). Panel A splits bonds into two groups based on the cross-sectional median of each attention-related variable. It reports the mean returns and alphas of the PM strategy for each subsample and the difference between them. Panel B presents the Fama and MacBeth (1973) regressions of one-month-ahead bond excess returns on PM, the attention-related variable, and their interaction, with a full set of controls used in Table 4. All independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. In both panels, the t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: PM strategy return under different bond subsample**

| | | High-Low | $\alpha_{\text{MKTB}}$ | $\alpha_{\text{FFDT}}$ | $\alpha_{\text{FFDTB}}$ |
|---|---|---|---|---|---|
| $IOR$ | Low | 0.41*** | 0.48*** | 0.47*** | 0.50*** |
| | | (4.11) | (3.94) | (4.20) | (4.33) |
| | High | 0.31*** | 0.33*** | 0.32*** | 0.34*** |
| | | (3.23) | (3.23) | (2.87) | (3.04) |
| | High-Low | -0.10 | -0.15** | -0.15** | -0.15** |
| | | (-1.61) | (-2.10) | (-2.50) | (-2.50) |
| $INV\_COMP$ | Low | 0.39*** | 0.42*** | 0.40*** | 0.43*** |
| | | (3.70) | (3.66) | (3.37) | (3.54) |
| | High | 0.34*** | 0.38*** | 0.38*** | 0.39*** |
| | | (3.87) | (3.78) | (3.51) | (3.51) |
| | High-Low | -0.05 | -0.04 | -0.02 | -0.04 |
| | | (-1.05) | (-0.79) | (-0.44) | (-0.81) |
| $AIA$ | Low | 0.31** | 0.53*** | 0.45*** | 0.47*** |
| | | (2.58) | (2.65) | (2.80) | (3.07) |
| | High | 0.23* | 0.40** | 0.38** | 0.39** |
| | | (1.97) | (2.48) | (2.40) | (2.60) |
| | High-Low | -0.08 | -0.13 | -0.08 | -0.08 |
| | | (-1.41) | (-1.31) | (-1.11) | (-1.16) |
| $ASV$ | Low | 0.37*** | 0.44*** | 0.45*** | 0.47*** |
| | | (2.83) | (3.25) | (3.61) | (3.84) |
| | High | 0.35*** | 0.48*** | 0.42*** | 0.45*** |
| | | (3.48) | (3.46) | (3.18) | (3.22) |
| | High-Low | -0.01 | 0.04 | -0.03 | -0.02 |
| | | (-0.16) | (0.39) | (-0.28) | (-0.17) |

**Panel B: Fama–MacBeth regression with interaction term**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $PM^{Bond}$ | 0.212*** | 0.140*** | 0.152*** | 0.147*** |
| | (3.51) | (4.96) | (3.62) | (5.49) |
| $PM^{Bond} \times IOR$ | -0.143 | | | |
| | (-1.24) | | | |
| $IOR$ | -0.001 | | | |
| | (-0.23) | | | |
| $PM^{Bond} \times INV\_COMP$ | | 0.200 | | |
| | | (1.07) | | |
| $INV\_COMP$ | | -0.001 | | |
| | | (-1.21) | | |
| $PM^{Bond} \times AIA$ | | | -0.027 | |
| | | | (-0.30) | |
| $AIA$ | | | -0.001 | |
| | | | (-1.65) | |
| $PM^{Bond} \times ASV$ | | | | 0.206* |
| | | | | (1.83) |
| $ASV$ | | | | -0.003** |
| | | | | (-2.29) |
| Control | Yes | Yes | Yes | Yes |
| $Adj.R^2$ | 27.6% | 27.2% | 32.4% | 28.0% |
| *Avg.#bonds* | 1932 | 1927 | 2185 | 2103 |

### Table 13: Mechanism Test: Factor Momentum

This table explores whether the bond PM effect is driven by factor momentum. We decompose the monthly bond excess return into its systematic and idiosyncratic components by regressing it on the bond-plus-stock six factors (the FFDTB model in the main text) on a rolling 36-month window. The systematic part is the fitted value in the regression and the idiosyncratic part is the regression residual. At the end of each month, we calculate the systematic (idiosyncratic) bond PM from peer bonds' systematic (idiosyncratic) returns. The table reports the Fama and MacBeth (1973) regression of one-month-ahead bond excess return on the two kinds of bond PMs, with a full set of controls used in Table 4. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| $PM^{Bond}$(systematic) | 0.082 | | 0.115* |
| | (1.52) | | (1.97) |
| $PM^{Bond}$(idiosyncratic) | | 0.103*** | 0.142*** |
| | | (3.52) | (4.48) |
| $RET^{Bond}$ | -0.170*** | -0.170*** | -0.173*** |
| | (-8.49) | (-8.27) | (-8.72) |
| $RET^{Stock}$ | 0.031*** | 0.031*** | 0.031*** |
| | (8.50) | (8.18) | (8.68) |
| $PM^{Stock}$ | 0.008* | 0.006 | 0.002 |
| | (1.86) | (1.25) | (0.47) |
| $Maturity$ | 0.013** | 0.013** | 0.013** |
| | (2.03) | (2.09) | (2.06) |
| $\ln(AMT)$ | -0.030 | -0.029 | -0.028 |
| | (-1.50) | (-1.46) | (-1.49) |
| $Rating$ | 0.003 | 0.005 | 0.003 |
| | (0.20) | (0.32) | (0.20) |
| $\beta$ | 0.002* | 0.002* | 0.002* |
| | (1.75) | (1.76) | (1.79) |
| $\beta^{VIX}$ | -0.080 | -0.074 | -0.071 |
| | (-0.50) | (-0.43) | (-0.45) |
| $VaR$ | 0.020 | 0.019 | 0.019 |
| | (0.87) | (0.84) | (0.87) |
| $IVOL$ | -0.067* | -0.066* | -0.065* |
| | (-1.80) | (-1.75) | (-1.75) |
| $ILLIQ$ | -1.019 | -1.112 | -1.089 |
| | (-0.39) | (-0.42) | (-0.42) |
| $Adj.R^2$ | 27.5% | 27.3% | 27.8% |
| $Avg.\#bonds$ | 2101 | 2101 | 2101 |

## Table 14: Mechanism Test: Inertial Fund Flow

This table examines the inertial fund flow channel for the bond PM effect by analyzing how common institutional ownership affects the predictive power of bond PM. At the end of each month, for each focal bond, we categorize its shared-analyst peers into two groups: co-held peers, which share at least one institutional owner with the focal bond, and non-co-held peers, which have entirely distinct institutional owners. We then calculate the bond PM from these two groups of bond peers separately and compare their predictive power for next-month bond returns in the Fama and MacBeth (1973) regression. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| $PM^{Bond}$(analyst&co-held) | 0.172*** | | 0.172*** |
| | (5.85) | | (5.63) |
| $PM^{Bond}$(analyst&non-co-held) | | 0.005 | -0.007 |
| | | (0.80) | (-1.43) |
| $RET^{Bond}$ | -0.196*** | -0.187*** | -0.197*** |
| | (-11.03) | (-10.24) | (-11.00) |
| $RET^{Stock}$ | 0.031*** | 0.032*** | 0.032*** |
| | (7.69) | (7.64) | (7.73) |
| $PM^{Stock}$ | -0.001 | 0.011*** | -0.000 |
| | (-0.38) | (2.63) | (-0.00) |
| $Maturity$ | 0.013* | 0.013* | 0.013* |
| | (1.95) | (1.89) | (1.97) |
| $\ln(AMT)$ | -0.047** | -0.040* | -0.047** |
| | (-2.14) | (-1.96) | (-2.11) |
| $Rating$ | 0.003 | 0.001 | 0.003 |
| | (0.19) | (0.05) | (0.15) |
| $\beta$ | 0.001 | 0.001 | 0.001 |
| | (1.04) | (1.13) | (1.02) |
| $\beta^{VIX}$ | 0.076 | 0.082 | 0.073 |
| | (0.65) | (0.68) | (0.62) |
| $VaR$ | 0.031 | 0.029 | 0.030 |
| | (1.27) | (1.16) | (1.24) |
| $IVOL$ | -0.042 | -0.035 | -0.040 |
| | (-1.21) | (-1.07) | (-1.14) |
| $ILLIQ$ | -2.366 | -2.626 | -2.451 |
| | (-1.14) | (-1.25) | (-1.18) |
| $Adj.R^2$ | 27.0% | 26.4% | 27.1% |
| $Avg.\#bonds$ | 1927 | 1886 | 1872 |

## Table 15: Bond Peer Momentum from Co-Holding Linkage

This table investigates the predictive power of bond PM based on the co-holding linkages. $PM^{Bond}$(co-held) is the equal-weighted average of peer bonds' returns over the past month. $PM^{Bond}$(co-held, count) and $PM^{Bond}$(co-held, int) weight these returns by the number of institutions that co-hold the bond pair and the co-holding fraction, respectively. We report Fama and MacBeth (1973) regressions of one-month-ahead bond excess returns on the co-holding and shared-analyst bond PM signals, including all controls from column (18) of Table 4. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $PM^{Bond}$(co-held) | -0.198 | -0.151 | | | | |
| | (-0.87) | (-0.66) | | | | |
| $PM^{Bond}$(co-held, count) | | | 0.104 | 0.112 | | |
| | | | (0.96) | (1.06) | | |
| $PM^{Bond}$(co-held, int) | | | | | 0.155* | 0.150* |
| | | | | | (1.97) | (1.95) |
| $PM^{Bond}$(analyst) | | 0.146*** | | 0.145*** | | 0.146*** |
| | | (5.60) | | (5.49) | | (5.59) |
| Control | Yes | Yes | Yes | Yes | Yes | Yes |
| $Adj.R^2$ | 26.4% | 27.1% | 26.5% | 27.3% | 26.4% | 27.2% |
| $Avg.\#bonds$ | 1959 | 1953 | 1959 | 1953 | 1959 | 1953 |

## Table 16: Limits to Arbitrage

This table examines whether high arbitrage cost prevents investors from arbitraging away the bond PM effect, using variables related to arbitrage costs (bond illiquidity $ILLIQ$ and bond idiosyncratic volatility $IVOL$). Panel A splits bonds into two groups based on the cross-sectional median of each arbitrage-cost variable. It reports the mean returns and alphas of the PM strategy for each subsample and the difference between them. Panel B presents the Fama and MacBeth (1973) regressions of one-month-ahead bond excess returns on PM, the arbitrage-cost variable, and their interaction, with a full set of controls used in Table 4. All independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. In both panels, the t-statistics in parentheses are adjusted according to Newey and West (1987) with 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: PM strategy return under different bond subsample**

| | | High-Low | $\alpha_{\mathrm{MKTB}}$ | $\alpha_{\mathrm{FFDT}}$ | $\alpha_{\mathrm{FFDTB}}$ |
|---|---|---|---|---|---|
| $ILLIQ$ | Low | 0.26*** | 0.34*** | 0.27*** | 0.30*** |
| | | (3.63) | (3.02) | (2.80) | (2.71) |
| | High | 0.44*** | 0.56*** | 0.53*** | 0.57*** |
| | | (3.65) | (3.91) | (3.70) | (3.89) |
| | High-Low | 0.19** | 0.22*** | 0.26*** | 0.27*** |
| | | (2.49) | (2.83) | (3.40) | (3.47) |
| $IVOL$ | Low | 0.10** | 0.14*** | 0.11** | 0.11** |
| | | (2.34) | (2.63) | (2.14) | (2.31) |
| | High | 0.66*** | 0.85*** | 0.77*** | 0.84*** |
| | | (3.52) | (3.75) | (3.61) | (3.79) |
| | High-Low | 0.56*** | 0.71*** | 0.65*** | 0.73*** |
| | | (3.47) | (3.56) | (3.56) | (3.84) |

**Panel B: Fama–MacBeth regression with interaction term**

| | (1) | (2) |
|---|---|---|
| $PM^{Bond}$ | 0.113*** | -0.034 |
| | (4.46) | (-0.89) |
| $PM^{Bond} \times ILLIQ \times 100$ | 8.208** | |
| | (2.26) | |
| $ILLIQ \times 100$ | 0.037 | |
| | (0.97) | |
| $PM^{Bond} \times IVOL$ | | 9.747*** |
| | | (4.26) |
| $IVOL$ | | -0.046 |
| | | (-1.09) |
| Control | Yes | Yes |
| $Adj.R^2$ | 28.3% | 28.8% |
| *Avg.#bonds* | 2103 | 2103 |