Comovement and the Joint Cross-section of Stock and Corporate Bond Returns

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Abstract

We study the pricing implications of firm-level stock–bond comovement in the joint cross-section of stock and corporate bond returns. We find that a trading strategy that longs (shorts) securities with low (high) changes in comovement delivers economically and statistically significant average monthly returns in both the stock and corporate bond markets. Such an effect is more pronounced for firms with low profitability and growth potential. The results are robust to different market conditions and risk characteristics and cannot be explained by established pricing factors from antecedent research. Comovement captures investors' views about the firm's overall risk and uncertainty prospects.

1. Introduction

Equities and bonds issued by the same company are closely related through the firm's capital structure. Even so, due to the difference in clienteles for both asset classes, the same piece of news or information can trigger different investors' reactions. More specifically, stockholders who benefit from good prospects of profitability and have exposure to unlimited upside potential may act differently from bondholders with capped benefits (Campbell and Taksler, 2003). Differences in the order of claims on the firm's net assets also contribute to the divergence in investors' actions and share demands. One exception is when the firm is perceived to be in serious trouble, as then both stock- and bondholders may face losing part or all of their investment. In these situations, investors who are cautious about risk might reduce or halt their involvement in any securities from the company, leading to a heightened correlation between the company's stocks and bonds (i.e., comovement hereafter).

Comovement de-facto measures the degree of covariance and correlation between the stocks and bonds issued by the same company. This level of correlation is reflective of the common reaction of equity and bond investors to changes in firm-specific outlook. When the outlook of the company is positive, investors tend to favor equity over bonds due to the potentially uncapped benefit enjoyed by equity holders. This creates a divergence in returns and reduces the correlation between the two assets. Conversely, in negative scenarios when the company's prospects impact profitability and its general ability to meet interest payments, both bond and equity holders are inclined to divest, leading to an increase in comovement between bond and equity returns. We posit that such increases in comovement proxy for investors' concerns about the firm's quality as well as their (firm-specific) distress risk expectations. This arises from an increased probability of coordinated trades across both asset classes when the overall perception is that the company is encountering financial difficulties.

At the market level, the time-varying correlation between stocks and bonds has been studied by Campbell and Ammer (1993), who find that investors tend to respond to news that jointly affects both markets by selling both assets. The fluctuating correlation was further linked to shifts in market risk, as evidenced by business cycle data (Koijen et al., 2017, Rossi and Timmermann, 2015), economic state variables (Bekaert et al., 2010), and market uncertainty (Baele et al., 2010, Connolly et al., 2007). This suggests that this cross-market connection encompasses significant informational value. Despite these efforts, little work has been devoted to investigating how stock–bond comovement affects asset returns at the firm level.

In this paper, we study the pricing implications of firm-specific stock-bond comovement, a measure that captures stock and bond investors' common reactions to changes in a firm's risk level, in the joint cross-sections of equities and bonds. We find that changes in firm-level stock–bond comovement (*ΔCOMOVE*) negatively explain the future returns of both stocks and bonds issued by the same firm in the cross-section. Equities in the top quintile (high *ΔCOMOVE*) underperform those in the bottom quintile (low *ΔCOMOVE*) by 88 basis points (bps) per month (*t*-stat = −4.05). The predictive power of the comovement measure also arises in the cross-section of bond returns, with those in the lowest *ΔCOMOVE* quintile generating a significant average monthly return of 25 bps (t-stat = −3.41) higher than those in the highest quintile. The results of bivariate sorts and Fama and MacBeth (1973) regressions further confirm that *ΔCOMOVE* affords significant predictive power after controlling for established factors known to explain cross-sectional variations in returns from both markets (see e.g., Jegadeesh and Titman, 1993; Amuihud, 2002). The comovement effect is stronger among firms with higher levels of financial risk and information asymmetry. In a regime-based analysis, we show that the predictive power of *ΔCOMOVE* is stronger during periods of high market volatility, high default risk, and low market liquidity. In further robustness checks, we confirm that the results remain consistent with *ΔCOMOVE* constructed using alternative samples and different formation periods. Our findings suggest that the *ΔCOMOVE* premium is not attributable to construction issues or bias from short sample periods. Collectively, these results point to a significant explanatory power originating from investors' common perceptions of the firm's overall risk and uncertainty prospects.

Our empirical findings contribute to the literature in several ways. First, we add to the growing literature on cross-asset linkages. Studies that are most closely related to our paper examine the pricing discrepancies between credit default swaps (CDS) and bond spreads issued by the same company, known as the CDS-bond basis. Since CDSs serve as insurance against defaults, they have been documented to be closely linked to bond value uncertainty (Fontana, 2011) and trading frictions (Bai and Collin-Dufresne, 2019, Oehmke and Zawadowski, 2017). Kim et al. (2016) study the pricing impact of the CDS-bond basis and document its significantly negative association with future bond returns. However, these findings tell us very little about how cross-asset linkages affect the cross-section of asset returns as they only cover small data samples and large firms (e.g., CDS-listed ones). Our paper unveils the significant explanatory power of stock-bond comovement in a cross-asset setting with a more representative sample of firms. The findings of our paper not only confirm the interconnectedness between equities and bonds at the firm level but also offer a promising agenda for future research explaining abnormal risk premia with cross-asset measures.

Our findings also contribute to the empirical asset pricing literature focused on the information content of cross-asset dynamics. While equity and corporate bond returns have, so far, largely been studied separately, the need for studies on their joint pricing is critical. Existing literature has shown that an increasing number of risk anomalies that have long been known to predict equities are also identified in the cross-section of corporate bond returns (Bai et al., 2019, Bali et al., 2021a, Fama and French, 1993). We complement these studies by constructing a firm-level variable that captures common information from both stock and bond markets. More importantly, we are the first research to perform such an analysis for the joint cross-section of stocks and bonds, highlighting the crucial role of cross-asset information in explaining future security returns. Prior work by Dickerson et al. (2022) focuses on predicting future variations in the covariance and realizing diversification benefits accordingly from investing in both types of securities. We examine the pricing implications of cross-asset comovement and show that it generates significant premia in both asset classes. The main findings of our paper provide practical guidance for mutual funds and investors, especially those who seek to manage a balanced portfolio involving stocks and bonds.

Another key contribution of our paper is to advance the literature on stock–bond comovement, as existing studies tend to remain at the aggregate market level without looking at firm-level comovement. Peng (2005) finds that investors' transactions tend to occur primarily in one market, preceding price changes that happen subsequently in the other market. Despite this evidence, researchers have not reached an agreement on the lead-lag roles of different asset classes (Garcia and Tsafack, 2011, Hartmann et al., 2004). Moreover, Hilscher et al. (2015) find that the linkage between equity and bond indexes at the aggregate level is too inconsistent to explain firm-level pricing dynamics. Hou (2007) also documents how certain firms react more sluggishly to new information at the market level, which highlights the value of studying the information quality of pricing factors at the firm level. Norden and Weber (2009) examine this lead-lag relation at the firm level over a small number of firms that issue equities, bonds, and CDSs. They find that stock returns lead CDS and bond spread changes and that comovement at the aggregate level is influenced by credit quality and the size of bond issues. No prior study, however, has investigated the firm-level relation between equities and corporate bonds for all the available publicly listed companies. To the best of our knowledge, our paper provides the first empirical evidence of the pricing implications of the stock–bond relation at the firm level and the negative effect of stock-bond comovement on the cross-sections of bond and stock returns.

The remainder of this paper is organized as follows. Section 2 describes the data and variables. Section 3 provides empirical results that demonstrate the cross-sectional predictive power of *ΔCOMOVE* for both the stock and bond markets, including a battery of robustness checks and validation tests. Section 4 concludes the paper. The online appendix contains technical details/definitions and presents additional results.

2. Data and Variables

This section describes the construction of our main variables, including the comovement measure which as discussed captures the common variability between returns on stocks and bonds issued by the same firm, firm-level security returns, and market-specific control variables.

Our comovement measure is constructed using equity and bond returns data. For equities, we obtain equity and accounting data from CRSP and COMPUSTAT, respectively, and calculate firm-level equity returns as:

$$R_{E_{i,t}} = \frac{S_{i,t}+D_{i,t}}{S_{i,t-1}} - 1, \tag{1}$$

where $S_{i,t}$ is the stock price of firm i, and $D_{i,t}$ is the dividend recorded during month t (if applicable). For bonds, we use intraday bond transaction data from the TRACE Enhanced dataset and obtain information on bond issues and issuer characteristics from the Mergent FISD. The process of data cleaning, merging, and filtering we follow adheres to the methods outlined in Dick-Nielsen (2014), Dick-Nielsen (2009), and Asquith et al. (2013), with additional details provided in Appendix A. Following Bessembinder et al. (2008), we compute monthly bond returns as:

$$R_{B_{i,j,t}} = \frac{B_{i,j,t} + AI_{i,j,t} + Coupon_{i,j,t}}{B_{i,j,t-1} + AI_{i,j,t-1}} - 1, \quad (2)$$

where $B_{i,j,t}$ is the price of bond j issued by firm i in month t, $AI_{i,j,t}$ is the accrued interest, and $Coupon_{i,j,t}$ is the coupon payment (if available). In addition, Bessembinder et al. (2008) argue that treating individual-level bond returns as separate observations introduces bias in empirical findings, especially concerning firms with multiple bond issues. To overcome this, we follow their approach by aggregating firms' outstanding bond returns into a value-weighted return. We then exclude firms operating in financial and insurance-related sectors, as they are subject to specific regulations that influence their leverage policies and thus their default risk.[1] Our final sample includes 143,387 observations of security returns for 1,614 companies spanning the period from August 2002 to December 2020.

To measure firm-specific bond–stock comovement, we compute the covariance based on the exponential weighted moving average (EWMA), which has demonstrated superior performance compared to other moving average estimators (Andersson et al., 2008, Bali and Karagozoglu, 2000). We compute monthly $COMOVE_t$ over a 60-month fixed window of past monthly returns with a minimum requirement of 48 available observations as:

$$COMOVE_t = \sqrt{(1-\lambda)\sum_{i=1}^{60} \lambda^{i-1} R_{E,t-i} R_{B,t-i}}, \quad (3)$$

where $R_{E,t-i} R_{B,t-i}$ is the product of paired monthly returns on bonds and equities issued by the same firm. λ is a decay factor that assigns more weight to recent observations because of their greater relevance in forecasting future returns. The selection of λ is guided by fitting a dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model (Engle, 2002) to paired stock and bond returns. This approach is chosen due to its empirical robustness, as demonstrated by Engle and Sheppard (2001), over conventional industry benchmarks in accommodating particular features of sampled firms when modeling their smoothing coefficients. To avoid incorporating heterogeneous information for λ in our analysis, we use the mean value of λ across all firms as our input in the estimation of $COMOVE_t$ for all firms.[2] Due to the high degree of serial correlation of $COMOVE_t$, we follow Bali et al. (2021b) and use the first difference of $COMOVE_t$,

[1] Our results and main findings hold when financial firms are included.

[2] The value of λ used is 0.80. Compared to the typical λ of 0.94 used by practitioners in EWMA when estimating volatility, the correlation exhibits lower average persistence. Our results are robust to the use of alternative λ values based on exponential weights estimated from different time periods.

denoted by $\Delta COMOVE$, as our main measure in further analyses. When a firm is perceived to be in financial distress, we expect to observe an elevated $\Delta COMOVE$.

[Table 1]

[Table 2]

[Table 3]

Definitions of firm characteristics and the control variables used are summarized in Table 1. Tables 2 and 3 present the descriptive statistics for $\Delta COMOVE$, security returns, and market-specific control variables for equity and bond markets respectively. Panels A in each table report the cross-sectional mean, median, standard deviation, and monthly return percentiles of our sample. Panels B in each table report pairwise correlations. Our final combined $\Delta COMOVE$ dataset includes bonds and stocks issued by 906 unique firms, for a total of 69,540 observations from September 2007 to December 2020. On average, there are approximately 432 observations per month in our sample. $\Delta COMOVE$ is, in general, close to being normally distributed with a mean of 0 and is slightly positively skewed. The average monthly equity and bond returns are 1.08% and 0.61%, respectively, and the average sizes of the equity and bond amounts outstanding are US$27.19 billion and US$0.59 billion, respectively. In general, our sample is not biased toward any characteristic group. It contains bonds with an average rating of 10 (BBB) and an average time-to-maturity of 9 years. Among the full sample of bonds, around 75% are investment grade, and the remaining 25% are high-yield bonds. $\Delta COMOVE$ does not correlate significantly with other equity characteristics except with $IVOL_E$ and MAX. In addition, it is important to note that the correlation between $\Delta COMOVE$ and contemporaneous bond and equity returns is negative, supporting the intuition that heightened comovement is mainly associated with declines in the prices of both assets.

3. Comovement and Asset Prices

In this section, we study the pricing implications of $\Delta COMOVE$. Our main hypothesis is that $\Delta COMOVE$, computed as the innovation in covariance between equities and bonds issued by the same firm, can explain subsequent security returns in the cross-section. Intuitively, when a firm is perceived to be in trouble, both equity and bond investors will reduce (or withdraw) their investments in (from) the company, resulting in increased comovement between stock and bond returns at the firm level. Conversely, when firm prospects are less uncertain, investors might act differently towards equities and bonds given their different payoff features, leading to a lower comovement. Therefore, we expect that ex-post returns will be significantly lower for firms with high $\Delta COMOVE$ in the cross-sections of both equities and bonds. [3]

[3] We also examine the pricing implications of $\Delta COMOVE$ for the difference between equity and bond returns of the same firm, defined as the firm-specific equity risk premium (ERP_f), and report the results in Appendix B.

3.1 Univariate portfolio analysis

To study whether firm-specific *ΔCOMOVE* is priced in the cross-section of security returns, we form five quintile portfolios each month by sorting equities and bonds based on the firm-specific *ΔCOMOVE* over the past month.[4] The results of this analysis for equities and bonds are reported in Tables 4 and 5, respectively. The average *ΔCOMOVE* of each quintile portfolio is summarized in the second column of each table, where the quintile 1 (5) portfolio contains securities with the lowest (highest) *ΔCOMOVE*. The remaining columns report average excess returns and time-series alphas (α^i), controlling for established risk factors for both equal-weighted and value-weighted quintile portfolios based on the following regression:

$$R_{t+1}^i = \alpha^i + \sum_{k=1}^{K} \beta_{k,t}^i X_{k,t} + \varepsilon_t^i, \qquad (4)$$

where R_{t+1}^i is the excess return of quintile portfolio i sorted on *ΔCOMOVE*. $X_{\mathrm{k},t}$ is a collection of risk factors observed at time *t* that have been documented to display significant explanatory power for the cross-section of security returns in different markets. For portfolio sorting on equity returns, we control for different combinations of equity risk factors, including the excess market return (MKT_E), size factor (SMB_E), book-to-market factor (HML_E), momentum factor (MOM_E), liquidity factor (LIQ), investment (I/A), and profitability (ROE) factors proposed by Fama and French (1993), Carhart (1997), Pástor and Stambaugh (2003), and Hou et al. (2015). For corporate bond portfolios, in addition to the aforementioned stock factors, we control for known bond factors including excess bond market returns (MKT_B), downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF) (Bai et al., 2019). We adopt the up-to-date version of BBW factors (MKT_B, DRF, CRF, LRF) from Dickerson et al. (2023). Additionally, we also show the alpha ($\alpha^{B}{}_{1}$) relative to MKT_B only given its outperformance among other return-based bond anomalies recently reported by Dickerson et al. (2023). The last row of each table reports the differences in average returns and alphas between the quintiles 1 and 5 portfolios in the unit of monthly percentages. In other words, they are the returns (alphas) on a "high-minus-low (HML)" zero investment portfolio that longs the securities in the highest *ΔCOMOVE* quintile and shorts those in the lowest *ΔCOMOVE* quintile. Newey and West (1987) adjusted t-statistics are reported in parentheses.

[Table 4]

Table 4 shows that the explanatory power of *ΔCOMOVE* holds for both equal- and value-weighted HML portfolios in the equity cross-section. For equal-weighted portfolios in column (1), the average excess return decreases monotonically from 1.41% to 0.54% with increasing *ΔCOMOVE*, resulting in a significant HML return difference of −0.88% per month (*t*-stat = −4.05). *ΔCOMOVE* remains a significant predictor that consistently adds to established equity factor models over the different

[4] Sorting into five portfolios ensures a good sample size for each quintile, with an average of 432 observations available per month. Our results are consistent when both securities returns are sorted into tercile portfolios. Results based on tercile portfolio sorting are reported in the Appendix in Table C4.

combinations considered in columns (2)-(5). Stocks in the highest *ΔCOMOVE* quintile generate an average monthly return of 0.72% higher than those in the lowest quintile when all equity risk factors are controlled for in column (5). This pattern is more pronounced for value-weighted portfolios, where the potential noise from small-cap stocks is not overrepresented or is partly mitigated. The results in columns (7) to (10) confirm a consistently higher alpha difference compared to the equal-weighted HML returns. More importantly, the significant negative alpha spread between extreme quintiles can be attributed to both the outperformance of the low-*ΔCOMOVE* stocks and the underperformance of the high-*ΔCOMOVE* stocks. This implies that equity investors are sensitive to changes exhibited in the recent trading history of stock–bond comovement in both directions.

[Table 5]

We turn to examine whether *ΔCOMOVE* can predict returns beyond the stock market. The results in Table 5 confirm that the negative association also holds between *ΔCOMOVE* and future bond excess returns. Consistent with our equities-based findings, the alphas on the five quintile bond portfolios decline monotonically from the lowest to the highest *ΔCOMOVE* portfolios, resulting in an HML return of −0.25% (*t*-stat = −3.41) per month. From columns (2)–(5), *ΔCOMOVE* continues to offer incremental information beyond the common risk factors of both the equity and bond markets. Dickerson et al. (2023) argue that the factors proposed in prior work rarely outperform MKT_B from an investment perspective. The results from column (3) highlight an interesting new finding. Using similar methods to Dickerson et al. (2023) for cleaning and filtering bond data, *ΔCOMOVE* avoids one of the construction issues aforementioned in their paper and yields a significantly negative return for the HML portfolio at −0.28% per month (*t*-stat = −2.76) when MKT_B is accounted for.[5] In addition, we find that the value-weighted results in column (6) are of a similar magnitude as that of an equal-weighted portfolio (column (1)) with sizable statistical significance. We also find that the significant explanatory power of *ΔCOMOVE* on bond returns is driven mainly by the outperformance of low-*ΔCOMOVE* bonds when known factors are controlled for.

In summary, we confirm that the explanatory power of *ΔCOMOVE* in the cross-section of stocks and bonds works in the same direction. We show that the consistent predictive power of *ΔCOMOVE* likely validates the idea that investors monitor and adjust their investments in both markets, resulting in a strong interconnection between markets at the firm level. This is also consistent with our hypothesis that *ΔCOMOVE* captures changes in firm quality as perceived by cross-asset investors. In addition, we notice the distinct patterns of characteristics across bond quintile portfolios. The extreme quintile portfolios have relatively higher average ratings and illiquidity, whereas their average sizes exhibit an opposite convex pattern. This mitigates the concerns that our results are driven by certain bond characteristics. Nonetheless, we further verify this later in various robustness checks.

[5] The bond factors employed in this study are obtained from the Open Source Bond Asset Pricing webpage (https://openbondassetpricing.com) by Alex Dickerson, Philippe Mueller, Cesare Robotti and Christian Julliard.

3.2 *Bivariate portfolio analysis*

To study the predictive power of *ΔCOMOVE* when established and known pricing factors in the equity and bond markets are controlled for, we perform a double-sort analysis over both asset classes following Ang et al. (2006). Specifically, for each month from September 2007 to December 2020, we form five quintile portfolios by sorting equities and bonds based on the market-specific characteristics described in Panel A of Table 1. Within each quintile, we further sort securities into five sub-quintile portfolios based on *ΔCOMOVE*. The five sub-quintile portfolios are then averaged across quintiles of the control variable. We report the risk-adjusted alphas of the five *ΔCOMOVE*-quintile portfolios on a value-weighted basis, along with the alpha difference between high- and low-*ΔCOMOVE* quintile portfolios reported in the last column. Table 6 reports the bivariate equity portfolio analysis results with seven-factor equity alphas (α^{E}_{7}) controlled for: MKT_E, SMB_E, HML_E, MOM_E, LIQ, I/A, and ROE, following Fama and French (1993), Carhart (1997), Pástor and Stambaugh (2003), and Hou et al. (2015).

[Table 6]

The explanatory power of *ΔCOMOVE* remains robust in Table 6 after accounting for various equity anomalies.[6] Unsurprisingly, the economic and statistical significance of *ΔCOMOVE* varies across different specifications. The HML alpha that accounts for $SIZE_E$ remains significant at −0.59% per month in row (1). We also find significant alpha differences of the HML portfolio at −0.65% and −0.64% when controlling for B/M and ROE respectively. This indicates that the lowest quintile may be overrepresented by firms with low earning or low profitability prospects. This hypothesis is further validated when controlling for DEFAULT as a direct proxy for firm-level credit risk, which is constructed from accounting information and bond market prices. Row (7) shows that the HML alpha reduces slightly to −0.56% (*t*-stat = −2.43). Such information overlap is consistent with the positive association documented by Dickerson et al. (2022) between their firm-level stock–bond covariance (σ_{DFJM}) and DEFAULT.[7] Nevertheless, other perceived distresses related to firm profitability and worthiness are also captured by *ΔCOMOVE*. Herein, we focus on the improved information quality of *ΔCOMOVE* through real-time market pricing dynamics that are available more promptly compared to accounting-based information characterizing DEFAULT and ROE. The HML alpha controlling for $ILLIQ_E$, while remaining highly significant, exhibits a reduction in economic significance in row (8), validating our conjecture that investors perceive changes in the firm risk level and adjust exposures in their portfolios accordingly. Result in row (9) with DISPER that captures differences in opinion among investors (Diether et al., 2002) also suggests that the HML alpha remains sizable and significant. The significance of *ΔCOMOVE* alpha confirms that estimating from historical trading data offers

[6] We also control for information asymmetry proxies including analysts' forecast error, forecast dispersion, accruals, analyst coverage, and the variance risk premium. Results of bivariate sorting with those controls are consistent and significant. We also look at the explanatory power of *ΔCOMOVE* only for firms that issue options and for firms with CDSs available. In both samples, results remain consistent.

[7] We will examine such association in more detail in Section 3.5.

incremental information toward market dynamics compared to analysts' forecast data. Similarly, the return spread of the HML portfolio decreases slightly to -0.61% and −0.63% per month (*t*-stat = -2.97 and −2.48) when controlling for MKT_E and VIX_E respectively, while the inclusion of other volatility-related controls improves its economic significance.[8] Such information overlap could be attributed to the fact that risk-averse investors may attempt to halt investment in companies with higher exposure to market-level uncertainty. However, the inflated risk level also unlocks equity investors' access to upside potential. *ΔCOMOVE*, therefore, provides additional insights beyond MKT_E and VIX_E that help identify firms with true financial problems flagged across both markets. In summary, despite the mild information overlaps with certain variables, *ΔCOMOVE* contains incremental information that goes beyond major known predictors of equity returns and remains significant in all cases. The incremental information content comes from investors' evaluations of changes in firm risk that have been incorporated in the joint dynamics between stocks and bonds and captured by changes in the comovement characteristic.

[Table 7]

Table 7 presents bivariate sorting analysis results of bond portfolios with nine-factor bond alphas (α^B_9), controlling for both equity factors and bond factors including MKT_B, LRF, CRF, and DRF, as proposed by Bai et al. (2019). We also consider the data construction issue documented in Dickerson et al. (2023) about these factors and repeat the analysis adjusted for the bond market factor only as a robustness check. The main findings remain consistent. The results in Table 7 confirm that *ΔCOMOVE* continues to predict future bond returns in the same direction after controlling for traded and non-traded factors documented in the bond pricing literature. Of all the characteristics examined in rows (1)– (8), none can explain the cross-sectional variation induced by *ΔCOMOVE*. We observe little impact of $ILLIQ_B$ on the predictive power of *ΔCOMOVE*. This provides additional evidence in favor of the findings of Goldberg and Nozawa (2021) that illiquidity is primarily a prevalent characteristic of corporate bonds rather than a factor that holds substantial pricing influence in the cross-section. Similarly, the results in rows (9) and (10) show that the long–short alpha remains significant at −0.27% and −0.31%, respectively, when we control for $IVOL_B$ and IMPVOL. This again validates the poorly diversified feature of the corporate bond market, where institutional investors dominate most transactions, resulting in a significant and consistently strong impact of *ΔCOMOVE* beyond idiosyncratic risk at the firm level (Chung et al., 2019). This feature also presents an important source of limits to arbitrage, which makes the bond market potentially slower in incorporating information from the options market. Our IMPVOL results suggest that the information transmission channel between equity and bond markets is nontrivial and contains incremental information beyond the

[8] For further robustness, we use idiosyncratic measures of *ΔCOMOVE* based on residuals obtained from regressions on MKT_E and MKT_B. Portfolio sorting results based on these idiosyncratic measures (i.e., "cleaned" from market risk factor information), confirm that the explanatory power of *ΔCOMOVE* is not affected by systematic information overlaps (see Appendix Table C5).

forward-looking information implied by the option market. The long-short alphas marginally decline in rows (11) to (13) controlling for exposures to market-level risk changes. These outcomes are in line with previous findings from the equity market and indicate that heightened risk levels stemming from macroeconomic shifts cannot sufficiently account for the firm-specific risk recognized by cross-asset investors. In particular, despite the dominant role of MKT_B in corporate bond pricing documented by Dickerson et al. (2023), our *ΔCOMOVE* factor shows consistent economic and statistical significance. Our findings provide valuable insights into understanding the dynamics of corporate bond returns through firm-level characteristics. Overall, the monotonically decreasing pattern is generally preserved for bond return results when moving from the lowest to the highest quintile. This suggests that *ΔCOMOVE* is a widespread effect priced in bond returns across different categories of characteristics. The above findings provide further support for our hypothesis that investors actively adjust their investments in both equity and bond markets. Such dynamic responses contribute to the convergence of information across markets, thereby offering additional insights that cannot be adequately captured by established bond factors, or even by factors implied from the options market.

3.3 Fama and MacBeth (1973) cross-sectional regressions

The results from the previous subsections suggest a consistent and significant negative effect of *ΔCOMOVE* on cross-sectional equity and bond returns at the portfolio level. We now test our main hypothesis using the Fama and MacBeth (1973) methodology, which allows us to understand linear interactions between *ΔCOMOVE* and other known risk factors at the firm level. Specifically, monthly cross-sectional regressions are run from September 2007 to December 2020 based on equity and bond returns for the following econometric specification:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \Delta COMOVE_{i,t} + \lambda_{2,t} \cdot X_{i,t} + \epsilon_{i,t+1}, \tag{5}$$

where $R_{i,t+1}$ is the excess security return of firm i in month t+1, and $\Delta COMOVE_{i,t}$ is the innovation of the covariance between stocks and bonds issued by firm i in month t as defined in Eq. (3). $X_{i,t}$ is the same collection of market-specific control variables adopted in Section 3.2, observed at time t for securities issued by firm i. Tables 8 and 9 report the time-series average of the coefficients on the independent variables based on equity and bond returns, respectively.

[Table 8]

The results in Table 8 lend further support for our hypothesis on the negative relations between *ΔCOMOVE* and future equity returns. The average slope coefficient on *ΔCOMOVE* is economically and statistically significant at −0.464 (t-stat = −2.86) without controls. This implies that a value-weighted portfolio of selling high-*ΔCOMOVE* stocks and buying low-*ΔCOMOVE* stocks could generate a return of 0.4% in the following month. The *ΔCOMOVE* variable retains significant predictive power, even after we include established predictors of equity returns. Column (2) documents the results with controls from the four-factor model of Fama and French (1993) and Carhart (1997), where the economic magnitude of the *ΔCOMOVE* coefficient remains significant at −0.296 (*t*-stat = −2.31). Consistent with the findings of Fama and French (1993) and Carhart (1997), the average slope on BM is negative and statistically significant, also indicating that growth firms are more sensitive to the adverse impact of higher comovement between equities and bonds. The value-versus-growth effect is no longer significant after the inclusion of IA and ROE in column (3), whereas the predictive power of *ΔCOMOVE* remains significant. In line with the portfolio-level findings from Table 6, this evidence rules out the issue raised by Hou et al. (2015) that the significant comovement risk premia may be a manifestation of investment and profitability effects. The results in column (4) further validate our hypothesis that the uncertainty captured by higher *ΔCOMOVE* is significantly associated with decreased participation in trading activity in the equity market, proxied by the illiquidity measure of Amihud (2002). However, *ΔCOMOVE* still dominates, with a significant average coefficient estimate of −0.296 (*t*-stat = −2.3). Column (5) additionally controls for DISPER, where *ΔCOMOVE* remains economically and statistically significant. The fact that DISPER changes in the same direction as *ΔCOMOVE* corroborates our hypothesis that stocks and bonds indeed comove more as the firm's uncertainty level goes up (i.e., situations when earnings are more difficult to forecast). We examine this hypothesis in detail on several proxies for firm-level information asymmetry in Section 3.4. Consistent with Table 6, Column (6) shows that *ΔCOMOVE* provides incremental information beyond volatility-based strategies when its coefficient increases to −0.306. We find that only the average coefficient on VIX_E remains consistently negative and significant in predicting future equity returns. This evidence further validates the findings of Baele et al. (2010) at the firm level, where investors who evaluate and adjust their investments in both markets are highly sensitive to market-level volatility changes. The insignificant $IVOL_E$ effect lends further support to Bali et al. (2017) on the absence of the idiosyncratic volatility puzzle unveiled by Ang et al. (2006). Consistent with Bali et al. (2017), we observe a reverse relationship between expected equity returns and $IVOL_E$ when MAX is accounted for in column (7). This evidence further complements our results, since high-*ΔCOMOVE* stocks are likely to attract investors who are more likely to suffer from under-diversification and exhibit a preference for lottery-like assets within one market. We observe an improved explanatory power of *ΔCOMOVE* at −0.373 (*t*-stat = −3.28) when additionally controlling for DEFAULT, COSKEW, and UNC_E in column (9). While Dickerson et al. (2022) document that these measures constitute the central economic force driving stock–bond covariance, only COSKEW remains positive and statistically significant at 0.437 (*t*-stat = 2.48). Different from the relation found in Harvey and Siddique (2000), this result indicates that systematic skewness affects firms that are closer to their default boundary, which are also the ones that are most affected by the negative price impact of *ΔCOMOVE*. The outperformance of *ΔCOMOVE* among these distress-related anomalies suggests that it captures information about firm quality during periods of financial turbulence, as investors may not necessarily be alarmed by having greater exposure to either market-level or firm-level risk. Moreover, the significance of ROE becomes apparent when distress effects are controlled for, indicating that the combination of $\Delta COMOVE$ and ROE captures the company's overall risk profile, yielding significant explanatory power.

[Table 9]

To substantiate this hypothesis in the corporate bond market, we run Fama and MacBeth (1973) cross-sectional regressions of bond returns on the previously described bond factors at the firm level. The results from Table 9 show that $\Delta COMOVE$ unequivocally dominates across all regressions. In the univariate setup, it generates an average coefficient of −0.1489 with a *t*-statistic of −3.468. When controlling for bond characteristics, column (2) shows that only bond maturity relates to the profitability of our strategy. While remaining significant, the predictability of $\Delta COMOVE$ goes down slightly to −0.077 and −0.066 (*t*-stat = −2.43 and −2.05), respectively, when controlling for MKT_B and $ILLIQ_B$ in columns (3) and (4). In line with the portfolio-level findings, the coefficient on $ILLIQ_B$ is not statistically significant. More importantly, the nontrivial pricing power of MKT_B in this case is consistent with that documented by Dickerson et al. (2023) who suggest that the market beta seems to be the only priced factor in the cross-section of corporate bond returns. Combined with the insignificant coefficient on MATURITY in column (4), we again confirm that bond prices are largely affected by firm-level exposure to changes in market conditions rather than their own pricing structure. $\Delta COMOVE$, however, exhibits incremental information in predicting the cross-section of future bond returns beyond MKT_B, as it summarizes investors' reactions toward intrinsic firm quality in a manner that differs from individual exposure toward the general market sentiment. In column (5), we document a significantly positive relation between $IVOL_B$ and future bond returns at the firm level, which contrasts with the negative pattern documented in the equity literature. However, this is in line with the findings of Bai et al. (2021) that bond investors demand higher compensation for holding securities with more volatile asset values, consequently elevating the possibility of hitting the default boundary. Nevertheless, we do not find evidence for the significant DEFAULT effect documented by Dickerson et al. (2022) in the cross-section of bonds. This is not surprising because investors may become aware of a firm-level crisis in advance and respond by selling both assets simultaneously during the estimation period. The increased level of $\Delta COMOVE$ therefore serves as a reliable indicator of impending default, manifesting well before it is reflected in balance sheet information or market bond prices. More importantly, consistent with the equity-level findings, we document a consistently strong predictive power of $\Delta COMOVE$ when DEFAULT is controlled for, suggesting that investors' default risk expectations are not only based on information from the bond market. A firm with higher $\Delta COMOVE$ is more likely to hit the default boundary, thus yielding lower subsequent bond returns. Similarly, the results in column (7) do not provide evidence supporting the statistically significant UNC_B effect documented in Bali et al. (2021b), which further corroborates the argument of Dickerson et al. (2023) that the uncertainty beta may be inadequate in explaining the cross-sectional variation in bond returns. Despite this, we report robust evidence of $\Delta COMOVE$ commanding statistically significant risk premia over and beyond the effects of conventional or known bond risk factors. In addition, consistent findings across the two asset classes support *ΔCOMOVE* as a pricing factor in the joint cross-sections of stocks and bonds. Nevertheless, the above findings also raise the question of whether *ΔCOMOVE* improves the risk–return trade-off for corporate bonds through the channel of financial risk and information asymmetry, which we further discuss in the next section.

3.4 Source of the ΔCOMOVE premium in equities and bonds

In the previous sections, we uncovered a significant relation between firm-level *ΔCOMOVE* and subsequent returns both in the equity and bond cross-sections. The findings suggest financial risk and information asymmetry should play a key role in explaining the predictability of the effect of *ΔCOMOVE* on future equity returns. We test this explanation using subsample analysis in this section.

Prior studies suggest that returns for firms with higher financial risk should be more sensitive to changes in *ΔCOMOVE*. For example, from the perspective of risk-shifting, Jensen and Meckling (2019) suggest that managers have incentives to increase equity value by investing in high-risk but negative NPV projects when there is a significant probability of default. Shareholders will harvest the benefits if projects perform well, whereas bondholders will bear the costs if the opposite occurs. However, the incentive to extract such benefits diminishes when the company is unlikely to survive and generate future profits for its shareholders. Both equity and bond holders tend to sell securities issued by a firm that is about to face financial distress, resulting in higher *ΔCOMOVE* and decreased future returns. Based on the above, we expect that *ΔCOMOVE* to induce larger reductions in future returns of firms with higher financial risk due to their higher probability of and the greater costs associated with financial distress. To measure and account for the severity of financial risk, we adopt an array of appropriate proxies following Chen and King (2014), including financial leverage, earning volatility, credit rating, and Altman Z-score.

Having found evidence that both equity and bond prices at the time of portfolio formation do not fully incorporate the information contained in *ΔCOMOVE*, we verify that information asymmetry may be an additional source of the *ΔCOMOVE* premium. Duffie and Lando (2001) find that the release of information is costly, and managers may have the incentive to not fully disclose information for private benefits. Outside investors do not have full information about the distribution of future cash flows, thus affecting future returns. Building on the work of DaDalt et al. (2002), our findings lend further support to the notion that *ΔCOMOVE* reflects how much both asset markets are integrated at the firm level, capturing the level of information asymmetry. This may lead to enhanced predictability of future cash flows, even before accounting disclosures are made. We, therefore, propose that a higher *ΔCOMOVE* is associated with a larger drop in future returns for firms with higher levels of information asymmetry. This conjecture is consistent with the hypothesis of DeMarzo and Duffie (1991) that opaque firms enjoy greater hedging benefits on future returns. To measure the extent of information asymmetry, we follow

DaDalt et al. (2002) and employ commonly used proxies, including forecast dispersion, accounting accruals, idiosyncratic volatility, illiquidity, and interest coverage.

[Table 10]

[Table 11]

Following Cosemans and Frehen (2021), Tables 10 and 11 report subgroup analysis results based on equity and bond returns, respectively. Panel A (B) performs univariate portfolio analysis on subgroups of firms with high and low financial risk (information asymmetry). As expected, Panel A in both tables shows that across all proxies for financial risk, firms with high financial risk generate a significantly higher long–short portfolio return over the next month. Even after controlling for the market-specific factor models, risk-adjusted alphas remain statistically significant and higher for long–short portfolios among firms with higher leverage, higher earnings volatility, lower credit rating, and lower Z-scores. While Panel B across Tables 10 and 11 demonstrates that the effect of information asymmetry is evident in both subgroups, we find a wider spread between extreme quintile portfolios among firms with higher information asymmetry. The consistent pattern indicates that investors who possess information advantages from both equity and bond markets are more likely to achieve higher returns trading on information asymmetry. In line with results based on the whole sample, the above findings further confirm that *ΔCOMOVE* affects bonds in the same direction as in equities. More importantly, it provides a stylized fact that *ΔCOMOVE* is unlikely to merely reflect model misspecification, but rather contains important pricing information through the channel of financial risk and information asymmetry.

3.5 Robustness checks

Herein, we examine the robustness of our main findings. First, we investigate whether our results are driven by small, illiquid, and low-priced stocks. Fama and French (2008) highlight the potential pitfalls of analyzing quintile-sort results with microcap stocks. They define stocks with a market capitalization below the 20^{th} NYSE percentile as microcap stocks, which yield a high cross-sectional dispersion of stock return distribution. Therefore, to ensure that the predictive power of *ΔCOMOVE* is not driven by the microstructure effects associated with microcap stocks, we rerun the univariate portfolio sorts across equity and bond returns of firms with a market capitalization above the 50^{th} (Panel A) and 20^{th} percentiles (Panel B) in Table 12. The results show that the value-weighted risk-adjusted alphas retain their negative predictive power after excluding microcap stocks. Even if we only include stocks larger than the 50^{th} percentile of NYSE market capitalization, *ΔCOMOVE* remains significant with a reduced magnitude after controlling for established and known factor models across different asset classes. This confirms that the predictive power of *ΔCOMOVE* is not exaggerated by excessive weighting on microcaps.

[Table 12]

[Table 13]

Second, we run a bivariate sorting analysis to examine whether our findings are driven by any of the default risk measures proposed by Dickerson et al. (2022) and summarize the results in Table 13. Panel A reports the results of *ΔCOMOVE*-sorted portfolios controlling for default risk measures, including market leverage, credit spread, and distance-to-default. The findings show that the predictive power of *ΔCOMOVE* remains intact when different default risk effects are controlled for. Panel B performs a reversed bivariate sorting analysis following Bali et al. (2011), and shows that the relation between default risk and future bond returns is no longer significant due to the moderating effect of *ΔCOMOVE*. This confirms that our measure offers incremental information to future bond returns relative to other default risk measures.

[Table 14]

For additional robustness, we further examine the extent to which these default risk measures explain *ΔCOMOVE* using Fama and MacBeth (1973) regressions in Table 14. We re-estimate the one-year-ahead stock-bond covariance (σ_{DFJM}) proposed by Dickerson et al. (2022) and test their hypothesis in columns (1) to (4). In line with their findings, our results confirm the positive association between σ_{DFJM} and default risk measures with significantly lower magnitude. We also find a negative relation between default risk measures and *ΔCOMOVE* constructed from the previous 60 months' observations in columns (5)– (8). The intuition behind this is that investors already responded to the elevated default risk levels by reducing their investments in either security during the estimation period, as proxied by a lower *ΔCOMOVE*. This again confirms that *ΔCOMOVE* summarizes incremental information that has distinct pricing power beyond, and well ahead of the default risk measures.

Third, we compare the predictive power of *ΔCOMOVE* estimated with a different window specification, following Bali et al. (2021b), and report the results in Appendix Table C1. Table C1 shows that if we instead use $\Delta COMOVE_{24}$ constructed over the past two years, similar results are obtained.

Fourth, we further validate our results over an expanded sample of all available bonds with fixed coupon payments, following the construction criteria adopted by Bai et al. (2019). We conduct univariate portfolio analysis based on the re-estimated $\Delta COMOVE_{new}$. The results reported in Appendix Table C2 show that the relation, associated significance, and related signs (all documented in Table 5) are maintained despite the lower explanatory power, which is primarily due to the relatively less balanced sample. We can, therefore, confirm that the explanatory power of stock–bond comovement characteristic identified in our paper is not limited to corporate bonds alone.

Finally, we check whether our results hold not only in the full sample but also across high versus low uncertainty (systemic risk) subperiods. Appendix Table C3 contrasts the performance of *ΔCOMOVE* in stable periods versus turbulent periods sorted using different criteria on equities and bonds, respectively, with results reported in Panel A(B). The findings confirm our main prediction that the long–short portfolio continues to generate a significantly negative alpha in turbulent times. Although the pricing impact of *ΔCOMOVE* is relatively weaker during stable periods, one must note that the benefit of being able to time it cannot be practically realized as we do not know whether we are in a high or low period ex-ante. More importantly, we show that the *ΔCOMOVE* premia are higher in both markets during periods of high market volatility, high systematic risk, and high uncertainty. This can be also attributed to higher volatility and the impaired balance sheets of firms during economic downturns, leading to a higher possibility of deterioration of firm quality. Our results are also robust when uncertainty years are excluded.

4. Conclusion

In this paper, we investigate the pricing implications of firm-level comovement between bonds and equities issued by the same company over the period 2007–2020. We show that *ΔCOMOVE* can negatively predict the future returns of equities and corporate bonds at both the portfolio and individual levels. The explanatory power of *ΔCOMOVE* remains consistent when a wide range of established risk factors are controlled for. Further analyses suggest that the significant explanatory power comes from investors' common views about firm quality exhibited in their recent trading history, which are evident well before they become apparent on firms' balance sheets. Such information is priced more strongly among firms with higher financial risk levels and higher information asymmetry. Our results are robust to alternative estimation methods and construction samples as well as subperiods with different systematic risk levels. When compared to previous asset pricing studies that examine the equity and bond markets separately, our study shows that by considering the joint cross-section of the two asset classes, one can capture important pricing information in and across both markets.

Besides validating this factor over longer timeframes, there is a need for further theoretical investigations to uncover the primary drivers behind *ΔCOMOVE* and our empirical findings. Given the robust pricing power of *ΔCOMOVE*, investors and fund managers can delve deeper into exploiting the diversification benefits that emanate from time-varying *ΔCOMOVE* in a multi-asset investment setting. Subsequent research should also consider the influence of *ΔCOMOVE* on the pricing of other risk-sensitive securities issued by the same firm. Furthermore, a promising avenue for future research lies in examining the pricing dynamics inherent in these interconnected relationships spanning different markets. The bias toward large companies, however, due to the limited sample size may be an issue in attempting to generalize findings to several other asset classes.

Table 1: Variable Definitions

This table contains the definitions and descriptions of the variables used in the paper.

Applied literature	Variable	Definition	Source
A. Equity and bond risk characteristics			
Bond	Credit spread (CS)	Difference between the yield of a corporate bond and the associated yield of the Treasury curve at the same maturity.	Collin-Dufresn et al. (2001)
Bond	Changes in implied volatility (IMPVOL)	Changes in the average of the call and put at-the-money implied volatility with 365 days of expiration.	Cao et al. (2023)
Bond	Distance-to-Default (DD)	The log of the distance between firm assets (item AT) and one-half of long-term debt value plus short-term debt divided by asset volatility.	Campbell and Thompson (2008)
Bond	Duration (DURATION)	Corporate bond duration in years.	TRACE
Bond	Market leverage (MLEV)	The ratio between total book debt (item LT) and the market value of equity plus total book debt.	Dickerson et al. (2022)
Bond	Maturity (MATURITY)	Corporate bond time-to-maturity in years.	TRACE
Bond	Rating (RATING)	Historical ratings provided by both Standard & Poor and Moody's rating agencies are assigned numbers, where 1 refers to a AAA rating, 2 refers to AA+, …, and 21 refers to CCC. The bond's final rating is determined as the average of ratings when both are available or as the rating provided by one of the two rating agencies when only one rating is available.	Bai et al. (2019)
Equity	Analysts' forecast dispersion (DISP)	The standard deviation of annual earnings-per-share forecasts is scaled by the absolute value of the average outstanding forecast.	Diether et al. (2002)
Equity	Asset growth (I/A)	Book assets (Compustat item AT) divided by lagged AT.	Hou et al. (2015)
Equity	Book-to-Market ratio (B/M)	Book value of stockholder equity plus deferred taxes and investment tax credit minus the book value of preferred stock at the end of the last fiscal year $t-1$, scaled by the market value of equity at the end of December of year $t-1$.	Davis et al. (2000)
Equity	Co-skewness (COSKEW)	Residual from the regression of excess stock returns against the contemporaneous excess return on the CRSP value-weighted index over 1-month Treasury bills based on the past 60 months of observations.	Harvey and Siddique (2000)
Equity	Lottery demand (MAX)	The average of the five highest daily returns of the stock during the previous month.	Bali et al. (2017)
Equity	Profitability (ROE)	Income before extraordinary items (item IBQ) divided by one-quarter-lagged book equity.	Hou et al. (2015)
Equity and bond	Default risk (DEFAULT)	The average of market leverage, distance-to-default (sign-corrected), and credit spread.	Dickerson et al. (2022)
Equity and bond	Idiosyncratic volatility ($IVOL_E$/$IVOL_B$)	The standard deviation of residuals from the regression of excess daily returns on the Fama and French three-factor model over the past month for stocks, and excess monthly returns on the Fama and French five-factor model over the past six months for bonds.	Ang et al. (2006), Chung et al. (2019)
Equity and bond	Illiquidity ($ILLIQ_E$/$ILLIQ_B$)	Stock illiquidity is defined as the ratio of the daily absolute stock return to the daily dollar trading volume averaged within the previous month. Bond illiquidity is measured as the autocovariance of the daily bond price changes within the previous month, multiplied by –1.	Amihud (2002), Bao et al. (2011)
Equity and bond	Market Beta (MKT_E/MKT_B)	Time-series regressions of stock (bond) excess returns on the excess stock (bond) market return over the prior 60 months.	Fama and French (1992), Dickerson et al. (2023)

Equity and bond	Momentum (MOM_E/MOM_B)	The cumulative return of the stock over 11 months (6 months) ending one month prior to the portfolio formation month.	Jegadeesh and Titman (1993), Jostova et al. (2013)
Equity and bond	Reversal (REV_E/REV_B)	The stock (bond) returns of the prior month.	Jegadeesh (1990), Bai et al. (2019)
Equity and bond	Size ($SIZE_E$/$SIZE_B$)	The natural logarithm of the product of the price per share (bond) and the number of shares outstanding (bond amount outstanding).	CRSP and Mergent FISD
Equity and bond	Uncertainty Beta (UNC_E/UNC_B)	Exposure of individual stocks (bonds) to the economic uncertainty index proposed by Jurado, Ludvigson and Ng (2015).	
Equity and bond	VIX Beta (VIX_E/VIX_B)	Beta from time-series regressions on daily (monthly) observations of excess stock (bond) returns on corresponding excess market portfolio returns and changes in the S&P 500 index option-implied variance.	Ang et al. (2006), Chung et al. (2019)

B. Proxies for financial risk and information asymmetry

Financial risk	Altman's Z-score (Z)	Z = 1.2 × (Working Capital/Total Assets) + 1.4 × (Retained Earnings/Total Assets) + 3.3 × (EBIT/Total Assets) + 0.6 × (Market Value of Equity/Total Liabilities) + 0.999 × (Sales/Total Assets).	Altman (1968)
	Leverage (LEV)	Total debt divided by the total market value of assets, where the market value of assets is the sum of total debt and market value of equity.	
	Earning volatility (EVOL)	The standard deviation of the first difference in EBITDA scaled by the book value of assets over the 3 years preceding and including the year investigated.	Smith and Stulz (1985)
Information asymmetry	Forecasts dispersion (STD)	The standard deviation of all earnings forecasts made by analysts in the 3 months before fiscal year-end.	DaDalt et al. (2002)
	Analyst coverage (NOA)	The log of one plus the number of analysts covering a firm.	
	Idiosyncratic volatility ($IVOL_E$/$IVOL_B$)	The standard deviation of residuals from the regression of excess daily returns on the Fama and French three-factor model over the past month for stocks.	Ang et al. (2006), Chung et al. (2019)
	Illiquidity ($ILLIQ_E$/$ILLIQ_B$)	Stock illiquidity is defined as the ratio of the daily absolute stock return to the daily dollar trading volume averaged within the previous month. The bond illiquidity is measured as the autocovariance of the daily bond price changes within the previous month, multiplied by –1.	Amihud (2002), Bao, Pan and Wang (2011)
	Interest coverage	The ratio of EBITDA (earnings before interest, taxes, depreciation, and amortization) to interest charges	-

Table 2: Summary Statistics for Equities

This table reports the summary statistics for the variables used in our equity analysis in Panel A and the correlation matrix in Panel B. *ΔCOMOVE* is the innovation of the exponentially weighted moving average (EWMA) covariance calculated using a minimum of 48 available observations over the past 60 months. R_E is the monthly equity returns reported in percentages. $SIZE_E$ is the dollar amount of outstanding equities reported in billions. B/M is the book-to-market ratio. MOM_E is the cumulative return from the start of month t-12 to the end of month t-2. REV_E is the equity return over the prior month. I/A and ROE are the asset growth ratio and returns on equity ratio as in Hou et al. (2015). DEFAULT is the average of leverage, distance-to-default, and credit spread measures proposed by Dickerson et al. (2022). $ILLIQ_E$ is the Amihud (2002) illiquidity measure estimated using one month of daily data. COSKEW is the coskewness measure in Harvey and Siddique (2000) estimated using the past 60 months' observations. $IVOL_E$ is the equity idiosyncratic volatility as in Ang et al. (2006) estimated using daily data of the previous month. DISPER is the standard deviation of annual earnings-per-share forecasts. MAX is the maximum return within the previous month as in Bali et al. (2011). MKT_E is the equity market beta estimated using the past 60 months' observations. VIX_E is the exposure of equity to the S&P 500 option implied volatility index. UNC_E is the exposure of equity to the economic uncertainty index proposed by Jurado et al. (2015). This sample period covers August 2007–December 2020.

Panel A: Summary Statistics

	ΔCOMOVE	R_E	$SIZE_E$	B/M	MOM_E	REV_E	I/A	ROE	DEFAULT	$ILLIQ_E$	DISPER	$IVOL_E$	COSKEW	MAX	MKT_E	VIX_E	UNC_E
Obs.	69540	69540	69540	65238	69228	68634	67612	65552	67047	69238	66605	69539	69456	69540	69532	68959	69343
Mean	0.00	1.08	27.19	-0.78	0.10	1.05	0.07	0.05	-0.13	-0.004	0.14	0.01	0.01	0.03	1.16	0.04	0.01
1%	-0.25	-24.90	0.21	-3.56	-0.59	-24.90	-0.33	-0.22	-2.32	0.000	0.00	0.00	-0.60	0.01	0.10	-1.73	-0.49
5%	-0.08	-13.76	0.63	-2.23	-0.39	-13.78	-0.13	-0.03	-1.71	0.000	0.01	0.01	-0.38	0.01	0.29	-0.88	-0.26
25%	-0.02	-3.74	3.10	-1.21	-0.09	-3.77	-0.02	0.01	-0.79	0.000	0.01	0.01	-0.14	0.01	0.72	-0.25	-0.07
50%	0.00	1.18	9.06	-0.67	0.09	1.17	0.04	0.03	-0.10	0.000	0.02	0.01	0.01	0.02	1.10	0.02	0.00
75%	0.01	5.80	24.74	-0.22	0.26	5.79	0.10	0.05	0.56	0.000	0.06	0.02	0.16	0.03	1.49	0.31	0.08
95%	0.06	15.45	118.21	0.32	0.62	15.42	0.33	0.13	1.41	0.005	0.37	0.03	0.39	0.06	2.27	1.04	0.27
99%	0.28	28.17	253.96	0.71	1.12	28.12	1.02	0.52	1.84	0.042	1.71	0.05	0.62	0.10	2.97	2.00	0.50
Std.	0.14	9.68	65.74	0.84	0.33	9.68	0.26	0.59	0.95	0.736	1.13	0.01	0.24	0.02	0.61	0.65	0.17

Panel B: Correlation Matrix

	ΔCOMOVE	R_E	$SIZE_E$	B/M	MOM_E	REV_E	I/A	ROE	DEFAULT	$ILLIQ_E$	DISPER	$IVOL_E$	COSKEW	MAX	MKT_E	VIX_E	UNC_E
ΔCOMOVE	1																
R_E	-0.05	1															
$SIZE_E$	0.00	0.02	1														
B/M	-0.01	0.01	-0.19	1													
MOM_E	-0.05	-0.04	0.06	0.00	1												
REV_E	-0.13	-0.02	0.02	0.01	0.23	1											
I/A	0.01	-0.01	0.03	-0.02	-0.04	-0.01	1										
ROE	0.00	-0.01	0.02	-0.17	0.01	-0.01	0.00	1									
DEFAULT	0.00	-0.06	-0.27	0.50	-0.26	-0.06	-0.01	-0.06	1								
$ILLIQ_E$	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.01	1							
DISPER	0.01	0.00	-0.02	0.06	-0.04	-0.01	-0.01	-0.01	0.09	0.01	1						
$IVOL_E$	0.21	-0.05	-0.16	0.11	-0.22	-0.14	0.02	-0.03	0.37	-0.02	0.10	1					
COSKEW	-0.02	0.07	0.00	-0.02	0.11	0.06	-0.03	-0.01	-0.04	0.00	0.01	0.05	1				
MAX	0.24	0.17	-0.12	0.11	-0.26	-0.20	0.02	-0.03	0.37	-0.01	0.10	0.82	0.04	1			
MKT_E	-0.01	0.03	-0.15	0.11	0.03	0.02	-0.02	-0.02	0.36	-0.01	0.09	0.31	0.27	0.34	1		
VIX_E	0.00	0.00	-0.03	0.05	-0.06	-0.01	0.00	-0.01	0.09	-0.01	0.02	0.08	0.01	0.09	0.08	1	
UNC_E	-0.03	0.09	0.01	-0.03	0.06	0.06	0.01	0.02	-0.06	0.02	-0.03	-0.06	0.15	-0.05	-0.04	-0.01	1

Table 3: Summary Statistics for Corporate Bonds

This table reports the summary statistics for the variables used in our bond analysis in Panel A and the correlation matrix in Panel B. *ΔCOMOVE* is the innovation of the exponentially weighted moving average (EWMA) covariance calculated using a minimum of 48 available observations over the past 60 months. R_B is the monthly bond returns reported as percentages. $SIZE_B$ is the dollar amount of outstanding bonds reported in billions. RATING is in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. MATURITY is the time-to-maturity of the bond in years. DURATION is the weighted average time in years until cash payments of the bond are received. $ILLIQ_B$ is the Bao et al. (2011) illiquidity measure computed as the autocovariance of the daily price changes within the previous month. REV_B is the bond return over the prior month. DEFAULT is the average of leverage, distance-to-default, and credit spread measures proposed by Dickerson et al. (2022). $IVOL_B$ is the bond idiosyncratic volatility estimated using the past six months of monthly data as in Chung et al. (2019). IMPVOL is the changes in the average of the call and put at-the-money implied volatility as in Cao et al. (2023). MKT_B is the bond market beta estimated using the past 60 months' observations. VIX_B is the exposure of bonds to the S&P 500 option implied volatility index. UNC_B is the exposure of bonds to the economic uncertainty index proposed by Jurado et al. (2015). This sample period covers August 2007–December 2020.

Panel A: Summary Statistics

	ΔCOMOVE	R_B	$SIZE_B$	RATING	MATURITY	DURATION	$ILLIQ_B$	REV_B	DEFAULT	$IVOL_B$	IMPVOL	MKT_B	VIX_B	UNC_B
Obs.	69540	69540	69540	69349	69540	69495	56082	68634	67047	67482	67327	68557	68782	68782
Mean	0.00	0.61	0.59	9.59	9.01	6.09	0.003	0.61	-0.13	0.09	0.00	0.83	-0.04	-0.11
1%	-0.25	-6.43	0.01	3.00	1.83	1.56	-0.001	-6.43	-2.32	0.00	-0.10	0.03	-0.48	-1.37
5%	-0.08	-2.25	0.02	5.00	3.17	2.73	0.000	-2.26	-1.71	0.00	-0.05	0.25	-0.29	-0.62
25%	-0.02	-0.24	0.08	7.36	5.33	4.32	0.000	-0.24	-0.79	0.01	-0.02	0.52	-0.11	-0.18
50%	0.00	0.54	0.21	9.00	7.66	5.65	0.001	0.54	-0.10	0.02	0.00	0.75	-0.01	-0.04
75%	0.01	1.45	0.58	12.00	12.23	7.68	0.002	1.45	0.56	0.04	0.01	1.02	0.04	0.05
95%	0.06	3.72	2.30	15.22	17.86	10.54	0.011	3.72	1.41	0.20	0.06	1.58	0.11	0.17
99%	0.28	7.74	6.82	16.63	23.31	12.47	0.038	7.74	1.84	1.34	0.13	2.73	0.18	0.32
Std.	0.14	2.44	1.16	3.17	4.86	2.43	0.019	2.43	0.95	0.59	0.04	0.52	0.14	0.33

Panel B: Correlation Matrix

	ΔCOMOVE	R_B	$SIZE_B$	RATING	MATURITY	DURATION	$ILLIQ_B$	REV_B	DEFAULT	$IVOL_B$	IMPVOL	MKT_B	VIX_B	UNC_B
ΔCOMOVE	1													
R_B	-0.28	1												
$SIZE_B$	0.00	0.00	1											
RATING	-0.01	0.04	-0.31	1										
MATURITY	0.01	0.01	0.24	-0.43	1									
DURATION	0.00	0.02	0.27	-0.48	0.95	1								
$ILLIQ_B$	0.15	-0.05	-0.05	0.06	0.01	-0.03	1							
REV_B	-0.14	0.03	0.00	0.03	0.02	0.02	-0.01	1						
DEFAULT	0.00	0.04	0.00	0.48	-0.16	-0.22	0.09	0.04	1					
$IVOL_B$	0.25	-0.23	-0.03	0.04	0.01	-0.01	0.10	-0.03	0.07	1				
IMPVOL	0.29	-0.39	0.00	-0.01	0.00	0.00	0.06	-0.07	0.02	0.14	1			
MKT_B	-0.01	0.07	0.09	0.18	0.23	0.21	0.06	0.06	0.19	0.05	-0.01	1		
VIX_B	0.01	-0.04	0.16	-0.61	0.30	0.35	-0.10	-0.04	-0.39	-0.08	0.00	-0.30	1	
UNC_B	0.02	-0.04	0.15	-0.37	0.17	0.21	-0.07	-0.04	-0.23	-0.02	0.02	-0.41	0.36	1

Table 4: Equity Quintile Portfolios Sorted on *ΔCOMOVE*

For each month, quintile portfolios are formed by sorting equities based on the *ΔCOMOVE*, where quintile 1(5) portfolio contains equities with the lowest (highest) *ΔCOMOVE* in the previous month. The *ΔCOMOVE* is the innovation of EWMA covariance between stock and bond returns issued by the same firm, which is calculated using a minimum of 48 observations over the past 60 months. The second column reports the average *ΔCOMOVE* for each quintile, and the remaining columns present the average equity excess returns and alphas for the equal-weighted and value-weighted portfolios separately. Following Fama and French (1992), Carhart (1997), and Hou et al. (2015), $\alpha^E_{5,1}$ is the alpha relative to the excess stock market return (MKT_E), size (SMB_E), book-to-market (HML_E), momentum (MOM_E), and liquidity (LIQ) factors; $\alpha^E_{5,2}$ is the alpha relative to MKT_E, SMB_E, HML_E, investment (I/A), and profitability factors (ROE); α^E_4 is the alpha relative to the MKT_E, SMB_E, I/A, and ROE factors; and α^E_7 is the alpha relative to the MKT_E, SMB_E, HML_E, MOM_E, LIQ, I/A, and ROE factors. The last row presents return and alpha differences between quintiles 1 and 5. All returns and alphas are denoted in percent per month. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2007–December 2020.

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	*ΔCOMOVE*	R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7	R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7
1 [Low]	-0.07	1.41	0.42	0.57	0.55	0.43	1.41	0.46	0.56	0.63	0.49
		(2.54)	(2.39)	(3.18)	(3.12)	(2.73)	(2.98)	(2.22)	(2.82)	(3.45)	(2.39)
2	-0.02	1.14	0.37	0.36	0.31	0.37	1.21	0.39	0.43	0.41	0.38
		(2.63)	(3.28)	(3.18)	(2.43)	(3.30)	(3.30)	(3.17)	(3.64)	(3.39)	(3.06)
3	0.00	0.98	0.29	0.22	0.17	0.28	0.95	0.28	0.19	0.15	0.27
		(2.33)	(2.90)	(1.89)	(1.21)	(2.88)	(2.63)	(2.51)	(1.69)	(1.11)	(2.43)
4	0.01	0.79	0.01	-0.02	-0.06	-0.01	0.70	-0.05	-0.09	-0.09	-0.07
		(2.01)	(0.13)	(-0.19)	(-0.47)	(-0.10)	(2.19)	(-0.45)	(-0.77)	(-0.75)	(-0.60)
5 [High]	0.07	0.54	-0.29	-0.28	-0.38	-0.29	0.53	-0.28	-0.29	-0.36	-0.30
		(1.07)	(-2.04)	(-2.00)	(-2.23)	(-2.00)	(1.24)	(-1.77)	(-2.14)	(-2.46)	(-1.91)
5-1		-0.88	-0.70	-0.85	-0.94	-0.72	-0.87	-0.75	-0.86	-0.99	-0.79
[High-Low]		(-4.05)	(-3.05)	(-4.20)	(-4.11)	(-3.22)	(-3.08)	(-2.48)	(-3.06)	(-3.63)	(-2.67)

Table 5: Bond Quintile Portfolios Sorted on *ΔCOMOVE*

For each month, quintile portfolios are formed by sorting bonds based on the *ΔCOMOVE*, where quintile 1(5) portfolio contains bonds with the lowest (highest) *ΔCOMOVE* during the previous month. The *ΔCOMOVE* is the innovation of EWMA covariance between stock and bond returns issued by the same firm, which is calculated using a minimum of 48 observations over the past 60 months. The second column reports the average *ΔCOMOVE* for each quintile, and the remaining columns present the average bond excess returns and alphas for the equal-weighted and value-weighted portfolios separately. Following Bali et al. (2021b), α_5^B is the alpha relative to five stock market factors including the excess stock market return (MKT_E), equity size (SMB_E), book-to-market (HML_E), equity momentum (MOM_E), and equity liquidity factors (LIQ); α_4^B is the alpha relative to four bond market factors including excess bond market return (MKT_B), downside risk (DRF), credit risk (CRF), and liquidity risk factors (LRF); and α_9^B is the alpha relative to a combination of five stock market factors and four bond market factors. Following Dickerson et al. (2023), we also report α_1^B relative to MKT_B only to avoid data handling issue documented in their paper. The last five columns report average bond characteristics for each quintile, including rating, maturity, size, duration, and illiquidity. The last row presents return and alpha differences between quintiles 1 and 5. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2007–December 2020.

		Equal weighted					Value weighted					Average Portfolio characteristics				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Quintile	*ΔCOMOVE*	R_B-R_f	α^B_5	α^B_1	α^B_4	α^B_9	R_B-R_f	α^B_5	α^B_1	α^B_4	α^B_9	Rating	Maturity	Size	Duration	Illiquidity
1 [Low]	-0.07	0.72	0.57	0.27	0.23	0.29	0.68	0.52	0.21	0.18	0.23	11.15	8.71	18.89	5.83	0.005
		(3.90)	(4.45)	(3.25)	(3.74)	(3.21)	(3.86)	(3.89)	(2.66)	(2.49)	(2.41)					
2	-0.02	0.59	0.48	0.24	0.19	0.22	0.58	0.45	0.19	0.14	0.14	9.43	9.14	19.22	6.13	0.004
		(4.52)	(4.67)	(4.08)	(3.51)	(3.14)	(4.29)	(3.67)	(3.05)	(3.39)	(2.65)					
3	0.00	0.54	0.43	0.19	0.14	0.16	0.53	0.41	0.16	0.11	0.12	8.79	8.92	19.31	6.02	0.003
		(4.55)	(4.30)	(3.36)	(2.59)	(2.61)	(4.44)	(3.65)	(2.44)	(2.30)	(2.04)					
4	0.01	0.48	0.38	0.13	0.08	0.11	0.50	0.35	0.08	0.05	0.04	8.76	9.00	19.30	6.08	0.003
		(3.88)	(3.35)	(2.07)	(1.75)	(2.27)	(3.89)	(2.57)	(1.21)	(1.02)	(0.80)					
5 [High]	0.07	0.47	0.33	-0.01	-0.03	0.02	0.43	0.26	-0.10	-0.10	-0.07	9.86	9.45	19.05	6.25	0.004
		(2.94)	(2.69)	(-0.12)	(-0.33)	(0.25)	(2.72)	(1.81)	(-0.94)	(-0.97)	(-0.73)					
5-1		-0.25	-0.24	-0.28	-0.26	-0.26	-0.26	-0.26	-0.31	-0.28	-0.30					
[High-Low]		(-3.41)	(-2.88)	(-2.76)	(-2.82)	(-3.09)	(-2.80)	(-2.38)	(-2.23)	(-2.21)	(-2.54)					

Table 6: Seven-factor Alphas of Equity Portfolios Sorted on *ΔCOMOVE*

This table reports seven-factor alphas (α_7^E) relative to the excess equity market return, equity size, book-to-market, momentum, liquidity, investment, and profitability factors, with Newey and West (1987) *t*-statistics in parentheses. The column "5–1" refers to the difference in α_7^E between quintile 5 and 1. We perform double sorts to control for various characteristics, which include equity size ($SIZE_E$), book-to-market (B/M), equity momentum (MOM_E), equity short-term reversal (REV_E), asset growth (I/A), profitability (ROE), default risk (DEFAULT), equity illiquidity ($ILLIQ_E$), dispersion in analysts' forecasts (DISPER), equity idiosyncratic volatility ($IVOL_E$), co-skewness (COSKEW), lottery demand (MAX), equity market beta (MKT_E), equity VIX beta (VIX_E), and equity uncertainty beta (UNC_E). For each month, we first sort stocks into five quintile portfolios based on one of the characteristics from the past month. Within each characteristic quintile, we further sort stocks into five quintiles based on *ΔCOMOVE*. The five *ΔCOMOVE*-sorted portfolios are then averaged over each of the five characteristic-sorted portfolios, thus representing comovement quintile portfolios controlling for the characteristics. Details on the construction of these variables are summarized in the Panel A of Table 1. The sample period covers September 2007–December 2020. All portfolios are value-weighted.

	Ranking on the *ΔCOMOVE*					
	1 [Low]	2	3	4	5 [High]	5-1 [High-Low]
(1) $SIZE_E$	0.26(1.89)	0.33(3.34)	0.06(0.68)	0.05(0.53)	-0.33(-2.83)	-0.59(-3.27)
(2) B/M	0.32(1.97)	0.15(1.09)	0.30(3.12)	-0.10(-0.79)	-0.33(-2.19)	-0.65(-2.59)
(3) MOM_E	0.38(2.49)	0.33(2.59)	0.13(1.36)	-0.01(-0.13)	-0.45(-2.81)	-0.83(-3.87)
(4) REV_E	0.42(2.07)	0.25(2.25)	0.23(2.34)	-0.09(-1.08)	-0.45(-3.08)	-0.87(-3.17)
(5) I/A	0.37(1.88)	0.20(1.87)	0.23(2.75)	-0.06(-0.68)	-0.31(-2.12)	-0.68(-2.58)
(6) ROE	0.27(1.63)	0.29(2.37)	0.20(2.12)	-0.16(-1.30)	-0.37(-2.39)	-0.64(-2.55)
(7) DEFAULT	0.26(1.73)	0.16(1.43)	0.14(1.21)	-0.21(-2.01)	-0.30(-2.32)	-0.56(-2.43)
(8) $ILLIQ_E$	0.30(2.03)	0.21(1.93)	0.17(2.00)	0.07(0.61)	-0.29(-2.44)	-0.59(-2.85)
(9) DISPER	0.29(1.91)	0.22(1.65)	0.19(1.78)	-0.12(-0.90)	-0.28(-1.97)	-0.58(-2.37)
(10) $IVOL_E$	0.47(3.35)	0.08(0.72)	0.09(0.73)	-0.16(-1.46)	-0.45(-3.31)	-0.92(-4.32)
(11) COSKEW	0.39(2.34)	0.46(3.57)	0.22(2.27)	-0.10(-0.95)	-0.40(-2.52)	-0.79(-3.21)
(12) MAX	0.40(2.26)	0.11(0.89)	0.09(0.80)	-0.21(-1.79)	-0.38(-2.76)	-0.77(-3.01)
(13) MKT_E	0.29(2.16)	0.12(0.90)	0.13(1.44)	-0.14(-1.25)	-0.32(-2.34)	-0.61(-2.97)
(14) VIX_E	0.27(1.59)	0.36(3.04)	0.16(1.66)	-0.11(-1.11)	-0.36(-2.48)	-0.63(-2.48)
(15) UNC_E	0.49(2.78)	0.18(1.66)	0.24(2.80)	-0.13(-1.37)	-0.39(-2.71)	-0.87(-3.56)

Table 7: Nine-factor Alphas of Bond Portfolios Sorted on *ΔCOMOVE*

This table reports nine-factor alphas (α_9^B) relative to the five stock market factors including the excess stock market return (MKT_E), equity size (SMB_E), book-to-market (HML_E), equity momentum (MOM_E), and equity liquidity factors (LIQ), together with excess bond market return, downside risk factor, credit risk factor, and bond liquidity risk factor. Newey and West (1987) *t*-statistics are reported in parentheses. The column "5–1" refers to the difference in α_9^B between quintiles 5 and 1. For each month, we perform double sorts to control for various characteristics, which include bond size ($SIZE_B$), credit rating (RATING), time-to-maturity (MATURITY), duration (DURATION), bond illiquidity ($ILLIQ_B$), bond momentum (MOM_B), bond short-term reversal (REV_B), default risk (DEFAULT), bond idiosyncratic volatility ($IVOL_B$), changes in implied volatility (IMPVOL), bond market beta (MKT_B), bond VIX beta (VIX_B), and bond uncertainty beta (UNC_B). We first sort bonds into five quintile portfolios based on one of the characteristics from the past month. Within each characteristic quintile, we further sort bonds into five quintiles based on *ΔCOMOVE*. The five *ΔCOMOVE*-sorted portfolios are then averaged over each of the five characteristic portfolios, thus representing comovement quintile portfolios controlling for the characteristics. Details on the construction of these variables are summarized in the Panel A of Table 1. The sample period covers September 2007–December 2020 for all controls. All portfolios are value-weighted.

	Ranking on the *ΔCOMOVE*					
	1 [Low]	2	3	4	5 [High]	5-1 [High-Low]
(1) $SIZE_B$	0.26(2.92)	0.15(3.02)	0.14(2.73)	0.11(2.13)	-0.02(-0.19)	-0.28(-3.17)
(2) RATING	0.17(2.70)	0.14(1.99)	0.15(2.90)	0.08(1.30)	-0.04(-0.39)	-0.20(-2.48)
(3) MATURITY	0.25(2.90)	0.13(2.53)	0.15(2.79)	0.05(1.04)	-0.00(-0.05)	-0.26(-2.59)
(4) DURATION	0.24(2.87)	0.14(2.69)	0.13(2.67)	0.07(1.25)	-0.03(-0.34)	-0.28(-2.72)
(5) $ILLIQ_B$	0.21(2.52)	0.12(2.15)	0.14(2.49)	0.07(1.08)	-0.10(-1.13)	-0.32(-2.73)
(6) MOM_B	0.19(2.32)	0.16(2.37)	0.09(1.95)	0.07(1.44)	-0.08(-0.83)	-0.27(-2.44)
(7) REV_B	0.19(2.24)	0.16(3.03)	0.14(2.58)	0.04(0.73)	-0.04(-0.45)	-0.23(-2.11)
(8) DEFAULT	0.18(2.31)	0.14(2.00)	0.09(2.28)	0.06(0.96)	-0.09(-0.93)	-0.27(-2.83)
(9) $IVOL_B$	0.21(2.38)	0.14(2.35)	0.11(1.95)	0.04(0.73)	-0.07(-0.73)	-0.27(-2.74)
(10) IMPVOL	0.21(2.36)	0.15(2.60)	0.10(1.77)	0.06(0.96)	-0.10(-1.07)	-0.31(-2.72)
(11) MKT_B	0.17(2.19)	0.13(2.60)	0.13(2.27)	0.07(1.19)	-0.09(-0.96)	-0.26(-2.43)
(12) VIX_B	0.17(2.23)	0.12(2.13)	0.14(2.51)	0.08(1.52)	-0.07(-0.77)	-0.24(-2.91)
(13) UNC_B	0.19(2.39)	0.14(2.04)	0.13(2.98)	0.11(1.70)	-0.04(-0.46)	-0.24(-2.78)

Table 8: Equity-level Fama–Macbeth Regressions

This table reports the time-series average of slope coefficients obtained from regressing monthly excess equity returns on *ΔCOMOVE* while controlling for a set of lagged predictive variables using the Fama and MacBeth (1973) method. The control variables include equity market beta (MKT_E), equity size ($SIZE_E$), book-to-market (B/M), momentum (MOM_E), short-term reversal (REV_E), asset growth (I/A), profitability (ROE), equity illiquidity ($ILLIQ_E$), dispersion in analysts' forecasts (DISPER), equity VIX beta (VIX_E), equity idiosyncratic volatility ($IVOL_E$), lottery demand (MAX), default risk (DEFAULT), co-skewness (COSKEW), and equity uncertainty beta (UNC_E). Details on the construction of these variables are summarized in the Panel A of Table 1. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2007–December 2020. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	R_E	R_E	R_E	R_E	R_E	R_E	R_E	R_E	R_E
Intercept	0.835*	0.640	0.648	0.538	0.465	0.467	0.440	0.308	0.364
	(1.97)	(1.43)	(1.46)	(1.18)	(1.00)	(1.03)	(0.97)	(0.65)	(0.77)
ΔCOMOVE	-0.464***	-0.296**	-0.299**	-0.296**	-0.297**	-0.306**	-0.339***	-0.367***	-0.373***
	(-2.86)	(-2.31)	(-2.34)	(-2.30)	(-2.49)	(-2.60)	(-2.90)	(-3.24)	(-3.28)
MKT_E		0.015	0.026	0.033	0.016	0.056	0.072	-0.141	-0.110
		(0.08)	(0.14)	(0.17)	(0.08)	(0.32)	(0.43)	(-0.71)	(-0.55)
$SIZE_E$		-0.117	-0.113	-0.070	-0.066	-0.086	-0.082	-0.094	-0.090
		(-1.64)	(-1.58)	(-0.93)	(-0.90)	(-1.17)	(-1.10)	(-1.42)	(-1.37)
BM		-0.123**	-0.093	-0.095	-0.082	-0.079	-0.069	-0.052	-0.031
		(-2.24)	(-1.27)	(-1.30)	(-1.10)	(-1.08)	(-0.94)	(-0.83)	(-0.50)
MOM_E		-0.128	-0.129	-0.127	-0.146	-0.119	-0.087	-0.122	-0.068
		(-0.73)	(-0.74)	(-0.73)	(-0.83)	(-0.71)	(-0.54)	(-0.66)	(-0.38)
REV_E		0.032	0.023	0.022	0.005	-0.021	-0.025	-0.108	-0.085
		(0.32)	(0.23)	(0.22)	(0.05)	(-0.22)	(-0.27)	(-1.19)	(-0.97)
IA			0.003	0.006	0.001	0.005	0.010	0.017	0.016
			(0.05)	(0.11)	(0.01)	(0.10)	(0.21)	(0.34)	(0.32)
ROE			0.362	0.363	0.333	0.348	0.344	0.332	0.397*
			(1.37)	(1.36)	(1.30)	(1.49)	(1.49)	(1.54)	(1.75)
$ILLIQ_E$				20.125**	30.692*	33.240*	35.566**	26.712	24.516
				(2.06)	(1.77)	(1.90)	(1.99)	(1.51)	(1.40)
DISPER					-0.158	-0.060	-0.020	-0.069	-0.060
					(-0.62)	(-0.26)	(-0.08)	(-0.30)	(-0.26)
VIX_E						-0.233**	-0.200**	-0.169*	-0.166*
						(-2.25)	(-2.00)	(-1.86)	(-1.83)
$IVOL_E$						-0.091	0.013	0.052	0.044
						(-1.07)	(0.11)	(0.44)	(0.37)
MAX							-0.238	-0.303	-0.288
							(-1.21)	(-1.57)	(-1.44)
DEFAULT								0.019	0.011
								(0.26)	(0.14)
COSKEW								0.443**	0.437**
								(2.56)	(2.48)
UNC_E									-0.093
									(-1.02)
N	68365	63284	63052	63052	61494	61461	61461	61055	61055
R-sq	0.019	0.142	0.151	0.156	0.165	0.184	0.192	0.227	0.233

Table 9: Bond-level Fama–Macbeth Regressions

This table reports the time-series average of slope coefficients obtained from regressing monthly excess bond returns on *ΔCOMOVE* while controlling for a set of lagged predictive variables using the Fama and MacBeth (1973) method. The control variables include bond size ($SIZE_B$), credit rating (RATING), time-to-maturity (MATURITY), bond short-term reversal (REV_B), bond illiquidity ($ILLIQ_B$), bond market beta (MKT_B), bond idiosyncratic volatility ($IVOL_B$), bond VIX beta (VIX_B), default risk (DEFAULT), and bond uncertainty beta (UNC_B). Details on the construction of these variables are summarized in the Panel A of Table 1. Newey and West (1987) adjusted *t*-statistics are reported in parentheses. The sample period covers September 2007–December 2020. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	R_B	R_B	R_B	R_B	R_B	R_B	R_B
Intercept	0.532***	0.521***	0.526***	0.574***	0.701***	0.695***	0.667***
	(4.00)	(3.75)	(3.83)	(3.89)	(4.08)	(4.20)	(3.31)
ΔCOMOVE	-0.148***	-0.090***	-0.077**	-0.066**	-0.061**	-0.061**	-0.060**
	(-3.46)	(-2.92)	(-2.43)	(-2.05)	(-2.31)	(-2.31)	(-2.30)
$SIZE_B$		-0.006	0.038	0.022	0.039	0.044	0.045
		(-0.28)	(1.19)	(0.74)	(1.20)	(1.24)	(1.31)
RATING		0.077	0.085	0.052	0.068	0.078**	0.058
		(1.19)	(1.44)	(0.90)	(1.44)	(2.07)	(1.53)
MATURITY		0.085**	0.080**	0.050	0.033	0.027	0.042
		(2.48)	(2.40)	(1.51)	(1.03)	(0.81)	(1.21)
REV_B		-0.001	0.036	0.057	0.037	0.030	0.017
		(-0.03)	(0.86)	(1.42)	(0.89)	(0.71)	(0.43)
$ILLIQ_B$			0.163	0.148	0.149	0.144	0.137
			(1.26)	(1.13)	(1.37)	(1.35)	(1.38)
MKT_B				0.108**	0.091**	0.095**	0.099**
				(2.54)	(2.06)	(2.16)	(2.25)
$IVOL_B$					1.288**	1.396**	0.932
					(2.02)	(2.16)	(1.23)
VIX_B					0.074	0.068	0.026
					(1.28)	(1.17)	(0.56)
DEFAULT						-0.031	-0.028
						(-0.95)	(-0.95)
UNC_B							-0.026
							(-0.23)
N	68365	67376	54711	54352	53996	52982	52982
R-sq	0.036	0.224	0.271	0.286	0.315	0.322	0.334

Table 10: Equity Subsample Analysis of Financial Risk and Information Asymmetry

This table reports excess equity returns and alphas of *ΔCOMOVE*-sorted quintile portfolios for high and low subgroups based on different measures of financial risk and information asymmetry in Panels A and B, respectively. Firms with high (low) financial risk are defined as ones with higher (lower) leverage ratio, higher (lower) earning volatility, lower (higher) credit rating and lower (higher) Altman Z-score than the median value for the sample period. Firms with high (low) information asymmetry are defined as ones with higher (lower) forecast dispersion, higher (lower) accounting accruals, higher (lower) equity idiosyncratic volatility, higher (lower) equity illiquidity and lower (higher) interest coverage than the median value for the sample period. For each of the quintile portfolios, we report the value-weighted average monthly excess equity returns. The last two rows show the differences in returns and seven-factor alphas between quintiles 5 and 1 computed relative to MKT_E, SMB_E, HML_E, MOM_E, LIQ, I/A, and ROE factors, following Hou et al. (2015). Details on the construction of these variables are summarized in the Panel B of Table 1. Corresponding *t*-statistics in parentheses are based on Newey and West (1987) standard errors. The sample period covers August 2007 –December 2020.

Panel A: Returns on *ΔCOMOVE* -sorted portfolios for high and low financial risk subgroups

	Leverage			Earning volatility			Credit Rating			Altman's Z-score		
Quintile	High	Low	High-low	High	Low	High-low	High	Low	High-low	High	Low	High-low
1 [Low]	1.19	1.14	0.05	1.40	1.02	0.38	1.24	1.44	-0.20	1.36	1.20	0.16
2	1.19	1.11	0.09	1.11	1.35	-0.24	0.79	0.97	-0.18	1.12	1.10	0.02
3	0.69	1.01	-0.33	0.69	1.07	-0.38	0.91	0.90	0.01	0.93	0.62	0.31
4	0.59	0.53	0.06	0.67	0.55	0.12	0.75	0.54	0.22	0.57	0.80	-0.23
5 [High]	0.11	0.89	-0.78	0.30	0.73	-0.43	0.27	0.57	-0.30	0.88	0.35	0.54
H-L return	-1.08	-0.25	-0.83	-1.10	-0.29	-0.81	-0.96	-0.87	-0.10	-0.48	-0.85	0.37
	(-2.96)	(-0.96)	(-2.32)	(-2.81)	(-0.92)	(-1.93)	(-2.15)	(-3.79)	(-0.24)	(-1.68)	(-2.48)	(1.07)
H-L a^{E}_{7}	-0.77	-0.06	-0.71	-1.04	-0.33	-0.70	-0.89	-0.71	-0.18	-0.37	-0.71	0.34
	(-1.99)	(-0.22)	(-2.02)	(-2.52)	(-1.03)	(-1.71)	(-1.91)	(-3.30)	(-0.38)	(-1.43)	(-1.87)	(0.91)

Panel B: Returns on *ΔCOMOVE* -sorted portfolios for high and low information asymmetry subgroups

	Forecasts dispersion			Accounting accruals			Equity idiosyncratic volatility			Equity illiquidity			Interest coverage		
Quintile	High	Low	High-low	High	Low	High-low	High	Low	High-low	High	Low	High-low	High	Low	High-low
1 [Low]	1.15	1.40	-0.24	1.35	1.35	0.00	1.12	1.31	-0.19	1.25	1.27	-0.02	1.22	1.07	0.15
2	0.96	1.17	-0.21	1.15	1.10	0.05	1.20	1.11	0.08	1.16	1.05	0.11	1.19	1.19	0.01
3	0.63	0.99	-0.36	1.01	0.85	0.15	0.73	0.87	-0.13	0.95	0.94	0.01	0.89	0.66	0.23
4	0.57	0.78	-0.20	0.59	0.59	0.00	0.62	0.64	-0.02	0.95	0.53	0.42	0.53	0.68	-0.15
5 [High]	-0.01	0.88	-0.88	0.52	0.78	-0.26	0.09	0.68	-0.59	0.42	0.52	-0.10	0.76	0.27	0.49
H-L return	-1.16	-0.52	-0.64	-0.83	-0.57	-0.26	-1.03	-0.63	-0.40	-0.83	-0.75	-0.08	-0.46	-0.80	0.34
	(-3.02)	(-1.82)	(-1.48)	(-2.50)	(-1.62)	(-0.77)	(-2.82)	(-3.17)	(-1.21)	(-2.90)	(-2.94)	(-0.27)	(-1.79)	(-2.08)	(0.89)
H-L a^{E}_{7}	-1.17	-0.47	-0.70	-0.88	-0.28	-0.61	-1.11	-0.42	-0.69	-0.65	-0.67	0.01	-0.26	-0.63	0.36
	(-2.82)	(-1.58)	(-1.60)	(-3.19)	(-0.74)	(-2.03)	(-2.76)	(-2.10)	(-1.82)	(-2.19)	(-2.67)	(0.05)	(-0.95)	(-1.43)	(0.85)

Table 11: Bond Subsample Analysis of Financial Risk and Information Asymmetry

This table reports excess bond returns and alphas of *ΔCOMOVE*-sorted quintile portfolios for high and low subgroups based on different measures of financial risk and information asymmetry in Panels A and B, respectively. Firms with high (low) financial risk are defined as ones with higher (lower) leverage ratio, higher (lower) earning volatility, lower (higher) credit rating and lower (higher) Altman Z-score than the median value for the sample period. Firms with high (low) information asymmetry are defined as ones with higher (lower) forecast dispersion, higher (lower) accounting accruals, higher (lower) bond idiosyncratic volatility, higher (lower) bond illiquidity and lower (higher) interest coverage than the median value for the sample period. For each of the quintile portfolios, we report the value-weighted average monthly excess bond returns. The last two rows show the differences in returns and nine-factor alphas between quintiles 5 and 1 computed relative to both equity factors and bond factors including MKT_B, DRF, CRF, and LRF factors. Details on the construction of these variables are summarized in the Panel B of Table 1. Corresponding *t*-statistics in parentheses are based on Newey and West (1987) standard errors. The sample period covers August 2007 –December 2020.

Panel A: Returns on *ΔCOMOVE* -sorted portfolios for high and low financial risk subgroups

	Leverage			Earning volatility			Credit Rating			Altman's Z-score		
Quintile	High	Low	High-low	High	Low	High-low	High	Low	High-low	High	Low	High-low
1 [Low]	0.68	0.63	0.05	0.54	0.64	-0.10	0.65	0.67	-0.02	0.75	0.61	0.13
2	0.61	0.55	0.06	0.50	0.62	-0.12	0.54	0.62	-0.08	0.66	0.50	0.16
3	0.51	0.52	-0.01	0.56	0.54	0.02	0.48	0.57	-0.09	0.68	0.52	0.16
4	0.51	0.48	0.03	0.44	0.50	-0.06	0.46	0.53	-0.07	0.66	0.50	0.17
5 [High]	0.37	0.46	-0.09	0.33	0.45	-0.12	0.45	0.43	0.02	0.57	0.44	0.12
H-L return	-0.31	-0.17	-0.14	-0.22	-0.20	-0.02	-0.20	-0.25	0.04	-0.18	-0.17	-0.01
	(-2.55)	(-2.74)	(-1.46)	(-2.08)	(-1.89)	(-0.18)	(-2.90)	(-2.42)	(0.59)	(-2.09)	(-3.07)	(-0.09)
H-L a^{B}_{9}	-0.30	-0.23	-0.07	-0.26	-0.23	-0.03	-0.20	-0.28	0.08	-0.23	-0.20	-0.03
	(-2.18)	(-2.90)	(-0.76)	(-1.81)	(-1.87)	(-0.35)	(-2.57)	(-2.44)	(1.03)	(-2.03)	(-3.11)	(-0.31)

Panel B: Returns on *ΔCOMOVE* -sorted portfolios for high and low information asymmetry subgroups

	Forecasts dispersion			Accounting accruals			Bond idiosyncratic volatility			Bond illiquidity			Interest coverage		
Quintile	High	Low	High-low	High	Low	High-low	High	Low	High-low	High	Low	High-low	High	Low	High-low
1 [Low]	0.86	0.68	0.18	0.70	0.67	0.02	0.80	0.57	0.23	0.87	0.60	0.27	0.61	0.69	-0.10
2	0.46	0.58	-0.13	0.58	0.59	-0.01	0.67	0.55	0.11	0.79	0.54	0.25	0.55	0.63	-0.10
3	0.61	0.52	0.08	0.52	0.54	-0.02	0.57	0.52	0.05	0.71	0.51	0.20	0.48	0.54	-0.08
4	0.70	0.51	0.18	0.48	0.49	-0.01	0.54	0.52	0.02	0.68	0.48	0.21	0.47	0.55	-0.08
5 [High]	0.28	0.45	-0.17	0.46	0.42	0.05	0.38	0.44	-0.06	0.62	0.39	0.23	0.40	0.46	-0.07
H-L return	-0.58	-0.23	-0.35	-0.23	-0.26	0.02	-0.42	-0.13	-0.29	-0.25	-0.20	-0.04	-0.20	-0.22	0.03
	(-3.00)	(-2.46)	(-1.80)	(-3.13)	(-2.31)	(0.31)	(-2.79)	(-2.13)	(-2.24)	(-2.00)	(-2.20)	(-0.30)	(-2.03)	(-2.31)	(0.24)
H-L a^{B}_{9}	-0.60	-0.27	-0.33	-0.29	-0.30	0.01	-0.35	-0.20	-0.15	-0.36	-0.27	-0.09	-0.23	-0.26	0.04
	(-3.55)	(-2.40)	(-2.15)	(-2.75)	(-2.29)	(0.22)	(-2.30)	(-2.46)	(-1.26)	(-2.89)	(-2.28)	(-0.97)	(-2.08)	(-2.14)	(0.42)

Table 12: Univariate Portfolios of Big and All-but-micro Securities Sorted by *ΔCOMOVE*

For each month, we first sort our sample into two subgroups of big and all-but-micro securities, which are defined as securities with sizes above the 50th and 20th percentiles, respectively, of end-of-June market capitalization for NYSE stocks. Within each subgroup, we then sort the securities into five quintile portfolios based on the *ΔCOMOVE*, where the quintile 1(5) portfolio contains securities with the lowest (highest) *ΔCOMOVE* during the previous month. The *ΔCOMOVE* is the innovation of the EWMA covariance between stock and bond returns issued by the same firm, which is calculated using a minimum of 48 observations over the past 60 months. The portfolios are value-weighted using the prior month's equity market capitalization. The average *ΔCOMOVE*, excess security returns, and portfolio alphas are reported for each quintile. Equity alphas are adjusted for MKT_E, SMB_E, HML_E, MOM_E, LIQ, I/A, and ROE factors. Bond alphas control for both equity factors and bond factors including MKT_B, DRF, CRF, and LRF factors. The last row presents the return and alpha differences between quintiles 1 and 5. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2007–December 2020.

Panel A: Univariate portfolio analysis based on big stocks only

Quintile	*ΔCOMOVE*	Equity returns					Bond returns				
		R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7	R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7
1 [Low]	-0.05	1.34	0.43	0.48	0.54	0.44	0.66	0.51	0.20	0.17	0.21
		(3.03)	(2.46)	(2.84)	(3.26)	(2.59)	(3.95)	(3.90)	(2.67)	(2.41)	(2.34)
2	-0.01	1.09	0.27	0.32	0.29	0.25	0.54	0.42	0.16	0.12	0.12
		(2.97)	(2.14)	(2.79)	(2.48)	(1.97)	(4.23)	(3.41)	(2.76)	(3.09)	(2.46)
3	0.00	0.83	0.16	0.07	0.07	0.14	0.52	0.40	0.14	0.10	0.10
		(2.42)	(1.54)	(0.62)	(0.56)	(1.43)	(4.35)	(3.61)	(2.26)	(2.21)	(1.83)
4	0.01	0.61	-0.09	-0.16	-0.18	-0.10	0.50	0.37	0.09	0.06	0.07
		(1.77)	(-0.83)	(-1.39)	(-1.38)	(-0.88)	(3.94)	(2.83)	(1.44)	(1.23)	(1.28)
5 [High]	0.06	0.54	-0.21	-0.26	-0.32	-0.23	0.45	0.28	-0.06	-0.07	-0.06
		(1.32)	(-1.55)	(-2.06)	(-2.38)	(-1.74)	(3.05)	(1.88)	(-0.67)	(-0.74)	(-0.67)
5-1		-0.80	-0.64	-0.74	-0.86	-0.68	-0.20	-0.23	-0.27	-0.24	-0.27
[High-Low]		(-3.08)	(-2.51)	(-2.97)	(-3.40)	(-2.67)	(-2.72)	(-2.26)	(-2.33)	(-2.30)	(-2.57)

Panel B: Univariate portfolio analysis based on all but microcap stocks

Quintile	*ΔCOMOVE*	Equity returns					Bond returns				
		R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7	R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7
1 [Low]	-0.06	1.38	0.40	0.51	0.58	0.43	0.68	0.52	0.21	0.18	0.22
		(2.92)	(1.97)	(2.70)	(3.30)	(2.18)	(3.90)	(3.92)	(2.71)	(2.51)	(2.41)
2	-0.02	1.16	0.36	0.38	0.35	0.34	0.58	0.45	0.20	0.15	0.15
		(3.14)	(2.92)	(3.29)	(2.93)	(2.78)	(4.31)	(3.70)	(3.03)	(3.39)	(2.63)
3	0.00	0.84	0.19	0.09	0.06	0.17	0.52	0.41	0.15	0.11	0.12
		(2.32)	(1.85)	(0.82)	(0.43)	(1.72)	(4.40)	(3.58)	(2.37)	(2.30)	(2.05)
4	0.01	0.66	-0.09	-0.13	-0.14	-0.10	0.50	0.35	0.08	0.05	0.04
		(2.01)	(-0.81)	(-1.17)	(-1.12)	(-0.92)	(3.90)	(2.59)	(1.24)	(1.07)	(0.83)
5 [High]	0.07	0.49	-0.32	-0.35	-0.41	-0.34	0.43	0.27	-0.09	-0.10	-0.07
		(1.14)	(-2.21)	(-2.73)	(-3.07)	(-2.37)	(2.76)	(1.86)	(-0.89)	(-0.93)	(-0.68)
5-1		-0.89	-0.72	-0.85	-0.99	-0.77	-0.25	-0.25	-0.30	-0.28	-0.29
[High-Low]		(-3.33)	(-2.52)	(-3.26)	(-3.87)	(-2.73)	(-2.74)	(-2.32)	(-2.23)	(-2.21)	(-2.52)

Table 13: Bivariate Bond Portfolios of Default Risk Measures and *ΔCOMOVE*

In Panel A, five quintile portfolios are formed every month from September 2007 to December 2020 by first sorting corporate bonds based on the default risk measures including market leverage, distance-to-default, credit spread, and default spread documented in the work of Dickerson et al. (2022). Within each quintile portfolio, corporate bonds are further sorted into five sub-quintiles based on the *ΔCOMOVE*. Hence, Panel A presents *ΔCOMOVE* quintile portfolio results controlling for different default risk measures. In Panel B, five quintile portfolios are formed by first sorting corporate bonds based on the *ΔCOMOVE*. Then within each quintile portfolio, corporate bonds are further sorted into five sub-quintiles based on the same set of default risk measures. Hence, Panel B presents default risk quintile portfolio results controlling for *ΔCOMOVE*. The alphas reported in both Panels A and B are adjusted for a combination of five stock market factors and four bond market factors. Newey and West (1987) *t*-statistics are reported in parentheses.

Panel A: First sort on default risk measures

	1 [Low]	2	3	4	5 [High]	5-1 [High-Low]
Market leverage	0.19(2.39)	0.17(2.25)	0.11(2.41)	0.04(0.66)	-0.09(-0.92)	-0.28(-2.67)
Distance-to-default	0.17(2.27)	0.13(1.81)	0.09(2.27)	0.07(1.26)	-0.07(-0.69)	-0.24(-2.62)
Credit spread	0.16(2.32)	0.12(1.94)	0.13(2.83)	0.11(1.73)	-0.03(-0.30)	-0.18(-2.37)
Default spread	0.18(2.30)	0.14(2.00)	0.09(2.29)	0.06(0.96)	-0.09(-0.93)	-0.27(-2.83)

Panel B: First sort on *ΔCOMOVE*

	1 [Low]	2	3	4	5 [High]	5-1 [High-Low]
Market leverage	0.13(2.08)	0.07(0.99)	0.12(1.65)	0.05(0.72)	0.06(1.36)	-0.07(-1.36)
Distance-to-default	0.09(1.11)	0.01(0.22)	0.07(1.31)	0.10(1.57)	0.12(1.70)	0.02(0.36)
Credit spread	0.14(2.19)	0.14(2.20)	0.10(1.63)	0.08(1.06)	0.06(0.48)	-0.08(-0.55)
Default spread	0.14(2.13)	0.11(1.41)	0.08(1.29)	0.07(1.16)	0.01(0.18)	-0.13(-1.95)

Table 14: Predictability of $\Delta COMOVE$ and σ_{DFJM} with Individual Default Risk Measures

This table presents results on the predictive relation between two measures of stock–bond comovement (σ_{DFJM} and $\Delta COMOVE$) and four different measures of default risk based on panel regressions. The dependent variable is σ_{DFJM} for columns (1)– (4) and $\Delta COMOVE$ for columns (4)– (8). σ_{DFJM} is computed as the one-year-ahead EWMA stock-bond covariance. $\Delta COMOVE$ is computed as the innovation of EWMA covariance between stock and bond returns issued by the same firm using a minimum of 48 observations over the past 60 months. Regressors include market leverage, distance-to-default, and credit spread constructed following Dickerson et al. (2022). The sample period covers August 2007 – December 2020. Newey and West (1987) *t*-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	σ_{DFJM}	σ_{DFJM}	σ_{DFJM}	σ_{DFJM}	$\Delta COMOVE$	$\Delta COMOVE$	$\Delta COMOVE$	$\Delta COMOVE$
Intercept	-0.038***	0.215***	0.032**	0.082***	0.001	-0.010*	-0.002	-0.002
	(-5.51)	(7.67)	(2.20)	(8.38)	(0.72)	(-1.89)	(-0.80)	(-0.74)
Leverage	0.266***				-0.007			
	(8.57)				(-1.33)			
Distance-to-default		-0.007***				0.001***		
		(-5.93)				(2.80)		
Credit spread			0.014**				-0.000	
			(2.07)				(-0.38)	
Default risk				0.075***				-0.004**
				(8.23)				(-2.23)
N	68612	68254	70100	67292	67856	67503	69327	67292
R-sq	0.086	0.153	0.165	0.138	0.024	0.051	0.046	0.040

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Comovement and the Joint Cross-section of Stock and Corporate Bond Returns

Internet Appendix

Appendix A

This appendix section describes the data cleaning and merging procedure for constructing our sample dataset.

1. TRACE

The main results of this paper rely on the TRACE Enhanced dataset, which provides intraday bond transaction information. However, this dataset appears to include a certain amount of problematic trades, as the records are self-reported by bond dealers and overstate the trading activity and depth of the market (Dick-Nielsen, 2009). Therefore, before further employing the transaction information, we first follow Dick-Nielsen (2014) to eliminate erroneous transaction records that are filed for signaling correction, cancellation, or reversal of original records. Another important factor that may affect the quality of the transaction information is extraneous trade reports. Since every dealer involved in bond trades is required to file a separate trade report, more than one redundant trade report would have been generated if more than one dealer was involved in the process. Therefore, we identify the exact matching reports and keep only one principal sell trade report to reflect trading activity properly. However, Dick-Nielsen (2009) found that there are still some trade reports that cannot be matched because of issues such as trade splitting and mismatches in reporting capacity codes. To address that, we follow Asquith et al. (2013) to modify related fields to identify and consolidate possible matches into one single record. Once the long-span dataset is constructed, we then address the price and volume issue, where both measures are winsorized at the top and bottom 1% to filter out extreme returns. Following Bai et al. (2019), we further eliminate bond transactions that (i) are labeled as when-issued or locked-in or have special sales conditions, (ii) have more than a two-day settlement, (iii) have a trading volume smaller than $10,000, or (iv) are priced under $5 or above $1,000.

2. Mergent FISD

The FISD database contains information on bond issues and issuer characteristics. To obtain qualified bonds, we first follow the construction manual of WRDS to rule out convertible, exchangeable, and other equity-linked bonds using bond type information. Following Bai et al. (2019), we then remove bonds that:

(i) are not listed or traded in the US public market, which includes bonds issued through private placement, bonds issued under the 144A rule, and bonds that do not trade in US dollars.

(ii) are structured notes, mortgage-backed, asset-backed, agency-backed, or equity-linked. Convertible bonds are also deleted from our dataset because their option feature will distort the return calculation and make it impossible to compare them with nonconvertible bonds.

(iii) are not included in the following types of bonds: US Corporate Debentures (CDEB), US Corporate Medium-Term Note (CMTN), US Corporate Medium Term Note Zero (CMTZ), and US Corporate Paper (CP).

(iv) have floating coupon rates.

(v) have less than one year to maturity from our sample, as bonds that mature in one year will be delisted from major bond indices.

3. Final bond dataset

The cleaned TRACE data is then merged with the FISD data based on the 9-digit CUSIP IDs. Approximately 5% of the transaction records are then dropped, as all the information is needed for the later calculation of bond return. Once we obtain the merged bond price dataset, the cleaned intraday price records are aggregated to obtain the lists of cleaned daily bond prices. Given the institutional and illiquid nature of the bond market (Edwards et al., 2007), the cost of trading is documented to be larger for small trades. In order to remove the noise of execution costs in the prices of small trades, we follow Bessembinder et al. (2008) to weigh each trade by its trading volume to construct daily bond prices. Given the evidence that the corporate bond market displays a relatively lower level of trading activity, we next convert the bond prices from daily to monthly frequency by taking the last available daily price of the bond at each month.

Before computing monthly bond returns, we need to calculate accrued interest for each observation, as this is not reported in our dataset. This is because only the bond owner can receive coupon payments at the payment date. The listed price will not reflect the real purchase price of a bond until the next payment, even though the interest has been accumulating every day between coupon payments. Therefore, the accumulated interest should be additionally calculated and added back to the listed bond prices to reflect the "dirty" price paid at settlement. As for zero-coupon bonds issued at a deep discount, no adjustment is needed, as it is already reflected in the listed price. The accrued interest is thus computed by multiplying the coupon rate and the day-count factor, which represents the percentage of the holding period until the end of the month to the time differences between coupon payments on a year basis. Similarly, for bonds that pay coupons at maturity, their day-count factor is calculated by dividing the number of days since the first date that interest accrues by the period between the first date and the maturity date. Once we obtain accrued interest for all the bonds included in our sample, we compute the monthly corporate bond return for firm *i* at time *t* as

$$r_{i,t} = \frac{P_{i,t} + AI_{i,t} + Coupon_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1$$

where $P_{i,t}$ is the transaction price, $AI_{i,t}$ is accrued interest, and $Coupon_{i,t}$ is the coupon payment of bond *i* in month *t* (if any).

4. New method linking back to CRSP

The bond CRSP link table from the WRDS database is commonly applied in previous studies to link fixed-income data with equity data issued by the same company at the individual bond level. However, several issues arise when applying the effective time range recorded for each linkage. First, the effective time range of equity data stopped updating in 2016, which forced some linkages to end in 2016 even though those equities are still active now. In this case, at least 200 observations have been missing for the last four years. Second, we identify prominent double-counting issues for companies that went through mergers and acquisitions. The overlapping periods correspond to the gap between deal announcement and deal completion, where different effective dates are applied in the WRDS link table for acquiring and target companies involved in the deals. Another issue regarding bonds issued by target companies is that the bond CRSP link table fails to account for the ones that continue to trade under the name of the acquirer company.

To address those issues, we propose a new matching method. Specifically, we first identify the issuers of each equity and bond by taking the first six characters of their CUSIP number, documented as CUSIP6. For each equity, we can identify each issuer with only one CUSIP, so that bonds sharing the same CUSIP6 with the equity can be mapped back to CRSP directly. However, more than one bond issuer is normally identified for the company that issues debt. We thus employ the tickers documented in the TRACE dataset to help identify other bond issuers of the same equity. We first obtain the ticker history for each equity available in the CRSP database. To address the issue that the effective records of some equities have not been updated since 2015, we manually adjust the wrongly recorded end date to the latest available trading date of each equity. Under each ticker documented in TRACE, we identify all the matching CUSIP6 as well as the available time range. We then match on the ticker and eliminate bond return records that fell beyond the effective periods to avoid double-counting issues. As for bonds that last longer than the ticker's effective period, we keep the ones for which a unique PERMNO can be found to match the corresponding ticker. Next, we eliminate bond return records that are double counted by the target or the acquirer companies involved in the merger and acquisition deals. We first obtain the effective date for all merger and acquisition deals documented in the SDC Platinum databases published by Thomson Reuters / Refinitiv. Then we map the effective date back to our dataset based on the CUSIP6 of the acquirer and target companies and restrict the bonds of target companies to be valid from effective dates. In order to obtain as many matches as we can, we repeat this process again on the ultimate parent of unmatched target companies. Finally, we obtain a bond return list that matches perfectly with the returns of equities issued by the same company. With this new method, we successfully identify another 33.91% of bond issues for an additional 128 companies from the TRACE dataset. However, the total amount of bond issues that successfully match with equity records does not change much.

Appendix B

In addition, we examine the pricing implications of Δ*COMOVE* for the difference between equity and aggregated bond returns of the same firm, defined as the firm-specific equity risk premium (ERP_f).

[Table B1]

Table B1 presents the results of univariate portfolio sorts controlling for the same collection of equity factor models as in Table 4. The alphas on the zero-cost strategy confirm that Δ*COMOVE* retains its negative predicting power in the cross-section of ERP_f in both equal-weight and value-weight setups. The average returns on the quintile portfolio decrease monotonically, where low-Δ*COMOVE* firms continue to yield a significant premium of 62 bps (59 bps) per month compared to those in the highest quintile. Moreover, risk-adjusted HML remains sizable after controlling for other established factors at −0.49% and −0.52% for equal- and value-weighted portfolios, respectively. Importantly, the negative ERP_f of the HML portfolio is still driven by the significant underperformance of the highest quintile portfolio. This again underscores the reliability of Δ*COMOVE* as an indicator of escalating risk levels, with potential losses borne by equity investors exhibiting exceptionally low risk aversion.

[Table B2]

Table B2 reports the results of bivariate sorting analysis on ex post ERP_f and confirms that the predictability of Δ*COMOVE* remains consistently significant across the same set of equity control variables adopted in Table 6. Most of the patterns from equity findings are generally preserved and become more pronounced. We show that both the economic and statistical significance of the HML portfolio reduces to a marginal level, or even becomes statistically insignificant after controlling for BM, ROE, or DEFAULT. Given the consistently significant underperformance of the highest quintile portfolio, our hypothesis that Δ*COMOVE* helps identify firms with escalating risk levels that have difficulty generating future profits is further strengthened. This evaluation plays a critical role in determining the level of compensation that investors demand to offset the extra risks associated with investing in equities instead of bonds. We also find that Δ*COMOVE* becomes marginally significant at −0.38% and −0.37% (*t*-stat = −2.2 and −1.81) when $ILLIQ_E$ and VIX_E are controlled for. This evidence confirms that firm-level exposures toward illiquidity and systematic volatility largely determine how willing investors are to take on risk and seek higher returns in holding equities compared to bonds, which is mainly captured in ERP_f. However, this does not encompass the entire risk profile that cross-asset investors evaluate. In addition, the significant information overlap between

Δ *COMOVE* and DISPER again validates our proposition that the negative Δ *COMOVE* premium is largely driven by investors' subjective evaluation of the firm's profitability and risk level, as exhibited in their recent trading history. Overall, Δ *COMOVE* dominates in explaining the level of risk compensation for holding equities instead of bonds by capturing additional aspects of risk that are not fully accounted for by either profitability- or volatility-related factors.

[Table B3]

Table B3 reports the results of Fama and MacBeth (1973) regressions examining the same collection of equity-specific controlling variables on ERP_f. We show that Δ *COMOVE* continues to predict ex post ERP_f at a 95% confidence level across different model specifications. In the univariate regression setup, it generates an average slope coefficient of −0.315 with a significant *t*-statistic of −2.18. This implies that firms in the first quintile portfolio have equities that outperform same-firm bonds by 19 basis points per month when compared to those in the fifth quintile portfolio. The predictive power of individual control variables from Table 8 is generally preserved or becomes even stronger among results based on ERP_f. The statistical significance of the coefficient on Δ*COMOVE* falls below the 5% level, controlling for Fama and French (1993) and Carhart (1997), in column (2). This confirms that our measure indeed captures firm-specific risk levels against the market portfolio, which is better rewarded in the equity market. Similar result is also observed when profitability-related variables such as BM and ROE are included as controls. However, none of these explanations are likely to tell the whole story. The robust predicting power of Δ*COMOVE* indicates that it may capture what people find unappealing about firm quality in a way that simple accounting measures of firm quality are too crude to do. More importantly, we again observe that the pricing power of Δ*COMOVE* goes up further in magnitude if we control for default anomalies in columns (8) and (9), with the ROE effect becoming significant. These results confirm our equity-level findings that the combination of Δ*COMOVE* and profitability-related variables constitutes the company's overall risk profile, which demands higher compensation for bearing additional risk in the equity market. Nevertheless, we fail to find evidence in the cross-section of ERP_f for some patterns observed in Table 8. We find that both VIX_E and $IVOL_E$ become economically and statistically significant in predicting subsequent ERP_f. We also observe a stronger pricing impact of the MAX effect, as well as its reversing impact on $IVOL_E$ in column (9). These results are consistent with the fact that stockholders benefit more from their access to unlimited upside potential, which is captured by firm-specific idiosyncratic risk levels and extreme positive returns within the previous month. In addition, column (8) shows that the $ILLIQ_E$ effect becomes insignificant when simultaneously controlling for distress-related variables, since distressed stocks typically exhibit higher illiquidity risk that demands greater compensation to hold compared to bonds issued by the same firm. Overall, the outcomes derived from the firm-level analysis largely confirm our portfolio-level findings. The magnitude of the $\Delta COMOVE$ effect, even after controlling for all variables, remains very similar to the one reported without controls. This reaffirms the strength and robustness of our measure as a potential predictor in both markets, which can hardly be mitigated by any of the control variables considered.

Table B1: Univariate Portfolios of Firm-specific Equity Risk Premium Sorted by *ΔCOMOVE*

For each month, quintile portfolios are formed by sorting firm-specific equity risk premium (ERP_f) based on the *ΔCOMOVE*, where quintile 1(5) portfolio with equities that generate ERP_f with the lowest (highest) *ΔCOMOVE* during the previous month. The *ΔCOMOVE* is the innovation of EWMA covariance between stock and bond returns issued by the same firm calculated using a minimum of 48 observations over the past 60 months. The second column reports the average *ΔCOMOVE* for each quintile, and the remaining columns present the average ERP_f and alphas for the equal-weighted and value-weighted portfolios separately. Following Fama and French (1993, 2005) and Hou, Xue, and Zhang (2015), $\alpha^P_{5,1}$ is the alpha relative to the excess stock market return (MKT_E), size (SMB_E), book-to-market (HML_E), momentum (MOM_E), and liquidity factors (LIQ); $\alpha^P_{5,2}$ is the alpha relative to MKT_E, SMB_E, HML_E, investment (I/A), and profitability factors (ROE); α^P_4 is the alpha relative to the MKT_E, SMB_E, I/A, and ROE factors; and α^E_7 is the alpha relative to the MKT_E, SMB_E, HML_E, MOM_E, LIQ, I/A, and ROE factors. The last row presents return and alpha differences between quintiles 1 and 5. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period is from September 2007 to December 2020.

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	*ΔCOMOVE*	R_P-R_f	$\alpha^P_{5,1}$	$\alpha^P_{5,2}$	α^P_4	α^P_7	R_P-R_f	$\alpha^P_{5,1}$	$\alpha^P_{5,2}$	α^P_4	α^P_7
1 [Low]	-0.07	0.64	-0.21	-0.05	-0.10	-0.21	0.65	-0.15	-0.10	-0.07	-0.14
		(1.40)	(-1.19)	(-0.29)	(-0.61)	(-1.24)	(1.52)	(-0.75)	(-0.51)	(-0.41)	(-0.70)
2	-0.02	0.50	-0.17	-0.17	-0.25	-0.18	0.58	-0.12	-0.12	-0.18	-0.15
		(1.28)	(-1.55)	(-1.55)	(-2.01)	(-1.64)	(1.59)	(-0.97)	(-0.88)	(-1.38)	(-1.18)
3	0.00	0.39	-0.20	-0.27	-0.34	-0.22	0.36	-0.19	-0.32	-0.39	-0.22
		(0.99)	(-1.88)	(-2.29)	(-2.45)	(-1.98)	(0.95)	(-1.49)	(-2.25)	(-2.35)	(-1.78)
4	0.01	0.25	-0.41	-0.44	-0.49	-0.45	0.18	-0.44	-0.52	-0.54	-0.47
		(0.73)	(-3.06)	(-3.26)	(-3.49)	(-3.34)	(0.56)	(-2.60)	(-3.00)	(-3.15)	(-2.77)
5 [High]	0.07	0.02	-0.67	-0.68	-0.76	-0.70	0.06	-0.61	-0.69	-0.74	-0.66
		(0.04)	(-4.47)	(-5.13)	(-5.27)	(-4.58)	(0.14)	(-3.13)	(-3.45)	(-3.72)	(-3.36)
5-1		-0.62	-0.46	-0.63	-0.65	-0.49	-0.59	-0.47	-0.59	-0.66	-0.52
[High-Low]		(-3.30)	(-2.41)	(-3.39)	(-3.46)	(-2.65)	(-2.37)	(-1.85)	(-2.37)	(-2.95)	(-2.06)

Table B2: Seven-factor Alphas of Firm-specific Equity Risk Premium Portfolio Sorted on *ΔCOMOVE*

This table reports seven-factor alphas (α_7^P) relative to the excess equity market return, equity size, book-to-market, momentum, liquidity, investment, and profitability factors, with robust Newey and West (1987) *t*-statistics in parentheses. The column "5–1" refers to the difference in α_7^P between quintile 5 and 1. For each month, we perform double sorts on ERP_f to control for various characteristics, which includes equity size ($SIZE_E$), book-to-market (B/M), equity momentum (MOM_E), equity short-term reversal (REV_E), I/A, ROE, default risk (DEFAULT), equity illiquidity ($ILLIQ_E$), dispersion in analysts' forecasts (DISPER), equity idiosyncratic volatility ($IVOL_E$), co-skewness (COSKEW), lottery demand (MAX), equity market beta (MKT_E), equity VIX beta (VIX_E), and equity uncertainty beta (UNC_E). For each month, we first sort ERP_f into five quintile portfolios based on one of the characteristics of the previous month. Within each characteristic quintile, we further sort ERP_f into five quintiles based on *ΔCOMOVE*. The five *ΔCOMOVE*-sorted portfolios are then averaged over each of the five characteristic portfolios, thus representing comovement quintile portfolios controlling for the characteristics. Details on the construction of these variables are summarized in the Panel A of Table 1. The sample period covers September 2007 to December 2020 for all controls. All portfolios are value weighted.

		Ranking on the *ΔCOMOVE*					
		1 [Low]	2	3	4	5 [High]	5-1 [High-Low]
(1)	$SIZE_E$	-0.34(-2.20)	-0.20(-1.81)	-0.44(-4.30)	-0.44(-3.44)	-0.76(-5.18)	-0.42(-2.65)
(2)	B/M	-0.25(-1.39)	-0.38(-2.97)	-0.19(-1.50)	-0.54(-3.46)	-0.70(-3.44)	-0.45(-2.04)
(3)	MOM_E	-0.24(-1.47)	-0.19(-1.36)	-0.35(-2.58)	-0.44(-2.75)	-0.79(-4.07)	-0.54(-3.07)
(4)	REV_E	-0.19(-0.96)	-0.28(-2.14)	-0.27(-2.00)	-0.51(-3.41)	-0.82(-4.59)	-0.63(-2.66)
(5)	I/A	-0.24(-1.21)	-0.33(-2.67)	-0.26(-2.13)	-0.48(-3.35)	-0.70(-3.63)	-0.46(-1.98)
(6)	ROE	-0.31(-1.74)	-0.24(-1.82)	-0.29(-2.58)	-0.57(-3.31)	-0.74(-3.71)	-0.43(-1.97)
(7)	DEFAULT	-0.31(-1.97)	-0.32(-2.55)	-0.34(-2.48)	-0.62(-3.57)	-0.67(-3.95)	-0.37(-1.78)
(8)	$ILLIQ_E$	-0.33(-2.12)	-0.32(-3.08)	-0.33(-2.87)	-0.41(-2.85)	-0.71(-4.70)	-0.38(-2.20)
(9)	DISPER	-0.31(-1.78)	-0.29(-2.05)	-0.30(-2.04)	-0.52(-2.95)	-0.67(-3.42)	-0.36(-1.60)
(10)	$IVOL_E$	-0.15(-0.95)	-0.45(-3.50)	-0.38(-2.62)	-0.59(-3.80)	-0.82(-4.55)	-0.67(-3.64)
(11)	COSKEW	-0.24(-1.29)	-0.10(-0.80)	-0.28(-2.13)	-0.52(-4.41)	-0.75(-3.76)	-0.51(-2.46)
(12)	MAX	-0.22(-1.19)	-0.44(-2.85)	-0.42(-2.71)	-0.64(-3.86)	-0.77(-4.30)	-0.55(-2.50)
(13)	MKT_E	-0.30(-1.81)	-0.40(-3.24)	-0.36(-2.65)	-0.54(-3.18)	-0.72(-3.71)	-0.43(-2.40)
(14)	VIX_E	-0.36(-2.09)	-0.17(-1.28)	-0.34(-2.86)	-0.51(-3.07)	-0.73(-4.21)	-0.37(-1.81)
(15)	UNC_E	-0.13(-0.71)	-0.33(-2.48)	-0.26(-2.27)	-0.56(-3.85)	-0.77(-4.24)	-0.64(-3.11)

Table B3: Premium-level Fama–Macbeth Cross-sectional Regressions

This table reports the time-series average of slope coefficients obtained from regressing monthly ERP_f on *ΔCOMOVE* while controlling for a set of lagged predictive variables using the Fama and MacBeth (1973) methodology. The control variables include equity market beta (MKT_E), equity size ($SIZE_E$), book-to-market (B/M), equity momentum (MOM_E), equity short-term reversal (REV_E), I/A, ROE, equity illiquidity ($ILLIQ_E$), dispersion in analysts' forecasts (DISPER), VIX beta (VIX_E), equity idiosyncratic volatility ($IVOL_E$), lottery demand (MAX), default risk (DEFAULT), co-skewness (COSKEW), and uncertainty beta (UNC_E). Newey and West (1987) adjusted *t*-statistics are reported in parentheses. The sample period is September 2007 to December 2020 for all controls. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

	(1) ERP_f	(2) ERP_f	(3) ERP_f	(4) ERP_f	(5) ERP_f	(6) ERP_f	(7) ERP_f	(8) ERP_f	(9) ERP_f
Intercept	0.250	0.042	0.047	-0.043	-0.136	-0.115	-0.118	-0.183	-0.125
	(0.67)	(0.10)	(0.11)	(-0.10)	(-0.32)	(-0.28)	(-0.29)	(-0.44)	(-0.30)
ΔCOMOVE	-0.315**	-0.223*	-0.222*	-0.221*	-0.233**	-0.249**	-0.262**	-0.291***	-0.296***
	(-2.18)	(-1.86)	(-1.86)	(-1.84)	(-2.08)	(-2.23)	(-2.42)	(-2.73)	(-2.79)
MKT_E		-0.028	-0.019	-0.016	-0.030	0.030	0.094	-0.075	-0.048
		(-0.16)	(-0.12)	(-0.10)	(-0.18)	(0.19)	(0.62)	(-0.42)	(-0.27)
$SIZE_E$		-0.110	-0.109	-0.078	-0.060	-0.096	-0.095	-0.123*	-0.118
		(-1.53)	(-1.49)	(-1.03)	(-0.85)	(-1.29)	(-1.29)	(-1.67)	(-1.63)
BM		-0.136**	-0.106	-0.108	-0.098	-0.095	-0.084	-0.054	-0.031
		(-2.47)	(-1.47)	(-1.51)	(-1.32)	(-1.29)	(-1.13)	(-0.86)	(-0.49)
MOM_E		-0.145	-0.146	-0.145	-0.162	-0.152	-0.129	-0.174	-0.115
		(-0.87)	(-0.88)	(-0.87)	(-0.96)	(-0.93)	(-0.81)	(-0.97)	(-0.68)
REV_E		-0.024	-0.034	-0.037	-0.048	-0.066	-0.070	-0.128	-0.104
		(-0.28)	(-0.40)	(-0.44)	(-0.56)	(-0.80)	(-0.87)	(-1.63)	(-1.35)
IA			-0.003	-0.000	-0.005	0.002	0.007	0.014	0.014
			(-0.05)	(-0.00)	(-0.11)	(0.05)	(0.15)	(0.31)	(0.30)
ROE			0.376	0.373	0.342	0.341	0.335	0.345*	0.424*
			(1.60)	(1.58)	(1.52)	(1.59)	(1.56)	(1.67)	(1.92)
$ILLIQ_E$				16.085*	29.972*	31.209*	34.171*	25.328	23.550
				(1.75)	(1.71)	(1.75)	(1.87)	(1.38)	(1.29)
DISPER					-0.078	0.026	0.089	0.052	0.055
					(-0.34)	(0.12)	(0.39)	(0.23)	(0.24)
VIX_E						-0.183*	-0.139	-0.115	-0.111
						(-1.97)	(-1.57)	(-1.37)	(-1.34)
$IVOL_E$						-0.144*	0.060	0.100	0.088
						(-1.82)	(0.51)	(0.89)	(0.78)
MAX							-0.420**	-0.481**	-0.458**
							(-2.21)	(-2.57)	(-2.36)
DEFAULT								-0.016	-0.025
								(-0.24)	(-0.37)
COSKEW								0.392**	0.389**
								(2.45)	(2.38)
UNC_E									-0.122
									(-1.36)
N	68365	63284	63052	63052	61494	61461	61461	61055	61055
R-sq	0.016	0.129	0.137	0.142	0.150	0.167	0.176	0.210	0.215

Appendix C

Table C1: Univariate Portfolio Analysis Based on $\Delta COMOVE_{24}$

For each month, quintile portfolios are formed by sorting securities based on the $\Delta COMOVE_{24}$, which is computed as the innovation of the EWMA covariance between stock and bond returns issued by the same firm using a minimum of 24 observations over the past 60 months. The second column reports the average value of $\Delta COMOVE_{24}$ for each quintile, and the remaining columns present the average excess returns and alphas for value-weighted portfolios. For equity returns, we report alphas relative to stock market factors including MKT_E, SMB_E, HML_E, MOM_E, LIQ, I/A, and ROE factors. For bond returns, we report alphas adjusted for both stock market factors and bond factors including MKT_B, DRF, CRF, and LRF factors. The last row presents return and alpha differences between quintile 1 and quintile 5. Newey and West (1987) *t*-statistics are given in parentheses. The sample period covers September 2007–December 2020.

Panel A: Univariate portfolio analysis on equity returns

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	$\Delta COMOVE_{24}$	R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7	R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7
1 [Low]	-0.07	1.44	0.41	0.58	0.56	0.42	1.43	0.46	0.58	0.64	0.49
		(2.53)	(2.26)	(3.12)	(2.99)	(2.52)	(3.02)	(2.15)	(2.85)	(3.37)	(2.33)
2	-0.02	1.16	0.36	0.37	0.32	0.37	1.21	0.37	0.40	0.38	0.36
		(2.60)	(3.03)	(3.02)	(2.46)	(3.11)	(3.24)	(3.25)	(3.77)	(3.52)	(3.14)
3	0.00	1.00	0.28	0.23	0.19	0.28	0.93	0.25	0.18	0.14	0.24
		(2.38)	(2.89)	(2.00)	(1.42)	(2.87)	(2.61)	(2.37)	(1.60)	(1.09)	(2.30)
4	0.01	0.79	0.03	-0.01	-0.06	0.01	0.68	-0.07	-0.12	-0.12	-0.09
		(1.96)	(0.34)	(-0.07)	(-0.45)	(0.14)	(2.05)	(-0.74)	(-1.15)	(-1.10)	(-0.88)
5 [High]	0.07	0.60	-0.22	-0.22	-0.31	-0.22	0.54	-0.28	-0.29	-0.35	-0.30
		(1.22)	(-1.55)	(-1.52)	(-1.84)	(-1.50)	(1.27)	(-1.84)	(-2.09)	(-2.42)	(-1.93)
5-1		-0.83	-0.63	-0.79	-0.88	-0.65	-0.89	-0.74	-0.86	-0.99	-0.79
[High-Low]		(-3.68)	(-2.63)	(-3.74)	(-3.69)	(-2.75)	(-3.08)	(-2.46)	(-3.00)	(-3.52)	(-2.60)

Panel B: Univariate portfolio analysis on bond returns

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	$\Delta COMOVE_{24}$	R_B-R_f	α^B_5	α^B_1	α^B_4	α^B_9	R_B-R_f	α^B_5	α^B_1	α^B_4	α^B_9
1 [Low]	-0.08	0.76	0.61	0.31	0.27	0.33	0.70	0.54	0.22	0.20	0.24
		(3.92)	(4.66)	(3.43)	(4.12)	(3.38)	(3.87)	(3.98)	(2.73)	(2.58)	(2.51)
2	-0.02	0.59	0.48	0.24	0.19	0.22	0.59	0.45	0.19	0.14	0.14
		(4.54)	(4.70)	(4.36)	(3.75)	(3.17)	(4.28)	(3.63)	(3.00)	(3.42)	(2.61)
3	0.00	0.55	0.45	0.21	0.16	0.18	0.53	0.41	0.16	0.12	0.13
		(4.75)	(4.48)	(3.66)	(2.84)	(2.89)	(4.51)	(3.71)	(2.49)	(2.36)	(2.08)
4	0.01	0.48	0.37	0.13	0.08	0.10	0.50	0.34	0.07	0.04	0.03
		(3.84)	(3.26)	(2.03)	(1.80)	(2.27)	(3.83)	(2.42)	(1.09)	(0.88)	(0.63)
5 [High]	0.08	0.51	0.38	0.03	-0.02	0.03	0.44	0.27	-0.10	-0.10	-0.08
		(2.95)	(2.77)	(0.23)	(-0.15)	(0.27)	(2.77)	(1.81)	(-0.90)	(-0.91)	(-0.75)
5-1		-0.25	-0.23	-0.29	-0.29	-0.30	-0.26	-0.27	-0.32	-0.30	-0.32
[High-Low]		(-2.94)	(-2.53)	(-2.48)	(-2.60)	(-3.02)	(-2.71)	(-2.34)	(-2.23)	(-2.21)	(-2.60)

Table C2: Univariate Portfolios Analysis Based on *ΔCOMOVE$_{new}$*

For each month, quintile portfolios are formed by sorting securities based on the *ΔCOMOVE$_{new}$*, which is computed as the innovation of the EWMA covariance between stock and bond returns issued by the same firm using a minimum of 48 observations over the past 60 months. It is based on a new dataset that contains all types of bonds with the same features as corporate bonds constructed following Bali et al. (2021b). The second column reports the average value of *ΔCOMOVE$_{new}$* for each quintile, and the remaining columns present the average excess returns and alphas for value-weighted portfolios. For equity returns, we report alphas relative to stock market factors including MKT_E, SMB_E, HML_E, MOM_E, LIQ, I/A, and ROE factors. For bond returns, we report alphas adjusted for both stock market factors and bond factors including MKT_B, DRF, CRF, and LRF factors. The last row presents return and alpha differences between quintile 1 and quintile 5. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2007–December 2020.

Panel A: Univariate portfolio analysis on equity returns

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	$\Delta COMOVE_{new}$	R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7	R_E-R_f	$\alpha^E_{5,1}$	$\alpha^E_{5,2}$	α^E_4	α^E_7
1 [Low]	-0.07	1.37	0.42	0.56	0.55	0.44	1.43	0.47	0.62	0.68	0.51
		(2.43)	(2.18)	(3.01)	(2.91)	(2.57)	(3.16)	(2.31)	(3.24)	(3.73)	(2.55)
2	-0.02	1.16	0.38	0.38	0.33	0.38	1.18	0.38	0.39	0.38	0.37
		(2.66)	(3.03)	(2.87)	(2.36)	(3.12)	(3.14)	(2.89)	(3.17)	(2.99)	(2.78)
3	0.00	1.03	0.34	0.28	0.23	0.33	0.93	0.27	0.20	0.14	0.26
		(2.65)	(3.33)	(2.66)	(1.69)	(3.39)	(2.81)	(2.12)	(1.54)	(0.92)	(2.03)
4	0.01	0.69	-0.07	-0.11	-0.16	-0.09	0.65	-0.09	-0.15	-0.15	-0.11
		(1.65)	(-0.70)	(-0.96)	(-1.15)	(-0.80)	(1.83)	(-0.89)	(-1.37)	(-1.35)	(-1.01)
5 [High]	0.07	0.43	-0.37	-0.36	-0.48	-0.36	0.45	-0.33	-0.36	-0.43	-0.34
		(0.90)	(-2.50)	(-2.60)	(-2.82)	(-2.41)	(1.11)	(-2.04)	(-2.31)	(-2.67)	(-2.10)
5-1		-0.94	-0.79	-0.93	-1.03	-0.81	-0.97	-0.80	-0.98	-1.11	-0.85
[High-Low]		(-3.79)	(-2.89)	(-3.73)	(-3.98)	(-3.00)	(-3.30)	(-2.60)	(-3.30)	(-3.87)	(-2.75)

Panel B: Univariate portfolio analysis on bond returns

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	$\Delta COMOVE_{new}$	R_B-R_f	α^B_5	α^B_1	α^B_4	α^B_9	R_B-R_f	α^B_5	α^B_1	α^B_4	α^B_9
1 [Low]	-0.07	0.73	0.55	0.25	0.24	0.29	0.67	0.50	0.19	0.18	0.22
		(3.88)	(4.34)	(3.15)	(3.58)	(3.20)	(3.87)	(3.71)	(2.66)	(2.49)	(2.44)
2	-0.02	0.59	0.46	0.21	0.18	0.19	0.58	0.43	0.18	0.14	0.13
		(4.59)	(4.30)	(4.57)	(3.75)	(3.26)	(4.31)	(3.51)	(2.96)	(3.42)	(2.59)
3	0.00	0.53	0.42	0.17	0.13	0.14	0.52	0.40	0.15	0.11	0.11
		(4.65)	(4.11)	(3.16)	(2.37)	(2.42)	(4.51)	(3.52)	(2.34)	(2.41)	(2.10)
4	0.01	0.50	0.37	0.12	0.08	0.09	0.51	0.34	0.07	0.05	0.03
		(4.16)	(3.20)	(2.14)	(1.62)	(1.62)	(3.95)	(2.53)	(1.12)	(0.97)	(0.60)
5 [High]	0.07	0.50	0.31	-0.03	-0.04	-0.02	0.43	0.25	-0.08	-0.09	-0.07
		(2.90)	(2.27)	(-0.27)	(-0.43)	(-0.18)	(2.80)	(1.73)	(-0.94)	(-0.96)	(-0.79)
5-1		-0.23	-0.25	-0.28	-0.28	-0.30	-0.24	-0.25	-0.28	-0.27	-0.29
[High-Low]		(-2.88)	(-2.59)	(-2.64)	(-2.83)	(-3.03)	(-2.72)	(-2.29)	(-2.29)	(-2.25)	(-2.45)

Table C3: Subperiod Univariate Portfolios of Bond Returns Sorted by *ΔCOMOVE*

For each month, we first sort our sample into two subperiod samples based on the median value of the CRE index (the difference between Moody's BAA and AAA corporate bond yield), VIX index (S&P 500 index option-implied volatility), and UNC index (economic uncertainty index proposed by Jurado et al. (2015)). Within each subgroup, we then sort equities (Panel A) and bonds (Panel B) into five quintile portfolios based on the *ΔCOMOVE*, where the quintile 1(5) portfolio contains bonds with the lowest (highest) *ΔCOMOVE* during the previous month. The *ΔCOMOVE* is the innovation of EWMA covariance between stock and bond returns issued by the same firm calculated using a minimum of 48 observations over the past 60 months. Portfolios are value-weighted using the prior month's equity market capitalization as weights. We report equity portfolio alphas in Panel A(B) for each quintile controlling for equity factors including MKT_E, SMB_E, HML_E, MOM_E, LIQ, I/A, and ROE following Hou et al. (2015), and a combination of five stock market factors and four bond market factors including MKT_B, DRF, CRF, and LRF factors following Bali et al. (2021b). The last row presents return and alpha differences between quintile 1 and quintile 5. Newey and West (1987) *t*-statistics are given in parentheses. The sample period covers September 2007–December 2020.

Panel A: Univariate portfolio analysis on equity returns

	CRE index		VIX index		UNC index	
Quintile	High	Low	High	Low	High	Low
1 [Low]	0.53	0.32	0.76	0.28	0.56	0.49
	(1.47)	(2.01)	(2.07)	(1.64)	(1.45)	(2.67)
2	0.56	0.11	0.49	0.10	0.58	0.02
	(2.87)	(0.78)	(1.89)	(0.72)	(2.84)	(0.12)
3	0.26	0.10	0.29	0.16	0.25	0.10
	(2.18)	(0.67)	(1.97)	(1.26)	(1.44)	(1.06)
4	-0.10	-0.24	0.17	-0.24	0.17	-0.45
	(-0.57)	(-1.70)	(0.93)	(-1.91)	(1.00)	(-2.68)
5 [High]	-0.62	0.01	-0.64	-0.07	-0.40	-0.11
	(-2.44)	(0.06)	(-2.20)	(-0.47)	(-1.51)	(-0.62)
5-1	-1.15	-0.31	-1.40	-0.36	-0.95	-0.60
[High-Low]	(-2.21)	(-1.25)	(-2.72)	(-1.38)	(-1.72)	(-2.11)

Panel B: Univariate portfolio analysis on bond returns

	CRE index		VIX index		UNC index	
Quintile	High	Low	High	Low	High	Low
1 [Low]	0.46	0.06	0.50	-0.02	0.43	0.04
	(3.04)	(1.45)	(3.41)	(-0.45)	(2.69)	(0.87)
2	0.31	0.07	0.28	0.04	0.25	0.04
	(4.11)	(2.94)	(3.27)	(1.77)	(2.66)	(1.33)
3	0.25	0.08	0.19	0.06	0.21	0.05
	(2.44)	(3.09)	(1.59)	(2.69)	(1.77)	(2.47)
4	0.08	0.07	0.08	0.01	0.08	-0.01
	(0.85)	(3.06)	(0.76)	(0.74)	(0.73)	(-0.47)
5 [High]	-0.08	0.01	-0.12	-0.02	-0.04	-0.07
	(-0.52)	(0.23)	(-0.67)	(-0.62)	(-0.20)	(-1.80)
5-1	-0.54	-0.05	-0.62	-0.00	-0.47	-0.10
[High-Low]	(-2.82)	(-0.55)	(-2.94)	(-0.01)	(-2.05)	(-2.00)

Table C4: Tercile Portfolios of Bond and Equity Returns Sorted by *ΔCOMOVE*

For each month, quintile portfolios are formed by sorting equities (Panel A) and bonds (Panel B) based on the *ΔCOMOVE*, where quintile 1(3) portfolio contains securities with the lowest (highest) *ΔCOMOVE* in the previous month. The *ΔCOMOVE* is the innovation of EWMA covariance between stock and bond returns issued by the same firm, which is calculated using a minimum of 48 observations over the past 60 months. The second column reports the average *ΔCOMOVE* for each quintile, and the remaining columns present the average equity and bond excess returns and alphas for the equal-weighted and value-weighted portfolios separately. For equity, following Fama and French (1992), Carhart (1997), and Hou et al. (2015), $\alpha^{E}_{5,1}$ is the alpha relative to the excess stock market return (MKT_E), size (SMB_E), book-to-market (HML_E), momentum (MOM_E), and liquidity (LIQ) factors; $\alpha^{E}_{5,2}$ is the alpha relative to MKT_E, SMB_E, HML_E, investment (I/A), and profitability factors (ROE); α^{E}_{4} is the alpha relative to the MKT_E, SMB_E, I/A, and ROE factors; and α^{E}_{7} is the alpha relative to the MKT_E, SMB_E, HML_E, MOM_E, LIQ, I/A, and ROE factors. For bond, following Bali et al. (2021b), α^{B}_{5} is the alpha relative to five stock market factors including the excess stock market return (MKT_E), equity size (SMB_E), book-to-market (HML_E), equity momentum (MOM_E), and equity liquidity factors (LIQ); α^{B}_{4} is the alpha relative to four bond market factors including excess bond market return (MKT_B), downside risk (DRF), credit risk (CRF), and liquidity risk factors (LRF); and α^{B}_{9} is the alpha relative to a combination of five stock market factors and four bond market factors. Following Dickerson et al. (2023), we also report α^{B}_{1} relative to MKT_B only to avoid data handling issue documented in their paper. The last row presents return and alpha differences between quintiles 1 and 3. All returns and alphas are denoted in percent per month. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2007–December 2020.

Panel A: Univariate portfolio analysis on equity returns

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	*ΔCOMOVE*	R_E-R_f	$\alpha^{E}_{5,1}$	$\alpha^{E}_{5,2}$	α^{E}_{4}	α^{E}_{7}	R_E-R_f	$\alpha^{E}_{5,1}$	$\alpha^{E}_{5,2}$	α^{E}_{4}	α^{E}_{7}
1 [Low]	-0.05	1.31	0.39	0.49	0.46	0.40	1.32	0.44	0.48	0.50	0.44
		(2.59)	(2.84)	(3.58)	(3.40)	(3.17)	(3.41)	(3.44)	(4.00)	(4.20)	(3.37)
2	0.00	0.96	0.26	0.20	0.15	0.25	0.95	0.25	0.21	0.18	0.24
		(2.35)	(2.94)	(2.00)	(1.15)	(2.94)	(2.80)	(2.66)	(2.09)	(1.72)	(2.53)
3 [High]	0.05	0.64	-0.17	-0.18	-0.25	-0.18	0.58	-0.18	-0.22	-0.26	-0.19
		(1.42)	(-1.46)	(-1.54)	(-1.74)	(-1.51)	(1.52)	(-1.62)	(-2.07)	(-2.30)	(-1.78)
3-1		-0.67	-0.55	-0.67	-0.71	-0.57	-0.73	-0.62	-0.69	-0.76	-0.63
[High-Low]		(-3.73)	(-2.95)	(-3.89)	(-3.89)	(-3.12)	(-3.87)	(-3.17)	(-3.84)	(-4.07)	(-3.24)

Panel B: Univariate portfolio analysis on bond returns

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	*ΔCOMOVE*	R_B-R_f	α^{B}_{5}	α^{B}_{1}	α^{B}_{4}	α^{B}_{9}	R_B-R_f	α^{B}_{5}	α^{B}_{1}	α^{B}_{4}	α^{B}_{9}
1 [Low]	-0.05	0.67	0.54	0.26	0.22	0.26	0.63	0.49	0.21	0.17	0.19
		(4.15)	(4.65)	(3.78)	(3.89)	(3.24)	(4.10)	(3.99)	(2.94)	(2.70)	(2.41)
2	0.00	0.54	0.43	0.19	0.14	0.16	0.52	0.40	0.14	0.09	0.10
		(4.48)	(4.19)	(3.44)	(2.78)	(2.88)	(4.27)	(3.37)	(2.36)	(2.62)	(2.27)
3 [High]	0.05	0.47	0.35	0.05	0.02	0.06	0.46	0.29	-0.03	-0.04	-0.04
		(3.32)	(3.02)	(0.65)	(0.27)	(0.84)	(3.25)	(2.03)	(-0.36)	(-0.53)	(-0.47)
3-1		-0.20	-0.19	-0.21	-0.20	-0.20	-0.17	-0.20	-0.23	-0.21	-0.23
[High-Low]		(-3.14)	(-2.72)	(-2.90)	(-3.11)	(-3.13)	(-2.57)	(-2.12)	(-2.36)	(-2.40)	(-2.68)

Table C5: Portfolios of Bond and Equity Returns Sorted by idiosyncratic *ΔCOMOVE*

This table reports average excess returns and alphas based on idiosyncratic component of *ΔCOMOVE*. In particular, we run the following regressions using a 60-month rolling window:

Equity: $\Delta COMOVE_t = \alpha_t + \beta_t MKT_{E,t} + \varepsilon_{E,t}$

Bond: $\Delta COMOVE_t = \alpha_t + \beta_t MKT_{B,t} + \varepsilon_{B,t}$

For each month, quintile portfolios are formed by sorting equities (Panel A) and bonds (Panel B) based on the $\varepsilon_{E,t}$ and $\varepsilon_{B,t}$ respectively, where quintile 1(5) portfolio contains securities with the lowest (highest) $\varepsilon_{E,t}$ or $\varepsilon_{B,t}$ in the previous month. The *ΔCOMOVE* is the innovation of EWMA covariance between stock and bond returns issued by the same firm, which is calculated using a minimum of 48 observations over the past 60 months. The second column reports the average *ΔCOMOVE* for each quintile, and the remaining columns present the average equity and bond excess returns and alphas for the equal-weighted and value-weighted portfolios separately. Factors employed are the same as in Table C4. The last row presents return and alpha differences between quintiles 1 and 5. All returns and alphas are denoted in percent per month. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2007–December 2020.

Panel A: Univariate portfolio analysis on equity returns

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	*ΔCOMOVE*	R_E-R_f	$\alpha^E_{5.1}$	$\alpha^E_{5.2}$	α^E_4	α^E_7	R_E-R_f	$\alpha^E_{5.1}$	$\alpha^E_{5.2}$	α^E_4	α^E_7
1 [Low]	-0.07	1.47	0.35	0.45	0.34	0.40	1.29	0.21	0.31	0.28	0.27
		(3.12)	(2.76)	(3.33)	(2.05)	(3.27)	(3.63)	(1.40)	(1.93)	(1.76)	(1.74)
2	-0.01	1.31	0.31	0.32	0.23	0.31	1.33	0.35	0.37	0.33	0.33
		(3.66)	(2.15)	(2.16)	(1.37)	(2.17)	(4.30)	(2.07)	(1.97)	(1.75)	(1.90)
3	0.00	1.08	0.11	0.10	0.02	0.10	1.13	0.15	0.11	0.06	0.13
		(3.31)	(0.79)	(0.66)	(0.11)	(0.70)	(4.27)	(1.13)	(0.85)	(0.39)	(0.98)
4	0.01	1.03	0.03	0.00	-0.08	0.02	0.87	-0.11	-0.15	-0.21	-0.13
		(3.22)	(0.25)	(-0.04)	(-0.47)	(0.15)	(3.22)	(-0.98)	(-1.41)	(-1.52)	(-1.22)
5 [High]	0.07	0.87	-0.26	-0.30	-0.42	-0.25	0.75	-0.34	-0.38	-0.44	-0.34
		(1.98)	(-1.93)	(-2.14)	(-2.30)	(-1.85)	(2.42)	(-2.52)	(-2.88)	(-3.09)	(-2.62)
5-1		-0.60	-0.60	-0.75	-0.76	-0.65	-0.54	-0.55	-0.69	-0.72	-0.61
[High-Low]		(-3.09)	(-3.64)	(-3.59)	(-3.29)	(-3.55)	(-2.45)	(-2.53)	(-2.95)	(-3.10)	(-2.64)

Panel B: Univariate portfolio analysis on bond returns

		Equal weighted					Value weighted				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile	*ΔCOMOVE*	R_B-R_f	α^B_5	α^B_1	α^B_4	α^B_9	R_B-R_f	α^B_5	α^B_1	α^B_4	α^B_9
1 [Low]	-0.07	0.6	0.41	0.17	0.14	0.15	0.55	0.36	0.11	0.09	0.08
		(3.70)	(3.08)	(1.98)	(2.57)	(2.90)	(3.48)	(2.64)	(1.41)	(1.44)	(1.60)
2	-0.01	0.46	0.33	0.11	0.06	0.07	0.48	0.33	0.10	0.07	0.06
		(3.90)	(2.85)	(2.44)	(1.57)	(1.95)	(3.61)	(2.58)	(1.39)	(2.24)	(1.83)
3	0.00	0.46	0.35	0.12	0.06	0.08	0.45	0.33	0.09	0.06	0.06
		(4.23)	(3.09)	(2.33)	(1.44)	(2.35)	(3.66)	(2.56)	(1.17)	(1.82)	(1.63)
4	0.01	0.43	0.32	0.09	0.05	0.08	0.43	0.31	0.06	0.03	0.05
		(4.01)	(2.79)	(1.79)	(1.23)	(2.31)	(3.43)	(2.38)	(0.79)	(1.30)	(1.58)
5 [High]	0.07	0.42	0.23	-0.11	-0.14	-0.09	0.36	0.17	-0.20	-0.22	-0.18
		(2.98)	(1.66)	(-1.06)	(-1.53)	(-1.76)	(2.46)	(1.15)	(-2.46)	(-2.35)	(-2.82)
5-1		-0.18	-0.18	-0.28	-0.28	-0.24	-0.19	-0.19	-0.31	-0.31	-0.26
[High-Low]		(-2.17)	(-2.66)	(-2.44)	(-2.45)	(-3.28)	(-2.26)	(-2.88)	(-2.40)	(-2.28)	(-3.15)

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