In Search of the Idiosyncratic Volatility Puzzle in the Corporate Bond Market*

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Abstract

We propose a novel measure of idiosyncratic risk for corporate bonds and find an insignificant relation between idiosyncratic risk and the cross-section of future bond returns, suggesting that institutional investors dominating the bond market hold well-diversified portfolios with a negligible exposure to bond-specific risk. We show that common idiosyncratic volatility (CIV) is priced in the cross-section of both equities and bonds. While the CIV premium remains significantly negative in the equity market after controlling for the long-established risk factors, it is explained in the bond market by the downside, credit, and liquidity risk factors of corporate bonds.

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1 Introduction

Assuming that assets are perfectly liquid (frictionless) and that investors have complete information, the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) indicates that firm-specific risk should not command a risk premium since investors can create well-diversified portfolios that have zero exposure to firm-specific risk. Alternatively, if investors do not hold a large number of assets in their portfolios thus cannot diversify firm-specific risk, then they care about total risk (Merton, 1987), that is, idiosyncratic risk will affect equilibrium asset prices and command a positive risk premium (Levy, 1978).

Empirically, the most widely-cited study on idiosyncratic risk, Ang, Hodrick, Xing, and Zhang (2006), demonstrates a negative relation between idiosyncratic volatility and future equity returns. This result is highly inconsistent with theoretical predictions and thus considered a puzzle. Several subsequent papers have proposed explanations for the idiosyncratic volatility (IVOL) puzzle based on liquidity (Bali and Cakici, 2008; Han and Lesmond, 2011), lottery demand (Bali, Cakici, and Whitelaw, 2011), short-term reversal (Fu, 2009; Huang et al., 2010), average variance beta (Chen and Petkova, 2012), and retail trading proportion (Han and Kumar, 2013). Hou and Loh (2016) evaluate existing explanations and find that many of them resolve less than 10% of the puzzle, though explanations based on investors' lottery preference show some promise in solving the IVOL puzzle in the equity market.

This paper is the first to propose a novel measure of idiosyncratic risk for corporate bonds and examine its relationship with future bond returns. We investigate the IVOL puzzle in the corporate bond market by testing the direction and significance of a cross-sectional relation between idiosyncratic volatility and expected bond returns. We form value-weighted univariate portfolios by sorting corporate bonds into quintiles based on their idiosyncratic volatility and find that the risk-adjusted return (alpha) spread between the highest and lowest idiosyncratic volatility quintiles is positive but economically and statistically insignificant: 0.25% per month (t-stat = 1.54). This result suggests that institutional investors that dominate the corporate bond market hold well-diversified portfolios with a negligible exposure to bond-specific risk so that idiosyncratic volatility does not command a significant risk premium in the corporate bond market.

One may wonder why the cross-sectional relation between idiosyncratic risk and corporate bond returns has so far not been examined, despite the vast literature investigating the role of idiosyncratic risk in the equity market. One obvious reason is the absence of a well-established and robust factor model for corporate bonds. Factors commonly used in the corporate bond literature are constructed from either stock-level data (such as the value and momentum factors) or aggregate macroeconomic variables (such as the default and term spreads), hence their predictive power is limited for bond-level returns.

Bai, Bali, and Wen (2019, hereafter BBW) examine existing factor models and find that they perform poorly in explaining the industry- and size/maturity-sorted portfolios of corporate bonds. BBW propose that it is crucial to rely on the prominent features of corporate bonds when constructing bond-implied risk factors to explain the cross-sectional variations in corporate bond returns. They introduce novel risk factors based on downside risk, credit risk, and liquidity risk of corporate bonds and show that these bond factors have significant risk premia and outperform all other models in the literature.

Inspired by BBW, we revisit the IVOL puzzle in the corporate bond market by proposing new measures of idiosyncratic and systematic risk of corporate bonds. Assembling a comprehensive dataset of 1.2 million bond return observations from January 1997 to December 2017, we conduct nonparametric portfolio analyses. For each bond and each month in our sample, we regress the monthly excess returns of corporate bonds on BBW's risk factors: the bond market excess return (MKT), downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF), using the past three years of monthly data. Idiosyncratic risk of an individual bond is measured by the residual variance of bond excess returns from the monthly time-series regressions. Accordingly, systematic risk of an individual bond is defined as the difference between total and residual variance, which is a function of the variance and covariance of the risk factors as well as bond exposures to the risk factors.

Confirming theoretical predictions, we find a significant and positive relationship between systematic risk and future bond returns.[1] Bonds in the highest systematic risk quintile generate 6.24% to 9.36% per annum higher return than bonds in the lowest systematic risk quintile, with the premium stemming from the superior performance of bonds with high systematic risk (long leg of the arbitrage portfolio). Such results remain robust after controlling for various bond characteristics simultaneously in Fama-MacBeth (1973) regressions. In contrast to systematic risk, idiosyncratic risk has no significant explanatory power. When comparing the relative performance of systematic and idiosyncratic risk in terms of their ability to explain the cross-sectional differences in future bond returns, we find that idiosyncratic risk becomes even weaker, both economically and statistically, after controlling for systematic risk, whereas systematic risk remains a significant determinant of the cross-sectional dispersion in bond returns after controlling for idiosyncratic risk.

Another contribution of this paper is to show that using a robust risk factor model is important in constructing systematic and idiosyncratic risk measures for corporate bonds. We consider three benchmark models in the literature and construct alternative measures of systematic and idiosyncratic risk. The first benchmark is the one-factor model of Elton et al. (1995) that relies on the aggregate corporate bond market portfolio (MKT). Second, we extend the one-factor model by including the term and default factors (TERM, DEF) used by Fama and French (1993) and Bessembinder et al. (2009). The third benchmark is the six-factor model of Chung, Wang, and Wu (2019) which extends the second benchmark (three-factor model) by adding the size, book-to-market, and market volatility factors (SMB, HML, ΔVIX).

We find that proxies of systematic risk generated by alternative factor models do not predict the cross-sectional variation in future bond returns, whereas proxies of idiosyncratic risk

[1] Koijen, Lustig, and Van Nieuwerburgh (2017) show that bond factors which predict future economic activity at business cycle horizons are priced in the cross-section of bond returns, highlighting the role of systematic risk in corporate bond returns.

from these models positively predict future bond returns. However, after accounting for bond exposures to the downside, credit, and liquidity risk factors of BBW, there is no significant link between idiosyncratic volatility and future bond returns.[2] These results indicate that the risk factors of BBW provide an accurate characterization of systematic risk in the corporate bond market. Thus, the BBW-based composite measure of systematic variance is a priced risk factor, whereas there is no IVOL puzzle in the corporate bond market.

Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) provide evidence of a strong co-movement of idiosyncratic volatility of individual stocks and show that volatility co-movement is a prominent feature of firm-level cash flows. They further develop a common idiosyncratic volatility (CIV) factor, and find that shocks to this common component of idiosyncratic volatility are priced in the cross-section of individual stocks. We supplement Herskovic et al. (2016) by showing that CIV of corporate bonds is also priced in the cross-section of corporate bond raw returns but is subsumed by BBW factors. The results in this paper and Herskovic et al. (2016) jointly suggest that idiosyncratic volatility of corporate bonds are mainly attributable to shocks to institutional investors' preferences or other sources of discount rate variation captured by broad risk measures of corporate bonds (downside, credit, and liquidity risk); whereas idiosyncratic volatility of stocks captures the volatility of persistent cash flow growth (in addition to the discount rate variations), which is difficult to be explained by conventional equity market factors.

Lastly, we examine the differences between the roles played by equity-specific and bond-specific measures of idiosyncratic risk in the cross-sectional pricing of equities versus bonds. To make a fair comparison, we employ the same decomposition methodology to construct idiosyncratic risk measures of individual stocks using the five-factor model of Fama and French (2015) and the four-factor model of Hou, Xue, and Zhang (2015). We find no evidence of a significant relation between systematic risk and future stock returns, but a strong negative

[2] Chung, Wang, and Wu (2019) find a significantly positive relation between idiosyncratic volatility and risk-adjusted returns since they use the Fama-French (2015) five-factor model to estimate the risk-adjusted returns (alphas) of corporate bonds. We are able to replicate their findings reported in their Table 6. However, when we use the risk factors of BBW, the alpha spread disappears in idiosyncratic volatility-sorted portfolios.

link exists between idiosyncratic volatility and future equity returns, consistent with Ang et al. (2006). These findings are in sharp contrast to those in the corporate bond market. We provide an explanation for these contradictory findings based on investor preferences and clienteles in the bond and equity markets.

According to the Flow of Funds report released by the Federal Reserve Board, corporate bonds are primarily held by institutional investors such as insurance companies, mutual funds, and pension funds, while a significant amount of equities is held by retail investors. As of 2018, retail investors own about 6% in the corporate bond market versus 37% in the equity market. Clearly, equities and bonds are mainly traded (or held) by markedly different groups of investors: retail vs. institutional investors with distinct risk appetites, preferences, and investment objectives. Thus, investor clientele can be a plausible cause of the different idiosyncratic risk-return relations in the bond and equity markets. Indeed, we find that in the equity market, the IVOL puzzle is more pronounced for stocks largely held by retail investors, whereas there is no significant relation between idiosyncratic volatility and future returns for stocks largely held by institutional investors. When we investigate the interaction between institutional ownership and idiosyncratic volatility for corporate bonds, we find that the idiosyncratic volatility effect is uniformly weak in the cross-section of corporate bonds, which does not differ in bonds with low vs. high institutional ownership. Hence, differing institutional (retail) investors' preferences and investment objectives can be a plausible explanation for the significance of systematic risk (idiosyncratic risk) in the bond (equity) market.

In the remainder of this paper, we introduce the data and variables in Section 2, examine the cross-sectional relation between idiosyncratic risk, systematic risk and future bond returns in Section 3, and test alternative measures of idiosyncratic risk in Section 4. Section 5 provides an explanation for the contradictory role of idiosyncratic risk in the cross-sectional pricing of equities versus bonds. Section 6 concludes the paper.

2 Data

2.1 Corporate bond returns

We compile corporate bond pricing data from the National Association of Insurance Commissioners database (NAIC) and the enhanced version of the Trade Reporting and Compliance Engine (TRACE) for the sample period from January 1994 to December 2017, with the TRACE data starting from July 2002. We then merge corporate bond pricing data with the Mergent fixed income securities database to obtain bond characteristics such as offering amount, offering date, maturity date, coupon rate, coupon type, interest payment frequency, bond type, bond rating, bond option features, and issuer information.

For bond pricing data, we adopt the filtering criteria proposed by Bai, Bali, and Wen (2019). Specifically, we remove bonds that (i) are not listed or traded in the U.S. public market, or not issued by U.S. companies; (ii) are structured notes, mortgage-backed, asset-backed, agency-backed, or equity-linked; (iii) are convertible; (iv) trade under \$5 or above \$1,000; (v) have floating coupon rates; and (vi) have less than one year to maturity. For intraday data, we also eliminate bond transactions that (vii) are labeled as when-issued, locked-in, or have special sales conditions; (viii) are canceled, and (ix) have a trading volume smaller than \$10,000. From the original intraday transaction records, we first calculate the daily clean price as the trading volume-weighted average of intraday prices to minimize the effect of bid-ask spreads in prices, following Bessembinder et al. (2009).

The corporate bond return in month-t is computed as

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

where $P_{i,t}$ is the end-of-month transaction price, $AI_{i,t}$ is accrued interest on the same day of bond prices, and $Coupon_{i,t}$ is the coupon payment in month t, if any. The end-of-month price refers to the last daily observation if there are multiple trading records in the last ten days of a given month. We denote $R_{i,t}$ as bond i's excess return, $R_{i,t} = r_{i,t} - r_{f,t}$, where $r_{f,t}$ is the risk-free rate proxied by the one-month Treasury bill rate.

2.2 Corporate bond and equity holdings

To investigate the clientele effect in the equity and bond markets, we also collect asset holding data. For equities holdings, we use the Thomson Reuters' institutional holdings (13F) database that covers all investment companies including banks, insurance companies, mutual funds, pension funds, university endowments, and other types of professional investment advisors for the sample period of 1980-2017. For bond holdings, we use the eMaxx data from Thomson Reuters that covers investment companies including insurance companies, mutual funds, and pension funds for the sample period of 2001-2017 (the earliest bond holding data starts from 2001). For each asset, equity or corporate bond, we aggregate the shares held by all investors provided in the data and label it as institutional ownership, *INST*.

2.3 Idiosyncratic and systematic risk of corporate bonds

For each month, we use a 36-month rolling window to estimate the monthly variance (total risk) of corporate bonds:

$$\sigma^2_{i,t} = \frac{1}{n-1}\sum_{t=1}^{n}(R_{i,t} - \overline{R}_i)^2, \tag{2}$$

where $R_{i,t} = r_{i,t} - r_{f,t}$ is the excess return on bond i in month t, $\bar{R}_i = \frac{\sum_{t=1}^{n} R_{i,t}}{n}$ is the sample average of excess returns over the past 36 months ($n = 36$), and $\sigma^2_{i,t}$ is the sample variance of monthly excess returns over the past 36 months.

After computing the total risk of each bond, we divide the total variance (σ^2_i) into its systematic and idiosyncratic components. Our objective is to investigate whether the systematic or idiosyncratic component has any predictive power on future corporate bond returns. We use the factor model of Bai, Bali, and Wen (2019) that introduces the downside risk, credit risk, and liquidity risk factors based on independently sorted bivariate portfolios of bond-level credit rating, value-at-risk, and illiquidity:[3]

$$R_{i,t} = \alpha_i + \beta_{1,i} \cdot MKT_t + \beta_{2,i} \cdot DRF_t + \beta_{3,i} \cdot CRF_t + \beta_{4,i} \cdot LRF_t + \epsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the excess return on bond i in month t. Total risk of bond i is measured by the variance of $R_{i,t}$, denoted by σ_i^2. Idiosyncratic (or residual) risk of bond i is proxied by the variance of $\epsilon_{i,t}$ in Eq. (3), denoted by $\sigma_{\epsilon,i}^2$. Systematic risk of bond i is defined as the difference between total and residual variance, $SR = \sigma_i^2 - \sigma_{\epsilon,i}^2$, and it is a function of the variance of the MKT, DRF, CRF, and LRF factors, the cross-covariances of the MKT, DRF, CRF, and LRF factors, and the exposures of the bond's excess returns to the MKT, DRF, CRF, and LRF factors (i.e., factor loadings). That is, systematic risk of bond i is attributable to the overall volatility of the four factors as well as the factors' cross-covariances.

2.4 Alternative factor models

We consider three different factor models to estimate the risk-adjusted returns (alphas) of corporate bond portfolios sorted by systematic risk and idiosyncratic risk, respectively.

The first one is the *5-factor model with equity market factors*, including the excess return on the market portfolio proxied by the value-weighted stock market index (MKT^{Stock}) in the Center for Research in Security Prices (CRSP), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM^{Stock}), and the liquidity risk factor (LIQ^{Stock}), following Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003).[4]

The second one is the *5-factor model with bond market factors*, including the aggregate

[3] DRF is the downside risk factor, defined as the value-weighted average return difference between the highest-VaR portfolio minus the lowest-VaR portfolio within each rating portfolio. CRF is the credit risk factor, defined as the value-weighted average return difference between the highest credit risk portfolio minus the lowest credit risk portfolio within each illiquidity portfolio. LRF is the liquidity risk factor, defined as the value-weighted average return difference between the highest illiquidity portfolio minus the lowest illiquidity portfolio within each rating portfolio.

[4] The factors MKT^{Stock} (excess market return), SMB (small minus big), HML (high minus low), MOM (winner minus loser), and LIQ (liquidity risk) are described in and obtained from Kenneth French's and Lubos Pastor's online data libraries: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ and http://faculty.chicagobooth.edu/lubos.pastor/research/.

corporate bond market (MKT), the default spread factor (DEF), the term spread factor (TERM), the bond liquidity factor (LIQ^{Bond}), and the bond momentum factor (MOM^{Bond}), following Fama and French (1993), Elton, Gruber, and Blake (1995), Lin, Wang, and Wu (2011), and Jostova et al. (2013). The excess bond market return (MKT) is proxied by the return of the Merrill Lynch Aggregate Bond Market Index in excess of the one-month T-bill rate.[5] Following Fama and French (1993), we define the default factor (DEF) as the difference between the return on a market portfolio of long-term corporate bonds (the composite portfolio on the corporate bond module from Ibbotson Associates) and the long-term government bond return, and we define the term factor (TERM) as the difference between the monthly long-term government bond return (from Ibbotson Associates) and the one-month Treasury bill rate. The bond momentum factor (MOM^{Bond}) is constructed from 5×5 bivariate portfolios of credit rating and bond momentum, defined as the cumulative returns over months from $t-7$ to $t-2$ (formation period). We construct the liquidity risk factor (LIQ^{Bond}) in line with Lin, Wang, and Wu (2011).

The third one is the *10-factor model* combining the five equity market factors and the five bond market factors described above.

2.5 Summary statistics

After applying the data filtering criteria in Section 2.1, our sample includes 22,231 bonds issued by 7,915 unique firms, for a total of 1,226,357 bond-month return observations covering the sample period from January 1997 to December 2017.[6] Panel A of Table 1 reports the time-series average of the cross-sectional bond return distribution and bond characteristics. Bonds in our sample have an average monthly return of 0.59%, an average rating of 8 (i.e.,

[5]We also consider alternative bond market proxies such as the Barclays Aggregate Bond Index and the value-weighted average returns of all corporate bonds in our sample. The results from these alternative bond market proxies are similar to those reported in our tables.

[6]Our key variables of interest – systematic and idiosyncratic risk – are estimated using monthly returns over the past 36 months. A bond is included in the risk calculations if it has at least 24 monthly return observations in the 36-month rolling window before the test month. Thus, the final sample size reduces from 1,226,357 to 715,612 bond-month return observations for the period January 1997 – December 2017.

BBB+), an average issue size of 419 million dollars, and an average time-to-maturity of 9.14 years. The sample consists of 75% investment-grade bonds and 25% high-yield bonds.[7]

Panel B of Table 1 presents the correlation matrix for the bond-level characteristics. Following Bai, Bali, and Wen (2019), our proxy for downside risk is the 5% Value-at-Risk (VaR), the second lowest monthly return observation over the past 36 months.[8] Following Bao, Pan, and Wang (2011), bond-level illiquidity is proxied by the autocovariance of daily bond price changes within each month. As shown in Panel B, systematic risk is positively associated with rating, maturity, downside risk, and bond-level illiquidity, with respective correlations of 0.334, 0.098, 0.545, and 0.084. These numbers indicate that bonds with higher credit risk, longer maturity (proxying for higher interest rate risk), higher downside risk, and lower liquidity have higher systematic risk. Bond size is negatively correlated with systematic risk, implying that smaller and illiquid bonds have higher systematic risk.

3 Systematic Risk vs. Idiosyncratic Risk in the Cross-Section of Corporate Bonds

In this section, we test whether the systematic or idiosyncratic component has a predictive power over future corporate bond returns.

3.1 The predictive power of systematic risk

We first test the significance of a cross-sectional relation between systematic risk and future bond returns using portfolio analysis. For each month from January 1997 to December 2017, we form value-weighted univariate portfolios by sorting corporate bonds into quintiles based on their systematic risk (SR), where quintile 1 contains bonds with the lowest SR and quintile

[7]We collect bond-level rating information from Mergent FISD historical ratings and assign a number to facilitate the analysis. Specifically, 1 refers to a AAA rating, 2 refers to AA+, ..., and 21 refers to CCC. Investment-grade bonds have ratings from 1 (AAA) to 10 (BBB-). Non-investment-grade bonds have ratings above 10. A larger number indicates higher credit risk or lower credit quality. We determine a bond's rating as the average of ratings provided by S&P and Moody's when both are available, or as the rating provided by one of the two rating agencies when only one rating is available.

[8]Following BBW, we multiply the original VaR measure by -1 so that a higher value is associated with higher downside risk for convenience of interpretation.

5 contains bonds with the highest SR. Table 2 shows, for each quintile, the average systematic risk of bonds, the next month average excess return, the 5-factor alpha from stock market factors, the 5-factor alpha from bond market factors, and the 10-factor alpha from both stock and bond market factors. The last six columns report the average bond characteristics for each quintile, including the bond market beta, illiquidity, downside risk, credit rating, time-to-maturity, and bond size. The last row displays the differences in the average returns and the alphas between quintile 5 and quintile 1. The average excess returns and alphas are defined in terms of monthly percentages. Newey-West (1987) adjusted t-statistics with six lags are reported in parentheses.

Moving from quintile 1 to quintile 5, the average excess return on the SR-sorted portfolios increases monotonically from 0.09% to 0.86% per month. This indicates a monthly average return difference of 0.78% between quintiles 5 and 1 with a Newey-West t-statistic of 2.64, implying that this positive return difference is economically and statistically significant. This result shows that corporate bonds in the highest SR quintile generate 9.36% per annum higher average return than bonds in the lowest SR quintile do.

In addition to the average excess returns, Table 2 presents the intercepts (alphas) from the regression of the quintile excess portfolio returns on a constant, the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the liquidity factor (LIQ) described in Section 2.4. The third column of Table 2 shows that, similar to the average excess returns, the 5-factor alpha from stock market factors also increases monotonically from 0.06% to 0.68% per month, moving from the low-SR to the high-SR quintile, indicating a positive and significant alpha spread of 0.62% per month (t-stat.= 2.76).

Beyond the well-known stock market factors, we also test whether the significant return difference between High-SR bonds and Low-SR bonds is explained by prominent bond market factors. Similar to our earlier findings from the average excess returns and the 5-factor alphas from stock market factors, the fourth column of Table 2 shows that, moving from the low-

SR to the high-SR quintile, the 5-factor alpha from bond market factors increases almost monotonically from 0.02% to 0.59% per month. The corresponding 5-factor alpha spread between quintiles 5 and 1 is positive and highly significant: 0.58% per month with a t-statistic of 2.65. The fifth column of Table 2 presents the 10-factor alpha for each quintile from the combined five stock and five bond market factors. Consistent with our earlier results, the 10-factor alpha is 0.52% per month with a t-statistic of 2.59. Overall, these results indicate that the commonly used stock and bond market factors do not explain the significantly positive systematic risk premium in the corporate bond market.

Next, we investigate the source of the significant risk-adjusted return (alpha) spread between the high- and low-SR bonds. As reported in Table 2, the 10-factor alpha in quintile 1 (low-SR bonds) is insignificant, whereas the 10-factor alpha in quintile 5 (high-SR bonds) is positive and highly significant. Hence, we conclude that the significantly positive alpha spread between the high- and low-SR bonds is due to the outperformance by high-SR bonds (long leg of the arbitrage portfolio), but not due to the underperformance by low-SR bonds (short leg of the arbitrage portfolio).[9]

Finally, we examine the average characteristics of SR-sorted bond portfolios. As shown in the last six columns of Table 2, high-SR bonds have higher bond market beta, lower liquidity, higher downside risk, lower credit quality, and longer maturity. These results suggest a risk-based explanation for the outperformance of bonds with higher systematic risk.

3.2 Is there an IVOL puzzle in the corporate bond market?

In sharp contrast to the findings in Table 2, Table 3 presents evidence for the poor performance of idiosyncratic risk (IR) in predicting the cross-sectional variation in future bond returns. Compared to Table 2, the average return spread between quintiles 5 and 1 in Table 3 is

[9]In Table A.1 of the online appendix, we test the significance of a cross-sectional relation between total risk (volatility) and future bond returns. Similar to our findings in Table 2 for SR-sorted portfolios, Table A.1 shows that the average return and alpha spreads between high-VOL and low-VOL quintiles are positive and highly significant and the significantly positive alpha spread is driven by the outperformance of high-volatility bonds, but not due to the underperformance of low-volatility bonds.

much weaker economically: 0.49% per month (t-stat. $= 3.27$). More importantly, the 10-factor alpha spread between the high-IR and low-IR quintiles is economically and statistically insignificant at 0.25% per month (t-stat. $= 1.54$). These results show that the standard equity and bond market factors explain the average return spread in idiosyncratic volatility-sorted portfolios.

As discussed earlier, corporate bonds are primarily held by institutional investors such as insurance companies, mutual funds, and pension funds. The insignificant 10-factor alpha spread in Table 3 suggests that institutional investors in the corporate bond market are able to create well-diversified portfolios with a small exposure to bond-specific risk so that idiosyncratic volatility does not command a significant risk premium in the bond market. Since institutional investors do not demand compensation for not being able to diversify firm-specific risk, there is no significantly positive link between idiosyncratic risk and the cross-section of future bond returns, consistent with the theoretical models of Levy (1978) and Merton (1987). Thus, we conclude that there is no IVOL puzzle in the corporate bond market.

3.3 Bivariate portfolios of systematic risk and idiosyncratic risk

In this section, we investigate the predictive power of systematic and idiosyncratic risk measures while accounting for the interaction between them. Specifically, we perform a bivariate portfolio analysis for systematic risk by controlling for idiosyncratic risk, and then we conduct the same test for idiosyncratic risk while controlling for systematic risk.

3.3.1 Bivariate portfolios of systematic risk controlling for idiosyncratic risk

We first test whether the positive relation between systematic risk and future bond returns remains significant after controlling for idiosyncratic risk. To perform this test, we form quintile portfolios every month from January 1997 to December 2017 by first sorting corporate bonds into five quintiles based on their idiosyncratic risk. Then, within each IR-sorted portfolio, bonds are further sorted into five sub-quintiles based on their systematic risk. This methodology produces sub-quintile bond portfolios with dispersion in SR but nearly identical IR values under each IR-sorted quintile. SR,1 represents the lowest SR-ranked bond quintiles within each of the five IR-ranked quintiles. Similarly, SR,5 represents the highest SR-ranked quintiles within each of the five IR-ranked quintiles. Panel A of Table 4 shows the average systematic risk and the next month average return for each quintile. Moving from portfolio SR,1 to SR,5, the average return increases almost monotonically from 0.30% to 1.00% per month. The average return difference between portfolio SR,5 and SR,1 (i.e., high-SR bonds versus low-SR bonds) is 0.70% per month with a t-statistic of 2.80, indicating that the positive relation between systematic risk and future bond returns remains significant after controlling for idiosyncratic risk.

We also check whether this significant return spread between portfolio SR,5 and portfolio SR,1 is explained by long-established equity and bond market factors. The 5-factor stock, 5-factor bond, and 10-factor alpha spreads are all positive at 0.62%, 0.46%, and 0.43% per month, and statistically significant. Thus, first controlling for idiosyncratic risk and then controlling for stock and bond market factors, the risk-adjusted return spread between the high-SR and low-SR bonds remains positive and significant.

3.3.2 Bivariate portfolios of idiosyncratic risk controlling for systematic risk

We now investigate the relation between idiosyncratic risk and future bond returns after controlling for systematic risk. To perform this test, we reverse the engineering in the above subsection and sort corporate bonds first by SR then by IR within each SR-sorted portfolio. In Table 4, Panel B shows that the average return spread between portfolio IR,5 and IR,1 is positive but economically small, at 0.18% per month, and statistically insignificant with a t-statistic of 1.29, indicating that the significant relation between idiosyncratic risk and future raw returns disappears after controlling for systematic risk. In addition, the differences in the 5-factor stock, 5-factor bond, and 10-factor alphas are all economically small and statistically insignificant. Overall, the bivariate portfolio analyses indicate that compared to idiosyncratic risk, the composite measure of systematic risk is a more powerful determinant of the cross-sectional variation in corporate bond returns.

3.4 Investment-grade vs. non-investment-grade bonds

We now examine whether the main findings would change for the subsample of bonds with different credit quality. We repeat the analysis in Sections 3.1 and 3.2 separately for bonds with investment-grade and non-investment-grade ratings.

After conditioning on credit ratings, the return and alpha spreads between the high- and low-SR portfolios are 0.42% and 0.27% per month, respectively, and are statistically significant for investment-grade bonds, as shown in Table 5. The systematic risk premia are economically larger for non-investment-grade bonds: 0.96% and 0.88% per month, respectively. In contrast to the findings on systematic risk, the alpha spreads between the high- and low-IR portfolios are small and insignificant for both investment-grade bonds (−0.08% per month with *t*-stat. = −0.85) and non-investment-grade bonds (0.20% per month with *t*-stat. = 0.57).

These results indicate that idiosyncratic volatility does not command a risk premium for corporate bonds, regardless of their credit ratings. Meanwhile, there is a significant and positive relation between systematic risk and future bond returns, which is in particular stronger for non-investment-grade bonds.

3.5 Fama-MacBeth cross-sectional regressions

We have so far tested the significance of systematic and idiosyncratic risk measures as determinants of the cross-section of future bond returns at the portfolio level. To examine their impact simultaneously, we use Fama and MacBeth (1973) regressions and control for other risk characteristics including the bond market beta, default beta, term beta, bond-level illiquidity, credit rating, year-to-maturity, bond amount outstanding, and lagged bond return.[10]

[10]The bond market beta (β^{MKT}), default beta (β^{DEF}), and term beta (β^{TERM}) are the risk exposures to the aggregate bond market factor, the default factor, and the term factor obtained from a 36-month rolling

Monthly cross-sectional regressions are run for the following specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot SR_{i,t} + \lambda_{2,t} \cdot IR_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{k,t} + \varepsilon_{i,t+1}, \tag{4}$$

where $R_{i,t+1}$ is the excess return on bond i in month $t+1$.

Table 6 reports the time series average of the intercept, slope coefficients (λ's), and the adjusted R^2 values over the 252 months from January 1997 to December 2017. The univariate regression results confirm those in portfolio analysis. In Regression (1), the average slope, $\lambda_{1,t}$, from the monthly regressions of excess returns on SR alone is 2.166 with a t-statistic of 4.61. The economic magnitude of the associated effect is similar to that documented in Table 2. The spread in average SR between low-SR and high-SR portfolios is approximately 0.43%, and multiplying this spread by the average slope of 2.166 produces an estimated monthly return difference of 93 basis points.[11] Similarly, the estimate of idiosyncratic risk premium, $\lambda_{2,t}$, is positive and significant in univariate regression (2), consistent with the significantly positive raw return spread reported in Table 3. When including both SR and IR in regression (3), systematic risk premium remains, while idiosyncratic risk premium disappears.

After controlling various bond characteristics in regressions (4)−(6), the results remain robust that there is no premium for idiosyncratic risk, but a significantly positive premium for systematic risk. These results show that the composite measure of systematic risk has distinct information beyond bond size, maturity, rating, liquidity, market risk, and default risk, and that it is a strong and robust predictor of future bond returns.

Our findings are consistent with theoretical predictions. We attribute the alignment to the fact that we construct an economically sensible measure of systematic risk not only because we choose robust risk factors that capture common variation in corporate bond returns, but also because of the way we synthesize information over these factors. Our systematic risk measure

window estimation.

[11] Note that the ordinary least squares (OLS) methodology used in the Fama-MacBeth regressions gives an equal weight to each cross-sectional observation so that the regression results are more aligned with the equal-weighted portfolios. That is why the economic significance of SR obtained from Fama-MacBeth regressions, 0.93% per month, is somewhat higher than the 0.78% per month obtained from the value-weighted portfolios (see Table 2).

is a function that synthesizes the variance of the underlying factors, the cross-covariances of the factors, and the exposures of bond returns to the factors. Motivated by the fact that downside risk, credit risk, and liquidity risk jointly play an important role in determining expected bond returns, one needs a comprehensive measure that can integrate the covariances of these risk factors as well as their own variances. Thus, the conventional measure, such as the market beta, is not sufficient to capture the broad systematic risk in the corporate bond market.

To investigate the source of systematic risk, we test whether exposures of corporate bonds to the DRF, CRF, and LRF factors can predict the cross-sectional variations in future bond returns. Specifically, for each bond and each month in our sample, we estimate the factor betas from the monthly rolling regressions of excess bond returns on the DRF, CRF, and LRF factors over a 36-month rolling window after controlling for the bond market factor. Then, we examine the cross-sectional relation between β^{DRF}, β^{CRF}, and β^{LRF} and expected returns at the bond level using Fama and MacBeth (1973) regressions. Consistent with the findings in Bai, Bali, and Wen (2019), Table A.2 of the online appendix shows that the cross-sectional relations between future bond returns and three factor betas (β^{DRF}, β^{CRF}, β^{LRF}) are positive and highly significant. Thus, we conclude that not just the variances and cross-covariances of the factors, but the significant factor loadings also contribute to the predictive power of systematic risk in explaining the cross-sectional dispersion in future bond returns.[12]

4 Alternative Measures of Systematic and Idiosyncratic Risk

In this section, we utilize alternative factor models to generate systematic and idiosyncratic risk of corporate bonds. We show that measures of systematic risk estimated with these

[12]Once we establish the fact that systematic risk plays a significant role in the cross-sectional pricing of corporate bonds, we examine the time-series predictive power of aggregate systematic risk in forecasting bond market returns and volatility. Table A.3 of the online appendix presents a significantly positive time-series relation between aggregate systematic risk and future returns on the aggregate bond market portfolio, indicating a positive intertemporal risk-return tradeoff in the corporate bond market. We also construct a systematic risk factor based on the independently sorted bivariate portfolios of credit rating and systematic risk, and show in Section A.1 of the online appendix that the systematic risk factor earns a positive price of risk in the cross-section of corporate bonds.

alternative factor models do not predict the cross-sectional bond returns, whereas measures of idiosyncratic risk from these models positively and significantly predict future bond returns, though this positive relation is fully explained by the DRF, CRF, and LRF factors of Bai, Bali, and Wen (2019). That is, after accounting for bond exposures to the downside, credit, and liquidity risk factors, there is no significant link between idiosyncratic volatility and future bond returns.

We construct risk measures based on three following benchmark factor models in comparison to our measures described in Section 2.3:

1. One-factor model of Elton, Gruber, and Blake (1995):
$$R_{i,t} = \alpha_i + \beta_{1,i} MKT_t + \epsilon_{i,t}. \tag{5}$$
2. Three-factor model of Fama and French (1993), Elton, Gruber, and Blake (1995), and Bessembinder et al. (2009):
$$R_{i,t} = \alpha_i + \beta_{1,i} MKT_t + \beta_{2,i} DEF_t + \beta_{3,i} TERM_t + \epsilon_{i,t}. \tag{6}$$
3. Six-factor model of Chung, Wang, and Wu (2019):
$$R_{i,t} = \alpha_i + \beta_{1,i} MKT_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} DEF_t + \beta_{5,i} TERM_t + \beta_{6,i} \Delta VIX_t + \epsilon_{i,t}. \tag{7}$$

In the above factor models, $R_{i,t}$ is the excess return of bond i in month t, MKT_t is the corporate bond market excess return, SMB_t, HML_t, and ΔVIX_t denote the size factor, the book-to-market factor, and the market volatility factor in the stock market, and DEF_t and $TERM_t$ denote the default factor and the term factor.The total risk of bond i is measured by the variance of $R_{i,t}$, denoted by σ_i^2. Idiosyncratic risk of bond i is proxied with the variance of $\epsilon_{i,t}$, denoted by $\sigma_{\epsilon,i}^2$. Consistent with our original measure of systematic risk, we define systematic risk of bond i as the difference between total and residual variance, $SR = \sigma_i^2 - \sigma_{\epsilon,i}^2$, which is a function combining the variance of the factors, their cross-covariances, and the exposures of the bond's excess returns to the factors.

Table 7 presents the portfolio-level results of systematic and idiosyncratic risk based on the above factor models. Panel A shows that, for all alternative measures of systematic risk, there is no significant relation between systematic risk and the cross-section of future bond returns. Specifically, the average return spreads between the high- and low-SR portfolios are positive but insignificant. Similarly, the 10-factor and the BBW alpha spreads are economically small and insignificant, ranging from -0.24% to 0.21% per month. These results are in sharp contrast to our findings in Table 2, which demonstrates a significant and positive link between SR and future bond returns using the SR measure based on the BBW four-factor model.

The findings for IR-sorted portfolios are the opposite. Panel B shows that the average return spreads between the high- and low-IR portfolios are economically and statistically significant, ranging from 0.70% to 0.79% per month. Also, the 10-factor alpha spreads are significant for all three IR measures based on Eqs.(5)−(7). However, the positive return spreads are fully explained by the BBW four-factor model. Specifically, the BBW alpha spreads between the high- and low-IR portfolios are small and insignificant, ranging from 0.08% (t-stat. = 0.45) to 0.14% (t-stat. = 0.77) per month. Overall, Table 7 highlights the importance of the downside risk, credit risk, and liquidity risk factors of BBW in defining systematic risk of corporate bonds.

5 Bond Exposure to Common Idiosyncratic Volatility Factor

Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) provide evidence that firm-specific idiosyncratic volatilities are integrated and the exposure to CIV shocks (CIV-beta) is priced in the cross-section of individual stocks, that is, stocks with high (low) CIV-beta generate low (high) expected returns. This is because stocks that tend to gain value with an increase in CIV are valuable hedges to increases in households' marginal utility thus generate lower average returns.[13]

[13] Herskovic et al. (2016) introduce a heterogeneous agent model with incomplete markets that supports their empirical findings. In the model, households' consumption risk takes over the same factor structure of the idiosyncratic cash flow risk of firms and hence common fluctuations in idiosyncratic risk enter the pricing kernel of households and, as a result, CIV is a priced state variable in the model.

5.1 CIV-beta sorted portfolios of individual stocks

In this section, we confirm the main empirical findings of Herskovic et al. (2016) for individual stocks based on the extended sample period of July 1963−December 2017 and using factor models developed by Fama and French (2015) and Hou, Xue, and Zhang (2015). Specifically, we show that stocks with more negative CIV exposure carry economically and significantly higher returns than stocks with less negative or positive exposure. This result remains strong after controlling for the equity market, size, value, profitability, and investment factors, as well as stock exposure to the market variance shocks.

Table 8 presents results from the value-weighted quintile portfolios of stocks sorted by their CIV-beta. Panel A shows that moving from quintile 1 to quintile 5, the average excess stock return on the CIV-beta portfolios decreases from 0.78% to 0.26% per month. This result indicates that stocks in the lowest CIV-beta quintile generate 6.36% per annum higher return than stocks in the highest CIV-beta quintile. Adjusting for the 5-factor model in Fama and French (2015) and the Q-factor model Hou, Xue, and Zhang (2015), the alpha spread is significant at −0.32% (t-stat. = −2.51) and −0.37% (t-stat. = −2.60), respectively. Overall, our results indicate a significantly negative CIV risk premium in the cross-section of individual stocks, consistent with the findings of Herskovic et al. (2016).[14]

5.2 CIV-beta sorted portfolios of corporate bonds

Motivated by Herskovic et al. (2016), we test whether bond exposures to CIV changes in the bond market are priced in the cross-section of corporate bonds. Following their methodology, we first calculate monthly realized variance of the corporate bond market using daily returns on the aggregate bond market index. Second, we estimate monthly idiosyncratic variance of

[14] Herskovic et al. (2016) use the three-factor model of Fama-French (1993) with the market, size (SMB), and value (HML) factors when calculating the risk-adjusted return (alpha) of long-short portfolios of stocks sorted by CIV-beta. Panel A of Table 8 shows that an additional control of the investment and profitability factors of Fama and French (2015) and Hou, Xue, and Zhang (2015) in the estimation of the alpha on CIV-beta sorted portfolios does not affect the significantly negative relation between CIV-beta and future stock returns, providing further evidence for the robustness of the common idiosyncratic volatility risk premium in the equity market.

corporate bonds in TRACE using daily bond returns in a month.[15] Third, we calculate the CIV factor in the bond market as the equal-weighted average of the monthly idiosyncratic variances across all corporate bonds. Fourth, we construct CIV shocks as monthly changes in the bond CIV factor. Finally, for each month from July 2002 to December 2017, we regress monthly individual bond excess returns on monthly CIV shocks using a rolling estimation window with 24 to 36 months of data (as available), controlling for changes in the corporate bond market volatility. A bond's exposure to the CIV shock in the aforementioned rolling regressions is referred to as the bond's CIV-beta.

Next, we test the significance of a cross-sectional relation between CIV-beta and future returns on corporate bonds using portfolio analysis. For each month from July 2004 to December 2017, we form the value-weighted univariate portfolios by sorting corporate bonds into quintiles based on their CIV-beta, where quintile 1 contains bonds with the lowest CIV-beta and quintile 5 contains bonds with the highest CIV-beta.

Consistent with the findings in the equity market, Panel B of Table 8 shows that bonds with more negative exposure to CIV innovations earn higher future returns. The average return spread between quintiles 5 and 1 is -0.57% per month and highly significant, both economically and statistically. Also, the return spread cannot be explained by the 10-factor model which combines five stock market factors and five bond market factors; the 10-factor alpha spread is economically large at -0.51% per month and highly significant with a t-statistic of -2.94.[16] However, the negative return spread on CIV-sorted portfolios of corporate bonds is explained by the BBW 4-factor model. Specifically, the BBW alpha spread between the high- and low-CIV-beta portfolios is economically small and statistically insignificant; -0.10% per month (t-stat. $= -1.06$).

[15] For each bond in TRACE and for each month from July 2002 to December 2017, we estimate daily market model regressions of individual bond excess returns on the aggregate excess bond market returns. Monthly idiosyncratic volatility of a corporate bond is defined as the variance of the daily residuals in a month from the aforementioned market model regressions.

[16] Herskovic et al. (2016) use monthly returns on four investment-grade portfolios (AAA, AA, A, and BBB) for the period January 1980 – December 2010 and estimate the common idiosyncratic volatility risk premium for the combined portfolio of the ten size, ten value, and four corporate bond portfolios. They find that CIV is priced with a significantly negative risk premium, whereas the equity market volatility is not.

Finally, given that the CIV factor of corporate bonds and stocks could manifest itself via uncertainty in cash flows and/or discount rates, we apply the return decomposition framework of Campbell (1991) and Vuolteenaho (2002) to bond and stock returns separately. Specifically, we calculate unexpected returns and discount rate news ($e_{DR,t}$), and then back out residual cash flow news ($e_{CF,t}$) as the difference between unexpected returns and discount rate news through the panel VAR process. We then regress the CIV factor of corporate bonds (stocks) on the associated variations in cash flows and discount rate news of bonds (stocks). For corporate bond CIV-factor, we find that the coefficient on the variance of discount rate news is positve and significant at 0.32 (t-stat. $= 3.25$), whereas the coefficient on the variance of cash flow news is statistically insignificant. In sharp contrast, for the stock CIV-factor, the coefficients on both discount rate and cash flow news have significantly positive loadings, 0.27 (t-stat. $= 2.71$) and 0.40 (t-stat. $= 2.43$), respectively, indicating that both the uncertainty in cash flows and the uncertainty in discount rates play a role in explaining the stock CIV-factor.

Overall, we find that common idiosyncratic volatility is priced in the cross-section of corporate bond raw returns but is subsumed by the downside risk, credit risk, and liquidity risk factors of BBW. Thus, the results presented in this paper and Herskovic et al. (2016) jointly suggest that idiosyncratic volatility of corporate bonds are to a great extent attributable to shocks to institutional investors' preferences or other sources of discount rate variation largely captured by the liquidity, credit quality, and distributional characteristics of corporate bonds; whereas idiosyncratic volatility of stocks largely measure the volatility of persistent cash flow growth (in addition to the discount rate variations), which is difficult to be captured by traditional equity market factors.

6 Investigating the Role of Systematic and Idiosyncratic Risk in the Bond and Equity Markets

In this section, we examine the different roles played by systematic and idiosyncratic risk in the cross-sectional pricing of equities versus bonds. First, we propose a similar measure of systematic risk for individual stocks and revisit the IVOL puzzle in the equity market. Then, we explore the impact of investor clientele on the predictive power of idiosyncratic risk for future stock and bond returns.

6.1 Revisiting the IVOL puzzle in the equity market

Our composite measure of systematic risk for corporate bonds is a function of the variance of the underlying bond factors, the cross-covariances of the factors, and the bond exposures to these factors. Thus, the key input to construct a sound measure of systematic risk is to use economically sensible risk factors that capture common return variation in corporate bonds and that provide an accurate characterization of firm fundamentals.

In this section, we propose a similar comprehensive measure of systematic risk for individual stocks using the powerful equity factor models proposed by Fama and French (2015) and Hou, Xue, and Zhang (2015). Specifically, we construct a composite measure of systematic risk for individual stocks based on the five-factor model of Fama and French (2015) in Eq. (8) and the four-factor model of Hou, Xue, and Zhang (2015) in Eq. (9):

$$R_{i,d} = \alpha_i + \beta_{1,i} \cdot MKT_d^{Stock} + \beta_{2,i} \cdot SMB_d + \beta_{3,i} \cdot HML_d + \beta_{4,i} \cdot RMW_d + \beta_{5,i} \cdot CMA_d + \epsilon_{i,d}, \quad (8)$$

$$R_{i,d} = \alpha_i + \beta_{1,i} \cdot MKT_d^{Stock} + \beta_{2,i} \cdot ME_{Q,d} + \beta_{3,i} \cdot ROE_{Q,d} + \beta_{4,i} \cdot IA_{Q,d} + \epsilon_{i,d}. \quad (9)$$

where $R_{i,d}$ is the excess return of stock i on day d, and MKT_d^{Stock}, SMB_d, HML_d, RMW_d, and CMA_d in Eq. (8) are the daily equity market, size, book-to-market, profitability, and investment factors of Fama and French (2015). In Eq. (9), $ME_{Q,d}$, $ROE_{Q,d}$, and $IA_{Q,d}$ are the daily size, profitability, and investment Q factors of Hou, Xue, and Zhang (2015), respectively.[17]

[17] The MKT, SMB, HML, RMW, and CMA factors of Fama-French (2015) are obtained from the data library of Ken French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/) for the longest sample period from July 1963 to December 2017. The Q factors (ME_Q, ROE_Q, and IA_Q) are obtained from the authors of Hou, Xue, and Zhang (2015) for the longest sample period from January 1967 to December 2017.

The total risk of stock i is measured by the variance of $R_{i,d}$ (σ_i^2), calculated as the sum of squared daily returns in a month. Idiosyncratic risk is measured by the variance of $\epsilon_{i,d}$ ($\sigma_{\epsilon,i}^2$).[18] Systematic risk of stock i is defined as the difference between the total and residual variance, $SR = \sigma_i^2 - \sigma_{\epsilon,i}^2$. Following Ang et al. (2006) and subsequent work on idiosyncratic volatility in the equity market, Eqs. (8) and (9) are estimated using daily returns over the past month, requiring at least 15 daily return observations in a month.

Table 9 presents results from the value-weighted univariate portfolios of stocks sorted separately by systematic risk and idiosyncratic risk. Consistent with the IVOL puzzle literature, systematic risk estimated either in Eq (8) or (9) does not predict the cross-sectional variation in equity returns, whereas the IVOL puzzle remains significant in the equity market. One potential explanation is that investors hold concave preferences thus like positive skewness. If positive skewness is a desirable characteristic of a return distribution, then the fact that diversification destroys portfolio skewness makes investors to be willing to hold a limited number of stocks in their portfolios.[19]

Since individual investors do not hold a large number of stocks in their portfolios, they are unable to diversify firm-specific risk. Thus, according to the theoretical models of Levy (1978) and Merton (1987), stocks with higher idiosyncratic risk require higher returns to compensate for imperfect diversification, justifying a positive (not negative) cross-sectional relation between idiosyncratic risk and future equity returns. Since the IVOL puzzle is known to be significant only in the sample of stocks largely held by individual investors (to be confirmed in the next section), we conclude that retail investors' demand for positive skewness dominates their aversion to volatility so that retail investors prefer to hold a small number

[18]Following Ang et al. (2006) and subsequent literature on idiosyncratic volatility, we use daily returns in a month to estimate idiosyncratic volatility of individual stocks.

[19]The literature shows that the portfolios of individual investors are, in general, not well-diversified. For example, Polkovnichenko (2005) examines a survey of 14 million households and shows that the median number of stocks in household portfolios is two in 1989, 1992, 1995, and 1998. The median increases to three stocks in 2001. Based on 40,000 stock accounts at a brokerage firm, Goetzmann and Kumar (2008) find that the median number of stocks in a portfolio of individual investors is three in the 1991-1996 period. Odean (1999) and Barber and Odean (2001) also report the median number of stocks in individual investors' portfolios as two to three.

of lottery-like stocks with large positive skewness. Given that lottery stocks tend to have high idiosyncratic volatility and low future returns, retail investors' preference for lottery-like securities show some promise in solving the idiosyncratic volatility puzzle in the equity market (e.g., Kumar, 2009, Bali et al., 2011, and Hou and Loh, 2016).

6.2 The investor clientele effect in the equity and bond markets

The Flow of Funds report released by the Federal Reserve Board shows the composition of investors in the U.S. equity and corporate bond markets. Over the period of 1986 to 2017, the primary holders of corporate bonds are institutional investors (78% on average), in particular, insurance companies, mutual funds, and pension funds, whereas the main holders of equities are retail investors (household sector, 43%), then mutual funds (33%) and pension funds (15%). Since equities and bonds are mainly held by different groups of investors (retail vs. institutional investors), the difference in investor preferences and clienteles can be a plausible cause for the significance of systematic risk (idiosyncratic risk) in the bond (equity) market.

We first investigate the effect of investor clientele on the predictive power of idiosyncratic risk for future stock returns. To perform this task, we form quintile portfolios every month from January 1980 to December 2017 by sorting individual stocks into portfolios based on institutional ownership, then within each ownership portfolio, we further sort stocks into sub-quintiles based on their idiosyncratic risk. Table 10 shows that the negative cross-sectional relation between idiosyncratic risk and future returns is more pronounced among stocks with low institutional ownership (i.e., stocks largely held by retail investors). More importantly, the IVOL puzzle disappears among stocks with high institutional ownership. This result is consistent with the evidence provided by Kumar (2009) and Han and Kumar (2013) that retail investors tend to be more attracted to high volatility stocks because of their lottery-like features, and such behavior leads to the negative cross-sectional relation between idiosyncratic volatility and future stock returns.

We conduct a similar analysis for corporate bonds using Thompson Reuter's eMAXX bond holdings data. This dataset has a comprehensive coverage of quarterly fixed income holdings for U.S. institutional investors such as insurance companies and mutual funds. For a given bond i in quarter t, the measure of institutional ownership is defined as:

$$INST_{it} = \sum_j \left(\frac{Holding_{ijt}}{OutstandingAmt_{it}} \right) = \sum_j h_{jt}, \tag{10}$$

where $Holding_{ijt}$ is the par amount holdings of investor j on bond i during quarter t, $OutstandingAmt_{it}$ is bond i's outstanding amount, and h_{jt} is the fraction of the outstanding amount held by investor j, in percentage.

We examine whether the idiosyncratic volatility effect in corporate bonds is uniform across bonds with high and low institutional ownership. Specifically, we form value-weighted bivariate portfolios by sorting corporate bonds into 5×5 quintile portfolios based on institutional ownership and idiosyncratic volatility estimated in Eq. (3). Table 11 reports the 10-factor alpha for each of the 25 portfolios for month $t+1$ and shows that the 10-factor alpha spread between high-IR and low-IR quintiles is economically small and statistically insignificant in all quintiles of institutional ownership. Moreover, the magnitude of the alpha spreads is uniform across all INST quintiles, indicating that the idiosyncratic volatility effect does not differ in bonds with low vs. high institutional ownership.

7 Conclusion

In this paper, we propose novel measures of systematic and idiosyncratic risk for individual corporate bonds and test their significance in the cross-sectional pricing of corporate bonds. We find that the newly proposed measure of systematic risk has a strong predictive power on future bond returns, and the positive systematic risk premium is driven by the outperformance of bonds with high systematic risk. Given the powerful presence of systematic risk in the cross-sectional pricing of corporate bonds, the IVOL puzzle well-documented in the stock market no longer exists in the bond market. This finding suggests that the institutional investors dominating the bond market hold well-diversified portfolios with a negligible exposure to bond-specific risk so that idiosyncratic volatility does not command a significant risk premium in the bond market.

To gain a better understanding of the different roles played by systematic and idiosyncratic risk in the pricing of equities versus bonds, we investigate the interaction between investor clientele and these risk measures. Clearly, equities and bonds are disintegrated in terms of primary players in these two markets. We find that retail investors with a strong preference for small, illiquid, and high-volatility stocks play an important role in the equity market. Specifically, the negative relationship between idiosyncratic volatility and future stock returns is more pronounced among stocks largely held by retail investors, but the IVOL puzzle disappears among stocks with high institutional ownership. In contrast to the findings in the equity market, there is no significant link between idiosyncratic volatility and future returns on corporate bonds with high or low institutional ownership; that is, the IVOL puzzle does not exist in the cross-section of corporate bonds. Thus, our results provide a plausible explanation for the significance of systematic risk (idiosyncratic risk) based on differing investor preferences and clienteles in the bond (equity) market.

References

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259–299.

Bai, J., Bali, T. G., Wen, Q., 2019. Common risk factors in the cross-section of corporate bond returns. Journal of Financial Economics 131, 619–642.

Bali, T. G., Cakici, N., 2008. Idiosyncratic volatility and the cross-section of expected returns. Journal of Financial and Quantitative Analysis 43, 29–58.

Bali, T. G., Cakici, N., Whitelaw, R. F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427–446.

Bao, J., Pan, J., Wang, J., 2011. The illiquidity of corporate bonds. Journal of Finance 66, 911–946.

Barber, B., Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. Quarterly Journal of Economics 116, 261–292.

Bessembinder, H., Kahle, K. M., Maxwell, W. F., Xu, D., 2009. Measuring abnormal bond performance. Review of Financial Studies 22, 4219–4258.

Campbell, J., 1991. A variance decomposition for stock returns. The Economic Journal 101, 157–179.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Chen, Z., Petkova, R., 2012. Does idiosyncratic volatility proxy for risk exposure? Review of Financial Studies 25, 2745–2787.

Chung, K., Wang, J., Wu, C., 2019. Volatility and the cross-section of corporate bond returns. Journal of Financial Economics, forthcoming.

Elton, E. J., Gruber, M. J., Blake, C., 1995. Fundamental economic variables, expected returns, and bond fund performance. Journal of Finance 50, 1229–1256.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Fu, F., 2009. Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics 91, 24–37.

Goetzmann, W. N., Kumar, A., 2008. Equity portfolio diversification. Review of Finance 12, 433–463.

Han, B., Kumar, A., 2013. Speculative retail trading and asset prices. Journal of Financial and Quantitative Analysis 48, 377–404.

Han, Y., Lesmond, D., 2011. Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. Review of Financial Studies 24, 1590–1629.

Herskovic, B., Kelly, B., Lustig, H., Nieuwerburgh, S. V., 2016. The common factor in idiosyncratic volatility: quantitative asset pricing implications. Journal of Financial Economics 119, 249–283.

Hou, K., Loh, R., 2016. Have we solved the idiosyncratic volatility puzzle? Journal of Financial Economics 121, 167–194.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: an investment approach. Review of Financial Studies 28, 650–705.

Huang, W., Liu, Q., Rhee, S. G., Zhang, L., 2010. Return reversals, idiosyncratic risk, and expected returns. Review of Financial Studies 23, 147–168.

Jostova, G., Nikolova, S., Philipov, A., Stahel, C., 2013. Momentum in corporate bond returns. Review of Financial Studies 26, 1649–1693.

Koijen, R., Lustig, H., Nieuwerburgh, S. V., 2017. The cross-section and time-series of stock and bond returns. Journal of Monetary Economics 88, 50–69.

Kumar, A., 2009. Who gambles in the stock market? Journal of Finance 64, 1889–1933.

Levy, H., 1978. Equilibrium in an imperfect market: a constraint on the number of securities in the portfolio. American Economic Review 68, 643–658.

Lin, H., Wang, J., Wu, C., 2011. Liquidity risk and the cross-section of expected corporate bond returns. Journal of Financial Economics 99, 628–650.

Lintner, J., 1965. The valuation of risky assets and the selection of risky investments in stock portfolios and capital budgets. Review of Economics and Statistics 47, 13–37.

Merton, R. C., 1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483–510.

Mossin, J., 1966. Equilibrium in a capital asset market. Econometrica 34, 768–783.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Odean, T., 1999. Do investors trade too much? American Economic Review 89, 1279–1298.

Pastor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Polkovnichenko, V., 2005. Household portfolio diversification: A case for rank-dependent preferences. Review of Financial Studies 18, 1467–1502.

Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance 19, 425–442.

Vuolteenaho, T., 2002. What drives firm-level stock returns? Journal of Finance 42, 233–264.

Table 1: Descriptive Statistics

Panel A reports the number of bond-month observations, the cross-sectional mean, median, standard deviation and percentiles for corporate bond monthly returns and bond characteristics including credit rating, time-to-maturity (Maturity, year), amount outstanding (Size, $ billion), downside risk (5% Value-at-Risk, VaR), illiquidity (ILLIQ), and systematic risk (SR). Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means higher credit risk. Numerical ratings of 10 or below (BBB- or better) are considered investment grade. Downside risk is the 5% Value-at-Risk (VaR) of corporate bond return, defined as the second lowest monthly return observation over the past 36 months. The original VaR measure is multiplied by -1 so that a higher VaR indicates higher downside risk. Bond illiquidity is computed as the autocovariance of the daily price changes within each month, multiplied by -1. Systematic risk is defined as the difference between total and idiosyncratic variance using a 36-month rolling window. The factor model used to generate systematic risk is the 4-factor model of Bai, Bali, and Wen (2019) including the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factors (LRF) . Panel B reports the time-series average of the cross-sectional correlations. The sample period is from January 1997 to December 2017.

Panel A: Cross-sectional statistics over the sample period of January 1997 – December 2017

					Percentiles					
	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Bond return (%)	1,226,357	0.59	0.51	3.55	-8.43	-4.01	-0.63	1.72	5.29	10.97
Rating	1,201,491	8	7	4	2	3	5	10	16	18
Time-to-maturity (maturity, year)	1,232,683	9.14	6.50	8.34	1.18	1.66	3.73	12.21	23.96	32.21
Amount Out (size, $billion)	1,232,683	0.42	0.29	0.46	0.02	0.04	0.13	0.52	1.28	2.36
Downside risk (5% VaR)	704,002	4.83	3.56	4.61	0.59	1.01	2.20	5.80	13.12	23.11
ILLIQ	643,804	1.62	0.65	3.22	-0.96	-0.21	0.09	2.39	5.23	14.06
Systematic Risk (SR, %)	715,612	0.11	0.03	0.26	0.00	0.00	0.01	0.09	0.59	1.02

Panel B: Average cross-sectional correlations

	Rating	Maturity	Size	VaR	ILLIQ	SR
Rating	1	-0.083	-0.030	0.418	0.075	0.334
Maturity		1	-0.029	0.155	0.109	0.098
Size			1	-0.021	-0.163	-0.046
VaR				1	0.101	0.545
ILLIQ					1	0.084
SR						1

Table 2: Univariate Portfolios of Corporate Bonds Sorted by Systematic Risk

Quintile portfolios are formed every month from January 1997 to December 2017 by sorting corporate bonds based on systematic risk (SR), defined as the difference between total and idiosyncratic variance from regression (3). The benchmark model used to generate systematic risk is BBW 4-factor model with the excess bond market return, the downside risk factor, the credit risk factor, and the liquidity risk factor. Quintile 1 is the portfolio with the lowest SR and Quintile 5 is the portfolio with the highest SR. The portfolios are value-weighted using amount outstanding as weights. Table reports the average SR, the next-month average excess return, the 5-factor alpha from stock market factors, the 5-factor alpha from bond market factors, the 10-factor alpha for each quintile. The last six columns report average portfolio characteristics including bond beta (β^{MKT}), illiquidity (ILLIQ), downside risk (VaR), credit rating, time-to-maturity (years), and amount outstanding (size, in $billion) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the factor models. The 5-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM^{Stock}), and the stock liquidity factor (LIQ^{Stock}). The 5-factor model with bond market factors includes the excess bond market return (MKT), the default factor (DEF), the term factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines the five stock and five bond market factors. Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average SR	Average return	5-factor stock alpha	5-factor bond alpha	10-factor alpha	Average portfolio characteristics					
						β^{MKT}	ILLIQ	VaR	Rating	Maturity	Size
Low	0.01	0.09	0.06	0.02	0.01	0.32	0.12	2.08	6.87	4.32	0.48
		(1.31)	(0.98)	(0.35)	(0.14)						
2	0.02	0.22	0.19	0.03	0.02	0.58	0.19	2.95	7.35	6.01	0.47
		(2.30)	(2.02)	(0.53)	(0.36)						
3	0.03	0.30	0.25	0.01	-0.00	0.82	0.29	3.78	7.56	7.90	0.49
		(2.37)	(2.09)	(0.13)	(-0.01)						
4	0.07	0.40	0.31	0.28	0.24	1.10	0.58	5.31	8.03	10.99	0.48
		(2.22)	(2.02)	(1.02)	(0.52)						
High	0.44	0.86	0.68	0.59	0.52	1.69	1.04	10.65	10.43	12.50	0.46
		(2.51)	(2.55)	(2.96)	(2.41)						
High−Low		0.78***	0.62***	0.58***	0.52**						
		(2.64)	(2.76)	(2.65)	(2.59)						

Table 3: Univariate Portfolios of Corporate Bonds Sorted by Idiosyncratic Risk

Quintile portfolios are formed every month from January 1997 to December 2017 by sorting corporate bonds based on idiosyncratic risk (IR), defined as the residual variance from regression (3). The benchmark model used to generate idiosyncratic risk is BBW 4-factor model with the excess bond market return, the downside risk factor, the credit risk factor, and the liquidity risk factor. Quintile 1 is the portfolio with the lowest IR and Quintile 5 is the portfolio with the highest IR. The portfolios are value-weighted using amount outstanding as weights. Table reports the average IR, the next-month average excess return, the 5-factor alpha from stock market factors, the 5-factor alpha from bond market factors, the 10-factor alpha for each quintile. The last six columns report average portfolio characteristics including bond beta (β^{MKT}), illiquidity (ILLIQ), downside risk (VaR), credit rating, time-to-maturity (years), and amount outstanding (size, in \$billion) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the factor models. The 5-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM^{Stock}), and the stock liquidity factor (LIQ^{Stock}). The 5-factor model with bond market factors includes the excess bond market return (MKT), the default factor (DEF), the term factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines the five stock and five bond market factors. Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	5-factor stock	5-factor bond	10-factor	Average portfolio characteristics					
	IR	return	alpha	alpha	alpha	β^{MKT}	ILLIQ	VaR5	Rating	Maturity	Size
Low	0.01	0.12	0.11	-0.01	-0.00	0.61	0.04	1.80	6.36	4.37	0.64
		(1.94)	(1.73)	(-0.20)	(-0.02)						
2	0.02	0.24	0.22	0.01	0.01	0.74	0.12	2.75	7.18	6.72	0.47
		(3.05)	(2.52)	(0.22)	(0.24)						
3	0.05	0.28	0.22	-0.03	-0.05	0.88	0.26	3.82	7.50	9.52	0.44
		(2.63)	(1.90)	(-0.36)	(-0.64)						
4	0.11	0.34	0.24	-0.01	-0.05	1.00	0.51	5.31	8.04	10.89	0.43
		(2.57)	(1.75)	(-0.13)	(-0.53)						
High	0.63	0.61	0.44	0.42	0.25	1.28	1.34	11.10	11.17	10.18	0.39
		(3.49)	(2.43)	(2.47)	(1.66)						
High−Low		0.49***	0.34**	0.43**	0.25						
		(3.27)	(2.07)	(2.38)	(1.54)						

Table 4: Bivariate Portfolios of Corporate Bonds Sorted by Systematic Risk and Idiosyncratic Risk

In Panel A, quintile portfolios are formed every month from January 1997 to December 2017 by first sorting corporate bonds based on their idiosyncratic risk. Then, within each IR portfolios, corporate bonds are sorted into subquintiles based on their systematic risk. Quintile SR,1 is the portfolio of corporate bonds with the lowest SR within each IR quintile portfolio, and Quintile SR,5 is the portfolio of corporate bonds with the highest SR with each IR quintile portfolio. Panel A reports the average SRs within each IR quintile as well as the next month average return of corporate bonds for each quintile. The last four rows present the differences in the monthly returns, the 5-factor stock alpha, the 5-factor bond alpha, and the 10-factor alpha between Quintile SR,5 and Quintile SR,1. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Panel B replicates the same procedure for quintile portfolios of corporate bonds sorted by IR after controlling for SR.

Panel A: Corporate bonds sorted by SR after controlling for IR

SR quintiles after controlling for IR	Avg SR in each IR quintile	Next month avg returns
SR,1	0.02	0.30
SR,2	0.05	0.33
SR,3	0.09	0.39
SR,4	0.14	0.53
SR,5	0.27	1.00
SR,5−SR,1 return diff.		0.70***
		(2.80)
SR,5−SR,1 5-factor stock alpha diff.		0.62**
		(2.56)
SR,5−SR,1 5-factor bond alpha diff.		0.46**
		(2.48)
SR,5−SR,1 10-factor alpha diff.		0.43**
		(2.27)

Panel B: Corporate bonds sorted by IR after controlling for SR

IR quintiles after controlling for SR	Avg IR in each SR quintile	Next month avg returns
IR,1	0.03	0.24
IR,2	0.07	0.27
IR,3	0.12	0.31
IR,4	0.19	0.37
IR,5	0.41	0.42
IR,5−IR,1 return diff.		0.18
		(1.29)
IR,5−IR,1 5-factor stock alpha diff.		0.22
		(1.14)
IR,5−IR,1 5-factor bond alpha diff.		0.15
		(1.10)
IR,5−IR,1 10-factor alpha diff.		0.11
		(1.04)

Table 5: Investment-Grade Versus Non-Investment-Grade Corporate Bonds

This table repeats the univariate portfolio analyses by sorting corporate bonds based on the systematic risk (SR) and idiosyncratic risk (IR) in Tables 2 and 3 for investment-grade corporate bonds in Panel A and non-investment-grade ones in Panel B.

Panel A: Investment-grade bonds

	SR		IR	
	Average return	10-factor alpha	Average return	10-factor alpha
Low	0.06	-0.01	0.09	-0.00
	(0.97)	(-0.20)	(1.61)	(-0.17)
2	0.18	0.04	0.21	0.01
	(2.26)	(1.34)	(2.88)	(0.44)
3	0.26	0.03	0.26	-0.04
	(2.62)	(0.91)	(2.69)	(-0.83)
4	0.35	0.08	0.28	-0.10
	(2.67)	(2.16)	(2.53)	(-1.49)
High	0.48	0.26	0.32	-0.08
	(2.80)	(1.52)	(2.56)	(-1.12)
High−Low	0.42***	0.27**	0.23**	-0.08
	(3.25)	(2.03)	(2.49)	(-0.85)

Panel B: Non-investment-grade bonds

	SR		IR	
	Average return	10-factor alpha	Average return	10-factor alpha
Low	0.33	0.17	0.07	0.09
	(2.16)	(1.68)	(0.52)	(0.68)
2	0.34	0.09	0.38	0.06
	(1.77)	(0.55)	(2.19)	(0.37)
3	0.39	-0.10	0.25	-0.05
	(1.42)	(-0.45)	(1.20)	(-0.34)
4	0.56	0.23	0.35	-0.07
	(1.25)	(0.90)	(1.30)	(-0.33)
High	1.16	1.05	0.38	0.28
	(1.78)	(2.05)	(2.03)	(0.90)
High−Low	0.96***	0.88**	0.31**	0.20
	(2.70)	(2.63)	(2.23)	(0.57)

Table 6: Bond-level Fama-MacBeth Cross-Sectional Regressions

This table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on systematic risk and idiosyncratic risk with and without control variables. Bond characteristics include credit rating, illiquidity, time-to-maturity and the natural logarithm of amount outstanding. Other control variables consist of the bond market beta (β^{MKT}), the default beta (β^{DEF}), the term beta (β^{TERM}), and bond return in previous month (REV). Fama-MacBeth regressions are run each month for the period from January 1997 to December 2017. Newey-West (1987) t-statistics are reported in parentheses.The last column reports the average adjusted R^2 values. Numbers in bold denote statistical significance at the 5% level or better.

	Intercept	SR	IR	β^{MKT}	β^{DEF}	β^{TERM}	Rating	ILLIQ	Maturity	Size	REV	Adj. R^2
(1)	0.281	**2.166**										0.056
	(2.44)	(4.61)										
(2)	0.241		**0.635**									0.045
	(2.30)		(2.49)									
(3)	0.240	**0.921**	-0.529									0.057
	(2.35)	(4.56)	(-0.78)									
(4)	0.048	**1.192**		0.066	0.104	-0.066	0.009	**0.029**	0.021	0.008	**-0.106**	0.168
	(0.42)	(2.49)		(0.74)	(0.81)	(-0.30)	(0.41)	(5.22)	(0.78)	(0.33)	(-4.05)	
(5)	0.138		-0.006	0.008	0.116	-0.063	0.001	**0.030**	-0.013	-0.002	**-0.089**	0.152
	(1.10)		(-0.03)	(0.11)	(0.95)	(-0.26)	(0.05)	(5.47)	(-0.68)	(-0.05)	(-5.27)	
(6)	0.145	**0.839**	-0.306	0.038	0.132	-0.090	-0.002	**0.029**	-0.016	-0.004	**-0.088**	0.156
	(1.18)	(2.50)	(-0.32)	(0.48)	(1.16)	(-0.39)	(-0.07)	(4.87)	(-0.87)	(-0.16)	(-4.94)	

Table 7: Systematic Risk and Idiosyncratic Risk Based on Alternative Factor Models

Quintile portfolios are formed every month from January 1997 to December 2017 by sorting corporate bonds based on systematic risk, defined as the difference between total and idiosyncratic variance from the following benchmark models.
Model 1: $R_{i,t} = \alpha_i + \beta_{1,i}MKT_t + \epsilon_{i,t}$,
Model 2: $R_{i,t} = \alpha_i + \beta_{1,i}MKT_t + \beta_{2,i}DEF_t + \beta_{3,i}TERM_t + \epsilon_{i,t}$,
Model 3: $R_{i,t} = \alpha_i + \beta_{1,i}MKT_t + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}DEF_t + \beta_{5,i}TERM_t + \beta_{6,i}\Delta VIX_t + \epsilon_{i,t}$.

Quintile 1 is the portfolio with the lowest SR and Quintile 5 is the portfolio with the highest SR. The portfolios are value-weighted using amount outstanding as weights. Table reports the next-month average excess return, the 10-factor alpha, and the BBW 4-factor alpha for each quintile. The 10-factor model combines five stock and five bond market factors. The BBW 4-factor model considers the excess bond market return, the downside risk factor, the credit risk factor, and the liquidity risk factor. Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Quintile portfolios of corporate bonds sorted by systematic risk

	Average return	10-factor alpha	BBW 4-factor alpha	Average return	10-factor alpha	BBW 4-factor alpha	Average return	10-factor alpha	BBW 4-factor alpha
		Model 1			Model 2			Model 3	
Low	0.10	-0.07	-0.06	0.10	0.01	0.04	0.09	0.00	0.05
	(1.06)	(-0.83)	(-0.74)	(1.53)	(0.14)	(1.56)	(1.47)	(0.04)	-2.17
2	0.18	0.00	0.02	0.19	0.02	0.07	0.20	0.01	0.04
	(1.94)	(0.02)	(0.49)	(2.01)	(0.32)	(2.37)	(2.03)	(0.16)	(1.31)
3	0.26	-0.01	0.01	0.29	-0.02	0.01	0.29	-0.04	0.00
	(2.22)	(-0.12)	(0.32)	(2.40)	(-0.31)	(0.42)	(2.38)	(-0.51)	(0.07)
4	0.34	0.01	0.01	0.35	-0.01	-0.05	0.34	-0.01	-0.08
	(2.36)	(0.10)	(0.13)	(2.21)	(-0.09)	(-0.70)	(2.09)	(-0.13)	(-1.03)
High	0.39	0.14	0.04	0.42	-0.08	-0.20	0.42	-0.08	-0.19
	(2.24)	(1.03)	(0.28)	(1.49)	(-0.51)	(-0.80)	(1.50)	(-0.51)	(-0.72)
High−Low	0.29	0.21	0.10	0.32	-0.08	-0.24	0.33	-0.08	-0.24
	(1.64)	(1.12)	(0.73)	(1.34)	(-0.53)	(-0.98)	(1.35)	(-0.49)	(-0.93)

Table 7. (Continued)

Panel B: Quintile portfolios of corporate bonds sorted by idiosyncratic risk

	Average return	10-factor alpha	BBW 4-factor alpha	Average return	10-factor alpha	BBW 4-factor alpha	Average return	10-factor alpha	BBW 4-factor alpha
	Model 1			Model 2			Model 3		
Low	0.12	-0.00	0.03	0.12	-0.00	0.03	0.22	-0.02	0.02
	(1.64)	(-0.08)	(1.36)	(1.64)	(-0.08)	(1.13)	(1.69)	(-0.42)	(0.86)
2	0.22	-0.02	0.03	0.22	-0.02	0.02	0.25	-0.02	0.02
	(2.26)	(-0.35)	(0.96)	(2.26)	(-0.35)	(0.86)	(2.39)	(-0.37)	(0.51)
3	0.29	-0.02	-0.04	0.29	-0.02	-0.03	0.29	-0.02	-0.04
	(2.18)	(-0.26)	(-0.85)	(2.18)	(-0.26)	(-0.70)	(2.10)	(-0.27)	(-0.90)
4	0.41	0.00	-0.18	0.41	0.00	-0.19	0.42	0.04	-0.17
	(2.08)	(0.04)	(-2.00)	(2.08)	(0.04)	(-2.12)	(2.02)	(0.42)	(-1.94)
High	0.90	0.54	0.12	0.90	0.54	0.14	0.92	0.65	0.16
	(2.40)	(2.55)	(0.64)	(2.40)	(2.55)	(0.75)	(2.79)	(3.36)	(0.89)
High−Low	0.79**	0.54**	0.08	0.79**	0.54**	0.11	0.70**	0.67***	0.14
	(2.37)	(2.46)	(0.45)	(2.37)	(2.46)	(0.60)	(2.58)	(3.21)	(0.77)

Table 8: Portfolios Formed on Common Idiosyncratic Volatility (CIV) Beta

The table reports the average excess returns and alphas for CIV-beta-sorted stock portfolios in Panel A and for corporate bond portfolios in Panel B. Quintile 1 is the portfolio with the lowest CIV-beta and Quintile 5 is the portfolio with the highest CIV-beta. The portfolios are value-weighted using market cap as weights. In Panel A, the benchmark models used to calculate alpha are the i) Fama-French (2015) 5-factor model (MKT^{Stock}, SMB, HML, RMW, and CMA), and ii) Hou, Xue, and Zhang (2015) Q-factor model (MKT^{Stock}, ME, IA, and ROE). In Panel B, the 10-factor model combines the five stock and five bond market factors. The BBW 4-factor model includes the excess bond market return, the downside risk factor, the credit risk factor, and the liquidity risk factor. The sample period for stock portfolios in Panel A is from July 1963 to December 2017. The sample period for corporate bond portfolios in Panel B is from July 2004 to December 2017. Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios of stocks sorted on CIV-beta

Quintiles	Average CIV-beta	Average return	FF 5-factor alpha	Q-factor alpha
Low CIV-beta	-0.76	0.78	0.19	0.21
2	-0.54	0.59	0.07	0.10
3	-0.32	0.48	0.02	0.07
4	0.20	0.49	0.02	0.09
High CIV-beta	0.84	0.26	-0.13	-0.16
High−Low	1.60	-0.53**	-0.32**	-0.37**
Return/Alpha diff.	(12.30)	(-2.85)	(-2.51)	(-2.60)

Panel B: Portfolios of corporate bonds sorted on CIV-beta

Quintiles	Average CIV-beta	Average return	10-factor alpha	BBW 4-factor alpha
Low CIV-beta	-0.25	0.78	0.79	0.16
2	-0.10	0.25	0.27	0.04
3	-0.05	0.13	0.15	0.09
4	-0.01	0.08	0.09	-0.02
High CIV-beta	0.16	0.21	0.23	0.06
High−Low	0.40	-0.57***	-0.51***	-0.10
Return/Alpha diff.	(10.75)	(-3.05)	(-2.94)	(-1.06)

Table 9: Confirming the IVOL Puzzle in the Stock Market

This table tests the IVOL puzzle in the stock market. Systematic risk and idiosyncratic risk are estimated based on the Fama-French (2015) 5-factor model (MKT^{Stock}, SMB, HML, RMW, and CMA) in Panel A and the Hou, Xue, and Zhang (2015) Q-factor model (MKT^{Stock}, ME, IA, and ROE) in Panel B. Quintile portfolios are formed every month by sorting stocks based on systematic risk and idiosyncratic risk. The estimation is based on daily returns in a month, requiring at least 15 daily observations in a month. The sample period for Fama-French (2015) 5-factor model is from July 1963 to December 2017 and that for the Q-factor model is from January 1967 to December 2017. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A: SR and IR estimated using Fama-French (2015) 5-factor model

	SR	Avg return	FF 5-factor alpha	Q-factor alpha
Low	0.00	0.56	0.56	0.60
		(3.68)	(3.66)	(3.76)
2	0.01	0.61	0.65	0.69
		(3.76)	(3.91)	(3.99)
3	0.02	0.64	0.70	0.71
		(3.28)	(3.59)	(3.31)
4	0.05	0.59	0.69	0.67
		(2.32)	(2.80)	(2.25)
High	0.16	0.10	0.20	0.11
		(0.29)	(0.58)	(0.26)
High−Low		-0.45	-0.36	-0.49
		(-1.58)	(-1.26)	(-1.36)

Low	**IR**	Average return	FF 5-factor alpha	Q-factor alpha
Low	0.01	0.54	0.57	0.63
		(3.46)	(3.57)	(3.77)
2	0.02	0.61	0.67	0.67
		(3.09)	(3.44)	(2.99)
3	0.04	0.66	0.74	0.75
		(2.65)	(3.09)	(2.65)
4	0.09	0.39	0.44	0.42
		(1.25)	(1.47)	(1.13)
High	0.36	-0.23	-0.22	-0.24
		(-0.63)	(-0.65)	(-0.54)
High−Low		-0.77***	-0.80***	-0.86**
		(-2.72)	(-2.78)	(-2.37)

Panel B: SR and IR estimated using Hou, Xue, and Zhang (2015) Q-factor model

	SR	Average return	FF 5-factor alpha	Q-factor alpha
Low	0.00	0.66	0.68	0.68
		(4.02)	(4.00)	(4.06)
2	0.01	0.75	0.81	0.79
		(4.35)	(4.32)	(4.37)
3	0.02	0.74	0.83	0.78
		(3.42)	(3.67)	(3.40)
4	0.05	0.72	0.88	0.81
		(2.65)	(3.25)	(2.70)
High	0.15	0.17	0.37	0.29
		(0.44)	(0.99)	(0.65)
High−Low		-0.49	-0.31	-0.39
		(-1.50)	(-0.98)	(-0.97)

	IR	Average return	FF 5-factor alpha	Q-factor alpha
Low	0.01	0.69	0.75	0.73
		(4.07)	(4.01)	(4.09)
2	0.02	0.66	0.75	0.69
		(3.02)	(3.30)	(2.92)
3	0.04	0.76	0.89	0.82
		(2.73)	(3.22)	(2.71)
4	0.09	0.47	0.57	0.52
		(1.37)	(1.72)	(1.32)
High	0.32	-0.07	0.01	-0.01
		(-0.18)	(0.04)	(-0.02)
High−Low		-0.76**	-0.73**	-0.74**
		(-2.44)	(-2.34)	(-2.27)

Table 10: Institutional Ownership and Equity Idiosyncratic Risk

Quintile portfolios are formed every month from January 1980 to December 2017 by first sorting individual stocks based on institutional ownership. Then within each institutional ownership quintile, individual stocks are further sorted into sub-quintiles based on their idiosyncratic risk. The benchmark model used to generate idiosyncratic risk is the Fama-French 5-factor model (MKT^{Stock}), SMB, HML, RMW, and CMA). The estimation is based on daily returns in a month, requiring at least 15 daily observations in a month. "INST,1" is the portfolio of stocks with the lowest institutional ownership and "INST,5" is the portfolio of stocks with the highest institutional ownership. The portfolios are value-weighted using market cap as weights. Table reports the next-month average excess return, the Fama-French 5-factor alpha, and the Q-factor alpha between the highest and lowest quintile within each institutional ownership quintile. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	IR,1	IR,2	IR,3	IR,4	IR,5	IR,5−IR,1	FF 5- factor alpha	Q-factor alpha
INST,1	0.62	0.39	-0.21	-1.01	-2.42	-3.03***	-2.85***	-3.01***
	(2.60)	(1.29)	(-0.59)	(-2.10)	(-5.50)	(-8.58)	(-8.83)	(-6.88)
INST,2	0.72	0.58	0.19	-0.13	-1.31	-2.03***	-2.09***	-2.11***
	(4.61)	(2.25)	(0.49)	(-0.26)	(-2.09)	(-3.46)	(-4.34)	(-3.32)
INST,3	0.71	0.37	0.52	-0.06	-0.32	-1.02**	-0.91*	-0.95*
	(4.01)	(1.47)	(1.46)	(-0.12)	(-0.59)	(-1.99)	(-1.92)	(-1.66)
INST,4	0.81	0.69	0.81	0.47	0.18	-0.63	-0.66	-0.62
	(4.24)	(2.92)	(3.09)	(1.30)	(0.44)	(-1.67)	(-1.55)	(-1.39)
INST,5	0.85	0.76	0.81	0.81	0.81	-0.04	-0.04	-0.02
	(4.17)	(3.26)	(3.09)	(2.77)	(2.36)	(-0.16)	(-0.14)	(-0.07)

Table 11: Institutional Ownership and Bond Idiosyncratic Risk

Quintile portfolios are formed every month from January 2001 to December 2017 by first sorting corporate bonds based on institutional ownership. Then within each institutional ownership quintile, individual bonds are further sorted into sub-quintiles based on their idiosyncratic risk. The benchmark model used to generate idiosyncratic risk is the BBW 4-factor model (MKT, DRF, CRF, and LRF). "INST,1" is the portfolio of bonds with the lowest institutional ownership and "INST,5" is the portfolio of bonds with the highest institutional ownership. The portfolios are value-weighted using bond amount outstanding as weights. Table reports the 10-factor alpha between the highest- and lowest-IR quintile within each institutional ownership quintile. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	IR,1	IR,2	IR,3	IR,4	IR,5	IR,5−IR,1
INST,1	0.03	0.12	-0.10	0.06	0.13	0.10
	(0.57)	(1.49)	(-0.77)	(0.43)	(0.34)	(0.24)
INST,2	0.08	0.14	0.04	0.05	0.03	-0.04
	(1.59)	(3.62)	(0.79)	(0.53)	(0.15)	(-0.23)
INST,3	0.05	0.07	0.14	0.05	0.09	0.04
	(1.68)	(1.89)	(2.12)	(0.82)	(0.74)	(0.29)
INST,4	0.06	0.10	0.07	-0.03	0.23	0.17
	(2.89)	(3.40)	(1.36)	(-0.41)	(2.21)	(1.59)
INST,5	0.06	0.16	0.09	0.08	0.05	-0.01
	(1.85)	(4.82)	(1.63)	(1.55)	(0.41)	(-0.08)

In Search of the Idiosyncratic Volatility Puzzle in the Corporate Bond Market

Online Appendix

To save space in the paper, we present additional analyses in the Online Appendix. Fig. A.1 plots the monthly time-series of aggregate SR between January 1997 to December 2017 for the equal-, value-, and rating-weighted cross-sectional average of bond systematic risk. Table A.1 tests the significance of a cross-sectional relation between total risk (volatility) and future bond returns. Table A.2 shows that the cross-sectional relations between future bond returns and three factor betas (β^{DRF}, β^{CRF}, and β^{LRF}) are significantly positive. Table A.3 (Section A.1) presents the performance of the aggregate systematic risk in predicting future aggregate bond market returns and bond market volatility for different horizons.

A.1 Testing the Consistency of Systematic Risk with the ICAPM

Although the aggregate market portfolio is the only systematic risk factor in a simple CAPM world, follow-up studies consider additional sources of systematic risk. For example, Fama (1970) points out that, in a multi-period economy, investors have an incentive to hedge against future stochastic shifts in the investment opportunity set. Merton (1973) indicates that state variables that are correlated with changes in consumption and investment opportunities are priced in capital markets in the sense that an asset's covariance with those state variables affects its expected returns. Thus, any variables that affect future consumption and investment decisions could be a priced risk factor in equilibrium. Ross (1976) further documents that securities affected by such systematic risk factors should earn risk premia in a risk-averse economy.

Over the past four decades, the empirical asset pricing literature has produced a large number of variables related to the cross-section of equity returns, and many of the documented predictors of stock returns capture the same (or similar) underlying economic phenomena. Some of these cross-sectional return predictors have been justified as empirical applications of Merton's ICAPM, leading Fama (1991) to view the ICAPM as a safe harbor to facilitate data mining exercise, especially for authors claiming that the ICAPM provides a theoretical support for relatively unscripted risk factors in their models. Maio and Santa-Clara (2012) show that although the ICAPM does not directly identify the "state variables" underlying the risk factors, there are some restrictions that these state variables must satisfy. According to Merton's (1973) ICAPM, the state variables related to changes in the investment opportunity set are supposed to predict the distribution of future market returns. Moreover, the innovations in these state variables should be priced factors in the cross-section.

Maio and Santa-Clara (2012) focus on three restrictions of the ICAPM. First, the candidates for ICAPM state variables must forecast the first or second moment of market returns. As will be discussed in Section A.1.1, the aggregate measure of systematic risk significantly predicts future bond market returns and bond market volatility, satisfying the first ICAPM restriction. Second, if a given state variable predicts positive (negative) expected market returns, the corresponding risk factor should earn a positive (negative) price of risk in cross-sectional tests. Since our state variable, the composite measure of systematic risk, predicts positive expected bond market returns, the corresponding systematic risk factor is expected to earn a positive price of risk in the cross-section of corporate bonds. Section A.1.2 shows that bond exposure to the systematic risk factor predicts higher returns in the cross-section of corporate bonds, satisfying the second ICAPM restriction. The third restriction associated with the ICAPM is that the price of systematic risk estimated from the cross-sectional regressions must generate an economically sensible estimate of the coefficient of relative risk aversion of the representative investor. Section A.1.2 provides empirical evidence satisfying the third ICAPM restriction as well.

A.1.1 The Time-Series Predictive Power of Aggregate Systematic Risk

We have so far shown that the composite measure of systematic risk estimated with the aggregate bond market, downside risk, credit risk, and liquidity risk factors of BBW is a strong predictor of the cross-sectional differences in future bond returns. In this section, we test whether the composite measure of systematic risk predicts the first and second moments of the return distribution of the aggregate bond market portfolio. Specifically, we construct aggregate systematic risk using the cross-sectional average of bond-level systematic risk measures and investigate its predictive power for the future returns and volatility of the aggregate bond market portfolio.

The intertemporal relation between expected return and risk in the equity market has been one of the most extensively studied topics in financial economics. Most asset pricing models postulate a positive intertemporal relation between the market portfolio's expected return and risk, which is often defined by the variance or standard deviation of market returns. However, the literature has not yet reached an agreement on the existence of such a positive risk-return tradeoff for stock market indices.[20] Many studies fail to identify a robust and significant intertemporal relation between risk and return on the aggregate stock market portfolio.

French, Schwert, and Stambaugh (1987) find that the risk-return coefficient is not significantly different from zero when they use past daily returns to estimate the monthly conditional variance. Follow-up studies by Campbell and Hentchel (1992), Glosten, Jagannathan, and Runkle (1993), Harrison and Zhang (1999), and Bollerslev and Zhou (2006) rely on the GARCH-in-mean and realized volatility models that provide no evidence of a robust, significant link between risk and return on the equity market portfolio. Several studies even find that the intertemporal relation between risk and return is negative. Examples include Campbell (1987), Nelson (1991), Glosten et al. (1993), Whitelaw (1994), Harvey (2001), and Brandt and Kang (2004). Some studies do provide evidence supporting a positive and significant link between expected return and risk in the equity market (e.g., Bollerslev et al., 1988; Ghysels et al., 2005; Guo and Whitelaw, 2006; Bali, 2008; and Bali and Engle, 2010).

For the first time in the literature, we examine the intertemporal relation between expected return and systematic risk for the aggregate bond market portfolio. We consider three new aggregate measures of systematic risk using different weighting schemes: the equal-weighted, value-weighted, and rating-weighted average systematic risk. Fig. A.1 plots the time-series of the aggregate systematic risk over the sample period from January 1997 to December 2017. The three measures of aggregate SR are highly correlated with an average correlation coefficient of 0.95, and all spike during the Great Recession.[21] To test the time-series predictive power of aggregate systematic risk, we control for a large set of macroeconomic variables proxying for business cycle fluctuations:

$$Y_{t+\tau} = \alpha + \gamma_1 \cdot SR_t + \gamma_2 \cdot X_t^k + \epsilon_{t+1}, \qquad k = 1, ..., 6; \quad \tau = 1, 2, ..., 12 \tag{A.1}$$

where $Y_{t+\tau}$ is one of the two dependent variables, the monthly bond market excess return (MKT) and the monthly bond market variance (MKT^{VOL}), calculated as the sum of squared daily bond market returns in a month. X_t^k is a vector of control variables. Following Goyal and Welch (2008), we control for variables related to macro fundamentals including the log earnings-to-price ratio (EP), the log dividend-to-price ratio (DP), the book-to-market ratio (BM), the difference between long-term yield on government bonds and the one-month Treasury-bill (TERM), the difference between BAA- and AAA-rated corporate bond yields (DEF), and the equity market variance (SVAR).

Table A.3 presents the performance of the aggregate systematic risk in predicting τ-

[20] Due to the fact that the conditional volatility of stock market returns is not observable, different approaches and specifications used by previous studies in estimating the conditional volatility are largely responsible for the conflicting empirical evidence.

[21] As a result, we use the equal-weighted average SR (SR^{EW}) in our time-series predictive regressions, and the results are similar when we use the other two measures of aggregate SR.

month ahead aggregate bond market returns and bond market volatility for different horizons ($\tau = 1, 2, ..., 12$). Panel A shows that the estimated slope coefficients (γ_1) in Eq. (A.1) are significantly positive, indicating the strong predictive power of aggregate systematic risk on future bond market returns up to 10 months, even after controlling for a number of time-series return predictors. Further, the adjusted R^2 in the multivariate regression declines from 9.53% for one-month-ahead predictability to 0.66% for 12-month-ahead predictability, suggesting that the aggregate measure of systematic risk has the best performance in predicting the one-month-ahead returns on the bond market portfolio.

Panel B of Table A.3 reports the forecasting performance of the aggregate systematic risk in predicting future bond market volatility (MKT^{VOL}). Maio and Santa-Clara (2012) investigate the ICAPM restrictions in the time-series and cross-sectional predictability, and show that the cross-sectional variable (when aggregated) should predict future market return and market volatility, if the variable is interpreted as a state variable that affects investment opportunity set in the ICAPM. Panel B provides evidence consistent with this interpretation. Specifically, the aggregate systematic risk positively predicts future bond market volatility up to seven months into the future, indicating that the composite measure of systematic risk satisfies the first ICAPM restriction. The results also show that high systematic risk in the corporate bond market robustly predicts high future returns on the bond market portfolio, indicating a positive intertemporal risk-return tradeoff in the corporate bond market, while the equity literature is still not in agreement on the direction of a time-series relation between expected return and risk in the equity market.

A.1.2 The positive price of systematic risk in the cross-section of corporate bonds

In this section, we test whether systematic risk is consistent with Merton' theoretical model based on the second and third restrictions of the ICAPM. Specifically, we form a systematic risk factor and investigate whether the systematic risk factor earns a positive price of risk in the cross-section of corporate bond returns (second restriction). Then, we examine if the price of the systematic risk factor estimated from the cross-sectional regressions generates an economically plausible magnitude of the relative risk aversion coefficient (third restriction).

We build a systematic risk factor of corporate bonds following the factor construction methodology of Bai, Bali, and Wen (2019). That is, for each month from January 1997 to December 2017, we form bivariate portfolios by independently sorting bonds into five quintiles based on their credit rating and five quintiles based on their systematic risk. The systematic risk factor, SRF, is the value-weighted average return difference between the highest-SR portfolio and the lowest-SR portfolio across the rating portfolios. The average return on the newly proposed systematic risk factor is positive and highly significant, at 0.54% per month (t-stat. = 3.47), which is consistent with our earlier findings on the significantly positive systematic risk premium in the cross-section of both IG and NIG bonds.

Next, for each bond and each month in our sample, we estimate corporate bond exposure to the systematic risk factor (β^{SRF}) from the monthly rolling regressions of excess bond returns on the SRF factor over a 36-month rolling window while controlling for the bond market factor (MKT):

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{SRF} \cdot SRF + \epsilon_{i,t}, \tag{A.2}$$

where $R_{i,t}$ is the excess return on bond i in month t, and MKT_t and SRF_t are the excess returns on the bond market and systematic risk factors in month t, respectively. $\beta_{i,t}^{MKT}$ and $\beta_{i,t}^{SRF}$ are the bond exposures to the market and systematic risk factors, respectively. Once we estimate $\beta_{i,t}^{MKT}$ and $\beta_{i,t}^{SRF}$ for each bond and each month in our sample, we test whether the systematic risk factor (SRF) earns a positive price of risk in the cross-section of corporate bond returns. Specifically, we examine the cross-sectional relation between β^{SRF} and expected returns at the bond level using Fama and MacBeth (1973) regressions:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{MKT} + \lambda_{2,t} \cdot \beta_{i,t}^{SRF} + \epsilon_{i,t+1}. \tag{A.3}$$

The average slope coefficient ($\overline{\lambda}_2$) from the cross-sectional regressions of one-month-ahead bond excess returns on β^{SRF} turns out to be positive and statistically significant: 0.43 (t-stat. = 4.75). Whereas, the average slope ($\overline{\lambda}_1$) on β^{MKT} is positive but statistically insignificant: 0.14 (t-stat.= 0.80). Thus, our results indicate that the composite measure of systematic risk predicts positive expected bond market returns and that the systematic risk factor earns a positive price of risk in the cross-section of corporate bonds, consistent with the second ICAPM restriction. The intuition for this result is simple. An asset that covaries positively with the risk factor also covaries positively with future expected returns. It does not provide a hedge for reinvestment risk because it offers lower returns when market returns are expected to be lower. Hence, a risk-averse investor does require a positive risk premium to invest in such an asset, implying a positive price of risk for the factor.

Finally, we investigate whether the price of the systematic risk factor estimated from the cross-sectional regressions produces an economically sensible estimate of expected excess return on the bond market. Bali and Engle (2010) show that Merton's (1973) ICAPM implies the following conditional intertemporal relation:

$$E_t(R_{t+1}) = A \cdot Cov_t(R_{i,t+1}, MKT_{t+1}) + B \cdot Cov_t(R_{i,t+1}, SRF_{t+1}), \tag{A.4}$$

where $R_{i,t+1}$ is the excess return on bond i at time $t+1$, and MKT_{t+1} and SRF_{t+1} are the excess returns on the market and systematic risk factors at time $t+1$, respectively. $E_t(R_{i,t+1})$ is the time-t expected excess return of bond i at time $t+1$, $Cov_t(R_{i,t+1}, MKT_{t+1})$ is the time-t expected conditional covariance between $R_{i,t+1}$ and MKT_{t+1}, and $Cov_t(R_{i,t+1}, SRF_{t+1})$ is the time-t expected conditional covariance between $R_{i,t+1}$ and SRF_{t+1}. The parameter A in Eq. (A.4) is the relative risk aversion of market investors, and B measures the market's aggregate reaction to shifts in a state variable that governs the stochastic investment opportunity set. Thus, Eq. (A.4) indicates that in equilibrium, investors are compensated in terms of expected return for bearing market risk and for bearing the risk of unfavorable shifts in the investment opportunity set.[22]

Following Bali and Engle (2010), we aggregate Eq. (A.4) and write the static (unconditional) version of the conditional ICAPM to determine the economic significance of A and B:

$$E(MKT) = A \cdot \sigma^2_{MKT} + B \cdot \sigma_{MKT,SRF}, \tag{A.5}$$

where $E(MKT)$ is the unconditional expected excess return on the bond market portfolio, σ^2_{MKT} is the unconditional variance of excess returns on the bond market portfolio, and $\sigma_{MKT,SRF}$ is the unconditional covariance between excess returns on the market and systematic risk factors.

We use the price of market risk ($\overline{\lambda}_1$) and the price of systematic risk factor ($\overline{\lambda}_2$) estimated from the cross-sectional regressions in Eq. (A.3) to proxy for A and B in Eq. (A.5), respectively. Substituting the sample estimates of $\sigma^2_{MKT} = 0.023$ and $\sigma_{MKT,SRF} = 0.021$ along with ($A = \overline{\lambda}_1/\sigma^2_{MKT} = 6.09$) and ($B = \overline{\lambda}_2/\sigma^2_{SRF} = 6.94$) into Eq. (A.5) gives 0.29% per month, which is very close to the average excess return on the bond market portfolio in our sample, 0.33% per month. These results indicate that the price of the systematic risk factor generates an economically sensible estimate of expected excess return on the bond market, and hence the implied relative risk aversion of bond market investors, satisfying the third ICAPM restriction. Since the composite measure of systematic risk satisfies all three restrictions of the ICAPM, we conclude that Merton's (1973) model provides a theoretical support for the systematic risk factor in the corporate bond market.

[22] Since the conditional variances of MKT_{t+1} and SRF_{t+1} are identical across bonds, Eq. (A.4) can be written in terms of the conditional betas ($\beta^{MKT}_{i,t}$, $\beta^{SRF}_{i,t}$) as in Eq. (A.3).

References

Bali, T. G., 2008. The intertemporal relation between expected returns and risk. Journal of Financial Economics 87, 101-131.

Bali, T. G., Engle, R. F., 2010. The intertemporal capital asset pricing model with dynamic conditional correlations. Journal of Monetary Economics 57, 377-390.

Bollerslev, T., Engle, R. F., Wooldridge, J., 1988. A capital asset pricing model with time-varying covariances. Journal of Political Economy 96, 116-131.

Bollerslev, T., Zhou, H., 2006. Volatility puzzles: a simple framework for gauging return-volatility regressions. Journal of Econometrics 131, 123-150.

Brandt, M., Kang, Q., 2004. On the relationship between the conditional mean and volatility of stock returns: a latent var approach. Journal of Financial Economics 72, 217-257.

Campbell, J. Y., 1987. Stock returns and the term structure. Journal of Financial Economics 18, 373-399.

Campbell, J. Y., Hentchel, L., 1992. No news is good news: an asymmetric model of changing volatility in stock returns. Journal of Financial Economics 31, 281-318.

Fama, E. F., 1970. Efficient capital markets: A review of theory and empirical work. Journal of Finance 25, 383-417.

Fama, E. F., 1991. Efficient capital markets: Ii. Journal of Finance 46, 1575-1617.

French, K. R., Schwert, G., Stambaugh, R., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3-29.

Ghysels, E., Santa-Clara, P., Valkanov, R., 2005. There is a risk-return trade-o after all. Journal of Financial Economics 76, 509-548.

Glosten, L., Jagannathan, R., Runkle, D., 1993. On the relation between the expected value and the volatility of the nominal excess returns on stocks. Journal of Finance 48, 1779-1801.

Goyal, A., Welch, I., 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455-1508.

Guo, H., Whitelaw, R., 2006. Uncovering the risk-return relation in the stock market. Journal of Finance 61, 1433-1463.

Harrison, P., Zhang, H., 1999. An investigation of the risk and return relation at long horizons. Review of Economics and Statistics 81, 399-408.

Harvey, C. R., 2001. The specification of conditional expectations. Journal of Empirical Finance 8, 573-637.

Maio, P., Santa-Clara, P., 2012. Multifactor models and their consistency with the icapm. Journal of Financial Economics 106, 586-613.

Merton, R. C., 1973. An intertemporal capital asset pricing model. Econometrica 41, 867-887.

Nelson, D., 1991. Conditional heteroskedasticity in asset returns: a new approach. Econometrica

59, 347-370.

Ross, S. A., 1976. The arbitrage theory of capital asset pricing model (capm). Journal of Economic Theory 13, 341-360.

Whitelaw, R. F., 1994. Time variations and covariations in the expectation and volatility of stock market returns. Journal of Finance 49, 515-541.

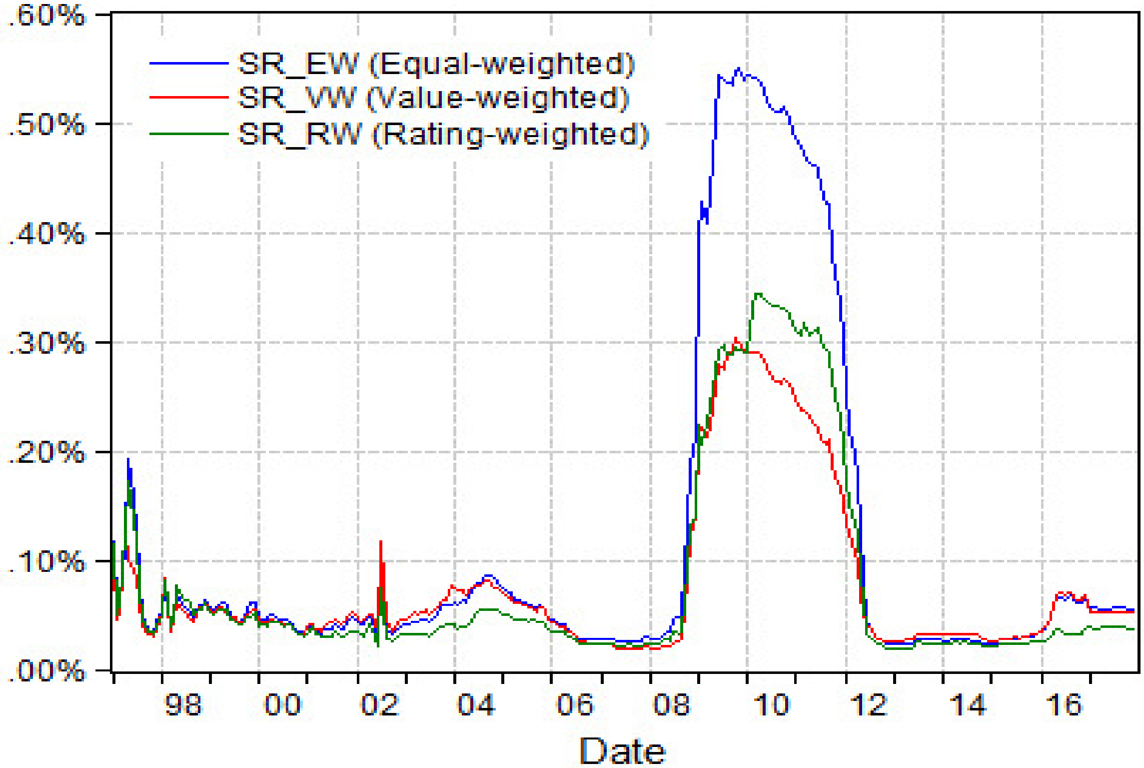

Fig. A.1. Systematic risk (SR) over time. This figure plots the monthly time-series of aggregate SR between January 1997 to December 2017 for the equal-, value-, and rating-weighted cross-sectional average of bond systematic risk.

Table A.1: Univariate portfolios of corporate bonds sorted by total variance (VOL)

Quintile portfolios are formed every month from January 1997 to December 2017 by sorting corporate bonds based on the total variance. Quintile 1 is the portfolio with the lowest VOL and Quintile 5 is the portfolio with the highest VOL. The portfolios are value-weighted using amount outstanding as weights. Table reports the average VOL (%), the next-month average excess return, the 5-factor alpha from stock market factors, the 5-factor alpha from bond market factors, and the 10-factor alpha for each quintile. The last six columns report average portfolio characteristics including bond beta (β^{MKT}), illiquidity (ILLIQ), downside risk (5% Value-at-Risk), credit rating, time-to-maturity (years), and amount outstanding (size, in $billion) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the factor models. The 5-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM^{Stock}), and the stock liquidity factor (LIQ^{Stock}). The 5-factor model with bond market factors includes the excess bond market return (MKT), the default factor (DEF), the term factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines the five stock and five bond market factors. Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	5-factor stock	5-factor bond	10-factor	Average portfolio characteristics					
	VOL	return	alpha	alpha	alpha	β^{MKT}	ILLIQ	VaR	Rating	Maturity	Size
Low	0.02	0.09	0.08	-0.01	-0.00	0.44	0.05	1.65	6.43	3.73	0.56
		(1.34)	(1.23)	(-0.14)	(-0.12)						
2	0.05	0.21	0.18	-0.02	-0.02	0.68	0.12	2.75	7.18	6.15	0.49
		(2.08)	(1.82)	(-0.32)	(-0.33)						
3	0.09	0.28	0.24	-0.01	-0.03	0.83	0.31	3.81	7.53	8.65	0.46
		(2.20)	(1.91)	(-0.17)	(-0.29)						
4	0.18	0.40	0.30	0.25	0.22	1.09	0.56	5.38	7.99	11.98	0.44
		(2.01)	(1.74)	(0.56)	(0.19)						
High	1.06	1.03	0.81	0.82	0.71	1.47	1.20	11.21	11.10	11.17	0.42
		(2.65)	(2.69)	(3.37)	(2.96)						
High − Low		0.94***	0.73***	0.83***	0.72***						
		(2.75)	(2.81)	(3.27)	(2.75)						

Table A.2: Are exposures to bond factors priced?

This table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the bond market betas, with and without control variables. The bond market betas (β^{MKT}, β^{DRF}, β^{CRF}, and β^{LRF}) are estimated for each bond from the time-series regressions of bond excess returns on the excess bond market return and the associated bond factors (DRF, CRF, or LRF) using a 36-month rolling window estimation. Bond characteristics include credit rating, illiquidity (ILLIQ), bond return in previous month (REV), time to maturity (years), and the natural logarithm of bond amount outstanding (Size). Numbers in bold denote statistical significance at the 5% level or better.

	Intercept	β^{MKT}	β^{DRF}	β^{CRF}	β^{LRF}	Rating	ILLIQ	Maturity	Size	REV	Adj. R^2
(1)	0.229	-0.150	**0.207**	**0.120**	**0.218**						0.097
	(2.62)	(-1.65)	(2.81)	(2.41)	(2.86)						
(2)	-0.332	-0.106	**0.188**	**0.127**	**0.194**	**0.072**					0.127
	(-3.27)	(-1.53)	(2.79)	(2.53)	(3.29)	(4.34)					
(3)	0.160	0.296	**0.193**	**0.221**	**0.220**		**0.094**				0.121
	(1.47)	(3.05)	(2.98)	(1.79)	(2.34)		(3.23)				
(4)	0.200	-0.173	**0.195**	**0.117**	**0.247**			0.001			0.121
	(2.57)	(-1.84)	(2.84)	(2.30)	(3.81)			(0.16)			
(5)	0.254	-0.163	**0.189**	**0.104**	**0.242**				-0.064		0.104
	(2.56)	(-1.74)	(2.60)	(2.05)	(3.88)				(-1.28)		
(6)	0.244	-0.125	**0.206**	**0.100**	**0.220**					**-0.090**	0.123
	(3.17)	(-1.94)	(2.63)	(2.06)	(4.08)					(-6.81)	
(7)	-0.112	0.104	**0.066**	**0.116**	**0.152**	0.025	**0.093**	0.027	0.033	**-0.103**	0.162
	(-1.42)	(1.35)	(2.28)	(2.03)	(2.78)	(1.40)	(5.84)	(1.32)	(1.28)	(-4.58)	

Table A.3: Predicting aggregate bond market returns and volatility

This table reports results of aggregate systematic risk (SR) in predicting N-month ahead aggregate bond market returns and volatility for different horizons from month 1 to 12. MKT is the excess bond market return. MKT^{Vol} is the aggregate monthly bond market variance, defined as the sum of squared daily bond market returns in a month. The benchmark model used to generate systematic risk is the 4-factor model with the excess bond market return (MKT), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factor (LRF). Aggregate systematic risk is the equal-weighted average of the corporate bond systematic risk for each month. Control variables include the log earnings-to-price ratio (EP), the log dividend-to-price ratio (DP), the aggregate book-to-market ratio (BM), the term spread (TERM), the default spread (DEF), and the equity variance (SVAR). The Newey-West adjusted t-statistics are given in parentheses.

Panel A: Dep. var = MKT

Forecasting horizon	Intercept	SR	EP	DP	BM	TERM	DEF	SVAR	Adj.R^2
N=1	-2.22	1.22***	-0.31	-0.20	1.59	0.08**	0.21*	0.49***	9.53
	(-0.44)	(2.66)	(-1.23)	(-0.19)	(0.71)	(2.12)	(1.88)	(3.38)	
N=2	-4.24	1.41**	-0.50	-0.47	2.76	-0.06	-0.06	0.65***	9.03
	(-0.62)	(2.35)	(-1.52)	(-0.35)	(0.92)	(-1.51)	(-1.23)	(4.57)	
N=3	-4.44	1.29**	-0.80*	-0.30	3.27	-0.03	-0.06	0.02	3.74
	(-0.69)	(2.59)	(-1.92)	(-0.26)	(0.99)	(-0.57)	(-0.68)	(0.18)	
N=4	-3.04	1.10***	-0.68	-0.08	2.76	-0.00	0.06	0.04	3.92
	(-0.54)	(2.74)	(-1.62)	(-0.08)	(0.91)	(-0.05)	(0.95)	(0.18)	
N=5	-3.55	1.10***	-0.74*	-0.15	2.85	0.03	-0.05	0.11	4.13
	(-0.58)	(2.64)	(-1.77)	(-0.15)	(0.82)	(0.59)	(-0.93)	(0.84)	
N=6	-0.86	1.05**	-0.29	0.05	0.82	0.00	0.06	0.48***	3.78
	(-0.13)	(2.57)	(-0.61)	(0.05)	(0.23)	(0.10)	(0.96)	(2.88)	
N=7	-1.06	0.95**	-0.14	-0.09	0.87	-0.02	0.06	0.72***	5.93
	(-0.19)	(2.39)	(-0.46)	(-0.09)	(0.30)	(-1.07)	(1.24)	(5.57)	
N=8	0.40	0.95**	-0.14	0.20	-0.00	-0.02	-0.04	0.57***	4.32
	(0.08)	(2.40)	(-0.41)	(0.23)	(-0.00)	(-0.91)	(-0.68)	(3.75)	
N=9	-1.43	0.65*	-0.19	-0.15	1.07	0.02	0.09*	0.56***	3.19
	(-0.30)	(1.69)	(-0.59)	(-0.17)	(0.48)	(0.50)	(1.81)	(3.98)	
N=10	-0.31	0.73*	-0.33	0.18	0.47	-0.01	-0.04	0.36***	1.74
	(-0.06)	(1.68)	(-1.08)	(0.21)	(0.19)	(-0.55)	(-0.56)	(4.05)	
N=11	-1.53	0.63	-0.62*	0.15	1.44	-0.02	-0.12*	0.07	1.99
	(-0.29)	(1.18)	(-1.73)	(0.16)	(0.54)	(-0.43)	(-1.76)	(0.65)	
N=12	-1.46	0.60	-0.67*	0.17	1.18	-0.04	-0.09*	-0.11	0.66
	(-0.25)	(1.07)	(-1.88)	(0.16)	(0.40)	(-1.61)	(-1.92)	(-0.82)	

Table A.3. (Continued)

Panel B: Dep. var = MKT^{Vol}

Forecasting horizon	Intercept	SR	EP	DP	BM	TERM	DEF	SVAR	Adj.R^2
N=1	-13.86	10.68***	-5.10***	-3.96	-8.13	0.03	-0.56	10.58***	70.97
	(-0.58)	(3.75)	(-2.90)	(-0.89)	(-0.55)	(0.20)	(-1.56)	(7.27)	
N=2	-14.55	10.38***	-5.05***	-4.48	-10.38	0.04	-0.49	8.60***	51.95
	(-0.41)	(2.86)	(-2.78)	(-0.64)	(-0.54)	(0.28)	(-1.18)	(6.28)	
N=3	4.08	10.38**	-3.78*	-1.85	-23.55	0.04	-0.41	7.10***	40.11
	(0.09)	(2.28)	(-1.68)	(-0.21)	(-1.04)	(0.47)	(-1.25)	(5.35)	
N=4	24.36	10.57**	-2.29	1.02	-37.40	0.07	-0.43	6.06***	34.60
	(0.45)	(2.07)	(-0.85)	(0.10)	(-1.45)	(0.86)	(-1.07)	(5.01)	
N=5	41.37	11.08**	-0.94	3.34	-49.11*	-0.14	-0.60	5.41***	32.05
	(0.71)	(2.05)	(-0.33)	(0.30)	(-1.78)	(-1.36)	(-1.43)	(4.26)	
N=6	62.86	11.43*	0.58	6.45	-63.40**	-0.19	-0.46	4.47***	29.32
	(0.96)	(1.94)	(0.18)	(0.52)	(-2.03)	(-1.54)	(-1.64)	(3.55)	
N=7	81.05	11.58*	1.57	9.37	-74.48**	-0.22**	-0.45**	3.43***	28.12
	(1.15)	(1.81)	(0.48)	(0.71)	(-2.22)	(-2.02)	(-2.07)	(2.60)	
N=8	88.65	10.98	1.83	10.71	-78.71**	-0.22*	-0.42*	2.71**	26.89
	(1.22)	(1.61)	(0.57)	(0.79)	(-2.27)	(-1.85)	(-1.68)	(2.03)	
N=9	87.68	10.16	1.51	10.68	-78.16**	-0.10	-0.46*	1.93	24.94
	(1.21)	(1.43)	(0.47)	(0.80)	(-2.24)	(-0.94)	(-1.80)	(1.58)	
N=10	84.81	9.82	1.60	9.93	-77.39**	-0.14	-0.37*	1.85	24.16
	(1.19)	(1.36)	(0.50)	(0.76)	(-2.18)	(-1.09)	(-1.92)	(1.60)	
N=11	76.69	9.55	1.30	8.41	-73.71**	-0.04	-0.42	1.75	23.60
	(1.10)	(1.35)	(0.41)	(0.67)	(-2.06)	(-0.33)	(-1.60)	(1.58)	
N=12	78.37	9.11	1.67	8.49	-74.20**	0.06	-0.32	1.46	22.19
	(1.15)	(1.31)	(0.54)	(0.70)	(-2.04)	(0.56)	(-1.08)	(1.36)	