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ABSTRACT

We propose a comprehensive measure of systematic risk for corporate bonds as a nonlinear function of robust risk factors and find a significantly positive link between systematic risk and the time-series and cross-section of future bond returns. We also find a positive but insignificant relation between idiosyncratic risk and future bond returns, suggesting that institutional investors dominating the bond market hold well-diversified portfolios with a negligible exposure to bond-specific risk. The composite measure of systematic risk also predicts the distribution of future market returns, and the systematic risk factor earns a positive price of risk, consistent with Merton's (1973) ICAPM.

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1 Introduction

According to the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966), the cross-sectional variation in expected returns of different securities is driven only by the cross-sectional variation in their market betas. This hypothesis is perhaps the most studied, and also one of the most strongly refuted hypotheses in empirical asset pricing.[1] Despite the vast literature investigating the role of systematic risk in the cross-sectional pricing of individual stocks, far less effort has been devoted to explaining the cross-sectional dispersion in corporate bond returns. This paper is the first to propose a novel measure of systematic risk for corporate bonds and examine its relationship with expected bond returns.

Bai, Bali, and Wen (2019, hereafter BBW) introduce common risk factors based on the downside risk, credit risk, and liquidity risk of corporate bonds. They show that these novel bond factors have significant risk premia and outperform all other models considered in the literature in explaining the returns of the industry- and size/maturity-sorted portfolios of corporate bonds. Extending the original work of BBW, this paper introduces a composite measure of systematic risk for individual corporate bonds, defined as a nonlinear function of the aggregate bond market portfolio (MKT), downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF). Specifically, the composite measure of systematic risk synthesizes the variance of the MKT, DRF, CRF, and LRF factors, these factors' cross-covariances, and the exposures of corporate bond returns to these factors.

We contribute to the literature by analyzing corporate bonds' aggregate exposure to the new bond factors (DRF, CRF, LRF) and by investigating the performance of this broad measure of systematic risk in predicting both time-series and cross-sectional bond returns. We assemble a comprehensive dataset of corporate bonds from January 1997 to December 2017, including over 1.2 million monthly bond return observations for a total of 22,231 bonds issued by 7,915 firms. Then, we test the significance of a cross-sectional relation between systematic

[1] Over the past four decades, a number of studies provide evidence that firm characteristics such as firm size, value-to-price ratios, investment, profitability, and past returns do have significant explanatory power for average stock returns, while market beta has no power.

risk and future returns using portfolio-level analysis, and find that bonds in the highest systematic risk quintile generate 6.24% to 9.36% more annualized raw and risk-adjusted returns than bonds in the lowest systematic risk quintile, with the systematic risk premium stemming from the outperformance 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.

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. Maio and Santa-Clara (2012) investigate the restrictions of the cross-sectional and time-series predictability in the intertemporal capital asset pricing model (ICAPM, Merton, 1973), and show that a 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. Aggregating systematic risk across bonds, either equal-weighted, value-weighted, or rating-weighted, we find that the aggregate measure of systematic risk significantly predicts future bond market returns and bond market volatility, even after controlling for a large set of macroeconomic variables capturing business cycle fluctuations. We also construct a new systematic risk factor based on the independently sorted bivariate portfolios of credit rating and systematic risk, and show that the systematic risk factor earns a positive price of risk in the cross-section of corporate bonds. Moreover, the price of systematic risk estimated from the cross-sectional regressions yields an economically sensible estimate of the relative risk aversion of bond market investors. Since the composite measure of systematic risk satisfies all restrictions of the ICAPM on the time-series and cross-sectional predictability, we conclude that Merton's model provides a theoretical background for the systematic risk factor in the corporate bond market.

Dynamic asset pricing models starting with Merton's (1973) ICAPM provide a theoretical framework that gives a positive equilibrium relation between the conditional first and second moments of excess returns on the market portfolio. Despite the importance of the positive risk-return tradeoff and the theoretical appeal of Merton's result, empirical studies are not in agreement on the direction of an intertemporal relation between expected return and risk in the equity market. Many studies fail to identify a robust and significant intertemporal relation between risk and return on the equity market portfolio. Several studies even find that the intertemporal relation between risk and return is negative. Some recent work does document a positive and significant time-series relation between expected return and risk in the equity market.[2] It is important to note that we find a significantly positive time-series relation between systematic risk and expected returns on the aggregate bond market portfolio, indicating a positive intertemporal risk-return tradeoff in the corporate bond market, while the equity literature has not yet reached an agreement on the existence of such a positive risk-return tradeoff in the equity market.

In addition to proposing a new measure of systematic risk and testing its cross-sectional and time-series predictive power, this paper further contributes to the literature by investigating the idiosyncratic volatility puzzle in the corporate bond market. Assuming that assets are perfectly liquid (frictionless) and that investors have complete information, firm-specific risk does not command a risk premium because investors can create well-diversified portfolios that have zero exposure to firm-specific risk. The corresponding empirical implication is that measures of firm-specific risk, or risk that is not related to a systematic risk factor, should exhibit no relation with future returns. Theoretically, however, Levy (1978) shows that if investors do not hold a large number of assets in their portfolios, and are hence unable to diversify firm-specific risk, idiosyncratic risk affects equilibrium asset prices. Merton (1987) indicates that if investors cannot hold the market portfolio, then they care about total risk, not simply market risk. Therefore, firms with larger total or idiosyncratic risk require higher returns to compensate for imperfect diversification.

The most widely-cited study on idiosyncratic risk and expected returns is Ang, Hodrick,

[2]See, e.g., French, Schwert, and Stambaugh (1987), Bollerslev, Engle, and Wooldridge (1988), Nelson (1991), Campbell and Hentchel (1992), Glosten, Jagannathan, and Runkle (1993), Whitelaw (1994), Harrison and Zhang (1999), Harvey (2001), Brandt and Kang (2004), Ghysels, Santa-Clara, and Valkanov (2005), Bollerslev and Zhou (2006), Guo and Whitelaw (2006), Bali (2008), and Bali and Engle (2010).

Xing, and Zhang (2006), which demonstrates a strong negative cross-sectional relation between idiosyncratic volatility and future stock returns. This result is highly inconsistent with theoretical predictions and thus considered as a puzzle. Several subsequent papers have proposed explanations for the idiosyncratic volatility 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).[3]

We re-examine the idiosyncratic volatility puzzle in the corporate bond market by testing the direction and significance of a cross-sectional relation between idiosyncratic volatility and future bond returns. Idiosyncratic volatility is measured by the variance of the residuals from the monthly time-series regressions of bond excess returns on the MKT, DRF, CRF, and LRF factors of BBW. 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. Furthermore, 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.

To assess the relative performance of our composite measure of risk, 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, Gruber, and Blake (1995) that relies on the aggregate corporate bond market portfolio (MKT). Second, we

[3] Hou and Loh (2016) find that many existing explanations resolve less than 10% of the puzzle. On the other hand, explanations based on investors' lottery preferences and market frictions show some promise in solving the idiosyncratic volatility puzzle. Together, all existing explanations account for 29-54% of the puzzle in individual stocks and 78-84% of the puzzle in idiosyncratic volatility-sorted portfolios.

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, also the most comprehensive one, is the six-factor model in Chung, Wang, and Wu (2019), which extends the second benchmark (three-factor model) by adding the size, book-to-market, and market volatility factors ($SMB, HML, \Delta VIX$). We find that proxies of systematic risk generated by these alternative factor models do not predict the cross-sectional variation in future bond returns, whereas proxies of idiosyncratic risk 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.[4] These results indicate that the risk factors of BBW provide an accurate characterization of systematic risk in the corporate bond market, and hence the BBW-based composite measure of systematic variance is a priced risk factor.

Lastly, we examine the differences between the roles of systematic and firm-specific risk measures in the cross-sectional pricing of equities versus bonds. To make a fair comparison, we employ the same composite methodology to construct systematic and 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 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 differing 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

[4] 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.

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 a markedly different group 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 (systematic/idiosyncratic) risk-return relations in the bond and equity markets.

Indeed, we find that in the equity market, the idiosyncratic volatility 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. In the corporate bond market, the systematic risk premium is stronger for corporate bonds largely held by active institutional investors. We explain these results by showing that institutional investors with higher exposures to common risk factors tend to have stronger timing abilities and higher future returns. That is, institutional investors with stronger timing abilities willingly take direct exposures to the systematic risk factors, relying on their market- and volatility-timing abilities to generate superior returns. Since these are active institutions with dynamic investment strategies that are highly exposed to systematic risk, timing the switch in economic trends is essential to their success. Accordingly, the systematic risk premium is stronger (weaker) for corporate bonds largely held by active (passive) institutional investors. Thus, our findings offer a plausible explanation for the significance of systematic risk (idiosyncratic risk) in the bond (equity) market based on differing investor preferences and clienteles.

In the remainder of this paper, we introduce the data and variables in Section 2, examine the cross-sectional relation between systematic risk, idiosyncratic risk and future bond returns in Section 3, and test alternative measures of systematic risk in Section 4. Section 5 investigates whether the newly proposed measure of systematic risk is consistent with Merton's (1973) theoretical model. Section 6 provides an explanation for the contradictory role of systematic and idiosyncratic risk in the cross-sectional pricing of equities versus bonds. Section 7 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 five 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 data

To investigate the clientele effect in the equity and bond markets, we also collect asset holdings data. For equities holdings, we use the Thomson-Reuters' institutional holdings (13F) database that covers all investment companies, including banks, insurance companies, parents of mutual funds, pension funds, university endowments, and numerous other types of professional investment advisors for the sample period of 1980-2017. For bond holdings, we use eMaxx data from Thomson-Reuters that cover investment companies, including insurance companies, mutual funds, and pension funds for the sample period of 2001-2017 (the earliest bond holdings data start 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, $INST$.

It is worth noting that indicators for institutional ownership have different interpretations for equities and bonds. For example, when we sort the entire equity (bond) sample into five quintiles by institutional ownership, the first quintile with the lowest institutional ownership ($INST$,1) for equity portfolios refers to equities largely held by retail investors, whereas ($INST$,1) for bond portfolios refers to bonds still held by institutional investors even in the lowest institutional ownership quintile. This is due to the different sources of equity and bond holdings data, with the bond holdings data compiled solely from institutional investors and also from a partial list of institutional investors (hedge funds are not included).

2.3 A composite measure of systematic risk in the bond market

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

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

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 mean of excess returns over the past 36 months ($n = 36$), and $\sigma_{i,t}^2$ 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_i^2) into its systematic and unsystematic components. Our objective is to investigate whether the systematic or unsystematic 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 the independently sorted bivariate portfolios of bond-level credit rating, value-at-risk, and bond-level illiquidity:[5]

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

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. The unsystematic (or residual) risk of bond i is proxied by the variance of $\epsilon_{i,t}$ in Eq. (3), denoted by $\sigma_{\epsilon,i}^2$. The systematic risk of bond i is defined as the difference between total and unsystematic 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, the systematic risk of bond i is measured by the bond's systematic variance attributable to the overall volatility of the four factors as well as the factors' cross-covariances.

[5] 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.

2.4 Alternative factor models

We consider three different factor models to estimate the risk-adjusted returns (alphas) of corporate bond portfolios sorted by total risk, 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).[6]

The second one is the *5-factor model with bond market factors*, including the aggregate 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.[7] 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,

[6]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/.

[7]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.

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.[8] 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., 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.[9]

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.[10] 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

[8]Our key variables of interest – total, 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.

[9]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.

[10]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.

smaller and illiquid bonds have higher systematic risk.

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

3.1 The predictive power of total risk

We first test the significance of a cross-sectional relation between volatility and future returns on corporate bonds using portfolio-level 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 total variance (VOL), where quintile 1 contains bonds with the lowest volatility and quintile 5 contains bonds with the highest volatility. Table 2 shows, for each quintile, the average volatility 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 (β^{MKT}), illiquidity (ILLIQ), downside risk (VaR), 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 volatility-sorted portfolios increases monotonically from 0.09% to 1.03% per month. This indicates a monthly average return difference of 0.94% between quintiles 5 and 1 with a Newey-West t-statistic of 2.75, implying that this positive return difference is economically and statistically significant. This result shows that corporate bonds in the highest VOL quintile generate 11.28% per annum higher average return than bonds in the lowest VOL 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 0.08% to 0.81% per month, moving from the Low-VOL to the High-VOL quintile, indicating a positive and significant alpha spread of 0.73% per month (t-stat.=2.81).

Beyond the well-known stock market factors (size, book-to-market, momentum, and liquidity), we also test whether the significant return difference between High-VOL bonds and Low-VOL 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-VOL to the High-VOL quintile, the 5-factor alpha from bond market factors increases almost monotonically from -0.01% to 0.82% per month. The corresponding 5-factor alpha spread between quintiles 5 and 1 is positive and highly significant: 0.83% per month with a t-statistic of 3.27. 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, moving from the Low-VOL to the High-VOL quintile, the 10-factor alpha increases almost monotonically from -0.00% to 0.71% per month, generating a positive and highly significant risk-adjusted return spread of 0.72% per month with a t-statistic of 2.75.

Next, we investigate the source of the significant risk-adjusted return (alpha) spread between the high- and low-volatility bonds. As reported in Table 2, the 10-factor alpha in quintile 1 (low-volatility bonds) is insignificant, whereas the 10-factor alpha in quintile 5 (high-volatility bonds) is positive and highly significant. Hence, we conclude that the significantly positive alpha spread between the high- and low-volatility bonds is due to outperformance by High-VOL bonds, but not to underperformance by Low-VOL bonds.

Finally, we examine the average bond characteristics of volatility-sorted portfolios. As shown in the last six columns of Table 2, high-volatility bonds have higher bond market beta

(β^{MKT}), higher illiquidity (or lower liquidity), higher downside risk, higher credit rating (or lower credit quality), longer maturity, and smaller size. These results suggest a risk-based explanation for the outperformance of bonds with higher volatility.

3.2 The predictive power of systematic risk

After presenting the economic and statistical significance of total variance, we now divide total variance into its systematic and unsystematic components described in Section 2.3. We then test whether the systematic or unsystematic component has a stronger predictive power over future corporate bond returns.

Table 3 provides evidence for the strong predictive power of systematic risk (SR) for future bond returns. 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, showing that corporate bonds in the highest SR quintile generate 9.36% per annum higher returns than bonds in the lowest SR quintile do. Similar to the findings from the average excess returns, the 5- and 10-factor alpha differences between quintiles 5 and 1 are all positive and economically and statistically significant at 0.62% (t-stat.= 2.76), 0.58% (t-stat.=2.65), and 0.52% (t-stat.=2.59) per month. 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.

We also investigate the source of this significant alpha spread between the highest and lowest SR quintiles and find that the 10-factor alpha is significantly positive for bonds in the highest SR quintile, whereas it is economically and statistically insignificant for bonds in the lowest SR quintile, indicating that the systematic risk premium is driven by outperformance by high-SR bonds (long leg of the arbitrage portfolio), but not due to underperformance by low-SR bonds (short leg of the arbitrage portfolio). Similar to our findings from the volatility-sorted portfolios, Table 3 also shows that bonds with higher systematic risk have higher market beta, lower liquidity, higher downside risk, lower credit quality, longer maturity, and smaller size, supporting a risk-based explanation for the outperformance of bonds with higher systematic risk.

3.3 The idiosyncratic volatility puzzle in the corporate bond market?

In sharp contrast to the findings in Table 3, Table 4 presents evidence for the poor performance of residual or unsystematic risk (USR) in predicting the cross-sectional variation in future bond returns. Compared to Table 3, the average return spread between quintiles 5 and 1 in Table 4 is much weaker economically: 0.49% per month (t-stat.=3.27). More importantly, the 10-factor alpha spread between the high- and low-USR 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 4 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 idiosyncratic volatility puzzle in the corporate bond market.

3.4 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.

3.4.1 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, in Panel A of Table 5, we form quintile portfolios every month from January 1997 to December 2017 by first sorting corporate bonds into five quintiles based on their unsystematic risk (USR). Then, within each USR-sorted portfolio, bonds are sorted further into five sub-quintiles based on their systematic risk (SR). This methodology, under each USR-sorted quintile, produces sub-quintile portfolios of bonds with dispersion in SR and nearly identical USR values (i.e., these newly generated SR sub-quintile portfolios control for differences in USR). SR,1 represents the lowest SR-ranked bond quintiles within each of the five USR-ranked quintiles. Similarly, SR,5 represents the highest SR-ranked quintiles within each of the five USR-ranked quintiles. Panel A of Table 5 shows the average systematic risk and the next month average return for each quintile. Moving from Quintile SR,1 to Quintile SR,5, the average return on the SR portfolios increases almost monotonically from 0.30% to 1.00% per month. The average return difference between Quintiles 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 Quintile SR,5 and Quintile 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 with respective t-statistics of 2.25, 2.48, and 2.27. 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 statistically significant.

3.4.2 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, quintile portfolios are formed every month from January 1997 to December 2017 by first sorting corporate bonds into five quintiles based on their systematic risk (SR). Then, within each SR-sorted portfolio, bonds are sorted further into five sub-quintiles based on their unsystematic risk (USR). Table 5, Panel B shows that the average return spread between Quintiles USR,5 and USR,1 (i.e., high-USR bonds versus low-USR bonds) 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 the idiosyncratic risk and future *raw* returns disappears after controlling for the systematic risk. Finally, Panel B of Table 5 shows that in addition to the raw return difference, the 5-factor stock, 5-factor bond, and 10-factor alpha differences are all economically small and statistically insignificant. Overall, the bivariate portfolio-level analyses indicate that compared to idiosyncratic risk, the composite measure of systematic risk is a more powerful determinant of the cross-sectional differences in corporate bond returns.

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

We now examine whether and how our main findings would change if our analysis was applied to bonds with different credit risks. We perform this test by forming univariate quintile portfolios of VOL (total risk), SR (systematic risk), and USR (idiosyncratic risk) separately for the investment-grade and non-investment-grade bonds and by analyzing the next month return and alpha differences between the high-risk and low-risk quintiles.

Table 6 reports, for each bond group, the next month average return and 10-factor alpha spreads between quintiles 5 and 1. After conditioning on credit ratings, the return and alpha spreads between the high- and low-volatility quintiles are, respectively, 0.55% and 0.32%

per month, and are statistically significant for investment-grade bonds. The corresponding return and alpha spreads are much higher and highly significant for non-investment-grade bonds: 1.21% and 0.90% per month, respectively. Similarly, the return and alpha spreads between the high- and low-SR quintiles are positive, at 0.42% and 0.27% per month, and statistically significant for investment-grade bonds. As expected, the systematic risk premia are economically larger for non-investment-grade bonds: 0.88% and 0.96% per month. In contrast to the findings on systematic risk, the alpha spreads between the high- and low-USR quintiles are economically small and statistically 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 on one hand, idiosyncratic volatility does not command a significant risk premium in the sample of investment- or non-investment-grade bonds. On the other hand, there is a strong, positive relation between systematic risk and future returns conditioned on the credit quality of corporate bonds. Specifically, the cross-sectional relation between systematic risk and expected returns is stronger for non-investment-grade bonds, but the positive link between systematic risk and future returns remains significant for investment-grade bonds as well.

3.6 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. We now examine the cross-sectional relation between systematic risk, idiosyncratic risk, and expected returns at the bond level using Fama and MacBeth (1973) regressions. We present the time-series averages of the slope coefficients from the regressions of one-month-ahead excess bond returns on systematic risk (SR), unsystematic risk (USR), and the control variables, including the bond market beta (β^{MKT}), default beta (β^{DEF}), term beta (β^{TERM}), bond-level illiquidity (ILLIQ), credit rating, year-to-maturity (MAT), bond amount outstanding (SIZE), and previous month bond return (REV).[11] The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables on average have non-zero premium. Monthly cross-sectional regressions are run for the following specification and nested versions thereof:

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

where $R_{i,t+1}$ is the excess return on bond i in month $t+1$. The predictive cross-sectional regressions are run on the one-month lagged measures of systematic risk (SR), unsystematic risk (USR), and the lagged control variables.

Table 7 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 Newey-West adjusted t-statistics are reported in parentheses. The univariate regression results show a positive and significant relation between systematic risk (SR) and the cross-section of future bond returns. 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 3 for the univariate quintile portfolios of SR. The spread in average SR between quintiles 5 and 1 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.[12]

Regression specification (2) in Table 7 shows that after we control for β^{MKT}, β^{DEF}, β^{TERM}, illiquidity, credit rating, maturity, size, and the previous month return, the average slope coefficient of SR remains positive and highly significant. In other words, controlling for bond characteristics does not affect the significance of systematic risk in the corporate bond market.

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

[12]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 3).

Regression (3) tests the cross-sectional predictive power of unsystematic risk (USR) for future bond returns. The average slope, $\lambda_{2,t}$, is positive and significant in univariate regressions, consistent with the significantly positive raw return spread reported in Table 4. However, in Regression (4), the predictive power of USR disappears when controlling for the bond characteristics simultaneously. The coefficient on USR is economically and statistically insignificant: -0.006 with a t-statistic of -0.03, consistent with the insignificant 10-factor alpha spread presented in Table 4.

Regression (5) tests the cross-sectional predictive power of SR while controlling for USR. Importantly, the average slope coefficient on SR remains positive and highly significant, 0.921 (t-stat. $= 4.56$), indicating that the predictive power of SR is not subsumed by the idiosyncratic risk. Whereas, the predictive power of USR disappears in the bivariate regression specification (5) controlling for SR, consistent with the bivariate portfolio results reported in Table 5.

The last specification, Regression (6), presents results from the multivariate regressions with both systematic and idiosyncratic risk measures while simultaneously controlling for β^{MKT}, β^{DEF}, β^{TERM}, illiquidity, credit rating, maturity, size, and the one-month lagged return. Similar to our findings in Regressions (2) and (4), the systematic risk premium is positive and highly significant, whereas idiosyncratic volatility does not command a risk premium after controlling for the bond characteristics. These results show that the composite measure of systematic risk has distinct, significant 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.

3.7 Are corporate bond exposures to the risk factors priced?

We attribute our theoretically consistent finding on the positive relation between systematic risk and future bond returns primarily to the fact that we construct an economically sensible measure of systematic risk, not only because we choose the 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 is a function of the variance of the underlying factors, the cross-covariances of the factors, and the exposures of bond excess 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, we think that 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. That being said, we now investigate the source of systematic risk by testing whether exposures of corporate bonds to the DRF, CRF, and LRF factors can predict the cross-sectional variations in future bond returns. Motivated by Daniel and Titman (1997) and Brennan, Chordia, and Subrahmanyam (1998), we investigate this issue using bond-level cross-sectional regressions. 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 (MKT):

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{Factor} \cdot Factor_t + \epsilon_{i,t}, \tag{5}$$

where $Factor_t$ is one of the three value-weighted bond risk factors (DRF, CRF, and LRF), and $\beta_{i,t}^{Factor}$ refers to $\beta_{i,t}^{DRF}$, $\beta_{i,t}^{CRF}$, or $\beta_{i,t}^{LRF}$.

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. Regression (1) in Table 8 presents positive and significant relations between all three factor betas (β^{DRF}, β^{CRF}, β^{LRF}) and the cross-section of future bond returns. Then, regressions (2) to (6) sequentially control for the risk and non-risk features of corporate bonds, that is, rating, illiquidity, maturity, size, and lagged return. Finally, Regression (7) simultaneously controls for all characteristics. All regressions present similar results: 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.

4 Alternative Measures of Systematic Risk

In this section, we utilize alternative factor models to generate systematic and idiosyncratic risk of individual corporate bonds. We show that measures of systematic risk estimated with these alternative factor models do not predict the cross-sectional bond returns, whereas measures of unsystematic 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 benchmark factor models in comparison to our measures described in Section 2.3:

1. One-factor model of Elton, Gruber, and Blake (1995):

$$R_{i,t} = \alpha_i + \beta_{1,i} MKT_t + \epsilon_{i,t}. \tag{6}$$

2. Three-factor model of Fama and French (1993), Elton, Gruber, and Blake (1995), and Bessembinder et al. (2009):

$$R_{i,t} = \alpha_i + \beta_{1,i} MKT_t + \beta_{2,i} DEF_t + \beta_{3,i} TERM_t + \epsilon_{i,t}. \tag{7}$$

3. Six-factor model of Chung, Wang, and Wu (2019):

$$R_{i,t} = \alpha_i + \beta_{1,i} MKT_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} DEF_t + \beta_{5,i} TERM_t + \beta_{6,i} \Delta VIX_t + \epsilon_{i,t}. \tag{8}$$

In the above factor models, $R_{i,t}$ is the excess return of bond i in month t, MKT_t, SMB_t, HML_t, DEF_t, $TERM_t$, and ΔVIX_t denote the aggregate corporate bond market excess return, the size factor, the book-to-market factor, the default factor, the term factor, and the market volatility factor, respectively.[13] The total risk of bond i is measured by the variance of $R_{i,t}$, denoted by σ_i^2. The unsystematic (or residual) 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 the systematic risk of bond i as the difference between total and unsystematic variance, $SR = \sigma_i^2 - \sigma_{\epsilon,i}^2$, which is a function of the variance of the factors, their cross-covariances, and the exposures of the bond's excess returns to the factors.

Table 9 presents the portfolio-level results of systematic and unsystematic risk based on the above three factor models. For each month from January 1997 to December 2017, we form value-weighted univariate portfolios by sorting corporate bonds into quintiles based on different measures of systematic risk (in Panel A) or unsystematic risk (in Panel B), where quintile 1 contains bonds with the lowest SR (or USR) and quintile 5 contains bonds with the highest SR (or USR).

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 quintiles are positive but insignificant. Similarly, the 10-factor and the BBW alpha spreads between quintiles 5 and 1 are economically small and statistically insignificant, ranging from -0.24% to 0.21% per month. These results are in sharp contrast to the findings in Table 3, which demonstrates a significantly positive link between SR and future bond returns using the BBW-factor-generated SR measure.

The findings for USR-sorted portfolios are the opposite. Panel B shows that the average return spreads between the high- and low-USR quintiles are economically and statistically significant, ranging from 0.70% to 0.79% per month. Also, the 10-factor alpha spreads for the USR-sorted portfolios are economically and statistically significant for all three USR mea-

[13] Chung, Wang, and Wu (2019) show that market volatility risk is priced in the cross-section of corporate bond returns. Based on a similar specification in Eq.(8), they also document a positive relation between idiosyncratic volatility and future bond returns.

sures based on Eqs.(6)−(8). However, the positive return spreads are fully explained by the BBW 4-factor model. Specifically, the BBW alpha spreads between the high- and low-USR portfolios are small and insignificant, ranging from 0.08% (t-stat=0.45) to 0.14% (t-stat=0.77) per month. Overall, Table 9 highlights the importance of the downside risk, credit risk, and liquidity risk factors of BBW in defining systematic risk of corporate bonds.

5 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 5.1, 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 5.2 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 5.2 provides empirical evidence satisfying the third ICAPM restriction as well.

5.1 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.[14] 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. Figure 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

[14] 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.

of 0.95, and all spike during the Great Recession.[15] 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:

$$Y_{t+\tau} = \alpha + \gamma_1 \cdot SR_t + \gamma_2 \cdot X_t^k + \epsilon_{t+1}, \qquad k = 1, ..., 6; \quad \tau = 1, 2, ..., 12 \tag{9}$$

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 10 presents the performance of the aggregate systematic risk in predicting τ-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. (9) 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 10 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

[15] 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.

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.

5.2 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):

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{SRF} \cdot SRF + \epsilon_{i,t}, \tag{10}$$

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:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{MKT} + \lambda_{2,t} \cdot \beta_{i,t}^{SRF} + \epsilon_{i,t+1}. \tag{11}$$

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:

$$E_t(R_{t+1}) = A \cdot Cov_t(R_{i,t+1}, MKT_{t+1}) + B \cdot Cov_t(R_{i,t+1}, SRF_{t+1}), \tag{12}$$

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. (12) 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. (12) 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.[16]

Following Bali and Engle (2010), we aggregate Eq. (12) and write the static (unconditional) version of the conditional ICAPM to determine the economic significance of A and B:

$$E(MKT) = A \cdot \sigma^2_{MKT} + B \cdot \sigma_{MKT,SRF}, \tag{13}$$

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. (11) to proxy for A and B in Eq. (13), respectively. Substituting the sample estimates of $\sigma^2_{MKT} = 0.023$ and $\sigma_{MKT,SRF} = 0.021$ along with ($A =$

[16] Since the conditional variances of MKT_{t+1} and SRF_{t+1} are identical across bonds, Eq. (12) can be written in terms of the conditional betas ($\beta^{MKT}_{i,t}$, $\beta^{SRF}_{i,t}$) as in Eq. (11).

$\overline{\lambda}_1/\sigma^2_{MKT} = 6.09$) and ($B = \overline{\lambda}_2/\sigma^2_{SRF} = 6.94$) into Eq. (13) 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.

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 firm-specific risk in the cross-sectional pricing of equities versus bonds. First, we propose a similar measure of systematic risk for individual stocks and test whether this measure predicts the cross-section of expected stock returns. Second, we revisit the idiosyncratic volatility puzzle in the equity market. Third, we explore the impact of investor clientele on the predictive power of idiosyncratic risk for future stock returns and on the predictive power of systematic risk for future bond returns.

6.1 A composite measure of systematic risk 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. (14) and the four-factor model of Hou, Xue, and Zhang (2015) in Eq. (15):

$$R_{i,d} = \alpha_i + \beta_{1,i} \cdot MKT_d^{Stock} + \beta_{2,i} \cdot SMB_d + \beta_{3,i} \cdot HML_d + \beta_{4,i} \cdot RMW_d + \beta_{5,i} \cdot CMA_d + \epsilon_{i,d}, \quad (14)$$

$$R_{i,d} = \alpha_i + \beta_{1,i} \cdot MKT_d^{Stock} + \beta_{2,i} \cdot ME_{Q,d} + \beta_{3,i} \cdot ROE_{Q,d} + \beta_{4,i} \cdot IA_{Q,d} + \epsilon_{i,d}. \quad (15)$$

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. (14) are the daily equity market, size, book-to-market, profitability, and investment factors of Fama and French (2015), respectively. In Eq. (15), $ME_{Q,d}$, $ROE_{Q,d}$, and $IA_{Q,d}$ are the daily size, profitability, and investment Q factors of Hou, Xue, and Zhang (2015), respectively.[17]

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. The unsystematic (or idiosyncratic) risk of stock i is measured by the variance of $\epsilon_{i,d}$, denoted by $\sigma_{\epsilon,i}^2$. The systematic risk of stock i is defined as the difference between the total and unsystematic 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. (14) and (15) are estimated using daily returns over the past one month, requiring at least 15 daily return observations in a month. Eqs. (14) and (15) also generate two different measures of systematic and idiosyncratic risk for individual equities; one based on the five-factor model of Fama and French (2015) and the other building on the four-factor model of Hou, Xue, and Zhang (2015).

Table 11 presents results from the value-weighted univariate portfolios of stocks sorted by total risk, systematic risk, and idiosyncratic risk. We use both the five-factor model of Fama and French (2015) and the four-factor model of Hou, Xue, and Zhang (2015) to estimate the

[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.

one-month-ahead risk-adjusted returns (alphas) of total risk, systematic risk, and idiosyncratic risk sorted portfolios. Consistent with the idiosyncratic volatility puzzle in the equity literature, Panel A of Table 11 reports a strong negative relation between total risk and future stock returns. As shown in the first four columns of Panel A, the average return and alpha spreads range from -0.80% to -0.89% per month and are statistically significant for the sample period 1963-2017, indicating that stocks in the highest total risk quintile underperform those in the lowest quintile by about 9.6% per annum. The last four columns of Panel A present similar results in terms of the economic and statistical significance of the low volatility effect for the sample period 1967-2017. In contrast to our findings for corporate bonds, Panels B and C show that the low volatility effect in Panel A is driven by the negative relation between idiosyncratic volatility and future stock returns, but not due to the systematic risk of individual stocks.

As presented in the first four columns of Panels B and C, when systematic and idiosyncratic risk measures are estimated with the five-factor model of Fama and French (2015), the monthly return and alpha spreads between the highest and lowest systematic risk quintiles are insignificant, ranging from -0.36% (t-stat.$= -1.26$) to -0.49% (t-stat.$= -1.36$), whereas the return and alpha spreads between the highest and lowest idiosyncratic volatility quintiles are economically large and highly significant, ranging from -0.77% (t-stat. $= -2.72$) to -0.86% (t-stat. $= -2.37$). Finally, the last four columns of Panels B and C present similar results when SR and USR measures are estimated using the four-factor model of Hou, Xue, and Zhang (2015), confirming the insignificant (significant) cross-sectional relation between SR (USR) and future equity returns.[18]

Overall, these results indicate that systematic risk does not predict the cross-sectional variation in equity returns, whereas the idiosyncratic volatility puzzle remains significant in the equity market even when we use the composite measures of systematic and idiosyncratic

[18]In untabulated results, we estimate SR and USR measures using the extended factor models of Fama and French (2015) and Hou, Xue, and Zhang (2015) with an additional momentum factor of Carhart (1997). The results are similar to those reported in Table 11, validating the insignificance (significance) of SR (USR) in predicting the cross-sectional differences in stock returns.

variance, estimated with the new methodology proposed in this paper. One potential explanation of the idiosyncratic volatility puzzle is that investors hold concave preferences and like positive skewness. If positive skewness is a desirable characteristic of a return distribution, then the fact that the simple act of diversification destroys portfolio skewness (or eliminates idiosyncratic skewness) is a likely explanation of observed behavior. That is, investors who care about the third-moment of the return distribution would be willing to hold a limited number of stocks in their portfolios, the exact number being a function of each individual's skewness/variance awareness. Those who are most concerned with skewness (variance) will hold a relatively small (large) number of stocks in their portfolios. Since the idiosyncratic volatility puzzle is known to be significant only in the sample of stocks largely held by individual investors (which will be confirmed in the next section), we can conclude that retail investors' demand for positive skewness dominates their aversion to volatility so that retail investors prefer to hold a small number of lottery-like stocks with large positive skewness, and lottery stocks happen to have high idiosyncratic volatility and low future returns.

Although diversification is critical in eliminating idiosyncratic risk, a closer examination of the portfolios of individual investors suggests that these 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. These results are similar to the findings of earlier studies. For example, Blume and Friend (1975) and Blume, Crockett, and Friend (1974) provide evidence that the average number of stocks in household portfolios is about 3.41 in 1967. Odean (1999) and Barber and Odean (2001) also report the median number of stocks in individual investors' portfolios as two to three. In more recent work, Dorn and Huberman (2005, 2010) use trading records between 1995 and 2000 of over 20,000 customers of a German discount brokerage and find that the typical portfolio consists of little more than three stocks.

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 retail investors are known to hold a small number of positively skewed, high-volatility stocks, explanations based on retail investors' preferences 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 quintiles based on institutional ownership, then within each ownership quintile, we further sort stocks into sub-quintiles based on their unsystematic risk (USR). Table 12 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 idiosyncratic volatility puzzle disappears among stocks with high institutional ownership. This result is consistent with the direct or indirect evidence provided by Kumar (2009), Han and Kumar (2013), and Bali, Brown, Murray, and Tang (2017) 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 to investigate the interaction between the clientele effect and systematic risk in the corporate bond market. Table 13 shows that within all institutional ownership quintiles, there is a monotonically increasing pattern in the average returns on SR-sorted portfolios moving from the low-SR to high-SR quintile, producing a significantly positive link between systematic risk and average returns of corporate bonds. However, the last three columns in Panel A provide evidence that the positive relation between the composite measure of systematic risk and risk-adjusted return is more pronounced among bonds with relatively low institutional ownership. That being said, it is difficult to identify retail ownership in corporate bond holdings data because the bond market is dominated by instiutional investors.

Thus, we try to gain a better understanding of the driving force of the significant relation between systematic risk and future bond returns by examining the key characteristics of the 5×5 bivariate portfolios of corporate bonds sorted by systematic risk and institutional ownership. Panel B of Table 13 presents the average systematic risk (SR) and the average exposures to the downside risk, credit risk, and liquidity risk factors (β^{DRF}, β^{CRF}, and β^{LRF}) in the 25 portfolios. We observe strong evidence that institutions in the low-INST quintile hold bonds with higher systematic risk and higher exposures to the DRF, CRF, and LRF factors. This explains why the systematic risk premium is strongest for bonds in low-institutional-ownership quintile.

Lastly, we investigate whether institutional investors holding bonds with high systematic risk actively adjust their exposures to the systematic risk factor in the corporate bond market.

Following the market-timing model of Treynor and Mazuy (1966), we run time-series regressions of the 25 SR&INST-sorted portfolios' excess returns ($R^p_{i,t}$) on the bond market excess returns (MKT_t) and the squared excess market returns (MKT_t^2):

$$R^p_{i,t} = \alpha_i + \beta_{1,i} MKT_t + \beta_{2,i} MKT_t^2 + \epsilon_{i,t}, \tag{16}$$

where $\beta_{2,i}$ captures the market-timing ability of institutions in each of the 25 SR&INST-sorted portfolios.

Panel C of Table 13 shows that institutions in the low-INST quintile have positive and much higher market-timing coefficients ($\beta_{2,i}$) compared to those in the remaining four INST quintiles. Combining this particular finding with the results in Panel B of Table 13 indicates that institutions in INST,1 have stronger market-timing ability, and they have higher systematic risk and higher future returns. Consistent with the market-timing ability of institutions, these results suggest that by predicting fluctuations in the systematic risk factors, institutional investors can adjust their bond portfolio exposures up or down in a timely fashion to generate superior returns. Indeed, we find that institutional investors, particularly those with higher systematic risk and higher exposures to the DRF, CRF, and LRF factors, correctly adjust their aggregate exposure to the common risk factors, and hence there exists a positive and stronger link between their systematic risk and future returns.

7 Conclusion

In this paper, we propose a novel measure of systematic risk for individual corporate bonds and test its significance in both the time-series and cross-sectional pricing of corporate bonds. We find that the newly proposed measure of systematic risk has a strong predictive power on the cross-sectional dispersion in future bond returns, and the positive systematic risk premium is driven by the outperformance of bonds with high systematic risk. Moreover, the aggregate measure of systematic risk significantly predicts positive expected bond market returns, and the corresponding systematic risk factor earns a positive price of risk in the cross-section of corporate bonds. The price of systematic risk estimated from the cross-sectional tests also generates an economically sensible estimate of the relative risk aversion of bond market investors. Since the composite measure of systematic risk satisfies all restrictions of Merton's (1973) ICAPM on the time-series and cross-sectional predictability, we conclude that Merton's model provides a theoretical support for the systematic risk factor in the corporate bond market.

Given the powerful presence of systematic risk in the time-series and cross-sectional pricing of corporate bonds, the idiosyncratic volatility puzzle that is 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 firm-specific risk measures 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 idiosyncratic volatility puzzle disappears among stocks with high institutional ownership. On the contrary, the systematic risk premium is stronger for corporate bonds largely held by institutional investors with market- and volatility-timing abilities due to their talent in taking direct exposures to the systematic risk factors in the bond market and hence generating superior bond returns. Overall, 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.

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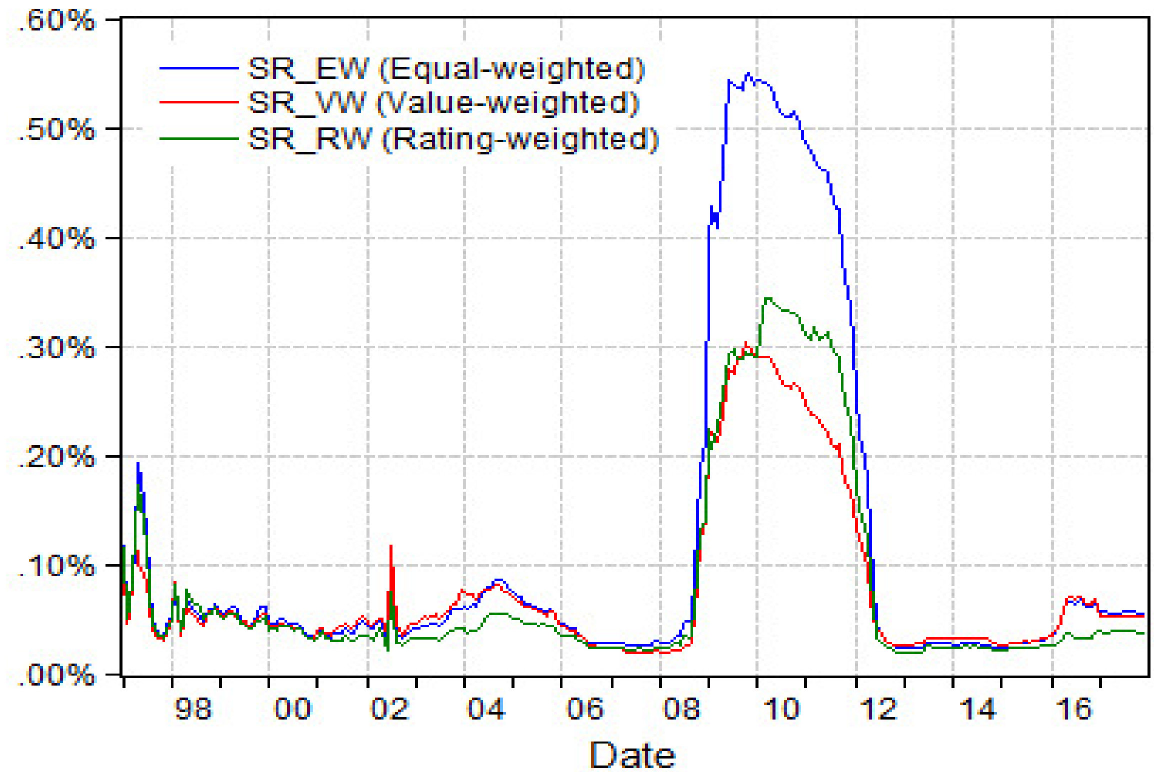

Fig.1. Systematic risk (SR) over time. This figure plots the monthly time-series of aggregate SR between January 1997 to December 2017 for the equal-, value-, and rating-weighted cross-sectional average of bond systematic risk.

Table 1: Descriptive Statistics

Panel A reports the number of bond-month observations, the cross-sectional mean, median, standard deviation and monthly return percentiles of corporate bonds, and bond characteristics including credit rating, time-to-maturity (Maturity, year), amount outstanding (Size, $ million), 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, and ratings of 11 or higher (BB+ or worse) are labeled high yield. 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 (SR) is defined as the difference between total and unsystematic (residual) return variance using a 36-month rolling window. The benchmark model used to generate systematic risk is the 4-factor model with the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factors (LRF) of Bai, Bali, and Wen (2019). 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(BBB+)	7(A-)	4	2(AA+)	3(AA)	5(A+)	10(BBB-)	16(B-)	18(C)
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, $million)	1,232,683	418.99	292.97	462.41	20.76	39.94	129.35	522.30	1281.05	2360.41
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 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 3: Univariate portfolios of corporate bonds sorted by systematic risk (SR)

Quintile portfolios are formed every month from January 1997 to December 2017 by sorting corporate bonds based on the systematic risk (SR), defined as the difference between total and unsystematic (residual) variance from the first stage regressions. 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). 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, and the 4-factor based on Bai, Bali, and Wen (2019). 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					
	SR	return	alpha	alpha	alpha	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 4: Univariate portfolios of corporate bonds sorted by unsystematic risk (USR)

Quintile portfolios are formed every month from January 1997 to December 2017 by sorting corporate bonds based on the unsystematic risk (USR), defined as the residual variance from the first stage regressions. 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). Quintile 1 is the portfolio with the lowest USR and Quintile 5 is the portfolio with the highest USR. The portfolios are value-weighted using amount outstanding as weights. Table reports the average USR, 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, and the 4-factor based on Bai, Bali, and Wen (2019). 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					
	USR	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 5: Bivariate portfolios of corporate bonds sorted by systematic risk (SR) and residual risk (USR)

In Panel A, quintile portfolios are formed every month from January 1997 to December 2017 by first sorting corporate bonds based on their residual risk. Then, within each USR 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 USR quintile portfolio, and Quintile SR,5 is the portfolio of corporate bonds with the highest SR with each USR quintile portfolio. Panel A reports the average SRs within each USR quintile as well as the next month average return of corporate bonds for the corresponding quintile. The last four rows present the differences between Quintile SR,5 and Quintile SR,1 the monthly returns; the alphas with respect to the 5-factor model with stock market factors, the 5-factor model with with bond market factors, and the 10-factor model that combines the five stock and five bond market factors. 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 USR after controlling for SR.

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

SR quintiles after controlling for USR	Average SR in each USR quintile	Next month average 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 USR after controlling for SR

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

Table 6: Investment-grade versus Non-investment-grade corporate bonds

Quintile portfolios are formed every month from January 1997 to December 2017 by sorting corporate bonds based on the total variance (VOL), systematic risk (SR), and unsystematic risk (USR). 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). USR is defined as the residual variance from the first stage regressions. Quintile 1 is the portfolio with the lowest sorting variable and Quintile 5 is the portfolio with the highest sorting variable. The portfolios are value-weighted using amount outstanding as weights. Table reports the next-month average excess return and the 10-factor alpha for each quintile. 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.

Panel A: Investment-grade bonds

	VOL		SR		USR	
	Average return	10-factor alpha	Average return	10-factor alpha	Average return	10-factor alpha
Low	0.08	0.01	0.06	-0.01	0.09	-0.00
	(1.30)	(0.47)	(0.97)	(-0.20)	(1.61)	(-0.17)
2	0.19	0.02	0.18	0.04	0.21	0.01
	(2.29)	(0.71)	(2.26)	(1.34)	(2.88)	(0.44)
3	0.26	0.00	0.26	0.03	0.26	-0.04
	(2.40)	(0.09)	(2.62)	(0.91)	(2.69)	(-0.83)
4	0.36	0.09	0.35	0.08	0.28	-0.10
	(2.55)	(1.53)	(2.67)	(2.16)	(2.53)	(-1.49)
High	0.63	0.33	0.48	0.26	0.32	-0.08
	(2.94)	(1.51)	(2.80)	(1.52)	(2.56)	(-1.12)
High − Low	0.55***	0.32**	0.42***	0.27**	0.23**	-0.08
	(3.28)	(2.32)	(3.25)	(2.03)	(2.49)	(-0.85)

Panel B: Non-investment-grade bonds

	VOL		SR		USR	
	Average return	10-factor alpha	Average return	10-factor alpha	Average return	10-factor alpha
Low	0.20	0.11	0.33	0.17	0.07	0.09
	(1.63)	(0.88)	(2.16)	(1.68)	(0.52)	(0.68)
2	0.31	0.08	0.34	0.09	0.38	0.06
	(2.06)	(0.45)	(1.77)	(0.55)	(2.19)	(0.37)
3	0.30	-0.07	0.39	-0.10	0.25	-0.05
	(1.45)	(-0.40)	(1.42)	(-0.45)	(1.20)	(-0.34)
4	0.52	0.19	0.56	0.23	0.35	-0.07
	(1.80)	(0.84)	(1.25)	(0.90)	(1.30)	(-0.33)
High	1.29	1.01	1.16	1.05	0.38	0.28
	(2.90)	(2.29)	(1.78)	(2.05)	(2.03)	(0.90)
High - Low	1.21***	0.90***	0.96***	0.88**	0.31**	0.20
	(3.09)	(2.72)	(2.70)	(2.63)	(2.23)	(0.57)

Table 7: 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 the systematic risk (SR) and unsystematic (residual) risk (USR) with and without control variables. Bond characteristics include credit rating, illiquidity (ILLIQ), time-to-maturity (years) and the natural logarithm of amount outstanding (Size). 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. Other control variables are the bond market beta (β^{MKT}), the default beta (β^{DEF}), the term beta (β^{TERM}), and bond return in previous month (REV). The Fama and MacBeth regressions are run each month for the period from January 1997 to December 2017. Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last column reports the average adjusted R^2 values. Numbers in bold denote statistical significance at the 5% level or better.

	Intercept	SR	USR	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)	0.048	**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)	
(3)	0.241		**0.635**									0.045
	(2.30)		(2.49)									
(4)	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)	
(5)	0.240	**0.921**	-0.529									0.057
	(2.35)	(4.56)	(-0.78)									
(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 8: 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 9: Systematic risk (SR) and unsystematic risk (USR) based on alternative factor models

Quintile portfolios are formed every month from January 1997 to December 2017 by sorting corporate bonds based on the systematic risk (SR), defined as the difference between total and unsystematic (residual) variance from the first stage regressions. Three benchmark models are used to generate systematic risk,

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 4-factor alpha from bond market factors for each quintile. The 10-factor model combines the five stock and five bond market factors. The 4-factor model with bond market factors includes the excess bond market return (MKT), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factor (LRF). 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
Return/Alpha diff.	(1.64)	(1.12)	(0.73)	(1.34)	(-0.53)	(-0.98)	(1.35)	(-0.49)	(-0.93)

Table 9. (Continued)

Panel B: Quintile portfolios of corporate bonds sorted by unsystematic 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
Return/Alpha diff.	(2.37)	(2.46)	(0.45)	(2.37)	(2.46)	(0.60)	(2.58)	(3.21)	(0.77)

Table 10: 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 10. (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)	

Table 11: Univariate portfolios of stocks sorted by total variance, systematic risk, and unsystematic risk

Quintile portfolios are formed every month by sorting stocks based on the total variance, systematic risk, and unsystematic risk. Quintile 1 is the portfolio with the lowest value and Quintile 5 is the portfolio with the highest value. The portfolios are value-weighted using market cap as weights. Two benchmark models used to generate systematic risk is the i) Fama-French (2015) 5-factor model with the excess stock market return (MKT^{Stock}), SMB, HML, RMW (the profitability factor), and CMA (the investment factor), and ii) Hou, Xue, and Zhang (2015) Q-factor model with the excess stock market return (MKT^{Stock}), ME, IA (the investment factor), and ROE (the profitability factor). 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. The sample period for the Q-factor model is from January 1967 to December 2017. Table reports the next-month average excess return, the Fama-French (2015) 5-factor alpha, and the Q-factor alpha. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sorted on VOL^{Stock}

SR and USR estimated using Fama-French (2015) 5-factor model					SR and USR estimated using Hou, Xue, and Zhang (2015) Q-factor model				
	VOL	Average return	FF 5-factor alpha	Q-factor alpha		VOL	Average return	FF 5-factor alpha	Q-factor alpha
Low	0.01	0.56	0.59	0.64	Low	0.01	0.70	0.76	0.75
		(3.79)	(3.91)	(4.18)			(4.52)	(4.52)	(4.69)
2	0.04	0.59	0.63	0.66	2	0.04	0.72	0.79	0.76
		(3.20)	(3.42)	(3.26)			(3.57)	(3.73)	(3.58)
3	0.07	0.71	0.82	0.82	3	0.07	0.79	0.92	0.84
		(3.00)	(3.60)	(3.09)			(2.98)	(3.47)	(2.91)
4	0.14	0.43	0.51	0.46	4	0.14	0.55	0.73	0.63
		(1.41)	(1.69)	(1.23)			(1.59)	(2.15)	(1.60)
High	0.50	-0.29	-0.21	-0.22	High	0.45	-0.19	-0.04	-0.06
		(-0.72)	(-0.58)	(-0.46)			(-0.43)	(-0.10)	(-0.12)
High − Low		-0.84***	-0.80**	-0.86**	High − Low		-0.89***	-0.80**	-0.81**
Return/Alpha diff.		(-2.60)	(-2.54)	(-2.12)	Return/Alpha diff.		(-2.81)	(-2.38)	(-2.19)

Panel B: Sorted on SR^{Stock}

	SR	Average return	FF 5-factor alpha	Q-factor alpha	Low	SR	Average return	FF 5-factor alpha	Q-factor alpha
Low	0.00	0.56	0.56	0.60	Low	0.00	0.66	0.68	0.68
		(3.68)	(3.66)	(3.76)			(4.02)	(4.00)	(4.06)
2	0.01	0.61	0.65	0.69	2	0.01	0.75	0.81	0.79
		(3.76)	(3.91)	(3.99)			(4.35)	(4.32)	(4.37)
3	0.02	0.64	0.70	0.71	3	0.02	0.74	0.83	0.78
		(3.28)	(3.59)	(3.31)			(3.42)	(3.67)	(3.40)
4	0.05	0.59	0.69	0.67	4	0.05	0.72	0.88	0.81
		(2.32)	(2.80)	(2.25)			(2.65)	(3.25)	(2.70)
High	0.16	0.10	0.20	0.11	High	0.15	0.17	0.37	0.29
		(0.29)	(0.58)	(0.26)			(0.44)	(0.99)	(0.65)
High − Low		-0.45	-0.36	-0.49	High − Low		-0.49	-0.31	-0.39
Return/Alpha diff.		(-1.58)	(-1.26)	(-1.36)	Return/Alpha diff.		(-1.50)	(-0.98)	(-0.97)

Table 11. (Continued)

SR and USR estimated using Fama-French (2015) 5-factor model					SR and USR estimated using Hou, Xue, and Zhang (2015) Q-factor model				
PanelC: Sorted on USR^{Stock}									
	USR	Average return	FF 5-factor alpha	Q-factor alpha		USR	Average return	FF 5-factor alpha	Q-factor alpha
Low	0.01	0.54	0.57	0.63	Low	0.01	0.69	0.75	0.73
		(3.46)	(3.57)	(3.77)			(4.07)	(4.01)	(4.09)
2	0.02	0.61	0.67	0.67	2	0.02	0.66	0.75	0.69
		(3.09)	(3.44)	(2.99)			(3.02)	(3.30)	(2.92)
3	0.04	0.66	0.74	0.75	3	0.04	0.76	0.89	0.82
		(2.65)	(3.09)	(2.65)			(2.73)	(3.22)	(2.71)
4	0.09	0.39	0.44	0.42	4	0.09	0.47	0.57	0.52
		(1.25)	(1.47)	(1.13)			(1.37)	(1.72)	(1.32)
High	0.36	-0.23	-0.22	-0.24	High	0.32	-0.07	0.01	-0.01
		(-0.63)	(-0.65)	(-0.54)			(-0.18)	(0.04)	(-0.02)
High − Low		-0.77***	-0.80***	-0.86**	High − Low		-0.76**	-0.73**	-0.74**
Return/Alpha diff.		(-2.72)	(-2.78)	(-2.37)	Return/Alpha diff.		(-2.44)	(-2.34)	(-2.27)

Table 12: Institutional ownership and equity unsystematic 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 unsystematic risk (USR). The benchmark model used to generate systematic risk is the Fama-French 5-factor model with the excess stock market return (MKT^{Stock}), SMB, HML, RMW (the profitability factor), and CMA (the investment factor). 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 individual stocks with the lowest institutional ownership and "INST,5" is the portfolio of individual 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.

	USR,1	USR,2	USR,3	USR,4	USR,5	USR,5 − USR,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 13: Institutional ownership and corporate bond systematic risk

Quintile portfolios are formed every month from January 1997 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 systematic risk (SR) in Panel A. Systematic risk (SR) is defined as the difference between total and unsystematic (residual) variance from the first stage regressions. 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). "INST,1" is the portfolio of individual bonds with the lowest institutional ownership and "INST,5" is the portfolio of individual stocks with the highest institutional ownership. The portfolios are value-weighted using amount outstanding as weights. Panel A reports the next-month average excess return, the 5-factor alpha from bond market factors, the 10-factor alpha, and the BBW alpha based on Bai, Bali, and Wen (2019) between the highest- and lowest-SR quintile within each institutional ownership quintile. Panel B reports the portfolio characteristics of each of the 25 portfolios, including SR, the exposure to the downside risk factor (β^{DRF}), the exposure to the credit risk factor (β^{CRF}), and the exposure to the liquidity risk factor (β^{LRF}). Panel C reports the market-timing coefficients. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sort on INST then on SR^{Bond}

	SR,1	SR,2	SR,3	SR,4	SR,5	SR,5 − SR,1	5-factor bond alpha	10-factor alpha	BBW alpha
INST,1	0.22	0.44	0.67	0.94	1.80	1.59***	1.48***	1.42***	0.60**
	(2.42)	(2.93)	(1.96)	(2.29)	(3.74)	(3.80)	(3.68)	(3.26)	(2.40)
INST,2	0.13	0.29	0.43	0.67	1.55	1.42***	1.09***	1.04***	0.47*
	(2.39)	(3.04)	(2.93)	(2.67)	(3.04)	(3.04)	(3.39)	(3.01)	(1.77)
INST,3	0.20	0.31	0.37	0.51	0.82	0.62**	0.35*	0.35*	-0.06
	(3.81)	(3.50)	(2.75)	(2.81)	(2.65)	(2.32)	(1.89)	(1.72)	(-0.39)
INST,4	0.24	0.36	0.42	0.47	0.68	0.44**	0.17	0.15	-0.08
	(3.20)	(3.52)	(3.53)	(3.04)	(2.74)	(2.29)	(1.62)	(1.16)	(-0.84)
INST,5	0.29	0.37	0.41	0.46	0.67	0.38**	0.14	0.13	-0.08
	(3.68)	(3.37)	(2.95)	(3.11)	(2.74)	(2.12)	(1.17)	(1.00)	(-0.69)

Panel B: Portfolio characteristics and exposures to risk factors

	SR						β^{DRF}					
	SR,1	SR,2	SR,3	SR,4	SR,5	Average	SR,1	SR,2	SR,3	SR,4	SR,5	Average
INST,1	0.005	0.015	0.039	0.183	0.480	0.155	-0.031	-0.037	-0.004	0.120	0.240	0.064
INST,2	0.006	0.017	0.038	0.093	0.359	0.095	-0.002	-0.020	-0.021	0.012	0.162	0.022
INST,3	0.005	0.016	0.030	0.059	0.196	0.065	-0.006	-0.002	0.000	0.049	0.180	0.048
INST,4	0.007	0.017	0.030	0.053	0.169	0.059	-0.003	-0.001	-0.010	0.036	0.194	0.047
INST,5	0.008	0.018	0.032	0.053	0.163	0.057	-0.007	-0.002	-0.003	0.041	0.194	0.048

Table 13. (Continued)

Panel B: Portfolio characteristics and exposures to risk factors (continued)

	β^{CRF}						β^{LRF}					
	SR,1	SR,2	SR,3	SR,4	SR,5	Average	SR,1	SR,2	SR,3	SR,4	SR,5	Average
INST,1	0.008	0.032	0.037	0.159	0.824	0.228	0.002	0.005	0.098	0.483	1.599	0.470
INST,2	-0.002	-0.002	0.006	0.002	0.342	0.061	-0.005	-0.009	0.018	0.148	0.911	0.191
INST,3	0.015	0.024	0.028	0.033	0.214	0.066	0.008	0.010	0.021	0.125	0.650	0.174
INST,4	0.026	0.045	0.046	0.094	0.289	0.106	0.032	0.040	0.035	0.120	0.570	0.171
INST,5	0.015	0.024	0.041	0.110	0.327	0.108	0.071	0.097	0.112	0.195	0.616	0.226

Panel C: Market-timing coefficients

	β^{Timing}					
	SR,1	SR,2	SR,3	SR,4	SR,5	Average
INST,1	-0.040	0.011	-0.026	0.055	0.155	0.031
INST,2	-0.010	0.004	0.009	0.035	0.036	0.015
INST,3	-0.009	-0.002	-0.004	0.013	0.079	0.015
INST,4	-0.006	0.005	-0.005	0.003	0.002	0.000
INST,5	-0.009	0.001	-0.004	-0.002	0.028	0.003