Do the Distributional Characteristics of Corporate Bonds Predict Their Future Returns?*

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Abstract

We investigate whether the distributional characteristics of corporate bonds predict the cross-sectional differences in future bond returns. The results indicate a significantly positive (negative) link between volatility (skewness) and expected returns, whereas kurtosis does not make a robust incremental contribution to predictability. These findings remain intact after controlling for transaction costs, liquidity, and bond characteristics. We also propose new risk factors based on the distributional moments of corporate bond returns and show that these factors represent an important source of common return variation missing from the long-established stock and bond market factors.

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1 Introduction

The distribution of individual security returns plays a central role in optimal asset allocation, derivative pricing, and risk management. Over the past three decades, academics and practitioners have therefore devoted substantial efforts to modeling and estimating the distribution of individual stock returns. However, little attention has been paid to the distribution of corporate bond returns. Trading and the outstanding amount of corporate bonds have increased substantially over time, indicating that, at present, bond positions play a larger role in investors' portfolios than they have at any time in the past.[1] Institutional investors in particular make extensive use of corporate bonds when constructing their portfolios.[2] Therefore, a detailed examination of the distribution of corporate bond returns is crucial to understanding the true risks inherent to institutional investors' portfolios.

We investigate the distributional characteristics of corporate bonds and find that the empirical distribution of bond returns is skewed, peaked around the mode, and has fat-tails, implying that extreme returns occur much more frequently than predicted by the normal distribution. Hence, ignoring non-normality features of the return distribution significantly understates downside risk in bond portfolios, potentially posing a solvency risk for bond investors. This study is motivated by our empirical observation that the distribution of corporate bond returns exhibits a significant departure from normality. We argue for a pricing framework for corporate bonds that builds in non-normality up front because, beyond its pure statistical merit, the framework offers a significant, practical benefit for investors: the potential to improve portfolio efficiency and reduce its risk relative to unpredictable, extreme negative events.

The paper is also inspired by unique market features, the types of investors and investors' attitudes toward risk in the corporate bond market. First and foremost, firms that issue cor-

[1]Corporate bonds constitute one of the largest components of the U.S. bond market, which is considered the largest security market in the world. According to the Federal Reserve database, the total market value of outstanding corporate bonds in the United States was approximately $1.74 trillion in 1990 and it increased monotonically to $11.10 trillion by the end of 2013. This implies an annual growth rate of 8.5% per annum from 1990 to 2013. The corporate bond market is active as well. Over the past 12 years, daily trading volume has been in the range between $12.6 billion and $19.7 billion, with an average of $15.9 billion (source: www.sifma.org).

[2]According to flow of fund data during 1986-2012, approximately 82% of corporate bonds were held by institutional investors, including insurance companies, mutual funds and pension funds. The participation rate of individual investors in the corporate bond market is very low.

porate bonds suffer from potential default risk given the legal requirements for the payments of coupons and principals, whereas firms that issue stocks have relatively lower exposure to bankruptcy. This main disparity makes credit risk particularly important in determining corporate bond returns. Second, bondholders are more sensitive to downside risk than stockholders. Bondholders gain the cash flow of fixed coupon and principal payments and, thus, hardly benefit from the euphoric news in firm fundamentals. Since the upside payoffs are capped, the bond payoff relation with investor beliefs about the underlying fundamental becomes concave, whereas the equity payoff relation with investor beliefs regarding the underlying fundamental is linear (e.g., Hong and Sraer (2013)). Third, given the relatively low level of liquidity in the corporate bond market, care must be taken to determine the appropriate price and model used in the estimation of abnormal returns of bond portfolios (e.g., Bessembinder, Kahle, Maxwell, and Xu (2009)).

The challenge of coming up with an accurate, comprehensive measure of credit risk, downside risk, and liquidity risk of corporate bonds remains. We conjecture that one way to characterize a wide range of risks embedded in bond portfolios is to rely on the high-order moments of the empirical return distribution that capture the magnitude and frequency of large price movements in corporate bonds. Thus, we test if the distributional characteristics of bond returns – volatility, skewness, and kurtosis – provide potential clues regarding the reasonable proxies for the common risk factors in corporate bond returns.

In this paper, we assemble a comprehensive dataset of corporate bond returns from January 1973 to December 2014, including over one million monthly bond return observations, for a total of 17,335 bonds issued by 4,244 firms. Then, for the first time in the literature, we investigate whether the distributional characteristics of corporate bonds predict the cross-sectional differences in future bond returns. First, we test the significance of a cross-sectional relation between volatility and future returns on corporate bonds using portfolio-level analysis, and find that bonds in the highest volatility quintile generate 6.30% to 7.64% more raw and risk-adjusted returns per annum than bonds in the lowest volatility quintile. We also test if the positive relation between volatility and future returns holds when controlling for bond characteristics, and find that volatility remains a significant predictor after controlling for credit rating, maturity, size, and liquidity risk of corporate bonds.[3]

Second, we examine the cross-sectional relation between skewness and future bond returns. Bivariate portfolio results show that, after controlling for the volatility of bond returns and well-known stock and bond market factors, bonds in the lowest skewness quintile generate 2.89% to 3.61% more raw and risk-adjusted returns per annum than bonds in the highest skewness quintile, consistent with the three-moment asset pricing models in that risk-averse investors prefer positively skewed assets to negatively skewed assets. We also find that the significantly negative return spread between high- and low-skew bonds is due to outperformance by low-skew (negative skew) bonds, but not to underperformance by high-skew (positive skew) bonds.

Third, we investigate the significance of a cross-sectional relation between kurtosis and future returns. Univariate portfolio analyses show that bonds in the highest kurtosis quintile generate 4.34% to 4.87% more raw and risk-adjusted returns per annum than bonds in the lowest kurtosis quintile. Bivariate portfolio-level analyses indicate that the predictive relation between kurtosis and bond returns remains positive, but economically and statistically weak after controlling for credit rating, maturity, and size of corporate bonds.

We also test the significance of volatility, skewness, and kurtosis simultaneously using bond-level cross-sectional regressions. The Fama-MacBeth (1973) regression results echo the portfolio analysis, indicating that the volatility and skewness of corporate bonds predict their future returns, whereas kurtosis does not make a robust incremental contribution to such predictability. Our main findings remain intact after conducting a battery of robustness checks, such as accounting for transaction costs, controlling for bond illiquidity and liquidity risk, using only transaction data, and performing subsample analyses.

Once we establish that the distributional characteristics of corporate bonds predict their future returns, we decompose total volatility, skewness, and kurtosis into their systematic and idiosyncratic (firm-specific) components and test if the cross-sectional pricing of the distributional moments is driven by systematic or idiosyncratic components. Portfolio-level analyses

[3]Although the positive relation between volatility and expected returns is stronger for high-yield bonds, bonds with longer maturity, bonds with lower market value, and bonds with higher liquidity risk, a significantly positive link between volatility and returns exists for investment-grade bonds, short- and medium-term bonds, bonds with large market value, and bonds with low liquidity risk.

and Fama-MacBeth regressions show that the significantly positive (negative) relation between total volatility (total skewness) and future bond returns is driven by the differences in idiosyncratic volatility (idiosyncratic skewness), but not by the differences in the market beta or co-skewness of corporate bonds.

Finally, we propose new risk factors based on the distributional characteristics of corporate bonds and test if the long-established stock and bond market factors in the literature explain our distribution-based risk factors.[4] Since the volatility, skewness, and kurtosis of bond returns are found to be correlated with credit risk, we rely on the conditional bivariate portfolios using credit rating as the first sorting variable and the distributional moments as the second sorting variable when constructing new risk factors, namely, the volatility factor (VOL^F), the skewness factor ($SKEW^F$), and the kurtosis factor ($KURT^F$). We also construct a broad, common risk factor, VSK, using the first principal component of these newly proposed VOL^F, $SKEW^F$, and $KURT^F$ factors.

We run time-series factor regressions to assess the explanatory power of the new risk factors. The intercepts (alphas) from these time-series regressions represent the abnormal returns, not explained by the standard stock and bond market factors. When we use the most general 10-factor model that combines all the commonly used stock and bond market factors, we find that the alphas for the VOL^F, $SKEW^F$, and $KURT^F$ factors are all economically and statistically significant; 0.45% per month (t-statistic = 4.81), −0.19% per month (t-statistic = −2.90), and 0.17% per month (t-statistic = 2.17), respectively. Finally, the alpha for the common risk factor (VSK) is 0.47% per month with a t-statistic of 4.52. These significant alphas indicate that the new bond market risk factors represent an important source of common return variation missing from the long-established stock and bond market risk factors.

These results suggest that the newly proposed distribution-based risk factors provid proxies for a comprehensive measure of substantive risk embedded in corporate bonds that cannot be

[4] The long-established stock market factors include the five factors of Fama and French (1993), Carhart (1997) and Pastor and Stambaugh (2003): the excess stock market return (MKT), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the liquidity factor (LIQ). The standard bond market factors include the excess bond market return (Elton, Gruber, and Blake (1995)), the default spread (DEF) and the term spread (TERM) factors of Fama and French (1993), the corporate bond momentum factor of Jostova, Nikolova, Philipov, and Stahel (2013), and the corporate bond liquidity factor.

fully characterized by the existing stock and/or bond market risk factors.

This paper is organized as follows. Section 2 provides a literature review. Section 3 describes the data and variables used in our empirical analyses. Section 4 investigates the predictive power of volatility, skewness, and kurtosis for future bond returns. Section 5 decomposes volatility, skewness, and kurtosis into their systematic and idiosyncratic components and tests whether the cross-sectional pricing of the distributional moments is driven by their systematic or firm-specific components. Section 6 investigates the impact of transaction costs and liquidity on our main findings and conducts a battery of robustness checks. Section 7 introduces new risk factors for corporate bonds using the distributional moments of bond returns, and demonstrates that the long-established stock and bond market risk factors cannot explain the distribution-based risk factors. Section 8 concludes the paper.

2 Literature Review

This paper contributes to the literature on the cross-sectional determinants of corporate bond returns. Fama and French (1993) first show that default and term premia are important risk factors for corporate bond pricing. Gebhardt, Hvidkjaer, and Swaminathan (2005) test the pricing power of the exposures to default and term spreads and find that they are significantly related to the cross-section of bond returns. Lin, Wang, and Wu (2011) construct the market liquidity risk factor and show that it is priced in the cross-section of corporate bond returns. Acharya, Amihud, and Bharath (2013) show that corporate bonds are exposed to liquidity shocks in equity and Treasury markets. Jostova, Nikolova, Philipov, and Stahel (2013) investigate whether the momentum anomaly exists in the corporate bond market. Bongaerts, DeJong, and Driessen (2016) study the effect of expected liquidity and liquidity risk on corporate bond returns. Additionally, two recent papers, Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2016) and Choi and Kim (2016) examine whether equity return predictors predict the cross-sectional differences in bond returns.

This paper distinguishes from the aforementioned literature in three important ways. First, we provide novel evidence that the distributional characteristics of bond returns, especially volatility and skewness, are robustly priced in the cross-section of expected bond returns.

These findings remain intact after controlling for default and term premia, bond liquidity risk, bond exposures to well-known stock and bond market factors, and bond characteristics, such as credit rating, maturity, and size. We also contribute to the asset pricing literature on high-order moments by providing theoretically consistent evidence for the corporate bond market. The literature has not yet reached an agreement on the positive (negative) risk-return tradeoff between volatility/kurtosis (skewness) and the cross-section of individual stocks or options.[5] Our results, however, demonstrate a theoretically consistent positive (negative) and significant relation between volatility/kurtosis (skewness) and corporate bond returns.

Second, we decompose total volatility, skewness, and kurtosis into their systematic and idiosyncratic components and show that the cross-sectional differences in bond returns are explained by the cross-sectional differences in idiosyncratic volatility and idiosyncratic skewness, not by the cross-sectional differences in systematic risk (market beta) or systematic skewness (co-skewness). We also find that neither systematic kurtosis (co-kurtosis) nor idiosyncratic kurtosis predicts the cross-sectional dispersion in future bond returns.

Lastly, we propose new risk factors based on the distributional moments of corporate bonds, and show that the new risk factors represent an important source of common return variation missing from the long-established stock and bond market factors. As noted by Bessembinder, Kahle, Maxwell, and Xu (2009), existing factor models (e.g., Fama and French (1993); Elton, Gruber, and Blake (1995)) are not well specified to test abnormal bond returns, possibly due to insufficient controls for potential omitted risk factors. Yet it is important for institutional investors to use an appropriate risk factor model to price corporate bonds and measure the abnormal returns of corporate bond portfolios. Our newly proposed distribution-based risk factor model provides a sound measure of abnormal returns after accounting for substantive risk embedded in corporate bonds, which cannot be fully characterized by existing risk factors.

This paper contributes to the literature by providing new evidence on the risk-return

[5] There is an ongoing debate on the cross-sectional relation between distributional characteristics and future stock returns. For example, Ang, Hodrick, Xing, and Zhang (2006) find a significantly negative link between stock returns and lagged idiosyncratic volatility, whereas Fu (2009) provides evidence of a positive and significant relation between conditional volatility and future stock returns. Empirical studies testing the ability of skewness (or related measures) to predict cross-sectional variation in stock returns have produced mixed results. Xing, Zhang, and Zhao (2010) find a theoretically contradictory positive relation between skewness and future stock returns, while Bali, Cakici, and Whitelaw (2011) find a theoretically consistent negative relation. Aside from Dittmar (2002), who finds evidence that kurtosis plays an important role in pricing individual stocks, the literature on kurtosis is sparse.

analysis of corporate bonds. We present novel evidence that the distributional moments of corporate bonds are priced in the cross-section of bond expected returns. A large number of articles examine the determinants of credit spreads through either structural or reduced-form models,[6] while only a few examine the cross-section of corporate bond returns through a formal asset pricing model.[7] Our paper differs from the above literature by analyzing the cross-section of corporate bond returns (not yield spreads) through factor models.

3 Data and Variables

3.1 Corporate Bond Data

The corporate bond dataset is compiled from six major sources: the Lehman Brothers fixed income database (Lehman), Datastream, the National Association of Insurance Commissioners database (NAIC), Bloomberg, the enhanced version of the Trade Reporting and Compliance Engine (TRACE), and the Mergent fixed income securities database (FISD). The Lehman data cover the sample period from January 1973 to March 1998; Datastream reports corporate bond information from January 1990 to June 2014. Both Lehman and Datastream provide prices based on dealer quotes. NAIC reports the transaction information by insurance companies for the period from January 1994 to July 2013; Bloomberg provides daily bond prices from January 1997 to December 2004; and the TRACE records the transactions of the entire corporate bond market from July 2002 to December 2014. The two datasets, NAIC and TRACE, provide prices based on real transactions.

Our goal is to examine the distributional characteristics of corporate bonds and their link to expected bond returns. The cornerstone of our analysis is an accurate measure of corporate bond returns. We highlight the following filtering criteria in order to choose qualified bonds. For all data sources, we first remove bonds that are not listed or traded on the U.S. public market, which include bonds issued through private placement, bonds issued under the

[6] Over the past decade, a large number of studies contribute to the understanding of explaining the credit spread puzzle, including but not limited to Elton, Gruber, Agrawal, and Mann (2001), Longstaff, Mithal, and Neis (2005), Chen, Lesmond, and Wei (2007), Chen, Collin-Dufresne, and Goldstein (2009), Ericsson, Jacobs, and Oviedo (2009), Huang and Huang (2012), and Bai and Wu (2015).

[7] There are other related papers, but they address either the time series analyses of bond returns/yields (Blume, Keim, and Patel (1991)) or the change in bond yields (Collin-Dufresne, Goldstein, and Martin (2001)).

144A rule, bonds that do not trade in US dollars, and bond issuers not in the jurisdiction of the United States. Second, we focus on corporate bonds that are not structured notes, not mortgage backed or asset backed. We also remove the bonds that are agency-backed or equity-linked.

Third, we exclude convertible bonds since this option feature distorts the return calculation and makes it impossible to compare the returns of convertible and non-convertible bonds.[8] Fourth, corporate bonds trading under five dollars per share usually are considered to be at default or close to default; their return calculated in the standard way of price and accrued interest cannot reflect the firm fundamental or risk premia required for compensation, so we remove bonds if their quoted or trade-based prices are less than five dollars. We also remove bonds if their prices are larger than one thousand dollars. Fifth, we remove bonds with a floating rate; that means the sample comprises only bonds with a fixed or zero coupon. This rule is applied based on the consideration of accuracy in bond return calculation, given the challenge in tracking a floating-coupon bond's cash flows.

Our last rule excludes any bonds with less than one year to maturity. This rule is applied to all major corporate bond indices such as the Barclays Capital corporate bond index, the Bank of America Merrill Lynch corporate bond index, and the Citigroup corporate bond index. If a bond has less than one year to maturity, it will be delisted from major bond indices; hence, index-tracking investors will change their holding positions. This operation will distort the bond return calculation; hence, we remove them from our sample.

Among all six corporate bond datasets, TRACE provides the most detailed information on bond transactions at the intraday frequency. Beyond the above filtering criteria, we further clean up TRACE transaction records by eliminating when-issued bonds, locked-in bonds, and bonds with commission trading, special prices, or special sales conditions. We remove transaction records that are cancelled and adjust records that are subsequently corrected or reversed. Bond trades with more than 2-day settlement are also removed from our sample. In addition, we exclude transaction volumes smaller than $100,000 to mitigate the impact of

[8]Bonds also contain other option features such as being putable, redeemable/callable, exchangeable, and fungible. Except callable bonds, bonds with other option features are a relatively small portion in the sample. However, callable bonds constitute approximately 67% of the whole sample. Hence, we keep the callable bonds in our final sample and conduct a robustness check for a smaller sample by filtering out the bonds with option features. The main findings turn out to be similar to those reported in our tables.

retail investors.

To calculate corporate bond returns, we must have the integral input of the accrued interest, which relies on the information on the coupon rate, the interest payment frequency, and the maturity date. After merging bond price data (TRACE, NAIC, Bloomberg, Datastream, Lehman) to bond characteristics data (Mergent FISD), we further eliminate bonds with incomplete information in either coupon, interest frequency, or maturity date.

Finally, we adopt the following principle to handle the overlapping observations among different data sets. If two or more datasets have overlapping observations at any point in time, we give priority to the dataset that reports the transaction-based bond prices. For example, TRACE will dominate other datasets in the recent decade. If there are no transaction data or the coverage of the data is too small, we give priority to the dataset that has a relatively larger coverage on bonds/firms and can be better matched to the bond characteristic data, FISD. For example, Bloomberg daily quotes data are preferred to those of Datastream for the period for 1998 to 2002 because of its larger coverage and higher percentage of matching rate to FISD.

After implementing the above filtering criteria, matching with rating data (Section 3.2) and calculating bond returns (Section 3.3), our final sample includes 17,335 bonds issued by 4,244 unique firms, for a total of 1,088,174 bond-month return observations during the sample period of January 1973 to December 2014. This is by far the most complete corporate bond dataset in the literature.

3.2 Corporate Bond Rating

Corporate bond credit ratings capture information on default risk and, hence, is an important control variable in our analysis. We collect bond-level rating information from Mergent FISD historical ratings. If a bond is rated only by Moody's or by Standard & Poor's, we use that rating. If a bond is rated by both rating agencies, we use the average rating. All ratings are assigned a number to facilitate the analysis; for example, 1 refers to a AAA rating, 2 refers to AA+, 21 refers to CCC, and so forth. Investment-grade bonds have ratings from 1 (AAA) to 10 (BBB-). Non-investment-grade bonds have ratings above 10.

3.3 Corporate Bond Return

The monthly corporate bond return at time 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 transaction price, $AI_{i,t}$ is accrued interest, and $Coupon_{i,t}$ is the coupon payment, if any, of bond i in month t. The quote-based datasets of Lehman and Datastream provide month-end prices and returns. The NAIC and Bloomberg data provide daily prices and the time-stamped TRACE data provide intraday clean prices. For TRACE, we first calculate the daily clean price as the trading volume-weighted average of intraday prices, following Bessembinder et al. (2009), which helps minimize the effect of bid-ask spreads in prices.

The literature suggests that the daily bond data can be converted to monthly prices in various ways.[9] In this paper, we adopt a method that gleans all possibilities for calculating a reasonable monthly return. There are three scenarios for a return to be realized at the end of month t: (i) from the end of month $t-1$ to the end of month t, (ii) from the beginning of month t to the end of month t, and (iii) from the beginning of month t to the beginning of month $t+1$. All previously documented methods can be categorized in the first scenario.

[9] Lin, Wang, and Wu (2011) use the last transaction price at the end of each month. If the transaction does not fall in the last trading day of the month, they interpolate the last price of the month and the first price of the following month. Jostova et al. (2013) and Chordia et al. (2016) use the last available daily price from the last five trading days of the month as the month-end price.

However, scenarios (ii) and (iii) also occur frequently throughout the sample. We calculate monthly returns for all three scenarios, where the end (beginning) of the month refers to the last (first) five trading days of each month. If there are multiple trading records in the five-day window, the one closest to the last trading day of the month is selected. If a monthly return can be realized in more than one scenario, the realized return in the first scenario (from month-end $t-1$ to month-end t) is selected.

3.4 Volatility, Skewness, and Kurtosis

In probability theory and statistics, the variance (volatility) is used as a measure of how far a set of numbers are separated from one another. In particular, the variance is the second moment of a distribution, describing how far the numbers lie from the mean (expected value). Skewness is a measure of the asymmetry of a probability distribution. Negative skewness is often viewed as a proxy for left tail risk to the extent that it is consistent with a long left tail in the distribution of returns, with the bulk of the values (possibly including the median) to the right of the mean. High-kurtosis means that more variance can be attributed to infrequent extreme returns and is consistent with a sharper peak and longer tails than would be implied by a normal distribution.

We use a 60-month rolling-window estimation to generate the monthly time-series measures of volatility, skewness, and kurtosis for each bond in our sample:[10]

$$\begin{aligned} VOL_{i,t} &= \frac{1}{n-1}\sum_{t=1}^{n}(R_{i,t}-\overline{R}_i)^2, \\ SKEW_{i,t} &= \frac{1}{n}\sum_{t=1}^{n}\left(\frac{R_{i,t}-\overline{R}_i}{\sigma_{i,t}}\right)^3, \\ KURT_{i,t} &= \frac{1}{n}\sum_{t=1}^{n}\left(\frac{R_{i,t}-\overline{R}_i}{\sigma_{i,t}}\right)^4 - 3, \end{aligned} \tag{2}$$

where $R_{i,t} = r_{i,t} - r_{f,t}$ is the return on bond i in month t in excess of the risk-free rate, proxied by one-month T-bill return; $\bar{R}_i = \frac{\sum_{t=1}^{n} R_{i,t}}{n}$ is the sample mean of excess returns over the past

[10]A bond is included in our sample if it has at least 24 monthly return observations in the 60-month rolling window before the test month. Our data start in January 1973 and we report regression/portfolio results beginning in January 1975. Until January 1978, we use the criterion of at least 24 monthly return observations to justify bond qualification. After January 1978, we adopt the rule of a 60-month rolling window.

60 months ($n = 60$); $VOL_{i,t}$, $SKEW_{i,t}$, and $KURT_{i,t}$ are the sample variance, skewness, and kurtosis of monthly returns over the past 60 months, respectively; and $\sigma_{i,t} = \sqrt{VOL_{i,t}}$ is the sample standard deviation of monthly returns on bond i over the past 60 months, defined as the square root of the variance.[11]

3.5 Normality Test for Corporate Bond Returns

In this section, we report the distributional characteristics of monthly corporate bond returns. For each bond in our sample from January 1975 to December 2014, we compute the volatility, skewness, and kurtosis of monthly returns. Panel A of Table 1 shows their summary statistics. Panel B tests whether these high-order moments are significantly different from zero based on the time-series distribution of bond returns. Among 17,335 bonds, all of them have significant volatility at the 10% level or better. In addition, 7,738 bonds exhibit positive skewness and 9,597 bonds exhibit negative skewness. Among the bonds with positive (negative) skewness, 56.0% (50.3%) are statistically significant at the 10% level or better. Finally, the majority of bonds (15,518) exhibit positive excess kurtosis, and among these bonds, 75.7% are statistically significant at the 10% level or better. We also conduct the Jarque-Bera (JB) normality test, and the last column of Panel B shows that 74.6% of the bonds in our sample exhibit significant JB statistics, rejecting the null hypothesis of normality at the 10% level or better.[12]

Panel C of Table 1 tests whether these high-order moments are significantly different from zero based on the cross-sectional distribution of bond returns. For each month from January 1975 to December 2014, we compute the volatility (%), skewness, and excess kurtosis of the cross-sectional observations of bond returns and test whether these distributional moments are significantly different from zero. We find that the JB statistics are significant for all months in the sample period, rejecting the null hypothesis of normal distribution of the cross-sectional bond returns.

[11]To reduce the influence of outliers in the second-stage portfolio-level analyses and cross-sectional regressions, we winsorize volatility, skewness, and kurtosis at 1% and 99%. Our results are similar without winsorization or with winsorization at 0.5% and 99.5%. Our results are also robust to different rolling windows in estimating volatility, skewness, and kurtosis, e.g., a rolling window of 24 and 36 months instead of 60 months. These robust results are available upon request.

[12]For 64% of the corporate bonds in our sample, the JB statistics are significant at the 5% level or better, rejecting the null hypothesis of normality.

To understand the asset pricing implications of these significant higher-order moments in corporate bond returns, we examine the relation between volatility, skewness, kurtosis and the cross-section of expected bond returns in the next section.

4 Volatility, Skewness, Kurtosis and the Cross-Section of Expected Bond Returns

4.1 Volatility and Corporate Bond Returns

The mean-variance theory of portfolio choice determines the optimum asset mix by maximizing the expected risk premium per unit of risk in a mean-variance framework or maximizing the expected value of a utility function approximated by the portfolio's expected return and variance. In both cases, the market risk of the portfolio is defined in terms of the variance (or standard deviation) of the portfolio's returns. Although a vast stream of literature investigates the cross-sectional relation between volatility and expected returns on individual stocks, our paper is the first to examine the predictive power of volatility in the cross-section of corporate bond returns.

4.1.1 Univariate Portfolio Analysis of Volatility

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 1975 to December 2014, we form equal-weighted univariate portfolios by sorting corporate bonds into quintiles based on their volatility (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 in each quintile, the next month average excess return, and 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 three columns report the average credit rating, average maturity, and average bond amount outstanding (size) for each quintile. The last row in Table 2 displays the differences in average returns of quintiles 5 and 1 and the differences in the alphas of quintiles 5 and 1. Average excess returns and alphas are defined in terms of monthly percentages. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Moving from quintile 1 to quintile 5, the average excess return on the volatility portfolios increases monotonically from 0.04% to 0.67% per month. This indicates a monthly average return difference of 0.64% between quintiles 5 and 1 with a Newey-West t-statistic of 4.00, showing that this positive return difference is economically and statistically significant. This result indicates that corporate bonds in the highest VOL quintile generate 7.68% per annum higher return than bonds in the lowest VOL quintile do.

In addition to the average excess returns, Table 2 also presents the intercepts (alphas) from the regression of the quintile excess portfolio returns on a constant, the excess stock market return (MKT^{Stock}), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), and a liquidity factor (LIQ), following Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003).[13] 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 -0.07% to 0.48% per month, moving from the Low-VOL to the High-VOL quintile, indicating a positive and significant alpha difference of 0.54% per month (t-stat.= 3.37).

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 can be explained by prominent bond market factors. Following Elton et al. (2001) and Bessembinder et al. (2009), we use the aggregate corporate bond market, default spread and term spread factors. The excess bond market return (MKT^{Bond}) is constructed as the value-weighted average of individual bond returns in excess of the one-month T-bill return. The default spread factor (DEF) is defined as the monthly change in the difference between BAA- and AAA-rated corporate bond yields. The term spread factor (TERM) is defined as the monthly change in the difference between 10-year and 3-month constant-maturity Treasury yields. In addition to using the MKT^{Bond}, DEF, and TERM, we use the momentum

[13]The factors MKT (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/.

and liquidity factors for the corporate bond market. Following Jostova et al. (2013), the bond momentum factor (MOM^{Bond}) is constructed from 5×5 bivariate portfolios of size and bond momentum, defined as the cumulative return over months from $t-7$ to $t-2$ (formation period). The bond liquidity factor (LIQ^{Bond}) is generated based on the monthly change (i.e., innovations) in the aggregate Roll (1984) measure using a 60-month rolling window.[14]

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 -0.09% to 0.46% per month. The corresponding 5-factor alpha difference between quintiles 5 and 1 is positive and highly significant; 0.55% per month with a t-statistic of 4.34. 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 -0.08% to 0.45% per month, generating a positive and highly significant risk-adjusted return spread of 0.53% per month with a t-statistic of 3.91.[15]

These results indicate that, after controlling for a large number of stock and bond market factors, the return difference between high- and low-volatility bonds remains positive and highly significant. Next, we investigate the source of significant return and alpha differences between high- and low-volatility bonds: Is it due to outperformance by High-VOL bonds, underperformance by Low-VOL bonds, or both? For this, we focus on the economic and statistical significance of the risk-adjusted returns of quintile 1 versus those of quintile 5. As reported in Table 2, in quintile 1 (low-volatility bonds), the 5- and 10-factor alphas from bond market factors are negative and statistically significant, whereas the corresponding 5- and 10-factor alphas in quintile 5 (high-volatility bonds) are positive and statistically significant. Hence, we conclude that the significantly positive alpha spread between high- and low-volatility bonds is due to both underperformance by Low-VOL bonds and outperformance

[14]We also form an alternative bond liquidity factor based on 5×5 bivariate portfolios of size and monthly change in the bond-level Roll (1984) measure. The 5-factor alphas from this alternative factor are very similar to those reported in Table 2.

[15]Tables A.1 and A.2 of the online appendix present results from the univariate portfolios sorted by volatility for investment-grade and non-investment-grade bonds separately. The results indicate that the return and alpha spreads are economically and statistically significant for both investment-grade and non-investment-grade bonds.

by High-VOL bonds.[16]

Finally, we examine the average characteristics of individual bonds in volatility portfolios. As presented in the last three columns of Table 2, high-volatility bonds have a lower credit rating, longer maturity, and smaller size. As we move from the Low-VOL to the High-VOL quintiles, credit rating and bond maturity monotonically increase, whereas the bond amount outstanding monotonically decreases. This creates a potential concern about the interaction between volatility and bond characteristics. We provide different ways of handling this interaction. Specifically, we test whether the positive relation between volatility and the cross-section of bond returns still holds once we control for credit rating, maturity, and size using bivariate portfolio sorts and Fama-MacBeth (1973) regressions in later subsections. In Section 6.2, we will provide a comprehensive analysis of bond liquidity and transaction costs, as well as their potential impacts on our main findings.

4.1.2 Bivariate Portfolio Analysis of Volatility and Bond Characteristics

Table A.3 of the online appendix presents the results from the bivariate sorts of volatility and bond characteristics. In Panel A of Table A.3, we form quintile portfolios every month from January 1975 to December 2014 by first sorting corporate bonds into five quintiles based on their credit rating. Then, within each rating portfolio, bonds are sorted further into five sub-quintiles based on their volatility. This methodology, under each rating-sorted quintile, produces sub-quintile portfolios of bonds with dispersion in volatility and nearly identical ratings (i.e., these newly generated volatility sub-quintile portfolios control for differences in ratings). VOL,1 represents the lowest volatility-ranked bond quintiles within each of the five rating-ranked quintiles. Similarly, VOL,5 represents the highest volatility-ranked quintiles within each of the five rating-ranked quintiles. Panel A of Table A.3 shows that the 5- and 10-factor alphas increase monotonically from the VOL,1 to the VOL,5 quintiles. More importantly, the return and alpha differences between quintiles 5 and 1 are in the range of 0.39% and 0.43% per month and statistically significant. These results indicate that after controlling

[16] In quintile 1, the 5-factor alpha from stock market factors is negative but statistically insignificant. Hence, the risk-adjusted returns from stock market factors indicate that the significantly positive alpha spread between high- and low-volatility bonds is due to outperformance by High-VOL bonds, but not to underperformance by Low-VOL bonds.

for credit ratings, the return and alpha spreads between high- and low-volatility bonds remain positive and highly significant. We further investigate the interaction between volatility and credit rating by sorting investment-grade and non-investment-grade bonds separately into bivariate quintile portfolios based on their volatility and credit ratings. After controlling for credits ratings, the return and alpha differences between the VOL,1 and VOL,5 quintiles are in the range of 0.20% and 0.22% per month and statistically significant for investment-grade bonds; the differences are much higher for non-investment-grade bonds, in the range of 0.80% and 0.89% per month, and statistically significant. As expected, the positive relation between volatility and expected returns is stronger for non-investment-grade bonds, but the significantly positive link between volatility and returns exists for investment-grade bonds, even after we control for credit ratings.

Panel B of Table A.3 presents the results from the bivariate sorts of volatility and maturity. After controlling for bond maturity, the alpha differences between high- and low-volatility bonds remain positive, in the range of 0.39% and 0.43% per month, and they are highly significant. We further examine the interaction between volatility and maturity by sorting short-maturity bonds (1 year $\leq$ maturity $\leq$ 5 years), medium-maturity bonds (5 years $<$ maturity $\leq$ 10 years), and long-maturity bonds (maturity $>$ 10 years) separately into bivariate quintile portfolios based on their volatility and maturity. After controlling for maturity, the return and alpha spreads between the VOL,1 and VOL,5 quintiles are in the range of 0.26% and 0.32% per month for short-maturity bonds, 0.32% and 0.35% per month for medium-maturity bonds, and 0.30% and 0.37% per month for long-maturity bonds. Although the economic significance of these return and alpha spreads is similar across the three maturity groups, the statistical significance of the return and alpha differences between high- and low-volatility bonds is greater for long-maturity bonds. This result makes sense because longer-term bonds usually offer higher interest rates but may entail additional risks.[17]

Panel C of Table A.3 presents the results from the bivariate sorts of volatility and amount outstanding. After controlling for size, the alpha differences between high- and low-volatility

[17]As the bond's maturity lengthens, there is more time for rates to change and, hence, for the price of the bond to be affected. Therefore, bonds with longer maturities generally present greater interest rate risk than bonds of similar credit quality with shorter maturities. To compensate investors for this interest rate risk, long-term bonds generally offer higher yields than short-term bonds of the same credit quality do.

bonds remain positive, ranging from 0.35% to 0.41% per month, and are highly significant. We further examine the interaction between volatility and size by sorting small and large bonds separately into bivariate quintile portfolios based on their volatility and size.[18] After controlling for size, the return and alpha differences between the VOL,1 and VOL,5 quintiles range from 0.45% to 0.49% per month for small bonds and from 0.30% to 0.33% per month for large bonds. As expected, the positive relation between volatility and expected returns is stronger for bonds with low market value, but the significantly positive link between volatility and returns exists for bonds with high market value, even after controlling for size.

4.2 Skewness and Corporate Bond Returns

Modeling portfolio risk with the traditional volatility measures implies that investors are concerned only about the average variation (and co-variation) of asset returns and are not allowed to treat the negative and positive tails of the return distribution separately. However, there is a wealth of experimental evidence on loss aversion (Kahneman et al. (1990)). According to the three-moment asset pricing models of Arditti (1967), Arditti and Levy (1975), and Kane (1982), investors have an aversion to variance and a preference for positive skewness, implying that the expected return is a function of both volatility and skewness. To be consistent with the three-moment asset pricing models, we test the significance of a cross-sectional relation between skewness and future bond returns while controlling for volatility.

4.2.1 Bivariate Portfolio Analysis of Skewness and Volatility

To perform this test, we form equal-weighted bivariate portfolios every month from January 1975 to December 2014 by first sorting corporate bonds into five quintiles based on their volatility. Then, within each volatility portfolio, bonds are sorted further into five sub-quintiles based on their skewness. This methodology, under each volatility-sorted quintiles, produces sub-quintile portfolios of bonds with dispersion in skewness and nearly identical volatilities (i.e., these newly generated skewness sub-quintile portfolios control for differences in volatilities). In Table 3, SKEW,1 represents the lowest skewness-ranked bond quintiles within each of

[18] For each month from January 1975 to December 2014, individual bonds are ranked by their market value and then decomposed into two groups (small vs. big) based on the median market value.

the five volatility-ranked quintiles. Similarly, SKEW,5 represents the highest skewness-ranked bond quintiles within each of the five volatility-ranked quintiles.

Table 3 shows the average skewness of bonds in each quintile, the next month average excess return, and the 5- and 10-factor alphas for each quintile. The last three columns report the average rating, average maturity, and average bond amount outstanding for each skewness quintile. The last row in Table 3 displays the differences in the average returns of quintiles 5 and 1 and the differences in the alphas of quintiles 5 and 1.

Moving from quintile 1 to quintile 5, the average excess return on the skewness portfolios decreases almost monotonically from 0.45% to 0.21% per month, indicating a monthly average return difference of -0.24% per month between quintiles 5 and 1 with a Newey-West t-statistic of -3.78. This result implies that after controlling for volatility, corporate bonds in the lowest-SKEW quintile generate 2.9% more annual returns than bonds do in the highest-SKEW quintile. Table 3 also shows that the 5- and 10-factor alpha differences between the high- and low-skewness quintiles are also negative, in the range of -0.24% and -0.30% per month, with t-statistics ranging from -3.31 to -4.22; this is consistent with the three-moment asset pricing models in that risk-averse investors prefer positively skewed assets to negatively skewed assets.

These results indicate that after controlling for the volatility of bond returns and well-known stock and bond market factors, the cross-sectional relation between skewness and future bond returns remains negative and highly significant. Next, we investigate the source of significant alpha spreads between high- and low-skewness bonds. As reported in Table 3, the 5- and 10-factor alphas of bonds in quintile 1 (low-skew bonds) are positive and economically and statistically significant, whereas the 5- and 10-factor alphas of bonds in quintile 5 (high-skew bonds) are statistically insignificant. Hence, we conclude that the significantly negative alpha spread between High- and Low-SKEW bonds is due to outperformance by Low-SKEW (negative skew) bonds but not to underperformance by High-SKEW (positive skew) bonds.

The last three columns of Table 3 present the average characteristics of bonds in the skewness portfolios. There is no significant difference in the credit rating, maturity, or market value of bonds between the low- and high-SKEW quintiles because the volatility is controlled for when we form the skewness portfolios. However, we still test whether the negative relation between skewness and the cross-section of bond returns holds once we control for credit rating, maturity, and size using bivariate portfolio sorts and Fama-MacBeth regressions.

4.2.2 Bivariate Portfolio Analysis of Skewness and Bond Characteristics

Table A.4 of the online appendix presents the results from the bivariate sorts of skewness and bond characteristics. After controlling for credit ratings, the 5- and 10-factor alpha differences between high- and low-skewness bonds remain negative, approximately -0.21% per month, and statistically significant. We further investigate the interaction between skewness and credit rating by sorting investment-grade and non-investment-grade bonds separately into bivariate quintile portfolios based on their skewness and credit ratings. After controlling for credit ratings, the alpha differences between the SKEW,1 and SKEW,5 quintiles are in the range of -0.13% and -0.20% per month and statistically significant for investment-grade bonds. For non-investment-grade bonds, the alpha spreads between the SKEW,1 and SKEW,5 quintiles are much higher in absolute magnitude, in the range of -0.46% and -0.56% per month, and highly significant. As expected, the negative relation between skewness and expected returns is stronger for non-investment-grade bonds, but the significantly negative link between skewness and returns exists for investment-grade bonds, even after we control for credit ratings.

Panel B of Table A.4 shows that, after controlling for maturity, the 5- and 10-factor alpha differences between high- and low-skewness bonds remain negative, in the range of -0.22% and 0.32% per month, and statistically significant. We further investigate the interaction between skewness and maturity by sorting short-, medium-, and long-maturity bonds separately into bivariate quintile portfolios based on their skewness and maturity. After controlling for maturity, the alpha spreads between the SKEW,1 and SKEW,5 quintiles are negative and statistically significant for short-, medium-, and long-term bonds.

Panel C of Table A.4 shows that, after controlling for size, the 5- and 10-factor alpha differences between the SKEW,1 and SKEW,5 quintiles remain negative, in the range of -0.21% and -0.27% per month, and statistically significant. We further investigate the interaction between skewness and bond size for small and large bonds separately and find that after controlling for size, the negative relation between skewness and expected returns is stronger for bonds with low market value, but the significantly negative link between skewness and returns exists for bonds with high market value, even after we control for size.

4.3 Kurtosis and Corporate Bond Returns

Dittmar (2002) extends the three-moment asset-pricing model using the restriction of decreasing absolute prudence. Kimball (1993) proposes this restriction in response to Pratt and Zeckhauser (1987), who find that decreasing absolute risk aversion does not rule out certain counterintuitive risk-taking behaviors. For example, any risk-averse agent should be unwilling to accept a bet with a negative expected payoff. Pratt and Zeckhauser show that, if an agent's preferences are restricted to only exhibiting decreasing absolute risk aversion, the agent could be willing to take this negative mean sequential gamble. Kimball shows that standard risk aversion rules out the aforementioned behavior. Sufficient conditions for standard risk aversion are decreasing absolute risk aversion and decreasing absolute prudence, $-d(U'''/U'')/dW < 0$. Thus, the assumptions of positive marginal utility, risk aversion, decreasing absolute risk aversion, and decreasing absolute prudence imply $U'''' < 0$, that is, a preference for lower kurtosis: investors are averse to kurtosis and prefer assets with lower probability mass in the tails of the distribution to assets with higher probability mass in the tails of the distribution.

Although Dittmar (2002) examines the significance of kurtosis in predicting future stock returns, the predictive power of kurtosis has not been investigated for alternative asset classes. This paper is the first to investigate whether kurtosis predicts the cross-sectional differences in bond returns.

4.3.1 Univariate Portfolio Analysis of Kurtosis

We test the significance of a cross-sectional relation between kurtosis and future bond returns using equal-weighted quintile portfolios. Table 4 shows that, when moving from quintile 1 to quintile 5, the average excess return on the kurtosis portfolios increases almost monotonically from 0.16% to 0.53% per month, indicating a monthly average return difference of 0.37% per month between quintiles 5 and 1, with a t-statistic of 2.96. This result implies that corporate bonds in the highest KURT quintile generate 4.4% more annual returns than bonds in the lowest KURT quintile do. Table 4 also shows that the 5- and 10-factor alpha differences between the highest and lowest kurtosis quintile are also positive, in the range of 0.36% and 0.41% per month with t-statistics ranging from 3.07 to 3.20. Our result for individual bonds is consistent with Dittmar's (2002) finding for individual stocks that risk-averse investors prefer high expected return and low kurtosis.

Next, we investigate the source of significant alpha spreads between high- and low-kurtosis bonds. As reported in Table 4, the 5- and 10-factor alphas of bonds in quintile 1 (low-kurtosis bonds) are statistically insignificant, whereas the 5- and 10-factor alphas of bonds in quintile 5 (high-kurtosis bonds) are economically and statistically significant. Hence, we conclude that the significantly positive return spread between High- and Low-KURT bonds is due to outperformance by High-KURT bonds, but not to underperformance by Low-KURT bonds.

The last three columns of Table 4 present the average characteristics of bonds in the kurtosis portfolios. Bonds with high-kurtosis have higher credit ratings, shorter maturity, and lower market value. As we move from the Low- to High-KURT quintiles, the average credit rating increases, whereas average maturity and average market value decrease almost monotonically. We provide two different ways of handling the potential interaction of kurtosis with the bond characteristics. We test whether the positive relation between kurtosis and future bond returns still holds after accounting for credit rating, maturity, and size based on bivariate portfolio sorts and Fama-MacBeth regressions.

4.3.2 Bivariate Portfolio Analysis of Kurtosis and Bond Characteristics

Table A.5 presents the results from the bivariate sorts of kurtosis and bond characteristics. After controlling for credit ratings, the 5- and 10-factor alpha differences between high- and low-kurtosis bonds remain positive, ranging from 0.20% to 0.24% per month, and statistically significant. We further investigate the interaction between kurtosis and credit ratings for investment-grade and non-investment-grade bonds separately and find that, after controlling for credit ratings, the alpha differences between the KURT,1 and KURT,5 quintiles are positive but statistically insignificant for investment-grade bonds. For non-investment-grade bonds, the alpha differences between the KURT,1 and KURT,5 quintiles are much higher, ranging from 0.47% to 0.58% per month, and highly significant.

Panel B of Table A.5 shows that after controlling for maturity, the 5- and 10-factor alpha differences between high- and low-kurtosis bonds remain positive, approximately 0.21% per month, and statistically significant. We further investigate the interaction between kurtosis and maturity for short-, medium-, and long-maturity bonds separately and find that after controlling for maturity, the alpha spreads between the KURT,1 and KURT,5 quintiles are all significant, ranging from 0.22% to 0.27% per month for short-maturity bonds, 0.31% to 0.35% per month for medium-maturity bonds, and 0.20% to 0.24% per month for long-maturity bonds.

Panel C of Table A.5 shows that, after controlling for size, the 5- and 10-factor alpha differences between high- and low-kurtosis bonds remain positive, 0.23% per month, and statistically significant. We further investigate the interaction between kurtosis and bond size for small and large bonds separately and find that after controlling for size, the positive relation between kurtosis and expected returns is stronger for bonds with low market value, but the significantly positive link between kurtosis and returns also exists for bonds with high market value.

4.4 Fama-MacBeth Regression Results

So far, we have tested the significance of volatility, skewness, and kurtosis as a determinant of the cross-section of future bond returns at the portfolio level. We now examine the cross-sectional relation between volatility, skewness, and kurtosis 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 volatility (VOL), skewness ($SKEW$), kurtosis ($KURT$), and the control variables. 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:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot VOL_{i,t} + \lambda_{2,t} \cdot SKEW_{i,t} + \lambda_{3,t} \cdot KURT_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{k,t} + \varepsilon_{i,t+1}, \quad (3)$$

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 values of the distributional moments and control variables.

Table 5 reports the time series average of the intercept and slope coefficients λ's and the average adjusted R^2 values over the 480 months from January 1975 to December 2014. The

Newey-West adjusted t-statistics are reported in parentheses. The control variables are bond characteristics such as credit rating ($RATE$), maturity (MAT), amount outstanding ($SIZE$) and bond exposures to the aggregate stock market (β^{Stock}), the aggregate bond market (β^{Bond}), default spread (β^{DEF}), and term spread (β^{TERM}). The univariate regression results show a positive and statistically significant relation between volatility and the cross-section of future bond returns. The average slope, $\lambda_{1,t}$, from the monthly regressions of excess returns on VOL alone is 0.017 with a t-statistic of 3.81. The economic magnitude of the associated effect is similar to that documented in Table 2 for the univariate quintile portfolios of volatility. The spread in average volatility between quintiles 5 and 1 is approximately 39.12 ($=6.59^2 - 2.07^2$), multiplying this spread by the average slope of 0.017 yields an estimated monthly risk premium of 67 basis points.

The average slope, $\lambda_{2,t}$, from the univariate cross-sectional regressions of excess bond returns on SKEW is negative but statistically insignificant. Consistent with the univariate quintile portfolios of kurtosis in Table 4, the average slope, $\lambda_{3,t}$, from the univariate cross-sectional regressions of excess bond returns on KURT is positive, 0.063, and highly significant with a t-statistic of 3.30. As shown in the first column of Table 4, the spread in average kurtosis between quintiles 5 and 1 is approximately 6.76. Multiplying this spread by the average slope of 0.063 yields an estimated monthly risk premium of 43 basis points.

Regression specifications (4) to (6) in Table 5 show that, after controlling for credit rating, maturity, size, β^{Stock}, β^{Bond}, β^{DEF}, and β^{TERM}, the average slope on volatility and kurtosis remains positive and statistically significant, and the average slope on skewness is negative and statistically significant at the 5% level.

In general, the coefficients of the individual control variables are economically and s-tatistically weaker than the distributional moments of corporate bonds. Depending on the specification, non-investment-grade bonds are expected to generate higher future returns than investment-grade bonds since the average slope on credit ratings is positive and significant in some cases. The predictive power of maturity and size seems to be subsumed by the distributional moments and credit rating, as the average slopes on maturity and size are statistically insignificant. Among the bond exposures to well-known stock and bond market factors, only β^{Stock} and β^{Bond} seem to have significant predictive power in some cases, whereas β^{DEF} and

β^{TERM} do not explain the cross-sectional dispersion in future bond returns.

Regression (7) presents the bivariate regression results from the cross-sectional regressions of excess bond returns on VOL and SKEW. Consistent with the bivariate quintile portfolios of volatility and skewness in Table 3, the average slope on VOL is significantly positive at 0.018 (t-stat.= 3.77), and the average slope on SKEW is significantly negative at -0.192 (t-stat.= -4.04). The economic magnitudes of the associated volatility and skewness effects are also similar to those documented in Table 3: the spread in average skewness between quintiles 5 and 1 is approximately 1.83, implying an estimated skewness premium of 35 basis points per month. Regression (8) replicates the bivariate regressions with volatility and skewness after controlling for the bond characteristics and exposures, and the results are robust, as in Regression (7).

Regression (9) tests the cross-sectional predictive power of volatility, skewness, and kurtosis simultaneously. Consistent with the mean-variance portfolio theory and the three-moment asset pricing models, the average slope on VOL is significantly positive at 0.023 (t-stat.= 3.20), and the average slope on SKEW is significantly negative at -0.179 (t-stat.= -3.49). Although the average slope on KURT is positive, it is not statistically significant, implying that, after controlling for volatility and skewness, kurtosis does not predict future returns on corporate bonds. This result confirms the finding from the trivariate sorts of volatility, skewness, and kurtosis reported in Table A.6 of the online appendix.[19]

The last two specifications, Regressions (10) to (11), present results from the multivariate regressions with all three distributional characteristics (VOL, SKEW, KURT) after controlling for the bond characteristics and exposures. Similar to our findings from Regression (9), the cross-sectional relation between volatility (skewness) and future bond returns is positive (negative) and highly significant after accounting for all other controls, whereas the cross-sectional relation between kurtosis and expected bond returns is flat.[20]

[19]For trivariate sorting, tercile portfolios are formed by sorting bonds into three portfolios; first based on their volatility; then within each volatility portfolio, bonds are sorted further into three sub-terciles based on their skewness; and finally, within each skewness portfolio, bonds are sorted further into three sub-terciles based on their kurtosis. Table A.6 shows that the return and alpha differences between high-KURT and low-KURT portfolios are in the range of 0.08% and 0.15% per month but statistically insignificant, indicating that after controlling for volatility and skewness, kurtosis does not make a significant incremental contribution to the predictability of future bond returns.

[20]Section A.1 of the online appendix shows that although the magnitudes of ex-ante bond-level and ex-post portfolio-level measures of volatility/skewness are somewhat different, they are moving in the same direction,

5 Volatility, Skewness, and Kurtosis Decomposition

In this section, we first investigate whether the cross-sectional pricing of total risk is driven by systematic risk and/or firm-specific (idiosyncratic) risk. Then, we examine whether the predictive power of total skewness is induced by systematic skewness and/or idiosyncratic skewness. Finally, we decompose total kurtosis and test the significance of a cross-sectional relation between systematic kurtosis, idiosyncratic kurtosis and future bond returns.

5.1 Volatility Decomposition: Market Beta and Idiosyncratic Volatility

The mean-variance portfolio theory of Markowitz (1952) indicates a positive cross-sectional relation between total risk and expected returns. The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) extends the mean-variance portfolio theory by decomposing total risk into two components: systematic risk (market beta) and firm-specific risk (idiosyncratic volatility):

$$\sigma_i^2 = \beta_i^2 \sigma_m^2 + \sigma_{\varepsilon,i}^2, \tag{4}$$

where σ_i^2 is the total variance of bond i, $\beta_i^2 \sigma_m^2$ is the systematic risk component, which represents the part of bond's variance that is attributable to overall market volatility, and $\sigma_{\varepsilon_i}^2$ is the bond's unsystematic risk component, which represents the part of bond's variance that is specific to each bond and not attributable to overall volatility of the corporate bond market.

The primary implication of the CAPM is that market beta (β_i) determines the cross-sectional differences in expected returns, whereas firm-specific volatility ($\sigma_{\varepsilon_i}^2$) is unlikely to affect asset returns because investors hold the market portfolio in which idiosyncratic risk is diversified away. However, a number of studies document that investors hold less than perfectly diversified portfolios.[21] There is also theoretical evidence that idiosyncratic volatility is positively related to the cross-section of expected returns if investors demand compensation

implying that investors expect higher returns to hold bonds with high volatility and low skewness; this is reflected in the ex post portfolio-level measures of volatility and skewness. However, the ex-ante bond-level and the ex-post portfolio-level measures of kurtosis are not as highly correlated as in the case of the volatility and skewness measures. This provides additional evidence that kurtosis is not as strong as volatility and skewness in terms of predicting the cross-sectional differences in future bond returns.

[21] See, e.g., Blume and Friend (1975), Odean (1999), Barber and Odean (2000), Mitton and Vorkink (2007), and Goetzmann and Kumar (2008).

for not being able to diversify firm-specific variance. Levy (1978) theoretically shows that idiosyncratic risk affects equilibrium asset prices if investors do not hold many assets in their portfolios. Merton (1987) indicates that if investors cannot hold the market portfolio they will care about idiosyncratic risk, not simply market risk. Therefore, firms with larger idiosyncratic variance require higher returns to compensate for imperfect diversification.

We now test if the cross-sectional pricing of total volatility is driven by the cross-sectional differences in the market beta or the idiosyncratic volatility of corporate bonds. To be consistent with total volatility estimates, the market beta of bond i (β_i^{Bond}) is estimated from the regressions of individual bond excess returns on the excess bond market returns based on a 60-month rolling window. The idiosyncratic risk of bond i ($IVOL_i$) is defined as the standard deviation of the residuals ($\varepsilon_{i,t}$) from the CAPM equation: $R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$.[22]

We examine the cross-sectional relation between market beta, idiosyncratic volatility, and expected returns at the bond level using Fama and MacBeth regressions. Monthly predictive cross-sectional regressions are run for the following specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{Bond} + \lambda_{2,t} \cdot IVOL_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{k,t} + \varepsilon_{i,t+1}, \tag{5}$$

where $R_{i,t+1}$ is the one-month-ahead excess return on bond i, $\beta_{i,t}^{Bond}$ and $IVOL_{i,t}$ are the lagged market beta and idiosyncratic volatility of bond i, respectively. The control variables in equation (5) are credit rating, maturity, amount outstanding (size), and bond exposures to the aggregate stock market (β_i^{Stock}), default spread (β_i^{DEF}), and term spread (β_i^{TERM}).

Table 6 presents the time-series averages of the slope coefficients from the regressions of one-month-ahead excess bond returns on market beta ($\beta_{i,t}^{Bond}$), idiosyncratic volatility ($IVOL_{i,t}$), and the control variables. Regressions (1) and (2) show that there is a positive and significant relation between market beta and future bond returns with and without controlling for bond characteristics and exposures. Regressions (3) and (4) provide evidence of a positive and highly significant relation between idiosyncratic volatility and future bond returns with and without accounting for the same set of controls.

[22] At an earlier stage of the study, we use two alternative measures of idiosyncratic volatility estimated with the 5-factor models (stock and bond market factors) and the results turn out to be very similar to those reported in the paper. Table 6 presents results from the parsimonious measure of idiosyncratic volatility to be consistent with the variance decomposition in equation (4).

When tested individually, Regressions (1) to (4) indicate significant cross-sectional pricing of systematic and idiosyncratic risks on corporate bonds. However, the results change dramatically when we investigate their predictive power jointly in the same regression. Regressions (5), (6), and (7) note that there is a positive and highly significant relation only between idiosyncratic volatility and corporate bond returns, whereas the cross-sectional relation between market beta and bond returns is flat. This result remains intact with and without controlling for the characteristics and factor exposures of individual bonds.

Overall, we conclude that the significantly positive return and alpha spreads from volatility-sorted portfolios represent compensation for differences in the level of idiosyncratic volatility of individual bonds, not for differences in their market betas.

5.2 Skewness Decomposition: Co-skewness and Idiosyncratic Skewness

Kraus and Litzenberger (1976) extend the CAPM to incorporate the effect of skewness on asset returns. In this model, investors hold concave preferences and prefer positive skewness.[23] More importantly, systematic skewness (co-skewness) determines the cross-sectional differences in expected returns, whereas firm-specific skewness (idiosyncratic skewness) is unlikely to affect asset returns because investors hold the market portfolio in which idiosyncratic skewness is diversified away. However, as mentioned earlier, previous studies provide evidence of investors' choice of holding under-diversified portfolios. 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 assets in their portfolios, with 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 assets in their portfolios.

Harvey and Siddique (2000), Mitton and Vorkink (2007), and Boyer, Mitton, and Vorkink (2010) provide empirical support for the three-moment asset pricing models that stocks with high co-skewness, high idiosyncratic skewness, and high expected skewness have low subse-

[23] Friend and Westerfield (1980), Sears and Wei (1984), Barone-Adesi (1985), and Lim (1989) test the empirical validity of the three-moment asset pricing model proposed by Kraus and Litzenberger (1976).

quent returns. Following the aforementioned studies, we decompose total skewness into two components; systematic skewness and idiosyncratic skewness, which are estimated based on the following time-series regression for each bond using a 60-month rolling window:

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \gamma_i \cdot R_{m,t}^2 + \varepsilon_{i,t}, \tag{6}$$

where $R_{i,t}$ is the excess return on bond i, $R_{m,t}$ is the excess return on the bond market portfolio, γ_i is the systematic skewness (co-skewness) of bond i and the idiosyncratic skewness ($ISKEW$) of bond i is defined as the skewness of the residuals ($\varepsilon_{i,t}$) in equation (6).

We test whether the systematic and/or idiosyncratic components of total skewness predict the cross-sectional differences in corporate bond returns with and without controlling for the systematic and/or idiosyncratic components of total volatility. We examine the cross-sectional relation between co-skewness (COSKEW), idiosyncratic skewness (ISKEW), and expected returns at the bond level based on the following Fama and MacBeth regressions:

$$\begin{aligned} R_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{Bond} + \lambda_{2,t} \cdot IVOL_{i,t} + \lambda_{3,t} \cdot COSKEW_{i,t} + \lambda_{4,t} \cdot ISKEW_{i,t} \\ &\quad + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{k,t} + \varepsilon_{i,t+1}, \end{aligned} \tag{7}$$

where the control variables in equation (7) are credit rating, maturity, amount outstanding (size), and bond exposures to the aggregate stock market (β_i^{Stock}), default spread (β_i^{DEF}), and term spread (β_i^{TERM}).

Table 7 presents the time-series averages of the slope coefficients from equation (7). Regressions (1) and (2) in Table 7 show that there is a negative but statistically insignificant relation between co-skewness and future bond returns with and without controlling for bond characteristics and exposures. Consistent with demand for idiosyncratic skewness (or lottery-like payoffs), Regressions (3) and (4) provide evidence of a negative and highly significant relation between idiosyncratic skewness and future bond returns with and without accounting for the same set of controls.

When examined jointly in a multivariate regression setting, the predictive power of co-skewness and idiosyncratic skewness remains intact. Regressions (5), (6), and (7) show significantly negative cross-sectional pricing of idiosyncratic skewness of corporate bonds, whereas the negative relation between co-skewness and future bond returns remains statistically insignificant. The last three regressions in Table 7 investigate the significance of market beta, idiosyncratic volatility, co-skewness, and idiosyncratic skewness simultaneously with and without accounting for bond characteristics and exposures. The results show that the cross-sectional differences in corporate bond returns are explained by the cross-sectional differences in the level of idiosyncratic volatility and idiosyncratic skewness of corporate bonds, not by the cross-sectional differences in systematic risk or systematic skewness.

5.3 Kurtosis Decomposition: Co-kurtosis and Idiosyncratic Kurtosis

In this section, following Dittmar (2002), we decompose total kurtosis into two components; systematic kurtosis and idiosyncratic kurtosis, which are estimated based on the following time-series regression for each bond using a 60-month rolling window:

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \gamma_i \cdot R^2_{m,t} + \kappa_i \cdot R^3_{m,t} + \varepsilon_{i,t}, \tag{8}$$

where κ_i is the systematic kurtosis (co-kurtosis) of bond i and the idiosyncratic kurtosis ($IKURT$) of bond i is defined as the kurtosis of the residuals ($\varepsilon_{i,t}$) in equation (8).

We investigate whether the systematic and/or idiosyncratic components of total kurtosis predict the cross-sectional differences in corporate bond returns with and without controlling for the systematic and/or idiosyncratic components of total volatility and total skewness. We examine the cross-sectional relation between co-kurtosis (COKURT), idiosyncratic kurtosis (IKURT), and expected returns at the bond level based on the following Fama and MacBeth regressions:

$$\begin{aligned} R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta^{Bond}_{i,t} + \lambda_{2,t} \cdot IVOL_{i,t} + \lambda_{3,t} \cdot COSKEW_{i,t} + \lambda_{4,t} \cdot ISKEW_{i,t} \\ + \lambda_{5,t} \cdot COKURT_{i,t} + \lambda_{6,t} \cdot IKURT_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{k,t} + \varepsilon_{i,t+1}. \end{aligned} \tag{9}$$

Table A.7 of the online appendix presents the time-series averages of the slope coefficients from equation (9). Regressions (1) to (7) in Table A.7 show that there is no significant relation between the components of total kurtosis and future bond returns without accounting for the components of total volatility and skewness. In Regressions (8) to (10), we control for the market beta, idiosyncratic volatility, co-skewness, and idiosyncratic skewness and find similar results. Neither co-kurtosis nor idiosyncratic kurtosis predicts the cross-sectional dispersion in future bond returns.

6 Bond Liquidity and Other Robustness Check

Liquidity is an important concern in the corporate bond market. All alphas found in previous sections are subject to stringent tests in the real world. In subsection 6.1, we estimate the transaction cost for hedge portfolios and test whether the alphas remain economically and statistically significant after accounting for transaction costs. To address liquidity concerns, we also reexamine the earlier Fama-MacBeth regression results controlling for bond illiquidity level or bond liquidity risk in subsection 6.2. To address other related concerns, we further conduct a battery of robustness checks in subsection 6.3.

6.1 Transaction Costs

In this subsection, we investigate the impact of transaction costs on hedge portfolios sorted by volatility, skewness and kurtosis. We estimate portfolio transaction costs through bond trading illiquidity and portfolio turnover, a method also used by Chordia et al. (2016). Bond illiquidity is based on the measure of Bao, Pan, and Wang (2011), which extracts the transitory component from bond prices. Specifically, let $\Delta p_t = p_t - p_{t-1}$ be the log price change from $t-1$ to t, then bond illiquidity is defined as

$$ILLIQ = -Cov_t(\Delta p_{itd}, \Delta p_{itd+1}), \tag{10}$$

where Δp_{itd} is the log price change for bond i on day d of month t.[24] We compute $ILLIQ$ at the bond level and its cross-sectional average for each portfolio every month. The time-series average of the illiquidity measure, multiplied by the time-series average of the portfolio turnover rate, is reported as transaction costs (denoted as *Trans Costs*).

[24]As discussed by Niederhoffer and Osborne (1966), Roll (1984), and Grossman and Miller (1988), lack of liquidity in an asset leads to transitory components in its price, and thus the magnitude of such transitory price movements reflects the degree of illiquidity in the market. Since transitory price movements lead to negatively autocorrelated price changes, the negative of the autocovariance in relative price changes in eq. (10) provides a meaningful measure of illiquidity.

Table 8 of the online appendix shows the estimated transaction costs for bond portfolios sorted by VOL, SKEW and KURT. The results indicate that the estimated transaction costs are smaller than the return and alpha spreads for the volatility-sorted portfolios. The average transaction cost for the volatility-sorted portfolio is approximately 0.137% per month for all bonds, 0.100% per month for investment-grade bonds, and 0.225% per month for non-investment-grade bonds. Deducting these transaction cost estimates from the return and alpha spreads, reported in Table 2, Tables A.1 and A.2 of the online appendix, provide clear evidence that after accounting for transaction costs, the return and alpha spreads in the volatility-sorted portfolios remain economically significant; ranging from 4.66% to 6.00% per annum for all bonds, 2.96% to 3.92% per annum for investment-grade bonds, and more than 10% per annum for non-investment-grade bonds. Similarly, the average transaction cost for the skewness-sorted portfolios (after controlling for volatility) is approximately 0.100% per month for all bonds, 0.061% per month for investment-grade bonds, and 0.189% per month for non-investment-grade bonds. The average transaction cost for the kurtosis-sorted portfolios is approximately 0.087% per month for all bonds, 0.069% per month for investment-grade bonds, and 0.155% per month for non-investment-grade bonds.

Overall, these results indicate that the key distributional characteristics of corporate bonds are strong determinants of the cross-sectional dispersion in future returns, even after accounting for transaction costs.

6.2 Controlling for Bond Illiquidity and Liquidity Risk

In addition to estimating transaction costs for hedge portfolios, we test whether the significant relation between volatility, skewness, kurtosis, and future bond returns remains intact after controlling for corporate bond illiquidity or liquidity risk in the Fama-MacBeth regressions.

For corporate bond illiquidity, we consider three proxies. The first proxy is $ILLIQ$, as defined in the previous subsection. The second proxy is Amihud's (2002) illiquidity measure. We first calculate the daily price impact as the daily absolute return scaled by daily trading volume. Then, the monthly illiquidity measure of Amihud is defined as the daily price impact averaged in a month. The third proxy is Roll's measure, calculated using historical returns from a rolling 60-month window similar to the construction of VOL, SKEW, and KURT:

$Roll = 2\sqrt{-\text{cov}(R_t, R_{t-1})}$ if $\text{cov}(R_t, R_{t-1}) < 0$; otherwise, $Roll = 0$ (R_t is the bond excess return in month t). Note that the first two proxies require daily transaction data, and hence, they are available only for the subsample period of 2002 to 2014. The Roll's measure has a longer period, from 1975 to 2014.

For liquidity risk exposure, we use two measures, LIQ1 and LIQ2, constructed by Lin, Wang, and Wu (2011).[25] The LIQ1 measure is the corporate bond liquidity beta using the method of Pastor and Stambaugh (2003), and LIQ2 is the corporate bond beta on Amihud's (2002) illiquidity measure.

In Table A.8, Panel A shows that controlling for illiquidity and other bond characteristics (rating, maturity, and size), the significantly positive (negative) relation between volatility (skewness) and future bond returns remains intact. It is worth noting that corporate bond illiquidity alone, under the proxy of $ILLIQ$, is positively related to future bond returns, which is consistent with theoretical predictions. Panel B shows that controlling for liquidity risk exposure and other bond characteristics (rating, maturity, and size), the significantly positive (negative) relation between volatility (skewness) and future bond returns also remains intact.

6.3 Robustness Check

6.3.1 Value-Weighted Portfolios

Bonds with severe liquidity concerns are often those with small size. We replicate our main findings using the value-weighted portfolios, which mitigate the impact of illiquid small bond transactions. Panel A of Table 9 presents results from the value-weighted portfolios using the bonds' outstanding dollar values as weights. The results remain economically and statistically significant for the volatility-, skewness-, and kurtosis-sorted portfolios. For the value-weighted portfolios, corporate bonds in the highest volatility quintile generate 0.340% $\sim$ 0.511% per month higher return than bonds in the lowest volatility quintile. After controlling for volatility, corporate bonds in the lowest skewness quintile generate 0.203% $\sim$ 0.259% per month higher returns than bonds in the highest skewness quintile. In addition, corporate bonds in the

[25] We thank Junbo Wang for providing us with the data on LIQ1 and LIQ2 used by Lin, Wang, and Wu (2011). The monthly data on LIQ1 and LIQ2 are available from January 1999 to March 2009. In their paper, both proxies of the corporate bond market liquidity factor are defined as innovation to the market liquidity series through a fitting ARMA model, and market liquidity is calculated as the average of bond-level liquidity.

highest kurtosis quintile generate 0.200% $\sim$ 0.295% per month higher returns than bonds in the lowest kurtosis quintile. These results suggest that after bond size has been taken into account, the distributional moments of corporate bonds predict their future returns.

6.3.2 Non-Financial Firms

Our empirical analyses have so far been based on the entire bond sample issued by both financial and non-financial firms. After excluding bonds issued by financial firms, Panel B of Table 9 shows that our main results remain intact. Specifically, the average raw and risk-adjusted return spreads between high-volatility and low-volatility quintiles are in the range of 0.504% and 0.619% per month and highly significant. The average raw and risk-adjusted return spreads between high-skewness and low-skewness quintiles are in the range of -0.228% and -0.275%. Additionally, the average raw and risk-adjusted return spreads between high-kurtosis and low-kurtosis quintiles are in the range of 0.339% and 0.362%. Overall, these results are very similar to those obtained for the full sample including both financial and non-financial firms.

6.3.3 Lehman Non-Transaction Data

As discussed in Section 3, our bond data are gathered from a wide range of data sources that contain a mix of quoted and transaction prices. In this subsection, we focus on a subsample of the Lehman data covering the period from 1973 to 1996. As presented in Panel C of Table 9, the average excess return spreads in volatility- and skewness-sorted portfolios are, respectively, 0.698% and -0.166% per month and highly significant. The average return spread in kurtosis-sorted portfolios is 0.455%. Similarly, the 5- and 10-factor alpha spreads are large in magnitude and highly significant, indicating strong cross-sectional relations between volatility, skewness, kurtosis, and future bond returns.

6.3.4 TRACE Transaction Data

Bessembinder, Maxwell, and Venkataraman (2006) highlight the importance of using TRACE daily transaction data. We now focus on the subsample of TRACE transaction data from July 2002 to December 2014. Panel D of Table 9 reports our key results for VOL-, SKEW-, and KURT-sorted portfolios using the TRACE data. Our main findings remain very similar to those obtained from the full sample, although with the real transaction data from 2002 to 2014, our results are even stronger. Corporate bonds in the highest volatility (lowest skewness) quintile generate 0.732% (0.361%) per month higher returns than bonds in the lowest volatility (highest skewness) quintile. Corporate bonds in the highest kurtosis quintile generate 0.534% per month higher returns than bonds in the lowest kurtosis quintile.

6.3.5 Results over the Business Cycle

We also investigate the significance of a cross-sectional relation between volatility, skewness, kurtosis and future bond returns during periods of high and low economic activity. We determine increases and decreases in economic activity according to the Chicago Fed National Activity Index (CFNAI), which is a monthly index designed to assess overall economic activity and related inflationary pressure (see, e.g., Allen, Bali, and Tang (2012)).[26] We find that the positive relation between volatility and future bond returns is significant in both good and bad states, although the results are stronger in bad economic states; see Panels E and F of Table 9. During periods of high economic activity, corporate bonds in the highest volatility (lowest skewness) quintile generate 0.631% (0.172%) per month higher average returns than those in the lowest volatility (highest skewness) quintile. During periods of low economic activity, corporate bonds in the highest volatility (lowest skewness) quintile generate 0.645% (0.324%) per month higher average returns than those in the lowest volatility (highest skewness) quintile.

6.3.6 Characteristic-adjusted Returns

In addition to using raw and risk-adjusted returns, we also examine whether the distributional characteristics of bonds are significantly linked to the characteristic-adjusted returns (i.e., controlling for bond size and credit rating simultaneously). Our methodology of creating characteristic-benchmark portfolios is in a vein similar to Daniel and Titman (1997). First, we form 5×5 bivariate portfolios by sorting corporate bonds into quintiles based on size and

[26] The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity. It is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward trend growth over time, a positive index reading corresponds to growth above trend (good state) and a negative index reading corresponds to growth below trend (bad state).

credit rating, and then compute the equal-weighted average returns of these 25 portfolios. Second, we identify the bonds in VOL-, SKEW-, or KURT-sorted portfolios, which are also placed in one of those 25 size-rating portfolios. Characteristic-adjusted returns are calculated as the difference between individual bond returns and the average returns of the characteristic-matched portfolio. Table A.9 of the online appendix shows that the average excess return spreads in volatility- and skewness-sorted portfolios are, respectively, 0.491% and -0.140% per month and highly significant. The average return spread in kurtosis-sorted portfolios is 0.201% and statistically significant. Similarly, the 5- and 10-factor alpha spreads are large in magnitude and highly significant, indicating strong cross-sectional relations between volatility, skewness, kurtosis, and future characteristic-adjusted returns.

6.3.7 Firm-level Analysis

Throughout the paper, our empirical analyses are based on the bond-level data since we test whether the distributional characteristics of *individual* bonds predict their future returns. However, firms often have multiple bonds outstanding at the same time. To control for bonds issued by the same firm in our cross-sectional regressions, for each month in our sample, we pick one bond with the median size as the representative for the firm and re-run the Fama-MacBeth regressions using this firm-level data. As presented in Table A.10 of the online appendix, our main findings from the firm-level regressions remain qualitatively similar to those obtained from the bond-level regressions. Both the univariate and multivariate regression results present a positive (negative) and statistically significant relation between volatility (skewness) and future firm-level bond returns.

7 Do Existing Stock and Bond Market Factors Explain the VOL, SKEW and KURT Factors?

We have so far shown that the distributional characteristics (VOL, SKEW, and KURT) of corporate bonds are powerful predictors of the cross-sectional variation in future returns, even after controlling for a large number of bond characteristics, bond exposures to well-known factors, bond-level illiquidity, liquidity risk, and transaction costs. These results suggest that the distributional moments, consistent with asset pricing models, are reasonable proxies for common risk factors in bond returns. To investigate this thoroughly, in this section, we propose new risk factors based on the distributional moments of corporate bond returns and then test if these distribution-based risk factors are explained by the long-established stock and bond market factors.

7.1 New Risk Factors Based on the Distributional Characteristics of Corporate Bond Returns

We use double sorts to construct common risk factors for corporate bonds because the volatility, skewness, and kurtosis of bond returns are correlated with credit rating. As expected, corporate bonds with high volatility and negative skewness (a proxy for left-tail risk) have high credit risk. Consistent with these findings, corporate bonds with high kurtosis also have high credit risk. Thus, it is natural to use credit risk as the first sorting variable in the construction of these new risk factors of corporate bonds. For each month from January 1975 to December 2014, we form portfolios by first sorting corporate bonds into five quintiles based on their credit rating; then, within each rating portfolio, bonds are sorted further into five sub-quintiles separately based on their volatility, skewness, or kurtosis. The VOL^F factor is the average return difference between the highest volatility portfolio and the lowest volatility portfolio within each rating portfolio. This methodology, under each rating-sorted quintile, produces sub-quintile portfolios of bonds with dispersion in volatility and nearly identical ratings. Similarly, the $SKEW^F$ factor is the average return difference between the highest skewness portfolio and the lowest skewness portfolio within each rating portfolio. The $KURT^F$ factor is the average return difference between the highest kurtosis portfolio and the lowest kurtosis portfolio within each rating portfolio. We also construct a broad, common factor of **V**olatility, **S**kewness, and **K**urtosis (denoted by VSK), using the first principal component of VOL^F, $SKEW^F$ and $KURT^F$ factors. The principal component analysis leads to the following factor loadings that define the VSK factor: $VSK = 0.67 \times VOL^F - 0.26 \times SKEW^F + 0.69 \times KURT^F$. Figure 1 plots the time-series of VOL^F, $SKEW^F$ and $KURT^F$ factors and the common risk factor, VSK, from January 1975 to December 2014.

Panel A of Table 10 reports the summary statistics for the new risk factors (VOL^F, $SKEW^F$ and $KURT^F$). Over the period from January 1975 to December 2014, the VOL^F factor has an economically and statistically significant risk premium of 0.54% per month with a t-statistic of 5.66. The $SKEW^F$ and $KURT^F$ factors also have significant risk premia of -0.16% per month (t-stat.= -2.75) and 0.17% per month (t-stat.= 2.46), respectively. Consistent with these findings, the VSK factor has an economically and statistically significant risk premium as well: 0.52% per month with a t-statistic of 5.21.

Since risk premia are expected to be higher during financial and economic downturns, we examine the average risk premia for the newly proposed VSK factor during good and bad economic states. As expected, we find that the average risk premium on the VSK factor is higher during bad economic states: 0.67% per month (t-stat.= 3.45) during periods of low economic activity (CFNAI $<$ 0) and 0.40% per month (t-stat.= 4.69) during periods of high economic activity (CFNAI $>$ 0). We looked into this further for recessionary vs. non-recessionary periods and find that the average risk premium on the VSK factor is much higher at 1.00% per month (t-stat.= 2.14) during recessionary periods (CFNAI $<$ -0.7), whereas it is 0.42% per month (t-stat.= 6.17) during non-recessionary periods (CFNAI $>$ -0.7). Finally, we examine the bond risk premia during the recent financial crisis and find that the average risk premium on the VSK factor is extremely large at 1.86% per month for the period from June 2007 to June 2009. These magnitudes provide clear evidence that the distribution-based common factor of corporate bonds generates economically large risk premia during economic downturns.

7.2 Time-Series Analysis

To determine whether the conventional stock and bond market risk factors explain the newly proposed distribution-based risk factors of corporate bonds, we conduct a formal test using the following time-series regression:

$$VSK_t = \alpha + \sum_{k=1}^{K} \beta_k Factor_{k,t}^{Stock} + \sum_{l=1}^{L} \beta_l Factor_{l,t}^{Bond} + \varepsilon_t, \tag{11}$$

where VSK is the common risk factor obtained from the first principal component of the VOL^F, $SKEW^F$ and $KURT^F$ factors. $Factor_{k,t}^{Stock}$ denotes a vector of stock market factors; MKT^{Stock}, SMB, HML, MOM, and LIQ and $Factor_{k,t}^{Bond}$ denote a vector of bond market factors; MKT^{Bond}, DEF, TERM, MOM^{Bond}, and LIQ^{Bond}.

Equation (11) is re-estimated separately for each of the newly proposed risk factors by replacing the VSK factor on the left-hand side with the VOL^F, $SKEW^F$ and $KURT^F$ factors. These factor regression results are presented in Table 10. The intercepts (alphas) in equation (11) represent the abnormal returns not explained by the standard stock and bond market factors. The alphas are defined in terms of monthly percentages. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Panel B of Table 10 reports the regression results using the stock market factors as explanatory variables. In Model 1 (i.e., the market model) where the only explanatory variable is the excess stock market return, all the intercepts are economically and statistically significant. The alphas for the VOL^F, $SKEW^F$ and $KURT^F$ factors are 0.45% per month (t-stat.= 4.84), -0.17% per month (t-stat.= -2.73), and 0.15% (t-stat.= 2.08), respectively. Consistent with these findings, the CAPM alpha for the VSK factor is positive and highly significant; 0.45% per month (t-stat.= 4.64). In Model 2, where the explanatory variables include five commonly-used stock market factors of Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003), all the alphas remain economically large and statistically significant. The adjusted-R^2 values from these regressions are in the range of -0.17% and 14.61%, suggesting that the commonly-used stock market factors have low explanatory power for the distribution-based risk factors of corporate bonds. In particular, the adjusted-R^2 values are very low for the $SKEW^F$ factor. Overall, these results suggest that the newly proposed bond market factors capture important source of common return variation in corporate bonds missing from the traditional stock market factors.

Panel C of Table 10 shows the regression results using the standard bond market risk factors as explanatory variables. In Model 3 where the only explanatory variable is the excess bond market return, all the intercepts are economically and statistically significant. The alphas for the VOL^F, $SKEW^F$ and $KURT^F$ factors are 0.47% per month (t-stat.= 5.62), -0.16% per month (t-stat.= -2.99), and 0.18% (t-stat.= 2.50), respectively. Consistent with these findings, the CAPM alpha for the VSK factor is positive and highly significant; 0.48% per month (t-stat.= 5.10). In Model 4, where the explanatory variables include the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}), all the intercepts remain both economically strong and statistically significant. The adjusted-R^2 values from these regressions are in the range of -0.16% and 20.29%. In particular, the adjusted-R^2 values are very low for the $SKEW^F$ and VSK factors, implying that the commonly used bond market risk factors have low explanatory power for the distribution-based risk factors of corporate bonds.

Panel D of Table 10 presents the regression results from the extended 10-factor model, combining all the stock and bond market factors. The results are consistent with our earlier findings. First, the alphas of all distribution-based bond risk factors are economically and statistically significant, indicating that the existing stock and bond market factors are not sufficient to capture the information content in these new bond risk factors. Second, the explanatory power of the existing factors is considerably low for the new bond market factors. Combining all factors together, they explain approximately 26.86% of the VOL^F factor, 1.80% of the $SKEW^F$ factor, 12.52% of the $KURT^F$ factor, and 19.01% of the VSK factor. These findings suggest that our new bond market risk factors represent an important source of common return variation missing from the long-established stock and bond market risk factors.

8 Conclusion

In spite of the dominance of the mean-variance portfolio theory, there has been longstanding interest in whether high-order moments (skewness, kurtosis, and tail risk) play a special role in determining expected returns. An extensive stream of literature examines the significance of distributional moments in predicting future stock and option returns, but almost no work has been conducted on the predictive power of volatility and higher order moments of bond returns. This paper is the first to investigate if the distributional characteristics of corporate bonds predict the cross-sectional differences in future bond returns.

We test the significance of a cross-sectional relation between volatility and future returns on corporate bonds using portfolio-level analysis, and find that bonds in the highest volatility quintile generate 6.30% to 7.68% more annual raw and risk-adjusted returns than bonds in the lowest volatility quintile. After controlling for the volatility of bond returns and well-known stock and bond market factors, bivariate portfolio results show that bonds in the lowest skewness quintile generate 2.90% to 3.61% more annual raw and risk-adjusted returns than bonds in the highest skewness quintile, consistent with investors' preference for positively skewed assets. Bonds in the highest kurtosis quintile generate 4.49% to 4.87% more annual raw and risk-adjusted returns than bonds in the lowest kurtosis quintile. These results are consistent with theoretical models with high-order moments, in contrast to the mixed findings for the cross-section of stock and option returns.

We disintegrate total volatility, skewness, and kurtosis into their systematic and idiosyncratic components and test if the cross-sectional pricing of the distributional moments is driven by their systematic or firm-specific components. We find that the risk-adjusted return spreads in volatility-(skewness-) sorted portfolios represent compensation for differences in the level of idiosyncratic volatility (idiosyncratic skewness), not for differences in market beta (co-skewness).

Finally, based on the cross-sectional asset pricing results from portfolio-level analyses, we generate new risk factors of corporate bonds using bivariate sorts of credit rating and the distributional characteristics, VOL^F, $SKEW^F$, $KURT^F$ and their first principal component VSK. We show that the existing risk factors in the stock/bond literature do not have significant explanatory power for our newly proposed risk factors. Thus, the distribution-based risk factors of corporate bonds contain additional predictive power beyond current predictors.

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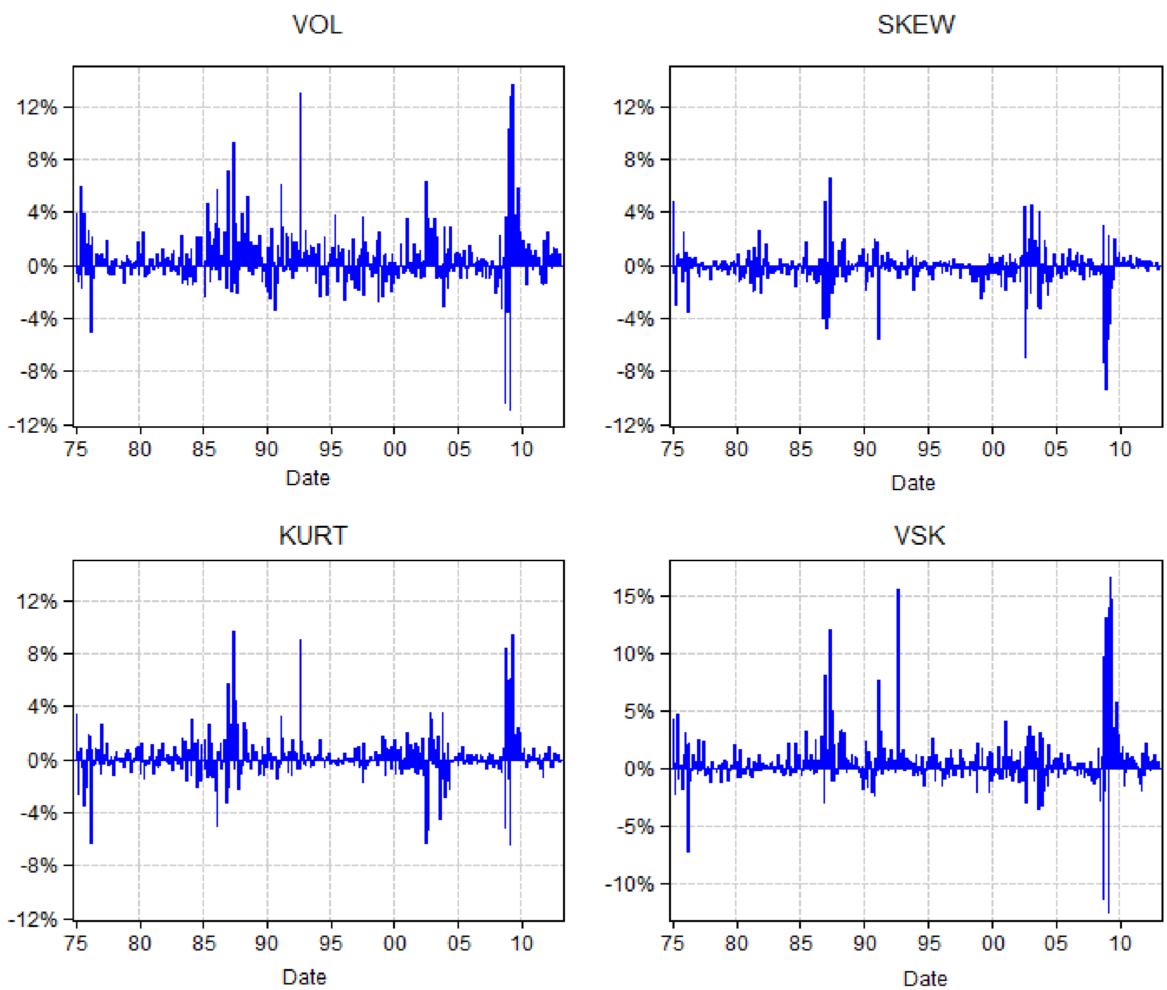
Figure 1: VOL^F, $SKEW^F$, $KURT^F$ **and the** VSK **Factors: 1975 – 2014**



This figure plots the monthly time-series of the distribution-based risk factors VOL^F, $SKEW^F$ and $KURT^F$ and the common risk factor, VSK, from January 1975 to December 2014. The volatility factor (VOL^F) is constructed by first sorting corporate bonds on credit rating into quintiles, then within each rating portfolio, corporate bonds are sorted into sub-quintiles based on the volatility. VOL^F is the average return difference between the highest VOL portfolio and the lowest VOL portfolio within each rating portfolio. The skewness factor ($SKEW^F$) is constructed by first sorting corporate bonds on credit rating into quintiles, then within each rating portfolio, corporate bonds are sorted into sub-quintiles based on the skewness. $SKEW^F$ is the average return difference between the highest SKEW portfolio and the lowest SKEW portfolio within each rating portfolio. The kurtosis factor ($KURT^F$) is constructed by first sorting corporate bonds on credit rating into quintiles, then within each rating portfolio, corporate bonds are sorted into sub-quintiles based on the kurtosis. $KURT^F$ is the average return difference between the highest KURT portfolio and the lowest KURT portfolio within each rating portfolio. The common risk factor, VSK, is constructed using the first principal component of VOL^F, $SKEW^F$ and $KURT^F$ factors, $VSK = 0.67 \times VOL^F - 0.26 \times SKEW^F + 0.69 \times KURT^F$.

Table 1: **Summary Statistics and Normality Test for Corporate Bond Returns**

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 (TTM, year), amount outstanding (Size, $ billion), return volatility (%), skewness (%), and kurtosis (%). 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. Panel B reports the total number of bonds and the percentage of bonds with significant and insignificant return moments, for the time-series distribution of all corporate bond returns. For each bond in our sample from January 1975 to December 2014, we compute the volatility, skewness, and excess kurtosis of monthly returns, and then test whether these high-order moments are significantly different from zero. Panel C reports the total number of months and the number of months with significant and insignificant return moments for the cross-sectional distribution of monthly corporate bond returns. For each month from January 1975 to December 2014, we compute the return moments including volatility, skewness, and kurtosis using the cross-section of bond returns, and test whether these distributional moments are significantly different from zero. Table also reports the Jarque-Bera (JB) statistics for the normality test of the distribution of corporate bond returns. The median p-value is reported to test the statistical significance of the return moments and the significance of the JB statistics. The sample period is from January 1975 to December 2014.

Panel A: Cross-sectional statistics over the sample period of January 1975−December 2014

					Percentiles					
	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Bond Return (%)	1,088,174	0.64	0.62	2.70	-6.39	-2.85	-0.45	1.64	4.16	8.57
Rating	1,081,903	7.67	6.98	3.99	1.67	2.52	4.99	9.33	15.67	19.90
TTM (year)	1,088,174	14.30	12.21	7.70	4.43	5.36	8.46	19.16	28.71	34.90
Size ($bil)	1,084,116	0.25	0.19	0.24	0.03	0.04	0.11	0.31	0.70	1.28
Volatility (%)	656,426	3.36	3.00	1.76	1.43	1.74	2.40	3.73	6.47	10.65
Skewness (%)	656,426	0.06	0.05	0.76	-2.09	-1.08	-0.31	0.38	1.25	2.47
Kurtosis (%)	656,426	2.24	1.35	3.14	-0.63	-0.28	0.51	2.76	7.97	16.10

Panel B: Time-series distribution of all corporate bond returns

		Skewness		Kurtosis		Normality
	Volatility	Positive	Negative	Positive	Negative	JB-stat
Total # of bonds	17,335	7,738	9,597	15,518	1,817	17,335
% of bonds significant	100.00	55.98	50.26	75.69	0.88	74.62
Median p-value	0.00	0.00	0.00	0.00	0.00	0.00
% of bonds insignificant	0.00	44.02	49.74	24.31	99.12	25.38

Panel C: Cross-sectional distribution of monthly corporate bond returns

		Skewness		Kurtosis		Normality
	Volatility	Positive	Negative	Positive	Negative	JB-stat
Total # of months	480	240	240	478	2	480
# of months significant	479	236	237	477	2	480
Median p-value	0.00	0.00	0.00	0.00	0.00	0.00
# of months insignificant	1	4	3	1	0	0

Table 2: **Univariate Portfolios of Corporate Bonds Sorted by Volatility (VOL)**

Quintile portfolios are formed every month from January 1975 to December 2014 by sorting corporate bonds into quintiles based on their 60-month rolling total variance (VOL). Quintile 1 is the portfolio with the lowest volatility, and Quintile 5 is the portfolio with the highest volatility. Table reports the average volatility, 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 three columns report average portfolio characteristics including bond rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 5- and 10-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), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines 5 stock market factors and 5 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 significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average volatility	Average excess return	5-factor stock alpha	5-factor bond alpha	10-factor alpha	Average Portfolio Characteristics		
						Rating	Maturity	Size
Low VOL	2.065	0.036	-0.065	-0.091	-0.077	6.692	9.908	0.286
		(0.41)	(-0.77)	(-2.83)	(-2.30)			
2	2.663	0.101	-0.021	-0.051	-0.034	6.820	12.572	0.265
		(0.98)	(-0.21)	(-1.97)	(-1.28)			
3	3.145	0.114	-0.041	-0.054	-0.046	6.788	14.773	0.253
		(0.97)	(-0.37)	(-1.97)	(-1.28)			
4	3.758	0.259	0.101	0.067	0.081	7.175	17.382	0.252
		(1.84)	(0.73)	(1.27)	(1.27)			
High VOL	6.587	0.674	0.478	0.457	0.448	10.349	16.626	0.234
		(3.28)	(2.43)	(3.76)	(3.44)			
High − Low		0.637***	0.544***	0.548***	0.525***			
Return/Alpha diff.		(4.00)	(3.37)	(4.34)	(3.91)			

Table 3: **Bivariate Portfolios of Corporate Bonds Sorted by SKEW Controlling for VOL**

Quintile portfolios are formed every month from January 1975 to December 2014 by first sorting corporate bonds into quintiles based on their 60-month rolling total variance (VOL). Then, within each volatility portfolio, corporate bonds are sorted into sub-quintiles based on their 60-month rolling skewness ($SKEW$). "Quintile SKEW,1" is the portfolio of corporate bonds with the lowest $SKEW$ within each volatility portfolio and "Quintile SKEW, 5" is the portfolio of corporate bonds with the highest $SKEW$ within each volatility portfolio. Table reports the average $SKEW$ within each volatility portfolio, 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 three columns report average portfolio characteristics including bond rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 5- and 10-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), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines 5 stock market factors and 5 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 significance at the 10%, 5%, and 1% levels, respectively.

$SKEW$ Quintiles after	Average	Average	5-factor stock	5-factor bond	10-factor	Average Portfolio Characteristics		
controlling for VOL	skew	excess return	alpha	alpha	alpha	Rating	Maturity	Size
SKEW,1	-0.884	0.453	0.408	0.356	0.419	8.729	12.667	0.262
		(3.12)	(2.42)	(4.73)	(4.19)			
SKEW,2	-0.235	0.299	0.194	0.136	0.180	7.526	14.577	0.271
		(2.40)	(1.45)	(2.82)	(2.85)			
SKEW,3	0.037	0.214	0.067	0.056	0.065	6.964	15.016	0.266
		(1.71)	(0.51)	(1.20)	(1.04)			
SKEW,4	0.335	0.248	0.116	0.078	0.101	7.001	14.809	0.251
		(2.10)	(1.00)	(1.48)	(1.14)			
SKEW,5	0.948	0.211	0.103	0.108	0.119	7.701	13.060	0.240
		(1.75)	(0.87)	(1.09)	(1.27)			
SKEW,5 − SKEW,1		-0.241***	-0.301***	-0.242***	-0.295***			
Return/Alpha diff.		(-3.78)	(-3.31)	(-4.22)	(-3.61)			

Table 4: **Univariate Portfolios of Corporate Bonds Sorted by Kurtosis (KURT)**

Quintile portfolios are formed every month from January 1975 to December 2014 by sorting corporate bonds into quintiles based on their 60-month rolling kurtosis ($KURT$). Quintile 1 is the portfolio with the lowest kurtosis, and Quintile 5 is the portfolio with the highest kurtosis. Table reports the average kurtosis, 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 three columns report average portfolio characteristics including bond rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 5- and 10-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), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines 5 stock market factors and 5 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 significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	5-factor stock	5-factor bond	10-factor	Average Portfolio Characteristics		
	kurtosis	excess return	alpha	alpha	alpha	Rating	Maturity	Size
Low KURT	-0.076	0.155	-0.004	-0.012	-0.033	6.804	15.348	0.260
		(1.26)	(-0.03)	(-0.30)	(-0.68)			
2	0.669	0.147	-0.001	-0.020	-0.010	6.847	15.280	0.260
		(1.22)	(-0.01)	(-0.72)	(-0.35)			
3	1.362	0.185	0.041	0.014	0.035	6.970	14.566	0.279
		(1.45)	(0.33)	(0.39)	(0.71)			
4	2.413	0.152	-0.016	-0.022	-0.026	7.485	13.799	0.251
		(1.15)	(-0.14)	(-0.50)	(-0.47)			
High KURT	6.679	0.529	0.402	0.350	0.373	9.692	12.148	0.243
		(3.05)	(2.42)	(3.39)	(3.51)			
High − Low		0.374***	0.406***	0.362***	0.406***			
Return/Alpha diff.		(2.96)	(3.09)	(3.07)	(3.20)			

Table 5: **Fama-MacBeth Cross-Sectional Regressions with VOL, SKEW, and KURT**

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 total variance (VOL), skewness (SKEW), and kurtosis (KURT) with and without the control variables. Bond characteristics are credit rating, time-to-maturity (years) and amount outstanding (size, in billions of dollars). Ratings are in conventional numerical scores, where 1 represents a AAA rating and 21 reflects a C rating. Higher numerical score means lower ratings. The Fama and MacBeth cross-sectional regressions are run each month for the period January 1975 to December 2014. Other controls include bond exposures (betas) to the aggregate stock market (β^{Stock}), the aggregate bond market (β^{Bond}), default spread (β^{DEF}), and term spread (β^{TERM}), which are estimated using a 60-month rolling window. Each row represents a cross-sectional regression. 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 of the average slope coefficients.

Model	Intercept	VOL	SKEW	KURT	Rating	Maturity	Size	β^{Stock}	β^{Bond}	β^{DEF}	β^{TERM}	R^2_{adj}
(1)	-0.048	**0.017**										0.042
	(-0.44)	(3.81)										
(2)	0.204		-0.038									0.012
	(1.64)		(-0.85)									
(3)	0.089			**0.063**								0.018
	(0.76)			(3.30)								
(4)	-0.117	**0.014**			0.006	0.002	-0.195	0.112	0.103	0.000	0.007	0.151
	(-0.77)	(3.21)			(0.76)	(0.79)	(-0.62)	(0.44)	(0.57)	(0.02)	(0.27)	
(5)	-0.474		**-0.148**		**0.050**	0.001	0.490	**1.079**	**0.210**	-0.012	-0.012	0.134
	(-1.60)		(-2.16)		(2.28)	(0.39)	(1.05)	(1.94)	(2.12)	(-1.00)	(-0.28)	
(6)	-0.141			**0.056**	**0.021**	-0.001	0.838	1.657	**0.140**	-0.040	-0.042	0.131
	(-0.69)			(2.23)	(2.26)	(-0.19)	(1.07)	(1.28)	(2.24)	(-1.15)	(-0.78)	
(7)	-0.073	**0.018**	**-0.192**									0.055
	(-0.67)	(3.77)	(-4.04)									
(8)	-0.134	**0.011**	**-0.243**		0.007	0.002	0.603	0.970	0.086	-0.013	0.024	0.157
	(-0.47)	(3.08)	(-2.70)		(0.91)	(0.39)	(1.06)	(1.11)	(0.44)	(-0.84)	(0.56)	
(9)	-0.086	**0.023**	**-0.179**	-0.012								0.071
	(-0.75)	(3.20)	(-3.49)	(-0.87)								
(10)	-0.141	**0.015**	**-0.166**	-0.021	0.014	0.001	0.057					0.112
	(-1.23)	(3.15)	(-3.86)	(-1.04)	(1.39)	(0.29)	(0.53)					
(11)	-0.332	**0.011**	**-0.251**	0.002	0.024	0.002	0.669	1.168	0.132	-0.014	-0.012	0.160
	(-0.93)	(3.07)	(-3.15)	(0.09)	(1.00)	(0.31)	(1.13)	(1.44)	(0.72)	(-0.93)	(-0.25)	

Table 6: **Fama-MacBeth Cross-Sectional Regressions with Systematic and Idiosyncratic Risk**

This table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on systematic risk and idiosyncratic risk with and without the control variables. Systematic risk (β^{Bond}) is estimated using a 60-month rolling window using individual bond excess returns against the excess bond market return; idiosyncratic risk (IVOL) is the standard deviation of the residuals from the above regression. Bond characteristics are credit rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars). Ratings are in conventional numerical scores, where 1 represents a AAA rating and 21 reflects a C rating. Higher numerical score means lower ratings. The Fama and MacBeth cross-sectional regressions are run each month for the period January 1975 to December 2014. Other controls include bond exposures (betas) to the aggregate stock market (β^{Stock}), default spread (β^{DEF}), and term spread (β^{TERM}), which are estimated using a 60-month rolling window. Each row represents a cross-sectional regression. 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 of the average slope coefficients.

Model	Intercept	β^{Bond}	IVOL	Rating	Maturity	Size	β^{Stock}	β^{DEF}	β^{TERM}	R^2_{adj}
(1)	-0.014	**0.250**								0.069
	(-0.16)	(2.37)								
(2)	-0.408	**0.309**		**0.044**	0.000	-0.186	**0.294**	-0.007	-0.002	0.154
	(-2.98)	(3.42)		(2.84)	(0.18)	(-0.87)	(1.92)	(-1.33)	(-0.12)	
(3)	-0.165		**0.179**							0.054
	(-1.44)		(6.09)							
(4)	-0.282		**0.139**	0.016	0.002	-0.013	0.117	-0.005	-0.011	0.140
	(-2.22)		(4.45)	(1.62)	(0.70)	(-0.05)	(0.73)	(-0.77)	(-0.85)	
(5)	-0.305	0.182	**0.166**							0.113
	(-3.59)	(1.13)	(6.30)							
(6)	-0.455	0.214	**0.154**	**0.021**	-0.002	0.146				0.144
	(-4.31)	(1.35)	(6.02)	(2.51)	(-0.85)	(1.39)				
(7)	-0.352	0.188	**0.172**	0.023	-0.006	0.955	0.608	-0.034	0.001	0.170
	(-2.30)	(1.20)	(3.52)	(1.60)	(-1.26)	(0.99)	(1.06)	(-1.20)	(0.04)	

Table 7: **Fama-MacBeth Cross-Sectional Regressions with Co-skewness and Idiosyncratic Skewness**

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 coskewness and idiosyncratic skewness with and without the control variables. Co-skewness (COSKEW) is estimated using a 60-month rolling window using individual bond excess returns against the excess bond market return and its squared term. Idiosyncratic skewness (ISKEW) is the skewness of the residuals from the co-skewness regression. Bond characteristics are credit rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars). Ratings are in conventional numerical scores, where 1 represents a AAA rating and 21 reflects a C rating. Higher numerical score means lower ratings. The Fama and MacBeth cross-sectional regressions are run each month for the period January 1975 to December 2014. Other controls include bond exposures (betas) to the aggregate stock market (β^{Stock}), default spread (β^{DEF}), and term spread (β^{TERM}), which are estimated using a 60-month rolling window. Each row represents a cross-sectional regression. 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 of the average slope coefficients.

Model	Intercept	COSKEW	ISKEW	β^{Bond}	IVOL	Rating	Maturity	Size	β^{Stock}	β^{DEF}	β^{TERM}	R^2_{adj}
(1)	0.238	-0.005										0.013
	(2.06)	(-1.19)										
(2)	-0.223	-0.011				**0.045**	0.006	0.602	1.311	-0.022	-0.002	0.133
	(-1.09)	(-1.18)				(2.81)	(1.00)	(1.07)	(1.34)	(-1.42)	(-0.11)	
(3)	0.232		**-0.060**									0.011
	(2.01)		(-2.87)									
(4)	-0.178		**-0.067**			**0.042**	**0.005**	0.141	0.306	**-0.009**	0.015	0.127
	(-1.46)		(-3.88)			(3.11)	(1.84)	(0.69)	(1.65)	(-2.09)	(0.88)	
(5)	0.212	-0.008	**-0.066**									0.023
	(1.83)	(-1.34)	(-2.92)									
(6)	-0.254	-0.007	**-0.080**			**0.042**	0.007	0.073				0.113
	(-2.26)	(-1.09)	(-3.94)			(4.72)	(2.65)	(0.56)				
(7)	-0.350	-0.062	**-0.010**			**0.042**	0.005	1.379	3.398	-0.062	0.007	0.139
	(-1.36)	(-1.29)	(-3.19)			(3.13)	(0.90)	(1.25)	(1.27)	(-1.28)	(0.35)	
(8)	-0.359	-0.008	**-0.107**	0.282	**0.111**							0.127
	(-3.62)	(-1.66)	(-4.04)	(1.09)	(2.74)							
(9)	-0.615	-0.013	**-0.122**	0.301	**0.138**	**0.019**	0.001	0.083				0.162
	(-3.19)	(-1.30)	(-4.00)	(1.39)	(4.15)	(1.90)	(0.21)	(0.44)				
(10)	-1.060	-0.051	**-0.189**	0.395	**0.094**	0.058	-0.003	1.621	3.029	-0.057	-0.081	0.171
	(-1.31)	(-1.62)	(-2.83)	(1.61)	(2.54)	(1.38)	(-0.29)	(0.85)	(0.99)	(-0.96)	(-1.15)	

Table 8: **Transaction Costs for Bond Portfolios Sorted by VOL, SKEW, and KURT**

This table reports the estimated transaction costs for bond portfolios sorted by volatility (VOL), skewness (SKEW) and kurtosis (KURT). We estimate the portfolio transaction costs (TransCost), following Chordia et al. (2016). TransCost is the product of the time-series average of the illiquidity measure, as in Bao, Pan, and Wang (2011), multiplied by the time-series average of the portfolio turnover rate. The transaction costs are in percentage per month, from July 2002 to December 2014 using TRACE Enhanced data.

	Low	2	3	4	High	TransCost
			Panel A: All Bonds			
VOL	0.018	0.013	0.018	0.031	0.119	0.137
SKEW	0.064	0.037	0.021	0.021	0.036	0.100
KURT	0.018	0.025	0.029	0.033	0.070	0.087
			Panel B: Investment-grade bonds			
VOL	0.022	0.013	0.018	0.024	0.078	0.100
SKEW	0.035	0.027	0.017	0.016	0.025	0.061
KURT	0.019	0.016	0.018	0.021	0.050	0.069
			Panel C: Non-investment-grade bonds			
VOL	0.017	0.017	0.071	0.076	0.208	0.225
SKEW	0.120	0.098	0.043	0.060	0.070	0.189
KURT	0.029	0.084	0.062	0.074	0.126	0.155

Table 9: **Robustness Check**

This table reports a battery of robustness checks on corporate bond portfolios sorted by volatility (VOL), skewness (SKEW), and kurtosis (KURT). Panel A reports the value-weighted portfolio results, using bond outstanding dollar value as the weights. Panel B presents the results for bonds issued by non-financial firms only. Panel C uses the Lehman data only. Panel D uses the TRACE transaction data only. Panel E reports the results during periods of high economic activity, based on the Chicago Fed National Activity Index (CFNAI > 0). Panels F reports the results during periods of low economic activity (CFNAI < 0). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

High − Low	Average excess return	5-factor stock alpha	5-factor bond alpha	10-factor alpha
		Panel A: Value-weighting		
VOL	0.511***	0.340**	0.418***	0.348**
SKEW	-0.203***	-0.203***	-0.203***	-0.259***
KURT	0.295**	0.298**	0.284**	0.200**
		Panel B: Non-financial firms		
VOL	0.619***	0.506***	0.538***	0.504***
SKEW	-0.229***	-0.275***	-0.228***	-0.274***
KURT	0.358***	0.352***	0.339***	0.362***
		Panel C: Lehman Non-Transaction Data Only		
VOL	0.698***	0.568***	0.604***	0.554***
SKEW	-0.166***	-0.172***	-0.160***	-0.167***
KURT	0.455***	0.476***	0.469***	0.483***
		Panel D: TRACE Transaction Data Only		
VOL	0.732***	0.619***	0.685***	0.666***
SKEW	-0.361***	-0.431***	-0.324***	-0.430***
KURT	0.534***	0.558***	0.397***	0.414***
		Panel E: High Economic Activity		
VOL	0.631***	0.460***	0.393**	0.508***
SKEW	-0.172***	-0.174***	-0.183***	-0.177***
KURT	0.385**	0.360**	0.371**	0.342*
		Panel F: Low Economic Activity		
VOL	0.645**	0.568**	0.628**	0.540***
SKEW	-0.323**	-0.409***	-0.262***	-0.343***
KURT	0.320*	0.421**	0.215*	0.348*

Table 10: **Time-series Regressions of VOL^F, $SKEW^F$, $KURT^F$ and VSK Factors on the Stock and Bond Market Factors**

Panel A of this table reports the summary statistics of VOL^F, $SKEW^F$, $KURT^F$ and the common risk factor, VSK. The VSK factor is constructed using the first principal component of VOL^F, $SKEW^F$ and $KURT^F$ factors: $VSK = 0.67 \times VOL^F - 0.26 \times SKEW^F + 0.69 \times KURT^F$. Panels B, C, and D report the intercept (α) and slope coefficients from time-series regressions of these new risk factors on the commonly-used stock and bond market factors. The stock market factors include the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the Pastor-Stambaugh stock liquidity factor (LIQ). The bond market factors include the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The sample period is from January 1975 to December 2014.

Panel A: Summary statistics

	VOL^F	$SKEW^F$	$KURT^F$	VSK
Mean	0.54	-0.16	0.17	0.52
t-stat	(5.66)	(-2.75)	(2.46)	(5.21)

Panel B: Regressions with stock market factors

Dep. Var	α	MKT^{Stock}	SMB	HML	MOM	LIQ	R^2_{adj} (%)
		Model 1: CAPM with excess stock market return					
VOL^F	**0.45**	**0.13**					7.81
	(4.84)	(3.90)					
$SKEW^F$	**-0.17**	0.01					-0.17
	(-2.73)	(0.27)					
$KURT^F$	**0.15**	0.03					0.43
	(2.08)	(1.02)					
VSK	**0.45**	**0.11**					4.44
	(4.64)	(2.74)					
		Model 2: Fama-French (1993), Carhart (1997), Pastor-Stambaugh (2003)					
VOL^F	**0.48**	0.14	0.02	**0.08**	**-0.10**	-2.91	14.61
	(4.35)	**(4.19)**	(0.57)	(2.05)	(-2.31)	(-1.13)	
$SKEW^F$	**-0.20**	0.01	0.02	0.04	0.02	1.69	0.78
	(-2.85)	(0.26)	(0.84)	(1.34)	(1.14)	(0.88)	
$KURT^F$	**0.19**	0.01	**0.07**	0.03	**-0.09**	-0.76	8.71
	(2.20)	(0.45)	(3.50)	(0.93)	(-3.01)	(-0.49)	
VSK	**0.51**	**0.10**	**0.06**	0.06	**-0.14**	-2.92	13.79
	(4.20)	(2.46)	(2.10)	(1.37)	(-2.61)	(-1.03)	

Table 10. (Continued)

Panel C: Regressions with bond market factors

Dep. Var	α	MKT^{Bond}	DEF	TERM	MOM^{Bond}	LIQ^{Bond}	R^2_{adj} (%)
				Model 3: CAPM with excess bond market return			
VOL^F	**0.47**	**0.41**					19.11
	(5.62)	(5.75)					
$SKEW^F$	**-0.16**	0.01					-0.16
	(-2.99)	(0.26)					
$KURT^F$	**0.18**	-0.02					-0.11
	(2.50)	(-0.44)					
VSK	**0.48**	**0.25**					6.53
	(5.10)	(3.18)					
				Model 4: Elton-Gruber-Blake (1995), Bessembinder et al. (2009), extended with MOM^{Bond} and LIQ^{Bond}			
VOL^F	**0.46**	**0.40**	-1.14	-0.05	-0.30	0.30	20.29
	(5.82)	(5.70)	(-1.08)	(-0.21)	(-1.16)	(0.71)	
$SKEW^F$	**-0.17**	0.00	-0.41	**-0.20**	0.19	-0.10	1.31
	(-3.15)	(-0.01)	(-0.40)	(-1.86)	(1.65)	(-0.28)	
$KURT^F$	**0.16**	-0.03	0.43	**0.46**	-0.32	0.54	5.72
	(2.46)	(-0.55)	(0.41)	(1.97)	(-1.57)	(1.44)	
VSK	**0.47**	**0.25**	-0.36	0.34	-0.47	0.60	10.11
	(5.32)	(3.03)	(-0.23)	(1.19)	(-1.50)	(1.16)	

Panel D: Regressions with stock and bond market factors

Dep. Var	α	MKT^{Stock}	MKT^{Bond}	SMB	HML	MOM	LIQ	DEF	TERM	MOM^{Bond}	LIQ^{Bond}	R^2_{adj} (%)
						Model 5: 10-factor model, combining five stock and five bond market factors						
VOL^F	**0.45**	**0.09**	**0.29**	0.05	0.07	**-0.09**	-2.33	-0.44	**-0.38**	-0.30	0.23	26.86
	(4.81)	(2.20)	(4.30)	(1.62)	(1.61)	(-2.75)	(-1.08)	(-0.36)	(-2.17)	(-1.43)	(0.60)	
$SKEW^F$	**-0.19**	-0.01	0.01	0.00	0.02	0.02	2.25	-0.46	-0.19	0.17	-0.07	1.80
	(-2.90)	(-0.37)	(0.10)	(0.25)	(0.74)	(1.18)	(1.25)	(-0.45)	(-1.64)	(1.46)	(-0.22)	
$KURT^F$	**0.17**	0.04	-0.09	**0.07**	0.05	**-0.08**	-0.91	0.93	0.20	**-0.31**	0.46	12.52
	(2.17)	(1.55)	**(-1.98)**	(2.90)	(1.52)	(-3.02)	(-0.57)	(0.80)	(1.07)	(-1.81)	(1.30)	
VSK	**0.47**	**0.09**	0.13	**0.08**	0.08	**-0.12**	-2.78	0.47	-0.07	**-0.46**	0.50	19.01
	(4.52)	(2.08)	(1.71)	(2.55)	(1.56)	(-2.94)	(-1.04)	(0.27)	(-0.34)	(-1.80)	(1.04)	

Do the Distributional Characteristics of Corporate Bonds Predict Their Future Returns?

Online Appendix

To save space in the paper, we present some of our findings in the Online Appendix. Section A.1 investigates the ex-post portfolio-level measures of volatility, skewness, and kurtosis. Tables A.1 and A.2 present results from the quintile portfolios of corporate bonds sorted by VOL for investment-grade and non-investment-grade bonds, respectively. Table A.3 presents results from the quintile portfolios of corporate bonds sorted by VOL controlling for credit rating, maturity, and size. Table A.4 presents results from the quintile portfolios of corporate bonds sorted by SKEW controlling for credit rating, maturity, and size. Table A.5 presents results from the quintile portfolios of corporate bonds sorted by KURT controlling for credit rating, maturity, and size. Table A.6 presents results on the trivariate portfolios of corporate bonds sorted by VOL, SKEW, and KURT. Table A.7 presents Fama-MacBeth cross-sectional regressions with co-kurtosis and idiosyncratic kurtosis. Table A.8 presents Fama-MacBeth regression results, controlling for bond liquidity and liquidity risk. Table A.9 presents results for the characteristic-matched portfolios of VOL, SKEW, and KURT. Table A.10 presents Fama-MacBeth cross-sectional regressions controlling for distance-to-default. Table A.11 presents the ex-ante bond-level and ex-post portfolio-level measures of volatility, skewness, and kurtosis from daily data.

A.1 Ex-post Portfolio-Level Measures of Volatility, Skewness, and Kurtosis

To determine if investors do need additional compensation to hold corporate bonds with high volatility, we examine the persistence and cross-sectional patterns of pre-ranking and post-ranking volatility measures both at the individual bond and portfolio level. Note that the volatility measures and those underlying the portfolio sorts in Table 2 are for the portfolio formation month, not for the subsequent month over which we measure average returns. Investors may pay low (high) prices for stocks that have exhibited high (low) volatility in the past with the expectation that this behavior will be repeated in the future, but a natural question is whether these expectations are rational.

To investigate this issue, we compute the volatility of monthly returns of volatility-sorted portfolios and find that the ex-post portfolio-level measures of volatility have similar magnitudes and similar cross-sectional pattern as the ex-ante bond-level measures of volatility. Specifically, the ex-post volatility of portfolio returns is 2.00% for quintile 1, 2.58% for quintile 2, 3.04% for quintile 3, 3.64% for quintile 4, and 6.33% for quintile 5. Clearly, these ex-post portfolio-level measures of volatility increase monotonically as we move from quintile 1 to quintile 5 and they are also highly correlated with the ex-ante bond-level measures of average volatility reported in the first column of Table 2.

We find similar results for skewness and kurtosis. The ex-post skewness of monthly returns of skewness-sorted portfolios is 0.80 for quintile 1, 0.21 for quintile 2, 0.03 for quintile 3, 0.31 for quintile 4, and 0.87 for quintile 5. The ex-post kurtosis of monthly returns of kurtosis-sorted portfolios is 0.02 for quintile 1, 0.72 for quintile 2, 1.40 for quintile 3, 2.44 for quintile 4, and 6.60 for quintile 5. Evidently, these ex-post portfolio-level measures of skewness and kurtosis increase monotonically as we move from quintile 1 to quintile 5 and they are also highly correlated with the ex-ante bond-level measures of average skewness and kurtosis reported in the first column of Tables 3 and 4.

However, these results are not surprising because of the overlapping monthly return observations used in the estimation of volatility, skewness, and kurtosis measures.[27] In this section, we answer the same question "do investors need additional compensation to hold corporate bonds with high volatility, low skewness, and high kurtosis?" using non-overlapping monthly estimates of bond-level volatility, skewness, and kurtosis.

We replicate our main analyses using daily returns in TRACE database for the period July 2004−December 2014. We estimate the volatility, skewness, and kurtosis of corporate bonds using daily returns in a month so that there are no overlapping observations for the monthly estimates of bond-level volatility, skewness, and kurtosis.

[27] Since the distributional moments of corporate bonds are calculated based on a 60-month rolling window estimation, the pre-ranking bond-level measures and the post-ranking portfolio-level measures of volatility, skewness, and kurtosis are persistent (serially correlated) and highly cross-correlated as well.

The first column in Table A.11 of the online appendix shows that when moving from quintile 1 to quintile 5, the pre-ranking average volatility of individual bonds in volatility-sorted portfolios increases monotonically (by construction) from 1.79% to 11.65%. The second column in Table A.11 shows that the post-ranking volatility of monthly returns of volatility-sorted portfolios also increases monotonically from 3.14% to 9.92%. Although the magnitudes of these ex-ante bond-level and ex-post portfolio-level measures of volatility are somewhat different, they are moving in the same direction, implying that investors do indeed expect higher returns to hold bonds with high volatility and this is reflected in the ex post, portfolio-level measures of volatility.

Similar results are obtained for the non-overlapping monthly observations of skewness. The third column in Table A.11 shows that when moving from quintile 1 to quintile 5, the pre-ranking average skewness of individual bonds in skewness-sorted portfolios increases monotonically (by construction) from -1.50 to 0.96. The fourth column in Table A.11 shows that the post-ranking skewness of monthly returns of skewness-sorted portfolios also increases monotonically from -0.36 to 0.04. Although the magnitudes of these ex-ante bond-level and ex-post portfolio-level measures of skewness are different, they are moving in the same direction, implying that investors do indeed expect higher returns to hold bonds with negative skewness and this is reflected in the ex post, portfolio-level measures of skewness.

The last two columns in Table A.11 show that the ex-post portfolio-level measure of kurtosis from non-overlapping data does not increase monotonically as we move from quintile 1 to quintile 5, indicating that the ex-ante bond-level measures of kurtosis and the ex-post portfolio-level measures of kurtosis from non-overlapping data are not as highly correlated as in the case of the volatility and skewness measures. This provides another evidence that kurtosis is not as strong as volatility and skewness in terms of predicting the cross-sectional differences in future bond returns.

Table A.1: **Univariate Portfolios of Investment-Grade Bonds Sorted by Volatility (VOL)**

Quintile portfolios are formed every month from January 1975 to December 2014 by sorting corporate bonds into quintiles based on their 60-month rolling total variance (VOL). Quintile 1 is the portfolio with the lowest volatility, and Quintile 5 is the portfolio with the highest volatility. Table reports the average volatility, 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 three columns report average portfolio characteristics including bond rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 5- and 10-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), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines 5 stock market factors and 5 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 significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average volatility	Average excess return	5-factor stock alpha	5-factor bond alpha	10-factor alpha	Average Portfolio Characteristics		
						Rating	Maturity	Size
Low VOL	2.038	0.015	-0.087	-0.111	-0.097	5.999	9.786	0.299
		(0.17)	(-1.02)	(-3.28)	(-2.71)			
2	2.593	0.108	-0.007	-0.041	-0.026	6.033	12.143	0.274
		(1.06)	(-0.08)	(-1.58)	(-0.98)			
3	3.021	0.097	-0.043	-0.066	-0.050	5.936	14.666	0.265
		(0.84)	(-0.38)	(-2.26)	(-1.40)			
4	3.5	0.219	0.073	0.032	0.046	5.990	17.618	0.254
		(1.72)	(0.59)	(1.00)	(1.15)			
High VOL	5.119	0.443	0.302	0.236	0.263	6.597	19.162	0.254
		(2.84)	(1.89)	(3.79)	(3.23)			
High − Low		0.427***	0.389***	0.347***	0.360***			
Return/Alpha diff.		(4.23)	(3.34)	(4.61)	(3.84)			

Table A.2: **Univariate Portfolios of Non-Investment-Grade Bonds Sorted by Volatility (VOL)**

Quintile portfolios are formed every month from January 1975 to December 2014 by sorting corporate bonds into quintiles based on their 60-month rolling total variance (VOL). Quintile 1 is the portfolio with the lowest volatility, and Quintile 5 is the portfolio with the highest volatility. Table reports the average volatility, 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 three columns report average portfolio characteristics including bond rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 5- and 10-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), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines 5 stock market factors and 5 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 significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average volatility	Average excess return	5-factor stock alpha	5-factor bond alpha	10-factor alpha	Average Portfolio Characteristics		
						Rating	Maturity	Size
Low VOL	2.432	0.062	-0.040	-0.020	-0.015	13.298	9.031	0.219
		(0.57)	(-0.38)	(-0.34)	(-0.24)			
2	3.303	0.162	-0.015	0.027	-0.004	13.500	12.862	0.234
		(1.34)	(-0.13)	(0.52)	(-0.07)			
3	4.279	0.296	0.061	0.131	0.075	13.885	13.611	0.231
		(1.95)	(0.44)	(1.59)	(0.94)			
4	5.842	0.391	0.176	0.218	0.210	14.585	13.522	0.230
		(1.83)	(0.93)	(1.70)	(1.50)			
High VOL	9.815	1.260	1.096	1.113	1.047	16.185	12.943	0.221
		(3.62)	(3.36)	(3.96)	(3.96)			
High − Low		1.198***	1.136***	1.133***	1.062***			
Return/Alpha diff.		(4.05)	(4.07)	(4.46)	(4.49)			

Table A.3: **Quintile Portfolios of Corporate Bonds Sorted by VOL Controlling for Rating, Maturity, and Size**

Quintile portfolios are formed every month from January 1975 to December 2014 by first sorting corporate bonds into quintiles based on credit rating (Panel A), maturity (Panel B) or size (Panel C). Then, within each rating/size/maturity-sorted quintile portfolio, corporate bonds are further sorted into sub-quintiles based on their 60-month rolling total variance (VOL). "Quintile VOL,1" is the portfolio of corporate bonds with the lowest VOL within each rating/size/maturity-sorted quintile portfolio and "Quintile VOL, 5" is the portfolio of corporate bonds with the highest VOL within each rating/size/maturity-sorted quintile portfolio. Table shows 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 row shows the differences in alphas with respect to the 5- and 10-factor models. The 5-factor model with stock market factors (**M1**) includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors (**M2**) includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model (**M3**) combines 5 stock factors and 5 bond factors. Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Quintile portfolios of corporate bonds sorted by VOL controlling for credit rating

	All Bonds			Investment Grade			High Yield		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
VOL,1	-0.069	-0.096	-0.080	-0.065	-0.092	-0.068	-0.010	0.029	0.037
	(-0.77)	(-2.98)	(-2.28)	(-0.70)	(-2.73)	(-1.98)	(-0.09)	(0.44)	(0.52)
VOL,2	0.002	-0.026	-0.007	0.016	-0.024	0.001	0.063	0.115	0.070
	(0.02)	(-1.10)	(-0.27)	(0.16)	(-0.93)	(0.04)	(0.50)	(1.57)	(0.96)
VOL,3	0.059	0.043	0.049	-0.013	-0.047	-0.020	0.178	0.245	0.184
	(0.48)	(0.89)	(0.94)	(-0.12)	(-2.05)	(-0.91)	(0.95)	(1.74)	(1.38)
VOL,4	0.052	0.038	0.049	0.078	0.033	0.058	0.336	0.354	0.360
	(0.42)	(1.00)	(1.14)	(0.59)	(0.97)	(1.33)	(1.67)	(2.56)	(2.40)
VOL,5	0.358	0.325	0.306	0.151	0.112	0.133	0.805	0.916	0.840
	(2.32)	(4.31)	(3.97)	(0.65)	(1.99)	(1.29)	(2.69)	(3.51)	(3.21)
VOL,5 − VOL,1	0.427***	0.421***	0.386***	0.216**	0.204***	0.201**	0.815***	0.887***	0.803***
Return/Alpha diff.	(4.14)	(5.06)	(4.57)	(2.03)	(2.82)	(2.15)	(3.34)	(3.80)	(3.36)

Panel B: Quintile portfolios of corporate bonds sorted by VOL controlling for maturity

	All Bonds			Short Maturity Bonds			Medium Maturity Bonds			Long Maturity Bonds		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
VOL,1	-0.019	-0.066	-0.049	0.045	-0.021	-0.008	0.020	-0.041	-0.050	0.016	-0.046	-0.029
	(-0.19)	(-2.14)	(-1.52)	(0.71)	(-0.65)	(-0.27)	(0.21)	(-1.08)	(-1.21)	(0.15)	(-1.14)	(-0.71)
VOL,2	-0.017	-0.045	-0.024	-0.050	-0.075	-0.086	-0.015	-0.047	-0.039	-0.020	-0.067	-0.030
	(-0.16)	(-2.11)	(-1.01)	(-0.54)	(-1.20)	(-1.34)	(-0.15)	(-1.15)	(-0.94)	(-0.17)	(-1.63)	(-0.67)
VOL,3	0.014	-0.010	0.008	1.858	3.016	2.611	0.098	0.053	0.067	0.015	-0.016	-0.000
	(0.12)	(-0.33)	(0.21)	(0.81)	(1.21)	(1.07)	(0.87)	(1.05)	(1.09)	(0.12)	(-0.40)	(-0.00)
VOL,4	0.012	0.007	0.005	-0.348	-0.423	-0.430	0.048	-0.022	0.013	0.101	0.096	0.070
	(0.11)	(0.26)	(0.16)	(-1.03)	(-1.49)	(-1.39)	(0.39)	(-0.56)	(0.29)	(0.79)	(2.34)	(1.55)
VOL,5	0.375	0.362	0.328	0.366	0.284	0.248	0.341	0.291	0.296	0.329	0.324	0.269
	(2.00)	(3.06)	(2.85)	(2.44)	(1.95)	(1.61)	(1.67)	(2.17)	(2.15)	(1.83)	(2.99)	(2.55)
VOL,5 − VOL,1	0.394***	0.428***	0.378***	0.321**	0.305*	0.256*	0.321**	0.332**	0.346**	0.313**	0.371***	0.298***
Return/Alpha diff.	(2.75)	(3.48)	(3.19)	(2.14)	(1.96)	(1.80)	(2.17)	(2.30)	(2.36)	(2.28)	(3.28)	(2.64)

Panel C: Quintile portfolios of corporate bonds sorted by VOL controlling for size

	All Bonds			Small Bonds			Large Bonds		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
VOL,1	-0.040	-0.072	-0.051	-0.043	-0.062	-0.057	-0.069	-0.081	-0.053
	(-0.49)	(-2.42)	(-1.63)	(-0.53)	(-1.89)	(-1.63)	(-0.78)	(-2.52)	(-1.55)
VOL,2	-0.011	-0.042	-0.021	-0.023	-0.022	-0.047	-0.007	-0.034	-0.017
	(-0.12)	(-1.47)	(-0.71)	(-0.24)	(-0.55)	(-1.14)	(-0.07)	(-0.92)	(-0.43)
VOL,3	0.031	0.007	0.013	0.036	0.031	0.019	-0.021	-0.036	-0.011
	(0.29)	(0.23)	(0.39)	(0.34)	(0.69)	(0.37)	(-0.19)	(-1.18)	(-0.33)
VOL,4	0.076	0.043	0.068	0.029	0.044	0.009	0.009	-0.008	0.011
	(0.65)	(1.00)	(1.31)	(0.20)	(0.48)	(0.09)	(0.07)	(-0.27)	(0.32)
VOL,5	0.327	0.338	0.296	0.448	0.398	0.390	0.235	0.252	0.255
	(2.03)	(3.47)	(2.70)	(1.84)	(2.44)	(1.99)	(1.49)	(2.70)	(2.26)
VOL,5 − VOL,1	0.366***	0.410***	0.348***	0.492**	0.460***	0.447**	0.304**	0.333***	0.308***
Return/Alpha diff.	(3.05)	(4.12)	(3.30)	(2.59)	(3.21)	(2.58)	(2.22)	(3.34)	(2.62)

Table A.4: **Quintile Portfolios Sorted by SKEW Controlling for Credit Rating, Maturity, and Size**

Quintile portfolios are formed every month from January 1975 to December 2014 by first sorting corporate bonds into quintiles based on credit rating (Panel A), maturity (Panel B) or size (Panel C). Then, within each rating/size/maturity-sorted quintile portfolio, corporate bonds are further sorted into sub-quintiles based on their 60-month rolling total skewness ($SKEW$). "Quintile SKEW,1" is the portfolio of corporate bonds with the lowest $SKEW$ within each rating/size/maturity-sorted quintile portfolio and "Quintile SKEW, 5" is the portfolio of corporate bonds with the highest $SKEW$ within each rating/size/maturity-sorted quintile portfolio. Table shows 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 row shows the differences in alphas with respect to the 5- and 10-factor models. The 5-factor model with stock market factors (**M1**) includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors (**M2**) includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model (**M3**) combines 5 stock factors and 5 bond factors. Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Quintile portfolios of corporate bonds sorted by SKEW controlling for credit rating

	All Bonds			Investment Grade			High Yield		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
SKEW,1	0.371	0.285	0.341	0.173	0.103	0.150	1.062	1.015	1.088
	(2.57)	(4.15)	(4.03)	(1.27)	(1.87)	(2.33)	(4.72)	(7.58)	(5.97)
SKEW,2	0.158	0.107	0.148	0.114	0.057	0.091	0.547	0.512	0.553
	(1.32)	(2.84)	(3.02)	(0.97)	(1.63)	(2.66)	(3.17)	(4.63)	(4.06)
SKEW,3	0.076	0.051	0.078	0.016	-0.016	0.008	0.398	0.421	0.407
	(0.67)	(1.65)	(2.30)	(0.14)	(-0.54)	(0.25)	(2.67)	(5.29)	(4.03)
SKEW,4	0.120	0.096	0.107	0.045	0.008	0.034	0.482	0.455	0.499
	(1.04)	(2.96)	(2.92)	(0.38)	(0.29)	(0.97)	(2.73)	(4.71)	(3.92)
SKEW,5	0.166	0.075	0.145	-0.021	-0.029	-0.028	0.500	0.557	0.535
	(1.44)	(3.27)	(3.34)	(-0.20)	(-0.91)	(-0.77)	(3.34)	(5.63)	(5.38)
SKEW,5 − SKEW,1	-0.205***	-2.210***	-0.195**	-0.196**	-0.133***	-0.176***	-0.563***	-0.460***	-0.556***
Return/Alpha diff.	(-2.88)	(-2.97)	(-2.17)	(-2.37)	(-2.59)	(-2.61)	(-3.98)	(-4.36)	(-3.82)

Panel B: Quintile portfolios of corporate bonds sorted by SKEW controlling for maturity

	All Bonds			Short Maturity Bonds			Medium Maturity Bonds			Long Maturity Bonds		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
SKEW,1	0.499	0.374	0.475	0.619	0.364	0.483	0.600	0.440	0.516	0.421	0.295	0.375
	(3.35)	(4.71)	(4.42)	(3.31)	(3.61)	(3.46)	(3.93)	(5.27)	(5.02)	(2.85)	(3.86)	(4.72)
SKEW,2	0.120	0.073	0.102	-0.034	-0.089	-0.099	0.183	0.098	0.138	0.173	0.142	0.148
	(1.04)	(1.87)	(2.39)	(-0.23)	(-0.82)	(-0.78)	(1.52)	(1.89)	(2.06)	(1.30)	(2.61)	(2.69)
SKEW,3	0.025	0.011	0.021	0.059	0.033	0.022	0.124	0.054	0.089	0.093	0.058	0.073
	(0.23)	(0.40)	(0.70)	(0.51)	(0.36)	(0.22)	(1.09)	(1.20)	(1.51)	(0.71)	(1.33)	(1.50)
SKEW,4	0.076	0.042	0.065	0.159	0.106	0.104	0.090	0.057	0.069	0.055	0.028	0.038
	(0.69)	(1.77)	(2.39)	(1.63)	(1.29)	(1.29)	(0.86)	(1.18)	(1.40)	(0.44)	(0.65)	(0.83)
SKEW,5	0.183	0.159	0.158	0.306	0.172	0.205	0.272	0.247	0.252	0.171	0.110	0.126
	(1.62)	(4.04)	(3.66)	(2.74)	(3.11)	(3.06)	(2.31)	(4.35)	(4.02)	(1.37)	(2.09)	(2.25)
SKEW,5 − SKEW,1	-0.315***	-0.215***	-0.317***	-0.312**	-0.191**	-0.277**	-0.328**	-0.192**	-0.263**	-0.250***	-0.186**	-0.247***
Return/Alpha diff.	(-2.85)	(-2.64)	(-2.92)	(-2.37)	(-2.11)	(-2.39)	(-2.50)	(-2.30)	(-2.57)	(-2.83)	(-2.38)	(-2.96)

Panel C: Quintile portfolios of corporate bonds sorted by SKEW controlling for size

	All Bonds			Small Bonds			Large Bonds		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
SKEW,1	0.437	0.354	0.413	0.577	0.478	0.523	0.313	0.248	0.320
	(3.55)	(6.02)	(5.57)	(3.57)	(4.97)	(4.86)	(2.57)	(5.27)	(4.86)
SKEW,2	0.128	0.083	0.112	0.161	0.123	0.135	0.106	0.062	0.099
	(1.24)	(2.31)	(2.56)	(1.36)	(2.15)	(2.16)	(0.96)	(1.60)	(2.01)
SKEW,3	0.072	0.040	0.060	0.141	0.128	0.119	0.032	0.010	0.041
	(0.69)	(1.26)	(1.64)	(1.32)	(2.63)	(2.29)	(0.29)	(0.31)	(1.21)
SKEW,4	0.103	0.066	0.096	0.110	0.080	0.108	0.033	0.015	0.036
	(1.00)	(2.33)	(2.83)	(0.98)	(1.38)	(1.72)	(0.30)	(0.51)	(1.06)
SKEW,5	0.164	0.139	0.148	0.289	0.230	0.266	0.079	0.094	0.096
	(1.56)	(3.28)	(3.04)	(2.38)	(3.67)	(3.89)	(0.74)	(2.93)	(2.70)
SKEW,5 − SKEW,1	-0.272***	-0.214***	-0.264***	-0.287**	-0.247***	-0.256**	-0.233***	-0.153***	-0.223***
Return/Alpha diff.	(-3.39)	(-3.69)	(-3.42)	(-2.36)	(-3.14)	(-2.57)	(-3.27)	(-2.84)	(-3.15)

Table A.5: **Quintile Portfolios Sorted by KURT Controlling for Credit Rating, Maturity, and Size**

Quintile portfolios are formed every month from January 1975 to December 2014 by first sorting corporate bonds into quintiles based on credit rating (Panel A), maturity (Panel B) or size (Panel C). Then, within each rating/size/maturity-sorted quintile portfolio, corporate bonds are further sorted into sub-quintiles based on their 60-month rolling kurtosis ($KURT$). "Quintile KURT,1" is the portfolio of corporate bonds with the lowest $KURT$ within each rating/size/maturity-sorted quintile portfolio and "Quintile KURT, 5" is the portfolio of corporate bonds with the highest $KURT$ within each rating/size/maturity-sorted quintile portfolio. Table shows 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 row shows the differences in alphas with respect to the 5- and 10-factor models. The 5-factor model with stock market factors (**M1**) includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors (**M2**) includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model (**M3**) combines 5 stock factors and 5 bond factors. Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Quintile portfolios of corporate bonds sorted by KURT controlling for credit rating

	All Bonds			Investment Grade			High Yield		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
KURT,1	0.006	-0.007	-0.011	-0.021	-0.035	-0.021	0.187	0.321	0.256
	(0.06)	(-0.20)	(-0.31)	(-0.18)	(-1.33)	(-0.70)	(0.99)	(2.45)	(1.94)
KURT,2	0.024	0.012	0.017	0.040	0.011	0.023	0.129	0.227	0.137
	(0.22)	(0.38)	(0.52)	(0.35)	(0.33)	(0.68)	(0.92)	(2.37)	(1.45)
KURT,3	0.059	0.039	0.055	-0.028	-0.055	-0.038	0.075	0.127	0.081
	(0.53)	(1.10)	(1.28)	(-0.25)	(-1.83)	(-1.21)	(0.47)	(1.22)	(0.74)
KURT,4	0.066	0.048	0.055	0.070	0.020	0.046	0.264	0.269	0.285
	(0.59)	(1.36)	(1.24)	(0.63)	(0.72)	(1.25)	(1.82)	(2.41)	(2.50)
KURT,5	0.249	0.191	0.201	0.055	0.016	0.030	0.763	0.792	0.802
	(1.98)	(3.26)	(3.13)	(0.47)	(0.46)	(0.71)	(3.39)	(4.48)	(4.19)
KURT,5 − KURT, 1	0.242**	0.196***	0.212**	0.074	0.050	0.051	0.575***	0.470**	0.545**
Return/Alpha diff.	(2.53)	(2.65)	(2.56)	(1.11)	(1.08)	(1.02)	(2.60)	(2.26)	(2.49)

Panel B: Quintile portfolios of corporate bonds sorted by KURT controlling for maturity

	All Bonds			Short Maturity Bonds			Medium Maturity Bonds			Long Maturity Bonds		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
KURT,1	0.104	0.062	0.042	0.031	-0.034	-0.031	0.018	-0.048	-0.060	0.074	0.003	0.036
	(0.71)	(0.69)	(0.51)	(0.47)	(-1.17)	(-1.03)	(0.17)	(-1.25)	(-1.43)	(0.58)	(0.06)	(0.73)
KURT,2	-0.018	-0.031	-0.025	-0.293	-0.353	-0.352	-0.046	-0.061	-0.067	0.017	0.001	-0.001
	(-0.17)	(-1.27)	(-0.88)	(-2.14)	(-2.69)	(-2.72)	(-0.46)	(-1.38)	(-1.40)	(0.14)	(0.03)	(-0.02)
KURT,3	-0.007	-0.014	-0.011	1.917	3.046	2.658	0.108	0.048	0.070	-0.003	-0.004	-0.030
	(-0.07)	(-0.40)	(-0.25)	(0.84)	(1.35)	(1.25)	(0.96)	(0.74)	(0.90)	(-0.03)	(-0.09)	(-0.54)
KURT,4	0.046	0.019	0.036	-0.098	-0.158	-0.176	0.069	0.009	0.034	0.062	0.047	0.044
	(0.43)	(0.49)	(0.82)	(-0.53)	(-1.01)	(-1.04)	(0.60)	(0.16)	(0.52)	(0.53)	(1.04)	(0.88)
KURT,5	0.316	0.281	0.255	0.302	0.193	0.187	0.334	0.266	0.290	0.287	0.240	0.231
	(2.33)	(3.71)	(3.27)	(2.02)	(0.90)	(1.15)	(2.25)	(2.48)	(2.42)	(2.21)	(3.16)	(2.92)
KURT,5 − KURT, 1	0.212**	0.219***	0.213***	0.271**	0.227**	0.218**	0.316***	0.314***	0.350***	0.213*	0.237**	0.195*
Return/Alpha diff.	(2.55)	(2.76)	(2.90)	(2.59)	(2.22)	(2.13)	(2.83)	(2.66)	(2.73)	(2.16)	(2.53)	(1.92)

Panel C: Quintile portfolios of corporate bonds sorted by KURT controlling for size

	All Bonds			Small Bonds			Large Bonds		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
KURT,1	0.003	-0.012	-0.015	0.010	0.015	-0.010	-0.004	0.009	0.003
	(0.02)	(-0.33)	(-0.42)	(0.09)	(0.40)	(-0.23)	(-0.04)	(0.19)	(0.06)
KURT,2	0.019	-0.002	0.008	0.073	0.062	0.044	-0.007	-0.023	-0.014
	(0.19)	(-0.08)	(0.24)	(0.63)	(1.37)	(0.83)	(-0.07)	(-0.67)	(-0.38)
KURT,3	0.018	-0.003	-0.002	0.064	0.057	0.042	-0.029	-0.036	-0.022
	(0.16)	(-0.08)	(-0.04)	(0.54)	(0.85)	(0.55)	(-0.27)	(-1.23)	(-0.65)
KURT,4	0.099	0.067	0.092	0.104	0.078	0.064	0.062	0.030	0.062
	(0.95)	(1.61)	(1.74)	(0.72)	(0.95)	(0.66)	(0.57)	(0.84)	(1.35)
KURT,5	0.237	0.221	0.215	0.438	0.382	0.349	0.211	0.193	0.196
	(1.91)	(2.94)	(2.59)	(2.15)	(2.72)	(2.22)	(0.97)	(1.73)	(1.95)
KURT,5 − KURT, 1	0.234**	0.233***	0.230**	0.428**	0.366***	0.358**	0.215**	0.184**	0.193***
Return/Alpha diff.	(2.46)	(2.72)	(2.56)	(2.45)	(2.64)	(2.39)	(2.28)	(2.23)	(2.34)

Table A.6: **Trivariate Portfolios of Corporate Bonds Sorted by VOL, SKEW, and KURT**

Every month from January 1975 to December 2014, all corporate bonds in the sample are grouped into 27 portfolios based on trivariate dependent sorts of volatility (VOL), skewness ($SKEW$), and kurtosis ($KURT$). All bonds in the sample are first sorted into three portfolios based on their 60-month rolling total variance (VOL). Then, within each volatility portfolio, corporate bonds are sorted into three portfolios based on their 60-month rolling skewness ($SKEW$). Finally, all bonds in each of the nine resulting portfolios are sorted into three portfolios based on their 60-month rolling kurtosis ($KURT$). "KURT,1" is the portfolio of corporate bonds with the lowest $KURT$ within each VOL and SKEW portfolio and "KURT, 3" is the portfolio of corporate bonds with the highest $KURT$ within each VOL and SKEW portfolio. Table reports the average kurtosis, 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 three columns report average portfolio characteristics including bond rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 5- and 10-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), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines 5 stock market factors and 5 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 significance at the 10%, 5%, and 1% levels, respectively.

$KURT$ Terciles after controlling for VOL and $SKEW$	Average excess return	5-factor stock alpha	5-factor bond alpha	10-factor alpha	Average Portfolio Characteristics			
					Kurtosis	Rating	Maturity	Size
KURT,1	0.184	0.044	0.067	0.065	0.431	7.043	15.223	0.259
	(1.30)	(0.35)	(1.55)	(1.64)				
KURT,2	0.194	0.035	0.024	0.024	1.632	7.344	14.449	0.258
	(1.45)	(0.30)	(0.77)	(0.70)				
KURT,3	0.305	0.197	0.151	0.177	4.667	8.219	12.552	0.260
	(2.10)	(1.41)	(2.29)	(2.44)				
KURT,3 − KURT,1	0.120	0.153	0.084	0.111				
Return/Alpha diff.	(1.17)	(1.58)	(1.24)	(1.49)				

Table A.7: **Fama-MacBeth Cross-Sectional Regressions with Co-kurtosis and Idiosyncratic Kurtosis**

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 co-kurtosis and idiosyncratic kurtosis with and without the control variables. Co-kurtosis (COKURT) is estimated based on a 60-month rolling window from the regression of individual bond excess returns against the excess bond market return and its squared and cubed terms. Idiosyncratic curtosis (IKURT) is the kurtosis of the residuals from the co-kurtosis regression. Bond characteristics are credit rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars). Ratings are in conventional numerical scores, where 1 represents a AAA rating and 21 reflects a C rating. Higher numerical score means lower ratings. The Fama and MacBeth cross-sectional regressions are run each month for the period January 1975 to December 2014. Other controls include bond exposures (betas) to the aggregate stock market (β^{Stock}), default spread (β^{DEF}), and term spread (β^{TERM}), which are estimated using a 60-month rolling window. Each row represents a cross-sectional regression. 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 of the average slope coefficients.

Model	Intercept	COKURT	IKURT	β^{Bond}	IVOL	COSKEW	ISKEW	Rating	Maturity	Size	β^{Stock}	β^{DEF}	β^{TERM}	R^2_{adj}
(1)	0.243	0.536												0.012
	(2.11)	(0.34)												
(2)	-0.189	1.692						**0.048**	**0.006**	-0.074	**0.325**	**-0.010**	-0.002	0.141
	(-1.34)	(1.42)						(2.45)	(2.10)	(-0.32)	(1.96)	(-2.33)	(-0.01)	
(3)	0.175		0.021											0.010
	(1.57)		(1.05)											
(4)	-0.320		0.008					**0.061**	0.001	1.255	1.200	**-0.015**	0.024	0.132
	(-1.27)		(0.52)					(1.91)	(0.21)	(1.28)	(1.72)	(-2.90)	(1.27)	
(5)	0.173	0.297	0.021											0.021
	(1.55)	(0.19)	(1.09)											
(6)	-0.188	2.368	0.005					**0.042**	**0.006**	0.075				0.112
	(-1.67)	(1.04)	(0.48)					(4.66)	(2.18)	(0.60)				
(7)	0.308	4.949	-0.033					0.021	-0.015	4.195	3.483	-0.038	0.087	0.143
	(1.04)	(1.21)	(-0.84)					(1.76)	(-0.79)	(1.05)	(1.05)	(-1.57)	(1.46)	
(8)	-0.290	-0.500	-0.002	0.219	**0.135**	-0.006	**-0.098**							0.145
	(-2.30)	(-0.37)	(-0.36)	(1.34)	(3.17)	(-1.41)	(-3.24)							
(9)	-0.359	0.186	-0.020	0.157	**0.164**	0.015	**-0.138**	**0.023**	-0.004	1.217				0.171
	(-2.21)	(0.12)	(-0.77)	(1.28)	(5.69)	(0.75)	(-2.25)	(2.23)	(-0.83)	(1.00)				
(10)	-0.699	1.579	-0.024	0.186	**0.196**	0.064	**-0.175**	0.068	-0.010	1.304	-1.840	0.035	-0.003	0.186
	(-1.87)	(0.68)	(-0.84)	(1.15)	(3.37)	(1.07)	(-2.65)	(1.62)	(-1.39)	(1.04)	(-0.70)	(0.83)	(-0.17)	

Table A.8: **Controlling for Bond Liquidity and Liquidity Risk**

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 total variance (VOL), skewness (SKEW), and kurtosis (KURT) controlling for bond illiquidity level (Panel A) as well as liquidity risk (Panel B). Bond illiquidity level is proxied by the illiquidity measure (ILLIQ) of Bao, Pan, and Wang (2011), the Amihud (2002) illiquidity measure, and the Roll's measure calculated using historical returns from a rolling 60-month window similar to the construction of VOL, SKEW, and KURT. Bond liquidity risk is measured by the LIQ1 and LIQ2 exposures. LIQ1 is the Pastor-Stambaugh liquidity beta, as in Lin, Wang, and Wu (2011). LIQ2 is the Amihud illiquidity beta, as in Lin, Wang, and Wu (2011). Other control variables are credit rating, time-to-maturity (years), and amount outstanding (size, in billions of dollars). Ratings are in conventional numerical scores, where 1 represents a AAA rating and 21 reflects a C rating. Higher numerical score means lower ratings. Other controls include bond exposures (betas) to the aggregate stock market (β^{Stock}), the aggregate bond market (β^{Bond}), default spread (β^{DEF}), and term spread (β^{TERM}), which are estimated using a 60-month rolling window. Average slope coefficients are reported in separate columns for each variable. Each row represents a cross-sectional regression. 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 of the average slope coefficients.

Panel A: Controlling for bond illiquidity level

Model	Intercept	VOL	SKEW	KURT	Roll	ILLIQ	Amihud	Rating	Maturity	Size	β^{Stock}	β^{Bond}	β^{DEF}	β^{TERM}	R^2_{adj}
(1)	-0.238	**0.078**	**-0.195**	-0.054	0.029			0.019	0.002	0.362	-0.444	-0.431	-0.002	0.035	0.176
	(-1.39)	(3.18)	(-3.48)	(-1.47)	(0.71)			(1.94)	(0.40)	(0.95)	(-0.93)	(-1.21)	(-0.27)	(1.46)	
(2)	2.230	**0.058**	**-0.572**	0.044		**0.101**		0.214	-0.033	-1.199	-0.523	0.516	0.005	0.031	0.164
	(0.88)	(2.49)	(-3.11)	(0.34)		(3.54)		(0.98)	(-1.07)	(-0.97)	(-1.13)	(0.78)	(0.44)	(1.08)	
(3)	-0.651	**0.028**	**-0.332**	0.087			0.021	0.008	-0.004	0.451	-0.626	-0.132	0.022	-0.012	0.146
	(-1.01)	(2.25)	(-2.84)	(0.63)			(0.39)	(0.15)	(-0.25)	(0.89)	(-0.48)	(-0.64)	(1.32)	(-0.40)	

Panel B: Controlling for liquidity risk

Model	Intercept	VOL	SKEW	KURT	LIQ1	LIQ2	Rating	Maturity	Size	β^{Stock}	β^{Bond}	β^{DEF}	β^{TERM}	R^2_{adj}
(4)	0.496	**0.575**	**-1.582**	-1.684	-0.915		0.099	0.004	-1.300	-0.913	-0.596	0.269	-0.137	0.155
	(0.21)	(2.58)	(-2.86)	(-1.39)	(-1.29)		(0.82)	(0.05)	(-0.89)	(-0.54)	(-1.02)	(0.97)	(-0.79)	
(5)	1.044	**0.652**	**-0.794**	0.104		0.380	0.101	-0.089	0.229	-0.25	1.684	-0.011	-0.042	0.143
	(0.73)	(2.78)	(-2.44)	(0.61)		(0.93)	(1.59)	(-1.34)	(0.74)	(-1.02)	(1.05)	(-0.64)	(-1.46)	

Table A.9: **Characteristic-Adjusted Returns**

Table reports the next-month average characteristic-adjusted 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 portfolio. Panel A reports the univariate sort of corporate bonds based on the total variance (VOL). Panel B reports the bivariate sort based on the skewness ($SKEW$) controlling for VOL. Panel C reports the univariate sort based on the kurtosis ($KURT$). Characteristic-adjusted return is computed as the difference between individual bond return and the average return of the characteristic-matched portfolio, constructed from 5×5 bivariate portfolios of size and credit rating. 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), and the stock liquidity factor (LIQ). The 5-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The 10-factor model combines 5 stock market factors and 5 bond market factors. Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. The sample covers the period from July 2004 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average characteristic-adjusted return	5-factor stock alpha	5-factor bond alpha	10-factor alpha
	Panel A: Sorted by VOL			
Low VOL	-0.214	-0.328	-0.349	-0.337
2	-0.131	-0.259	-0.284	-0.269
3	-0.065	-0.209	-0.225	-0.218
4	-0.004	-0.18	-0.198	-0.181
High VOL	0.277	0.112	0.077	0.056
High − Low	0.491***	0.440***	0.425***	0.391***
Return/Alpha diff.	(4.51)	(4.01)	(4.88)	(4.49)
	Panel B: Sorted by SKEW Controlling for VOL			
SKEW,1	0.084	0.002	-0.021	0.016
SKEW,2	-0.009	-0.140	-0.180	-0.161
SKEW,3	-0.120	-0.297	-0.286	-0.294
SKEW,4	-0.074	-0.241	-0.251	-0.253
SKEW,5	-0.056	-0.194	-0.164	-0.177
SKEW,5 − SKEW,1	-0.140**	-0.195**	-0.143**	-0.191***
Return/Alpha diff.	(-2.28)	(-2.54)	(-2.35)	(-2.71)
	Panel C: Sorted by KURT			
Low KURT	-0.123	-0.294	-0.307	-0.312
2	-0.126	-0.282	-0.292	-0.288
3	-0.098	-0.244	-0.265	-0.248
4	-0.082	-0.24	-0.253	-0.25
High KURT	0.077	-0.053	-0.109	-0.1
High − Low	0.201**	0.242**	0.197***	0.211**
Return/Alpha diff.	(2.55)	(2.50)	(2.62)	(2.53)

Table A.10: **Firm-Level Fama-MacBeth Cross-Sectional Regressions Controlling for Distance-to-Default**

This table reports the average intercept and slope coefficients from the firm-level Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on total variance (VOL), skewness (SKEW), and kurtosis (KURT) with and without the control variables. The control variables are distance-to-default (DD), time-to-maturity (years), and amount outstanding (size, in billions of dollars). The Fama and MacBeth cross-sectional regressions are run each month for the period January 1975 to December 2014. Other controls include bond exposures (betas) to the aggregate stock market (β^{Stock}), the aggregate bond market (β^{Bond}), default spread (β^{DEF}), and term spread (β^{TERM}), which are estimated using a 60-month rolling window. Each row represents a cross-sectional regression. 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 of the average slope coefficients.

Model	Intercept	VOL	SKEW	KURT	DD	Maturity	Size	β^{Stock}	β^{Bond}	β^{DEF}	β^{TERM}	R^2_{adj}
(1)	0.082	**0.016**										0.052
	(0.74)	(3.49)										
(2)	0.356		-0.113									0.018
	(2.93)		(-1.39)									
(3)	0.129			**0.089**								0.022
	(1.15)			(4.44)								
(4)	0.143	**0.016**			**-0.071**	**0.012**	-0.513	-0.058	-0.127	0.005	-0.006	0.211
	(1.04)	(4.24)			(-2.31)	(2.07)	(-1.36)	(-0.26)	(-1.34)	(0.67)	(-0.25)	
(5)	-0.070		**-0.274**		**-0.079**	0.026	-0.771	0.328	0.094	0.001	-0.019	0.194
	(-0.22)		(-2.32)		(-1.87)	(1.19)	(-1.47)	(1.21)	(1.00)	(0.19)	(-0.69)	
(6)	-0.020			**0.070**	**-0.101**	**0.014**	-0.508	0.333	0.089	-0.002	-0.001	0.188
	(-0.14)			(2.05)	(-3.20)	(2.53)	(-1.39)	(1.48)	(0.99)	(-0.39)	(-0.03)	
(7)	0.082	**0.016**	**-0.197**									0.065
	(0.74)	(3.71)	(-4.91)									
(8)	0.234	**0.015**	**-0.195**		**-0.057**	0.006	-0.317	-0.281	-0.094	0.012	-0.018	0.220
	(1.30)	(3.50)	(-2.91)		(-1.85)	(0.83)	(-0.81)	(-0.70)	(-1.00)	(1.17)	(-0.63)	
(9)	0.031	**0.015**	**-0.188**	0.027								0.071
	(0.28)	(3.68)	(-3.12)	(1.52)								
(10)	0.099	**0.014**	**-0.133**	0.004	**-0.098**	0.005	-0.495					0.135
	(0.76)	(4.34)	(-3.40)	(0.34)	(-2.82)	(1.16)	(-1.37)					
(11)	-0.042	**0.018**	**-0.187**	-0.063	-0.052	**0.013**	-0.967	0.424	-0.049	-0.006	-0.002	0.230
	(-0.27)	(2.75)	(-2.51)	(-0.90)	(-1.53)	(2.13)	(-1.56)	(1.11)	(-0.45)	(-0.42)	(-0.09)	

Table A.11: **Ex-ante Bond-Level and Ex-post Portfolio-Level Measures of Volatility, Skewness, and Kurtosis from Daily Data (TRACE)**

Table reports the average ex-ante bond-level volatility and the ex-post portfolio-level volatility from the univariate sorts of corporate bonds based on the total variance (VOL); the average ex-ante bond-level skewness and the ex-post portfolio-level skewness from the univariate sorts of corporate bonds based on the total skewness (SKEW); the average ex-ante bond-level kurtosis and the ex-post portfolio-level kurtosis from the univariate sorts of corporate bonds based on the total kurtosis (KURT). The measures of volatility, skewness, and kurtosis are constructed using daily returns in a month. The sample covers the period from July 2004 to December 2014.

Quintiles	Pre-ranking VOL	Post-ranking VOL	Quintiles	Pre-ranking SKEW	Post-ranking SKEW	Quintiles	Pre-ranking KURT	Post-ranking KURT
Low VOL	1.792	3.143	SKEW,1	-1.496	-0.360	Low KURT	-0.839	0.890
2	2.952	4.220	SKEW,2	-0.482	-0.238	2	-0.130	1.122
3	4.252	5.323	SKEW,3	-0.084	-0.157	3	0.569	1.132
4	6.158	6.700	SKEW,4	0.278	-0.093	4	1.679	1.104
High VOL	11.650	9.924	SKEW,5	0.956	0.038	High KURT	5.472	1.161