Volatility and the cross-section of corporate bond returns☆

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Abstract

This paper examines the pricing of volatility risk and idiosyncratic volatility in the cross-section of corporate bond returns for the period of 1994-2016. Results show that bonds with high volatility betas have low expected returns, and this negative relation appears in all segments of corporate bonds. Further, bonds with high idiosyncratic bond (stock) volatility have high (low) expected returns, and this relation strengthens as ratings decrease. Conventional risk factors and bond/issuer characteristics cannot account for these cross-sectional relations. There is evidence that the effect of idiosyncratic stock volatility on expected bond returns works through the channel of contemporaneous stock returns.

JEL classification: G12, G13

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1. Introduction

Volatility and its relationship to asset prices have long attracted attention from financial economists. Although numerous studies have examined the temporal relation between returns and volatilities, whether the sensitivity of asset returns to aggregate volatility (i.e., volatility risk) is priced in the cross-section of asset returns has received much less attention. Moreover, while there is a vast literature investigating the effect of idiosyncratic volatility on expected stock returns, this issue has been relatively underexplored for corporate bond pricing.[1] Our study contributes to the literature by providing new evidence on the role of aggregate volatility risk and idiosyncratic volatility in the pricing of corporate bonds.

Existing theories suggest that market volatility can come from various sources of uncertainty. Time-varying market volatility can be driven by macroeconomic fluctuations (Bansal and Yaron, 2004; Bansal et al., 2014), changing expectations of future returns (Mele, 2007), and uncertainty about firm fundamentals (Veronesi, 1999; Guo and Savickas, 2008) and future economy. As market volatility increases, expected consumption decreases and investment opportunities deteriorate (Campbell, 1993, 1996; Campbell et al., 2013). Merton's (1973) intertemporal capital asset pricing model suggests that any state variable with pervasive effects on investment opportunities and investor welfare should be a priced factor in the cross-section of expected asset returns. Marketwide volatility appears to be a good candidate for such a priced state variable. Several studies have suggested that aggregate volatility risk is a plausible pricing factor in the market for risky assets (Bates, 2008; Pan, 2002; Santa-Clara and Yan, 2010; Campbell et al., 2013).

Ang et al. (2006) show that stocks with high return sensitivities to aggregate volatility innovations have low expected returns using the Chicago Board Options Exchange Market Volatility Index (VIX) as a volatility measure. The negative volatility risk premium supports the theory (Campbell, 1996; Campbell et al., 2013) that persistently high aggregate volatility, associated with deterioration in investment opportunities and market downturns (French, Schwert, and Stambaugh, 1987), reduces investor wealth

[1] Exceptions are Cremers et al. (2008), Bao et al. (2015), and Bai, Bali, and Wen (2018).

and consumption. Risk-averse investors therefore demand assets that provide a hedge against market volatility. Assets with high volatility betas provide a good hedge and thus draw high demand from investors, leading to high prices and low expected returns.

The findings of Ang et al. (2006) suggest that aggregate volatility is a priced state variable in the stock market. Given that stocks and bonds are contingent claims for cash flows within the same firm, a question that naturally arises is whether volatility risk is also priced in the corporate bond market. On the one hand, both bond and stock returns are exposed to volatility shocks, as the fortune of investors for both assets depends on the same firm value. On the other hand, bonds and stocks are different in many aspects, e.g., risk characteristics, contractual stipulations, and investment clientele. As such, bond and stock prices can react differently to volatility shocks and experience differing effects of volatility risk on their expected returns.

Besides aggregate volatility risk, there is substantial evidence that idiosyncratic volatility affects equity returns.[2] Ang et al. (2006) find that stocks with high idiosyncratic volatility have low expected returns, and that this relation cannot be explained by exposures to volatility risk or other risk factors. Ang et al. (2009), Stambaugh, Yu, and Yuan (2015), and Babenko, Boguth, and Tserlukevich (2016) report similar findings. However, other studies find that idiosyncratic volatility is positively related to expected returns of stocks (e.g., Lintner, 1965; Levy, 1978; Tinic and West, 1986; Merton, 1987; Lehmann, 1990; Campbell et al., 2001; Malkiel and Xu, 2002; Goyal and Santa-Clara, 2003; Guo and Savickas, 2008; Fu, 2009; Garcia, Mantilla-Garcia, and Martellini, 2014). Given the mixed empirical findings, our study offers additional insight into the sources of this effect by analyzing the relation between idiosyncratic volatility and the expected returns for another asset class with a different investment clientele and information environment (see also Ang et al., 2009; Cao and Han, 2013; Kang, Kondor, and Sadka, 2014). As the literature has shown that stock return volatility can affect yield spreads (Campbell and Taksler,

[2] Explanations for this effect include size effect (Bali and Cakici, 2008), return reversal (Huang et al., 2010), microstructure effect (Han and Lesmond, 2011), information disclosure (Boehme et al., 2009), arbitrage asymmetry (Stambaugh, Yu, and Yuan, 2015), exposure to risk factors (Chen and Petkova, 2012), and underdiversification (Ewens, Jones, and Rhodes-Kropf., 2013).

2003; Cremers et al., 2008), we investigate the joint effects of bond and stock idiosyncratic volatilities as well as volatility risk on the pricing of corporate bonds.

This paper provides several new findings that expand the current literature. First, we find that aggregate volatility risk is priced in the cross-section of expected corporate bond returns. The volatility risk premium is negative, which is both economically significant and robust to controlling for conventional risk factors of stocks and bonds, liquidity and information effects, and bond/issuer characteristics. The negative volatility risk premium is consistent with the findings in the options and equity markets (see Bakshi, Cao, and Chen, 2000; Ang et al., 2006; Cao and Han, 2013; Cremers, Halling, and Weinbaum, 2015), suggesting that the equity-based volatility risk factor priced in these markets is also priced in the corporate bond market. This evidence lends support to the idea that equity and bond markets are driven by a common volatility factor, and risk-averse bond investors are willing to pay a premium to hedge aggregate volatility risk.

The effect of volatility risk is pervasive and not concentrated in certain types of corporate bonds. Bonds with lower ratings tend to have a higher exposure to aggregate volatility risk and have a larger volatility risk premium. There is evidence that aggregate volatility risk is priced in the cross-section of corporate bonds within relatively homogeneous groups bearing the same credit rating, suggesting that volatility risk exhibits an intra-rating effect.

Unlike the equity literature, we find a positive cross-sectional relation between idiosyncratic bond volatility and expected bond returns, and this relation is stronger for lower-grade bonds. The positive relation is robust to controlling for exposures of returns to aggregate volatility and other risk factors and the cross-sectional effects of illiquidity, liquidity risk, credit quality, information dissemination, and institutional ownership. Our results suggest that the effect of idiosyncratic bond volatility is unlikely to be due to an omission of aggregate volatility risk or other factors in the conventional asset pricing model. Instead, it is a separate risk priced in the cross-section of expected bond returns.

Moreover, we find that firms with high idiosyncratic stock volatility have low expected bond returns, and that this negative relation is robust to controlling for the effects of aggregate volatility and other risk factors, idiosyncratic bond volatility, and bond/firm characteristics. The effect of stock return volatility is greater for bonds with lower ratings, a finding consistent with the view that heightened volatility increases the value of default options for riskier bonds (see Merton, 1974; Campbell and Taksler, 2003). Importantly, we find that the effect of idiosyncratic stock volatility on expected bond returns works through the channel of contemporaneous stock returns. The effect of idiosyncratic stock volatility on expected bond returns is considerably weakened once we control for the effect of contemporaneous stock returns.

Our paper is related to several recent studies on corporate bond pricing. Bai, Bali, and Wen (2018) explore whether the distributional characteristics of corporate bond returns can predict cross-sectional differences in future bond returns. They find a significantly positive (negative) relation between volatility (skewness) and corporate bond returns but no significant relation between kurtosis and returns. Their analysis focuses on the issue of whether bond distributional characteristics can predict bond returns in the cross-section. In contrast, we investigate the effects of both aggregate volatility risk and idiosyncratic volatility on expected bond returns and the robustness of these effects to controlling for a wide spectrum of cross-sectional effects. Moreover, we examine intra-rating volatility risk pricing, the interaction effects of both bond and stock volatilities with ratings, and the channel through which idiosyncratic volatility affects expected corporate bond returns. Bao et al. (2015) find a positive cross-sectional relation between credit spreads and bond return volatility, and that credit and illiquidity proxy variables explain a significant portion of this relation. Cremers et al. (2008) analyze the extent to which cross-sectional and time-series variations in yield spreads of corporate bonds can be explained by implied volatility and the implied-volatility skew of stock options. While these papers study the determinants of yield spreads, our paper focuses on the pricing of aggregate volatility risk and idiosyncratic volatilities in the cross-section of expected bond returns. In particular, we disentangle the volatility effects from a host of cross-sectional effects to rule out other economic explanations such as liquidity frictions and risk, information frictions, clientele structure, leverage, ratings, and other firm/bond characteristics.

The remainder of this paper is organized as follows. Section 2 explains our data and variable measurement methods. Section 3 conducts portfolio analyses and cross-sectional regression tests to determine whether aggregate volatility risk is priced in the whole bond universe and in each rating category. Section 4 examines the role of the idiosyncratic volatilities of bonds and stocks in the cross-section of expected corporate bond returns. Finally, Section 5 summarizes our main findings and concludes the paper.

2. Data and variable measurement

Corporate bond data come from the National Association of Insurance Commissioners (NAIC) database, the enhanced Trade Reporting and Compliance Engine (TRACE) database, and Mergent's Fixed Investment Securities Database (FISD). The NAIC database covers all transactions of corporate bonds by life, property, and casualty insurance companies and health maintenance organizations (HMOs) beginning from January 1994. The enhanced TRACE database contains the transactions of all publicly traded corporate bonds starting from July 2002. We combine the enhanced TRACE data from July 2002 to December 2016 with the NAIC data from January 1994 to June 2002. Our main results are based on this combined sample. We also conduct tests for the TRACE and NAIC (January 1994 to December 2016) subsamples to assess the robustness of our results.

The FISD database includes issuance information for all fixed-income securities that have a CUSIP or are likely to receive one soon. It contains issue- and issuer-specific information, such as coupon rates, issue date, maturity date, issue size, ratings, and other characteristics, for bonds maturing in 1990 or later. We use bond characteristic information from FISD to identify and eliminate non-US dollar-denominated bonds and bonds backed by mortgages or other assets. To avoid confounding effects of embedded options (e.g., call, sinking funds, and conversion), we focus on straight bonds in empirical tests. We exclude bonds with embedded options and bonds with a maturity of less than 1 year and longer than 30 years. In addition, we follow the data screening procedure in Bessembinder et al. (2009) to eliminate cancelled, corrected, commission, and small (below $100,000) trades. Our final sample includes 489,206 bond-month observations for 13,264 bonds issued by 2,309 firms from January 1994 to December 2016. Fig. 1

plots the number of bonds and firms in each month. We compute daily prices as the trade size-weighted average of intraday prices over the day and then use the month-end price to calculate returns (see Bessembinder et al., 2009). The monthly corporate bond return as of time t is computed as follows:

$$R_t = \frac{(P_t + AI_t) + C_t - (P_{t-1} + AI_{t-1})}{P_{t-1} + AI_{t-1}}, \tag{1}$$

where P_t is the price, AI_t is accrued interest, and C_t is the coupon payment, if any, in month t. We interpolate the prices of two adjacent trades if a transaction price does not fall on the last day of the month.

Liquidity has been shown to be a priced factor for corporate bonds. We consider the Amihud (2002) and Pastor-Stambaugh (2003, thereafter PS) liquidity indexes as measures of marketwide liquidity. The Amihud illiquidity of an individual bond is estimated monthly by $ILLIQ_{it} = \frac{1}{D_{it}} \sum_{k=1}^{D_{it}} \frac{|r_{i,k,t}|}{Volume_{i,k,t}}$, where $r_{i,k,t}$ is the return of bond i on day k in month t, $Volume_{i,k,t}$ is the respective daily volume in dollars, and D_{it} is the number of days for which transaction data are available for bond i. We aggregate illiquidity across bonds to generate a marketwide illiquidity index, $ILLIQ_{Mt} = (1/N_t) \sum_{i=1}^{N_t} ILLIQ_{it}$, where N_t is the number of bonds with transactions in month t. We then follow the procedure in Lin, Wang, and Wu (2011) to obtain illiquidity innovations using the following time-series regression:

$$\Delta ILLIQ_{Mt} = \alpha_0 + \phi_1 \Delta ILLIQ_{Mt-1} + \phi_2 \left(\frac{M_{t-1}}{M_t} \right) ILLIQ_{Mt-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2}, \tag{2}$$

where $\Delta ILLIQ_{Mt} = \left(\frac{M_t}{M_1} \right) (ILLIQ_{Mt} - ILLIQ_{Mt-1})$, and M_t is the total bond value at the beginning of month t.[3] For ease of interpretation and comparison with the PS measure, we add a negative sign to the Amihud index to convert it into a marketwide liquidity measure. The PS bond market liquidity index is constructed using the same method as in Pastor and Stambaugh (2003). We run time-series regressions of returns against lagged returns and signed volume, construct aggregate liquidity from the coefficients of

[3] Since we use the enhanced TRACE data, we avoid the estimation problem with different TRACE phases in Lin, Wang, and Wu (2011). The moving average components in Eq. (2) account for the autocorrelation in the residual term.

signed volume of individual bonds, and obtain liquidity innovations using the PS procedure. We require a bond to have at least ten transactions per month in the time-series regression.

We include the Fama-French three factors (Market, SMB, and HML), term and default spreads, and market volatility in the pricing of corporate bonds. The Fama-French three factors are retrieved from Ken French's website. The default spread (*DEF*) is the difference between the monthly returns of long-term investment-grade bonds and long-term government bonds. The long-term investment-grade bond returns are based on a value-weighted portfolio that includes all investment-grade bonds in our sample with at least ten years to maturity. The weight is determined by the market value of a bond, which is the number of units outstanding times market price of the bond. The term spread is the difference between the monthly return of the long-term government bond and the one-month T-bill rate, both obtained from the Federal Reserve Board. Market volatility is measured by VIX, the implied volatility of the Standard & Poor's (S&P) 500 stock index option that reflects expectation of stock market volatility over the next 30-day period. VIX data are downloaded from Yahoo.com. We use VIX innovations, ΔVIX, which are residuals from the AR(1) model, as a measure of the volatility risk factor.

Panel A in Table 1 reports summary statistics for bond characteristics. For the full sample, average coupon rate, maturity, and issue size are 5.53%, 6.77 years, and \$0.83 billion, respectively; bond age is 4.81 years, and the median rating is A. We use bond characteristics as control variables in empirical tests.

3. Aggregate volatility risk and the cross-section of expected returns

Prior studies suggest that a number of factors are priced in expected bond returns. Fama and French (1993) show that term and default factors are priced in corporate bonds, and Elton et al. (2001) find that the Fama-French (1993) three factors are priced. Liquidity is also a pricing factor for corporate bonds (see Lin, Wang, and Wu, 2011). It is important to control for these factors to gauge the effect of aggregate volatility factor on bond returns. We adopt the following multi-factor model to estimate bond betas:

$$\begin{aligned} r_{it} - r_{ft} = {} & \alpha_i + \beta_{iMKT} MKT_t + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iDEF} DEF_t + \beta_{iTERM} TERM_t + \beta_{iLIQ} LIQ_t \\ & + \beta_{i1} \Delta VIX_t + \beta_{i2} \Delta VIX_{t-1} + \varepsilon_{it}. \end{aligned} \tag{3}$$

The dependent variable is bond returns in excess of the one-month T-bill rate, MKT_t is the stock market excess return, SMB_t is the size factor, HML_t is the book-to-market ratio, DEF_t is the default spread, $TERM_t$ is the term spread, LIQ_t is the liquidity factor, and VIX_t is the volatility risk factor. Since bonds are not traded as frequently as stocks, their returns may not respond quickly to changes in market volatility and new information. To account for the potential lagged adjustment of bond returns to market volatility, we include the lagged innovations ΔVIX_{t-1} in Eq. (3). In empirical tests, we measure the VIX beta by the sum of β_{i1} and β_{i2} (i.e., $\beta_{iVIX} = \beta_{i1} + \beta_{i2}$), where β_{i2} captures the lagged response to aggregate volatility shocks.

Panel B in Table 1 shows summary statistics of the risk factors used in asset pricing tests. Panel C reports the loadings of risk factors estimated using all data in each sample. Betas are estimated from the seven-factor model in which the liquidity factor can be either the Amihud or PS measure. For the full sample (left panel), when using the PS (Amihud) liquidity index, the liquidity beta has a mean of 0.80 (1.24), and the default and market betas have mean values of 0.51 (0.50) and 0.10 (0.08), respectively. The full sample exhibits a high cross-sectional dispersion for VIX, liquidity, and other betas.

3.1. Portfolio analysis

We use the portfolio approach of Daniel and Titman (1997) and Gebhardt, Hvidkjaer, and Swaminathan (2005a) to examine whether expected bond returns are related to sensitivities to innovations in aggregate volatility. We first sort bonds into deciles at the end of month *t-1* according to their VIX betas estimated over the past 60-month rolling window, using the multiple factor model in Eq. (3) for the full sample. The first row in Panel A of Table 2 shows the average VIX beta for each portfolio. The second row in Panel A shows the average portfolio return in excess of the one-month T-bill rate in month *t*. The results show that portfolio excess returns decrease with VIX betas, and that the difference in average monthly excess returns between the highest and lowest VIX beta decile portfolios is -20 basis points (bps), which is significant at the 5% level.

The above excess returns do not account for the effects of bond rating and maturity. We next adjust returns for these bond characteristics. We divide bonds into 15 portfolios by five ratings (Aaa, Aa, A, Baa, and junk) and three maturities: short (less than five years), medium (five to ten years), and long (longer than ten years) and calculate average excess return for each portfolio. We then calculate the difference between the return of each bond and the return of the benchmark rating/maturity portfolio to which the bond belongs and obtain the returns adjusted for ratings and maturity. Finally, we calculate average adjusted returns of each portfolio and show the results in the third row of Panel A. The high-low portfolio adjusted return spread is -12 bps, which is significant at the 1% level (t-value = -2.59), indicating that the negative relation between bond returns and VIX betas is robust to adjustment for bond characteristics.

One theoretical explanation for this negative relation is that assets with high sensitivities to aggregate volatility provide a good hedge against downside market risk (Bakshi and Kapadia, 2003; Campbell et al., 2013). High demand for assets with a large VIX beta for hedging purposes increases their prices and lowers expected returns. Bond prices are sensitive to stock market volatility (Campbell and Taksler, 2003), which suggests a need for bond investors to hedge equity volatility risk. The hedging demand provides a risk-based explanation for the negative relation between expected bond returns and VIX betas.

Panel B of Table 2 reports the preranking betas and the postranking average of each characteristic for each portfolio. Results show a mild positive relation between market beta and VIX beta, which is similar to the finding of Ang et al. (2006). French, Schwert, and Stambaugh (1987) find that market (S&P 500) excess returns are positively related to market volatility using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-in-mean model. They suggest that this relation is consistent with the theory that the expected risk premium is positively related to predicted market volatility. Their analysis provides an explanation for why bonds that are more sensitive to market returns (market beta) tend to be more sensitive to market volatility (VIX beta).[4]

To see if return spreads can be explained by conventional risk factors, we run the Black-Jensen-Scholes (1972, BJS) time-series regression of long-short (10–1) portfolio returns against the Fama-French five (FF5) factors. The last two rows in Panel A of Table 2 reports alphas relative to the FF5-factor model (MKT, SMB, HML, TERM, and DEF), estimated using excess returns and characteristic-adjusted returns,

[4] Econometrically, in a two-factor model with market and VIX, betas tend to be positively correlated if market returns (realized risk premiums) are negatively related to volatility innovations (see Pindyck and Rubinfeld, 1976).

respectively (our results are robust to the FF3-factor model). Results show that lower FF5 alphas are associated with higher VIX betas. The long-short (10–1) portfolio alpha is -9 bps when alpha is estimated using excess returns and -14 bps when using characteristic-adjusted returns. Both are significant at the 5% level. Portfolio return spreads remain significant even after adjusting for systematic risk effects.

3.2. Robustness of portfolio analysis

The analysis above shows a strong negative relation between the VIX beta and expected bond returns. However, univariate relations could be confounded by the correlation of volatility risk with other variables. To assess the robustness of our results, we control for cross-sectional effects due to liquidity, liquidity risk, and bond/issuer characteristics. We first sort bonds into quintiles based on each of these control (characteristic) variables in each month, and within each quintile, we further sort bonds into five quintiles based on VIX beta. After forming the 5x5 characteristic and VIX beta portfolios, we average the return and alpha of each VIX beta quintile across the five characteristic portfolios. These quintile VIX beta portfolios control for differences in each characteristic. After controlling for each characteristic, we report average long-short portfolio (highest VIX beta quintile-lowest VIX beta quintile) returns and alphas to show the robustness of the volatility risk effect to each characteristic.[5] Besides these average returns and alphas, we provide long-short VIX beta portfolio returns and alphas for each characteristic quintile to check whether the effect of volatility risk may concentrate on certain types of bonds or firms.

3.2.1. Robustness to liquidity effects

When the market is volatile, liquidity tends to be low. Chung and Chuwonganant (2014) find that market volatility adversely affects market liquidity, and Guerrieri and Lorenzoni (2009) find that market volatility is positively related to liquidity constraints. These results raise a concern that the volatility risk effect could act as a proxy for the liquidity effect. To address this concern, we investigate the robustness of our results to controlling for the effects of liquidity.

Trading volume is widely used as a measure of liquidity; a more active market with higher trading

[5] These results are based on characteristic-adjusted returns and alphas relative to the FF5-factor model. Our results are robust to the use of raw excess returns and alphas relative to the FF3-factor model.

volume is perceived to be more liquid. Besides volume, we consider the Amihud measure for individual bonds, the implied roundtrip cost (IRC) from Dick-Nielsen, Feldhutter, and Lando (2012), and volatility of bond returns. The IRC is calculated as $(P_{max} - P_{min})/P_{max}$, where P_{max} is the highest price and P_{min} is the lowest price in the imputed round trip trades. We add a negative sign to the IRC to convert it into a liquidity measure for ease of comparison. Volatility is measured by standard deviation of returns.

The upper left panel of Table 3 shows the long-short return for each of the five portfolios formed by each liquidity measure, as well as the long-short return averaged across the five quintile portfolios (H-L). Results show that although there is some variation across liquidity portfolios, long-short portfolio returns are significant for all liquidity quintiles, indicating that the effect of VIX beta is not concentrated among certain types of bonds. The average long-short portfolio return over all volume quintiles (H-L) is -16 bps, which is significant at the 1% level. Portfolio sorts by Amihud bond-level liquidity, IRC, and return volatility show a similar pattern. Average long-short portfolio returns (H-L) range from -0.12 to -0.16, all significant at the 1% level. Controlling for liquidity characteristics cannot remove the volatility risk effect.

Besides the level of liquidity, we control for the effect of liquidity risk, using both the Amihud and PS liquidity betas. All long-short portfolio returns for each quintile remain significant after controlling for liquidity betas. The portfolio return spreads averaged across quintiles (H-L) are all significant at the 1% level. Thus, liquidity risk cannot explain the return spread of VIX beta portfolios either. This finding implies that liquidity risk and volatility risk are likely to be separately priced in corporate bonds.

The BJS alphas relative to the FF5 model, reported in the upper right panel of Table 3, show a similar pattern. The average long-short portfolio alphas (H-L) are all significant at the 1% level. Again, liquidity level and risk cannot account for the low risk-adjusted returns for bonds with high exposure to aggregate volatility risk, and the volatility risk effect is not concentrated in certain segments of bonds.

3.2.2. Controls for bond/issuer characteristics

Prior research shows that bond characteristics can explain cross-sectional variations in bond returns (Gebhardt, Hvidkjaer, and Swaminathan, 2005a; Li et al., 2009) because they capture missing risk factors. As these characteristics are often related to liquidity or default risk, they can have explanatory power for bond returns. Similarly, issuer characteristics such as firm age, leverage, and size can affect asset returns (Bali and Cakici, 2008). This raises the question of whether characteristics could explain cross-sectional variations in expected returns for bonds with different VIX betas. We next control for the effects of bond/issuer characteristics.

Table 3 (the second panel) shows that bond characteristics, such as maturity, coupon rates, and bond age, cannot account for the effect of VIX betas.[6] The effect of volatility risk does not appear to concentrate on bonds with certain characteristics. There remains a negative relation between average portfolio returns and β_{VIX} after controlling for bond characteristics. The long-short (H-L) portfolio returns averaged across characteristic quintiles range from -11 to -15 bps, all significant at the 1% level. Similarly, the average (H-L) alphas range from -6 to -10 bps, also all significant statistically. Thus, bond characteristics cannot explain the low average returns on bonds with high sensitivities to aggregate volatility shocks.

Small and young firms typically have high return volatility and returns. Additionally, bonds issued by high-leverage firms have high risk and returns. This raises a concern that volatility risk could be a proxy for these firm characteristics. We next control for the effects of issuer characteristics. Table 3 (the third panel) shows that issuer characteristics cannot account for the effects of VIX beta. The effect of VIX beta tends to be larger for firms with higher leverage. In general, this effect does not appear to concentrate on certain firm types. Average long-short portfolio adjusted returns (H-L) range from -7 to -13 bps, and the alpha spreads are from -7 to -9 bps. Firm characteristics cannot explain the effect of VIX betas.

3.2.3. Control for the effects of analyst forecasts

Financial theory suggests that a high divergence of opinion about the true value of a financial asset leads to a high speculative component of volume and low liquidity, as large changes in asset prices are needed to absorb the increase in trading volume (see Kandel and Pearson, 1995; Bamber, Barron, and Stober, 1999). Firms with more disperse analyst forecasts thus tend to have more volatile returns.

[6] The portfolio analysis based on ratings is conducted in Section 3.3.

Empirically, Jiang, Xu, and Yao (2009) and Barinov (2013) find that firms with a high dispersion of analyst forecasts have a high sensitivity of stock returns to market volatility. Diether, Malloy, and Scherbina (2002) show that stocks with high dispersion in analysts' earnings forecasts have lower average returns than those with low dispersion. Since stocks with high forecast dispersion have high volatility risk, the negative volatility risk premium could proxy for the dispersion effect. Further, analyst coverage improves a firm’s information environment (Kothari et al., 2016). Hou and Moskowitz (2005) show that stocks with more analysts following them incorporate new information into prices more quickly. Because investors value good information environment, stocks tracked by more analysts have lower returns. It could be that the negative volatility risk premium is a proxy for the effect of analyst coverage and information dissemination.

We next control for the cross-sectional effects of analyst coverage and forecast dispersion. Analyst data come from Thomson Reuters Institutional Brokers' Estimate System (I/B/E/S). Analyst coverage is measured by the number of analysts providing current fiscal year annual earnings estimates each month in the I/B/E/S database. Analyst forecast dispersion is the cross-sectional standard deviation of the most recently revised quarterly earnings per share estimates preceding the earnings announcement.

Table 3 (the bottom panel) reports the results with control for the number of analysts (# Analysts) and forecast dispersion. Results continue to show that bonds with high β_{VIX} have low average returns. The volatility risk effect is not concentrated in certain groups of bonds, though this effect varies across quintiles and seems greater for bonds with low analyst coverage. Average long-short (H-L) portfolio return spreads across analyst and dispersion quintiles are -12 and -9 bps and significant at the conventional level. Alphas show a similar pattern, with average spreads of -10 and 8 bps per month. Thus, the volatility risk effect cannot be explained by analyst coverage and forecast dispersion.

3.2.4. Control for the effects of institutional ownership

The literature suggests that institutional investors have better information (Healy, Hutton, and Palepu, 1999; Ajinkya, Bhojraj, and Sengupta, 2005). Since institutional investors are better informed, their trading contains information that affects return and volatility. Basak and Pavlova (2013) show that trading by institutions increases equity price volatility, and as institutional trading induces co-movements in asset prices, institutional investors demand assets that can hedge against volatility risk. The literature of the institutional ownership effects focuses on the equity market. Since bond and stock returns are correlated, institutional stock ownership could affect bond returns. To investigate this possibility, we control for the effect of institutional stock ownership. Our data come from Thomson Reuters Institutional Holdings 13F. This database covers hedge fund holdings for stocks (see Ben-David, Franzoni, and Moussawi, 2012).

Table 3 (the last two rows in the fourth panel) shows the results of controlling for institutional stock ownership. There is little evidence that the effect of volatility risk is concentrated in certain types of institutional ownership, although this effect varies across quintiles and appears to be stronger for firms with low institutional stock ownership. More important, the volatility risk effect is robust to controlling for institutional stock ownership. Average long-short portfolio return spreads (H-L) are -8 and -14 bps when controlling for the number (# S_Institution) and holdings (in percentage) of institutions (S_Holding), respectively; corresponding alphas are -10 and -9 bps, all significant at the conventional level. Thus, institutional stock holdings cannot account for the return spread of portfolios with different sensitivities to aggregate volatility.

We also examine the robustness of volatility risk pricing to institutional bond holdings,[7] using the institutional bond ownership data from Lipper eMAXX. The eMAXX database has comprehensive coverage of bond holdings by insurance firms, mutual funds, pension funds, and leading US banks, but its coverage of hedge funds is quite limited (see Dass and Massa, 2014; Becker and Ivashina, 2015). Thus, the bivariate portfolio analysis does not control for hedge fund holdings. Results (omitted for brevity) show that the volatility risk effect is also robust to controlling for the effect of ownership by insurance firms, mutual funds, pension funds, and banks.

3.3. Portfolio analysis by bond rating

Ratings are perhaps the most important risk metric used in the corporate bond market. Institutional

[7] Institutional bond ownership variables include the percentage of bond holdings and number of institutions and funds holding the bonds. Lipper eMAXX reports bond holdings at both the institutional investor and fund levels.

and individual investors rely heavily on ratings to make investment and trading decisions. Ratings influence bond returns as regulations affect which investors are able to hold a firm's bonds and the cost of holding a bond. In addition, investment styles, private investment mandates, and asset management policies restrict holdings by institutional investors for bonds with different ratings. These regulatory and institutional features make ratings an important risk characteristic, which may explain why firms with different ratings often exhibit different behaviors in asset pricing (e.g., return and earnings momentums and value anomaly). Given the special role of credit ratings, bonds of different ratings may have different exposures to aggregate volatility risk and risk-return trade-offs. To investigate this possibility, we examine bonds with different ratings.

Panel A of Table 4 reports VIX betas of quintile portfolios sorted by rating. VIX betas vary across bonds within each rating category. Differences in VIX betas between the highest and lowest quintile portfolios are all significant at the 1% level within each rating category. The beta spread increases as the rating decreases: 0.70 for Aaa bonds and 1.41 for junk bonds. This pattern is intuitive, as low-grade bonds have a higher standard deviation of returns. Assuming an identical distribution of correlations between bond returns and VIX across ratings, the distribution of VIX betas will naturally be more dispersed among low-grade bonds.

Panel B reports characteristic-adjusted and risk-adjusted returns (alphas) of VIX beta portfolios by rating. The highest VIX beta portfolios consistently deliver the lowest returns for bonds in all rating categories. The (5–1) return spreads are all significant at conventional levels. The return spread increases as the rating decreases. The FF5 alphas on the right panel show a similar pattern for risk-adjusted spreads. The results suggest that volatility risk is priced across rating categories.

Collectively, we find that lower-grade bonds have higher negative volatility risk premiums and greater dispersion of VIX betas. Within each rating category, there is wide dispersion in exposures of returns to aggregate volatility and characteristic-adjusted returns. VIX betas increase and returns decrease across quintiles in each rating category, suggesting the existence of intra-rating volatility risk pricing.

3.4. Cross-sectional regression tests

The portfolio analysis shows that bonds with higher VIX betas have lower expected returns. Cross-sectional variations in bond returns exhibit a monotonic relation with VIX beta that is robust to multiple controls. These results suggest that aggregate volatility is a priced risk factor in the corporate bond market. To substantiate this hypothesis, we perform cross-sectional regressions to test whether aggregate volatility is indeed a priced factor and estimate the price of volatility risk. In equilibrium, expected returns of corporate bonds should be related to factor loadings cross-sectionally. For the full model consisting of all risk factors in Eq. (3), the equilibrium relation is represented by the following cross-sectional regression:

$$\begin{aligned} r_{it} - r_{ft} = {} & \gamma_0 + \gamma_1 \beta_{iMKT} + \gamma_2 \beta_{iSMB} + \gamma_3 \beta_{iHML} + \gamma_4 \beta_{iDEF} + \gamma_5 \beta_{iTERM} + \gamma_6 \beta_{iLIQ} + \gamma_7 \beta_{iVIX} \\ & + \gamma_8 Coupon_i + \gamma_9 Size_i + \gamma_{10} Rating_i + \gamma_{11} Age_i + \gamma_{12} Maturity_i + u_i, \end{aligned} \tag{4}$$

where γ_i is the price of risk factor *i*. Besides risk factors, we consider bond characteristics, such as issue size, age, maturity, coupon, and ratings, to evaluate the importance of VIX beta relative to other risk factors and bond characteristics. We conduct cross-sectional tests using the Fama-MacBeth (1973) approach and correct the bias in standard errors using Shanken's (1992) method.

Table 5 reports the results of cross-sectional regression tests. Each variable on the right side of the regression is normalized by the cross-sectional standard deviation each month so that the coefficient of regression is readily interpretable as the premium per unit of standard deviation of each variable. Panel A show the results of regressions using the PS liquidity beta. The first row includes only market return and VIX factors to focus on the role of volatility risk with a control for market beta. Consistent with the portfolio analysis, the coefficient of VIX beta is negative and significant at the 1% level with a *t*-value of -2.73, suggesting that volatility risk is important in the pricing of corporate bonds. The second row adds the betas of bond market factors, default (*DEF*) and term (*TERM*) spreads. Both default and term betas are significant while VIX beta is significant at the 5% level. When including the liquidity beta, its coefficient is positive and significant, and VIX beta continues to be significant at the 5% level. Some studies show that volatility can explain book-to-market and size anomalies (Babenko et al., 2016). When we further add the betas of firm size (*SMB*) and book-to-market value (*HML*), the coefficients of these betas are insignificant, while VIX beta remains significant.

Panel B of Table 5 reports the results using the Amihud liquidity beta as a measure of liquidity risk. Results show a pattern similar to those using the PS liquidity beta. The coefficient of the Amihud liquidity beta is significantly positive, and that of VIX beta remains significantly negative in all specifications. These results show robustness to the use of different liquidity measures.

The effect of aggregate volatility is of economic significance. For example, given the estimated coefficient of VIX beta in the full factor model using the PS liquidity measure, a one standard deviation below the cross-sectional mean of VIX beta is associated with an increase of 14 bps per month (1.68% per annum) in bond returns. This is an economically significant effect. Results are similar based on the estimates using the Amihud liquidity beta in Panel B.

To examine the robustness of volatility risk pricing to bond characteristics, we include these variables in the last two rows of each panel in Table 5. Some bond characteristics appear to have explanatory power, consistent with previous findings. Importantly, the effect of VIX beta remains significant, even after controlling for the effects of bond characteristics. Further adding the size and book-to-market betas (the last row) has little effect on the significance of VIX beta.

Overall, the results suggest that volatility risk is priced in the corporate bond market. The effect of volatility risk is important over and beyond the effects of conventional risk factors in the bond and stock markets and bond characteristics. The effect of VIX beta is economically meaningful and statistically significant and robust to various model specifications and controls for characteristics.

3.4.1. Cross-sectional regression tests based on ratings

Avramov et al. (2013) show that credit risk has direct implications for asset pricing. Bonds with lower ratings are more sensitive to volatility in firms' investment outcomes because these bonds are closer to the default boundary. In addition, bonds in different rating categories can behave differently due to investment clientele, investment strategies and styles, and regulations. By examining bonds of different ratings, we can ascertain if volatility risk is priced in all ratings and whether volatility risk premiums vary with ratings.

We first perform cross-sectional tests using portfolios. Bonds are grouped by rating into 16 portfolios from Aaa to B3 and below. To increase the sample size for the test, we further divide bonds in each rating category into three maturity groups: short (less than five years), intermediate (five to ten years), and long maturities (greater than ten years). Portfolio returns are average returns of bonds in each portfolio rebalanced monthly. We again run Fama-MacBeth regressions with standard errors corrected by the Shanken (1992) method.

Panel C of Table 4 reports the results of cross-sectional regressions based on rating-maturity portfolio returns. Using portfolios substantially improves the efficiency of parameter estimation and goodness-of-fit by reducing noise. As shown, the coefficients of VIX beta are estimated with greater precision and are all highly significant. The model explains the cross-section of expected bond portfolio returns quite well, with an adjusted R^2 of 60%. Results confirm that volatility risk is priced regardless of which liquidity beta is used.

We next examine whether there is an intra-rating volatility risk pricing (i.e., whether volatility risk is priced for bonds within the same rating category). This analysis provides some insight as to whether the risk price of aggregate volatility varies across rating categories. Bonds of different ratings could attract investors with different preferences and risk aversion, resulting in differential risk premiums. Panel C of Table 5 reports the results of cross-sectional regressions of individual bonds by rating. To avoid cluttering the table, we only report coefficients of betas, *t*-values, and adjusted R^2. For brevity, we focus on the results based on the Pastor-Stambaugh liquidity measure, but our results are robust to the use of the Amihud liquidity measure. Results show that volatility risk pricing exhibits an intra-rating effect, indicating that volatility risk is priced even among relatively homogeneous bonds. Volatility risk premiums vary by rating category. The price of volatility risk is higher (in absolute terms) for junk bonds, consistent with the contention that investors have a higher preference for hedging the risk exposure of riskier bonds and are therefore willing to receive lower returns for bonds with higher VIX betas.

3.5. Subsample analysis

Our sample consists of both NAIC (before July 2002) and TRACE data. The NAIC covers corporate bond transactions of insurance companies and HMOs. Since insurance companies and HMOs are different from other investors, bonds held by these institutions may have different risk and return characteristics (see Becker and Ivashina, 2015). It will therefore be useful to see if results based on the subsample of NAIC bonds differs from those based on TRACE. Subsample analysis also enables us to check the robustness of previous results based on the NAIC data (Campbell and Taksler, 2003; Krishnan, Ritchken, and Thomson, 2005; Cai, Helwege, and Warga, 2007).

We provide descriptive statistics of the subsamples in Panel A of Table 1 (the right two panels). On average, bonds in the TRACE sample have lower ratings, smaller issue size, and shorter maturity than those in the NAIC sample. [8] Interestingly, the dispersion of ratings is quite similar for TRACE and NAIC subsamples, indicating that insurance companies and HMOs also hold high-risk bonds. [9] Panel C summarizes returns and betas for each subsample. Results show that bonds in the TRACE sample tend to have higher default, liquidity, and market betas. Fig. 2 and Fig. 3 show the number of bonds and firms in each subsample over time.[10]

To get a glimpse of the subsample volatility risk effect, we first report the results of univariate portfolio sorts on VIX beta in Panel C of Table 2. We adopt the same sorting procedure as we used for the full sample. Results show that the high-low return and alpha spreads are larger for the TRACE subsample. This pattern is perhaps not surprising, as TRACE covers a broader base of corporate bonds than the NAIC sample, which is dominated by insurance companies that usually prefer higher-rated bonds. Notwithstanding this difference, both samples exhibit a negative relation between bond returns and VIX betas, which is robust to the adjustment for bond characteristics and risk factors. For example, for the TRACE (NAIC) subsample, the (10-1) characteristic-adjusted return and alpha spreads are -21 (-10) and -15 (-9) basis points, respectively, both significant at the 1% (5%) level.

We rely on regression analysis to control for the cross-sectional effects of bond/issuer characteristics.

[8] These results should be interpreted with caution, as the sample period varies across TRACE and NAIC samples.
[9] Unreported results show that both TRACE and NAIC cover bonds with ratings from Aaa to D.
[10] For TRACE data, we have a total of 365,134 bond-month observations for 10,324 bonds issued by 1,818 firms for the period of 2002-2016, whereas for NAIC data, we have a total of 320,192 bond-month observations for 8,553 bonds issued by 1,868 firms for the period of 1994-2016.

Regression analysis has high statistical power relative to portfolio sorts with multiple dimensions. This advantage becomes more important for subsample analysis, as each subsample has a smaller sample size. Consequently, bivariate sorts lack power for subsamples, particularly for the NAIC subsample. Unlike portfolio analysis, regressions allow us to retain the test power while having effective control for multiple variables.[11]

Panel D of Table 5 shows the results of cross-sectional regressions for both subsamples. Consistent with portfolio analysis, the risk price of aggregate volatility is higher for the TRACE sample than for the NAIC. Controlling for the effects of conventional risk factors and characteristics, the coefficients of VIX beta (risk prices) are -0.12 and -0.06 (-0.09 and -0.06) for TRACE and NAIC, respectively, when using the Amihud (PS) liquidity beta in the regression. We also run regressions with control for other variables in Table 3. The coefficients of VIX beta remain significant for both subsamples, indicating that the effect of VIX beta is robust to controls for all other issuer/bond characteristics. There is strong evidence that volatility risk is priced in both subsamples. Thus, our results are robust to different subsamples.

4. Idiosyncratic volatility and the cross-section of expected returns

Prior studies show that stocks' expected returns depend on idiosyncratic volatility that does not arise from systematic risk factors.[12] It is unclear whether idiosyncratic volatility is also priced in the cross-section of bond returns and how the systematic risk of aggregate volatility fares against the effect of idiosyncratic volatility. In this section, we investigate the cross-sectional relation between expected bond returns and idiosyncratic volatility using the multi-factor model with VIX.

4.1. Portfolio analysis of idiosyncratic volatility effects

To examine the role of idiosyncratic volatility in the cross-section of expected bond returns, we start

[11] The issue of low power is a greater concern for the NAIC sample, as it contains fewer bonds, and average bond/month observations are much smaller over the sample period of 1994-2016 for portfolio analyses with multiple controls. For TRACE, the sample period is shorter (July 2002 to December 2016), which also reduces statistical power. However, as TRACE covers a much large number of bonds, the impact is smaller and bivariate sorts exhibit a pattern closer to that of the full sample.
[12] See Ang et al. (2006, 2009) and Babenko, Boguth, and Tserlukevich (2016).

with portfolio analysis using the full sample. In univariate portfolio analysis, we sort bonds into deciles each month based on the idiosyncratic bond volatility calculated from the returns over the past six months. In bivariate portfolio analysis, we use the procedure similar to volatility risk sorts to control for other cross-sectional effects.

We measure idiosyncratic volatility by the standard deviation of return residuals of individual bonds, estimated from the time-series regression of the model with Fama-French five factors and VIX. If aggregate volatility is a risk factor that is orthogonal to the FF factors, the sensitivity of returns to this factor, multiplied by the movement of marketwide volatility, could show up in the residuals of the FF5 model. To avoid this contamination effect, we include VIX in the multifactor model to calculate idiosyncratic volatility.[13] In analyzing the idiosyncratic volatility effect, we focus on the characteristic-adjusted returns and alphas relative to the FF5 model with VIX. Our results are robust to the estimates using raw excess returns, as well as to the alphas relative to the conventional FF3 model and the FF5 model without VIX.

Panel A of Table 6 reports average excess returns and characteristic-adjusted returns, and the alphas calculated using these returns, for the portfolios sorted on idiosyncratic bond volatility. The difference in characteristic-adjusted returns between high (10) and low (1) decile portfolios is 30 bps per month with a t-value of 3.08. The (10–1) alpha spread is 22 bps, which is also significant at the 1% level ($t = 2.65$). Results based on raw excess returns give larger (10-1) portfolio return and alpha spreads. Clearly, the FF5 factor model with VIX is unable to price these portfolios.

4.2. Robustness of portfolio analysis

To assess whether the positive relation between bond returns and idiosyncratic volatility (*IVol*) holds after controlling for various cross-sectional effects, we first sort bonds into quintiles each month by each control variable (characteristic); within each quintile, we further sort bonds into quintiles based on their idiosyncratic volatility. We then calculate the long-short portfolio (highest *IVol* – lowest *IVol*) returns

[13] We use the same idiosyncratic volatility measure later in regressions. Also, for brevity, we focus on the results based on the PS measure in both portfolio and regression analysis, and our results are robust to the Amihud measure.

and alphas for each of the five portfolios formed by each control variable. We also calculate the mean values of the long-short portfolio (H-L) returns and alphas across the five characteristic portfolios to assess the overall effect of idiosyncratic volatility on bond returns after controlling for each characteristic.

4.2.1. Controlling for the liquidity effect

Liquidity can affect bond returns, and less liquid bonds tend to have higher return volatility. To investigate the robustness of the idiosyncratic bond volatility effect to liquidity level and risk, we control for the effects of volume, the Amihud individual bond liquidity, IRC, return volatility, and liquidity betas. The top of Panel B in Table 6 shows the results of these bivariate sorts. The effect of idiosyncratic volatility shows up in all segments of corporate bonds, and this effect tends to increase with liquidity. Liquidity level and risk cannot account for the high return associated with high idiosyncratic bond volatility. Average long-short return spreads (H-L) range from 21 to 26 bps per month after controlling for liquidity level and risk, all significant at the 1% level. The spreads of alpha relative to the FF5 model with VIX are also all significant at the 1% level. Overall, these results indicate that the idiosyncratic volatility effect is robust to controlling for the effects of both liquidity level and risk.

4.2.2. Controlling for bond/issuer characteristics

We next control for the effects of bond characteristics such as rating, maturity, age, and coupon. Panel B shows that the effects of idiosyncratic risk are pervasive and tend to increase with default risk (rating), coupon rate, and bond age. Average long-short portfolio spreads (H-L) range from 16 to 29 bps, and alpha spreads from 15 to 25 bps, all significant at the conventional level, indicating that controlling for bond characteristics cannot remove the effect of idiosyncratic bond volatility.

Small, high-leverage, and young firms often have high expected returns. To check the robustness of the idiosyncratic risk effect, we control for these effects. Portfolio sorts by these characteristics show that the idiosyncratic volatility effect is not concentrated in certain types of firms. While small- and high-leverage firms tend to exhibit a high idiosyncratic risk effect, this relation is not strictly monotonic. Controlling for these cross-sectional effects yields (H-L) adjusted-return (alpha) spreads from 6 (11) to 39 (29) bps, all significant at least at the 5% level, indicating that issuer characteristics cannot explain away the idiosyncratic volatility effect either.

4.2.3. Controlling for analyst coverage and institutional ownerships

The effect of idiosyncratic volatility could reflect analyst forecast precision or institutional ownership (see Ang et al., 2009). We next control for the effects of these variables. The bottom of Panel B in Table 6 reports the results. Firms with lower analyst following and institutional ownership appear to have a higher idiosyncratic risk effect. Nevertheless, the effect of idiosyncratic risk is not restricted to only certain types of bonds. More importantly, the idiosyncratic volatility effect is robust to controlling for analyst coverage and institutional ownership variables.[14] Controlling for the number of analysts and analyst forecast dispersion, average long-short (H-L) adjusted-return (alpha) spreads are 14 and 20 bps (18 and 20 bps), respectively, all significant at the conventional level. Controlling for institutional stock holdings, the (H-L) adjusted-return spreads (alpha spreads) are 17 and 18 bps (17 and 19 bps), respectively, also all significant at the conventional level. Thus, analyst and institutional ownership variables cannot account for the idiosyncratic volatility effect.

4.3. Cross-sectional regressions with bond volatility

We next conduct cross-sectional regression tests by jointly considering the effects of both bond-specific volatilities (total return and idiosyncratic) and aggregate volatility risk. To better assess the robustness of idiosyncratic risk to the effect of exposure to aggregate volatility, we create a tradable volatility factor from VIX betas that reflects only systematic volatility risk. We use the long-short return of decile portfolios (10-1) sorted by VIX beta as a measure of the traded volatility factor, but our results are robust to the use of (5-1) return spreads. We estimate betas and idiosyncratic volatility from the FF5 model with the tradable volatility factor and use them in the cross-sectional regression test.

Panel A of Table 7 (the first two rows) reports the results of the Fama-MacBeth regression. Results show that both bond return volatility (*Vol*) and idiosyncratic volatility (*IVol*) have explanatory power for the cross-section of bond returns. Their coefficients are positive and significant at the 1% level, even after

[14] Results (omitted for brevity) show that the idiosyncratic risk effect is also robust to bond holdings by institutions.

controlling for the effects of volatility risk and other risk factors. The fact that both return and idiosyncratic volatilities remain highly significant suggests that firm-specific volatility has an important effect beyond that of aggregate volatility risk and other risk factors.

This finding raises the question of why the idiosyncratic volatility of bonds has such a significant effect on expected bond returns. First of all, the significance of return volatility is consistent with the classical risk-return trade-off paradigm. Further, although idiosyncratic volatility should not be priced in a frictionless market with complete information, Merton (1987) shows that assets with high idiosyncratic volatility will have high expected returns in a market where investors have limited access to information, because investors cannot diversify away firm-specific risks. Incomplete diversification can also arise from regulations. For example, insurance companies and pension funds often invest only in certain types of bonds due to regulatory constraints. This restriction can limit the ability of these investors to diversify. In addition, transaction costs for bonds are much higher than for stocks, which can lead to under diversification (Levy, 1978). The finding of a significant positive effect of idiosyncratic bond volatility is consistent with the theory of incomplete diversification due to limited information, regulatory constraints, transaction costs, or other market imperfections.

Moreover, in the fixed-income literature, Bao and Pan (2013) find that the abnormal volatility of corporate bonds that cannot be explained by the Merton (1974) model is primarily due to bond illiquidity. Since assets with low liquidity have high expected returns, idiosyncratic bond volatility could have a positive effect on expected returns through the channel of liquidity. Idiosyncratic volatility can also capture the effect of idiosyncratic default risk. Asset volatility includes both bond and stock volatilities. High asset volatility is associated with high default probability, as a firm with more volatile asset value is more likely to hit the default boundary. Recognizing this risk, investors will require higher returns, and this is true even if default risk is idiosyncratic. While our results could be explained by these factors, the exact source of the idiosyncratic bond volatility effect is yet to be determined.

4.4. Cross-sectional regressions with stock volatility

A firm with volatile equity value is more likely to reach the boundary condition for default (see

Campbell and Taksler, 2003) and therefore has a high-risk premium. To investigate the effect of stock return volatility on expected corporate bond returns, we include stock return volatility in the cross-sectional regression. Again, we employ two volatility measures: idiosyncratic and total return volatilities of stock returns, where idiosyncratic volatility is defined relative to the FF5-factor model with the tradable volatility factor. Following Ang et al. (2006), we calculate both idiosyncratic and total return volatilities of stocks using the daily data in the past month and include them in the cross-sectional regression for the current month. In this test, the sample is restricted to firms with both bonds and stocks.

Panel B of Table 7 (the first two rows) reports the results of cross-sectional regressions with stock volatilities. In line with the equity literature (e.g., Ang et al., 2006, 2009), the coefficients on stock idiosyncratic and return volatilities are both negative and statistically significant. The results are consistent with the finding of Campbell and Taksler (2003) that stock volatility affects bond pricing.

4.5. Interaction effects of default risk and volatilities

Bonds issued by a firm with a shorter distance to default are riskier. These high-risk bonds behave more like stocks, and their returns have a larger equity component. For firms closer to the default boundary, the chance of default gets higher as volatility increases. Therefore, returns for riskier bonds should be more sensitive to changes in the return volatility of assets, which include stocks and bonds. We test this hypothesis by examining the interaction effect of volatility with different levels of default probability. We use the rating as a proxy for default probability and include an interaction variable, *Vol*R* (or *IVol*R*), in the regression, where *R* is the rating indicator with a higher value for a lower-quality bond (see definitions in Table 1), and *Vol* (*IVol*) denotes total return (idiosyncratic) volatility.

Panel A of Table 7 (the last two rows) shows that the total return and idiosyncratic volatilities of bonds both exhibit a positive interaction effect with default risk. The coefficients of *Vol*R* and *IVol*R* are all significant at the 1% level, suggesting that the sensitivity of expected bond returns to firm-specific bond return volatilities is higher for lower-grade bonds. These results confirm that the effect of idiosyncratic bond volatility increases with default risk.

Panel B of Table 7 (the last two rows) shows similar interaction effects of default risk with stock return volatilities. The coefficients of interactions between stock volatility and rating are all significant at the conventional level and robust to controlling for the effect of volatility risk. The effects of both return and idiosyncratic volatilities of stocks on expected corporate bond returns increase with default probability. This finding is consistent with the view that lower-grade bonds have a larger equity component, and returns are thus more sensitive to equity return volatility.

4.6. Control for the correlation between stock and bond returns

Ang et al. (2006) show that high idiosyncratic stock volatility predicts low stock returns. As stock and bond returns are contemporaneously correlated at the firm level, the negative effect of past idiosyncratic stock volatility on bond returns could work through the channel of contemporaneous stock returns. To investigate this possibility, we control for the effects of stock returns. Following Gebhardt, Hvidkjaer, and Swaminathan (2005b), we use two methods to control for contemporaneous stock and bond correlation. In the first method, we run the cross-sectional regression by adding the contemporaneous stock return. In the second method, we use a two-step regression procedure where we first regress bond returns on contemporaneous stock returns firm-by-firm and then use the adjusted bond returns in the cross-section regression. The second method has the advantage of allowing the coefficient of stock returns to differ across firms, whereas the first method imposes the restriction of the same coefficient for all firms.

Prior research has also shown a spillover effect from past stock returns to future bond returns (Gebhardt, Hvidkjaer, and Swaminathan, 2005b). This finding suggests that lagged stock returns can predict bond returns. To capture this spillover effect, we further add the lagged stock return in the cross-sectional regression.

Panel C of Table 7 reports the results of controlling for the effects of stock returns. When we include the contemporaneous stock return (*Sret*) in the regression, its coefficient is positive and highly significant. However, the coefficient on stock return volatility is significant only at the 10% level. The impact is even bigger for stock idiosyncratic volatility, which becomes insignificant. These results suggest that the negative effect of past idiosyncratic stock volatility on bond returns works through the channel of positive contemporaneous correlation between stock and bonds. When we further include the lagged stock return

(*Sret1*) in the regression, its coefficient is positive and highly significant, consistent with the finding of Gebhardt, Hvidkjaer, and Swaminathan (2005b), but it has little impact on the coefficient of stock idiosyncratic or return volatility.

Panel D of Table 7 shows the results based on the second method to adjust the bond return for contemporaneous correlation with stock returns. This method shows even clearer evidence that stock-level volatility works through the channel of contemporaneous stock returns. Using this more flexible firm-by-firm contemporaneous adjustment, the effects of both return volatility and idiosyncratic volatility of stocks become insignificant. On the other hand, VIX beta remains highly significant with a negative sign, regardless of controlling for contemporaneous and lagged stock return effects. These results suggest that the negative effect of past idiosyncratic stock volatility works through the channel of contemporaneous stock returns but the volatility risk effect does not. High past idiosyncratic stock volatility predicts low bond returns mainly because high past idiosyncratic stock volatility predicts low stock returns, and stock and bond returns are positively correlated contemporaneously.

4.7. Cross-sectional regressions with both bond and stock volatilities

The above results show that bond and stock volatilities are both important for pricing corporate bonds. To further assess the role of bond and stock volatilities, we run horserace regressions with both volatility measures. If bond volatility contains information over and beyond stock volatility, it should remain significant even after controlling for the effect of stock volatility in the cross-sectional regression. Table 8 shows that this is indeed the case. When both bond and stock volatility measures are included in the regression, bond volatility continues to be significant at the 1% level regardless of whether we use the total return (*BVol*) or the idiosyncratic bond volatility (*BIVol*) measure, suggesting that bond volatility contains additional information important for bond pricing. In absolute terms, the coefficients of bond return volatility are much larger than that of stock return volatility, indicating that the former is more influential. The total return (*SVOL*) and idiosyncratic volatilities (*SIVOL*) of stocks are significant with a negative coefficient. However, these stock volatilities become insignificant after we further control for the effect of stock returns, again revealing that the effect of stock idiosyncratic volatility works through the channel of contemporaneous stock returns. By contrast, the effects of both idiosyncratic and return volatilities of bonds are robust to controlling for contemporaneous and lagged stock returns.

Bond and stock volatilities are correlated, which could induce a collinearity problem. To check the robustness of results to this potential problem, we also run regressions using a bond volatility measure orthogonalized by stock volatility. Results (omitted for brevity) show robustness to this adjustment. The orthogonal bond idiosyncratic and total return volatilities remain highly significant, while stock volatility effects are significant if we do not include contemporaneous stock returns in the regression. Controlling for the contemporaneous stock return, stock volatilities become insignificant, but bond volatility effects are unchanged. This finding confirms that idiosyncratic stock volatility works through the channel of contemporaneous stock returns but suggests that idiosyncratic bond volatility has a separate effect.

4.8. Subsample regressions

To provide some insight as to whether the effect of idiosyncratic volatility is sample-dependent, we examine this effect based on the subsamples of NAIC and TRACE, respectively. Panel C of Table 6 shows that long-short portfolio return and alpha spreads based on idiosyncratic bond volatility sorts are larger for the TRACE sample. The characteristic-adjusted return (alpha) spread is 32 (20) basis points for the TRACE subsample and 11 (12) basis points for the NAIC subsample.

To obtain more power for controlling other cross-sectional effects, we again rely on regression analysis. Table 9 reports the results of subsample regressions. Panel A shows that the effects of bond return and idiosyncratic volatility are significantly positive and increase with credit default risk (R) for both subsamples. The effects (risk prices) of bond-specific volatilities are greater for the TRACE subsample. Panel B shows that the effects of stock volatilities are negative and increase (in absolute terms) with credit risk for both subsamples. These results show that the effects of bond and stock idiosyncratic volatilities exist in both subsamples.[15]

Panels C and D show the subsample results after controlling for contemporaneous and past stock

[15] We also run regression with control for other characteristic variables in Panel B of Table 7. The coefficients of bond and stock idiosyncratic volatilities remain significant even after controlling for all issuer/bond characteristics.

returns. Once again, idiosyncratic stock volatility becomes insignificant after controlling for the effects of stock returns, suggesting the idiosyncratic volatility effect works through the stock return channel. This pattern prevails in both the TRACE and NAIC subsamples. Overall, our results show that the effects of idiosyncratic bond and stock volatilities are robust to different samples.

5. Conclusion

This paper examines the effect of volatility on the pricing of corporate bonds using a long-span data sample. We consider aggregate volatility as a state variable and investigate whether systematic volatility risk is priced in the cross-section of expected corporate bond returns. In addition, we study the role of both bond and stock idiosyncratic volatilities in the cross-section of average bond returns.

We find that the equity-based volatility risk factor that is priced in the options and equity markets is also priced in the corporate bond market. Consistent with the findings in the options and equity markets, bonds with high aggregate volatility risk have low average returns. This negative relation is robust to controlling for the effects of conventional risk factors, liquidity level and risk, information frictions, bond/issuer characteristics, and ratings. In contrast, bonds with high idiosyncratic bond volatility have high expected returns. This positive relation is robust to controlling for risk factors and characteristics as well as alternative model specifications. The effect of idiosyncratic bond volatility increases as the credit rating decreases. Exposures of bond returns to innovations in aggregate volatility and other risk factors in the stock and bond market accounts very little for the effect of idiosyncratic bond volatility. Additionally, the effect of idiosyncratic bond volatility is robust to controlling for idiosyncratic stock volatility and contemporaneous and lagged stock returns. These findings suggest that the effect of idiosyncratic bond volatility represents a separate source of risk for corporate bonds whose channel deserves further investigation in future studies.

We also find that bonds with high stock return volatility have low expected returns, and that this negative relation strengthens as bond rating decreases. However, the effect of stock idiosyncratic volatility becomes insignificant after controlling for contemporaneous stock returns, suggesting that it works through the channel of contemporaneous stock returns. Finally, the effects of volatility risk and idiosyncratic volatility are not concentrated in certain types of bonds. While they may vary with some firm/bond characteristics, in general, these effects are pervasive through all segments of corporate bonds. In addition, these effects appear in both the NAIC and TRACE subsamples.

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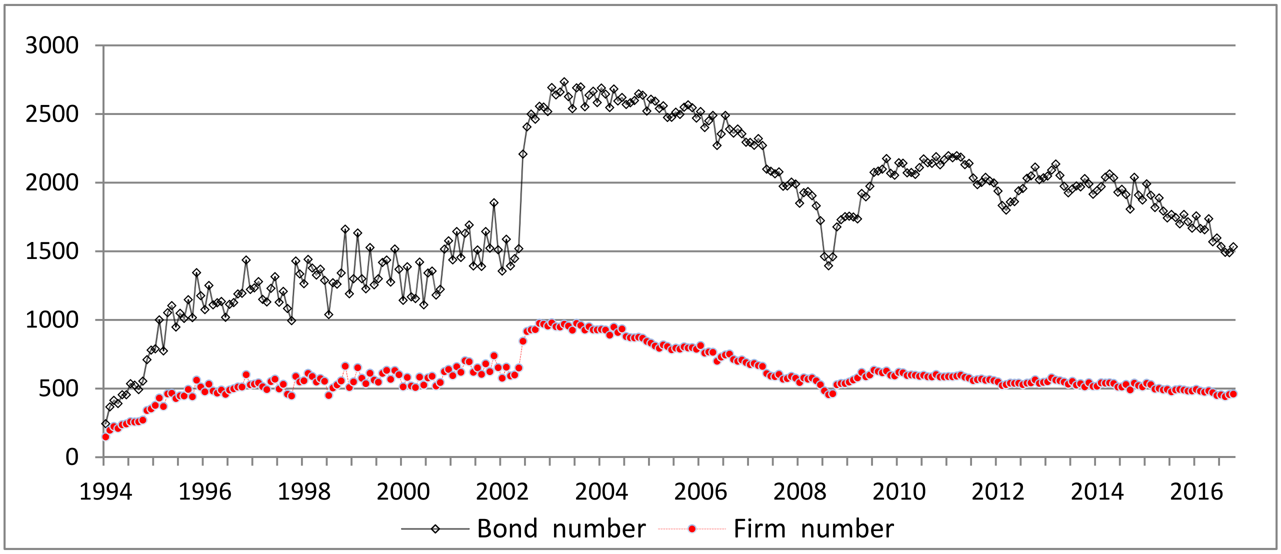

Fig. 1. Numbers of bonds and firms for the full sample (1994-2016) .This figure plots the number of bonds and firms in the whole sample in each month from January 1994 to December 2016.

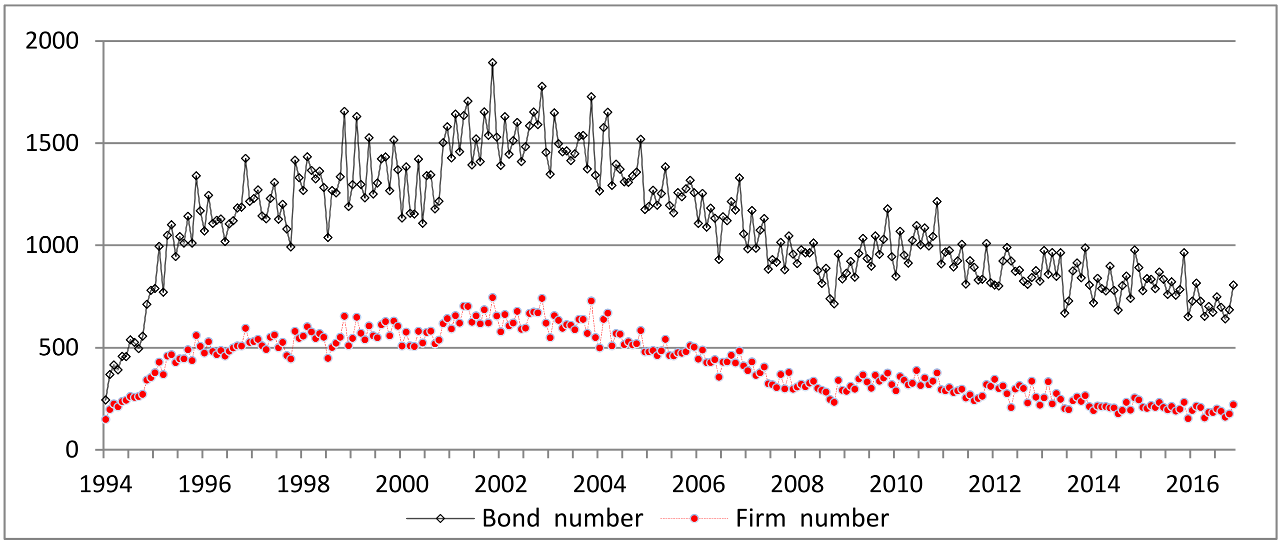

Fig. 2. Numbers of bonds and firms for the NAIC subsample (1994-2016) .This figure plots the number of bonds and firms in the NAIC subsample in each month from January 1994 to December 2016.

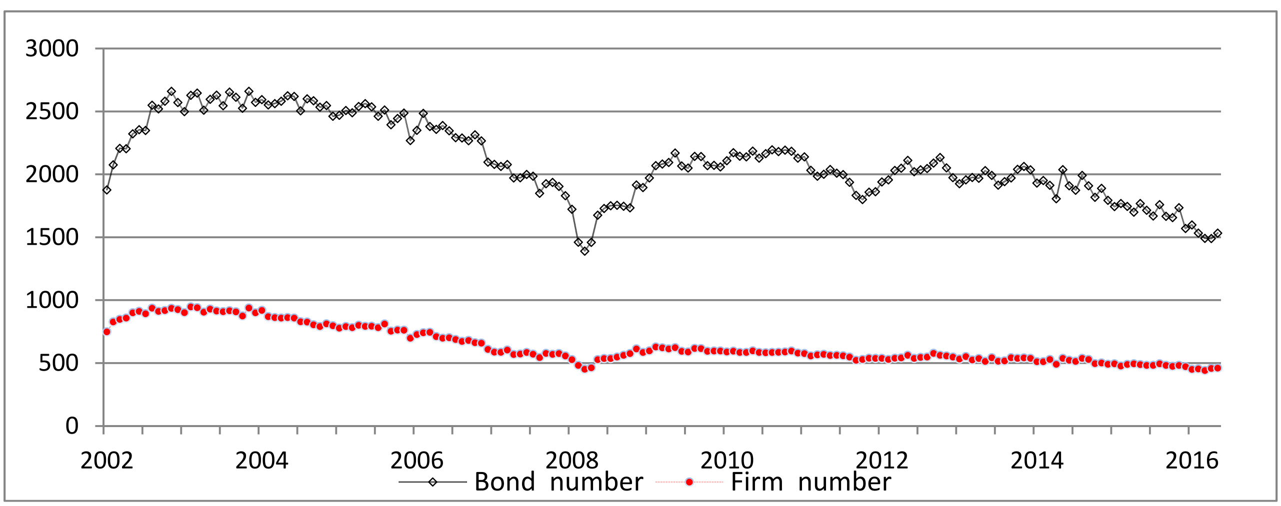

Fig. 3. Numbers of bonds and firms for the TRACE subsample (2002-2016) .This figure plots the number of bonds and firms in the TRACE subsample in each month from July 2002 to December 2016.

Table 1
Summary statistics
This table summarizes the data used in our empirical analysis. Panel A reports the summary of corporate bond characteristics. *Rating* is the Moody's bond rating (Aaa=0, Aa+=1,…, C=20, and D=21), and if the Moody's rating is unavailable, we use the S&P rating whenever possible. *Size* is the issue size in billions of dollars; *Maturity* is years to maturity; *Age* denotes years since issuance; and *Coupon* is the coupon rate. Panel B reports summary statistics for risk factors, *Market, SMB, HML*, default, term, liquidity, and *VIX* for the full sample period. *Market, SMB*, and *HML* are the Fama-French three factors downloaded from Kenneth French's data library. The default factor (*DEF*) is the difference between the return of a value-weighted portfolio of long-term investment-grade bonds in the sample and the return of long-term government bonds. The term factor (*TERM*) is the difference between the long-term government bond return and the one-month T-bill rate. *PS liquidity* is the Pastor-Stambaugh corporate bond liquidity factor. *VIX* is the Chicago Board Options Exchange (CBOE) volatility index. All variables except *VIX* are expressed in percentage. Panel C summarizes betas for individual bonds where the liquidity factor is either the Pastor-Stambaugh or Amihud measure in the time-series regression using each sample. Data are monthly and the full sample runs from January 1994 to December 2016. The sample period is from January 1994 to December 2016 for the NAIC subsample and from July 2002 to December 2016 for the TRACE subsample.

Panel A: Bond characteristics

	Full sample			NAIC			TRACE		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Rating	5.65	5.00	3.40	4.42	5.00	3.31	5.81	5.00	3.57
Size	0.83	0.30	2.10	3.23	0.50	7.07	0.56	0.30	0.68
Maturity	6.77	4.08	8.20	7.46	4.83	8.23	6.38	3.67	8.03
Age	4.81	3.42	4.41	4.46	3.42	4.00	5.13	3.58	4.75
Coupon	5.53	6.13	2.59	6.00	6.39	2.17	4.97	5.45	2.67

Panel B: Summary statistics of factors

	Mean	Median	Max	Min	Std. dev.
Market	0.65	1.19	11.35	-17.23	4.31
SMB	0.13	0.02	22.08	-17.17	3.32
HML	0.19	-0.06	12.91	-11.25	3.08
DEF	0.97	0.90	3.38	0.55	0.42
TERM	1.74	1.84	3.69	-0.70	1.11
PS liquidity	0.00	0.01	0.32	-0.53	0.07
VIX	20.18	18.48	59.89	10.42	7.75

Panel C: Summary statistics of betas

	Full sample			NAIC			TRACE		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Pastor-Stambaugh liquidity measure									
Return	0.05	-0.03	1.76	0.03	-0.03	1.88	0.03	-0.04	1.74
β_{MKT}	0.10	0.05	0.30	0.03	0.02	0.33	0.11	0.06	0.31
β_{SMB}	-0.04	-0.03	0.27	0.02	0.01	0.29	-0.06	-0.05	0.28
β_{HML}	0.03	0.01	0.31	0.05	0.04	0.36	0.03	0.01	0.33
β_{DEF}	0.51	0.63	2.13	0.15	0.23	5.85	0.79	0.74	3.85
β_{TERM}	-0.13	0.04	1.38	0.35	0.12	1.54	-0.12	0.09	1.48
β_{LIQ}	0.80	0.43	0.98	0.15	0.11	0.15	0.96	0.61	1.01
β_{VIX}	-0.02	-0.01	0.40	0.01	0.01	0.50	-0.05	-0.02	0.39
Amihud liquidity measure									
β_{MKT}	0.08	0.04	0.29	0.05	0.03	0.33	0.09	0.03	0.30
β_{SMB}	-0.04	-0.03	0.26	0.02	0.01	0.29	-0.07	-0.05	0.27
β_{HML}	0.04	0.01	0.30	0.05	0.03	0.36	0.04	0.01	0.31
β_{DEF}	0.50	0.66	2.04	0.14	0.23	6.39	0.70	0.69	3.75
β_{TERM}	-0.14	0.03	1.32	0.38	0.17	1.67	-0.13	0.09	1.38
β_{LIQ}	1.24	0.88	1.10	0.91	0.63	0.87	1.25	0.89	1.12
β_{VIX}	-0.02	0.00	0.39	0.03	0.03	0.51	-0.03	-0.02	0.38

Table 2

Portfolio analysis

This table reports mean returns, betas, bond characteristics, and alphas for each decile portfolio sorted by VIX beta. Bonds are sorted into deciles each month, each with an equal number of bonds, by the preranking VIX betas estimated by the Fama-MacBeth (1973) method. β_{VIX} is estimated over a five-year rolling window for each individual bond along with default, term, and other betas in time-series regression (3). Panel A reports the mean VIX beta, return, and alpha of each portfolio and the long-short (10-1) portfolio spreads. *Return* is average monthly returns (in percentage) of individual bonds in excess of one-month T-bill rates. *AdjRet* is the characteristic-adjusted returns adjusted for rating and maturity. In Panel B, average preranking factor betas are reported for each β_{VIX} portfolio. Average excess return, rating, issue size, maturity, age, and coupon rate are calculated for each ex post β_{VIX} portfolio. Panel C reports subsample portfolio sorts for NAIC and TRACE. Differences in average returns and alphas between the high and low β_{VIX} portfolios (10-1) and the corresponding *t*-values are reported. The signs ** and *** indicate significance at the 5% and 1% levels, respectively.

Panel A: Mean volatility beta, excess returns, and alphas of VIX beta decile portfolios

	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1	*t*-value
β_{VIX}	-0.76	-0.30	-0.16	-0.08	-0.02	0.02	0.07	0.14	0.26	0.70		
Return	0.21	0.23	0.10	0.11	0.05	0.03	0.03	-0.02	-0.01	0.01	-0.20**	(-2.42)
AdjRet	0.06	0.08	-0.01	0.00	-0.03	-0.04	-0.04	-0.08	-0.08	-0.06	-0.12***	(-2.59)
Return Alpha	0.05	0.08	0.00	0.00	-0.02	-0.04	-0.03	-0.06	-0.06	-0.05	-0.09**	(-1.97)
AdjRet Alpha	0.12	0.16	0.05	0.04	0.00	-0.02	0.00	-0.05	-0.03	-0.02	-0.14**	(-2.32)

Panel B: Mean values of other betas and bond characteristics of VIX beta decile portfolios

	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)
β_{MKT}	-0.13	0.14	0.22	-0.01	0.03	0.04	0.05	0.06	0.08	0.13
β_{SMB}	0.03	0.01	0.03	0.04	0.04	0.04	0.03	0.02	0.02	0.03
β_{HML}	0.00	0.11	0.04	0.02	0.02	0.02	0.01	0.01	0.02	0.03
β_{DEF}	0.37	0.30	0.15	0.51	0.48	0.34	0.23	0.30	0.33	0.31
β_{TERM}	0.34	0.34	0.20	0.14	0.12	0.09	0.08	0.10	0.12	0.15
β_{LIO}	1.36	1.41	0.84	0.85	0.60	0.47	0.37	0.37	0.44	0.58
Rating	7.36	6.94	6.12	6.56	5.95	5.43	4.96	4.74	4.95	5.38
Size	0.38	0.43	0.76	0.60	0.75	0.94	1.08	1.26	1.19	1.03
Maturity	8.91	9.52	7.46	7.71	5.98	4.53	3.86	3.85	4.44	5.64
Age	5.88	6.61	6.88	6.25	6.04	5.63	5.21	5.30	5.75	6.37
Coupon	5.58	5.90	6.07	5.73	5.54	5.32	5.05	5.14	5.51	5.86

Panel C: Subsample mean volatility beta, excess returns, and alphas of VIX beta decile portfolios

		1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1	*t*-value
NAIC	β_{VIX}	-0.89	-0.37	-0.19	-0.10	-0.03	0.03	0.10	0.19	0.35	0.91		
	Return	0.13	0.10	0.07	0.04	0.06	-0.03	-0.02	-0.01	-0.03	-0.05	-0.18***	(-2.66)
	AdjRet	0.06	-0.04	-0.02	-0.00	-0.02	-0.03	-0.02	-0.01	-0.03	-0.04	-0.10**	(-2.27)
	Return Alpha	0.11	0.06	0.04	0.04	0.03	-0.02	-0.04	-0.05	-0.03	-0.07	-0.18**	(-2.31)
	AdjRet Alpha	0.06	-0.03	-0.03	-0.01	0.02	-0.03	-0.01	-0.04	-0.01	-0.03	-0.09**	(-2.18)
TRACE	β_{VIX}	-0.77	-0.31	-0.17	-0.09	-0.04	0.00	0.04	0.10	0.21	0.64		
	Return	0.25	0.27	0.09	0.10	0.02	0.01	0.01	-0.01	-0.01	-0.03	-0.28***	(3.02)
	AdjRet	0.09	0.11	-0.02	0.00	-0.06	-0.06	-0.07	-0.06	-0.09	-0.11	-0.21***	(-4.51)
	Return Alpha	0.11	0.15	0.01	0.00	-0.06	-0.06	-0.05	-0.05	-0.06	-0.09	-0.19***	(-2.63)
	AdjRet Alpha	0.06	0.09	-0.01	-0.01	-0.05	-0.05	-0.04	-0.04	-0.06	-0.09	-0.15***	(-2.85)

Table 3
Portfolio sorts controlling for liquidity, liquidity risk and bond and issuer characteristics

This table reports characteristic-adjusted returns and alphas of the BJS time-series regression of the FF5-factor model, using adjusted returns for quintile portfolios with control for various cross-sectional effects. We first sort bonds into quintiles on each control variable each month, and for bonds within each quintile portfolio, we further sort them into five portfolios on β_{VIX} . The five portfolios sorted on β_{VIX} are then averaged over each of the five control variable portfolios. All portfolios are rebalanced monthly and equally weighted. Liquidity control variables include trading volume, Amihud liquidity, *IRC*, and volatility (standard deviation of bond returns). *IRC* is the implied roundtrip cost, which is an illiquidity measure suggested by Dick-Nielsen, Feldhutter, and Lando (2012). Liquidity risk variables include betas of the PS and Amihud liquidity factors. Bond characteristics include maturity, coupon, and bond age. Issuer characteristics include firm age, leverage (debt/equity ratio), and size (market capitalization). Analyst variables include the number of analysts and the dispersion of analyst forecasts, and institutional variables include the number of institutions (*# S_Institution*) and the percentage of shares held by institutions (*S_Holding*). Returns and alphas of each portfolio are expressed in percentage terms (monthly). We report the long-short returns/alphas for each characteristic portfolio from 1 to 5. Further, the column "H-L" refers to the long-short returns of portfolios sorted on β_{VIX}, averaged across characteristic quintiles. Numbers in parentheses are *t*-statistics. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Long-short returns for each quintile portfolio					Average		Long-short alphas for each quintile portfolio					Average	
Characteristic	1	2	3	4	5	H-L	*t*-value	1	2	3	4	5	H-L	*t*-value
Volume	-0.15***	-0.14**	-0.15***	-0.13**	-0.17***	-0.16***	(-4.48)	-0.13***	-0.11**	-0.13***	-0.10**	-0.11**	-0.10***	(-2.76)
Amihud	-0.10***	-0.10**	-0.20***	-0.20***	-0.09*	-0.15***	(-3.83)	-0.09**	-0.07*	-0.18***	-0.16***	-0.08*	-0.10***	(-2.89)
IRC	-0.10*	-0.14***	-0.18***	-0.17***	-0.11**	-0.16***	(-3.98)	-0.06*	-0.12***	-0.18***	-0.14***	-0.09*	-0.11***	(-3.11)
Volatility	-0.05*	-0.11***	-0.12***	-0.18***	-0.08*	-0.12***	(-3.02)	-0.06**	-0.10***	-0.10***	-0.14***	-0.06*	-0.09***	(-3.27)
PS beta	-0.14***	-0.12***	-0.16***	-0.08*	-0.07*	-0.13***	(-5.28)	-0.12***	-0.08**	-0.12***	-0.09*	-0.08*	-0.12***	(-4.10)
Amihud beta	-0.09**	-0.16***	-0.16***	-0.06*	-0.09**	-0.15***	(-4.51)	-0.07**	-0.14***	-0.14***	-0.05*	-0.06*	-0.08***	(-3.59)
Maturity	-0.13***	-0.13***	-0.07*	-0.09*	-0.03	-0.11***	(-3.29)	-0.10***	-0.13***	-0.04	-0.05*	0.00	-0.06*	(-1.84)
Coupon	-0.13**	-0.18***	-0.11**	-0.11**	-0.09	-0.15***	(-4.33)	-0.11**	-0.18***	-0.09*	-0.04	-0.06*	-0.09***	(-2.58)
Bond age	-0.03	-0.17***	-0.14**	-0.17***	-0.08*	-0.14***	(-3.96)	0.00	-0.14***	-0.09*	-0.16***	-0.05	-0.10**	(-2.28)
Firm age	-0.16**	-0.05	-0.16**	-0.04	-0.10*	-0.07*	(-1.71)	-0.18*	-0.02	-0.15**	-0.14**	-0.06*	-0.08*	(-1.80)
Leverage	-0.05	-0.15**	-0.21**	-0.22**	-0.11*	-0.12**	(-2.01)	-0.02	-0.15*	-0.14*	-0.18**	-0.06*	-0.07*	(-1.65)
Firm size	-0.13**	-0.05	-0.15**	-0.17**	-0.09*	-0.13**	(-1.98)	-0.07*	-0.03	-0.09*	-0.14**	-0.08*	-0.09*	(-1.75)
# Analysts	-0.31***	-0.07	-0.06	-0.21***	-0.15**	-0.12**	(-2.18)	-0.29**	-0.06	-0.05	-0.18**	-0.12*	-0.10*	(-1.82)
Dispersion	-0.13**	-0.17***	-0.15**	-0.02	-0.13*	-0.09*	(-1.89)	-0.12*	-0.15**	-0.13**	-0.04	-0.10*	-0.08*	(-1.89)
# S_Institution	-0.25***	-0.06	-0.09	-0.08*	-0.09*	-0.08*	(-1.70)	-0.24***	-0.05	-0.07	-0.05	-0.10*	-0.10*	(-1.70)
S_Holding	-0.18*	-0.15*	-0.14*	-0.22**	-0.16*	-0.14***	(-2.64)	-0.19*	-0.09	-0.14*	-0.21**	-0.13*	-0.09*	(-1.65)

Table 4

Distribution of VIX beta and excess returns of VIX beta portfolios by rating

This table reports average VIX beta (Panel A) and monthly characteristic-adjusted returns and alphas (Panel B) for each portfolio. For each month *t*, we first group bonds into five portfolios by rating (Aaa, Aa, A, Baa, and below) in the past month, and then within each portfolio, we sort bonds on their β_{VIX} loadings into quintile portfolios. All portfolios are rebalanced monthly and are equally weighted. The column "5-1" refers to the difference in monthly returns between portfolio 5 (highest β_{VIX}) and portfolio 1 (lowest β_{VIX}). Panel C reports the results of cross-sectional regression tests based on the portfolios formed by rating (Aaa to B3 & below) and maturity (≤5 years, 5 to 10 years, and ≥10 years). Numbers in parentheses are *t*-statistics. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Distribution of VIX beta by rating

β_{VIX}	1	2	3	4	5	5-1	*t*-value
Aaa	-0.32	-0.06	0.02	0.09	0.39	0.70***	(39.44)
Aa	-0.46	-0.15	-0.01	0.12	0.48	0.94***	(65.29)
A	-0.50	-0.11	0.00	0.10	0.46	0.95***	(84.40)
Baa	-0.57	-0.07	0.01	0.09	0.37	0.95***	(75.51)
Junk	-0.76	-0.25	-0.03	0.18	0.65	1.41***	(60.59)

Panel B: Returns of VIX beta portfolios by rating

Rating	Characteristic-adjusted returns							Alphas						
	1	2	3	4	5	5-1	*t*-value	1	2	3	4	5	5-1	*t*-value
Aaa	0.04	0.02	0.01	-0.01	-0.05	-0.09*	(-1.72)	0.03	0.02	0.01	-0.02	-0.04	-0.07*	(-1.81)
Aa	0.10	0.05	0.01	-0.02	-0.09	-0.19***	(-3.71)	0.09	0.06	0.01	-0.02	-0.08	-0.17***	(-2.97)
A	0.03	-0.02	-0.17	-0.20	-0.20	-0.23***	(-4.07)	0.04	0.02	-0.15	-0.15	-0.15	-0.19***	(-5.16)
Baa	0.08	0.01	-0.12	-0.12	-0.18	-0.26***	(-6.28)	0.09	0.01	-0.11	-0.12	-0.16	-0.25***	(-4.43)
Junk	0.18	0.14	-0.10	-0.12	-0.22	-0.41***	(-4.63)	0.18	0.14	-0.09	-0.15	-0.22	-0.40***	(-3.72)

Panel C: Cross-sectional regressions of rating-maturity portfolio returns

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	β_{VIX}	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
Pastor-Stambaugh liquidity measure													
0.47**	0.04	0.04	0.05	0.13***	0.05**	0.14***	-0.09***	-0.15***	-0.04*	0.14**	-0.01	0.02	0.595
(2.42)	(1.05)	(1.29)	(1.23)	(4.04)	(2.38)	(5.72)	(-2.91)	(-2.72)	(-1.76)	(2.16)	(-0.12)	(0.44)	
Amihud liquidity measure													
0.31*	0.01	0.01	0.07*	0.11***	0.07*	0.14***	-0.10***	-0.13**	-0.03	0.12*	0.00	0.01	0.600
(1.71)	(0.18)	(0.38)	(1.93)	(3.64)	(1.91)	(5.14)	(-2.63)	(-2.35)	(-1.50)	(1.92)	(0.02)	(0.16)	

Table 5
Asset pricing tests of individual bonds

This table reports the results of cross-sectional regression tests of individual bonds using the Fama-MacBeth methodology, where betas are estimated over a rolling past five-year window for each bond. The dependent variable is a bond's monthly return in excess of the one-month T-bill rate. β_{MKT}, β_{SMB}, β_{HML}, β_{DEF}, β_{TERM}, β_{LIQ}, and β_{VIX} are betas of market, firm size, book-to-market, default, term, liquidity, and VIX factors. In addition to risk factors, we consider bond characteristics such as coupon rate, issue size, rating, age, and maturity as explanatory variables. Panels A and B report results based on the Pastor-Stambaugh and Amihud liquidity indices, respectively. Panel C reports the regression results for each rating category, and Panel D shows regressions for NAIC and TRACE subsamples. Shanken's (1992) method is used to correct the bias in standard errors. Numbers in parentheses are t-statistics. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Pastor-Stambaugh liquidity measure

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	β_{VIX}	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
0.07	0.09***						-0.16***						0.022
(1.04)	(3.51)						(-2.73)						
0.06	0.10***			0.02***	0.04**		-0.15**						0.036
(0.99)	(3.55)			(3.83)	(2.25)		(-2.54)						
-0.01	0.07***			0.02***	0.05***	0.10***	-0.12**						0.051
(-0.17)	(2.78)			(4.34)	(2.96)	(4.03)	(-2.19)						
-0.01	0.10***	0.03	-0.04	0.02***	0.04***	0.10***	-0.14**						0.066
(-0.13)	(3.47)	(0.41)	(-0.87)	(4.33)	(2.56)	(4.07)	(-2.26)						
0.19**	0.03			0.02***	0.03**	0.07***	-0.09**	-0.07***	-0.12	0.04***	-0.18	0.01**	0.124
(2.50)	(1.19)			(4.05)	(1.96)	(3.73)	(-2.19)	(-7.98)	(-0.65)	(4.43)	(-0.51)	(2.24)	
0.17**	0.04	-0.08	-0.04	0.02***	0.03*	0.07***	-0.08**	-0.07***	-0.13	0.04***	-0.09	0.01**	0.134
(2.31)	(1.59)	(-1.13)	(-0.89)	(4.37)	(1.72)	(3.88)	(-1.97)	(-7.87)	(-0.68)	(4.65)	(-0.27)	(2.20)	

Panel B: Amihud liquidity measure

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	β_{VIX}	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
0.07	0.07***						-0.15***						0.019
(1.08)	(2.67)						(-2.60)						
0.06	0.08***			0.02***	0.04***		-0.14**						0.033
(0.98)	(2.90)			(4.31)	(2.76)		(-2.41)						
-0.02	0.06**			0.02***	0.05***	0.09***	-0.11**						0.053
(-0.38)	(2.38)			(4.83)	(3.01)	(3.21)	(-1.99)						
-0.02	0.08***	0.01	0.02	0.02***	0.05***	0.09***	-0.12**						0.068
(-0.36)	(2.98)	(0.00)	(0.33)	(4.73)	(2.71)	(3.24)	(-2.01)						
0.22***	0.03			0.02***	0.03**	0.04**	-0.11**	-0.07***	-0.20	0.03***	-0.05	0.01**	0.123
(3.02)	(1.47)			(4.19)	(2.34)	(1.95)	(-2.31)	(-8.21)	(-1.05)	(4.46)	(-0.14)	(2.40)	
0.21***	0.03	-0.10	-0.02	0.02***	0.03**	0.04**	-0.11**	-0.07***	-0.18	0.04***	-0.02	0.01**	0.133
(2.90)	(1.44)	(-1.42)	(-0.31)	(4.38)	(2.00)	(2.11)	(-2.11)	(-8.36)	(-0.98)	(4.82)	(-0.01)	(2.31)	

Panel C: Cross-sectional regressions of individual bonds by rating using the Amihud liquidity measure

Beta	*Aaa*	*Aa1*	*Aa2*	*Aa3*	*A1*	*A2*	*A3*	*Baa1*	*Baa2*	*Baa3*	*Ba*	*B & below*
β_{MKT}	-0.07	0.19	0.07^{*}	0.07^{**}	0.05^{**}	0.07^{**}	0.05^{*}	0.02	0.09^{**}	0.06	-0.03	0.07
	(-1.55)	(1.39)	(1.94)	(1.98)	(2.04)	(2.01)	(1.83)	(0.58)	(2.47)	(1.43)	(-0.68)	(0.52)
β_{SMB}	0.01	0.08^{***}	0.11^{**}	0.02	0.01	0.01	0.05^{*}	0.02	0.05^{*}	0.02	0.09	-0.02
	(0.12)	(3.09)	(2.54)	(0.83)	(0.51)	(0.34)	(1.87)	(0.87)	(1.73)	(0.46)	(1.61)	(-0.14)
β_{HML}	0.02	-0.01	-0.03	0.01	0.01	0.02	0.02	0.05^{**}	-0.01	-0.05	-0.02	0.05
	(-0.09)	(-0.07)	(-0.74)	(0.27)	(0.46)	(0.64)	(0.78)	(2.01)	(-0.45)	(-1.18)	(-0.54)	(0.01)
β_{DEF}	0.02^{*}	0.03	0.06^{*}	0.05^{*}	0.04^{**}	0.05^{*}	0.08^{**}	0.10^{*}	0.10^{***}	0.12^{*}	0.13^{***}	0.16^{**}
	(1.75)	(1.44)	(1.66)	(1.72)	(2.18)	(1.68)	(2.17)	(1.72)	(2.82)	(1.81)	(3.11)	(2.54)
β_{TERM}	0.07^{**}	0.08^{***}	0.09^{***}	0.07^{***}	0.04^{**}	0.11^{***}	0.07^{***}	0.09^{***}	0.07^{**}	0.12^{***}	0.10^{***}	0.06^{*}
	(2.29)	(3.72)	(3.96)	(2.71)	(2.23)	(4.17)	(3.37)	(3.26)	(2.37)	(3.34)	(3.91)	(1.82)
β_{LIQ}	0.04	0.03^{***}	0.07^{***}	0.07^{***}	0.05^{***}	0.04^{*}	0.05^{**}	0.06^{**}	0.05^{***}	0.08^{***}	0.07^{***}	0.09^{**}
	(1.36)	(2.60)	(2.82)	(3.74)	(2.83)	(1.68)	(2.09)	(2.26)	(2.68)	(2.94)	(2.92)	(2.48)
β_{VIX}	-0.06^{**}	-0.05^{*}	-0.06^{*}	-0.07^{**}	-0.06^{**}	-0.07^{***}	-0.05^{*}	-0.08^{**}	-0.10^{***}	-0.12^{**}	-0.16^{***}	-0.13^{***}
	(-2.09)	(-1.83)	(-1.89)	(-2.06)	(-2.16)	(-2.77)	(-1.88)	(2.48)	(-2.72)	(-2.44)	(-3.13)	(-2.69)
Adj. R^2	0.581	0.733	0.471	0.376	0.267	0.201	0.262	0.258	0.273	0.309	0.277	0.340

Panel D: Cross-sectional regressions based on NAIC and TRACE subsamples

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	β_{VIX}	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
NAIC	Pastor-Stambaugh liquidity measure													
	0.34^{***}	-0.01	-0.10	-0.04	0.03^{***}	0.04^{*}	0.08^{**}	-0.06^{**}	-0.12^{***}	0.00	0.05^{***}	-0.01	0.03^{***}	0.169
	(3.69)	(-0.10)	(-1.32)	(-0.69)	(4.75)	(1.74)	(1.96)	(-2.10)	(8.22)	(0.09)	(4.54)	(-1.52)	(4.53)	
	Amihud liquidity measure													
	0.33^{***}	0.06	-0.07	-0.09	0.02^{***}	0.04^{**}	0.06^{**}	-0.06^{**}	-0.12^{***}	0.01	0.05^{***}	-0.01	0.03^{***}	0.167
	(3.51)	(0.66)	(-0.80)	(-1.52)	(3.80)	(2.29)	(2.07)	(-2.30)	(-8.42)	(0.40)	(4.50)	(-0.75)	(4.49)	
TRACE	Pastor-Stambaugh liquidity measure													
	0.04	0.05	0.02	-0.05	0.03^{***}	0.09^{***}	0.14^{***}	-0.09^{*}	-0.06^{***}	0.00	0.03^{***}	0.00	0.01^{**}	0.137
	(0.70)	(0.50)	(0.23)	(-0.93)	(4.76)	(4.63)	(5.96)	(-1.91)	(-7.60)	(-0.81)	(4.26)	(0.89)	(2.03)	
	Amihud liquidity measure													
	0.07	0.05	-0.01	-0.03	0.03^{***}	0.10^{***}	0.09^{***}	-0.12^{**}	-0.07^{***}	0.00	0.03^{***}	0.00	0.01^{**}	0.136
	(1.32)	(0.45)	(-0.13)	(-0.51)	(4.93)	(5.26)	(4.25)	(-2.01)	(-7.71)	(-1.33)	(4.31)	(0.60)	(2.00)	

Table 6

Idiosyncratic bond volatility portfolio returns and alphas

Univariate sorts, portfolio sorts controlling for cross-sectional effects, and subsample univariate sorts are reported in Panels A, B, and C. Idiosyncratic volatility (*IVol*) is relative to the FF5-factor model. *Return* is excess returns and *AdjRet* is returns adjusted for rating and maturity. Alphas are from the FF5-factor model with VIX. Columns 1 to 5 report long-short returns/alphas for each portfolio, and column "H-L" reports long-short returns of portfolios sorted on β_{VIX} averaged across characteristic quintiles. All other variables are as defined in Table 3. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Univariate portfolio sorts on idiosyncratic bond volatility

IVol	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1	*t*-value
Return	-0.09	-0.08	-0.05	0.02	0.05	0.10	0.07	0.14	0.23	0.43	0.52***	(2.74)
AdjRet	-0.12	-0.12	-0.10	-0.06	-0.04	-0.00	0.01	0.03	0.06	0.18	0.30***	(3.08)
Return alpha	-0.11	-0.10	-0.07	-0.02	0.01	-0.00	0.04	0.09	0.13	0.28	0.39***	(3.16)
AdjRet alpha	-0.09	-0.10	-0.08	-0.05	-0.02	0.00	0.02	0.03	0.04	0.13	0.22***	(2.65)

Panel B: Idiosyncratic bond volatility portfolio sorts controlling for cross-sectional effects

	Long-short returns for each quintile portfolio					Average		Long-short alphas for each quintile portfolio					Average	
Characteristic	1	2	3	4	5	H-L	*t*-value	1	2	3	4	5	H-L	*t*-value
Volume	0.15**	0.29***	0.27***	0.41***	0.40***	0.24***	(3.76)	0.10*	0.23***	0.20**	0.33***	0.31***	0.23***	(3.32)
Amihud	0.13*	0.28***	0.38***	0.41***	0.45***	0.26***	(4.33)	0.25***	0.25***	0.30***	0.34***	0.34***	0.25***	(4.16)
IRC	0.07	0.10*	0.21***	0.31***	0.56***	0.21***	(3.81)	0.13**	0.08	0.19***	0.27***	0.47***	0.21***	(4.33)
Volatility	0.07**	0.16***	0.26***	0.42***	0.66***	0.25***	(5.22)	0.15***	0.16***	0.26***	0.38***	0.57***	0.26***	(6.70)
PS beta	0.26***	0.24***	0.37***	0.36***	0.32***	0.26***	(4.31)	0.23***	0.18**	0.32***	0.28***	0.21**	0.24***	(3.89)
Amihud beta	0.15**	0.34***	0.35***	0.28***	0.33***	0.24***	(4.08)	0.14**	0.29***	0.30***	0.22***	0.21**	0.23***	(3.73)
Rating	0.08*	0.15***	0.31***	0.21**	0.34***	0.16**	(1.99)	0.07	0.14**	0.23***	0.17**	0.58***	0.19**	(2.09)
Maturity	0.26***	0.15*	0.25***	0.18*	0.20*	0.19*	(1.79)	0.22***	0.11	0.18**	0.11	0.13*	0.15*	(1.87)
Coupon	0.23**	0.22***	0.35***	0.43***	0.45***	0.29***	(4.72)	0.17**	0.22***	0.31***	0.35***	0.35***	0.25***	(3.52)
Bond age	0.16*	0.25**	0.34***	0.45***	0.41***	0.28***	(4.29)	0.11	0.15*	0.28***	0.38***	0.33***	0.24***	(3.40)
Firm age	0.06*	0.07**	0.05	0.02	0.04	0.06**	(2.29)	0.07*	0.08*	0.03	0.07	0.13**	0.11**	(2.02)
Leverage	0.21*	0.22**	0.37***	0.33***	0.27*	0.26***	(4.00)	0.11	0.22**	0.26**	0.22**	0.17*	0.23***	(3.50)
Firm size	0.59***	0.31*	0.65***	0.44**	0.34*	0.39***	(4.64)	0.49***	0.21*	0.59***	0.28*	0.32***	0.29***	(4.18)
# Analysts	0.29**	0.08	0.09*	0.20**	0.26**	0.14*	(1.88)	0.20**	0.18**	0.17**	0.15	0.25***	0.18*	(1.82)
Dispersion	0.18**	0.20**	0.27***	0.19**	0.15*	0.20**	(2.27)	0.21**	0.20***	0.21***	0.15	0.17*	0.20**	(2.22)
#S Institution	0.19*	0.25**	0.10	0.16*	0.15*	0.17*	(1.84)	0.25**	0.14	0.14	0.17*	0.16*	0.17*	(1.78)
S Holding	0.26**	0.11	0.35***	0.15*	0.13*	0.18*	(1.90)	0.32**	0.14	0.31***	0.15*	0.10	0.19*	(1.84)

Panel C: Subsample results of univariate portfolio sorts on idiosyncratic bond volatility

	IVol	1	2	3	4	5	6	7	8	9	10	10-1	*t*-value
NAIC	*Return*	-0.04	-0.04	-0.04	0.00	0.02	0.09	0.07	0.11	0.10	0.22	0.26**	(2.48)
	AdjRet	-0.04	0.03	0.02	0.08	0.07	0.06	0.07	0.05	0.08	0.07	0.11*	(1.79)
	Return alpha	-0.05	-0.04	-0.04	-0.00	0.01	0.09	0.07	0.10	0.08	0.20	0.24***	(2.60)
	AdjRet alpha	-0.05	0.07	0.06	0.08	0.06	0.08	0.03	0.03	0.04	0.08	0.12**	(2.03)
TRACE	*Return*	-0.12	-0.12	-0.08	-0.02	0.03	0.07	0.13	0.21	0.16	0.38	0.51***	(2.80)
	AdjRet	-0.14	-0.15	-0.13	-0.09	-0.05	-0.03	0.01	0.06	0.05	0.17	0.32***	(3.52)
	Return alpha	-0.14	-0.15	-0.13	-0.09	-0.04	-0.02	0.02	0.07	0.08	0.19	0.33**	(2.39)
	AdjRet alpha	-0.10	-0.12	-0.10	-0.07	-0.03	-0.03	-0.00	0.02	0.05	0.10	0.20**	(2.08)

Table 7

Cross-sectional regressions with total and idiosyncratic return volatilities

This table reports cross-sectional regressions with total return volatility (*Vol*) and idiosyncratic volatility (*IVol)* of bonds (Panel A) or stocks (Panel B). Total return volatility and idiosyncratic volatility are estimated using returns over the past six months for bonds and daily returns over the past one month for stocks. Interaction variables between rating and volatility (*Vol*R* or *IVol*R*) capture the differential effect of ratings *R* (Aaa=0, Aa+=1,…, C=20, and D=21). β_{MKT}, β_{SMB}, β_{HML}, β_{DEF}, β_{TERM}, β_{L}, and β_{VIX} are betas of market, firm size, book-to-market, default, term, liquidity, and VIX factors. Bond characteristics include coupon rate, issue size, ratings, age, and maturity. Panel C reports the results of regressions with stock volatilities and contemporaneous (*Sret*) and lagged stock returns (*Sret1*). Panel D reports the results where bond returns are adjusted for the contemporaneous stock returns. Shanken's (1992) method is used to correct the bias in standard errors, and *t*-values are in parentheses. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bond idiosyncratic volatility

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{L}	β_{VIX}	*Vol*	*Vol*R*	*IVol*	*IVol*R*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
-0.06	0.02	-0.02	-0.02	0.07***	0.06**	0.05***	-0.03**	0.20***				-0.10***	0.02	0.07**	-0.03	0.01	0.190
(-0.97)	(0.83)	(-1.22)	(-1.24)	(3.39)	(2.50)	(3.22)	(-2.36)	(6.40)				(-4.54)	(1.33)	(2.51)	(-1.43)	(0.16)	
-0.03	0.02	-0.02	-0.01	0.08***	0.06***	0.07***	-0.05**			0.18***		-0.11***	0.01	0.08***	-0.01	0.02	0.190
(-0.53)	(0.72)	(-1.05)	(-0.78)	(3.49)	(2.62)	(4.21)	(-2.03)			(5.92)		(-5.22)	(0.64)	(2.62)	(-0.69)	(0.44)	
0.06	0.01	-0.03*	-0.02	0.07***	0.06**	0.05***	-0.03**	0.12***	0.05***			-0.09***	0.01		-0.03*	0.01	0.201
(1.09)	(0.54)	(-1.69)	(-1.14)	(3.30)	(2.55)	(3.39)	(-2.18)	(3.28)	(3.43)			(-4.53)	(0.91)		(-1.77)	(0.30)	
0.08	0.01	-0.03	-0.02	0.08***	0.06***	0.07***	-0.04**			0.10***	0.04***	-0.10***	0.00		-0.02	0.02	0.201
(1.47)	(0.38)	(-1.53)	(-0.90)	(3.42)	(2.60)	(4.40)	(-1.98)			(2.82)	(3.31)	(-5.22)	(0.16)		(-1.04)	(0.60)	

Panel B: Stock idiosyncratic volatility

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{L}	β_{VIX}	*Vol*	*Vol*R*	*IVol*	*IVol*R*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
0.27**	0.02	-0.03	-0.01	0.11***	0.06***	0.09***	-0.07***	-0.07***				-0.09***	-0.02	0.04	-0.01	0.08*	0.228
(2.17)	(1.11)	(-1.62)	(-0.80)	(5.52)	(3.20)	(5.54)	(-3.24)	(-2.76)				(-4.02)	(-0.92)	(1.23)	(-0.62)	(1.79)	
0.25**	0.02	-0.02	-0.01	0.12***	0.06***	0.08***	-0.07***			-0.06**		-0.09***	-0.02	0.03	-0.01	0.09*	0.228
(2.13)	(1.02)	(-1.35)	(-0.77)	(5.51)	(3.16)	(5.23)	(-3.11)			(-2.12)		(-3.66)	(-1.10)	(0.91)	(-0.64)	(1.88)	
0.38***	0.02	-0.03*	-0.01	0.12***	0.07***	0.09***	-0.07***	-0.07**	-0.01*			-0.10***	-0.02		-0.01	0.08*	0.231
(3.20)	(1.17)	(-1.67)	(-0.91)	(5.67)	(3.34)	(5.51)	(-3.15)	(-2.48)	(-1.95)			(-4.50)	(-0.87)		(-0.51)	(1.79)	
0.35***	0.02	-0.03	-0.02	0.12***	0.07***	0.09***	-0.08***			-0.06**	-0.01*	-0.09***	-0.02		-0.01	0.09*	0.231
(2.99)	(0.77)	(-1.35)	(-1.03)	(5.59)	(3.30)	(5.32)	(-3.16)			(-2.13)	(-1.94)	(-4.23)	(-1.07)		(-0.42)	(1.91)	

Panel C: Stock idiosyncratic volatility with stock returns

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{L}	β_{VIX}	*Vol*	*IVol*	*Sret*	*Sret1*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
0.17	0.03	-0.03*	-0.01	0.12***	0.06***	0.08***	-0.08***	-0.04*		0.39***		-0.09***	-0.01	0.03	-0.02	0.08*	0.247
(1.39)	(1.47)	(-1.90)	(-0.77)	(5.66)	(3.12)	(5.43)	(-3.34)	(-1.81)		(14.63)		(-3.79)	(-0.68)	(0.76)	(-0.88)	(1.75)	
0.18	0.03	-0.03	-0.01	0.12***	0.06***	0.08***	-0.08***	-0.04*		0.37***	0.22***	-0.09***	-0.02	0.01	-0.03	0.09*	0.259
(1.52)	(1.43)	(-1.57)	(-0.92)	(5.89)	(3.32)	(5.27)	(-3.53)	(-1.82)		(15.18)	(10.52)	(-3.66)	(-0.84)	(0.38)	(-1.28)	(1.87)	
0.18	0.03	-0.03*	-0.01	0.12***	0.06***	0.08***	-0.08***		0.01	0.39***		-0.09***	-0.02	0.02	-0.02	0.08*	0.248
(1.54)	(1.38)	(-1.76)	(-0.71)	(5.57)	(3.13)	(5.29)	(-3.38)		(0.43)	(15.22)		(-3.55)	(-0.82)	(0.50)	(-0.90)	(1.83)	
0.21*	0.03	-0.03	-0.01	0.12***	0.06***	0.08***	-0.08***		0.01	0.37***	0.23***	-0.08***	-0.02	0.01	-0.03	0.09*	0.260
(1.74)	(1.48)	(-1.38)	(-0.81)	(5.80)	(3.29)	(5.22)	(-3.61)		(0.43)	(15.84)	(10.69)	(-3.46)	(-0.93)	(0.17)	(-1.29)	(1.90)	

Panel D: Stock idiosyncratic volatility with bond returns adjusted for contemporaneous stock returns

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_L	β_{VIX}	*Vol*	*IVol*	*Sret1*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
0.00	-0.04*	-0.04**	-0.03	0.14***	0.05**	0.09***		0.02		0.17***	-0.09***	-0.02	0.03	0.00	0.07	0.246
(-0.01)	(-1.84)	(-2.34)	(-1.27)	(6.05)	(2.01)	(5.11)		(0.87)		(7.11)	(-3.97)	(-0.91)	(0.79)	(-0.18)	(1.39)	
0.01	-0.03	-0.04**	-0.02	0.15***	0.05**	0.10***	-0.07***	0.02		0.17***	-0.09***	-0.02	0.02	0.00	0.06	0.257
(0.04)	(-1.24)	(-2.02)	(-1.14)	(6.40)	(2.09)	(5.34)	(-2.59)	(0.83)		(7.15)	(-4.09)	(-0.99)	(0.45)	(0.04)	(1.20)	
0.03	-0.04*	-0.04**	-0.02	0.14***	0.06**	0.09***			0.04	0.18***	-0.09***	-0.02	0.01	-0.01	0.07	0.246
(0.28)	(-1.79)	(-2.17)	(-1.22)	(5.91)	(2.27)	(4.83)			(1.42)	(7.67)	(-3.86)	(-0.93)	(0.36)	-(0.34)	(1.42)	
0.02	-0.03	-0.03	-0.02	0.15***	0.05**	0.10***	-0.08***		0.04	0.18***	-0.08***	-0.02	0.00	0.00	0.06	0.257
(0.17)	(-1.19)	(-1.58)	(-1.21)	(6.37)	(2.23)	(5.09)	(-2.76)		(1.63)	(7.74)	(-3.89)	(-0.89)	(-0.08)	(-0.17)	(1.20)	

Table 8
Cross-sectional regressions with bond and stock volatilities

This table reports the results of Fama-MacBeth cross-sectional regressions with both bond and stock volatilities. *BVol* and *BIVol* (*SVol* and *SIVol*) are bond (stock) total and idiosyncratic return volatilities. Total return volatility and idiosyncratic volatility are estimated using daily observations over the past six months for bonds and the past one month for stocks. Idiosyncratic volatilities are calculated relative to the FF5-factor model with VIX. Other variables are as defined in Table 7. Shanken's (1992) method is used to correct the bias in standard errors, and *t*-values are in parentheses. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_L	β_{VIX}	*BVol*	*BIVol*	*SVOL*	*SIVOL*	*Sret*	*Sret1*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
0.04	0.03	-0.02	-0.03	0.12***	0.05**	0.07***	-0.10***	0.13***		-0.05*				-0.04	0.01	0.01	-0.08**	0.02	0.320
(0.23)	(1.06)	(-0.88)	(-1.09)	(4.10)	(2.13)	(3.44)	(-2.97)	(3.98)		(-1.76)				(-1.29)	(0.31)	(0.37)	(-2.43)	(0.37)	
-0.15	0.05	-0.05**	-0.03	0.13***	0.02*	0.05***	-0.11***	0.14***		-0.01		0.35***	0.23***	-0.02	0.01	-0.02	-0.10***	0.03	0.357
(-0.75)	(1.67)	(-2.22)	(-1.02)	(4.45)	(1.85)	(2.78)	(-3.31)	(4.32)		(-0.22)		(13.86)	(9.82)	(-0.62)	(0.48)	(-0.44)	(-2.83)	(0.61)	
0.04	0.02	-0.04	-0.02	0.12***	0.05**	0.08***	-0.09***		0.08**		-0.06**			-0.05	-0.01	0.01	-0.06**	0.05	0.321
(0.26)	(0.74)	(-1.57)	(-0.83)	(3.97)	(2.20)	(3.58)	(-2.93)		(2.55)		(-2.01)			(-1.40)	(-0.26)	(0.22)	(-1.98)	(0.98)	
-0.09	0.04	-0.05**	-0.02	0.13***	0.02**	0.05***	-0.11***		0.10***		-0.03	0.35***	0.22***	-0.03	0.00	-0.01	-0.09**	0.05	0.357
(-0.42)	(1.19)	(-2.12)	(-0.95)	(4.27)	(2.10)	(2.79)	(-3.46)		(3.24)		(-1.07)	(14.31)	(10.02)	(-0.73)	(0.07)	(-0.31)	(-2.44)	(1.05)	

Table 9

Subsample cross-sectional regressions with total and idiosyncratic return volatilities

This table reports the subsample results based on NAIC and TRACE data, respectively. All variables and test significance levels are as defined in Table 7.

Panel A: Bond idiosyncratic volatility

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{L}	β_{VIX}	*Vol*	*Vol*R*	*IVol*	*IVol*R*	*Coupon*	*Size*	*Age*	*Maturity*	Adj. R^2
NAIC	0.05	0.04	-0.03	-0.03	0.13***	0.11***	0.05**	-0.06*	0.12***	0.02**			-0.08***	0.01	-0.03	0.06	0.227
	(0.68)	(0.24)	(-0.90)	(-0.86)	(3.21)	(3.37)	(2.52)	(-1.75)	(4.76)	(2.14)			(-2.79)	(0.49)	(-0.81)	(1.08)	
	0.11	0.04	-0.02	-0.03	0.14***	0.11***	0.07***	-0.07*			0.10***	0.02**	-0.08**	-0.00	-0.02	0.07	0.225
	(1.42)	(0.29)	(-0.79)	(-0.69)	(3.32)	(3.38)	(3.34)	(-1.86)			(4.13)	(2.05)	(-3.02)	(-0.23)	(-0.43)	(1.23)	
TRACE	-0.04	0.00	-0.02	-0.03	0.06***	0.10***	0.06***	-0.06**	0.13***	0.04***			-0.09***	0.02	-0.04	-0.01	0.198
	(-0.83)	(0.08)	(-1.03)	(-1.37)	(2.59)	(3.93)	(3.21)	(-1.98)	(2.94)	(2.62)			(-3.62)	(1.05)	(-1.61)	(-0.28)	
	-0.02	0.01	-0.02	-0.03	0.07***	0.10***	0.07***	-0.08**			0.11**	0.04***	-0.10***	0.01	-0.02	0.00	0.198
	(-0.36)	(0.25)	(-0.98)	(-1.35)	(2.75)	(4.01)	(4.13)	(-2.37)			(2.44)	(2.61)	(-4.28)	(0.42)	(-1.01)	(-0.02)	

Panel B: Stock idiosyncratic volatility

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{L}	β_{MKT}	*Vol*	*Vol*R*	*IVol*	*IVol*R*	*Coupon*	*Size*	*Age*	*Maturity*	Adj. R^2
NAIC	0.70***	-0.01	-0.02	-0.01	0.13***	0.11***	0.11***	-0.06**	-0.16***	-0.02**			-0.15***	0.03	-0.01	0.14**	0.223
	(5.23)	(-0.14)	(-0.56)	(-0.46)	(4.20)	(3.26)	(4.99)	(-2.23)	(-5.03)	(-1.99)			(-5.96)	(1.06)	(-0.31)	(2.32)	
	0.62***	-0.01	-0.02	-0.01	0.13***	0.11***	0.11***	-0.06**			-0.19***	-0.02*	-0.15***	0.02	0.00	0.15**	0.223
	(4.88)	(-0.22)	(-0.69)	(-0.26)	(4.23)	(3.26)	(5.13)	(-2.19)			(-5.09)	(-1.67)	(-5.77)	(0.70)	(0.05)	(2.42)	
TRACE	0.17	0.02	-0.04*	0.00	0.12***	0.07***	0.07***	-0.10***	-0.05**	-0.02*			-0.10***	0.00	0.00	0.06	0.245
	(1.76)	(0.88)	(-1.78)	(0.18)	(5.76)	(3.62)	(3.82)	(-3.64)	(-2.28)	(-1.93)			(-4.00)	(0.03)	(0.11)	(1.24)	
	0.11	0.01	-0.03	0.01	0.12***	0.07***	0.07***	-0.11***			-0.03**	-0.02*	-0.09***	-0.01	0.00	0.07	0.244
	(1.20)	(0.57)	(-1.42)	(0.31)	(5.65)	(3.37)	(3.52)	(-3.58)			(-1.98)	(-1.86)	(-3.75)	(-0.32)	(0.06)	(1.35)	

Panel C: Stock idiosyncratic volatility with stock returns

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{L}	β_{MKT}	*Vol*	*IVol*	*Sret*	*Sret1*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
NAIC	0.37***	-0.01	-0.02	-0.01	0.14***	0.12***	0.11***	-0.06**	-0.04**		0.31***	0.30***	-0.16***	0.04	0.14***	-0.03	0.17***	0.251
	(2.60)	(-0.05)	(-0.57)	(-0.28)	(4.47)	(3.37)	(4.56)	(-2.25)	(-2.12)		(9.70)	(10.36)	(-5.91)	(1.42)	(3.29)	(-0.94)	(2.76)	
	0.32**	-0.01	-0.02	-0.01	0.15***	0.11***	0.11***	-0.06**		-0.05	0.29***	0.32***	-0.16***	0.04	0.13***	-0.02	0.17***	0.253
	(2.22)	(-0.21)	(-0.71)	(-0.18)	(4.58)	(3.28)	(4.70)	(-2.26)		(-1.56)	(9.59)	(10.45)	(-6.05)	(1.38)	(3.18)	(-0.70)	(2.78)	
TRACE	0.09	0.03	-0.03	0.01	0.13***	0.07***	0.07***	-0.11***	-0.03*		0.30***	0.18***	-0.10***	0.00	0.01	-0.01	0.07	0.268
	(0.82)	(1.40)	(-1.32)	(0.31)	(6.12)	(3.40)	(3.77)	(-3.92)	(-1.72)		(11.61)	(7.47)	(-3.46)	(0.15)	(0.31)	(-0.31)	(1.33)	
	0.08	0.03	-0.03	0.00	0.13***	0.07***	0.07***	-0.11***		0.01	0.31***	0.18***	-0.10***	0.00	0.00	-0.01	0.07	0.269
	(0.87)	(1.43)	(-1.18)	(0.27)	(6.02)	(3.49)	(3.68)	(-3.93)		(0.32)	(11.89)	(7.73)	(-3.37)	(-0.01)	(0.10)	(-0.37)	(1.37)	

Panel D: Stock idiosyncratic volatility with bond returns adjusted for contemporaneous stock returns

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{L}	β_{MKT}	*Vol*	*IVol*	*Sret1*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj. R^2
NAIC	0.30*	-0.01	-0.03	-0.02	0.16***	0.12***	0.15***	-0.09**	-0.05		0.26***	-0.17***	0.04	0.14***	-0.01	0.14**	0.298
	(1.70)	(-0.31)	(-0.89)	(-0.54)	(3.73)	(2.67)	(3.89)	(-2.31)	(-1.29)		(7.99)	(-4.82)	(1.45)	(2.85)	(-0.45)	(2.04)	
	0.25	-0.01	-0.02	-0.02	0.16***	0.11***	0.14***	-0.08**		-0.03	0.28***	-0.16***	0.04	0.12**	-0.01	0.14**	0.297
	(1.50)	(-0.13)	(-0.71)	(-0.45)	(3.69)	(2.63)	(3.89)	(-2.08)		(-0.74)	(8.54)	(-4.69)	(1.42)	(2.40)	(-0.42)	(2.13)	
TRACE	0.09	0.00	-0.04*	-0.02	0.13***	0.09***	0.11***	-0.12***	0.01		0.15***	-0.12***	-0.02	-0.01	0.04	0.07	0.242
	(0.77)	(-0.18)	(-1.91)	(-0.94)	(5.16)	(3.53)	(5.33)	(-3.61)	(-0.04)		(5.94)	(-4.64)	(-0.65)	(-0.30)	(1.36)	(1.23)	
	0.09	-0.01	-0.04*	-0.02	0.13***	0.09***	0.10***	-0.11***		0.02	0.15***	-0.11***	-0.02	-0.02	0.03	0.07	0.243
	(0.90)	(-0.33)	(-1.78)	(-0.87)	(5.06)	(3.65)	(5.00)	(-3.51)		(0.78)	(5.89)	(-4.59)	(-0.73)	(-0.61)	(1.22)	(1.27)	