Does stock return's idiosyncratic volatility still predict corporate bond returns?

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Abstract

In contrast to earlier decades, since the early 2000s, the average idiosyncratic volatility of stocks has fallen back to its pre-1990s level. Here, we examine whether decreasing volatility still helps to explain the cross-sectional variation of bond returns. Using a panel data of corporate bond returns spanning July 2002 to June 2016, we find that the average bond returns and lag idiosyncratic volatility are positively associated. The average returns on bonds with high sensitivities to average idiosyncratic volatilities exceed bonds with low sensitivities by about 2.4% for financial firms and 1.5% for nonfinancial firms. The positive association is robust when we control for size, bond ratings, leverage ratio, and bond maturity as well as the effects of default spread, term spread, and liquidity spread. The results suggest that idiosyncratic volatility is still an important factor in explaining the cross-sectional variation of average bond returns.

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1. Introduction

Merton' (1974) seminal paper and the ensuing burgeoning literature on structural models of credit pricing demonstrate that asset volatility is a critical, pertinent determinant of default risk (see, e.g., Acharya and Carpenter, 2002, for detailed analysis). This facet of firms is quite crucial in that when uncertainty about reported asset values is added to our consideration, credit spreads across virtually all maturities can be explained (Duffie and Lando, 2001). Campbell and Taksler (2003, hereafter CT) find that equity volatility—a proxy for asset volatility—can explain the cross-sectional variation of both bond yields and credit ratings. As Campbell, Lettau, Malkiel, and Xu (2001, hereafter CLMX)[1] note, given the rising equity idiosyncratic risk during the pre-2000s decades, the findings of CT further underscore the potential importance of idiosyncratic volatility in explaining credit spreads. CLMX indeed find that increasing idiosyncratic volatility explains the increase of U.S. corporate bond yields during the period of the 1970s to the late 1990s. However, recent evidence shows that idiosyncratic volatility fell back to pre-1990s levels after 2003 (Brandt et al., 2009) except during the period of the global financial crisis. Our Figure 1 shows that indeed post-2000, average idiosyncratic volatility declined. Moreover, average returns of corporate bonds commove almost perfectly with the idiosyncratic volatility. This then begs an important question: in the cross-section of bonds, does equity idiosyncratic volatility still explain bond returns?

[Insert Figure 1 here]

To be exact, we first examine the direction as well as the magnitude of the relation between idiosyncratic volatility and average bond returns and the predictability power of the one-month lagged idiosyncratic volatility. Second, we study whether the association is higher for financial

[1] CLMX find that the firm-level volatility of U.S. firms increased from 1962 to 1997 relative to market volatility.

firms. Third, we explore for what type of firms the aforementioned is stronger. What we find is that the coefficients on the lag idiosyncratic volatility are higher when firm-level risk is also higher. Finally, we examine whether smaller firms are more susceptible to the association, meaning that bond returns of smaller firms are driven more or less by idiosyncratic volatility than that of larger firms.

Using data ranging from July 2002 to June 2016, we regress bond returns on idiosyncratic volatility and some term structures and firm level control variables. This allows us to see whether idiosyncratic volatility can still explain the variation of bond returns during periods when firm-level volatility decreases. We use panel regressions to capture firm and time effects.[2] Initially, we create a series of proxies of idiosyncratic volatility using the existing measures[3] of idiosyncratic volatility. Moreover, we use bonds returns as dependent variables from the returns reported in the Wharton Research Data Service (WRDS) bond database, which is consistent with Lin et al. (2011). Then we regress the returns of bonds in this month on lag idiosyncratic volatility and some other control variables. We examine whether the last month's idiosyncratic volatility still can explain the cross-sectional variation of bond returns for this month. Second, we divide our sample into two subgroup: financial firms and nonfinancial firms. We follow the convention of Fama and French (1997) industry classifications to categorize the firms. We consider banks, insurance, and financial institutions as financial firms. Third, we test whether the association between idiosyncratic volatilities (IVOLs) and bond returns is more subject to the

[2] According to Petersen (2009), Fama and Macbeth (1973), ordinary least squares (OLS) and Newey West (NW) standard errors are biased if both firm and year fixed effects are present. Peterson shows that Fama and Macbeth standard errors are biased downward; NW standard errors are also biased but in small magnitudes. So clustering provides unbiased standard errors. In this study, we also cluster the data at both the industry and year levels.
[3] In this study, we use six proxies to capture idiosyncratic volatility. Idiosyncratic volatility measures the standard deviation of the unexplained factors of the factor pricing models (see Fu, 2009, for details). Among other measures, we use the low frequency measures of IVOL used in Goyal and Santa-Clara (2003). Campbell and Taksler (2003) measure equity volatility using the last 180 days' standard deviation of returns. We use the CLMX (2001) measure of idiosyncratic volatility.

smaller firms. To study the size effect, we create decile portfolios based on market cap and rebalance them monthly. Then we regress bond returns and lag IVOLs for each decile and compare the lag IVOL coefficients to observe whether the associations are more prominent for smaller firms. Finally, we examine the association controlling IVOLs, hypothesizing that the association is higher if idiosyncratic volatility is higher. We create decile portfolios based on idiosyncratic volatility and rebalance them monthly. After creating the deciles, we run the same regressions for each decile portfolio, compare the coefficients of IVOLs among the deciles, and perceive the difference between the coefficients of the lowest deciles and the highest deciles. We categorize our sample as two subsamples, financial firms and nonfinancial firms, and conduct the study separately since the capital structures of these two types of firms are different.

Results using all the proxies suggest that idiosyncratic volatility is still priced in corporate bond returns. First, we find that lag idiosyncratic risk is positively and significantly associated with average bond returns. This suggests that firm-level volatility can predict future bond returns that are consistent with Merton (1974); a firm's risky corporate bond can be considered a put option on the value of the firm. If the volatility of the stock increases, the price of the put option also increases. Henceforth, the increased idiosyncratic volatility of the stock may lead the firm to distress and positively associate with the bonds' returns. The coefficient of lag IVOL using the Fama-French (FF) Three-Factor Model is 0.043, meaning that if the IVOL of the previous month increases by 1%, then the bond return increase in this month is 0.043% on average. Second, separate analyses of financial and nonfinancial firms reveal that the positive association is prominent for financial firms. The difference of coefficients of lag $IVOL_{FF}$ of financial firms and nonfinancial firms is 0.037, meaning that if the idiosyncratic volatility of financial firms increases by 1%, then the expected bond returns will increase by .037 more than bonds returns of nonfinancial firms. Therefore, the result is economically significant. Third, we find that the association between IVOLs and bond returns decreases monotonically with increases of firms' size (size effect) using Goyal and Santa-Clara (2003) for both financial and nonfinancial firms. However, IVOLs using the Capital Asset Pricing Model (CAPM) are not monotonically decreasing with increases in firm size for financial and nonfinancial firms. Though the difference of the coefficients between lowest decile (decile 2, as decile 1 is not statistically significant) and highest decile is 0.056 for nonfinancial firms, nevertheless the trend is not monotonic. Finally, we find that coefficients of IVOLs increase by the increase of firm-level volatility. Though the trend of the increase is not monotonic, the difference of the coefficients of the highest and lowest deciles is 0.024 for financial firms and 0.015 for nonfinancial firms when we consider the IVOL proxy using the Fama-French Three Factor Model. Interestingly, the coefficients for the financial firms' deciles are higher than the coefficients of nonfinancial firms. This suggests that average bond returns for financial firms are more positively associated with the lag IVOL measures than that of nonfinancial firms. Our results are robust when we conduct the analyses controlling for bond rating, leverage ratio, and bond categories.

We make several contributions to the existing literature. First, to our knowledge, only this study offers an extended analysis of idiosyncratic volatility and bond returns after 2002 when idiosyncratic volatility decreased. Moreover, we use the six proxies of idiosyncratic volatilities of stocks used in the existing literature to examine the effect of idiosyncratic volatility on bond returns. Previous versions of the CT (2003) study use equity volatility, standard deviations of past 180 days returns; however, measures of idiosyncratic volatility using factor pricing models gets little attention to explain the variation of average bonds returns. Second, we extend our analysis within the subsamples of financial and nonfinancial firms. The motivation for analyzing firms separately is that the two types of firms possess different financial characteristics. Henceforth, we can understand the association in these two types of firms. Third, we create number of deciles portfolios—i.e., size, risk, and leverage ratios—and examine whether the coefficients of the decile portfolios are different from each other. Finally, we contribute to the literature by controlling the bonds' time to maturity. As we know, the higher the bond maturity, the higher the modified duration, other things remaining constant. Thus, this study extends bond literature regarding whether the association of IVOLs and bond returns is subject to time to maturity of the bonds.

The remainder of the paper is organized as follows. Section 2 presents a brief review of the literature. Section 3 explains the theoretical background and hypothesis development. Section 4 describes data and IVOL measures used for our empirical studies. Section 5 investigates whether IVOLs are priced in the cross-section of individual bond returns. Section 6 provides additional controls to check the robustness of our results. Section 7 summarizes our results and concludes the study.

2. Literature review

2.1. Idiosyncratic risk and stock returns

Merton (1973) Intertemporal Capital Asset Pricing Model (ICAPM) suggests that the relationship between risk and return is positive for the aggregate market level. All factor models emphasize that only systematic risks should be priced (Sharpe, 1964; Black, 1972; Mossin, 1966). In addition, a large body of literature, both empirical and theoretical studies, explains the dimension and magnitude of the relationship between idiosyncratic volatility and expected stock returns. Mayers (1976) incorporates nonhuman capital factors in the CAPM setting and relates the equation with the stock returns to their betas with market and market beta with market-wide idiosyncratic risk measures. The Barberis et al. (2001), Behavioral Model, in a set-up of prospect theory, shows that the relationship between the risk and return is positive. However, the idiosyncratic volatility stream of literature differs and mainly divides into two major classes. One school of thought believes that the association between idiosyncratic volatility and expected stock returns is positive. The other school of thought believes that the association is negative. Thus far, the discussions and conclusions are indecisive.

Merton (1987) predicts that the association between idiosyncratic volatility and expected returns is positive when investors do not diversify their portfolios. For an undiversified portfolio, investors expect additional returns for bearing firm-specific risks. Other studies heavily assume that the relationship of idiosyncratic volatility and expected returns is positive due to under-diversification (Levy, 1978; Malkiel and Xu, 2002). In one influential paper, Fu (2009) shows that idiosyncratic volatility is time varying and finds that the association is positive using Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) models. Lehman (1990) also finds positive significant association. In another study, Lintner (1965) shows that idiosyncratic volatility carries a positive coefficient for return of stocks. In addition, CLMX also claim that the relationship between idiosyncratic risk and return is undoubtedly positive.

Other streams of literature show that the association between idiosyncratic volatility and expected stock returns is negative. The intuition of negative association appears as investors want to hedge against changes in market volatility and increasing volatility in the market that adversely affects the expected returns of the stocks (Campbell, 1996; Chen and Epstein, 2002). Since investors are risk averse, they demand some stocks that hedge against market volatility. In consequence, the demand and price of those stocks soar up and eventually negatively affect expected stock returns. In a seminal paper, Ang et al. (AHXZ; 2006) show that the association between idiosyncratic volatility and expected returns is negative using innovations from the Volatility Index (VIX). Likewise, the relationship between idiosyncratic volatility and expected stock returns is negative as they are related to the disclosure quality and poor earnings predictions (Jiang, Xu, and Yao, 2009). In another study, Harvey and Siddique (2000) show that stocks those have high sensitivities to innovations of market volatility have high demands and that stocks have low expected returns. Studies conducted on 23 stock exchanges around the world, Ang, Hodrick, Xing, and Zhang (AHXZ; 2009) find that the negative association is robust.

2.2. Idiosyncratic risk and the bond returns

Previous literature documents the notion that corporate bond returns are predictable. Kiem and Stambaugh (1986) document that long-term bond returns with varying default rates can be predicted by the variables that reflect the levels of bonds and stocks price. Fama and French (1989) examine bond returns, finding that they can be predicted by the factors that predict stocks return. The credit spread between the long-term Baa bond yield and the short-term treasury rate can predict bond returns (Chang and Huang, 1990). In a study on Swedish lottery bonds, Green and Rydqvist (1997) find that the return of bonds command premiums when there is some idiosyncratic risk. Previous studies also try to explain the Treasury bill yield and idiosyncratic volatility. Duffee (1996) examines the different maturities of Treasury bill and finds that idiosyncratic volatility is partially responsible for the returns on Treasury bill. Kwan (1996) finds that stock prices tend to lead bond prices in reacting to information arrivals.

Though the body of literature on idiosyncratic volatility and expected stock returns is huge, both in cross-section and time series, an insignificant number of studies explain the relationship between idiosyncratic volatility and expected bond returns. In a seminal paper, Campbell and

Taksler (2003) show that the association between equity volatility and corporate bond yields is positive. They find that controlling for general factors such as the reference Treasury rate, issue size, years to maturity, and time-series dummies, the result is robust. The result of their paper further show the predictability of corporate bonds and treasury bonds and finds a rising relationship between idiosyncratic risk and increasing yields on corporate bonds relative to treasury bonds.

Several other studies explain the stock bond return relation with stock market volatility. Connolly et al. (2005) show that there is a negative relationship between uncertainty measures and future correlations of stock returns. The association between stocks and bond returns is positively associated in the long run; however, the short-run relationship has significant time variation (Fleming et al., 2003; Hartmann et al., 2004). In another study, Belo et al. (2014) find that bond returns can be more easily predicted than stock returns, and the shorter maturity bonds can be predicted with higher precision. However, Kwan (1996) finds that the correlation between the returns on individual stocks and yield changes of individual bonds for the same firm is negative and contemporaneously correlated. He also finds that lagged stock returns have explanatory power for current bond yield changes. The correlation between stocks and bonds decreases after the year 2000[4]. Baele et al. (2010) find that macroeconomic fundamentals such as interest rates, inflation, the output gap, and cash flow growth contribute little to explaining stock and bond correlations as opposed to other factors such as liquidity proxies.

3. Theoretical background and hypothesis development

The seminal papers of Merton (1974), and Black and Scholes (1973) state that corporate bonds are put options for bondholders. When the volatility of stocks increase, the price of put

[4] See Baele et al. (2010) for details.

options also increases, which benefits equity holders. However, increased volatility may drive firms to distress and consequently the risk of bonds may go up; bondholders may demand higher returns for the higher risk arising from distress. Campbell and Taksler (2003) find that firm-level unexplained risk can explain much of the variation in credit spreads and credit ratings; however, market volatility explains little.

Importantly, idiosyncratic volatility measures the components of returns that remain unexplained in factor-pricing models. More specifically, idiosyncratic volatility is generally the square root of the variance of the unexplained error terms. Henceforth, the sign of the idiosyncratic volatility always is positive. Crucially, firm-specific unexplained volatility (idiosyncratic volatility) does not carry the original sign of the error; consequently, it does not provide any specific information regarding return shock regardless of whether the shock is upside or downside.

There are mixed opinions on the explanatory power of idiosyncratic volatility to corporate bond yields. Kwan (1996) finds the effect of the mean value of firms rather considering volatility and thus studies the relationship between stocks and bond returns. The Black and Scholes (1973), Ingersoll (1977), and Merton (1974) papers are the pioneering papers for corporate bond pricing. They theoretically prove that bondholders take control of firms whose asset prices are less than the total price of liabilities, and henceforth these firms are assumed default. Consistent with these previous finding, our paper retests the result in the CT (2003) paper with some new measures of idiosyncratic risk. According to CT, firms with more volatile equity are more likely to reach boundary conditions for default, so bondholders demand higher risk premiums for the additional risk they assume. We construct the following hypotheses to retest whether idiosyncratic volatility still matters in explaining the cross-sectional returns on the bonds in periods of decreasing idiosyncratic volatility.

H1: Although idiosyncratic volatility is decreasing after 2003, idiosyncratic volatility is positively associated with bond returns.

If IVOL is driven by favorable firm-specific information, then bondholders may find firms safe and may demand lower returns of investing in bonds. However, bondholders will demand higher returns for bonds when IVOL is driven by negative information shocks. Previous economic theories suggest that the relationship between idiosyncratic volatility (risk) and expected stock returns is positively related (Merton, 1974), Goyal and Santa Clara (2003), CLMX, 2001). The standard deviation of returns usually considers as risk, though it captures both upside and downside shocks of return. CT show that equity volatility is positively associated with credit spreads and bond ratings. They show that IVOL increases over time as the impact of volatility to bond returns is positive and statistically significant. In this study, we show that though idiosyncratic volatility decrease after 2003, it still matters in explaining the cross-sectional average returns of corporate bonds.

H2: Positive association is more prominent for financial firms.

The financial structure of financial firms is different and more complex than that of nonfinancial firms. Financial firms are subject to more compliance issues in maintaining capital requirements and differing capital structures. The riskiness of investable assets of financial firms (banks) is an important determinant in maintaining the required capital reserves. Consequently, the higher the firm-specific risk, the higher the capital requirement. On the other hand, to maintain the higher capital requirement, financial firms need to invest less or borrow subordinate debt.[5] Investing less may decrease firms' profitability, and borrowing more debt may lead firms to more distress. Henceforth, we hypothesize that idiosyncratic volatility relates to the expected bond returns more for financial firms than that of nonfinancial firms.

H3: Given the decrease of idiosyncratic risk, the higher the average firm-specific risk the more the positive association.

Higher firm-specific risk implies that some firms are more risky than are others. Previous studies suggest that the higher the stock risk, the higher the stock returns (Merton, 1973). A large empirical literature has tried to prove the risk and return relation of stock market indices. Huang et al. (2009) find that the risk/return relationship increases monotonically by increasing idiosyncratic risk of each quintile portfolio. However, the risk of the firm-level and returns of bonds has gotten little attention. In this study, we try to crack the relationship between firm-level risk and bond returns. Since idiosyncratic risk increase the overall riskiness of the firms, bondholders of riskier firms will demand higher returns on average.

H4: The positive association is more projecting in smaller firms.

Banz (1981) finds that average risk-adjusted returns for smaller firms are higher than those of larger firms. Fama and French (1993) find that SMB has the explanatory power to capture the expected returns' variability. Previous literature shows that smaller firms are more susceptible to idiosyncratic risk (Bali et al., 2005; Liu and Di Iorio, 2016). The intuition is that smaller firms are riskier than larger firms, hence stock returns of smaller firms are higher than returns for larger firms. Consistent with the thought, I hypothesize that the cross-sectional bond returns for smaller firms are higher than for larger firms for both financial and nonfinancial firms.

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[5]According to the Basel Accord, subordinated bonds with more than five years of maturity are considered supplementary capital to maintain capital requirement. See details in Basel III: A global regulatory framework for more resilient banks and banking systems, December 2010 (Rev 2011).

4. Data, methodology and econometric analysis

We collected primary data for corporate bonds from the WRDS bond database, which is a unique cleaned database incorporating two sources: the Financial Industry Regulatory Authority (FINRA's) Trade Reporting and Compliance Engine (TRACE) and the Mergent FISD [6]database. TRACE database reports bond transaction-related data covering over-the-counter transactions for U.S. corporate bond market, while Mergent FISD data reports bond issue and issuer characteristics[7]. The TRACE database is from two separate data packages provided by FINRA: TRACE Standard (market data) and TRACE Enhanced. The former package was launched in July 2002 and initially included only investment-grade bond transactions having more than $1 billion in original issue size. By 2004, all other investment-grade bonds and high-yield bonds were added. Hence, the database may possess some selection bias in the beginning of our sample data.

The data uses in this study ranges from July 2002 to June 2016. WRDS bond data facilitates linkages between corporate bond data and Center for Research in Security Prices (CRSP) equity data issued by the same company through bond CRSP links. After collecting bond returns and issue-related data from the WRDS corporate bond database, we merged the data with the CRSP data for stock returns. Ignoring the missing bond return data and inappropriate merging with the CRSP data, the final data set was 10,47,926 monthly bond observations. The monthly return of market portfolio, HML, SMB, and momentum factors were collected from Professor Ken French's Website[8]. In addition to the Fama-French factors, bonds, and stocks returns, I use four

[6] According to WRDS, Mergent Fixed Income Security Database (FISD) is a comprehensive database for academia of publicly offered U.S. bonds. FISD contains more than 140000 corporate, corporate MTN, U.S. Agency, and U.S. Treasury debt securities.
[7] See WRDS bond data manual for details.
[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

state variables in the context of previous literature (CT, 2001; Fang and Huang, 2014). These are the short-term T-bill rate, the difference between the yields of 10-year and 1-year T-bonds (term spread), the difference between 10-year corporate Baa bonds and 10-year T-bonds (default spread), the difference between three-month LIBOR and three-month treasuries (liquidity spread). Data for the stated variables were collected from the *FRED*® Database of the Federal Reserve Bank of St. Louis. The term and liquidity spreads were used as proxies for the term structure of interest rates. The fundamental data of firms is collected from the Compustat yearly data. Merging CRSP and Compustat data was done by using the link a table, which uses GVKEY as the primary identifier of the firms. For each monthly observation, we merge the Compustat yearly data of the last financial reporting dates with the monthly bonds data.[9]

To calculate the idiosyncratic volatility, we use the daily stock returns of the issuing firms. There are 2,233 issuing firms in our sample, and there are 5,553,573 daily firm-level observations of 264,729 firm months. The monthly corporate bond returns as of time t is computed as consistent with Lin et al. (2011).[10]

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

where, BR_t, is the bond returns at time t, P_t is the transaction price, AI_t is the accrued interest and C_t is the coupon payment at time t.

[9] Suppose a company's financial year ends on December 31. Then we merge the yearly Compustat data with the next 11 months' bond data up to the next year's November 30 data. When the new Compustat data arrives on December 31, we consider the new Compustat data for the next 11 months' data to be merged with the monthly bond data.

[10] The WRDS bond database creates the bond return based on the price of the last month and accrued coupon interest. See page 5 of the WRDS bond database manual for details.

4.1. Creating IVOL using factor pricing models

In this section, we explain the methodologies that we used to determine idiosyncratic volatility. Idiosyncratic volatility can be defined as the firm-specific risk that is unique to each firm. Following the methodologies use by Ang et al. (2006) and Fu (2009), we measure idiosyncratic risk as follows: in each month, daily excess returns of individual stocks of the issuing firms are regressed on the market return (CAPM), on the Fama-French (1993, FF) factors, and on the Carhart (1997) Model.

$$r_{j,t} = a_j + \beta_j r_{m,t} + \varepsilon_{j,t\_CAPM}; \quad \varepsilon_{j,t\_CAPM} \sim N\left(0, \sigma^2_{\epsilon_{CAPM},j,t}\right) \tag{2.1}$$

$$r_{j,t} = a_j + \beta_j r_{m,t} + s_j SMB_t + h_j HML_t + \varepsilon_{j,t\_FF}; \; \varepsilon_{j,t\_FF} \sim N\left(0, \sigma^2_{\epsilon_{FF},j,t}\right) \tag{2.2}$$

$$\begin{aligned} r_{j,t} = a_j + \beta_j r_{m,t} + s_j SMB_t + h_j HML_t + u_j UMD_t + \varepsilon_{j,t_{FFM}}; \\ \varepsilon_{j,t\_FFM} \sim N\left(0, \sigma^2_{\epsilon_{FFM},j,t}\right) \end{aligned} \tag{2.3}$$

where, $r_{j,t}$ is the excess stock return of the jth stock at day t, $r_{m,t}$ is the market return on the value-weighted market portfolio. The coefficients s_j, h_j, and u_j are the factor loadings of the size factor, the value factor, and the momentum factor. The error term $\varepsilon_{j,t}$ is the error that remain unexplained in the model. $\varepsilon_{j,t}$ follows normal distribution with mean zero; the variance is $\sigma^2_{j,t}$. Stock returns and factors are used on daily returns from CRSP and Ken French's Website. For each model, we run time series regressions for each firms in each month. For each firm, the idiosyncratic risk is measured as the standard deviation of the errors of the time series regression. Following Fu (2009), to reduce the infrequent trading of idiosyncratic risk of stocks, we require at least 15 trading days of each firm in each month.[11] There are 264,729 firm months; 264,729 times 3 equals 794,187 time series regressions to predict error terms. Following French et al. (1987), after getting the standard deviation of the error terms, we transform the daily standard

[11] CRSP reports both daily returns and nonzero trading volume.

deviation of error terms to monthly standard deviations by multiplying the square root of the trading days of each month *T*.

$$IVOL_{CAPM,T} = \sqrt{T} * \sigma_{\epsilon,j,t}^{CAPM} \tag{2.4}$$

$$IVOL_{FF,T} = \sqrt{T} * \sigma_{\epsilon,j,t}^{FF} \tag{2.5}$$

$$IVOL_{Carhart,T} = \sqrt{T} * \sigma_{\epsilon,j,t}^{Carhart} \tag{2.6}$$

To examine the association of the idiosyncratic volatility to bond pricing, we run the following regression.

$$BR_{i,j,t} = \lambda_0 + \lambda_1 TERM_t + \lambda_2 DEF_t + \lambda_3 LIQ_t + \lambda_4 IVOL_{j,t-1} + \mu_{i,j,t} \tag{3}$$

where $BR_{i,j,t}$ is the price of *i*th bond of the *j*th firm at month *t*, $TERM_t$ is the return differential of the 10-year corporate and 1-year bonds at time *t*. DEF_t is the return differential of the long-term corporate Baa bond and the long-term government bond. LIQ_t is the difference between the yield rate of three-month LIBOR and three-month T-Bill. $IVOL_{t-1}$ is the lag innovation of the error term from CAPM, FF, and Carhart models. We use lag innovation to avoid endogeneity issues and to see whether the last month's idiosyncratic volatility can predict the cross-sectional bond returns in this month.

4.2. Time series analysis: IVOL innovation by Goyal and Santa-Clara (2003)

We use the Goyal and Santa-Clara (2003, GS)[12] innovation of low frequency idiosyncratic risk. Following their methodology, we create the monthly volatility of stock return by subtracting the square return of the market portfolio from each firms' square return. We use the monthly CRSP stock return to get low frequency volatility.

$$IVOL_{GS,t}^{lf} = \frac{1}{N_t}\sum_{i=1}^{N_t} r_{i,t}^2 - r_{ew,t}^2 \tag{4}$$

[12] We use the low frequency measures of IVOL used in Goyal and Santa-Clara, 2003 (see pp. 989, JF Vol LVIII. No.3).

The subscript *lf* stands for the low-frequency (risk calculated from the monthly stock return) idiosyncratic risk. Market return is calculated as the equally weighted return collected from CRSP. The factor pricing model in the empirical analysis is as follows.

$$BR_{i,j,t} = \lambda_0 + \lambda_1 TERM_t + \lambda_2 DEF_t + \lambda_3 LIQ_t + \lambda_4 IVOL_{GS,t-1}^{lf} + \mu_{i,j,t} \tag{5}$$

where $IVOLGS_{t-1}^{lf}$ is the low-frequency idiosyncratic volatility at month *t-1*.

4.3. Equity volatility uses in Campbell and Taksler (2003)

In their seminal paper, Campbell and Taksler (2003) measure equity volatility as the standard deviation of the excess return (percent) over the preceding 180 days.

$$EV_{CT} = \sigma_{j,t}^{180} \tag{6}$$

where EV_{CT} is the equity volatility, standard deviation (σ) is for firm *j* at time *t* over the last 180 days. The EV_{CT} measure is calculated on a daily rolling basis.[13] After calculating daily equity volatility, we merge month-end volatility with monthly bond data.

The econometric model is as follows.

$$BR_{i,j,t} = \lambda_0 + \lambda TERM_t + \lambda_2 DEF_t + \lambda_3 LIQ_t + \gamma_4 EV_{CT,i,j,t-1} + \mu_{i,j,t} \tag{7}$$

where $EV_{CT,I,j,t-1}$ is the equity volatility of bond *i* for firm *j* at time *t*-1 and $\mu_{i,j,t}$ is the error term with mean zero and constant variance.

4.4 Aggregate monthly idiosyncratic volatility uses in CLMX (2001)

Consistent with Brandt et al. (2009), we follow the volatility decomposition of CLMX (2001) and use daily stock returns to construct the aggregate monthly idiosyncratic risk. The daily firm-specific residual is calculated for each stock *j* that belongs to industry *i* as follows.

$$\epsilon_{ijst} = R_{ijdt} - R_{idt} \tag{8.1}$$

[13] We calculate the equity volatility for stock *i* at day *t*, then for the next day we take the last 180 days excess return. This is why equity volatility is much smoother than the other volatility measure, see Figure 2. After calculating daily equity volatility, we keep only the last month days observation to merge with monthly bond data.

where R_{ijst} is the return of security *j* of industry *i* on day *d* at month *t.* Then we create the month *t* idiosyncratic volatility (IVOL) of stock *j* that belongs to industry *i* as:

$$IV_{ijt} = \sum_{s=1}^{T} \epsilon_{ijst}^{2} \ . \quad (8.2)$$

Using the monthly idiosyncratic volatility, we run the following regression.

$$BR_{i,j,t} = \lambda_0 + \lambda_1 TERM_t + \lambda_2 DEF_t + \lambda_3 LIQ_t + \lambda_4 IVOL_{CLMX,i,j,t-1} + \mu_{i,j,t} \quad (9)$$

where $IVOL_{CLMX,I,j,t-1}$ is the idiosyncratic volatility using CLMX of bond *i* for firm *j* at time *t*-1 and $\mu_{i,j,t}$ is the error term with mean zero and constant variance.

[Insert Figure 2 here]

4.5. Descriptive statistics

Table 1 depicts the descriptive statistics for each of the variables used in this study. Panel A displays mean, median, standard deviation, minimum value, maximum value, skewness, kurtosis, and Augmented Dickey Fuller (ADF) results. To bring down the outliers to a specific value, we winsorize the variable to 98%, data below the first percentile set to the first percentile, and the data above the 99th percentile set to the 99th percentile.

Following Equation 1, we find that the mean bond return of traded bonds in each month is 0.6%. Skewness and kurtosis of the monthly return of bonds are 2.57 and 99.08, respectively, meaning that the distributions of the bond returns are on average positively skewed and leptokurtic. The ADF test result shows that bond returns are not serially correlated. The *p*-value of the ADF test of the bond return time series data is .01, so we can reject the null hypothesis that the data is nonstationary. The average monthly stock return of the bond issuing firms is 0.9% and the median is 1%. The individual stocks display that the returns are on average positively skewed and leptokurtic. As expected, the standard deviation of individual stock returns is higher than the standard deviation of individual bond returns. That means that on average bond returns are less risky than stock returns. The S&P return is the index return for the S&P 500 index. The average monthly S&P return is .67% and is almost normally distributed. The SMB, HML and Momentum factors are not serially correlated. The average monthly returns of the size factor SMB, value factor HML, and momentum factor UMD are .1%, .02%, and .1%, respectively. The mean of the $IVOL_{CAPM}, IVOL_{FF},\ IVOL_{MOM}, and\ IVOLGS_t^{lf}$ are 6.03%, 6.68%, 6.03%, and 1.03%, respectively, and they are not serially correlated. The *p*-value of all the idiosyncratic volatility data is less than 1%, which means that we can reject the null hypothesis that the volatilities are nonstationary. The means of TERM, DEF, and LIQ are 2.1%, 2.7%, and .4%, respectively. However, the Augmented Dickey Fuller test results of the serial correlation show that the factors are auto-correlated.

[Insert Table 1 here]

Panel B shows the number of trading bonds in each year and the highest number of bonds traded in a year by industry for the sample we used. Panel B shows that the number of bonds traded in each year increases over the year. The utility, financial, and banking sectors are the major industries in which bonds were traded the most. Before the financial crisis, the Utility sector was the highest bond issuing sector in the bond industry. As expected, during the period of the housing crisis (from 2006-2008), issuing of bonds decreased because of financial constraints, and financial firms were the leading bond issuers during and after the housing crisis. The highest number of bonds were reported in the year 2014 (16,746) in our sample. Panel C shows the 49 FF industries and the fraction of the bonds traded in each industry in the sample. In each month, we calculate the fraction of the bonds traded in the market. After calculating the monthly fraction, we calculate time series average fractions of the bonds per industry. The financial industries comprised of banking, insurance, and financials are the leading bond issuers. Almost

48.11% of the bonds on average are issued from the three industries. The utility industry is the next leading sector and issued on average 10.55% of the total traded bonds in our sample. The oil and telecom industries issued almost 4.5% and 4.8%, respectively, of the traded bonds on average.

5. Empirical analysis

5.1. Idiosyncratic volatility and bond returns

In this section, we consider how the idiosyncratic volatility of stocks of corresponding bond-issuing firms influence average returns of the bonds. Since idiosyncratic volatility is the firm-specific risk factor, the higher the idiosyncratic volatility means the more likely the firm may distress. Consequently, bondholders may feel that the bonds are risky and demand compensation for the additional firm-specific risk. If investors recognize the risk—the firm-specific idiosyncratic risk—they will demand higher yields of the particular bond, and the price or the value of the bond will eventually go down. Investors can capitalize higher returns if they buy a certain asset with lower value or price. This suggests that the return of the corporate bond is positively associated with the idiosyncratic risk.

Previous literature finds a positive association between idiosyncratic volatility and returns of stocks (Goyal and Santa-Clara, 2003; CLMX, 2001). Several studies of idiosyncratic volatilities and bond returns examine several folds: equity volatility is positively associated with the bond yield curve (CT, 2003). In this paper, we extend the literature on idiosyncratic volatility considering whether idiosyncratic volatility still matters in explaining cross-sectional returns of bonds since idiosyncratic volatility decreased from 2003. We hypothesize that idiosyncratic volatility still matters in explaining the expected cross-sectional bond returns. To find the expected association, we run regressions of Equations (3), (5), (7), and (9). We run a panel regression of bond ret, $BR_{i,j,t}$ as a dependent variable with lag idiosyncratic volatility, TERM, DEF, and LIQ variables. We run a panel regression with the fixed effect model. To avoid potential endogeneity, we use a fixed effect model. Since one firm may issue several bonds at a time, there might be a potential firm-level fixed effect. We also consider the year effect as our sample covers both crisis and noncrisis periods. Again, we use the lag independent variable of interest to avoid potential simultaneity issues, which may responsible for endogeneity in the long run. In Appendix 2, we also present the same regression with the random effect model as the random effect model test, the Breusch-Pagan test,[14] qualifies the regressions as a random effect. However, the results of the two models do not differ significantly and economically.

Models 1 through 3 are based on Equation (3). In Model 1, Table 2, the dependent variable is lag idiosyncratic volatility calculated from the CAPM. Models 2 and 3 in Table 2 consider $IVOL_{FF,\, t-1}$ and $IVOL_{Carhart,t\text{-}1}$, respectively. Model 4 considers the Goyal and Santa Clara low-frequency idiosyncratic volatility measure as the independent variable. Models 5 and 6 consider the CT and CLMX models correspondingly. All the idiosyncratic volatility coefficients of all six models are positive and statistically significant. The standard error is measured as the clustered standard error, as the clustered error is more efficient and unbiased than the OLS standard error or the Fama-MacBeth standard errors (Peterson, 2009).

Consistent with the previous literature, we find that the expected bond returns are positively and significantly associated with bond returns (CT, 2003; Fang and Hung, 2014). As expected, term spread and default spread are negatively associated with bond returns in our sample and are inconsistent with previous literature (Lin et al., 2011). The negative signs of the spreads are

[14] To test the presence of random effect, the Breusch-Pagan test statistics: $LM^2 = \frac{NT}{2(T-1)}\left\{\frac{\sum_{i=1}^{N}\left(\sum_{i=1}^{T}\hat{e}_u\right)^2}{\sum_{i=1}^{N}\sum_{i=1}^{T}\hat{e}_u}\right\}^2$. If the null hypothesis H_0: $\sigma_u^2 = 0$ is true, then there is no random effect.

strongly intuitive, as Term and Liquidity are the component of the term structure of the yield curve. Higher spreads may lead to higher yield curves, and consequently the present value of the price will be lower for higher yield rates. However, the other component of the Term structure default is positively and significantly associated with bond returns. As the partial composition of bond returns consists of the default spread, the higher the default spread the higher the bond returns. Moreover, unlike the computation of the prior two spreads, Term and Liquidity, the default spread the return differential of the long-term Baa corporate bond and long-term government bond) possess the important characteristics of bond returns, which captures the default risk of a corporate bond. However, the term and liquidity spreads do not capture the return component of bond returns; rather they capture the term spread of the yield curve.

[Insert Table 2 here]

The results support our first hypothesis that idiosyncratic volatility is positively associated with expected bond returns. Models 1 through 3, which apply the factor pricing models (CAPM, Three Factors, Four Factors) to calculate idiosyncratic volatility report that the lag IVOL coefficients are around .037, .043, and .043, respectively. The coefficients are statistically and economically significant in that if the lag IVOL of the stock increasse by 1%, the return for bonds of the corresponding firms will increase by .037%, .043%, and .0435% on average for Models 1, 2, and 3, respectively. In Model 4, we use the lag IVOL calculated consistent with Goyal and Santa-Clara (2003). We find that the $IVOL_{GS}$ is positively associated with expected bond returns. The coefficient of lag IVOL_GS is 0.23, and it is statistically significant at the 1% level. In Models 5 and 6, we use CT (2003) and CLMX (2001) measures to calculate idiosyncratic volatility. We find that the coefficients of lag IVOLs are .05 and .0008 and both are statistically significant. However, the results of the last model may not be economically significant. Both the firm and year fixed effects were considered to capture firm and year effects. The standard errors are clustered robust, and the clustering was done at the highest level, which is industry clustering rather firm-level clustering.[15]

5.2. Idiosyncratic volatility and bond returns: Issuer type

Financial sectors are among the major bond issuers in the U.S. on and around the housing crisis. From 2006 to 2016 (Table 1, Panel B), the major issuers of traded bonds in our sample are banks and financial institutions. We divide our sample into two subgroups: financial firms and nonfinancial firms. We consider banks, insurance companies, and financial intuitions (Fama and French, 1997, industry classification of banks, insurance, and financial industries) as financial firms. By nature, financial institutions possess different and more complex capital structures than other firms, as they need to maintain the minimum required capital based on their risk-based asset structures. The requirements of capital to reserves depend largely on the risk of these institutions bear for investable assets. The higher the firm-specific risk, the higher the capital requirement. According to the Basel Accords, banks are required to maintain the 8% of the capital ratio reserve. The 8% capital ratio can be decomposed into two parts: core capital and supplementary capital. Banks need to maintain at least 6% of their core capital; the remaining 2% is supplementary capital. Subordinated term debt with a minimum of five years of maturity is considered a component of supplementary capital.[16] Therefore, we assume that during the financial crisis, banks and financial institutions might have issued more subordinated bonds with more than five years to maturity to maintain the capital requirement. To understand the impact of

[15]According to the Cameron and Miller (2015), the fixed effect model alone cannot produce unbiased estimators. We need to add the clustered standard errors in the highest ranked level. The strict exogeneity assumption requires that the errors be uncorrelated with the explanatory variables for all units with cluster i. This assumption is often reasonable when a cluster effect c_i is explicitly included (Wooldrige, 2010, pp. 329)

[16] See details in Basel III: A global regulatory framework for more resilient banks and banking systems, December 2010 (Rev 2011).

idiosyncratic volatility on bond returns, we run a separate regression and examine the difference of the impact of idiosyncratic volatility on bond returns for financial and nonfinancial firms.

Panel A of Table 3 reports the regression results of bond returns on idiosyncratic volatility for financial firms. As firms' level volatility, idiosyncratic volatility, increases their capital requirements to maintain the provisions. The increased capital requirements may decrease available investable funds of financial firms or may increase the issue of subordinated long-term debt. Both actions, decreasing available funds and increasing subordinate bonds, may increase bondholder risk to claim the money; consequently, bondholders may demand higher returns for the added risk. First, the decreasing investable funds for maintaining higher provisions may negatively affect cash flow. Second, the increasing need to issue more subordinate long-term bonds may raise the yield rate of the issuing bonds. Subsequently, bond returns for financial institutions are more positively associated with idiosyncratic volatility than bond returns of nonfinancial institutes.

[Insert Table 3 here]

In Panel A of Table 3, the coefficients of idiosyncratic volatility of all the models are higher than the coefficients in Panel B, meaning that if financial firms' idiosyncratic volatility of the previous month increases by 1%, their bond returns increase more than those of nonfinancial firms. The magnitude of the *IVOL* coefficients are higher for financial institutions maybe because financial firms are subject to public confidence, so the increase in idiosyncratic volatility may decrease confidence in the lender and subsequently may increase bond returns because of the high yield-to-maturity requirement. The coefficients of lag $IVOL_{FF}$ for financial firms is .072, which is more than double the coefficient of $IVOL_{FF}$ for nonfinancial firms. The result is robust when we look at the other measures of IVOL. All the models show that the IVOL can better explain bonds returns for financial firms than those of nonfinancial firms.

5.3. Idiosyncratic volatility and bond returns by IVOL decile

Huang et al. (2009) find that the risk/return relationship increases monotonically by the increase of the idiosyncratic risk of each quintile portfolio. As we know, the higher the risk the higher the return (Merton, 1973). In this section, we extend our analysis to get the relationship between IVOL and expected bond returns controlling the IVOLs. Therefore, we sorted the bonds with the IVOL decile; the lowest decile (1) represents the less idiosyncratic volatile stocks and the highest decile (10) stocks have the highest firm-level idiosyncratic risk. In each month, we form the decile for each type of IVOL. After forming the decile for the first month, we rebalance the decile every month. The portfolio decile was created using sequential sorting. Since a higher IVOL represents higher firm-specific risks, increasing firm-level risk, bondholders should demand higher bond returns as the risk for the firm as well as bonds goes up. Firms in each decile of the last month (lag decile) are considered to explain the cross-sectional variation of expected bonds returns of this month.

Table 4 shows the regression between idiosyncratic volatility and bond returns sorted by the IVOL decile. As the previous section finds that the coefficients of lag IVOLs are different for financial and nonfinancial firms, in this section we analyze the association separately to capture the effect for financial and nonfinancial firms. Table 4 Panel A shows the coefficients of financial firms controlling IVOL. In Model 1, the independent variables are $IVOL\_CAPM_{t\text{-}1}$ and the control variables. The coefficients increase by decile but not monotonically. The difference of coefficients between decile 10 and decile 1 is .018, which means that by the increase of the firm-level risk, returns also increase. For the $IVOL\_FF_{t\text{-}1}$ and $IVOL\_Carhart_{t\text{-}1}$ as independent variable models, the difference of coefficients between decile 10 and decile 1 is .024, but the trend is not monotonic with the increase of the decile. In Model 4, we sort the sample based on the EV_{t-1}^{180} and find that the coefficients for the lowest decile are negative and the difference of coefficients between the highest and the lowest decile is -12.07, which is economically significant.

[Insert Table 4 here]

Table 4, Panel B reports the coefficients of lag IVOLs of nonfinancial firms controlling IVOL. The coefficients increase by the increase of the decile; however, the increase is not monotonic in this case either. The sign of the coefficients is consistent with Panel A, but the magnitude is smaller for nonfinancial firms. For Model 1, the coefficient differential from the highest decile to the lowest is about .015. The result also agrees in Models 2 and 3. The coefficients differentials for the highest decile to the lowest decile is about .015, though the increase is not monotonic for all deciles. Financial firms are less responsive to idiosyncratic volatility because they are more subject to public confidence and more vulnerable to firm-specific risk. The result is robust with the previous section in that if idiosyncratic volatility increases firm-specific risk, then bondholders of financial firms demand higher expected returns than do bondholders of nonfinancial firms.

5.4. Idiosyncratic volatility and bond returns sorted by market capitalization

To capture the size effect, in this section we sort the bond return data from the lowest to highest deciles by market capitalization. Previous empirical studies find that smaller firms have higher returns than those of larger firms (Banz, 1981; Fama and French, 1992). Since smaller firms characteristically have higher risk than do larger firms, the coefficients of return differentials of smaller firms and higher firms (SML) are positive. In line with these findings, our hypothesis also revolves around the notion that the association of bond returns of lower market capitalized firm is more susceptible than that of larger capitalized firms. To test the hypothesis, we sort the issuing firms from the lowest market capitalization to the highest. In each month, we sort the firms by market capitalization for both financial and nonfinancial firms. We rebalance the decile portfolios every month and then run panel regressions of Equations 3 and 4 using a lag decile so that we can avoid the endogeneity issue.

Table 5 shows the regression between idiosyncratic volatility and bond returns sorted by market capitalizations. Panel A represents the lag IVOL coefficients of financial firms control by the lag decile of market capitalization. Decile 1 represents firms with lowest market capitalization, and decile 10 represents firms with highest market capitalization. In the first model, the independent variables are $IVOL\_CAPM_{t-1}$ and other control variables. The coefficients of the first model are mixed, especially for smaller financial firms. In the first five deciles, the lag IVOL coefficients increase; however, the last five deciles show mixed results. Some decile's coefficients increase and some decrease. However, Models 2 and 3 ($IVOL\_FF_{t-1}$ and $IVOL\_Carhart_{t-1}$) show that smaller financial firms (except Decile 1) have higher bond returns with the same lag idiosyncratic risks. For all three models, the smallest financial firms' lag IVOL coefficients are smaller than the neighboring decile. Model 4 ($IVOL\_GS_{t-1}$) shows that the association between lag IVOL and bond returns is positive and the trend of the association is monotonically decreasing, which explains that the lag IVOL coefficients are higher for smaller firms.

[Insert Table 5 here]

Panel B of Table 5 depicts the lag IVOL coefficients of nonfinancial firms controlled by the lag decile of market capitalization. Consistent with Panel A, except for the smallest firms, the pattern of the coefficients is declining. The difference between the coefficients of Decile 10 and Decile 2 is almost .055 for the first model and .05 for the second and third models. For the fourth model (*IVOL_GS*$_{t-}$1), the coefficients of the lag IVOL decrease almost monotonically. For Decile 1, the coefficient of lag IVOL is .95 and statistically significant; for the largest firms the coefficients are -0.016 but not statistically significant. Thus, except for the smallest firms in our sample, the results of other decile are consistent with our hypothesis that the smaller the firm size the higher the association between idiosyncratic risk and bonds returns.

Section 6. Robustness check

6.1. Idiosyncratic volatility and bond return: Credit rating

According to default risk models, firms' credit ratings may have a potential impact on bond prices; hence may impact the returns of bonds as well (Griffin et al., 1982). In this section, we extend the study of bond returns and idiosyncratic risk in the context of two prominent types of bond ratings: S&P and Moody's. Moody's and S&P rate bonds by 22 categories from AAA to C (D for the S&P). Higher rated bonds are considered as more secure bonds. Hence, higher rated bonds are supposed to be less susceptible to idiosyncratic risk. Consistent with this belief, we test the association between idiosyncratic risk and expected bond returns with bond ratings. Of the 22 ratings categories, we categorize the bond ratings categories into five categories for ease of comparison (Appendix 3). Quintile 1 is the highest rated bonds, and Quintile 5 is lowest rated bonds for both the rating categories. Table 6, Panel A.i shows the S&P bond rating of financial firms. For all the models, the coefficients of the highest rated bonds are lower than the coefficients of the lowest rated bonds. Though the relationship is not monotonic, the trend is increasing from the highest to the lowest rated bonds.

Panel A.i of Table 6, shows that the coefficients of Quintile 5 of Models 1 through 3 (factor pricing models) are not statistically significant. However, all the coefficients are statistically significant for the $IVOL_{GS}$ model and the trend of the IVOL coefficients are almost monotonically increasing. Panel A.ii represents the lag IVOL coefficients of all the models for nonfinancial firms. The results for financial and nonfinancial firms are almost the in same sign, though the magnitudes are different. As usual, the coefficients for nonfinancial firms are lower compared to the corresponding nonfinancial quintile. Except for Quintile 5, all the coefficients are statistically significant. The lag IVOL coefficients are increasing, however, the trend of increasing is not monotonic.

Table 6, Panel B.i reports the lag IVOL coefficients of financial firms controlling the Moody's rating quintile. We create five categories of the rating from all Moody's rating categories. Quintile 1 possesses the highest rated bonds, and Quintile 5 represents the lowest rated bonds. Almost all the coefficients are statistically significant, and the trend of the coefficients is increasing. However, the increase of the coefficients is not monotonic. The results are consistent with the general belief that the coefficient of lag IVOLs of higher rated bonds are lower than that of lower rated bonds. Interestingly, the pattern of increasing IVOL with the decreasing rating is not true for Table 6, Panel B.ii (Models 1 through 3). $IVOL_{GS}$ coefficients increase in reverse, but some of the quintile coefficients are not statistically significant.

[Insert Table 6 here]

6.2. Idiosyncratic volatility and bond returns sorted by leverage ratio

Collin-Dufresne and Goldstein (2001) say that within the structural framework, leverage ratio triggers default rate when leverage ratio tends to unity. Hence, the credit spreads are expected to increase by the increase of the leverage ratio. Leverage ratio is considered one of the important indicators of firm's financial health. Firm with high leverage ratios seem to be more risky than firms with lower leverage ratios. Previous literature finds that there is strong positive association between equity volatility and financial leverage (Christie, 1982). Baker (1973) says that the higher rates of returns are earned by firms with relatively lower leverage. A series of studies shows the cross-sectional association of leverage and profitability, leverage, and rates of returns of stocks. However, few studies (Collin-Dufresne and Goldstein, 2001) try to reveal the association of stock volatility and bond returns controlled by the leverage ratio as a measure of risk. In this study, we will extend the literature of idiosyncratic volatility and cross-sectional don return by adding the effect of financial leverage.

Table 7 represents the coefficients of lag IVOLs controlled by the financial leverage decile. To calculate the leverage ratio, we consider only long-term debt (excluding short-term debt) rather total debt to capture long-term commitment. In each month, we create decile portfolios by financial leverage. We rebalance the portfolios in each months. Panel A of Table 7 shows the regression coefficients of the lag IVOLs for financial firms. In Model 1, among the 10 decile portfolios, five coefficients are statistically significant. There is an increasing pattern in the coefficients with increasing leverage ratios that is consistent with the research questions that the higher the risk (higher leverage) the higher the bond returns. Models 2 and 3 also show similar types of pattern in the results that the coefficients that are statistically significant are increasing by the increase of the financial leverage for financial firms.

[Insert Table 7]

Panel B of Table 7 represents the coefficients of lag IVOLs of the nonfinancial firms controlled by the financial leverage decile. For Model 1, the difference of the coefficients between lag 10 and lag 1 is almost .062. However, the trend of the coefficients is not monotonically increasing by the increase of the financial leverage. For Models 2 and 3, the difference of the coefficients between lag 10 and lag 1 is almost .061, though the trend of change by decile is not monotonic. In Model 4, except Decile 1 (lowest leverage ratio), the coefficients increase by the increase of the leverage ratio, and all the coefficients are statistically significant at the 1% level. Between the two categories of firms, financial and nonfinancial, the association and trend is more visible in the case of nonfinancial firms. The difference in the results may be due to the dissimilar capital structure of financial and nonfinancial firms.

6.3. Idiosyncratic volatility and bond returns categorized by time to maturity

By bond duration, we can understand that how sensitive a bond is with an increased interest rate of 1%. The higher the time to maturity the higher the sensitivity to the change of interest rate. This is referred as interest rate risk. Collin-Dufresne and Goldstein (2001) find that bonds with different maturities react differently with asset volatility. We extend the study of idiosyncratic volatility and bond returns controlling for time to maturity. For each bond, we calculate the time to maturity in each month, then regress the bond returns with IVOL controlling lag monthly time to maturity. In each month, we subcategorize bonds in seven categories based on time to maturity. Category 1 has the lowest time to maturity (less than 1 year) and category 7 bonds have the longest time to maturity (higher than 30 years).

Table 8 represents the coefficients of lag IVOLs controlled by time to maturity. To calculate time to maturity, we consider the remaining time to maturity. we use time to maturity rather total period of the bonds to capture the duration effect of the bonds as the duration of the bonds largely depends on time to maturity rather total period of the bonds. Panel A, Table 8 depicts the lag IVOL coefficients of financial firms. For Model 1, bonds maturing within 1 year have lag IVOL coefficients of .055 and the coefficients are statistically significant. The bonds that mature after 20 years have a lag IVOL coefficient of .074 and are statistically significant. However, coefficients of bonds that mature after 30 years are not statistically significant. For Models 2 and 3, the coefficients of lag IVOLs for bonds maturing within 1 year is .075 in both the cases. The coefficients are almost the same for all categories (except bonds that mature after 30 years). Other IVOL measures such as $IVOL\_GS_{t-1}$, EV_{t-1}^{180}, and $IVOL_{CLMX,t-1}$ show that the pattern of lag coefficients increases by the increase of the bonds' time to maturity.

[Insert Table 8 here]

Panel B, Table 8 represents the coefficients of lag IVOLs for nonfinancial firms control by time to maturity. For Model 1, coefficients of lag IVOLs are increasing (except bonds maturing after 30 years) by the increase of the time to maturity that is consistent with the research questions that the higher a bonds maturity, the more sensitive the bond returns with the idiosyncratic volatility. The difference between bonds maturing within 1 year and bonds maturing after 20 years is .031, which is economically significant. Models 2 and 3 also represent the increasing trend of coefficients with the increase of the bonds' time to maturity except for bonds that mature after 30 years. Other IVOL measures such as $IVOL\_GS_{t-1}$, EV_{t-1}^{180}, and $IVOL_{CLMX,t-1}$ show that the pattern of the lag coefficients increases by the increase of the bonds' time to maturity. Interestingly, bonds that mature after 30 years have no lag coefficients significant for all the models for both financial and nonfinancial firms. Though the increasing pattern of the coefficients of lag IVOLs is not monotonic for both categories of firm, we can claim that the bonds' returns are more sensitive for bonds that mature late.

6.4. Idiosyncratic volatility and bond returns categorized by types of bonds

The complex but attractive feature of convertible bonds is that bondholders have the right to convert the bonds to common stocks and may differ in the expectations of returns from the nonconvertible bonds. Since bondholders can convert the bonds to stocks at any time after the restricted period, bondholders demand lower returns for convertible bonds. Brennan and Schwartz (1980) state that the value of convertible bonds depends upon the value of conversion privilege: the risk and capital structure of the firm, the payout policy of the firm, and some other factors. In this section, we will extend the study of bond returns and idiosyncratic volatility in the context of convertibility. For sake of simplicity, we assume that idiosyncratic volatility affects convertible bonds less than nonconvertible bonds due to their convertability.

Table 9 represents the coefficients of the lag IVOLs of different types of bonds. In our sample, there are three types of bonds in both the convertible and nonconvertible bond categories. They are corporate debenture, corporate medium-term notes, and corporate medium-term zero coupon bonds. Panel A depicts the lag IVOL coefficients for financial firms of convertible and nonconvertible bonds. Panel.A.i shows that the coefficients of the lag IVOLs are statistically insignificant for all models. For convertible bonds, there is no significant association between bond returns and idiosyncratic volatility. Panel A.ii shows that the coefficients of all models for all types of nonconvertible bonds are significant. The lag IVOL coefficients of corporate medium-term notes are the highest among all three types of bonds.

[Insert Table 9 here]

Panel B of Table 9 depicts the lag IVOL coefficients for nonfinancial firms of convertible and nonconvertible bonds. Panel.B.i shows that only convertible corporate debenture bonds are in our sample. All the coefficients of the lag IVOLs of all the models are statistically insignificant, meaning that the association between the IVOL and bond returns is zero. Panel B.ii shows that the coefficients of Models 1 through 4 for corporate debenture and corporate medium-term notes of nonconvertible bonds of nonfinancial firms are significant. However, coefficients of lag IVOLs of corporate medium-term zero coupon bonds are not statistically significant. For the last two models, EV_{t-1}^{180} and $IVOL_{CLMX,t-1}$, almost all the coefficients are insignificant (except corporate medium-term notes).

7. Conclusion

In this paper, we study the association between idiosyncratic volatility and expected bond returns. We find that there is a positive and statistically significant association between them. When find that the association is more prominent for the financial firms than for nonfinancial firms. We also document that firms with higher idiosyncratic volatility have generally higher expected bonds returns than firms that are less sensitive to idiosyncratic volatility. Finally, we also find that expected bond returns of smaller nonfinancial firms are higher than that of larger nonfinancial firms.

The results are robust when we control for bond rating, leverage ratio, bond maturity, and bond types. This paper offers the window of opportunities to extend the literature by understanding more about idiosyncratic volatility and expected bond returns of financial firms, especially for banking companies.

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Table 1

Descriptive statistics

Panel A: Descriptive statistics									
	Mean	**Median**	**SD**	**Min**	**Max**	**Skew**	**Kurt**	**ADF**	**N**
Bond return	0.006220	0.004000	0.046050	-0.114060	0.12940	2.57430	99.085100	-435.800***	1,047,926
Stock return	0.009050	0.010000	0.101700	-0.263600	0.28480	2.58990	125.640000	-421.700***	984,267
S&P return	0.006740	0.011000	0.039031	-0.109900	0.08755	-0.47700	0.765300	-394.100***	984,267
Excess return	0.008200	0.009000	0.101700	-0.263800	0.28350	2.58280	125.590000	-420.800***	984,267
Risk free	0.000846	0.000100	0.001300	0.000000	0.00430	1.53724	1.030100	-2.310	984,267
Excess market return	0.007990	0.012000	0.039840	-0.103500	0.10190	-0.38010	0.376940	-28.540***	98,4267
SMB	0.001650	0.002000	0.022470	-0.042200	0.05430	0.08319	-0.508400	-30.250***	984,267
HML	0.000210	0.000200	0.022070	-0.072700	0.05890	-0.04472	1.038089	-25.380***	984,267
UMD	0.001100	0.004000	0.041017	-0.162800	0.10240	-0.90100	2.643700	-9.970***	984,267
$IVOl_{ff}$	0.060300	0.046000	0.057900	0.015980	0.26080	31.84000	6,302.000000	-181.300***	984,267
$IVOl_{CAPM}$	0.066830	0.051000	0.064253	0.018000	0.30870	25.99000	4,461.000000	-182.900***	984,267
$IVOl_{MOM}$	0.060310	0.046000	0.057920	0.015986	0.26085	31.84000	6,302.000000	-181.300***	983,785
$IVOL_{GS,t}^{lf}$	0.013718	0.009770	0.011130	0.004900	0.07340	3.14500	12.139000	-239.900***	986,915
VIX	19.138800	16.950000	7.990000	11.560000	46.35000	1.26420	2.432600	-4.951***	1,047,926
Term	0.021020	0.022500	0.010000	-0.004400	0.03680	-0.80250	0.158400	-1.729	1,047,707

Def	0.027350	0.027400	0.007770	0.015800	0.05620	1.40000	3.765000	-1.364	1,047,926
Liquidity	0.004030	0.002507	0.004010	0.001000	0.02186	3.56930	14.970000	-2.220	1,047,926

Panel B: Number of bonds traded per year and the highest number of bond traded industry

Year	**No. of bonds traded**	**Highest traded industry**	**Number of bonds in the industry**	**Year**	**No. of bonds traded**	**Highest traded industry**	**Number of bonds in the industry**
2002	8,119	Utility	1,405	2010	11,540	Banks	3,085
2003	8,713	Utility	1,575	2011	13,038	Banks	3,968
2004	,7938	Utility	1,238	2012	15,319	Banks	5,362
2005	7,639	Utility	1,113	2013	16,230	Banks	5,482
2006	7,547	Financial	1,167	2014	16,746	Banks	5,142
2007	7,816	Financial	1,386	2015	14,876	Banks	3,629
2008	8,822	Financial	1,991	2016	12,549	Financial	3,244

Panel C: Industry-wise percentage of traded bonds

Industry	Fraction of traded bonds	Industry	Fraction of traded bonds	Industry	Fraction of traded bonds	Industry	Fraction of traded bonds
Agriculture	0.000108	Drugs	0.013728	Ships	0.000745	Chips	0.008275
Food	0.012257	Chemicals	0.016082	Guns	0.001766	Lab Eq	0.001651
Soda	0.007200	Rubber	0.001123	Gold	0.003795	Paper	0.011302
Beer	0.005933	Textile	0.000522	Mines	0.005711	Boxes	0.002684
Smoke	0.003087	Building materials	0.006432	coal	0.001237	Transportation	0.024940
Toys	0.001399	Construction	0.007657	Oil	0.045365	Wholesale	0.010395
Fun	0.005051	Steel	0.006005	Utility	0.105449	Retail	0.032681
Books	0.006894	Fab pr	0.000324	Telecom	0.048740	Meals	0.007164
Household	0.008143	Mechanical	0.016671	Per SV	0.003387	Banks	0.227064
Cloths	0.002102	Electric Eq	0.012005	Bus SV	0.012059	Insurance	0.036567
Health	0.007297	Autos	0.016851	Hardware	0.007933	Real estate	0.000727
Medical Equipment	0.004222	Aerospace	0.008408	Software	0.008293	Financial	0.217095
						Other	0.002552

This table presents the descriptive statistics of the return of bond and stocks, the volatility measure, term structure and factors of the asset pricing. The sample period is from July 2002 to June 2016. Bond return is the monthly return for the each bond issue. Stock return is the CRSP monthly firm-level stock return. Excess market return is S&P return minus the risk-free rate. RF, HML, SMB, and MOM are the four factors used in the FF and Carhart model. IVOLs are created from the Equations 2 and 4. VIX is the CBOE volatility index. TERM is the difference of yield between 10-year and 1-year govt. bond. DEF is the default spread measures by the difference of the yield rate between 30-year Baa bonds and 30-year govt. bond. LIQ is the liquidity premium calculated as the difference of the yield between 3-month LIBOR and 3-month T-bill. ADF is the Augmented Dickey Fuller test for the presence of the unit root, where the null hypothesis is that the data is nonstationary. N is the number of observation .Panel B represents the number of bonds traded per year and the highest number of bonds traded in that year. Panel C shows FF 49 industry-wise fractions of bonds traded. The fraction is the equally weighted average of the fraction in each industry.

Table 2
Bond return and idiosyncratic risk

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Liquidity	-0.0185***	-0.0184***	-0.0184***	-0.0185***	-0.0183***	-0.0184***
	(-5.8335)	(-5.8338)	(-5.8338)	(-5.8436)	(-91.2321)	(-92.5480)
Term	-0.0626	-0.0634	-0.0634	-0.0727	-0.0427***	-0.0454***
	(-0.7572)	(-0.7734)	(-0.7734)	(-0.9424)	(-3.6695)	(-3.9191)
Default	0.4748***	0.4758***	0.4758***	0.4579***	0.5663***	0.5919***
	(3.7779)	(3.7321)	(3.7321)	(3.5425)	(46.7026)	(49.0000)
$IVOL\_CAPM_{t-1}$	0.0369***					
	(3.1212)					
$IVOL\_FF_{t-1}$		0.0435***				
		(3.3425)				
$IVOL\_Carhart_{t-1}$			0.0435***			
			(3.3425)			
$IVOL\_GS_{t-1}$				0.2375***		
				(3.7757)		
EV_{t-1}^{180}					0.0494***	
					(7.6224)	
$IVOL_{CLMX,t-1}$						0.0008***
						(5.3126)
Constant	-0.0022	-0.0028	-0.0028	-0.0019	-0.0018	-0.0029
	(-0.3781)	(-0.4798)	(-0.4791)	(-0.3245)	(-0.2412)	(-0.4916)
Observations	950,517	950,517	950,517	951,537	871,057	950,392
Adjusted R^2	0.0385	0.0387	0.0387	0.0385	0.0447	0.0393
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering Ind	Yes	Yes	Yes	Yes	No	No
Clustering Year	Yes	Yes	Yes	Yes	No	No

This table reports the panel regression results of individual bond returns on different measure of idiosyncratic risks, and a series of control variables. The panel regressions are run with the fixed effect model. The dependent variable is bond return, which is measured as per Equation (1). Term is the return differential of 10-year and 1-year T-bonds, the difference between 10-year corporate Baa bonds and the 10-year T-bond is referred to as default spread, and the difference between the 3-month LIBOR and 3-month treasury are termed as liquidity spread. $IVOL_{CAPM}$, $IVOL_{FF}$, and $IVOL_{Carhart}$ were determined by the CAPM, FF three factors, and Carhert (1997) four factors model. $IVOL_{GS}$ is the measure of low frequency idiosyncratic volatility measure used in Goyal and Santa-Clara (2003). EV_{t-1}^{180} is the equity volatility measure, standard deviation of excess return for past 180 days, used in Campbell and Taksler, 2003. $IVOL_{CLMX,t-1}$ is the IVOL measure used in Campbell et al. (2001). Robust t-values are reported in brackets. The firm and year fixed effect models were considered with the Clustering of Industry and Year. Standard errors are clustered robust. ***, **,and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively.

Table 3
Idiosyncratic volatility and the bond returns: Issuer type

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Panel A: Financial firms						
Liquidity	-0.026***	-0.026***	-0.026***	-0.026***	-0.025***	-0.026***
	(-3.701)	(-3.720)	(-3.720)	(-3.653)	(-3.573)	(-3.618)
Term	0.229	0.225	0.225	0.240	0.251	0.248
	(1.209)	(1.211)	(1.211)	(1.420)	(1.403)	(1.350)
Default	0.499**	0.513**	0.513**	0.600**	0.496*	0.658**
	(2.093)	(2.098)	(2.098)	(2.303)	(1.899)	(2.609)
$IVOL\_CAPM_{t-1}$	0.059***					
	(3.057)					
$IVOL\_FF_{t-1}$		0.072***				
		(3.457)				
$IVOL\_Carhart_{t-1}$			0.072***			
			(3.457)			
$IVOL\_GS_{t-1}$				0.305*		
				(2.011)		
EV_{t-1}^{180}					1.777***	
					(4.671)	
$IVOL_{CLMX,t-1}$						0.044***
						(2.889)
Constant	-0.018*	-0.019**	-0.019**	-0.025**	-0.015	-0.020*
	(-1.906)	(-2.059)	(-2.059)	(-2.519)	(-1.554)	(-2.013)
Observations	300,002	300,002	300,002	300,219	300,002	300,142
Adjusted R^2	0.034	0.034	0.034	0.033	0.034	0.032
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering Ind	Yes	Yes	Yes	Yes	Yes	Yes
Clustering Year	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Nonfinancial firms						
Liquidity	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***
	(-5.175)	(-5.171)	(-5.171)	(-5.256)	(-66.907)	(-66.855)
Term	-0.202***	-0.201***	-0.201***	-0.213***	-0.192***	-0.193***
	(-2.766)	(-2.760)	(-2.760)	(-3.054)	(-14.477)	(-14.525)
Default	0.439***	0.439***	0.439***	0.405***	0.514***	0.516***
	(3.362)	(3.353)	(3.353)	(3.334)	(36.989)	(37.132)
$IVOL\_CAPM_{t-1}$	0.032**					
	(2.261)					
$IVOL\_FF_{t-1}$		0.035**				
		(2.365)				
$IVOL\_Carhart_{t-1}$			0.035**			
			(2.365)			
$IVOL\_GS_{t-1}$				0.201***		
				(3.486)		
EV_{t-1}^{180}					0.027***	
					(4.649)	
$IVOL_{CLMX,t-1}$						0.000***
						(2.737)
Constant	0.003	0.003	0.003	0.005	0.008	0.008
	(0.563)	(0.530)	(0.530)	(0.800)	(1.160)	(1.153)
Observations	650,515	650,515	650,515	651,318	653,689	654,260
Adjusted R^2	0.046	0.046	0.046	0.046	0.045	0.044
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering Ind	Yes	Yes	Yes	Yes	Yes	Yes
Clustering Year	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the panel regression results of individual bond returns on different measure of idiosyncratic risks and a series of control variables. The panel regressions are run with the fixed effect model. The dependent variable is bond return, which is measured as per Equation (1). Term spread is the return differential of 10-year and 1-year T-bonds. The difference between 10-year corporate Baa bond and 10-year T-bond is referred to as default spread; the difference between 3-month LIBOR and 3-month Treasury is termed as Liquidity spread. $IVOL_{CAPM}$, $IVOL_{FF}$, and $IVOL_{Carhart}$ were determined by the CAPM, FF three factors, and Carhart (1997) four factors model. $IVOL_{GS}$ is the measure of low frequency idiosyncratic volatility measure used in Goyal and Santa-Clara (2003). EV_{t-1}^{180} is the equity volatility measure, standard deviation of excess return for past 180 days, used in Campbell and Taksler, 2003. $IVOL_{CLMX,t-1}$ is the IVOL measure used in Campbell et al. (2001). The firm and year fixed effect model has been considered with the Clustering of Industry and Year. Robust t-values are reported in brackets. Standard errors are clustered robust. ***, **,and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Panel A shows the regression results for the financial firms, and Panel B shows the result for the nonfinancial firms.

Table 4
Idiosyncratic volatility and the bond returns: Sorted by the idiosyncratic risk

Model	$IVOL\_CAPM_{t-1}$	$IVOL\_FF_{t-1}$	$IVOL\_Carhart_{t-1}$	EV_{t-1}^{180}
Panel A: Financial firms				
Decile 1	0.076	0.084	0.084	-12.076
	(7.129)***	(7.224)***	(7.224)***	(5.324)***
Decile 2	0.033	0.020	0.020	0.479
	(2.487)**	(1.358)	(1.358)	(0.195)
Decile 3	0.076	0.069	0.069	-3.846
	(5.257)***	(4.352)***	(4.352)***	(2.893)***
Decile 4	0.092	0.073	0.073	1.078
	(7.399)***	(11.572)***	(11.572)***	(0.706)
Decile 5	0.073	0.157	0.157	6.476
	(14.188)***	(8.362)***	(8.362)***	(7.894)***
Decile 6	0.108	0.059	0.059	-1.685
	(8.165)***	(2.606)***	(2.606)***	(2.127)**
Decile 7	0.090	-0.001	-0.001	-1.497
	(6.081)***	(0.069)	(0.069)	(2.412)**
Decile 8	0.013	0.070	0.070	1.234
	(1.075)	(5.199)***	(5.199)***	(2.547)**
Decile 9	0.122	0.122	0.122	-0.798
	(8.479)***	(7.500)***	(7.500)***	(3.010)***
Decile 10	0.094	0.108	0.108	0.345
	(9.828)***	(9.788)***	(9.788)***	(1.435)
Panel B: Nonfinancial firms				
Decile 1	0.024	0.028	0.028	-0.468
	(3.117)***	(3.347)***	(3.347)***	(0.298)
Decile 2	0.052	0.047	0.047	-1.598
	(5.947)***	(4.471)***	(4.471)***	(1.331)
Decile 3	0.053	0.047	0.047	4.449
	(7.002)***	(5.644)***	(5.644)***	(4.305)***
Decile 4	0.075	0.067	0.067	-4.654
	(9.631)***	(8.050)***	(8.050)***	(5.175)***
Decile 5	0.035	0.055	0.055	2.258
	(4.293)***	(6.144)***	(6.144)***	(3.087)***
Decile 6	0.046	0.030	0.030	0.647
	(6.432)***	(3.701)***	(3.701)***	(1.291)
Decile 7	0.056	0.057	0.057	6.118
	(6.758)***	(6.872)***	(6.872)***	(25.553)***
Decile 8	0.036	0.061	0.061	5.510
	(4.211)***	(6.291)***	(6.291)***	(11.476)***
Decile 9	0.055	0.047	0.047	4.230
	(7.316)***	(7.241)***	(7.241)***	(12.765)***
Decile 10	0.039	0.043	0.043	0.005
	(3.194)***	(3.057)***	(3.057)***	(0.404)

This table reports the panel regression coefficients of lag IVOLs. The data is sorted by the idiosyncratic volatility and rank as lowest deciles to the highest deciles. The dependent variable is bond return, which is measured as per Equation (9). The independent variables are term (the return differential of 10-year and 1-year T-bonds), default (the return differential between 10-year corporate Baa bond and 10-year T-bond is referred), and liquidity (the return deferential of 3-month LIBOR and 3-month Treasury is termed) and lag IVOL. IVOL_CAPM, IVOL_FF, IVOL_Carhart were determined by the CAPM, FF three factors, and Carhart (1997) four factors model. IVOL_Goyal is the measure of idiosyncratic volatility measure used in Goyal and Santa-Clara (2003). Std. error is calculated as the clustered robust standard error. T-values are reported in brackets. ***, **, and * represents the coefficients are statistically significant at the 1%, 5% and 10% levels, respectively. Panel A shows the regression results for the financial firms, and Panel B shows the result for the nonfinancial firms.

Table 5
Idiosyncratic volatility and bond returns: Sorted by market capitalizations

Model	$IVOL\_CAPM_{t-1}$	$IVOL\_FF_{t-1}$	$IVOL\_Carhart_{t-1}$	$IVOL\_GS_{t-1}$
Panel A: Financial Firms				
Decile 1	0.080	0.076	0.076	0.615
	(5.753)***	(5.191)***	(5.191)***	(12.328)***
Decile 2	0.103	0.121	0.121	0.475
	(10.983)***	(10.848)***	(10.848)***	(9.159)***
Decile 3	0.119	0.119	0.119	0.473
	(7.310)***	(6.814)***	(6.814)***	(12.071)***
Decile 4	0.012	0.015	0.015	0.396
	(0.741)	(0.840)	(0.840)	(8.701)***
Decile 5	0.139	0.113	0.113	0.224
	(7.641)***	(5.761)***	(5.761)***	(5.593)***
Decile 6	0.065	0.083	0.083	0.197
	(5.696)***	(6.462)***	(6.462)***	(5.178)***
Decile 7	0.014	0.052	0.052	0.175
	(0.709)	(2.142)**	(2.142)**	(5.153)***
Decile 8	0.092	0.136	0.136	0.165
	(5.277)***	(6.998)***	(6.998)***	(5.373)***
Decile 9	-0.006	0.013	0.013	0.155
	(0.494)	(0.861)	(0.861)	(5.034)***
Decile 10	0.105	0.078	0.078	0.079
	(7.581)***	(4.439)***	(4.439)***	(2.545)**
Panel B: Nonfinancial Firms				
Decile 1	0.025	0.030	0.030	0.950
	(2.804)	(2.792)***	(2.792)***	(17.435)***
Decile 2	0.071	0.065	0.065	0.459
	(8.027)***	(7.655)***	(7.655)***	(14.180)***
Decile 3	0.052	0.055	0.055	0.224
	(6.587)***	(6.727)***	(6.727)***	(10.787)***
Decile 4	0.045	0.048	0.048	0.125
	(5.277)***	(5.198)***	(5.198)***	(6.310)***
Decile 5	0.085	0.094	0.094	0.039
	(9.319)***	(9.060)***	(9.060)***	(2.175)**
Decile 6	0.048	0.056	0.056	0.098
	(4.801)***	(5.146)***	(5.146)***	(6.372)***
Decile 7	0.070	0.076	0.076	0.048
	(11.356)***	(11.568)***	(11.568)***	(3.250)***
Decile 8	0.030	0.041	0.041	0.077
	(4.395)***	(5.672)***	(5.672)***	(4.094)***
Decile 9	0.049	0.046	0.046	-0.011
	(6.318)***	(5.498)***	(5.498)***	(0.698)
Decile 10	0.015	0.014	0.014	-0.016
	(1.881)*	(1.591)	(1.591)	(1.223)

This table reports the panel regression coefficients of lag IVOLs. The data is sorted by market capitalization and ranked as lowest deciles to the highest deciles. The dependent variable is bond return, which is measured as per Equation (9). The independent variables are term (the return differential of 10-year and 1-year T-bonds), default (the return differential between 10-year corporate Baa bond and 10-year T-bond is referred), and liquidity (the return deferential of 3-month LIBOR and 3-month Treasury is termed) and lag IVOL. IVOL_CAPM, IVOL_FF, IVOL_Carhart were determined by the CAPM, FF three factors, and Carhart (1997) four factors model. IVOL_Goyal is the measure of idiosyncratic volatility measure used in Goyal and Santa-Clara (2003). Std. error is calculated as the clustered robust standard error. T-values are reported in brackets. ***, **, and * represents the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Panel A shows the regression results for the financial firms, and Panel B shows the result for the nonfinancial firms.

Table 6
Idiosyncratic volatility and bond returns: Credit rating

Model	$IVOL\_CAPM_{t-1}$	$IVOL\_FF_{t-1}$	$IVOL\_Carhart_{t-1}$	$IVOL\_GS_{t-1}$	EV_{t-1}^{180}	$IVOL_{CLMX,t-1}$
Panel A.i: S&P rating and financial firms						
NR	0.065	0.113	0.113	0.217	3.095	0.004
	(5.202)***	(7.065)***	(7.065)***	(7.956)***	(7.008)***	(0.437)
1	0.043	0.045	0.045	0.263	0.177	-0.001
	(3.488)***	(2.936)***	(2.936)***	(5.364)***	(1.184)	(0.059)
2	0.066	0.080	0.080	0.223	-1.184	-0.142
	(9.728)***	(9.552)***	(9.552)***	(14.170)***	(1.079)	(1.947)*
3	0.052	0.053	0.053	0.407	0.096	-0.035
	(4.649)***	(4.187)***	(4.187)***	(15.097)***	(0.104)	(2.341)**
4	0.121	0.129	0.129	0.724	2.034	0.028
	(5.983)***	(5.765)***	(5.765)***	(11.477)***	(2.665)***	(6.118)***
5	0.044	0.040	0.040	1.218	0.501	0.032
	(1.108)	(0.971)	(0.971)	(4.625)***	(1.428)	(10.101)***
Panel A.ii: S&P rating and nonfinancial firms						
NR	0.019	0.020	0.020	0.329	1.510	0.021
	(0.785)	(0.706)	(0.706)	(2.090)**	(4.687)***	(2.664)***
1	0.015	0.013	0.013	-0.014	-3.183	0.200
	(2.071)**	(1.745)*	(1.745)*	(1.142)	(2.887)***	(2.530)**
2	0.038	0.039	0.039	-0.019	5.933	-0.107
	(9.097)***	(8.955)***	(8.955)***	(2.277)**	(4.965)***	(0.914)
3	0.045	0.052	0.052	0.154	1.856	0.010
	(10.600)***	(11.390)***	(11.390)***	(17.509)***	(2.010)**	(0.342)
4	0.044	0.048	0.048	0.483	1.746	0.396
	(6.437)***	(6.317)***	(6.317)***	(17.554)***	(1.262)	(5.652)***
5	0.009	0.013	0.013	1.094	0.787	0.007
	(1.152)	(1.408)	(1.408)	(11.441)***	(2.944)***	(0.866)
Panel B.i: Moody's rating and financial firms						
NR	0.069	0.119	0.119	0.225	5.439	-0.003
	(4.575)***	(5.375)***	(5.375)***	(6.889)***	(6.564)***	(0.090)
1	0.020	-0.001	-0.001	0.207	0.568	-0.039
	(1.655)*	(0.044)	(0.044)	(7.090)***	(1.244)	(1.609)
2	0.047	0.041	0.041	0.286	0.808	-0.002
	(5.202)***	(3.884)***	(3.884)***	(12.008)***	(3.001)***	(0.151)
3	0.088	0.117	0.117	0.311	2.811	0.108
	(12.455)***	(14.382)***	(14.382)***	(15.110)***	(8.806)***	(13.418)***
4	0.046	0.059	0.059	0.793	2.837	0.043
	(2.223)**	(2.338)**	(2.338)**	(11.858)***	(4.226)***	(1.410)
5	0.094	0.079	0.079	0.966	2.823	0.088
	(2.776)***	(2.213)**	(2.213)**	(5.218)***	(3.158)***	(2.004)**
Panel B.ii. Moody's rating and nonfinancial firms						
NR	0.018	0.021	0.021	0.144	2.569	0.001
	(0.673)	(0.675)	(0.675)	(1.628)	(1.762)*	(0.101)
1	0.034	0.030	0.030	-0.073	1.450	0.015
	(2.930)***	(2.516)**	(2.516)**	(4.500)***	(2.149)**	(1.903)*
2	0.034	0.035	0.035	-0.004	1.281	0.018
	(9.845)***	(9.620)***	(9.620)***	(0.547)	(5.907)***	(4.077)***
3	0.019	0.026	0.026	0.150	3.922	0.073
	(5.088)***	(6.474)***	(6.474)***	(17.539)***	(13.340)***	(5.813)***
4	0.032	0.034	0.034	0.321	1.204	0.012
	(5.335)***	(5.186)***	(5.186)***	(15.957)***	(5.167)***	(1.507)
5	0.023	0.026	0.026	1.252	-0.021	0.000
	(2.082)**	(2.070)**	(2.070)**	(15.613)***	(0.982)	(0.206)

This table reports the panel regressions coefficients of lag IVOL for all six models. Panel A.i shows the regression coefficients of financial firms controlling by credit rating quintile of S&P 500. Panel A.ii shows the regression coefficients of nonfinancial firms controlling by credit rating quintile of S&P 500. Panel B.i shows the regression coefficients of financial firms controlling by credit rating quintile of Moody's. Panel B.ii shows the regression coefficients of nonfinancial firms controlling by credit rating quintile of Moody's. NR represents the firms are nonrated. The dependent variable is bond return, which is measured as per Equation (1). The independent variables are term (the return differential of 10-year and 1-year T-bonds), default (the return differential between 10-year corporate Baa bond and 10-year T-bond), and liquidity (the return deferential of 3-month LIBOR and 3-month Treasury is termed) and lag IVOL. IVOL_CAPM, IVOL_FF, IVOL_Carhart were determined by the CAPM, FF three factors, and Carhart (1997) four factors model. IVOL_Goyal is the measure of idiosyncratic volatility measure used in Goyal and Santa-Clara (2003).). EV_{t-1}^{180} is the equity volatility measure, standard deviation of excess return for past 180 days, used in Campbell and Taksler, 2003. $IVOL_{CLMX,t-1}$ is the IVOL measure used in Campbell et al. (2001).Std. error is calculated as the clustered robust. T-values are reported in brackets. ***, **, and * represent the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 7
Idiosyncratic volatility and the bond returns: Sorted by leverage ratio

Model	$IVOL\_CAPM_{t-1}$	$IVOL\_FF_{t-1}$	$IVOL\_Carhart_{t-1}$	$IVOL\_GS_{t-1}$
Panel A: Financial and leverage				
Decile 1	0.055	0.061	0.061	-2.994
	(1.605)	(1.585)	(1.585)	(1.235)
Decile 2	0.007	-0.012	-0.012	0.927
	(0.150)	(0.217)	(0.217)	(1.091)
Decile 3	0.044	0.097	0.097	3.262
	(2.033)**	(2.926)***	(2.926)***	(2.530)**
Decile 4	-0.025	-0.028	-0.028	5.350
	(0.940)	(0.943)	(0.943)	(1.084)
Decile 5	-0.096	-0.087	-0.087	1.127
	(3.422)***	(2.504)**	(2.504)**	(0.139)
Decile 6	0.026	0.033	0.033	-2.790
	(0.838)	(0.935)	(0.935)	(0.658)
Decile 7	0.106	0.106	0.106	1.774
	(3.497)***	(3.228)***	(3.228)***	(1.081)
Decile 8	0.061	0.109	0.109	0.543
	(3.234)***	(4.991)***	(4.991)***	(1.084)
Decile 9	0.093	0.102	0.102	0.166
	(3.637)***	(3.725)***	(3.725)***	(0.584)
Decile 10	0.028	0.011	0.011	-1.302
	(1.462)	(0.569)	(0.569)	(.601)
Panel A: Nonfinancial and leverage				
Decile 1	0.058	0.064	0.064	0.377
	(4.748)***	(4.928)***	(4.928)***	(9.593)***
Decile 2	-0.008	0.001	0.001	0.111
	(0.677)	(0.118)	(0.118)	(4.166)***
Decile 3	0.036	0.038	0.038	0.160
	(3.533)***	(3.364)***	(3.364)***	(7.691)***
Decile 4	0.056	0.065	0.065	0.141
	(4.794)***	(5.249)***	(5.249)***	(7.630)***
Decile 5	0.050	0.053	0.053	0.100
	(4.832)***	(4.748)***	(4.748)***	(5.191)***
Decile 6	0.043	0.051	0.051	0.072
	(3.348)***	(3.573)***	(3.573)***	(3.511)***
Decile 7	0.049	0.067	0.067	0.133
	(4.044)***	(4.779)***	(4.779)***	(6.705)***
Decile 8	0.005	0.008	0.008	0.153
	(0.501)	(0.719)	(0.719)	(7.742)***
Decile 9	0.083	0.090	0.090	0.330
	(8.379)***	(8.261)***	(8.261)***	(11.990)***
Decile 10	0.117	0.125	0.125	0.395
	(6.696)***	(6.841)***	(6.841)***	(11.105)***

This table reports the panel regression coefficients of lag IVOLs. The data is sorted by leverage ratios and rank as lowest decile (1) to highest decile (10). The dependent variable is bond return, which is measured per Equation (1). The independent variables are term (the return differential of 10-year and 1-year T-bonds), default (return differential between 10-year corporate Baa bonds and 10-year T-bonds), and liquidity (return deferential of 3-month LIBOR and 3-monthTtreasury), and lag IVOL. IVOL_capm, IVOL_FF, IVOL_Carhart were determined by CAPM, FF three-factors, and Carhart (1997) four factor model. IVOL_goyal is the measure of idiosyncratic volatility measure used in Goyal and Santa-Clara (2003). Standard. error is calculated as the clustered robust. T-values are reported in brackets. ***, **, and * represents the coefficients are statistically significant at the 1%, 5% and 10% levels, respectively. Panel A shows the regression results for financial firms, and Panel B shows the result for nonfinancial firms.

Table 8
Idiosyncratic volatility and bond returns: Categorized by time to maturity

	$IVOL\_CAPM_{t-1}$	$IVOL\_FF_{t-1}$	$IVOL\_Carhart_{t-}$	$IVOL\_GS_{t-1}$	EV_{t-1}^{180}	$IVOL_{CLMX,t-1}$
Panel A: Financial firms						
< 1 yr	0.055	0.075	0.075	0.238	1.530	0.030
	(7.603)***	(8.868)***	(8.868)***	(8.978)***	(6.610)***	(3.434)***
>1 yr but ≤ 3 yr	0.063	0.081	0.081	0.297	1.792	0.046
	(7.001)***	(7.361)***	(7.361)***	(11.689)***	(5.831)***	(4.142)***
>3 yr but ≤ 5 yr	0.055	0.067	0.067	0.345	2.086	0.054
	(4.375)***	(4.504)***	(4.504)***	(12.368)***	(5.022)***	(3.548)***
>5 yr but ≤10 yr	0.063	0.067	0.067	0.342	1.971	0.046
	(6.412)***	(5.852)***	(5.852)***	(13.174)***	(4.985)***	(3.618)***
>10 yr but ≤20 yr	0.068	0.079	0.079	0.315	2.717	0.057
	(4.278)***	(4.056)***	(4.056)***	(4.740)***	(3.705)***	(4.325)***
>20 yr but ≤30 yr	0.074	0.074	0.074	0.442	2.406	0.047
	(3.245)***	(2.795)***	(2.795)***	(8.038)***	(3.829)***	(1.278)
> 30 yrs	0.040	0.031	0.031	0.028	4.563	0.004
	(0.502)	(0.358)	(0.358)	(0.063)	(1.230)	(0.042)
Panel B: Nonfinancial firms						
< 1 yr	0.035	0.038	0.038	0.080	1.630	0.018
	(3.089)***	(3.081)***	(3.081)***	(5.706)***	(3.404)***	(1.685)*
>1 yr but ≤ 3 yr	0.042	0.047	0.047	0.198	1.920	0.012
	(3.407)***	(3.442)***	(3.442)***	(11.435)***	(4.471)***	(1.011)
>3 yr but ≤ 5 yr	0.046	0.054	0.054	0.366	1.944	0.013
	(3.972)***	(4.241)***	(4.241)***	(15.562)***	(5.663)***	(1.954)*
>5 yr but ≤10 yr	0.012	0.015	0.015	0.255	-0.012	0.000
	(1.865)*	(2.028)**	(2.028)**	(15.985)***	(0.461)	(0.107)
>10 yr but ≤ 20 yr	0.091	0.098	0.098	0.192	4.221	0.149
	(4.316)***	(4.427)***	(4.427)***	(6.466)***	(4.951)***	(2.980)***
>20 yr but ≤ 30 yr	0.066	0.073	0.073	0.040	2.177	0.029
	(7.372)***	(7.305)***	(7.305)***	(2.275)**	(3.881)***	(1.911)*
> 30 yrs	0.027	0.025	0.025	0.081	-0.417	0.007
	(1.572)	(1.387)	(1.387)	(0.648)	(0.573)	(1.814)*

This table reports the panel regression coefficients of lag IVOLs. The data is sorted by time to maturity and categorized from 1 to 7. Category 1 represents the smallest time to maturity bonds; category 7 represents the longest time to maturity bonds The dependent variable is bond return, which is measured per Equation (9). The independent variables are term (return differential of 10-year and 1-year T-bonds), default (return differential between 10-year corporate Baa bond and 10-year T-bond), liquidity (return deferential of 3-month LIBOR and 3-month Treasury) and lag IVOL. IVOL_CAPM, IVOL_FF, IVOL_Carhart were determined by the CAPM, FF three factors, and Carhart (1997) four factors model. IVOL_goyal is the measure of idiosyncratic volatility measure used in Goyal and Santa-Clara (2003).). EV_{t-1}^{180} is the equity volatility measure, standard deviation of excess return for past 180 days, used in Campbell and Taksler, 2003. $IVOL_{CLMX,t-1}$ is the IVOL measure used in Campbell et al. (2001). Standard error is calculated as the clustered robust standard error. T-values are reported in brackets. ***, **, and * represents the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Panel A shows the regression results for financial firms, and Panel B shows the result for nonfinancial firms.

Table 9
Idiosyncratic volatility and bond returns: Categorized by bond types

Model	$IVOL\_CAPM_{t-1}$	$IVOL\_FF_{t-1}$	$IVOL\_Carhart_{t-}$	$IVOL\_GS_{t-1}$	EV_CT	IV_CLMX
Panel A.i: Financial companies and convertible bond						
Corporate Debenture	0.086	0.186	0.186	0.146	-1.545	0.219
	(0.544)	(0.986)	(0.986)	(0.142)	(0.304)	(0.889)
Corporate MTN	0.169	0.211	0.211	0.630	9.280	0.125
	(1.213)	(1.374)	(1.374)	(1.013)	(1.744)*	(0.695)
Corporate MTZ	-0.088	-0.111	-0.111	0.141	0.521	-0.402
	(0.856)	(0.748)	(0.748)	(0.710)	(0.143)	(1.339)
Panel A.ii: Financial companies and nonconvertible						
Corporate Debenture	0.058	0.063	0.063	0.338	1.598	0.052
	(8.966)***	(8.364)***	(8.364)***	(21.097)***	(7.391)***	(6.553)***
Corporate MTN	0.081	0.095	0.095	0.362	2.018	0.053
	(9.983)***	(9.949)***	(9.949)***	(11.954)***	(6.572)***	(5.971)***
Corporate MTZ	0.044	0.077	0.077	0.224	2.301	-0.001
	(4.746)***	(6.975)***	(6.975)***	(8.659)***	(6.889)***	(0.061)
Panel B.i: Nonfinancial and convertible						
Corporate Debenture	-0.028	-0.054	-0.054	-0.177	-0.688	-0.033
	(0.446)	(0.849)	(0.849)	(0.172)	(0.122)	(1.283)
Panel B.ii: Nonfinancial and nonconvertible						
Corporate Debenture	0.026	0.030	0.030	0.206	0.023	0.000
	(4.376)***	(4.276)***	(4.276)***	(23.816)***	(0.836)	(0.770)
Corporate MTN	0.114	0.114	0.114	0.168	5.912	0.042
	(4.712)***	(4.680)***	(4.680)***	(5.820)***	(3.880)***	(1.284)
Corporate MTZ	0.491	0.503	0.503	0.561	41.694	2.808
	(1.713)*	(1.750)*	(1.750)*	(1.337)	(1.537)	(1.538)

This table reports panel regression coefficients of lag IVOLs. The data is categorized by bond types, convertible, and nonconvertible. Corporate MTN and Corporate MTZ are Corporate Medium-Term notes and Corporate Medium-Term Zero coupon bonds. The dependent variable is bond return, which is measured per Equation (1). The independent variables are term (return differential of 10-year and 1-year T-bonds), default (return differential between 10-year corporate Baa bond and 10-year T-bond), and liquidity (return deferential of 3-month LIBOR and 3-month Treasury) and lag IVOL. IVOL_CAPM, IVOL_FF, and IVOL_Carhart were determined by the CAPM, FF three factors, and Carhart (1997) four factors model. IVOL_goyal is the measure of idiosyncratic volatility measure used in Goyal and Santa-Clara (2003). EV_{t-1}^{180} is the equity volatility measure of Campbell and Taskler (2003). $IVOL_{CLMX,t-1}$ is the IVOL measure used in CLMX (2001). Standard error is calculated as the clustered robust standard error. T-values are reported in brackets. ***, **, and * represent the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Panel A shows regression results for financial firms, and Panel B shows result for nonfinancial firms.

Fig. 1

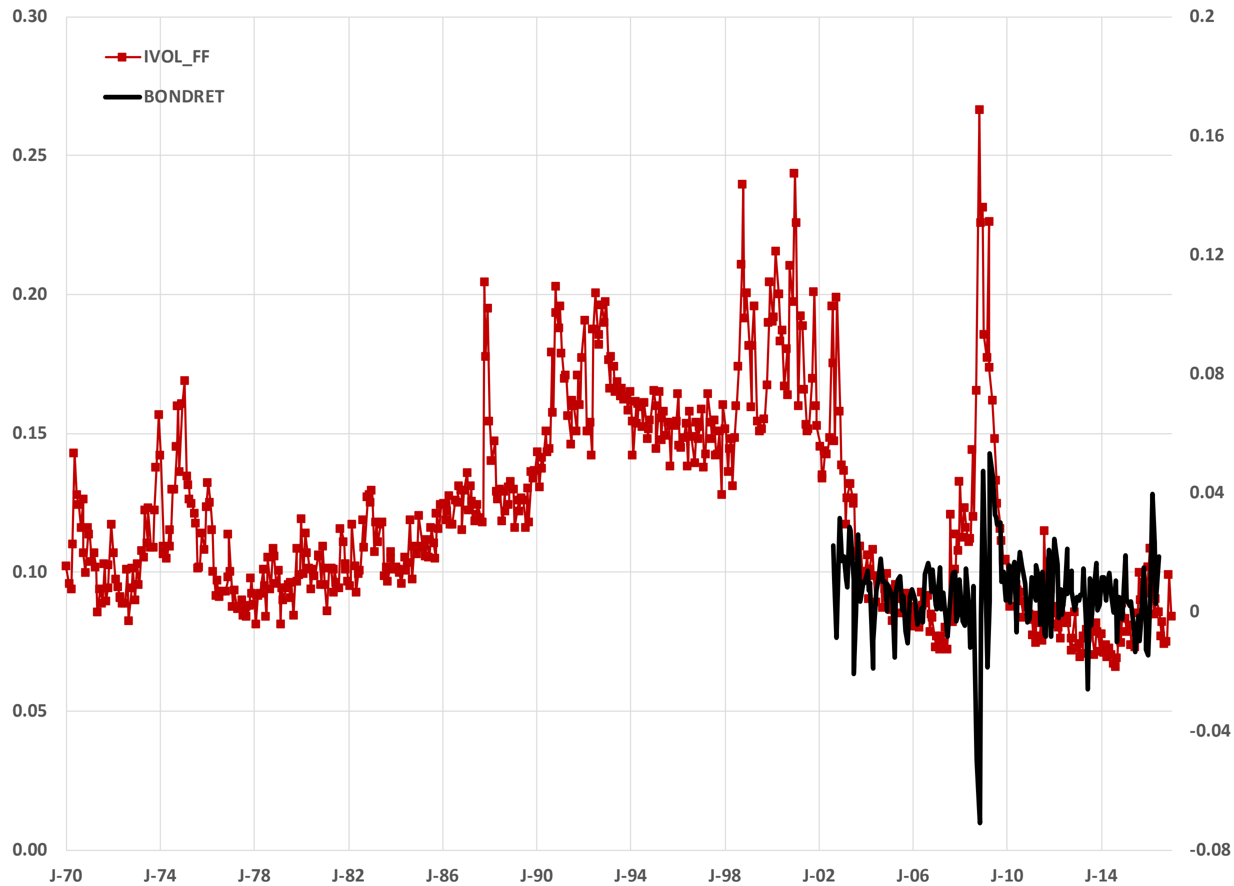

Fig. 1: This graph shows the time series plot of average idiosyncratic risk (right vertical axis) and average bond return (left vertical axis) in the sample. Idiosyncratic volatility (IVOL) is calculated using the standard deviation of the residuals of the Fama and French 3 Factors Model data used from January 1970 to November 2017. Bond returns is the average bond returns of the WRDS corporate bond data that are used in the study.

Fig. 2

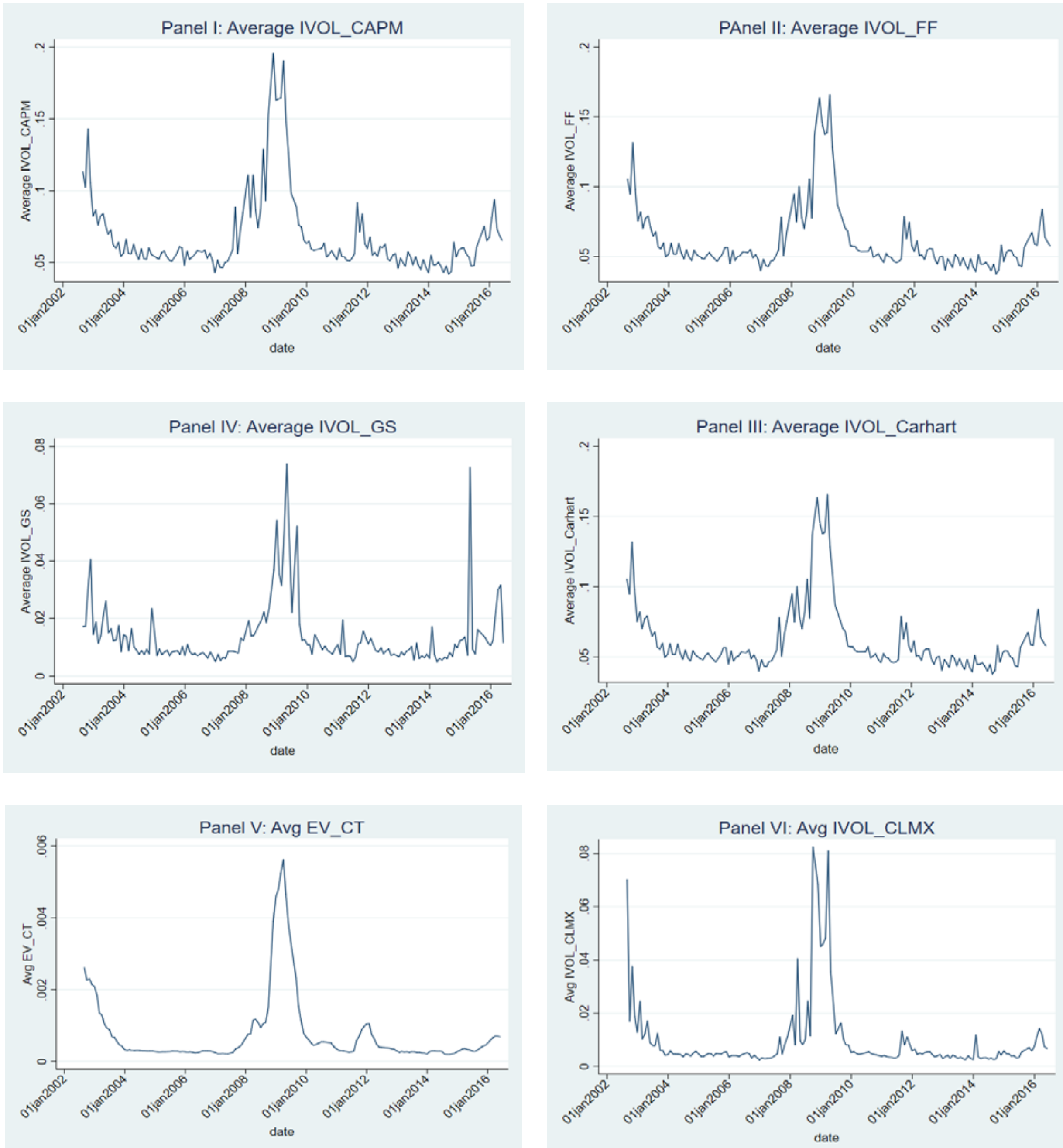

Fig. 2: Time series plot of idiosyncratic volatilities. Panel I shows the time series plot average IVOL measures using CAPM. Panel II shows the time series plot average IVOL measures using the Fama and French 3 Factor Model. Panel III shows the time series plot average IVOL measures using Carhart 4 Factor Model. Panel IV shows the time series plot average IVOL measures used in the Goyal and Santa-Clara (2003). Panel V shows the time series plot average IVOL measures used in Campbell and Taksler (2003). Panel VI shows the time series plot of average IVOL measures used in CLMX (2001).

Appendix

Appendix I: Data Source

Name of Data	**Details**	**Source**
Bond return	WRDS	WRDS bond database
Rating		WRDS bond database
Stock return data		CRSP
Fundamental data		Compustat
SML, HML, MOM		Ken French Website
Treasury rate data		FRED St. Louis

Appendix II

Bond return and idiosyncratic risk using random effect model

Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
Liquidity	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***
	(-58.674)	(-61.686)	(-61.686)	(-65.554)	(-118.852)	(-118.944)
Term	-0.173***	-0.104***	-0.104***	-0.117***	-0.106***	-0.106***
	(-37.544)	(-22.675)	(-22.675)	(-25.402)	(-19.929)	(-19.937)
Default	0.479***	0.543***	0.543***	0.431***	0.656***	0.661***
	(21.547)	(22.798)	(22.798)	(43.502)	(89.213)	(90.261)
$IVOL\_CAPM_{t-1}$	0.044***					
	(5.871)					
$IVOL\_FF_{t-1}$		0.049***				
		(5.155)				
$IVOL\_Carhart_{t-1}$			0.049***			
			(5.155)			
$IVOL\_GS_{t-1}$				0.275***		
				(36.394)		
EV_{t-1}^{180}					0.069***	
					(11.628)	
$IVOL_{CLMX,t-1}$						0.001***
						(5.740)
Constant	-0.001***	-0.005***	-0.005***	-0.002***	-0.005***	-0.005***
	(-4.493)	(-20.960)	(-20.960)	(-10.569)	(-21.692)	(-22.208)
Observations	954,456	953,692	953,692	954,750	953,691	954,402
Number of issue_id	28,212	28,181	28,181	28,187	28,181	28,186
Firm FE	No	No	No	No	No	No
Year FE	No	No	No	No	No	No
Clustering Ind	No	No	No	No	No	No
Clustering Year	No	No	No	No	No	No

This table reports the panel regression tests of individual bond returns on different measure of idiosyncratic risks, a number of control variables. The panel regressions are run with the random effect model. The dependent variable is bond return, which is measured per Equation (1). Term is the return differential of 10-year and 1-year T-bonds, difference between 10-year corporate Baa bond and 10-year T-bond is referred as default spread, difference between 3-month LIBOR and 3-month Treasury is termed as Liquidity spread.$IVOL_{CAPM}$, $IVOL_{FF}$, and $IVOL_{Carhart}$ were determined by the CAPM, FF three factors, and Carhart (1997) four factor model. $IVOL_{GS}$ is the measure of low frequency idiosyncratic volatility measure used in Goyal and Santa-Clara (2003). EV_{t-1}^{180} is the equity volatility measure, standard deviation of excess return for past 180 days, used in Cambell and Taksler,2003. $IVOL_{CLMX,t-1}$ is the IVOL measure used in CLMX (2001). Robust t-values are reported in brackets. Standard errors are clustered robust. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Appendix 3

Quintile of bond ratings of the two rating firms

	S&P	**Moody's**
Quintile 1	AAA	AAA
	AA+	AA1
	AA	AA2
	AA-	AA3
2	A+	A1
	A-	A2
	A-	A3
3	BBB+	BAA1
	BBB	BAA2
	BBB-	BAA3
4	BB+	BA1
	BB	BA2
	BB-	BA3
	B+	B1
	B	B2
5	B-	B3
	CCC+	CAA1
	CCC	CAA2
	CA	CAA3