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Implied Volatility Changes and Corporate Bond Returns*

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Abstract

Option implied volatility change has significant cross-sectional predictive power for the underlying firms' bond returns. Corporate bonds with large increases in implied volatility over the past month underperform those with large decreases in implied volatility by 0.6% per month. The evidence suggests that implied volatility changes contain information about uncertainty shocks to the firm. Our results are consistent with the notion that informed traders with new information about firm risk prefer to trade in the option market, and that the corporate bond market is slow in incorporating that information.

Keywords: Corporate bonds, implied volatility changes, default risk, information diffusion

JEL Classification: G10, G12, G14

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1. Introduction

Options are redundant assets only in perfect markets (Black and Scholes (1973) and Merton (1973)). Real world frictions such as transaction costs, short-sale constraints, and segmented markets may make informed traders migrate to options markets instead of stock or bond markets (Back (1993), Biais and Hillion (1994), and Figlewski and Webb (1993)). Numerous studies examine the information transmission from the option market to stock prices and show predictability of future stock returns from various option-related variables.[1] However, whether option market has relevant information for the future corporate bond return and, hence, contributes to the price discovery of corporate bonds has received much less attention. The size of the corporate bond market is non-trivial. According to the flow of funds accounts in the United States, outstanding amount of corporate bond issued by non-financial U.S. corporations was $6.2 trillion in 2018.[2] In this paper, we document that option prices contain important information for the price discovery in the corporate bond market by showing that changes in the implied volatility of equity options predict underlying firms' bond return.

The predictability from option implied volatility to stock or bond returns is consistent with economies where informed traders choose to trade in the option market before other markets, such as in Easley, O'Hara, and Srinivas (1998). An, Ang, Bali, and Cakici (2014) show that changes in implied volatilities have significant cross-sectional predictive power for future stock returns. Since stocks and bonds are contingent claims on the value of firm's asset, it may seem unsurprising that implied volatility changes also predict future corporate bond returns. There are at least three reasons why the findings from stock markets may not directly apply to bond markets.

First, stock and bond returns are not perfectly correlated (the average cross-sectional correlation in our sample is only 0.44). Corporate bonds with less credit risk have smaller hedge ratios and comove less with the stock. Second, corporate bond market also consists of more institutional and sophisticated investors than the stock market. Edwards, Harris, and Piwowar (2007) document a median trade size of $632,700 in the corporate bond market and find that in the corporate bond market transaction costs are lower for larger trades suggesting that institutions are

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[1] See, for example, Chakravarty, Gulen, and Mayhew (2004), Cao, Chen, and Griffin (2005), Pan and Poteshman (2006), Bali and Hovakimian (2009), Cremers and Winbaum (2010), Xing, Zhang, and Zhao (2010), Johnson and So (2012), Conrad, Dittmar, and Ghysels (2013), An, Ang, Bali, and Cakici (2014), Ge, Lin, and Pearson (2016), and Stilger, Kostakis, and Poon (2017).

[2] See Table L.213 in the financial accounts of the United States, Federal Reserve Board Z.1 flow of funds.

likely to be the typical traders in bonds. Third, following the seminal insights from Black and Scholes (1973) and Merton (1973), it is important to remember that a stock is a long position of call option on the firm's asset while a bond is a short position of put option on the firm's asset. Other things equal, stock and bond prices may react differently to volatility change of the firm's asset. As such, changes in implied volatilities could have different impacts on bond and stock prices and whether option market leads the corporate bond market remains an open question.

We study the predictability of the sample of corporate bonds from TRACE over the period 2002 to 2017. At the end of each month, we sort all bonds into decile portfolios based on change in implied volatilities of the underlying call ($\Delta CVOL$) or put ($\Delta PVOL$) options over the previous month. We keep these portfolios for one month and rebalance each month. We find that the bonds in the top decile (largest increase in implied volatility) underperform those in the bottom decile (largest decrease in implied volatility) by 0.52% (0.50%) per month when sorted by $\Delta CVOL$ ($\Delta PVOL$) with *t*-statistic of 3.57 (3.51). To ensure that the return differences are not a compensation for risk, we use a bond and stock market factor model. The stock market factors are the six factors from Fama and French (2018). The bond market factors include bond market return, downside risk, credit risk, liquidity risk, and reversal factor from Bai, Bali, and Wen (2019). After controlling for these 11 stock and bond market factors, the risk-adjusted return spreads between the top and bottom decile are even more significant at about 0.90% per month.

It is interesting to compare our results with those of An et al. (2014), who find that $\Delta CVOL$ ($\Delta PVOL$) predicts future stock returns positively (negatively). An et al. posit that $\Delta CVOL$ and $\Delta PVOL$ carry information about the fundamentals of firms. Our results tend to suggest that change in volatility could also convey information on the volatility risk of the underlying firm, which is likely to be captured by the common component of $\Delta CVOL$ and $\Delta PVOL$. In other words, an increase in $\Delta CVOL$ could be either due to good fundamental news or about increasing volatility while an increase in $\Delta PVOL$ could be either due to bad fundamental news or about increasing volatility. To evaluate the information content of $\Delta CVOL$ and $\Delta PVOL$, we repeat the portfolios sorts with $\Delta CVOL+\Delta PVOL$ and $\Delta CVOL-\Delta PVOL$ as sorting variables. We find that $\Delta CVOL+\Delta PVOL$ sorts produce a 10−1 return spread of −0.60% and a bond+stock alpha of −0.98% per month. In contrast, sorts on $\Delta CVOL-\Delta PVOL$ produce a spread in bond returns that is economically and statistically insignificant. We relabel $(\Delta CVOL+\Delta PVOL)/2$ as $\Delta ImpVOL$ in the rest of this introduction.

Prior literature shows that bond characteristics such as maturity, coupon, age, and ratings can explain the cross-section of corporate bond returns (see, for example, Gebhardt, Hvidkjaer, and Swaminathan (2005a, 2005b)). Therefore, we test whether the negative relation between Δ*ImpVOL* and future bond returns still holds after controlling for bond characteristics used in Bai, Bali, and Wen (2019). Bivariate portfolio sorts indicate that implied volatility change remains a significant predictor of future bond returns after controlling for bond characteristics such as size, maturity, credit rating, liquidity and lagged bond return. Although we do not observe strong patterns in the portfolios sorted by illiquidity or lagged bond return in the past month, we do find that the absolute return spread is larger for bonds with longer maturity and higher credit risk. The finding that the predictability is higher for lower-rated bonds is similar to that in Jostova, Nikolova, Philipov, and Stahel (2013) and Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017).

In recent work, Chung, Wang, and Wu (2019) find that bonds with high volatility betas or low idiosyncratic bond volatility have higher expected returns. To allay the concern that correlations between different volatility variables drives our results, we also control for bond volatility, bond idiosyncratic volatility, stock implied volatility, stock idiosyncratic volatility, and VIX beta. We do find that the absolute return spread sorted on the implied volatility changes is related to many of these other volatility variables. However, our results on Δ*ImpVOL* cannot be fully explained by these alternative volatility proxies, since the effect of changes in implied volatilities is robust to controlling for these volatility variables.

We further confirm the results from portfolio sorts using regression approach. We control for multiple variables simultaneously in the Fama and MacBeth (1973) regressions. The predictability of Δ*ImpVOL* is robust after controlling for all these bond characteristics. Δ*ImpVOL* is a significant predictor in the subsample of investment-grade and non-investment-grade bonds and remain robust after controlling for all bond and volatility characteristics.

Since the average maturity of the corporate bond is about eight years in our sample, we mainly use information from long-dated options. Our results are robust, albeit with a smaller magnitude, if we use implied volatility with 30, 60, or 90 days of expiration.[3] The predictability

[3] The implied volatility used in this paper is from options of longer maturities than those used in other studies in the stock market such as An et al. (2014). Our results on the bond market are consistent with Clements, Kalesnik, and Linnainmaa (2017), who also find that that the prices of long-dated options contain relevant information for predicting stock returns.

of future bond return by Δ*ImpVOL* is also robust in several sub-periods. In particular, the magnitude of the 10−1 return spread is relatively bigger when the economy is in recession, when the bond market liquidity is low, and when the funding liquidity is low.

Lastly, we examine why Δ*ImpVOL* negatively predicts future bond returns. We find that options markets have relevant information for predicting default risk, which is particularly important for determining bond returns. In particular, we find that implied volatility changes significantly predict the changes of expected default frequency and bond downgrades in the next month. This evidence suggests that the option market leads the price discovery process of the corporate bond market because they reflect the changes of default risk faster than the corporate bond market. We also find that implied volatility changes predict credit default swaps (CDS) returns. Given that CDS are highly sensitive to default risk changes, this predictability further supports the hypothesis that increase in implied volatility predicts higher default risk of the underlying firm, leading to lower bond return and higher CDS return.

A natural question is why the corporate bonds fail to impound the relevant information about the change in firm risk into bond prices. The slow adjustment of bond prices, that we document, might reflect slow diffusion of information from options to bonds, or limits to arbitrage in the bond market. While we are not able to conclusively disentangle these two hypotheses, we find both explanations play a role in explaining the predictability.

The hypothesis of slow diffusion of information is supported by four pieces of evidence. First, consistent with the implication of the sequential trading model in Easley, O'Hara, and Srinivas (1998), we find that the bond return predictability is the highest when option trading volumes increase the most and when bond trading volumes decrease the most. This suggests that some informed investors choose to trade in options before trading in bond market. Second, while bond return predictability is stronger among less liquid bonds, we find predictability in even very liquid bonds further pointing to slow diffusion of information as a likely cause of predictability. Third, we find that predictability is five to eight times stronger on rating announcement days than on other days. These findings are consistent with the idea that biased expectations drive our bond portfolio returns and they are partially corrected upon salient news arrival (Engelberg, McLean, and Pontiff (2018)). Fourth, we find that firms with high investor attention, measured by dual ownership of both stock and bond, exhibit weaker bond return predictability, suggesting that investors' inattention can partially explain the predictability of change in implied volatility.

Transaction cost analysis provides a rationale for why arbitrageurs do not enforce price efficiency in the bond market. While returns net of transaction costs of Edwards, Harris, and Piwowar (2007) are still positive and significant for large trade size ($1M), net returns to the trading strategy are not positive for smaller trade sizes ($100K) or for transaction cost estimates of Bao, Pan, and Wang (2011). Thus, slow diffusion of information due to investor inattention coupled with high limits to arbitrage explains why bond prices do not incorporate the information in the increase in default risk embedded in option prices.

Our paper contributes to the literature in two important ways. The first contribution is to demonstrate the informational role of options in the corporate bond market. The studies on the information transmission of options are mainly focused on the stock market. For example, several studies show that option related variables can predict stock returns, such as the volatility spread in Bali and Hovakimian (2009), deviation of put-call parity in Cremers and Weinbaum (2010), volatility smirk in Xing, Zhang, and Zhao (2010), option to stock volume ratio in Johnson and So (2012), changes in implied volatilities in An et al. (2014), and stock order imbalance induced by option transactions in Hu (2014). The relation between corporate bonds and options is relatively less well-studied. Some exceptions are Cremers, Driessen, and Maenhout (2008) who use option variables to explain credit spreads, Chung, Wang, and Wu (2019) who use VIX beta and implied volatility (but not its change) to predict bond returns, and Jiang and Mirzach (2019) who study the role of options in predicting credit rating changes. Our paper complements these studies by examining the information content from implied volatility changes on the corporate bond returns.

Second, we document a new predictor for the cross-section of corporate bond returns. Gebhardt, Hvidkjaer, and Swaminathan (2005a) find that some bond characteristics predict bond returns in addition to risk-related variables. Recently there have been a spate of studies analyzing predictability of the cross-section of bond returns and prices from bond and stock characteristics. See, for example, Bali, Subrahmanyam, and Wen (2019), Choi and Kim (2018), Chordia et al. (2017), Chung, Wang, and Wu (2019) and Jostova et al. (2013).[4] Bai, Bali, and Wen (2019) instead focus on risk-based explanations in proposing a new bond factor pricing model. Our paper differs from these studies in that we examine the information content from the derivatives market, which

[4] See also Lin, Wu, and Zhou (2018) who analyze a large set of predictors to predict aggregate bond returns.

is generally regarded as more informative.[5] Relatedly, our paper complements recent studies on factor investing in corporate bonds by constructing bond factors from options.[6]

The remainder of this paper is organized as follows. Section 2 describes our data and the construction of variables. Section 3 discusses the empirical evidence on the predictability of changes in implied volatilities for corporate bond returns. We discuss information content of the change in implied volatility in Section 4. Section 5 tests the slow diffusion of information and limits to arbitrage explanations for why the bond prices react with a delay. Section 6 concludes.

2. Data and Variables

2.1. Corporate bond data and bond return

We obtain corporate bond data from the enhanced version of the Trade Reporting and Compliance Engine (TRACE) for the sample period July 2002 to June 2017. Enhanced TRACE offers more trade records that span the entire over-the-counter market from earlier than those in the standard TRACE. Moreover, trade volumes are reported accurately and are not capped at certain levels based on bond ratings in enhanced TRACE (Bessembinder, Maxwell, and Venkataraman (2006)). We merge the enhanced TRACE dataset with the Mergent Fixed Income Securities Database (FISD) with issuance information for all fixed-income securities that have a Committee on Uniform Security Identification Procedures (CUSIP) number. FISD dataset contains bond characteristics, such as offering amount, offering date, maturity date, coupon rate, coupon type, interest payment frequency, bond type, and bond rating.

We follow Bai, Bali, and Wen (2019) and apply several filters to remove the following observations: (i) bonds that are not listed or traded in the U.S. public market; (ii) bonds that are structured notes, mortgage-backed, asset-backed, agency-backed, or equity-linked; (iii) convertible, sinking fund bonds, and bonds with a floater or odd frequency of coupon payments; (iv) trades under $5 or above $1,000; (v) bonds that have less than one year to maturity; (vi) intraday bond transactions that are labeled as when-issued, locked-in, or have special sales

[5] There are some studies that use information from one derivative market (options) to predict prices (spreads) or returns in other derivative market (CDS), or vice versa. For example, see Cao, Yu, and Zhong (2010), and Cao, Jin, Pearson, and Tang (2018).

[6] Factor investing papers construct bond factors using information from bonds (for example, Gebhardt, Hvidkjaer, and Swaminathan (2005a), Houweling and van Zundert (2017), and Jostova et al. (2013)), from stocks (for example, Bektić, Wenzler, Wegener, Schiereck, and Spielmann (2019) and Chordia et al. (2017)) or from stocks and bonds (for example, Israel, Palhares, and Richardson (2018)).

conditions, that have more than a two-day settlement, that are canceled and adjust records that are subsequently corrected or reversed.[7] Similar to Chordia et al. (2017), we study the cross-section of bond return instead of event analysis and, therefore, do not impose filters to remove bond transaction with trading volume smaller than $10,000 as in Bessembinder, Maxwell, and Venkataraman (2006).[8]

Following Bessembinder, Kahle, Maxwell, and Xu (2009), we calculate the trading volume-weighted average of intraday bond prices as daily prices. This approach puts more weights on the trades with low transaction costs and should more accurately reflect the bond price. To calculate monthly bond return, we use only the last observation during the last five trading days of each month. If there is no observation during these five days, the bond price is set to be missing.

The monthly corporate bond return at month t is calculated as

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

where P_t is the transaction price of the bond at the end of month t, AI_t is the accrued interest and C_t is the coupon payment from the end of month $t-1$ to the end of month t. We denote R_t as bond excess return, $R_t = r_t - r_{ft}$, where r_{ft} is the risk-free rate proxied by the one-month Treasury bill rate.

Besides bond return, we construct several bond characteristics using the TRACE and the FISD data. We calculate *Size* as the logarithm of offering amount of the bond. *Rating* is calculated as the numerical rating score provided by Moody's and Standard and Poor's.[9] Numerical score of one refers to AAA rating by S&P and Aaa rating by Moody. Numerical score of 21 refers to a C rating for both S&P and Moody. Ratings of ten or below are considered as investment-grade, and ratings above ten are considered as non-investment-grade. *Maturity* is the time-to-maturity of the bond in years. *Illiquidity* is the auto-covariance of daily bond price change in each month multiplied by −1 as defined in Bao, Pan, and Wang (2011). *Lag Return* is the bond return in the past month. Finally, *VaR* (5%) as the 5% Value-at-Risk of corporate bond return, defined as the second lowest monthly return over the past 36 months as in Bai, Bali, and Wen (2019).

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[7] We thank Jens Dick-Nielsen for providing SAS program to clean the reporting errors from Enhanced TRACE dataset.
[8] Our main findings are not sensitive to imposing this filter.
[9] Bond rating is the average of ratings provided by S&P and Moody's when both are available, or the rating provided by one of the two rating agencies when only one rating is available.

2.2. Option data

We obtain daily implied volatility data from the volatility surface data in OptionMetrics. OptionMetrics provides interpolated volatility surface for each stock on each day, using a kernel smoothing algorithm and options with various strike prices and maturities. Implied volatilities are calculated based on the industry-standard Cox-Ross-Rubinstein binomial tree model. This model can accommodate underlying securities with either discrete dividend payments or a continuous dividend yield, and American style stock options with early exercise features. This volatility surface dataset contains information of volatilities with various maturities and deltas. An implied volatility is only included if there exists enough option price data on that date to accurately interpolate the required values. One advantage of using the volatility surface data is that the maturities and deltas are fixed for each trading day, and hence there is no need to control for variations in expiration dates and strike prices.

In the main analysis of this study, we use implied volatilities with a delta of 0.5 and an expiration of 365 days for put and call options. We use month-end observation to calculate the changes in implied volatilities, which we denote as $\Delta CVOL$ for call options and $\Delta PVOL$ for put options, receptively. To avoid price pressure bias (Goncalves-Pinto, Grundy, Hameed, van der Heijden, and Zhu (2019)), we use implied volatility one day before the last five days of each month.

After merging the corporate bond data from TRACE with the option data from Option-Metrics, we have 881,625 bond-month observations from July 2002 to June 2017. The number of unique firms in our sample is 2,327. In Panel A of Table 1, we report the summary statistics of bond returns, changes in implied volatilities, and various bond characteristics. The bond sample has an average return of 0.51%, an average rating of 8.52 (BBB+), and an average maturity of 8.54 years. The average of implied volatility of put and call options is 0.31. The changes in implied volatilities of call and put options are both on average close to zero. The summary statistics are similar to those in the prior literature.

In Panel B of Table 1, we report the time-series average of the cross-sectional correlations of the variables. $\Delta CVOL$ and $\Delta PVOL$ have a moderate correlation of 0.58, indicating that the implied volatility changes of calls and puts might have a common component. The changes in implied volatilities are not correlated with implied volatility level, with a correlation of 0.08 and 0.11 for calls and puts, respectively. This suggests that innovations in implied volatility represent distinct information from the implied volatility level. This fact will be important to note for later when we control for various volatility characteristics. We observe that implied volatility is moderately correlated with *Rating* and *VaR*, with a correlation of 0.50 and −0.47, respectively. However, the correlations between changes in implied volatilities and various bond characteristics are much lower, ranging from −0.14 to 0.11. It is less likely, therefore, that the predictability, that we document later, is related to the heterogeneity in bond characteristics.

3. Changes in Implied Volatility and the Cross-Section of Corporate Bond Returns

3.1. Bond portfolios sorted on change in call or put implied volatility

For each month from July 2002 to June 2017, we form decile portfolios by sorting corporate bonds according to the change in the corresponding call and put implied volatilities, $\Delta CVOL$ and $\Delta PVOL$, of the underlying firms. Decile one contains bonds of firms with the largest decrease in implied volatilities in the previous month and decile ten contains bonds of firms with the largest increase in implied volatility in the previous month. The portfolios are value-weighted using the prior month's bond market capitalization as weights. The holding period for the bonds is one month and we rebalance the portfolios monthly.

We report the results for portfolios sorted on changes in implied volatilities of the call options, $\Delta CVOL$, in Panel A of Table 2. The returns are in percent per month and Newey-West *t*-statistics are reported in parenthesis below the returns. The average bond return in decile one is 0.95% and declines almost monotonically to 0.44% for bonds in decile ten. The difference in average raw returns between decile ten and one is −0.52% (*t*-statistic = −3.57). Thus, the negative relation between change in implied volatility and future bond return is both economically and statistically significant.

To examine whether the return spreads of the strategy can be explained by common risk factors in the bond and stock markets, we calculate the alpha of the strategy return using two factor models. We first use a bond factor model proposed by Bai, Bali, and Wen (2019), which consists of five bond market factors: excess bond market return (MKT_{bond}), downside risk factor (DRF), credit risk factor (CRF), liquidity risk factor (LRF), and reversal factor (REV).[10] We also consider stock market factors. We use a six-factor (MKT, SMB, HML, RMW, CMA, and MOM) stock

[10] We thank Turan Bali for providing us data on these factors and refer the readers to Bai, Bali, and Wen (2019) for details on the construction of these factors.

pricing model from Fama and French (2018). Data on these stock factors are obtained from Ken French's website. Our second factor model is a joint bond+stock model that uses the five bond market factors and the six stock market factors.

We first examine the factor loadings of the decile portfolios on these factors. In unreported results, we find that, with a few exceptions, factor loadings in the bond+stock model of decile one are similar to those of decile ten. One big exception is that the loading on the MKT_{bond} factor is 0.66 (0.12) for decile one (ten) leading to a negative (and statistically significant) loading on this factor for the 10−1 portfolio. The other two exceptions are loadings on the LRF and the REV factors. These are −0.37 (0.39) and −0.12 (0.31), respectively, for decile one (ten) leading to positive (and statistically significant) loading on these factors for the 10−1 portfolio. Loadings of the 10−1 portfolio on MKT and MOM are also positive, albeit smaller in magnitude. In general, therefore, the factor loadings of the 10−1 portfolio are positive. This also means that the alpha of the 10−1 portfolio is more negative than the raw return difference; and the bond+stock alpha is bigger (in absolute value) than the bond alpha. Thus, we find that the alphas of the 10−1 hedge portfolio from the bond factor model and from the bond+stock factor model are −0.58% (*t*-statistic = −2.53) and −0.90% (*t*-statistic = −4.94), respectively. The alphas also show a monotonic pattern across deciles. We conclude that the pattern in average returns across deciles is not explained by the common risk factor models.[11]

We also report several bond characteristics in each decile portfolios in the bottom part of Panel A of Table 2. The bond characteristics that we include are bond market beta (*Beta*), *Size*, *Maturity*, *Rating*, and *Illiquidity*. *Beta* is the regression coefficient of returns on bond market factor in the bond factor model. As noted earlier, *Beta* of decile one is higher than that of decile ten; however, the betas do not show a clear pattern across the other deciles. Similarly, we find no evidence that other bond characteristics are driving the cross-section pattern we have documented. *Size* is similar across deciles. Bonds in extreme deciles one and ten have shorter maturity, higher rating, and are less liquid compared to bonds in other deciles. However, the differences in these characteristics between deciles one and ten are not significant. This suggests that the relation between the changes in implied volatilities and future corporate bond return is unlikely to be

[11] We also calculate alphas from a factor model with lagged factors in addition to contemporaneous factors. This makes very little quantitative difference to the magnitude of alphas. For instance, the alpha from a bond+stock factor model is still −0.84% with a *t*-statistic of −4.67.

explained by these variables. Nevertheless, since there exists some relation between these characteristics and portfolio sorts, we will explore the impact of bond characteristics on portfolios returns in greater detail in the next subsection.

We report the results for portfolios sorted on changes in implied volatilities of the put options, $\Delta PVOL$, in Panel B of Table 2. Sorting by $\Delta PVOL$ yields similar results as those from sorting by $\Delta CVOL$. Raw average return of the decile portfolios decreases from 0.96% in decile one to 0.46% in decile ten, leading to a return spread of −0.50% (t-statistic = −3.51). The alphas of the 10−1 portfolio from the bond factor model and the bond+stock factor model are −0.64% (t-statistic = −2.72) and −0.89% (t-statistic = −4.40), respectively. Similar to the results for $\Delta CVOL$-sorted bonds, characteristics do not exhibit clear pattern from decile one to decile ten for portfolio sorts on $\Delta PVOL$ either.

3.2. Bond portfolios sorted on the common component of call and put implied volatility changes

It is interesting to note the consistency of our results for sorts involving $\Delta CVOL$ or $\Delta PVOL$. This is in contrast to An et al. (2014) who find that $\Delta CVOL$ ($\Delta PVOL$) predicts future stock returns positively (negatively). An et al. posit that change in implied volatility carries information about fundamental news of the underlying firm. Our results tend to suggest that the change in implied volatility could also convey information about volatility news of the underlying firm. The volatility news is likely to be captured by the common component of $\Delta CVOL$ and $\Delta PVOL$.

In other words, an increase in $\Delta CVOL$ could be either due to good fundamental news or about increasing volatility while an increase in $\Delta PVOL$ could be either due to bad fundamental news or about increasing volatility. One simple way to extract the common component of $\Delta CVOL$ and $\Delta PVOL$, that is related to volatility, is to take the sum $\Delta CVOL+\Delta PVOL$. In this case, the difference $\Delta CVOL-\Delta PVOL$ is likely to be related to fundamental news. The difference in the two changes in implied volatilities is, in fact, the main variable used by An et al. (2014).

We repeat the portfolios sorts in Table 3 with $\Delta CVOL+\Delta PVOL$ (Panel A) and $\Delta CVOL-\Delta PVOL$ (Panel B) as the sorting variables. Panel A shows that $\Delta CVOL+\Delta PVOL$ sorts produce a spread in returns and alphas that is even bigger than those reported in Table 2; the 10−1 return is −0.60% and the bond+stock alpha is −0.98% per month. In contrast, sorts on

$\Delta CVOL-\Delta PVOL$ produce a spread in bond returns that is economically and statistically insignificant.[12]

Since good fundamental news is good for both stocks and bonds, one might expect that even the $\Delta CVOL-\Delta PVOL$ sorts should produce a positive spread in bond returns. Note, however, that bonds have a limited upside (in contrast to stocks). The upside is even more limited for high-rated bonds. The conjecture is, however, more plausible for low-rated bonds. In unreported results, we do find that $\Delta CVOL-\Delta PVOL$ sorts produce a spread of 0.33% (albeit with a *t*-statistic of 1.04) for the sub-sample of non-investment-grade bonds.

Henceforth, we relabel $(\Delta CVOL+\Delta PVOL)/2$ as $\Delta ImpVOL$ and consider this as our main forecasting variable. We also consider $\Delta ImpVOL$ as indicative of future changes in volatility (see Christensen and Prabhala (1998) for an early study on the use of implied volatility to predict future volatility) and provide further evidence on this issue in Section 4.[13]

3.3. Longer holding horizons

Figure 1 plots $\Delta ImpVOL$ for an interval of six months around the portfolio formation month for deciles one and ten. Apart from the changes in the formation month, by construction, we do not observe large changes in implied volatility in the other months. This means that implied volatility stays at relatively high (low) levels for decile ten (one) after the shock in the formation month.

The behavior of $\Delta ImpVOL$ prompts us to investigate the longer-term predictability of $\Delta ImpVOL$ on corporate bond returns. We again form portfolios each month with $\Delta ImpVOL$ as the sorting variable, but now hold these portfolios over the next two to six months. Finally, we calculate the returns over the overlapping periods following Jegadeesh and Titman (1993). Table A1 shows the returns and alphas for the decile portfolios over extended holding horizons.

We find that the predictability declines rapidly. The average return spreads and their alphas are statistically significant for two-month holding period but there is a sharp drop in the second

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[12] We also check stock portfolio returns. Similar to An et al. (2014), we find that sorts on $\Delta CVOL-\Delta PVOL$ produce a bond+stock alpha of stock portfolios of 0.82% per month. However, sorts on $\Delta CVOL+\Delta PVOL$ produce a bond+stock alpha of stock portfolios of −0.53% per month, albeit statistically insignificant.

[13] We also do sorts using percentage change in *ImplVOL* rather than simple differences. In unreported results, we find that 10−1 spread in bond portfolio returns for $\%\Delta ImpVOL$-sorted portfolios is slightly lower at −0.40% but, nevertheless, strongly statistically significant with a *t*-statistic of −3.93.

month after portfolio formation. After the second month, the average return spreads and their alphas gradually decrease. For example, the average return for the 10−1 spread portfolio is −0.38% in the second month and −0.32% in the third month. These results are consistent with those in An et al. (2014), who report that predictability of stock returns from changes in implied volatility drops dramatically between the first and second month.

To investigate the information content of changes in volatilities over a longer period, we also consider Δ*ImpVOL* calculated over the past two and three months, instead of one month. The portfolio sorting results are reported in Appendix Table A2. We find that the average return spread sorted on Δ*ImpVOL* in the past two or three months remain statistically significant. The magnitude is similar to those sorted on Δ*ImpVOL* in the past month.

3.4. Control for bond characteristics: Double portfolio sorts

The univariate portfolio sort in Section 3.1 shows a strong negative relation between Δ*ImpVOL* and future bond returns. However, it is possible that Δ*ImpVOL* is correlated with bond characteristics and, thus, we are picking up the relation between bond returns and these characteristics. Indeed, prior studies have shown that bond characteristics such as maturity, coupon, age, and ratings can explain the cross section of corporate bond returns (see, for example, Gebhardt, Hvidkjaer, and Swaminathan (2005a) and Bai, Bali, and Wen (2019)). Portfolio characteristics reported in Table 2 also show that there is some relation between sorts and some characteristics. Therefore, to assess the robustness of our results, we control for characteristics in portfolio sorts.

We construct conditional double-sorted portfolios. We first sort bonds into quintile portfolios based on a single characteristic. Following Bai, Bali, and Wen (2019), we choose *Size*, *Maturity*, *Rating*, *Illiquidity*, and *Lag Return* as control characteristics. In sorting by rating, we do not sort into equal-sized bins but opt for sorting based on more intuitive classifications. In particular, the five quintiles contain bonds rated AAA to AA−, A+ to A−, BBB+ to BBB−, BB+ to BB−, and below respectively. Thus, the first three quintiles contain investment-grade bonds, and quintiles four and five contain non-investment-grade bonds.

Within each characteristic quintile, we further sort bonds into five quintiles based on Δ*ImpVOL*. We calculate the bond+stock alpha of the 5−1 hedge portfolio that is long in bonds with highest Δ*ImpVOL* and short in bonds with the lowest Δ*ImpVOL*. This long-short portfolio alpha is calculated for each of the characteristic quintile, and is similar to the approach in Chung, Wang, and Wu (2019). This approach not only shows that the returns/alphas are robust after controlling for characteristic but also shows the variation, if any, in the magnitude of profitability across quintiles of characteristics.

Results in Panel A of Table 4 show that although there is some variation across the size quintile portfolios, 5−1 portfolio alphas are significant for all quintiles, indicating that the effect of Δ*ImpVOL* is not concentrated among smaller or bigger bonds. This result is not surprising as Table 2 shows little variation in size across decile portfolios.

For portfolios sorted by maturity, we find that 5−1 portfolios alphas exhibit an increasing pattern (in absolute terms) from quintile one of short-maturity bonds to quintile five of long maturity bonds. For example, the 5−1 alpha for Δ*ImpVOL* sorted portfolios is 0.09% and −1.32% for quintiles one and five, respectively. Similar to our findings, Bai, Bali, and Wen (2019) find that the bond return spread between the top downside risk quintile and the bottom downside risk quintile is larger for long-term bonds.

Similar to prior studies such as Jostova et al. (2013) and Bai, Bali, and Wen (2019), we find stronger return predictability for low-rated bonds (quintile five of rating) than that for high-rated bonds (quintile one of rating). For example, the 5−1 alpha for Δ*ImpVOL* sorted portfolios is −0.69% for low-rated bonds, which is around seven times the magnitude of −0.09% for high-rated bonds. As we have included credit risk factor in our factor model, the alpha differences across rating categories are compensation beyond that has been accounted for by risk models.

Lin, Wang, and Wu (2011) and Bai, Bali, and Wen (2019) find that liquidity (risk) is priced in corporate bonds. While we see bond predictability in all quintiles of liquidity, the 5−1 alpha for Δ*ImpVOL* sorted portfolios is slightly higher (in absolute magnitude) at −1.19% for more illiquid bonds than it is for more liquid bonds at −0.75%.

We also find that Δ*ImpVOL* predictability is higher for past bond losers (5−1 alpha of −1.03%) than that for past bond winners (5−1 alpha of −0.56%). Since, prior literature finds evidence of corporate bond momentum (Gebhardt, Hvidkjaer, and Swaminathan (2005b) and Jostova, Nikolova, Philipov, and Stahel (2013)), it is possible that our signal of Δ*ImpVOL* counteracts the effect of momentum for some bonds). In fact, in unreported results, we find positive alpha of 0.13% (albeit statistically insignificant) for portfolio of past bond winners and high Δ*ImpVOL* indicating that the signal of past bond returns outweighs the signal of increase in implied volatility for these bonds.

Overall, we see that the predictability is related to some, but not all, characteristics. While we find evidence of predictability across most of our double-sorted portfolios, it is still possible that we have picked up the differences in bond characteristics. In Section 3.6, we control for those characteristics using regression approach.

Our approach of reporting 5−1 alphas for Δ*ImpVOL* sorts *for each* characteristic quintile is a strong test of predictability across characteristic quintiles. A less strong but, nevertheless, intuitive alternative approach is to calculate 5−1 alphas for Δ*ImpVOL after controlling* for each characteristic. This alternative approach is frequently used in the literature (see, for example, Ang, Hodrick, Xing, and Zhang (2006), Bai, Bali, and Wen (2019), and Chung, Wang, and Wu (2019)). In particular, we perform the same conditional sorts—first sort on a characteristic, and then within each characteristic quintile, further sort into quintiles based on Δ*ImpVOL*. We average the return for each Δ*ImpVOL* quintile across the five characteristic portfolios. This approach produces portfolios that vary in Δ*ImpVOL* but have similar bond characteristics.

We report the returns/alphas for each Δ*ImpVOL* quintile as well as the alpha for the 5−1 hedge portfolio in Appendix Table A3. We find that the 5−1 alphas for Δ*ImpVOL* sorted portfolios show little variation across characteristics. This result is consistent with the descriptive statistics of the portfolios in Table 2, which show little variation across characteristics. All the alphas are also statistically significant. The magnitude of alphas in Table A3 is roughly half of that in Table 2, as Table A3 uses quintile sorts (controlling for characteristics) while Table 2 uses decile sorts (unconditional on characteristics).

3.5. Control for volatility characteristics: Double portfolio sorts

Chung, Wang, and Wu (2019) find that bonds with high volatility betas or low idiosyncratic bond volatility have higher expected returns. Our main volatility sorting variable is different from that used by these authors. Nevertheless, there could be correlations amongst different volatility variables and, hence, our results could potentially be driven by the exposure to volatility risk and/or bond volatility. Therefore, in this subsection, we test whether volatility related characteristics can explain our results.

We use five different volatility related variables as control variables: bond volatility, bond idiosyncratic volatility, stock implied volatility, stock idiosyncratic volatility, and VIX beta. We follow Chung, Wang, and Wu (2019) in the construction of these variables. In particular, *Bond*

Vol is calculated as the standard deviation of daily bond returns within each month. We calculate the *Bond IdioVol* as the standard deviation of bond return residuals, estimated from the time-series regression with five Fama and French (2015) factors and change in VIX as volatility risk factor. *ImpVol* is the stock implied volatility, calculated as before, as the average of the call and put at-the-money implied volatility with 365 days of expiration. Similar to bond idiosyncratic volatility, *Stock IdioVol* is the standard deviation of stock return residuals, estimated from the time-series regression with the same factor model as that for bonds. Finally, *VIX Beta* is the regression coefficient of the change in VIX estimated from the same time series regression as that used to calculate bond idiosyncratic volatility.

We follow the same conditional sorting procedure as that in Section 3.3. In particular, we first sort bonds into quintile portfolios based on a volatility characteristic. Within each volatility characteristic quintile, we further sort bonds into five quintiles based on Δ*ImpVOL*. We calculate the stock+bond model alpha of the 5−1 hedge portfolio that is long in bonds with highest change in Δ*ImpVOL* and short in bonds with the lowest change in Δ*ImpVOL*.

Panel B of Table 4 shows that the effect of changes in implied volatilities on bond return predictability is not concentrated in any particular quintile of bonds with certain volatility characteristics. Almost all 5−1 alphas are statistically significant (with only three exceptions across the two panels); most are significant at the 1% level.

At the same time, the effect of Δ*ImpVOL* is related to volatility related characteristics. We find that 5−1 alphas are more negative for bonds with higher bond volatility, higher idiosyncratic bond volatility, higher stock implied volatility, and higher stock idiosyncratic volatility. The predictability of changes in implied volatilities does not show a clear pattern in the quintile portfolios sorted by *VIX Beta*.

We also calculate returns of Δ*ImpVOL* sorted portfolios controlling for the volatility characteristics in a manner similar to that explained towards the end of Section 3.4. Panel B of Appendix Table A3 show that 5−1 alphas for Δ*ImpVOL* sorted portfolios show little variation across volatility characteristics. Overall, our results show that the effect of changes in implied volatilities is related to stock and bond volatility but cannot be fully explained by them.

3.6. Fama-MacBeth regressions

We next examine the cross-sectional relation between changes in implied volatilities and bond returns at the individual bond level using Fama and MacBeth (1973) regressions. We estimate the regression across all bonds in each month and then report the cross-sectional average of the coefficients. We calculate Newey-West *t*-statistics with six lags and report them below the coefficients. All independent variables in all regressions are winsorized each month at the 0.5% level.

We report results for univariate regressions on Δ*ImpVOL* as well as regressions with controls. The control variables are the same ones that we use in Table 4, namely *Size*, *Rating*, *Maturity*, *Illiquidity*, and *Lag Return*. In addition, we also include *ImpVol* and *VaR* (5%) as control variables. Table 4 shows that profitability of our strategy is related to rating, maturity, and illiquidity of bonds. Bai, Bali, and Wen (2019) find that corporate bonds with higher downside risk, measured by *VaR*(5%), earn significantly higher return than bonds with lower down side risk. In addition, Bali, Subrahmanyam, and Wen (2019) also find that previous month's bond return has strong ability to predict future bond returns in the cross-section. We include lagged stock return based on evidence in Chordia et al. (2017) and Gebhardt, Hvidkjaer, and Swaminathan (2005b). We also include implied volatility as a control to make sure that the negative relation between changes in implied volatilities and future bond return is not driven by the level of implied volatility.

Panel A of Table 5 presents the results with the sample of all bonds with bond characteristics as control variables. Consistent with the findings in Bai, Bali, and Wen (2019), we find that the coefficients on *Lag Bond Return* and *VaR* (5%) are both strongly statistically significant. Consistent with the findings in Chordia et al. (2017), we find that the coefficient on *Lag Stock Return* is positive and strongly statistically significant. The coefficients on *ImpVol* are negative in all regressions, but none of them is statistically significant. Together with the low correlation between changes in implied volatilities and implied volatility level in Table 1, the results indicate that the effect of implied volatility level is very different from that of changes in implied volatilities. An et al. (2014) report similar differences between the impact of levels and changes in implied volatilities on stock returns. Coefficients on *Size* and *Illiquidity* are statistically significant in some specifications but not all while coefficients on *Rating* and *Maturity* are not statistically significant in any specification that we explore.

The average coefficient on Δ*ImpVOL* is -0.102 (*t*-statistic = -4.55) and barely changes after controlling for bond characteristics (-0.086, *t*-statistic = -5.28). To gauge the economic magnitude of these coefficients, note first that the difference in Δ*ImpVOL* is 11% as one goes from the first to the tenth decile of bonds. According to coefficient estimates in column three of Panel A of Table 5, bonds in the first decile of Δ*CVOL* outperform bonds in the tenth decile of Δ*CVOL* by 0.086×11% = 0.95%, ceteris paribus.

The last four columns of Panel A of Table 5 show Fama and MacBeth (1973) regression results for investment-grade and non-investment-grade bonds, respectively. Bonds with ratings of ten or below are considered investment-grade, and bonds with ratings above ten are considered non-investment-grade. The coefficient on Δ*ImpVOL* is slightly higher for non-investment-grade bonds than that for investment-grade bonds.

In Panel B of Table 5 we test whether the effect of Δ*ImpVOL* is robust after controlling for volatility related variables used in Table 4. We find that the coefficient on Δ*ImpVOL* is statistically significant across all categories of bonds. Other volatility variables are not significant in any of the regressions. Consistent with Chung, Wang, and Wu (2019), we find the coefficient of total bond return volatility to be positive and significant. However, after including changes in implied volatilities into the regression, we find that coefficients on VIX beta and idiosyncratic bond volatility become insignificant.

As an additional control variable, we also include changes in volatility from an EGARCH model. For each stock in a given month, we estimate the following EGARCH (1, 1) model using all the available historical monthly returns data (including the current month):

$$r_t = \sigma_t z_t; \quad \log \sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \log \sigma_{t-1}^2 + \gamma \left(|z_{t-1}| - \sqrt{2/\pi} \right), \tag{2}$$

where r_t is the stock return, σ_t is the conditional volatility, and z_t is the residual. For each EGARCH regression, we require at least 60 monthly observations and use 500 maximum iterations for convergence. This procedure generates a series of time-varying volatility for each month in the estimation window, and an out-of-sample forecasted volatility over the next month. Change in EGARCH volatility (*ΔVOL-EGARCH*) is then defined as the difference between the forecasted volatility of next month and the estimated volatility of current month. The coefficient on this variable is negative and statistically significant, implying that changes in volatility estimated using purely historical data also has predictive power for future bond returns.[14] Overall, the evidence suggests that change in implied volatility subsumes a large portion of information in other

[14] We also try other measure of uncertainty such as analyst forecast dispersion. However, we find that neither the forecast dispersion nor its change has any predictive power for bond returns.

volatility related variables.

3.7. Other robustness checks

3.7.1. Implied volatilities of options with alternative moneyness or maturities

Instead of using at-the-money options, we use out-of-the-money (OTM) options to calculate $\Delta ImpVOL$. We select OTM options from the volatility surface provided by OptionMetrics with delta equals to 0.25 for call options and −0.25 for put options. The rest of the sorting procedure remains the same. Returns and alphas of portfolios of bonds sorted on $\Delta ImpVOL$ of OTM options are presented in Appendix Table A4. A comparison of Table 3 and Appendix Table A4 reveals that the results barely change when using OTM options. We continue to find alphas around −1% for the 10−1 decile portfolio; the pattern of alphas is also almost monotonically decreasing as one goes from decile one to decile ten.

Next, we consider implied volatilities from options with shorter maturities. In Appendix Table A5, we report average returns and alphas for bond portfolios sorted by $\Delta ImpVOL$ with 30, 60, and 90 days of maturity. We continue to find economically and statistically significant return and alpha for the 10−1 decile portfolio across all maturities. At the same time, the results also show that the return spreads and alphas are in general higher (with higher t-statistics) for portfolios sorted by $\Delta ImpVOL$ with 90 days of maturity than those with 30 days of maturity. These results suggest that options with longer maturities contain information with higher predictability for future corporate bond returns. Our results are consistent with Clements, Kalesnik, and Linnainmaa (2017), in which they find options with longer maturities have higher predictability for future stock returns. These authors note that if the information is not extremely short-lived, then traders prefer a position in a long-dated option over rolling over short-dated options because the former is cheaper. Our empirical results support this hypothesis as we also find that long-dated option are more valuable for predicting future bond returns than short-dated options.

3.7.2. Different bonds

Our sample contains both callable as well as non-callable bonds. However, majority of the bond-month observations are from callable bonds (596,126 observations) rather than non-callable bonds (241,663 observations). Moreover, since option-like provisions of callable bonds might be more susceptible to information from option markets, we analyze predictability separately from these two categories of bonds. The value of a callable bond is equal to the difference between the value of an option-free bond and the value of the call option embedded in the bond. Hence, we expect the magnitude of predictability to be stronger for callable bonds. Table A6 in the appendix shows that, indeed, the absolute returns on the 10−1 portfolio are higher for callable bonds than those for non-callable bonds (bond+stock alpha of −1.17% versus −0.64%). Nevertheless, the economic magnitude and the statistical significance of predictability are high for both categories of bonds. We conclude that our results are not entirely driven by our inclusion of callable bonds in the sample.

3.7.3. Sub-period evidence

We also examine the impact of $\Delta ImpVOL$ on the bond excess returns and alphas for different sub-periods. For each sub-period, we calculate the returns and alphas of the 10−1 portfolio and report these alphas in Appendix Table A7.

We first split the full sample of 2002 to 2017 into crisis period and non-crisis period. This classification is based on the recession and expansion indicator from The National Bureau of Economic Research (NBER). Table A7 shows that our results remain statistically significant for crisis and non-crisis periods. Nevertheless, 10−1 results are much stronger during the crisis periods than those during the non-crisis period. For example, the raw return spread is −2.53% during crisis period versus −0.39% during the non-crisis period. This suggests that our predictability links to economic recession and default risk. Several studies provide similar empirical evidence that return predictability fluctuates over the business cycle and becomes stronger when economic conditions deteriorate. For example, Rapach, Strauss, and Zhou (2010) find that macro variables, such as the price dividend ratio, have better predictive power in recessions.

Then we partition the sample into “Market Return negative” and “Market Return positive” periods based on months in which S&P500 return are negative or positive, respectively. We do not find much difference in results across these two subsamples. For example, the 10−1 bond+stock alphas of portfolios are −1.13% and −1.00% in the two subsamples.

Next, we split the sample into periods according to aggregate bond market liquidity. Periods “Liquidity high” (“Liquidity low”) are the months when aggregate illiquidity is higher (lower) than average. The absolute return spread is higher during low liquidity period than that during high liquidity period, echoing the results from the crisis and non-crisis sample periods. For example, the 10−1 bond+stock alpha of portfolios is −1.45% and −0.79% in the two subsamples. The evidence is consistent with the informed trading model in Easley, O'Hara, and Srinivas (1998) that the predictability of option-implied information should be increasing in the illiquidity of the market that option-implied variables have predictive power. Similar to our findings, in the stock market, Xing, Zhang, and Zhao (2010) also find that the predictability of the slope of volatility smile increases with stock market illiquidity.

Finally, we split the sample into periods according to funding liquidity. Periods "Funding liquidity high" ("Funding liquidity low") are the months when the TED spreads are lower (higher) than median. The TED spread is calculated as the spread between three-month LIBOR and three-month T-Bill rate.[15] The absolute return spread is higher during low funding liquidity period than that during high funding liquidity period. For example, the 10−1 bond+stock alpha is −1.26% and −0.81% in the two subsamples, respectively. This is consistent with Macchiavelli and Zhou (2019) that funding liquidity and market liquidity are positively correlated and reinforce each other through a feedback loop.

Overall, the subperiod analysis shows that, while the profitability of our strategy is robust across different subperiods, the magnitude of the predictability is related to economic recession, bond market liquidity, and funding liquidity.

3.7.4. Single bond per firm

As a firm can have multiple bonds, one observation of $\Delta ImpVOL$ could match to multiple bond returns with different coupons and maturities of the same firm. One concern is that firms with many bond issues are over-weighted in the regressions and can bias the cross-sectional relation between implied volatility changes and future bond returns. To address this issue, we select one bond per firm using three different methods and re-run the Fama and MacBeth (1973) regression. We follow Chordia et al. (2017) and select bond and construct the subsample using the following three criteria: (1) we select bond with the shortest maturity as long as it is more than one year, (2) we select bond with the most recent issue (lowest age) and (3) we calculate equal-weighted average of the bond returns across each firm. The results are presented in Table A8. Our findings are in general robust in the three subsamples.

[15] We follow Asness, Moskowitz, and Pedersen (2013) and use TED spread to proxy for funding liquidity. A wider spread represents worse liquidity.

We run one additional test for firms that have both investment-grade and non-investment-grade bonds. For this (quite small) sub-sample of firms, we construct separate quintiles of these two categories of bonds by sorting on Δ*ImpVOL* (the sorting variable is the same for different kinds of bonds of the same firm). Consistent with the earlier evidence, we find in unreported results that the bond+stock factor model alpha for the 5−1 portfolio is small (and statistically insignificant) for investment-grade bonds but still negative (and statistically significant) for non-investment-grade bonds. Importantly, the difference of the 5−1 alpha for the two categories of bonds is statistically significant. These results are suggestive of both limits of arbitrage (non-investment-grade bonds are costlier to trade) as well as inattention (non-investment-grade bonds have less institutional holdings) as possible explanations of the predictability that we document. We return to a more complete investigation of these issues in Section 5.

4. The Information Content of Δ*ImpVOL*

So far, we have established a robust relation between Δ*ImpVOL* and future bond returns. Broadly speaking, these results show that bond prices at the time of portfolio formation do not incorporate information contained in options. In this section, we investigate the nature of information in Δ*ImpVOL* that leads to future negative bond returns. We first show that Δ*ImpVOL* predicts future changes in default risk. We then show that Δ*ImpVOL* also predicts CDS returns.

4.1. Predicting future change in default risk from Δ*ImpVOL*

Given that Δ*ImpVOL* signals an increase in future volatility, one hypothesis is that the increase in implied volatility might represent unexpected higher default risk in the next period and, consequently, lower bond prices in the future. To test this hypothesis, we investigate whether Δ*ImpVOL* predicts default risk of the firm. We consider two measures of default risk. The first measure is expected default frequency (*EDF*) at the firm level and the second measure is rating downgrade at the bond level.

To construct the first measure, we use the procedure in Bharath and Shumway (2008) to calculate *EDF*. The calculation follows the insights from the Merton (1974) distance to default model:

$$EDF = N\left(-\frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}\right), \tag{3}$$

where $N(\cdot)$ is the cumulative distribution function of the standard normal distribution, V is the total value of a firm, F is the face value of the firm's debt, μ is an estimate of the expected annual return of the firm's assets that is calculated using historical return of the firm's asset, and σ_V is the volatility of firm value. V and σ_V are solved numerically from the following two equations:

$$E = VN(d_1) - e^{-rT}FN(d_2) \ \text{ and } \ \sigma_E = (V/E)N(d_1)\sigma_V\,, \tag{4}$$

where E is the market value of the firm's equity, σ_E is the volatility of the firm's equity, and d_1 andd_2 are parameters defined in the usual way. We use the code provided from Tyler Shumway's website to calculate V, σ_V, and *EDF* for each firm from July 2002 to August 2017.[16]

The second default risk measure, bond rating downgrade, is obtained from the FISD Mergent database. We measure bond rating downgrade as dummy variable that is set equal to one is there is a future downgrade, and zero otherwise.

To investigate the information content of Δ*ImpVOL*, we run panel regressions for predicting future change of default risk measured over the next one, three, and six months in Table 6. The dependent variable is the change in *EDF* at the firm level in Panel A and the dummy variable of rating downgrade at the bond level in Panel B. The regressions in Panel B are estimated using linear probability model.

To predict future change in *EDF*, we include the following six market-value-based accounting variables as control variables following Campbell, Hilscher, and Szilagyi (2008): net income over market value of total assets (*NIMTA*), total liabilities over market value of total assets (*TLMTA*), logarithm of firm's market equity (*Size_equity*), stock of cash and short-term investments over the market value of total assets (*CASHMTA*), market-to-book value of the firm (*MB*) and price per share (*Price_equity*). We also consider three bond characteristics as control variables: the average logarithm of offering amount of all bonds in a firm (*Size_bond*), bond maturity (*Maturity*), and bond illiquidity (*Illiquidity*). We include firm fixed effects and month fixed effects in the panel regressions.

To predict future bond rating downgrades, we include implied volatility (*ImpVol*), bond

[16] We thank Tyler Shumway for providing his SAS code on his website. http://www-personal.umich.edu/~shumway/papers.dir/nuiter99_print.sas

maturity (*Maturity*), bond illiquidity (*Illiquidity*), bond return in the past month (*Lag Bond Return*), downside risk (*VaR (5%)*) and stock return in the past month (*Lag Stock Return*) as control variables. We include bond fixed effects and month fixed effects in all the panel regressions.

Panel A of Table 6 shows that Δ*ImpVOL* predicts future change of *EDF*. After controlling for accounting-based predictors in Campbell, Hilscher, and Szilagyi (2008), the coefficient estimate on Δ*ImpVOL* is positive at all horizons and statistically significant over the next month and the next six months horizons. Thus, the more is the increase in implied volatility, the higher is the increase in *EDF* in the next months. Panel B shows that the Δ*ImpVOL* significantly predicts future bond rating downgrades over the next one month, three months and six months, after controlling for several bond characteristics. For example, if Δ*ImpVOL* increases by one standard deviation, the probability of downgrade increases by 0.72% (= 0.277×0.026) over the next month and 1.28% (=0.494×0.026) over the next three months. Some other variables also significantly predict probability of future downgrades. For example, higher implied volatility and lower bond return in the previous month predict higher probability of downgrade in the next one month, three months and six months.

Overall, we find that changes in implied volatilities are both significant predictor for future changes in *EDF* and future probability of bond downgrade. The evidence suggests that informed traders with relevant default risk information prefer to trade in the option market (which allows higher leverage and higher potential for profits) before they trade in the corporate bond market. Large increases in implied volatility suggest higher default risk of the firm in the future. Corporate bond market slowly incorporates the default risk related information with a higher yield, lower price, and low return in the future.

4.2. Predicting returns of credit default swaps

Another class of securities that shares many features of bonds is credit default swap (CDS). If default risk of a firm increases, bond prices decrease to reflect higher yield, and CDS prices increase to reflect higher price of insurance. Since our previous sub-section shows that Δ*ImpVOL* predicts change in default probability, in this subsection, we directly study whether Δ*ImpVOL* predicts the CDS returns in a manner similar to that for the bond returns.

We use a comprehensive dataset of CDS spreads from the Markit Group Limited. The dataset contains daily quotes on CDS spreads for over 1,000 North American firms from February

2001 to August 2017. We focus on the sample from August 2002 to September 2014 because there are less than 30 observations before August 2002 and after September 2014. The average number of observations per month in our sample period is 1,004. We focus on the 5-year CDS spreads because these contracts are the most liquid and constitute over 85% of the entire CDS market. To maintain uniformity in contracts and the compatibility with previous studies such as in Griffin, Hong, and Kim (2016) and Lee, Naranjo, and Velioglu (2018), we only keep CDS for senior unsecured debt with a modified restructuring clause and denominated in US dollars. The monthly CDS return is defined as the month-end to month-end percentage change of CDS spreads.

For each month from August 2002 to September 2014, we construct quintile portfolios by sorting CDSs according to the change in implied volatilities $\Delta ImpVOL$ of the underlying firms. Quintile one contains CDS of firms with the largest decrease in implied volatilities in the previous month and quintile five contains CDS of firms with the largest increase in implied volatility in the previous month. The portfolios are equal-weighted. The holding period for the CDS is one month and we rebalance the portfolios monthly. The CDS returns on the quintile portfolios and the 5−1 portfolio are reported in Panel A of Table 7. Results show that the raw CDS return increases from 0.81% in quintile one to 2.85% in quintile five, leading to a return spread of 2.04% (*t*-statistic = 5.42).[17]

Panel B of Table 7 reports time-series averages of Fama and MacBeth (1973) regression coefficients and their corresponding *t*-statistics. We run firm-level predictive regressions at monthly frequency with CDS return as the dependent variable. Independent variables include $\Delta ImpVOL$, CDS return in the past month, stock return in the past month, bond return in the past month, and implied volatility level. Bond return at the firm level is calculated as the value-weighted return of all bonds of each firm. We find that $\Delta ImpVOL$ significantly predicts future CDS returns, after controlling for lagged CDS, stock, and bond return. In addition, we find lagged returns of related securities also significantly predict future CDS returns. Firms with larger lagged CDS return, lagged stock return and lagged bond return have higher CDS return in the next month.

To sum up, we find that $\Delta ImpVOL$ leads the CDS market similar to that for the bond market. The evidence is consistent with the explanation that increase in implied volatility predicts higher default risk of the underlying firm, leading to lower bond return and higher CDS return.

[17] CDS "prices" are credit spreads. Therefore, CDS returns are calculated from changes in spreads and, hence, the magnitude of CDS returns is not directly comparable to that of bond returns.

5. Why Does Δ*ImpVOL* Predict Future Bond Returns?

Why do the corporate bonds fail to immediately impound the relevant information about the change in firm risk into bond prices? The delay in corporate bond price reaction might reflect slow diffusion of information from options to bonds or impediments to trade in the corporate bond market. In this section, we provide additional evidence to bear on these two hypotheses. First, we study the effect of bond and option trading volume on bond return predictability. Second, we investigate the role of firm's dual ownership, as an investor-attention measure, in explaining the bond return predictability. Lastly, we examine how transaction cost affects the magnitude of the predictability.

We acknowledge upfront that it is not possible to completely disentangle the two hypotheses. For example, the speed of information incorporation might depend on the liquidity of the corporate bond market—lower is the bond market liquidity, slower the information is reflected in the bond price. Our modest goal is only to present evidence supporting one or the other hypothesis.

5.1. Option volume, bond volume, and informed trading

Easley, O'Hara, and Srinivas (1998) construct a sequential trading model to understand the informed trading in the option and stock markets. They show that, if at least some informed investors choose to trade in options before trading in underlying stocks, option prices will predict future stock price movements. This intuition can be echoed to the informational role of options in the bond market. If the informed trading hypothesis is correct, we would expect the predictive power of Δ*ImpVOL* to be stronger when more informed traders choose to trade in the option market and fewer informed traders trade in the bond market. We, therefore, analyze portfolios sorted on Δ*ImpVOL*, conditional on changes in option and bond trading volumes.

Each month, we first divide the bonds into two separate groups based on the median change in option or bond trading volume. For example, bonds with above (below) median change in option trading volume are in the High (Low) ΔOption Volume group. Similarly, bonds with above (below) median change in bond trading volume are in the High (Low) ΔBond Volume group. For each one of these four groups, we further sort the bonds by Δ*ImpVOL* into ten deciles and hold the portfolio for one month. We report the mean returns of the decile portfolios, the 10−1 return and alpha from the Bond+Stock 11-factor model in Table 8.

Consistent with the sequential trading model, we find that the predictability of Δ*ImpVOL* is the strongest for bonds in the High ΔOption Volume and Low ΔBond Volume group. The average return and Bond+Stock alpha for the 10−1 portfolio are −1.02% and −1.29%, with *t*-statistics of −3.26 and −3.80, respectively for this sub-sample. The risk-adjusted return spreads are smallest in the group of Low ΔOption Volume and Low ΔBond Volume, at −0.72% per month.

Note also that, while there is a variation in profits across the four groups, we continue to find statistically and economically significant profits in all groups. For instance, even in the in the group of High ΔOption Volume and High ΔBond Volume, where we expect the least limits to arbitrage, we find that the risk-adjusted return spreads are −0.82% per month.

5.2. Investor inattention and bond return predictability

The speed at which asset prices incorporate new information is affected by investors' limited attention. Limited attention can cause investors to ignore useful information, leading to price underreaction. Theoretical models such as Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2011) show how limited attention causes underreactions to news. There are numerous empirical studies on the effects of investors' limited attention (see, for example, Barber and Odean (2008), DellaVigna and Pollet (2009), and Peng and Xiong (2006)). In this section, we use rating change announcements and institutional dual ownership of a firm's stock and bond to examine the role of investors' attention on the predictability of Δ*ImpVOL* on bond returns.

5.2.1. Ratings announcement days

Engelberg, McLean, and Pontiff (2018) show that anomaly returns in the stock market are 50% higher on corporate news days and six times higher on earnings announcement days. This is consistent with the idea that biased expectations drive anomaly returns and they are partially corrected upon news arrival. Following this insight, we conjecture that the long-short bond portfolio return sorted by Δ*ImpVOL* is higher in magnitude around bond rating announcements, which are the most salient events in the corporate bond market.

To examine the effect of rating announcements on our anomaly returns, we follow Engelberg, McLean, and Pontiff (2018) and first run a panel regression of daily bond return in deciles one and ten on the rating day dummy variable. The dependent variable is daily bond return multiplied by 100. For each bond-month observation, we define a *Net* variable, which is equal to −1 if the bond belongs to decile one and equal to 1 if the bond belongs to decile ten. The rating day indicator (*RDAY*) equals one if the day is in one of the three-day-window around a rating announcement and equals zero on other days. We also include an interaction term, *Net*×*RDAY*, which indicates whether anomaly returns are higher or lower on rating days. Our panel regression includes time fixed effects and we cluster standard errors at time level. We report the panel regression results in Panel A of Table 9. We find that the coefficient on *Net* is −0.02 (*t*-statistic = −6.52), while that on *Net*×*RDAY* is −0.11 (*t*-statistic = −2.87). Thus, the long-short return is 5.5 times higher in magnitude on rating announcements than on other days.

We report average daily returns (in bps) of deciles one and ten on rating days and other days in Panel B of Table 9. We further split the rating announcements into downgrades and upgrades. We find that the long-short return is 8.3 times higher in magnitude on rating days (−25bps) than other days (−3bps). For downgrade announcement days, the anomaly return is as large as −58bps. For upgrades, the anomaly return is 0.27bps. The results are consistent with the idea that investors lower (raise) their expectations around downgrade (upgrade) announcements. The positive return of 17bps on decile ten around upgrades spotlights events where our signal of increase in implied volatility (implying increased risk and lower bond prices) is false. Correspondingly, our signal of an increase in implied volatility is deemed to be materially important for decile ten on downgrades, when the bond return is −82bps.

5.2.2. Dual ownership

Investors' attention can also be captured by institutional dual ownership of a firm's stock and bond. Following Bodnaruk and Rossi (2016), we define dual institutions for a company as financial institutions that hold at least 0.5% of stock and 0.5% of bond of that company. We then calculate the dual institutional ownership at bond level by aggregating the ownership of all dual institutions. Firms without dual institutions are defined to have zero dual ownership.[18] High dual ownership bonds are defined as bonds with dual institutional ownership above the median. Low dual ownership bonds are bond with dual institutional ownership below the median. The dual

[18] We thank Tao Chen for sharing the dataset on dual ownership variable. The bond holdings of mutual funds is from Thomson Reuters eMAXX (formerly Lipper eMAXX). The details of data construction can be found in Chen, Zhang, and Zhu (2019).

ownership variable is available at annual frequency from 2006 to 2015. The sample is relatively large-sized firms in the S&P 1500 index. Intuitively, financial institutions who hold both equity and bond of the same firm at the same time pay more attention to the information related to stock options than those that hold only bonds of the firm. Thus, we expect the predictability of $\Delta ImpVOL$ on future bond returns to be stronger for firms without dual ownership.

We report portfolio sorting results for the full subsample of S&P 1500 firms, firms with low dual ownership and firms with high dual ownership in the sample period of 2007 to 2016 in Table 10. The results for the sample of S&P 1500 firms are similar to those in Table 2. This illustrates that our sample selection does not create a bias for main results. Consistent with the investor inattention hypothesis, we find the portfolio return spread is larger in magnitude for the bonds with low dual ownership firms at −0.83% (t-statistic = −2.06) than that for bonds with high dual ownership firms at −0.49% (t-statistic = −2.10).

The results in this section, thus, suggest that investor attention plays a role in explaining the slow information diffusion from the option market to the corporate bond market.

5.3. Transaction cost analysis

Recall that the results in Panel A of Table 4 show that predictability exists in all bonds, regardless of their illiquidity, but also shows that the predictability is highest amongst more illiquid bonds. Section 5.1 also shows that our strategy is profitable in even illiquid bonds. However, both these analyses do not explicitly account for impact on illiquidity in trading. This is because, so far, we have assumed that all bonds are bought or sold at the volume-weighted transaction price at the month-end.

To examine the impact of trading cost on the profitability of our strategy, we estimate transaction costs using two approaches. In the first approach, we use the mean bid-ask spread estimates from Edwards, Harris, and Piwowar (2007). The relevant trading costs, EHP, are 18bps, 16bps, and 30 bps (68bps, 45bps, and 100 bps) for all bonds, investment-grade bonds, and non-investment-grade bonds, respectively for trade size of \$1M (\$100K). In the second approach, we use the Bao, Pan, and Wang (2011) measure (BPW). This is calculated as $2\sqrt{\gamma}$, where γ is the illiquidity measure in Roll (1984):

$$\gamma = \begin{cases} -\mathrm{cov}(r_d, r_{d-1}) & \text{if } \mathrm{cov}(r_d, r_{d-1}) < 0 \\ 0 & \text{otherwise} \end{cases}, \qquad (5)$$

where r_d is the corporate bond return on day d.

We report portfolio turnover, bid-ask spread, net return, and net alphas from the bond and bond+stock factor model for the long-short portfolio sorted by $\Delta ImpVOL$ in Table 11. The table shows results for the full sample and for the subsamples of investment-grade, and non-investment-grade bonds. Turnover is defined as the average sum of the percentage of a portfolio that is bought and the percentage of a portfolio that is sold in each month. Bid-ask spread is estimated using the EHP estimates or the BPW measure. Net return is the portfolio return net of transaction costs. The factor models are the same as those in Table 2.

For consistency with earlier tables, the hedge portfolio is defined to be long in decile ten and short in decile one. Thus, negative net returns show a profitable strategy while positive net returns show the lack of profitability accounting for transaction costs. Table 11 shows that net return of the long-short portfolio in the full sample is statistically significant if we use the EHP estimates for trade size of $1M. The alphas from the factor models are also statistically significant. When we use EHP estimates for trade size of $100K, net return and alphas are no longer statistically significant, and even reverse sign. Since the Bao, Pan, and Wang (2011) trading costs are much higher than those of Edwards, Harris, and Piwowar (2007), the trading strategy does not survive transaction costs using BPW bid-ask spreads—net returns for investment-grade and non-investment-grade samples are not statistically significant after subtracting the transaction cost. Overall, our results show that the trading strategy could be potentially profitable for large trading sizes. Nevertheless, high transaction costs might hinder trades that seek to exploit this arbitrage opportunity.[19]

To summarize the results in this section, we find that slow diffusion of information is largely responsible for predictability from options to bonds. While predictability is the highest when option trading volumes are high and when bond trading volumes are low, there is predictability in even very liquid bonds. Predictability is muted for bonds of firms where investors pay attention to both stocks and options. This lack of investor attention creates opportunities for arbitrageurs. However, the transaction costs analysis highlights the difficulty in taking advantage

[19] Table 7 shows predictability of CDS returns from implied volatility changes. It is well-documented that trading costs in CDS markets are substantially lower than those in the bond market. For example, Biswas, Nikolova, and Stahel (2015) show that, for trade sizes of $500K, bonds are three times more expensive to trade than CDS written on them. Therefore, investors could potentially explore the profitability through corporate bond market or CDS market depending on the transaction costs and trade size.

of this predictability. Thus, slow diffusion of information due to investor inattention coupled with high limits to arbitrage explains why bond prices react to information from options with a delay.

6. Conclusion

The price discovery role of options for the underlying stocks has been well documented in the literature. The price discovery role of options on bond market, however, is unknown. In this paper, we investigate whether option information contains relevant information for the future return of the corporate bond of the same underlying firm. In particular, we study implied volatility changes in the past month, where the implied volatility is obtained from at-the-money option with 365 days of maturity. We find that the firms with large increase in implied volatilities have low corporate bond return in the next month. If we form decile portfolios based on changes in implied volatilities, the spread in average return between the top and bottom decile portfolios is approximately 0.6% per month and highly statistically significant. The predictability of implied volatility changes on bond return is robust after controlling for stock and bond risk factors, bond characteristics, and other volatility characteristics. We further document that implied volatility changes have relevant information for predicting changes in default risk in the next months and for predicting future returns of credit default swaps. We also find evidence consistent with investor inattention driving predictability. The predictability is lower in low option and bond volume and is low in bonds with dual ownership of stocks and bonds holding by the same financial institutions. High transaction costs, however, present an important source of limits to arbitrage, which makes the bond market slow in incorporating information from the option market.

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Table 1: Descriptive Statistics

This table reports the summary statistics of bond return, changes in implied volatilities, and bond characteristics. *Return* is monthly bond return, reported in percent per month. Δ*CVOL* (Δ*PVOL*) is the change of implied volatility of at-the-money call (put) option with 365 days of maturity; the change is calculated using the month-end observations. *ImpVol* is the average implied volatility of at-the-money call and put options with 365 days of maturity. *Size* is the logarithm of offering amount of the bond. *Rating* is the numerical rating score, where 1 refers to a AAA rating by S&P and Aaa by Moody, 21 refers to a C rating for both S&P and Moody. Ratings of 10 or below are considered investment grade, and ratings above 10 are considered non-investment grade. *Maturity* is the time-to-maturity of the bond in years. *Illiquidity* is autocovariance of daily price change in each month, multiplied by −1. *Lag Return* is the corporate bond return in the past month. *VaR* (5%) is the 5% Value-at-Risk of corporate bond return, defined as the second lowest monthly return over the past 36 months. Panel A reports the number of bond-month observations, mean, standard deviation, median and percentiles of the variables. Panel B reports the time-series average of the cross-sectional correlation of the variables. All variables are winsorized each month at the 0.5% level. The sample period is from July 2002 to August 2017.

Panel A: Summary statistics

Variable	N	Mean	Standard deviation	10^{th} percentile	Lower quartile	Median	Upper quartile	90^{th} percentile
Return	881,625	0.51	3.20	−2.04	−0.45	0.34	1.48	3.25
Δ*CVOL*	881,625	0.00	0.04	−0.04	−0.02	0.00	0.01	0.04
Δ*PVOL*	881,625	0.00	0.04	−0.04	−0.02	0.00	0.01	0.04
ImpVol	881,625	0.31	0.15	0.18	0.21	0.27	0.36	0.48
Size	832,812	12.51	1.62	9.85	12.21	12.90	13.53	14.04
Rating	741,028	8.52	4.45	4.00	6.00	8.00	10.00	14.00
Maturity	832,778	8.54	8.63	1.17	2.76	5.63	9.68	23.69
Illiquidity	801,804	0.95	2.73	0.00	0.02	0.16	0.72	2.27
Lag Return	845,063	0.49	3.12	−2.00	−0.44	0.34	1.44	3.17
VaR (5%)	694,870	−0.04	0.04	−0.08	−0.05	−0.03	−0.01	−0.01

Panel B: Time-series average of cross-sectional correlations

	Δ*CVOL*	Δ*PVOL*	*ImpVol*	*Size*	*Rating*	*Maturity*	*Illiquidity*	*Lag Return*	*VaR* (5%)
Return	−0.04	−0.04	0.04	−0.02	0.06	0.04	0.03	−0.06	−0.08
Δ*CVOL*		0.58	0.08	0.00	−0.02	0.00	0.01	−0.13	0.02
Δ*PVOL*			0.11	0.00	−0.01	0.01	0.01	−0.14	0.01
ImpVol				−0.03	0.50	−0.09	0.07	0.00	−0.47
Size					0.02	−0.03	−0.23	−0.02	0.14
Rating						−0.10	0.04	0.05	−0.38
Maturity							0.19	0.03	−0.29
Illiquidity								0.01	−0.22
Lag Return									−0.03

Table 2: Portfolio of Bonds Sorted by $\Delta CVOL$ or $\Delta PVOL$

At the end of each month, we sort bonds into deciles. Decile 1 is the portfolio with the lowest changes in implied volatilities and decile 10 is the portfolio with the highest changes in implied volatilities. The implied volatility is calculated from at-the-money options with 365 days to maturity and the change is calculated as the difference over the last month. We use changes in implied volatilities of call options ($\Delta CVOL$) in Panel A and that of put options ($\Delta PVOL$) in Panel B. The portfolios are held for one month and rebalanced monthly. Portfolios are value-weighted using the prior month's bond market capitalization as weights. We report the average returns of the deciles as well as portfolio alphas. Alphas are calculated from a bond model and a bond+stock model. The bond model uses five factors (bond market, downside risk, credit risk, liquidity risk, and reversal) from Bai, Bali, and Wen (2018). The stock market factors are the six factors (market, size, value, investment, profitability, and momentum) from Fama and French (2018). The bond+stock model combines the five bond factors and the six stock market factors. All returns and alphas are in percent per month. Newey-West adjusted *t*-statistics are reported in parenthesis below returns/alphas. The last column reports the returns and alphas for the 10−1 portfolio. Finally, we also report a few bond characteristics for each decile. These characteristics are bond market factor beta, size, rating, maturity and illiquidity. Details on construction of these variables are provided in Table 1. The sample period is from July 2002 to August 2017.

	1	2	3	4	5	6	7	8	9	10	10−1
					Panel A: Portfolios sorted by $\Delta CVOL$						
Average Return	0.95	0.72	0.63	0.51	0.49	0.49	0.47	0.45	0.48	0.44	-0.52^{***}
	(4.29)	(4.70)	(5.11)	(4.81)	(4.53)	(4.28)	(3.83)	(3.89)	(3.35)	(2.28)	(−3.57)
Bond Alpha	0.23	0.21	0.02	0.01	−0.08	−0.11	−0.22	−0.16	−0.35	−0.35	-0.58^{**}
	(1.75)	(1.61)	(0.16)	(0.06)	(−0.70)	(−0.80)	(−1.26)	(−1.01)	(−1.91)	(−2.28)	(−2.53)
Bond+Stock Alpha	0.45	0.41	0.25	0.21	0.12	0.13	0.03	0.07	−0.14	−0.45	-0.90^{***}
	(4.40)	(4.14)	(5.80)	(4.10)	(2.66)	(2.54)	(0.59)	(1.07)	(−1.92)	(−3.20)	(−4.94)
Beta	0.59	0.55	0.56	0.51	0.47	0.65	0.68	0.63	0.76	0.49	
Size	12.47	12.41	12.48	12.43	12.46	12.43	12.47	12.52	12.47	12.42	
Maturity	7.80	8.44	8.73	8.73	8.71	8.78	8.72	8.65	8.58	7.97	
Rating	10.76	8.76	7.97	7.67	7.58	7.53	7.56	7.85	8.46	10.31	
Illiquidity	1.27	1.10	1.04	1.02	0.99	0.98	1.01	1.05	1.09	1.42	

	1	2	3	4	5	6	7	8	9	10	10−1
					Panel B: Portfolios sorted by $\Delta PVOL$						
Average Return	0.96	0.63	0.65	0.58	0.54	0.44	0.44	0.48	0.45	0.46	-0.50^{***}
	(4.39)	(4.85)	(5.14)	(5.17)	(4.52)	(4.25)	(3.62)	(4.14)	(2.75)	(2.35)	(−3.51)
Bond Alpha	0.24	0.07	0.13	0.06	−0.05	−0.10	−0.23	−0.18	−0.34	−0.40	-0.64^{***}
	(1.89)	(0.59)	(1.00)	(0.52)	(−0.40)	(−0.88)	(−1.15)	(−1.30)	(−1.49)	(−2.50)	(−2.72)
Bond+Stock Alpha	0.39	0.30	0.34	0.25	0.20	0.10	0.04	0.07	−0.07	−0.50	-0.89^{***}
	(3.92)	(6.89)	(4.21)	(4.85)	(3.89)	(2.20)	(0.73)	(1.32)	(−0.81)	(−3.23)	(−4.40)
Beta	0.48	0.59	0.54	0.46	0.54	0.57	0.72	0.69	0.80	0.58	
Size	12.47	12.44	12.41	12.44	12.49	12.51	12.45	12.48	12.50	12.42	
Maturity	7.72	8.46	8.61	8.70	8.79	8.82	8.70	8.68	8.60	7.98	
Rating	10.80	8.77	8.00	7.64	7.54	7.50	7.58	7.87	8.44	10.38	
Illiquidity	1.30	1.08	1.01	1.02	0.99	0.99	1.02	1.04	1.08	1.42	

Table 3: Return and Alphas of Portfolio of Bonds Sorted by $\Delta CVOL+\Delta PVOL$ or $\Delta CVOL-\Delta PVOL$

This table presents portfolio sort results for bonds sorted by the sum ($\Delta CVOL+\Delta PVOL$) (Panel A) and the difference ($\Delta CVOL-\Delta PVOL$) (Panel B) of call and put implied volatility changes. Portfolios are sorted as in Table 2. This table shows the returns and alphas on the decile portfolios and the 10−1 portfolio. All returns and alphas are in percent per month. Newey-West adjusted *t*-statistics are reported in parenthesis below returns/alphas. The sample period is from July 2002 to August 2017.

	1	2	3	4	5	6	7	8	9	10	10−1
Panel A: Portfolios sorted by ($\Delta CVOL+\Delta PVOL$)											
Average Return	0.98	0.64	0.61	0.65	0.48	0.51	0.51	0.39	0.45	0.38	−0.60***
	(4.50)	(4.61)	(4.83)	(5.16)	(4.40)	(3.95)	(4.74)	(3.05)	(3.39)	(1.85)	(−3.62)
Bond Alpha	0.24	0.17	0.01	0.07	−0.10	−0.10	−0.13	−0.34	−0.22	−0.47	−0.71***
	(1.93)	(1.28)	(0.09)	(0.53)	(−0.71)	(−0.71)	(−1.08)	(−1.55)	(−1.41)	(−3.09)	(−3.50)
Bond+Stock Alpha	0.42	0.37	0.25	0.28	0.13	0.16	0.09	−0.07	−0.03	−0.57	−0.98***
	(4.07)	(4.68)	(4.46)	(5.07)	(2.76)	(2.24)	(1.77)	(−1.06)	(−0.34)	(−3.74)	(−5.57)
Panel B: Portfolios sorted by ($\Delta CVOL-\Delta PVOL$)											
Average Return	0.67	0.52	0.50	0.50	0.55	0.47	0.50	0.49	0.57	0.80	0.13
	(3.07)	(4.22)	(4.22)	(4.06)	(4.60)	(4.16)	(4.08)	(4.34)	(4.33)	(4.00)	(1.03)
Bond Alpha	0.04	−0.11	−0.11	−0.16	−0.11	−0.15	−0.12	−0.14	−0.06	0.10	0.06
	(0.39)	(−0.96)	(−0.84)	(−1.08)	(−0.79)	(−1.06)	(−0.77)	(−0.94)	(−0.45)	(0.86)	(0.42)
Bond+Stock Alpha	0.21	0.08	0.09	0.08	0.13	0.07	0.12	0.08	0.13	0.15	−0.05
	(2.36)	(1.06)	(1.81)	(1.42)	(2.62)	(1.51)	(2.02)	(1.64)	(2.03)	(1.37)	(−0.37)

Table 4: Alphas of 5−1 Portfolio of Bonds Sorted by Δ*ImpVOL* Controlling for Bond and Volatility Characteristics

At the end of each month, we conditionally double sort the bonds into 5×5 quintiles. In Panel A, we first sort bonds into quintile portfolios based on a characteristic, which is size, maturity, rating, illiquidity or bond return in the past month. Details on the construction of these variables are in Table 1. In Panel B, we first sort bonds into quintile portfolios based on a volatility characteristic, which is bond volatility, bond idiosyncratic volatility, stock implied volatility, stock idiosyncratic volatility, and VIX beta. Bond volatility (*BondVol*) is calculated as the standard deviation of daily bond returns within each month. Bond idiosyncratic volatility (*Bond IdioVol*) is the standard deviation of bond return residuals, estimated from the time-series regression with five Fama and French (2015) factors and change in VIX as volatility risk factor. Stock implied volatility (*ImpVol*) is the average of the call and put at-the-money implied volatility with 365 days of expiration. Stock idiosyncratic volatility (*Stock IdioVol*) is the standard deviation of stock return residuals, estimated from the time-series regression with five stock factors and the volatility risk factor. *VIX beta* is the regression coefficient on change in VIX estimated from the same time-series regression used to estimate bond idiosyncratic volatility. Within each characteristic quintile, we further sort bonds into five quintiles based on Δ*ImpVOL* (≡ (Δ*CVOL*+Δ*PVOL*)/2). We calculate the bond+stock model alpha of the 5−1 hedge portfolio that is long in bonds with the highest changes in implied volatilities and short in bonds with the lowest changes in implied volatilities. The factor model is the same as that in Table 2. This alpha is calculated for hedge portfolios in each of the characteristic quintile. The table reports these alphas together with their Newey-West adjusted *t*-statistics in parenthesis. The sample period is from July 2002 to August 2017.

	1	2	3	4	5
Panel A: Controlling for bond characteristics					
Size	−0.58	−0.69***	−0.67***	−0.61***	−0.61***
	(−1.39)	(−5.18)	(−5.25)	(−4.86)	(−5.00)
Maturity	0.09	−0.48***	−0.92***	−0.77***	−1.32***
	(0.62)	(−4.55)	(−5.81)	(−4.98)	(−4.12)
Rating	−0.09	−0.73***	−0.63***	−0.51**	−0.69**
	(−1.44)	(−3.20)	(−3.63)	(−2.10)	(−2.14)
Illiquidity	−0.75***	−0.28***	−0.52***	−0.79***	−1.19***
	(−5.16)	(−3.77)	(−3.95)	(−4.47)	(−3.31)
Lag Return	−1.03***	−0.37***	−0.27***	−0.32***	−0.56**
	(−2.88)	(−3.40)	(−3.71)	(−4.12)	(−2.50)
Panel B: Controlling for volatility characteristics					
Bond Vol	−0.25***	−0.47***	−0.73***	−1.05***	−1.22***
	(−3.25)	(−3.91)	(−3.58)	(−5.11)	(−3.21)
Bond IdioVol	−0.17***	−0.36***	−0.55***	−0.98***	−1.22***
	(−3.29)	(−3.58)	(−4.07)	(−4.16)	(−3.12)
ImpVol	−0.10	−0.15***	−0.15	−0.22**	−0.78***
	(−1.45)	(−2.76)	(−1.61)	(−2.41)	(−3.12)
Stock IdioVol	−0.13**	−0.17*	−0.28**	−0.34**	−0.76***
	(−2.04)	(−1.67)	(−2.59)	(−2.18)	(−2.86)
VIX Beta	−0.93***	−0.55***	−0.42***	−0.51***	−1.21***
	(−4.00)	(−3.92)	(−4.43)	(−5.31)	(−4.31)

Table 5: Fama-MacBeth Regressions for the Cross-section of Bond Returns

This table presents time-series averages of the monthly Fama-MacBeth regression coefficients and their corresponding Newey-West adjusted *t*-statistics. Panel A controls for bond and stock characteristics. Panel B adds volatility related variables as additional control variables. All independent variables are winsorized each month at the 0.5% level. "Adj. R^2" is the average adjusted R^2 across months and "Obs." is the total number of observations. The sample period is from July 2002 to August 2017.

Panel A: Controlling for bond and stock characteristics

	Full sample		Investment-grade		Non-investment-grade	
Intercept	0.005***	0.006***	0.004***	0.006***	0.009***	0.017**
	(4.56)	(2.91)	(4.22)	(3.04)	(3.98)	(2.05)
Δ*ImpVOL*	−0.102***	−0.086***	−0.086***	−0.076***	−0.110***	−0.082***
	(−4.55)	(−5.28)	(−3.38)	(−7.17)	(−3.32)	(−3.55)
ImpVol		−0.001		−0.000		−0.002
		(−0.17)		(−0.15)		(−0.51)
Size		−0.036***		−0.027*		−0.110**
		(−2.94)		(−1.92)		(−2.28)
Rating		0.012		0.009	.	0.001
		(0.80)		(0.72)		(0.03)
Maturity		0.008		0.001		0.015
		(1.21)		(1.04)		(1.12)
Illiquidity		−0.001***		−0.001***		−0.000
		(−3.14)		(−4.83)		(−0.74)
Lag Bond Return		−0.134***		−0.188***		−0.104***
		(−8.12)		(−13.42)		(−4.76)
VaR (5%)		−0.068***		−0.077***		−0.050*
		(−3.11)		(−4.47)		(−1.94)
Lag Stock Return		0.070***		0.030***		0.105***
		(15.58)		(6.16)		(18.92)
Adj. R^2	0.016	0.236	0.015	0.249	0.023	0.260
Obs.	886,613	551,756	725,464	431,527	145,816	113,333

Panel B: Controlling for volatility characteristics			
	Full sample	Investment-grade	Non-investment-grade
Intercept	−0.005	−0.008**	0.020*
	(−1.37)	(−2.42)	(1.73)
Δ*ImpVOL*	−0.076***	−0.066***	−0.086***
	(−4.33)	(−5.04)	(−2.82)
ImpVol	−0.003	−0.001	−0.005
	(−0.69)	(−0.31)	(−0.97)
Size	0.048**	0.073***	−0.097
	(2.26)	(2.96)	(−1.57)
Rating	0.008	0.013	−0.017
	(0.68)	(1.12)	(−0.79)
Maturity	0.000	0.000	0.000
	(0.99)	(0.71)	(0.59)
Illiquidity	0.025	0.021	0.016
	(1.28)	(1.02)	(0.49)
Lag Bond Return	−0.102***	−0.169***	−0.082***
	(−5.56)	(−8.93)	(−3.88)
VaR (5%)	−0.044**	−0.065***	−0.040*
	(−2.48)	(−4.41)	(−1.89)
Bond Vol	0.080***	0.036***	0.115***
	(14.33)	(6.45)	(15.79)
Lag Stock Return	0.179**	0.176**	0.075
	(2.43)	(2.15)	(0.74)
Bond IdioVol	−0.088	−0.066	−0.081
	(−1.08)	(−0.75)	(−0.87)
Stock IdioVol	0.046	0.026	0.068
	(1.35)	(1.04)	(1.41)
VIX Beta	0.037	0.024	0.089*
	(0.97)	(0.94)	(1.70)
ΔVOL-EGARCH	−0.018**	−0.024***	−0.010
	(−2.54)	(−3.86)	(−0.97)
Adj. R^2	0.315	0.341	0.341
Obs.	273,664	211,389	59,105

Table 6: Predicting Change of Future Default Risk with Δ*ImpVOL*

This table reports panel regression results for predicting changes of future default risk with $\Delta ImpVOL$. The dependent variable is the change in expected default frequency (EDF) in Panel A and the bond rating downgrade dummy in Panel B. The dummy variable is equal to 1 if there is a downgrade of the bond and 0 otherwise. We run panel regressions at the firm level in Panel A and at the bond level in Panel B. We report regression result for changes in default risk in the future one, three, and six months in both panels. Independent variables in Panel A include changes in implied volatilities, net income over market value of total assets (*NIMTA*), total liabilities over market value of total assets (*TLMTA*), logarithm of firm's market equity (*Size_equity*), stock of cash and short-term investments over the market value of total assets (*CASHMTA*), market-to-book value of the firm (*MB*) and price per share (*Price_equity*). Independent variables in Panel B are similar to those in Table 6 Panel A. Newey-West adjusted *t*-statistics are provided in the parenthesis. All independent variables are winsorized each month at the 0.5% level. The sample period is from July 2002 to August 2017.

Panel A: Predict change of EDF (Firm level)			
	1 month	3 months	6 months
Δ*ImpVOL*	0.012***	0.008	0.044***
	(3.89)	(1.12)	(3.59)
NIMTA	−0.012*	0.009	0.043
	(−1.93)	(0.55)	(1.29)
TLMTA	−0.005***	−0.015***	−0.025***
	(−6.62)	(−7.46)	(−5.85)
Size_equity	0.001***	0.004***	0.008***
	(9.10)	(7.755)	(7.71)
CASHMTA	−0.001	−0.001	0.001
	(−0.97)	(−0.24)	(0.20)
MB	−0.001***	−0.004***	−0.008***
	(−7.29)	(−8.07)	(−8.73)
Price_equity	−0.001***	−0.003***	−0.006***
	(−3.72)	(−3.06)	(−2.74)
Firm fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Adj. R^2	0.104	0.141	0.180
Obs.	115,194	115,314	115,395

Panel B: Predict bond rating downgrades (Bond level)			
	1 month	3 months	6 months
ΔImpVOL	0.554***	0.988***	0.944***
	(4.47)	(3.12)	(4.10)
ImpVol	0.128**	0.513***	0.651***
	(2.17)	(7.95)	(9.40)
Maturity	0.005***	−0.002	−0.004**
	(3.38)	(−1.49)	(−2.33)
Illiquidity	0.010***	0.004	0.004
	(2.98)	(1.33)	(0.88)
Lag Bond Return	−0.211***	−0.380***	−0.356***
	(−5.57)	(−9.38)	(−7.59)
VaR (5%)	0.021	0.022	0.136
	(0.23)	(0.17)	(0.94)
Lag Stock Return	−0.021	−0.156***	−0.224***
	(−0.71)	(−5.85)	(−8.83)
Bond fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Adj. R^2	0.601	0.164	0.230
Obs.	609,506	609,506	609,506

Table 7: Predicting CDS Returns with Δ*ImpVOL*

This table reports portfolio results for credit default swap (CDS) returns sorted by Δ*ImpVOL* in Panel A and Fama-Macbeth regression results in Panel B. Panel A shows the CDS returns and alphas on the quintile portfolios and the 5−1 portfolio. All returns and alphas are in percent per month. The bond factor model and the bond+stock factor model are the same as those in Table 2. Panel B reports time-series averages of the Fama-MacBeth regression coefficients and their corresponding *t*-statistics. We run firm-level predictive regressions at monthly frequency with CDS return as the dependent variable. Independent variables include change in implied volatility, CDS return in the past month, stock return in the past month, bond return in the past month, and implied volatility. Bond return at the firm level is calculated as value-weighted return of all bonds of each firm. Newey-West adjusted *t*-statistics are provided in the parenthesis. All of these variables are winsorized each month at the 0.5% level. The sample period is from August 2002 to September 2014.

Panel A: Portfolio sorts

	1	2	3	4	5	5−1
Average Return	0.81	0.89	1.76	1.75	2.85	2.04^{***}
	(0.79)	(0.77)	(1.57)	(1.63)	(2.32)	(5.42)
Bond Alpha	1.10	1.68	2.52	2.52	3.81	2.71^{***}
	(1.38)	(1.59)	(2.44)	(2.71)	(3.78)	(5.09)
Bond+Stock Alpha	1.90	2.49	3.47	3.21	4.85	2.95^{***}
	(2.38)	(2.26)	(3.33)	(3.27)	(4.77)	(5.33)

Panel B: Fama-Macbeth regressions

Intercept	0.011	0.013
	(0.92)	(0.93)
Δ*ImpVOL*	0.476^{**}	0.390^{**}
	(2.48)	(2.09)
Lag CDS Return	-0.030^{**}	-0.038^{***}
	(−2.13)	(−2.79)
Lag Stock Return		-0.400^{***}
		(−14.34)
Lag Bond Return		-0.213^{***}
		(−3.64)
ImpVol		−0.004
		(−0.22)
Adj. R^2	0.025	0.087
Obs.	57,697	57,697

Table 8: Returns and Alphas of Portfolio of Bonds Sorted by Δ*ImpVOL* Conditional on Changes in Option and Bond Trading Volume

This table reports portfolio returns sorted by Δ*ImpVOL* (≡ Δ*CVOL*+Δ*PVOL*) conditional on changes in option and bond trading volume. For each month, we separate the bonds into two groups based on the median change in option trading volume (ΔOption volume) or median change in bond trading volume (ΔBond volume). For bonds in the intersection of each of these four groups, we further sort the bonds by Δ*ImpVOL*. We report the mean return of the ten portfolios and the 10−1 return in this table. Alpha is calculated from the Bond+Stock 11-factor model. Newey-West adjusted *t*-statistics are in parentheses. The sample period is from July 2002 to August 2017.

ΔOption volume	High	High	Low	Low
ΔBond volume	Low	High	Low	High
1	1.03	1.03	0.88	0.94
2	0.72	0.67	0.76	0.64
3	0.64	0.60	0.68	0.53
4	0.53	0.72	0.65	0.50
5	0.54	0.59	0.50	0.51
6	0.42	0.43	0.53	0.49
7	0.30	0.44	0.29	0.50
8	0.62	0.59	0.45	0.57
9	0.39	0.35	0.16	0.36
10	0.01	0.16	0.62	0.27
10−1	-1.02^{***}	-0.88^{***}	-0.27^{*}	-0.67^{***}
	(−3.26)	(−2.78)	(−1.90)	(−3.24)
Bond+Stock Alpha	-1.29^{***}	-0.82^{***}	-0.72^{***}	-0.92^{***}
	(−3.80)	(−3.51)	(−3.16)	(−4.64)

Table 9: Bond Return Predictability around Rating Announcement Days

This table reports bond returns around rating announcement days. Panel A reports results from a panel regression of daily returns on time fixed effects, the *Net* anomaly variable, rating-day dummy variable *RDAY*, and interaction between *Net* and *RDAY*. The dependent variable, daily bond return, is multiplied by 100. For each bond-month observation, the *Net* variable equals −1 if the bond belongs to decile one and equals 1 if the bond belongs to decile ten. *RDAY* is a dummy variable that equals one if the day is in one of the three days around a rating announcement, and zero otherwise. We report t-statistics in parenthesis using standard errors clustered on time. Panel B reports average daily returns of deciles one and ten on rating days and other days. We further split the rating announcements into downgrades and upgrades. The sample period is from July 2002 to August 2017.

Panel A: Panel regression of bond returns on rating announcement days

	Net	*Net*×*RDAY*	*RDAY*
	-0.02^{***}	-0.11^{***}	-0.32^{***}
	(−6.52)	(−2.87)	(−8.47)

Panel B: Returns of deciles one and ten on rating days and other days

	Rating day	Downgrade	Upgrade	Other days
Decile 1	−0.15	−0.24	−0.10	0.06
Decile 10	−0.40	−0.82	0.17	0.03
10−1	−0.25	−0.58	0.27	−0.03

Table 10: Impact of Firm-level Dual Ownership on Bond Return Predictability

We report returns (and Newey-West adjusted *t*-statistics in parentheses) of portfolio for bonds with low and high dual ownership in the S&P 1500 sample. We first define dual institution for a company as financial institutions that hold at least 0.5% of the outstanding stocks and 0.5% of the outstanding bonds of that company. Then we calculate the dual institutional ownership at bond level by aggregating the ownership of all dual institutions. High dual ownership bonds are defined as bonds with dual institutional ownership above the median. Low and zero dual ownership bonds are bond with dual institutional ownership below the median. The dual ownership is calculated on an annual basis. For each group, bonds are sorted every month in quintiles by $\Delta ImpVOL$. The sample period is from January 2007 to December 2016.

	1	2	3	4	5	5−1
S&P 1500 Sample	0.82	0.70	0.50	0.43	0.20	−0.61**
	(−2.71)	(−3.38)	(−2.95)	(−2.76)	(−0.84)	(−2.31)
Low Dual Ownership	0.89	0.66	0.58	0.4	0.06	−0.83**
	(−2.73)	(−2.78)	(−2.87)	(−2.38)	(−0.18)	(−2.06)
High Dual Ownership	0.76	0.71	0.42	0.45	0.27	−0.49**
	(−2.44)	(−3.86)	(−2.58)	(−2.74)	(−1.46)	(−2.10)

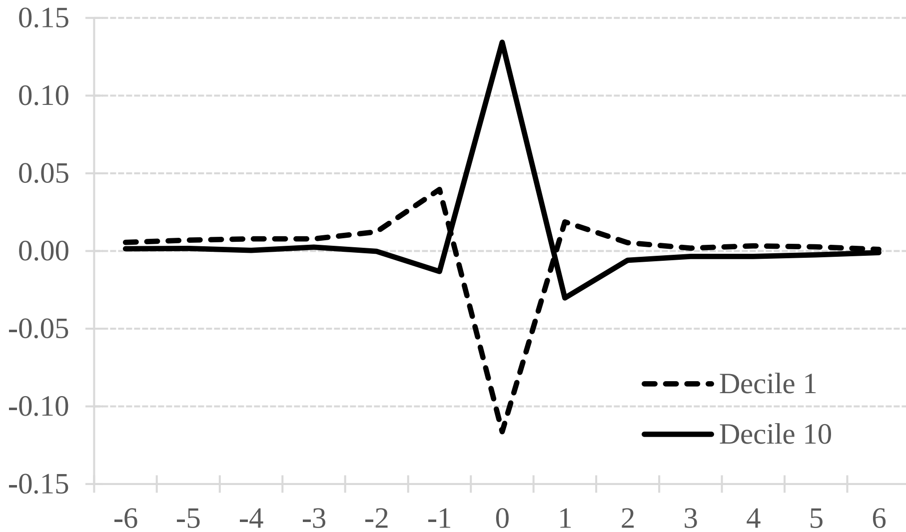
Table 11: Transaction Costs and Net Returns for Long-short Portfolio Sorted by Δ*ImpVOL*

This table presents portfolio results for bonds sorted by Δ*ImpVOL* after subtracting the transaction costs. We calculate returns on a long-short portfolio that is long the tenth and short the first decile. We form the portfolio for the full sample and for the subsamples of investment-grade bonds (IG) and non-investment-grade bonds (Junk). We use the mean bid-ask spread estimates from Edwards, Harris, and Piwowar (2007, EHP) for trade size $1M and $100K. We also calculate bid-ask spread following Bao, Pan, and Wang (2011, BPW). Turnover is defined as the average sum of the percentage of a portfolio that is bought and the percentage of a portfolio that is sold in each month. Net return is the portfolio return net of transaction costs. Positive net return indicates lack of predictability after accounting for transaction costs. We also report alpha from the bond factor model and the bond+stock factor model. The factor models are the same as those in Table 2. All returns are in percentage per month. The table reports these alphas together with their Newey-West adjusted *t*-statistics in parenthesis. The sample period is from July 2002 to August 2017.

	EHP ($1M)			EHP ($100K)			BPW		
	All	IG	Junk	All	IG	Junk	All	IG	Junk
Turnover	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71
Bid-ask Spread	0.18	0.16	0.30	0.68	0.45	1.00	1.29	1.19	1.68
Net Return	−0.30*	−0.04	−0.32	0.53	0.82	0.53	1.51	1.46	2.30
	(−1.74)	(−0.31)	(−1.19)	(3.07)	(6.17)	(1.97)	(5.89)	(6.25)	(6.11)
Bond Alpha	−0.53***	−0.39**	−0.36	0.29	0.45	0.48	0.85	0.75	1.50
	(−3.26)	(−2.43)	(−1.08)	(1.78)	(2.72)	(1.45)	(5.10)	(5.58)	(4.79)
Bond+Stock Alpha	−0.68***	−0.52***	−0.54*	0.14	0.32	0.29	0.77	0.68	1.41
	(−3.74)	(−2.74)	(−1.69)	(0.75)	(1.66)	(0.91)	(4.50)	(5.01)	(4.67)

Figure 1: Δ*ImpVOL* around portfolio formation month

This figure shows change of implied volatility, Δ*ImpVOL*, in the first and the tenth deciles sorted by Δ*ImpVOL*. The portfolios are formed at month *t* and the graph shows Δ*ImpVOL* from month *t*−6 to month *t*+6. The sample period is from July 2002 to August 2017.



Appendix Tables

Table A1: Return and Alphas of 10−1 Portfolio of Bonds Sorted by Δ*ImpVOL* Over Holding Periods of Two to Six Months

This table presents portfolio sort results for bonds sorted by Δ*ImpVOL* (≡ (Δ*CVOL*+Δ*PVOL*)/2). Portfolios are sorted as in Table 2. This table shows the returns and alphas on the 10−1 portfolio for holding horizon from two to six months. All returns and alphas are in percentage. Newey-West adjusted *t*-statistics are reported in parenthesis below returns/alphas. The sample period is from July 2002 to August 2017.

	Holding period in months				
	2	3	4	5	6
Average Return	−0.38***	−0.32***	−0.35***	−0.29***	−0.22**
	(−3.94)	(−3.18)	(−3.56)	(−3.20)	(−2.45)
Bond Alpha	−0.43***	−0.39***	−0.32**	−0.23*	−0.16
	(−2.82)	(−2.81)	(−2.28)	(−1.77)	(−1.33)
Bond+Stock Alpha	−0.59***	−0.47***	−0.40***	−0.32**	−0.21*
	(−4.65)	(−3.07)	(−2.79)	(−2.35)	(−1.81)

Table A2: Return and Alphas of Portfolios of Bonds Sorted on $\Delta ImpVOL$ Calculated Over the Past Two and Three Months

Portfolios are sorted as in Table 2 with $\Delta ImpVOL$ as the sorting variable, except that we calculate changes in implied volatilities in the past two and three months. This table shows the returns and alphas on the decile portfolios as well as the 10−1 portfolio. All returns and alphas are in percent per month. Newey-West adjusted *t*-statistics are reported in parenthesis below returns/alphas. The sample period is from July 2002 to August 2017.

	1	2	3	4	5	6	7	8	9	10	10−1
				Panel A: Portfolios sorted by $\Delta ImpVOL$ in the past two months							
Average Return	0.96	0.64	0.55	0.58	0.44	0.47	0.47	0.50	0.46	0.48	−0.49***
	(5.13)	(4.95)	(4.87)	(4.79)	(3.53)	(3.92)	(3.97)	(3.76)	(3.89)	(2.36)	(−3.70)
Bond Alpha	0.29	0.11	0.04	−0.00	−0.16	−0.15	−0.19	−0.15	−0.23	−0.48	−0.77***
	(3.03)	(1.09)	(0.29)	(−0.03)	(−0.82)	(−0.95)	(−1.12)	(−1.20)	(−1.59)	(−3.72)	(−5.31)
Bond+Stock Alpha	0.45	0.31	0.25	0.26	0.09	0.07	0.08	0.08	−0.07	−0.51	−0.97***
	(5.65)	(4.04)	(4.30)	(3.95)	(1.64)	(1.52)	(1.42)	(1.35)	(−0.80)	(−3.79)	(−6.80)
				Panel B: Portfolios sorted by $\Delta ImpVOL$ in the past three months							
Average Return	1.01	0.69	0.60	0.55	0.50	0.43	0.44	0.43	0.38	0.48	−0.53***
	(5.60)	(5.54)	(4.88)	(4.91)	(4.47)	(3.75)	(3.68)	(3.64)	(2.61)	(2.10)	(−3.64)
Bond Alpha	0.32	0.19	−0.03	−0.09	−0.10	−0.13	−0.20	−0.15	−0.36	−0.37	−0.69***
	(2.80)	(1.66)	(−0.23)	(−0.58)	(−0.73)	(−0.87)	(−1.33)	(−1.17)	(−1.99)	(−2.89)	(−3.50)
Bond+Stock Alpha	0.47	0.37	0.21	0.16	0.15	0.11	0.02	0.04	−0.10	−0.41	−0.89***
	(5.95)	(5.36)	(4.70)	(3.87)	(3.52)	(2.45)	(0.40)	(1.04)	(−1.13)	(−3.16)	(−5.17)

Table A3: Portfolios on Bonds Sorted on Change in Implied Volatilities Controlling for Bond and Volatility Characteristics

After forming the conditional 5×5 portfolios, we average the return of each $\Delta ImpVOL$ quintile across the five characteristic portfolios. This table presents alphas of these quintile portfolios and that of the 5−1 portfolio. The alpha is based on Bond+Stock factor model. All alphas are in percent per month. Newey-West adjusted *t*-statistics are reported in parenthesis below alphas. The sample period is from July 2002 to August 2017.

	1	2	3	4	5	5−1
	Panel A: Controlling for bond characteristics					
Size	0.31	0.27	0.16	0.02	−0.32	−0.63***
	(3.90)	(5.04)	(4.93)	(0.45)	(−3.71)	(−4.37)
Maturity	0.39	0.25	0.15	0.01	−0.29	−0.68***
	(6.20)	(5.04)	(3.20)	(0.30)	(−3.03)	(−4.77)
Rating	0.32	0.27	0.16	0.10	−0.28	−0.60***
	(5.22)	(5.45)	(3.08)	(1.90)	(−3.03)	(−4.92)
Illiquidity	0.41	0.29	0.15	0.02	−0.30	−0.71***
	(6.18)	(5.41)	(3.08)	(0.36)	(−2.89)	(−4.82)
Lag Return	0.33	0.32	0.13	−0.01	−0.18	−0.51***
	(6.75)	(4.37)	(2.82)	(−0.30)	(−2.16)	(−4.57)
	Panel B: Controlling for volatility characteristics					
Bond Vol	0.43	0.37	0.15	−0.03	−0.32	−0.74***
	(6.51)	(4.67)	(2.78)	(−0.54)	(−2.74)	(−4.88)
Bond IdioVol	0.36	0.32	0.13	−0.04	−0.30	−0.65***
	(5.95)	(5.54)	(2.55)	(−0.89)	(−2.73)	(−4.84)
Stock ImpVol	0.27	0.18	0.08	0.07	−0.01	−0.28***
	(4.61)	(3.75)	(1.49)	(1.80)	(−0.19)	(−4.50)
Stock IdioVol	0.26	0.28	0.11	0.00	−0.07	−0.34***
	(6.39)	(5.11)	(2.15)	(0.10)	(−1.14)	(−5.01)
VIX Beta	0.41	0.28	0.16	0.01	−0.31	−0.72***
	(6.71)	(4.89)	(2.81)	(0.27)	(−3.06)	(−5.27)

Table A4: Return and Alphas of Portfolios of Bonds Sorted on Δ*ImpVOL* Calculated Using OTM Options

Portfolios are sorted as in Table 2 with Δ*ImpVOL* as the sorting variable, except that we use out-of-the-money options (OTM) instead of at-the-money options to calculate changes in implied volatilities. We select OTM options from the volatility surface provided by Option-Metrics with delta equal to 0.25 for call options and −0.25 for put options. This table shows the returns and alphas on the decile portfolios as well as the 10−1 portfolio. All returns and alphas are in percent per month. Newey-West adjusted *t*-statistics are reported in parenthesis below returns/alphas. The sample period is from July 2002 to August 2017.

	1	2	3	4	5	6	7	8	9	10	10−1
Average Return	0.94	0.70	0.62	0.66	0.49	0.42	0.47	0.49	0.43	0.37	−0.58***
	(4.83)	(4.58)	(5.17)	(4.44)	(4.72)	(3.10)	(4.46)	(4.39)	(3.05)	(1.85)	(−4.00)
Bond Alpha	0.29	0.15	0.05	0.08	−0.02	−0.26	−0.14	−0.16	−0.33	−0.44	−0.73***
	(2.14)	(1.30)	(0.41)	(0.49)	(−0.17)	(−1.29)	(−1.03)	(−1.31)	(−1.84)	(−3.02)	(−3.57)
Bond+Stock Alpha	0.41	0.40	0.26	0.36	0.16	0.04	0.11	0.00	−0.10	−0.56	−0.97***
	(3.57)	(5.83)	(5.47)	(2.84)	(2.94)	(0.62)	(2.19)	(0.03)	(−1.39)	(−3.73)	(−5.50)

Table A5: Return and Alphas of Portfolios of Bonds Sorted on Δ*ImpVOL* Calculated Using Options with Different Maturities

Portfolios are sorted as in Table 2 with Δ*ImpVOL* as the sorting variable, except that we use options of 30 days (Panel A), 60 days (Panel B), and 90 days (Panel C) to maturity instead of options with 365 days to maturity to calculate changes in implied volatilities. This table shows the returns and alphas on the decile portfolios as well as the 10−1 portfolio. All returns and alphas are in percent per month. Newey-West adjusted *t*-statistics are reported in parenthesis below returns/alphas. The sample period is from July 2002 to August 2017.

	1	2	3	4	5	6	7	8	9	10	10−1
					Panel A：Portfolios sorted by Δ*ImpVOL* (30 days)						
Average Return	0.78	0.64	0.62	0.62	0.52	0.46	0.42	0.52	0.47	0.47	−0.31***
	(4.30)	(4.96)	(4.81)	(3.72)	(4.07)	(4.54)	(4.12)	(4.31)	(3.24)	(2.63)	(−2.64)
Bond Alpha	0.11	0.17	0.00	−0.06	−0.12	−0.07	−0.14	−0.23	−0.28	−0.20	−0.31
	(0.83)	(1.43)	(0.02)	(−0.35)	(−0.88)	(−0.53)	(−1.06)	(−1.47)	(−1.51)	(−1.52)	(−1.45)
Bond+Stock Alpha	0.28	0.36	0.25	0.23	0.11	0.14	0.06	0.01	−0.07	−0.29	−0.57***
	(3.42)	(4.51)	(4.57)	(2.40)	(2.63)	(2.97)	(1.01)	(0.14)	(−0.91)	(−2.32)	(−3.63)
					Panel B：Portfolios sorted by Δ*ImpVOL* (60 days)						
Average Return	0.78	0.66	0.66	0.58	0.55	0.50	0.53	0.51	0.43	0.44	−0.34**
	(3.78)	(4.99)	(3.92)	(3.96)	(4.14)	(4.13)	(4.17)	(4.20)	(2.81)	(2.17)	(−2.59)
Bond Alpha	0.18	0.15	−0.01	−0.11	−0.11	−0.02	−0.27	−0.19	−0.26	−0.31	−0.49*
	(1.16)	(1.13)	(−0.10)	(−0.56)	(−0.79)	(−0.25)	(−1.37)	(−1.17)	(−1.35)	(−2.00)	(−1.96)
Bond+Stock Alpha	0.36	0.35	0.30	0.14	0.19	0.19	0.01	0.05	−0.02	−0.41	−0.77***
	(3.87)	(5.58)	(4.24)	(1.63)	(2.40)	(3.55)	(0.12)	(0.80)	(−0.24)	(−3.00)	(−4.45)
					Panel C：Portfolios sorted by Δ*ImpVOL* (90 days)						
Average Return	0.87	0.59	0.63	0.64	0.56	0.57	0.48	0.48	0.38	0.40	−0.47***
	(4.12)	(3.90)	(4.51)	(4.70)	(4.03)	(4.55)	(3.83)	(3.91)	(2.56)	(1.98)	(−3.83)
Bond Alpha	0.31	0.01	0.02	0.07	−0.08	−0.09	−0.29	−0.16	−0.37	−0.36	−0.67***
	(2.49)	(0.05)	(0.14)	(0.47)	(−0.52)	(−0.65)	(−1.48)	(−1.11)	(−2.04)	(−2.28)	(−3.65)
Bond+Stock Alpha	0.48	0.24	0.30	0.31	0.21	0.18	−0.03	0.05	−0.13	−0.45	−0.93***
	(4.60)	(2.63)	(4.92)	(3.28)	(2.37)	(4.08)	(−0.35)	(0.82)	(−1.76)	(−3.04)	(−5.59)

Table A6: Return and Alphas of Bond Portfolios Sorted on Δ*ImpVOL*: Subsample of Callable and Non-Callable Bonds

This table shows portfolio results for the subsample of callable bonds in Panel A and non-callable bonds in Panel B. Portfolios are sorted as in Table 2 with Δ*ImpVOL* as the sorting variable. The table shows the returns and alphas on the decile portfolios as well as the 10−1 portfolio. All returns and alphas are in percent per month. Newey-West adjusted *t*-statistics are reported in parenthesis below returns/alphas. The sample period is from July 2002 to August 2017.

	1	2	3	4	5	6	7	8	9	10	10−1
					Panel A： Callable bonds (591,126 observations)						
Average Return	1.17	0.79	0.70	0.67	0.57	0.52	0.48	0.48	0.41	0.31	−0.86***
	(4.21)	(4.76)	(4.73)	(5.00)	(4.97)	(4.45)	(4.06)	(3.81)	(2.63)	(1.20)	(−3.32)
Bond Alpha	0.21	0.11	0.02	0.03	0.01	−0.12	−0.18	−0.23	−0.39	−0.62	−0.83***
	(1.16)	(1.00)	(0.16)	(0.24)	(0.05)	(−1.08)	(−1.29)	(−1.21)	(−2.21)	(−4.23)	(−3.29)
Bond+Stock Alpha	0.48	0.36	0.28	0.28	0.20	0.12	0.10	0.03	−0.22	−0.69	−1.17***
	(4.11)	(5.93)	(4.58)	(4.09)	(3.23)	(2.39)	(1.82)	(0.34)	(−2.02)	(−3.64)	(−4.51)
					Panel B： Non-callable bonds (241,663 observations)						
Average Return	0.84	0.67	0.56	0.62	0.59	0.54	0.40	0.48	0.58	0.50	−0.34*
	(3.04)	(3.86)	(4.33)	(4.67)	(5.57)	(4.22)	(2.41)	(3.63)	(5.28)	(2.22)	(−1.87)
Bond Alpha	0.14	0.11	0.20	0.33	0.31	0.16	0.10	−0.01	0.04	−0.41	−0.55**
	(0.97)	(0.71)	(2.01)	(3.49)	(4.05)	(2.95)	(0.67)	(−0.07)	(0.35)	(−1.51)	(−2.25)
Bond+Stock Alpha	0.16	0.27	0.18	0.35	0.28	0.16	0.05	−0.11	−0.02	−0.48	−0.64***
	(1.14)	(1.68)	(1.83)	(3.09)	(4.40)	(3.23)	(0.37)	(−0.80)	(−0.20)	(−2.11)	(−2.62)

Table A7: Return and Alphas of 10−1 Portfolio of Bonds Sorted on Δ*ImpVOL* During Sub-periods

Portfolios are sorted as in Table 2 with Δ*ImpVOL* as the sorting variable. This table shows the returns and alphas on the 10−1 portfolio in different sub-samples. The non-crisis and crisis months are the recession and expansion months from The National Bureau of Economic Research (NBER). Subsamples "Market Ret negative (positive)" represents the months in which S&P500 return is negative (positive). "Liquidity high (low)" is the period when aggregate bond illiquidity is lower (higher) than average. "Funding liquidity high (low)" is the period when the TED spread is lower (higher) than median. All returns and alphas are in percent per month. Newey-West adjusted *t*-statistics are reported in parenthesis below returns/alphas. The sample period is from July 2002 to August 2017.

	Crisis period		Market return		Bond liquidity		Funding liquidity	
	No	Yes	Negative	Positive	High	Low	High	Low
Average Return	-0.39^{***}	-2.53^{**}	-0.71^{**}	-0.54^{**}	-0.46^{***}	-0.89^{**}	-0.41^{***}	-1.15^{**}
	(−3.24)	(−2.32)	(−2.59)	(−2.48)	(−3.89)	(−2.04)	(−2.85)	(−2.36)
Bond Alpha	-0.77^{***}	-3.06^{**}	-0.79^{**}	-0.94^{***}	-0.85^{***}	-1.11^{*}	-0.79^{***}	-1.19^{*}
	(−5.02)	(−2.55)	(−2.29)	(−2.99)	(−5.73)	(−1.72)	(−4.92)	(−1.99)
Bond+Stock Alpha	-0.79^{***}	-3.86^{***}	-1.13^{***}	-1.00^{***}	-0.79^{***}	-1.45^{**}	-0.81^{***}	-1.26^{**}
	(−4.93)	(−4.39)	(−3.59)	(−2.98)	(−5.43)	(−2.45)	(−4.77)	(−2.28)

Table A8: Fama-MacBeth Regressions: Single Bond Return per Firm

This table presents time-series average of the monthly Fama-MacBeth regression coefficients and their corresponding Newey-West adjusted *t*-statistics. We use only one bond for each firm in regressions. The bond return is for a bond with the shortest maturity (columns 1 to 3) or the lowest age (columns 4 to 6) or the bond return is the equal-weighted average of all bond return for a given firm (columns 7 to 9). All independent variables are winsorized each month at the 0.5% level. "Adj. R^2" is the average adjusted R^2 across months and "Obs." is the total number of observations. The sample period is from July 2002 to August 2017.

	Shortest maturity	Lowest age	Average bond return of a firm
Intercept	0.003	0.013^{***}	0.010^{***}
	(0.91)	(3.40)	(3.94)
Δ*ImpVOL*	-0.028^{***}	-0.050^{***}	-0.046^{***}
	(−3.58)	(−4.91)	(−5.61)
ImpVol	0.000	−0.003	−0.001
	(0.02)	(−0.90)	(−0.40)
Size	−0.018	-0.075^{**}	-0.058^{***}
	(−0.94)	(−2.54)	(−2.98)
Rating	0.015^{**}	0.014	0.014
	(2.04)	(1.55)	(1.44)
Maturity	0.000^{***}	0.000^{***}	0.000^{*}
	(3.92)	(2.69)	(1.86)
Illiquidity	−0.042	-0.144^{***}	-0.111^{***}
	(−1.12)	(−3.33)	(−4.24)
Lag Return	-0.042^{**}	-0.047^{***}	-0.025^{*}
	(−2.50)	(−2.93)	(−1.67)
VaR (5%)	-0.035^{**}	−0.025	-0.031^{**}
	(−2.27)	(−1.58)	(−2.34)
Adj. R^2	0.174^{***}	0.185^{***}	0.194^{***}
Obs.	83,779	64,902	107,727