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Title of Paper

Liquidity, Credit Quality, and the Relation between Volatility and Trading Activity: Evidence from the Corporate Bond Market

Authors' List

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Liquidity, Credit Quality, and the Relation between Volatility and Trading Activity: Evidence from the Corporate Bond Market

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JEL classification: G12; G13

Keywords: Search frictions; information asymmetry; credit risk; volatility; trading cost; volume; flights-to-quality; flights-to-liquidity; interactive effects

1. Introduction

Price volatility and volume are two of the most closely watched trading variables in the financial market. Both are constantly monitored by practitioners and regulators who have a great deal of interest in trading risk, capital adequacy, price discovery and liquidity. Likewise, academicians have long been interested in volatility and trading behaviors, and a bulk of literature has been devoted to understanding their relation.[1] As trading technologies evolve, researchers have looked into different dimensions of market quality, but price and trading behaviors remain the focal points of many recent empirical studies. As an example, volatility and trading liquidity continue to be important issues in recent high frequency trading research (see, for example, Nishimura, 2010; Hendershott, Jones, and Menkveld, 2011; Hendershott and Moulton, 2011; Kirilenko, Kyle, Samadi and Tuzun, 2011; Jarrow and Protter, 2012; Hendershott and Riordan, 2013).

A bulk of literature has documented a significant positive relation between trading volume and price volatility, and this relation appears to be robust to different asset classes and trading intervals (see Karpoff, 1987; Bessembinder and Seguin, 1993; Foster and Viswanathan, 1993; Jones, Kaul, and Lipson, 1994; Chan and Fong, 2000; Downing and Zhang, 2004; Fleming, Kirby, and Ostdiek, 2006a). When volume is further decomposed into trading frequency and size components, it has been shown that the former has the most explanatory power for volatility of stock returns (Jones, Kaul, and Lipson, 1994). Theories have been proposed to explain these relations, which include competitive microstructure models (e.g., Pfleiderer, 1984; Grundy and McNichols, 1989; Kim and Verrecchia, 1991), strategic microstructure models (Kyle, 1985; Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990; Holden and Subrahmanyam, 1992), and information flow models (e.g., Tauchen and Pitts, 1983; Harris, 1986; Schwert, 1989, 1990; Hasbrouck, 1991; Gallant, Rossi, and Tauchen, 1992; Andersen, 1996; Engle and Russell, 1998; Dufour and Engle, 2000, Fleming, Kirby, and Ostdiek, 1998, 2006a, 2006b; Fleming and Paye, 2011). These models have built on the information theory of marketmaking to explain the relation

[1] A classic example is the study by Admati and Pfleiderer (1988), who develop a theory for the pattern of volume and volatility at the intraday level. See Karpoff (1987) for a survey.

between price volatility of a security and its trading volume.[2]

In a separate vein, the search-based theory has suggested that illiquidity can generate the familiar microstructural phenomena without asymmetric information. Duffie, Garleanu and Pedersen (2005) develop a model of marketmaking with trading frictions and show that illiquidity affects prices and widens bid-ask spreads under symmetric information.[3] Extending the model to include risk aversion and risk limits, Duffie, Garleanu and Pedersen (2007) show that the liquidity discount is larger when trading frictions and risk aversion are higher, and volatility and illiquidity are positively correlated. Considering funding liquidity, Brunnermeier and Pedersen (2009) show that volatility is high when liquidity is low and that this relation is stronger for riskier securities. Garleanu and Pedersen (2011) find that securities with lower funding liquidity have higher price volatility, as speculators are unable to take on positions to smooth price fluctuations. A common thread of these studies is that illiquidity and search frictions can be important factors driving price volatility and spreads even in the absence of asymmetric information.

Empirical studies on volatility and its relation with trading behavior and have a long history in finance. Studies of this relation have improved our understanding of the price discovery process and have led to the development of important models that form the foundation of modern market microstructure and intermediation theories. Much of the empirical research in this area has attempted to distinguish between the effects of informational and non-informational factors on price volatility. Identifying the sources of volatility is important for understanding price discovery and information efficiency of financial markets. For example, price volatility can be due to information flow or market frictions. It is important to differentiate these effects in assessing information efficiency and quality of financial markets.

This paper expands the literature by investigating the roles of illiquidity and credit risk in the relation between trading activity and price volatility in the corporate bond market using transaction data, whose

[2] Past studies have found that volume contains fundamental information about a given security (see Campbell, Grossman and Wang, 1993; Blume, Easley and O'Hara, 1994; Lee and Swaminathan, 2000).
[3] Several studies for the equity market have touched the issue of liquidity under information asymmetry (see Kyle, 1985; Admati and Pfleiderer, 1988; Easley, Kiefer, O'Hara and Paperman, 1996; Li and Wu, 2006).

quality has improved dramatically since the establishment of TRACE (the Trade Reporting and Compliance Engine) in 2002. The selection of the corporate bond market for this study offers several advantages. First, the over-the-counter (OTC) market structure of corporate bonds provides an ideal laboratory for examining the implications of the search-based models advanced by Duffie et al. (2005, 2007) and others. Corporate bonds are traded in an OTC market where traders are required to search and negotiate with counterparties. The cost of search for counterparties and information is high when a market is inactive and opaque. The corporate bond market is not as active and transparent as the stock market and illiquidity has long been a concern to bond investors, making it an ideal place for studying the role of illiquidity in microstructural phenomena. Moreover, the population of corporate bonds has a wide dispersion in credit quality, [4] which permits tests of the differential effects of illiquidity on the volatility-volume relation for securities with varying risk as implied by the search-based model.

Second, the corporate bond market provides additional evidence to compare and contrast with other markets. The corporate bond market differs from stock and derivatives markets in several aspects. Aside from the differences in the market structure and trading process, the corporate bond market consists of securities with different return and risk characteristics, and trading is dominated by institutional investors. In addition, there are differences in trade and disclosure regulations between bond and other markets which may affect insiders' trading behavior. [5] These features shape a distinct microstructure for the corporate bond market. Investigating the sources of price volatility in the corporate bond market improves our understanding of price discovery in different markets, which is important for developing a general theory to explain microstructure phenomena across markets with different assets.

Last, from the investment and policy perspectives, understanding volatility and trading behaviors is essential for forming the trading strategies of portfolio managers, asset allocations, firm-level issuance decisions and for assessing market quality. Our empirical findings aid in these decisions.

[4] This contrasts with the municipal bond market where a large portion of bonds are insured and have low risk of default.
[5] As pointed out by Kwan (1996), the laws require insiders to disclosure their trades for stock, option and equity-linked bond trades, but there is no such requirement for corporate bonds.

Our paper provides the first comprehensive empirical analysis on the relation between trading activity and price volatility in the corporate bond market using a large transaction data set. By trading activity, we mean a combination of trading volume, frequency and size. By examining this relation across bonds with varying liquidity and risk characteristics and over different market liquidity environments, we document several unique findings that expand the current literature.

First, we find that liquidity plays an important role in the relation between the volatility of a corporate bond and its trading activity. High volatility associated with trading volume therefore does not necessarily imply high information asymmetry. Our finding supports the hypothesis of search-based models that when search frictions are high or liquidity is low, the impact of trading on prices of corporate bonds is high. This in turn implies a stronger relation between price volatility and volume when liquidity is low. Consistent with this hypothesis, trades with small size and trades of old bonds (off-the-run) have a higher correlation with price volatility. Furthermore, the correlation is stronger for bonds with a small issue amount (low supply) and low trading volume. Results suggest that search frictions are an important factor determining the relation between price volatility and trading activity.

Second, there is a significantly positive relation between trading frequency and volatility and a significantly negative relation between trade size and volatility in the corporate bond market. The former is consistent with the finding for the stock market. However, the latter finding is in sharp contrast with that for the stock market. This phenomenon can be attributed to higher trading costs and search frictions for small corporate bond trades.

Third, the relation between volatility and trading activity varies across bonds with different characteristics. The strength of this relation rises with credit risk and maturity. The relation tends to be stronger for callable and convertible bonds. More importantly, the relation between price volatility and trading volume is conditional on liquidity, risk and information asymmetry. We find that the relation is stronger for firms with high analyst earning forecast dispersion, high risk and low liquidity. Results strongly suggest the hypothesis that the relation between price volatility and trading volume is highly nonlinear, which depends on information asymmetry, risk and search frictions.

Finally, the effects of illiquidity and credit quality on the relation between volatility and trading volume become much stronger in times of stress. Tests on these relations over the normal and crisis periods show that the illiquidity effect magnifies during times of liquidity crisis and heightened market uncertainty. Results are consistent with the contention that when market liquidity dries up, it is much harder to find counterparties to trade for riskier securities and, as a consequence, trades for riskier bonds have higher impacts on price volatility. The relation between price volatility and trading frequency and trade size becomes much stronger during the subprime crisis, which can be attributed to the flights-to-liquidity and flights-to-quality and the interaction of these effects.

Overall, there is strong evidence that supports the hypothesis of the search-based theory in an over-the-counter trading environment. Prior research has focused on the informational role of trading in the equity market and has suggested that price volatility is mainly due to the revelation of private information and the public information announcement. By analyzing the trading and volatility behaviors for firms with different characteristics and in a different market structure, we document strong evidence that search frictions and riskiness of bonds are additional sources of price volatility. As in the stock market, asymmetric information plays an important role in the volatility-volume relation in the corporate bond market. The novel finding of this study is that liquidity and issuer risk are also important drivers of the relation between volatility and trading volume in the corporate bond market. Our empirical results suggest that the relation between price volatility and trading volume is highly nonlinear, which depends on both informational and non-informational factors. Specifically, this relation is stronger for riskier bonds and bonds with higher information asymmetry and lower liquidity, and varies over time.

Our work is related to a number of studies on the volatility-volume relation in financial markets (see Jones, Kaul, and Lipson, 1994; Chan and Fong, 2000; Downing and Zhang, 2004; Fleming, Kirby, and Ostdiek, 2006a). In particular, our focus on the corporate bond market is closely related to the study by Downing and Zhang (2004), which studies the relation between price volatility and trading volume in the municipal bond market. Like the muni market, the corporate bond market is an over-the-counter (OTC) market and trading is dominated by institutions. However, there are notable differences between these markets. First of all, in terms of opacity and liquidity, the corporate bond market lies between the muni and stock markets. Although the corporate bond market is less transparent than the stock market, it is more transparent than the muni market in terms of the disclosure of information for issuers and trading.[6] The corporate bond market is also more liquid than the muni market in terms of trading cost and frequency (see Harris and Piwowar, 2006; Edwards, Harris and Piwowar, 2007).[7] Moreover, there is greater dispersion in credit ratings, and private information is more important for corporate bonds. These differences between the corporate and municipal bond markets can result in significant discrepancies in price discovery of the two markets.

Like Downing and Zhang (2004), we find that number of trades has a positive relation with price volatility but trade size has a negative relation with price volatility. The negative coefficient of trade size likely reflects institutional trading and cost of trading. However, we find a positive relation between volume and price volatility whereas Downing and Zhang find a negative relation when volume is used as the sole trading variable in the volatility regression. We interpret the positive coefficient of trading volume as reflecting the relative importance of private information for corporate bonds. In addition, we find that the volatility-volume relation is stronger for low-grade bonds. This contrasts sharply with Downing and Zhang's finding that the volatility-volume relation is much stronger for high-grade bonds. This discrepancy is likely due to the difference in the importance of firm information and credit risk for bond pricing, particularly for low-grade corporate bonds. Low-grade bond prices tend to be more

[6] Municipal bond issuers are not subject to the same financial disclosure requirements as are publicly traded companies. By contrast, corporate bond issuers regularly maintain a quarterly data feed on their activities (e.g., 10-Q and 10-K forms). Besides better information disclosure for issuers, the corporate bond market has improved trading information disclosure and efficiency significantly after the establishment of TRACE and development of an electronic trading system (Hendershott and Madhavan, 2014).

[7] Harris and Piwowar (2006) show that the round-trip trading cost of municipal bonds is 2% of the price for a representative retail order size of $20,000 and 1% for an institutional order size of $200,000. These contrast with 1.24% and 0.48% for corporate bonds (see Edwards et al., 2007). In addition, on average corporate bonds trade 2.4 times per day, but there is only one transaction per week for municipal bonds (see Harris and Piwowar, 2006; Edwards et al., 2007).

sensitive to financial information (e.g., earnings announcements) than high-grade bond prices. Most importantly, we investigate the effects of firm characteristics on the volatility-volume relation in different market environments. This analysis differentiates our work from existing studies that examine the volatility-volume relation. We find that the relation between price volatility and volume depends on issuer characteristics related to information asymmetry, risk and search frictions. Our results strongly suggest that the volatility-volume relation is highly nonlinear, which is conditional on information asymmetry, risk and search frictions. This unique finding provides new insights into the price discovery process of the corporate bond market.

Our work is also related to several recent studies that examine the impacts of liquidity shocks on bond prices and trading volume during the financial crisis (Acharya, Amihud and Bharath, 2013; Friewald, Jankowitsch and Subrahmanyam, 2012; Dick-Nielsen, Feldhutter and Lando, 2012). These papers focus on the issue of whether liquidity is an important pricing factor in the US corporate bond market and whether the effect of liquidity on yield spreads becomes stronger during the subprime crisis. Our paper complements these studies by investigating the effects of liquidity and credit quality on the relation between volatility and trading activity during normal and crisis periods. Our findings suggest that non-informational factors play an important role in the relation between the volatility of a bond and its trading activity.

The rest of the paper is organized as follows. Section 2 discusses the relations between volatility and volume implied by information- and search-based models and proposes test hypotheses. Section 3 discusses the data sample and Section 4 presents empirical results. Section 5 further examines the relation between trading activity and price volatility during the credit crunch period when liquidity dries up for risky securities. Sectional 6 performs robustness tests. Finally, Section 7 summarizes main findings and concludes the paper.

2. Volatility, volume and illiquidity: Synthesis and test hypotheses

The information-based theory predicts that volume and volatility are positively correlated under information frictions (e.g., Admati and Pfleiderer, 1988). According to this theory, informed traders choose to trade when volume is high and therefore transactions and price movements are clustered in time, leading to a positive correlation between the volatility of a security and its trading volume. By contrast, the search-based theory predicts that price volatility is positively related to illiquidity under search frictions (e.g., Duffie et al., 2005, 2007). While each theory has its own merits by focusing on a particular dimension of marketmaking, financial markets in the real world typically are characterized by both information and liquidity frictions. As such, observed microstructural phenomena are likely to be caused by a mixture of the effects of these frictions, which can be better explained by a combination of both theories. In this section, we synthesize the information- and search-based theories and propose tests of their implications.

The search-based models of Duffie et al. (2005, 2007) generate a number of important microstructure implications under information symmetry. Market liquidity is low when search frictions are high, as it is more difficult to locate and match buyers and sellers. Small trades are less liquid because smaller traders have greater difficulty locating counterparties and have fewer search options. By contrast, large (institutional) traders are more sophisticated and can locate counterparties more easily; large trades are therefore more liquid. Trades of credit-risky bonds are less liquid because providers of liquidity such as underwriters and hedge funds bear extra risk as they search for long-term investors. Similarly, it takes longer time to contact suitable counterparties for off-the-run (old) bonds, and this delay in search can have significant price and volatility effects. Extending the Duffie et al. (2007) model to the case of multiple assets, Vayanos and Wang (2007) show that securities with a larger free float (shares available for trade) are more liquid. This suggests that bonds with a large issuance amount or supply are more liquid. In general, these models predict that trades of bonds with greater search frictions have a higher impact on price volatility.

While the search-based theory prescribes the relation between search frictions and illiquidity and their effects on volatility of prices, it is moot in regards to the effect of illiquidity on the volatility-volume relation. We propose a heuristic search-based model in the Appendix to link price volatility to trading volume, which forms the basis for our empirical tests. The proposed model predicts a negative impact of liquidity on the volatility-volume relation under symmetric information and search frictions (see the Appendix).

By contrast, the information-based theory predicts a positive impact of information on the volatility-volume relation. The empirical literature has shown that information asymmetry exists in most financial markets, including the market of government securities with simple payoffs (see, for example, Brandt and Kavajecz, 2004; Green 2004; Li et al., 2009). However, the information-based theory abstracts from the issue of search frictions. As there are significant search frictions in the OTC market, the prediction of the information-based model must be tempered by the implications of the search-based model.

More specifically, the positive relation between volatility and volume prescribed by the information-based theory should be conditional on search efficiency, which is stronger when search efficiency is low and weaker when it is high. To see this, we employ a standard regression model of volatility (*VOL*) on volume (*V*):

$$VOL = \alpha + \beta V + \varepsilon \tag{1}$$

Standard information-based models predict that β is positive $(\beta = \Delta VOL / \Delta V > 0)$.

In the presence of search frictions, the sensitivity (β) of volatility to volume should be conditional on search efficiency or liquidity. When liquidity is low, the search-based model predicts that volatility is high $(\Delta VOL \uparrow)$ and volume is low $(\Delta V \downarrow)$.[8] This leads to a β value larger than that implied by the information-based model because for any given level of volume in (1), the corresponding price volatility is higher. Conversely, when liquidity is high or search friction is low, volatility is low $(\Delta VOL \downarrow)$ and volume is high $(\Delta V \uparrow)$, leading to a β value smaller than that predicted by the information-based model. We examine these implications using corporate bond data.

In the empirical investigation, we further divide volume into trade number and size components.

[8] See the analysis in the Appendix.

Prior studies on the equity market have shown that number of trades subsumes most information in volume (see Jones et al., 1994; Chan and Fong, 2000) and it will be interesting to see if this condition holds in the corporate bond market as well. At the same time, it has been shown that small trades of bonds exhibit different characteristics in terms of liquidity and trader type (see Duffie et al., 2005, 2007; Bessembinder et al., 2006; Edwards et al., 2007; Goldstein et al., 2007). Small trades have higher trading costs in the corporate bond market as predicted by the search-based theory. Thus, trade size may play a different role in the corporate bond market. By decomposing trading volume into trade number and size, we explore the role of each trading component in affecting volatility.

Based on the preceding analysis and the related literature, we propose the following test hypotheses.

H1: There exists a positive relation between volume and volatility in the corporate bond market. Furthermore, volatility of corporate bonds has a positive relation with trading frequency and a negative relation with trade size.

H2: The relation between trading activity and volatility is stronger for less liquid bonds.

H3: The relation between trading activity and volatility is stronger for bonds with higher risk.

H4: The relation between trading activity and volatility is stronger during times of financial crisis with heightened default risk and liquidity dry-up.

In Hypothesis 1, the positive volatility-volume relation is implied by the information-based theory. As bonds and stocks are claims on the same firm assets, asymmetric information at the firm level should affect both securities. Also, when volume is decomposed into trade number and size, the former should have a positive correlation with volatility if it subsumes most information in volume. On the other hand, we hypothesize that trade size of corporate bonds will have a negative effect on volatility for the following reasons. The literature has documented that trade size plays only a limited informational role even in the equity and derivatives markets where information asymmetry is more prevalent. At the same time, small traders have limited search options and incur high trading costs in the OTC market. Taken together, this implies that the negative liquidity effect on volatility should dominate the positive information effect for trade size of corporate bonds. Moreover, if the relation between volume and volatility is positive for corporate bonds, the positive effect of trade frequency on volatility must outweigh the negative effect of trade size. Thus, Hypothesis 1 presents a joint test of these predictions.

Hypothesis 2 directly draws on the implications of the search-based model. We test this hypothesis using bonds with different liquidity characteristics such as age (g), trade size (q) and issuance amounts (v). As new bonds are more liquid than old bonds, the relation between volatility and trading variables is expected be stronger for old bonds. Similarly, bonds with a smaller issuance amount and trade size have higher search frictions, so the relation should be stronger for these bonds.

Hypothesis 3 is also based on the findings in the search literature. Underwriters and hedge funds bear extra risk in searching for long-term investors and therefore are less willing to provide liquidity to risky securities. Trading risky securities on margin also takes a longer time because brokers need to verify counterparties' credit standing more carefully. Inefficient search and lower liquidity imply a stronger relation between trading and price volatility for riskier bonds. We examine bonds in different risk characteristics to test this hypothesis.

Finally, in Hypothesis 4, we examine the relation during the normal and crisis periods and test the significance of the differences in volatility impacts of trading variables in the two regimes. The search-based models predict that the effects of illiquidity and risk on volatility increase in times of stress. We test this implication and explore the possibility of an interactive effect of illiquidity and credit risk. The period of subprime crisis provides an excellent opportunity to examine the effects of flights-to-liquidity, flights-to-quality and their interactions. We now turn to empirical tests.

3. Data

Corporate bond data are from TRACE and the Fixed Investment Securities Database (FISD). We retrieve price and trade data from the TRACE database, and credit ratings, coupon, issue amount, issue date, maturity date, and other bond characteristic information from FISD. The data items in the TRACE database include transaction price, time, and par value of transactions for publicly traded OTC corporate bonds. In addition, we collect data for issuer characteristics and stock returns from Compustat and CRSP.

To improve the transparency of the bond market, bond dealers were required by NASD to report their transactions through the TRACE system starting from July 1, 2002. By October 2004, the TRACE system had covered all publicly traded corporate bonds in the OTC market except trades executed through the NYSE's Automated Bond System. As less than 5% of corporate bonds are listed on the NYSE, the current TRACE dataset covers most publicly traded bonds. The FISD database provides issue information for all US corporate bonds maturing in 1990 or later.

As TRACE initially covered only a small subset of corporate bonds, to obtain a large sample, our study period commences in October 2004, in which trades of all publicly issued corporate bonds were disseminated, and runs through June 2012. The sample period encompasses the subprime crisis period, making it suitable for comparing the effect of trades on price volatility in normal and illiquid times. We impose the following criteria to screen the data. First, we drop the observations with apparent recording error. Second, we exclude bonds with remaining time to maturity of less than one year as these bonds are rarely traded. Third, we follow the data screening procedure suggested by Bessembinder, Kahle, Maxwell, and Xu (2009) to eliminate cancelled, corrected, and commission trades. Finally, we drop those bonds whose rating cannot be identified from the FISD. We primarily use the Moody's rating, but where unavailable we use the Standard and Poor's rating when possible.

Corporate bonds are typically not traded as frequently as stocks and Treasuries. This presents a significant challenge to the study of the volatility-volume relation using the time-series analysis, as we are unable to construct an unbroken time series of prices for most bonds in our data sample. To overcome this problem, we perform cross-sectional tests based on the weekly interval instead.[9] We employ two robust price volatility measures used in the fixed-income literature. The first measures price volatility by weekly high minus low prices divided by weekly average price, that is, $RVOL_{i,t} = \frac{\max P_{i,t} - \min P_{i,t}}{\overline{P_{i,t}}}$. This is essentially a range estimator of volatility that uses the highest and lowest price

[9] Downing and Zhang (2004) use a similar method in their study on municipal bonds.

information in the time-series price movement within a week. It has been shown that the range estimator is more robust to microstructure noise than the realized volatility measures such as squared or absolute returns widely used in microstructure studies (see Garman and Klass, 1980, Parkinson, 1980; Alizadeh, Brandt and Diebold, 2002). Downing and Zhang (2004) use this volatility measure in their study of the asymmetric information of trades in the municipal bond market and find that it is an effective price volatility measure for infrequently traded securities.

The second measure is based on a log range volatility measure recommended by Alizadeh, Brandt and Diebold (2002). They show that this log range measure is robust to the bid-ask bounce and microstructure noise. Barclay, Hendershott and Kotz (2006) use this volatility measure in their study of the trading venue choices by dealers trading on- and off-the-run bonds in the Treasury market. They find that their empirical results are robust to using the log range volatility measure for less frequently traded off-the-run securities and to using the Parkinson (1980) volatility estimate with or without a correction for trading frequency. Following Alizadeh et al. (2002), the log range volatility for bond *i* at time *t* is calculated as $LVOL_{i,t} = exp[\ln(\max P_{i,t} - \min P_{i,t}) - 0.43]$.

Constructing both volatility measures requires a minimum of two trades per week. However, to obtain a more reliable volatility measure, we require that a bond must have at least four transactions within the week to be included in the sample.[10] Moreover, in addition to the above two volatility measures, we use standard deviation as an alternative measure to check the robustness of our empirical results. Our final sample contains a total of 1,677,378 bond-week observations.

Figure 1 shows the histograms of the number of trades. Panel A of Figure 1 shows the histogram of the number of trades in each bond over the entire sample period and Panel B shows the histogram of the number of trades per week for each bond. As shown, in Panel A, a large number of bonds in our sample have trades of less than 5 over the entire period. Panel B shows that most bonds in the sample trade less than 10 times per week. Figure 2 shows the profile for the number of bonds and transactions across time

[10] This restriction constrains our sample to relatively active bonds. However, our results are quite robust to this restriction.

from the period of October 2004 to June 2012. Panel A shows that the number of bonds in each month ranges between 8,000 to a little over 12,000. Panel B shows the number of bond transactions. Both the number of bonds and number of transactions increase after 2008.

[Insert Figures 1 and 2 here]

Table 1 summarizes trading data and bond characteristics of the sample used in our study. Mean and standard deviation for each variable are reported for the whole sample as well as for subsamples stratified by age, maturity, rating, and bond provisions. As indicated, return volatility based on the range measure (*RVOL*) tends to be larger than that based on the log range measure (*LVOL*), but the overall pattern across ratings and maturities is similar for both volatility measures in relative magnitude. Volatility (in percentage) is higher for bonds with lower quality and longer maturity. On average, there are about 24 trades per week, par volume is 8.2 million per week, and trade size is about 0.34 million per trade. Average maturity is 9.5 years, average bond is about 4.5 years old and average coupon rate is 5.96 percent. There is a wide range of ratings from AAA to B in our final sample, with an average rating equal to BBB+.[11] Although investment-grade bonds dominate the sample, the size of speculative-grade bonds is sufficiently large (about 27% of the sample) for in-depth analysis.

Coupon rates are higher and volume, trade size, trading frequency and issue size are lower for speculative-grade bonds. More than half of the data sample contains bonds (short) with maturity between one and seven years. There are many more seasoned bonds (age > 3 months) than new bonds (age ≤ 3 months). Newly issued bonds are traded more frequently than old bonds. Finally, callable bonds account for a significant portion of the sample. About 65% of the observations in our sample involve bonds with a call provision.

[Insert Table 1 here]

4. Empirical results

In this section, we present empirical estimation and tests for the implications of the search-based

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[11] Because the number of AAA bonds is small, we combine AAA and AA bonds together in empirical tests.

model. We first report the results of cross-sectional regressions of price volatility against trading variables with controls on bond characteristics for the whole sample, followed by the results for subsamples of bonds with different characteristics.

4.1. Weekly cross-sectional regressions

For each week, we estimate the cross-sectional regression below and compute average coefficients and the Fama-MacBeth (1973) *t* statistics from the weekly series of parameter estimates:

$$VOL_{it} = \alpha_0 + \sum_{j=1}^{p} \alpha_j TA_{it,j} + \sum_{k=1}^{q} \beta_k CV_{it,k} + \varepsilon_{it}. \quad (2)$$

VOL_{it} is price volatility (in percentage) for bond *i* which can be the range-based measure (*RVOL*), the log range measure (*LVOL*) or standard deviation of returns for each bond-week observation (*t*), TA_{it} represents trading variables, such as trade number, size and volume (in millions of par) per week, and CV_{it} represents bond characteristic variables, such as coupon, maturity, age, rating, and issue size, which are used as controls. The standard errors of Fama-MacBeth regressions are corrected for the effect of autocorrelation.

The above cross-sectional regression does not include lagged volatility or trading variables. The traditional information-flow models for the volatility-volume relation build on the contemporaneous relation between the two variables (see, for example, Harris, 1986; Tauchen and Pitts, 1983; Andersen, 1996). In these models, volatility and volume are jointly conditional on information arrivals. Volatility and trading volume are determined concurrently (and instantaneously) by information flow and there is no causal relation between volatility and volume. Likewise, both competitive and strategic microstructure models generate implications for a positive volatility-volume relation without imposing restrictions on the dynamic structure and the direction of causality for the two variables. However, empirical studies on the equity market that test the volatility-volume relation often include the lagged volatility variables to account for volatility persistence. These empirical studies are usually based on time-series regressions. As we indicated earlier, most corporate bonds are infrequently traded, and it is difficult to construct an unbroken time series of returns for each bond in the sample. We thus use the cross-sectional regression of the Fama-French type instead of the time-series regression in our empirical tests. In this cross-sectional regression, we can only estimate one coefficient on each explanatory variable for the whole sample, instead of a coefficient for each bond issue, and we are unable to control for persistence in volatility or lagged effects of trading variables at the issuer level.

To understand the role of each individual trading variable, we report base results of regressions with a single trading variable as well as a combination of different trading variables. Panel A of Table 2 reports results of regressions based on the range volatility measure (*RVOL*) for the whole sample period. The first regression includes number of trades (*NT*) as an explanatory variable and shows that it has a significantly positive relation with volatility. [12] When replacing *NT* with trading volume (*V*), the result shows that volume is significantly positively related to volatility. These results meet the prediction of the information-based models stated in Hypothesis 1 and the past findings for the equity and futures markets. The positive volume coefficient contrasts with the finding of Downing and Zhang (2004) for the muni market. The third regression uses average trade size (*ATS*) as an explanatory variable. The result shows that it has a significantly negative relation with volatility, which contradicts the finding for the equity market but is quite consistent with the prediction of the search-based models. Smaller trades have higher trading costs (Edwards, Harris and Piwowar, 2007) and fewer search options (Duffie, Garleanu and Pedersen, 2005, 2007). The effects of these frictions explain the negative coefficient of trade size.

[Insert Table 2 here]

When both trade number and size are included as explanatory variables, the coefficient of trade size remains significantly negative and that of trade number is positive and significant. Consistent with the positive volatility-volume relation, the positive effect of trade number outweighs the negative effect of trade size. [13] These findings support Hypothesis 1. Finally, when trade number and volume are both incorporated, the coefficient of volume becomes insignificant. It appears that the positive effect of

[12] The number of trades is scaled by 100 to place the coefficient of *NT* in a desirable range.
[13] Given the *NT* coefficient 3.96, the *ATS* coefficient -0.94, and the means of *NT* and *ATS* in Table 1, on average the effects of trade number and trade size are 0.95 (=3.96x24.09/100) and -0.32 (-0.94x0.34), respectively.

volume on volatility is subsumed by trading frequency.

The coefficients of control variables are mostly significant and of expected signs. The significant positive coefficient of the rating (higher value means lower quality) implies that the relation between credit worthiness and volatility is negative. Long-maturity bonds have higher volatility and high-coupon bonds have lower volatility. This is because duration is a positive function of maturity and a negative function of coupon rates, and price volatility is positively related to duration. The coefficient of issue size (*Amount*) is negative and that of age is positive. Small-issue bonds and old bonds are less liquid, which explains the higher volatility for these bonds.

Panel B reports regression results based on the log range volatility measure (*LVOL*). Results show a similar pattern for the relations between volatility and trading variables. Again, price volatility is positively related to number of trades and negatively related to trade size. Volume is positively related to volatility but it becomes insignificant when we add the number of trades as an explanatory variable.

Besides the range-based volatility estimators, we use standard deviation of returns as an alternative measure. Panel C reports the results using standard deviation (*STD*) as the volatility measure. Results show a similar pattern in that trade number is positively related to volatility and trade size is negatively related to volatility. The magnitude of coefficients for trade number and size is quite close to that based on the log range volatility estimator.

Overall, the evidence clearly indicates that price volatility is driven in opposite directions by number of trades and trade size. Moreover, credit risk, maturity and bond age have a positive effect on price volatility, and issue size has a negative effect on price volatility. These results are robust to different volatility measures. As there are no apparent advantages of using the other volatility estimators, for brevity we focus on the range volatility measure (*RVOL*) in our remaining analysis.

4.2. Subsample results

Table 3 reports regression results for subsamples stratified by risk, maturity, provision and trade side. We first sort the sample by issuer risk. The first set of regressions in Panel A reports results by rating.

Results show a stronger relation for lower-grade bonds. The coefficient of number of trades increases monotonically as the rating decreases. This finding is consistent with the prediction of the search-based model (Hypothesis 3) that it is more difficult to find counterparties to trade risky securities in the OTC market and thus the relation between volatility and trading frequency is stronger for riskier bonds.

The rating could be biased or not frequently updated and so it may not be a perfect measure for issuer risk. For robustness, we also use several other financial variables that contain information about issuer risk as controls. These include the ratio of operating income to sales, the ratio of long-term debt to total assets (leverage), dividends (per share), and weekly stock return volatility (see also Dick-Nielsen et al., 2012; Blume, Lim and MacKinlay, 1998). These variables are either calculated from data or directly obtained from Compustat and CRSP. The issuer risk is higher when the ratio of operating income to sales and dividends are lower, and leverage and stock return volatility are higher. We sort the sample into the top, middle two, and bottom quartiles for each variable. Results for bond subsamples sorted by each variable are reported in the remaining part of Panel A in Table 3. Results again show a positive coefficient of number of trades and a negative coefficient of trade size. The relation between volatility and number of trades is positive and stronger when the issuer risk is higher. The coefficient of number of trades increases monotonically as leverage and stock return volatility increase and the ratio of operating income to sales and dividends decrease. These results are consistent with the regression results sorted by rating. Thus, our results are robust to different proxies for issuer risk.

[Insert Table 3 here]

Panel B reports regression results across bond maturities. Results show that trading variables have a larger impact on volatility for longer-maturity bonds. Edwards, Harris and Piwowar (2007) find that liquidity is lower for bonds with longer maturities. The stronger relation between volatility and trading variables may reflect lower liquidity of these bonds.

Panel C contrasts results for straight bonds with those for callable and convertible bonds. We focus on bonds with call and conversion provisions because they have sufficient observations for reliable estimation each week. Results show that callable bonds have a stronger positive relation between price volatility and number of trades and a stronger negative relation between volatility and trade size. The coefficient of number of trades is 5.46 and that of trade size is -1.07 for callable bonds. Correspondingly, the coefficients are 2.27 and -0.74, respectively for straight bonds which contain no provisions. Similarly, the relations between price volatility and trading variables are stronger for convertible bonds. The coefficient of number of trades is 5.31 and that of trade size is -1.37 for these bonds. These coefficients are again larger in absolute terms than those for straight bonds. Results show that callable and convertible bonds have stronger relations between volatility and trading variables.

A number of models with intermediaries have focused on the effect of signed trades (order flow) on price changes (see, for example, Hasbrouck, 1991; Dufour and Engle, 2000). Trade side provides additional information that allows for more detailed testing. For example, the price impact of trades can be asymmetric in that a large sell order tends to have a greater impact on prices (discount) than a buy order of similar size. This asymmetric price impact is more likely to occur in an illiquid market (Green, Li and Schurhoff, 2010). We next examine this possibility by running regressions with buy and sell orders separately. Trade side (buy/sell) information is reported in the TRACE database beginning from November 2008. We use the subset of the data sample over the period from November 2008 to June 2012 to conduct this test.

Panel D of Table 3 reports the results of regressions based on buy and sell orders separately. We divide all trades into buys and sells each week and run the weekly cross-sectional regressions of price volatility associated with buy-initiated or sell-initiated trades (bid-to-bid or ask-to-ask). Results continue to show that the effect of number of trades is positive and that of trade size is negative. A notable difference is that the coefficient of number of trades is larger for sell orders, suggesting that the impact of trading on price volatility is asymmetric.

4.3. Order imbalances

A related issue is whether the order imbalance plays a role in the relation between volatility and trades. Market microstructure models (Kyle, 1985; Admati and Pfleiderer, 1988) predict that net order flow affects price volatility. Chan and Fong (2000) examine the effect of order imbalances in the stock market and find that the volatility-volume relation becomes weaker after incorporating order imbalance into the regression model.

We next investigate whether order imbalance affects the relation of volume-volatility in the corporate bond market. We identify buyer- and seller-initiated trades, and calculate the order imbalance as the absolute value of the difference between the numbers of buy and sell orders each week. We then run the weekly cross-sectional volatility-volume regressions by incorporating order imbalances as an additional explanatory variable. The sample period is again from November 2008 to June 2012 when trade side information is available in the TRACE database.

Panel E of Table 3 reports regression results with order imbalances for the whole sample period and two subperiods. The coefficient of order imbalances is significantly positive, indicating that higher order imbalances are associated with higher volatilities. The subperiod analysis shows that the order imbalance is more important in the crisis period (November 2008 to December, 2009) than in the normal period (January 2010 to June 2012).[14] Duffie et al. (2007) suggests that price response to order imbalances reflects delays in reaching trading decisions and in mobilizing capital. This may explain the larger and more significant coefficients of order imbalances during the crisis. More importantly, the effects of number of trades remain positive and that of trade size negative, both highly significant. The coefficient of number of trades is little affected by the inclusion of order imbalances, suggesting that trading frequency is not a proxy for order imbalances.

4.4. Illiquidity and the price impact of trades

The price impact of trades in the OTC market tends to be higher because the investor search is less efficient (see Duffie, Garleanu and Pedersen, 2005, 2007; Ashcraft and Duffie, 2007; Duffie, Malamud, and Manso, 2013). The analysis in Section 2 suggests that there should be a stronger relation between

[14] The definition of the normal period is somewhat different from that in the later empirical analysis dealing with the impact of financial crisis because of the data availability for trade side (buy or sell orders) here.

trading volume and volatility for less liquid bonds. In this section, we test this liquidity hypothesis more systematically.

To examine the role of liquidity in explaining the relation between volatility and trading variables, we divide the sample into quartiles by bond-specific liquidity characteristics. Here we focus on the effect of differential illiquidity at the bond level on the volatility impact of trades across bonds by holding the aggregate illiquidity level constant. Conventional liquidity proxies are volume, bid-ask spreads, trade size, age, issue size and depth. As bid-ask spreads and depth for corporate bonds are unavailable, we use the remaining variables to test the effect of bond-level liquidity. Liquidity is high when trading volume is high because more active markets tend to be more liquid. If we measure liquidity by trading cost or search options, bonds with large trade size have higher liquidity as trading cost is lower (see Edwards et al., 2007) and the number of search options is higher (see Duffie et al., 2007). Bonds with large issue size increase their general availability in the market and liquidity. The use of age as a liquidity measure parallels the notion of on- and off-the-run bonds in the Treasury market. There is substantial evidence that old bonds are less liquid than new bonds (see Krishnamurthy, 2002; Brandt and Kavajecz, 2004).

Volume and trade size are not clean measures for liquidity as they also contain information (as documented by past studies for the equity market). Similarly, bond age and issue amount may also contain information. For robustness, we add the Amihud measure to capture bond illiquidity. The Amihud measure is widely used as a measure of illiquidity (see, for example, Acharya and Pedersen, 2005; Lin, Wang and Wu, 2011). The Amihud measure for each individual bond is constructed using the following formula (see Amihud, 2002):

$$ILLIQ_{it} = \frac{1}{Days_{it}} \sum_{d=1}^{Days_{it}} \frac{|r_{i,d,t}|}{Vol_{i,d,t}}$$

where $r_{i,d,t}$ is the return for bond i on day d, $Vol_{i,d,t}$ is the respective daily volume in dollars, and $Days_{it}$ is the number of days for which transaction data are available for bond i. We calculate this illiquidity measure for each individual bond each week.

We sort the sample into the top, middle two, and bottom quartiles by contemporaneous volume, trade size, issue size, and the Amihud measure. For bond age, we first single out bonds with an age of 3 months or less because of the super liquidity of these newly issued bonds (e.g., on-the-run). We then sort the remaining bonds into top, middle two, and bottom quartiles by age. We run regressions for each group stratified by each liquidity proxy. If the liquidity hypothesis holds, we should observe a stronger relation between trading activity and price volatility for bonds with lower liquidity.

Panel A of Table 4 reports results of regressions by volume. Consistent with the liquidity hypothesis, the relation between volatility and trading variables is much stronger for bonds with lower trading volume. The magnitude of the coefficient of number of trades for bonds with low trading volume is about ten times that for bonds with high volume. Results suggest that illiquidity is an important determinant for the impact of trades on price volatility. The impact of trade size on price volatility also depends on liquidity. The coefficient of trade size becomes more negative as volume decreases. The coefficient of trade size is only -0.66 for bonds with high volume but -16.50 for bonds with low volume. This finding is consistent with the prediction of the search-based model that smaller investors have fewer search options and therefore their trades have larger price impacts when liquidity is low.

[Insert Table 4 here]

Panel B of Table 4 reports regression results for subsamples stratified by trade size. The impact of trading variables on price volatility (in absolute terms) generally increases as trade size decreases. Results support the hypothesis that when liquidity is low, volatility impacts of trading variables are high.

Our results across trade-size categories contrast with the findings in the equity market. Chan and Fong (2000) find that trading frequency for medium trades has a larger impact on volatility than that for small/large trades of stocks and conclude that medium trades contain the most information. This evidence is consistent with Barclay and Warner's (1993) finding that medium-sized trades contribute most to stock price changes. By contrast, we find that the coefficient of trading frequency is the largest for small bond trades. Results suggest that trade size plays a different role in the corporate bond market.

Panel C shows results of regressions by bond age. The coefficients of trade size and number are relatively small (in absolute terms) for newly issued bonds (≤ 3 months). The absolute value of trading variable coefficients gets larger as the bond ages. For example, the coefficient of number of transactions is 1.79 for bonds with an age of less than or equal to three months and 4.29 for the oldest bonds.

Panel D reports results by the issuance amount of bonds. The impact of trading variables increases as the issue size decreases. The coefficient of number of trades increases monotonically from 2.01 for bonds with the largest issue size to 15.47 for bonds with the smallest issue size. At the same time, coefficient of trade size declines from -0.82 to -3.19.

Panel E reports the results by the Amihud measure. Results again show that the relation between price volatility and number of trades increases monotonically with illiquidity. The coefficient of number of trades increases from 2.29 for the most liquid bonds (the last quartile) to 14.86 for the least liquid bonds (the first quartile). Results strongly suggest that the relation between volatility and trading frequency depends on liquidity. A similar pattern is found for the coefficient of trade size.

In summary, there is clear evidence that the impact of trading variables on price volatility depends on bond liquidity characteristics. The relations between volatility and trading variables are consistently high for illiquid bonds. Results strongly support Hypothesis 2 and suggest that liquidity plays an important role in the relation between volatility and trading activity in the corporate bond market.

4.5. Control for the effect of analyst forecast dispersions

The preceding results are based on univariate sorts by bond liquidity characteristic with no control for the information effect. We next run the regressions by controlling for the effect of information asymmetry. Following Guntay and Hackbarth (2010) and Dick-Nielsen et al. (2012), we use dispersion of analyst earnings forecasts obtained from IBES as a measure of information asymmetry.[15] The literature has suggested that greater analyst forecast dispersion leads to higher information asymmetry (see Brandt and Kavajecz, 2004; Green, 2004). Earnings forecast dispersion can arise from either heterogeneous private information or different interpretations of public information by analysts. The

[15] See Guntay and Hackbarth (2010) for the definition and procedure for obtaining analyst earnings forecast dispersion.

former arises because each analyst may possess different private information for firms' earnings. The latter can be attributed to several possible reasons, one of which is that analysts may have their own models to analyze public information related to earnings and profitability. Green (2004) shows that high analyst forecast dispersion is associated with high information asymmetry.

To control for the effects of information asymmetry and illiquidity, we perform bivariate sorts on the sample by analyst earnings forecast dispersion and the Amihud illiquidity measure. Bonds are sorted each week independently into three forecast dispersion groups and three Amihud illiquidity groups (high, medium and low). This results in nine groups of bonds in the intersection of illiquidity and earnings forecast dispersion. The bivariate sort generates the variation in illiquidity independent of the variation in information asymmetry. By controlling for the effect of information asymmetry, we can see more clearly the role of illiquidity in the volatility-volume relation and vice versa. We then estimate volatility regressions for each group to assess the effects of information asymmetry and liquidity. Table 5 reports the results of these conditional regressions.

[Insert Table 5 here]

An interesting pattern emerges in Table 5. First, controlling for the effect of information asymmetry, we find that the coefficient of number of trades increases monotonically with the Amihud illiquidity measure. For example, when analyst earnings forecast dispersion is high, the coefficient increases from 1.94 for bonds with low Amihud illiquidity to 11.91 for bonds with high Amihud illiquidity. The difference in the *NT* coefficients between bonds with high and low Amihud illiquidity increases as the earnings forecast dispersion or information asymmetry increases. On the other hand, given the Amihud illiquidity measure, the coefficient of number of transactions increases as analyst earnings forecast dispersion increases. For example, given the high Amihud illiquidity level, the coefficient increases from 8.20 for bonds with low information asymmetry to 11.91 for bonds with high information asymmetry.

The effect of number of trades on volatility depends on the interactions of illiquidity and information asymmetry. The positive relation between volatility and number of trades is the strongest for bonds with high illiquidity and high information asymmetry, and the weakest for bonds with high liquidity and low information asymmetry. These findings are consistent with the predictions of both information- and search-based theories. Results strongly suggest that the relation between price volatility and number of trades is nonlinear, which depends on illiquidity and the degree of information asymmetry. This finding is robust to different liquidity proxies. Besides the Amihud measure, we also use other liquidity proxies to perform bivariate sorts and conditional regressions. Results (omitted for brevity) based on other liquidity proxies show a similar pattern.

4.6. Control for the effect of credit risk

Both illiquidity and credit risk are correlated with price volatility. However, it is not clear how they may affect the relation between price volatility and trading activity. To examine this issue, we perform bivariate sorts by credit risk and illiquidity. Bonds are sorted each week by credit rating and the Amihud illiquidity measure independently. This generates 12 bond groups classified by rating and illiquidity. The bivariate sorts allow us to examine the effect of illiquidity on the relation between volatility and trading activity by controlling for the effect of credit risk, and vice versa.[16] This objective is accomplished by performing conditional volatility regressions for each group. During the financial crisis, liquidity falls and credit risk and volatility increase. To evade potential endogeneity among these variables induced by crisis events, we choose a tranquil period from October 2004 to June 2007 for this test.

Table 6 reports results of conditional regressions for bond groups categorized from bivariate sorts by rating and the Amihud illiquidity measure. Results can be summarized as follows. First, controlling for the effect of credit risk, the coefficient of number of trades increases monotonically as the Amihud illiquidity measure increases. Thus, conditional on credit risk, illiquidity has an unequivocally independent positive effect on the relation between price volatility and number of trades. The sensitivity of the relation between price volatility and number of trades to bond illiquidity increases as the rating decreases. Second, controlling for the effect of illiquidity, the coefficient of number of trades increases as

[16] This control mechanism is similar to that in Beber, Brandt and Kavajecz (2009), who use the top quartile of positive net orderflow to define a flight out of the bond market to sort out the liquidity effect. In the present case, we control the effect of credit risk to identify the liquidity effect.

the rating decreases. Third, there is an interactive effect between credit risk and illiquidity. The positive relation between price volatility and number of trades is the strongest for bonds with a low rating and low liquidity and the weakest for bonds with a high rating and high liquidity. Results strongly suggest that the relation between price volatility and trading frequency is nonlinear, which depends on illiquidity and credit risk. Besides the Amihud measure, we also perform the analysis using other liquidity proxies and find that our results are robust to different liquidity measures.

[Insert Table 6 here]

5. Price volatility and trading during the subprime crisis

The recent subprime crisis presents a window of opportunity to understand the roles of liquidity and credit quality in explaining the relation between price volatility and trading activity in the corporate bond market. The global financial crisis originated from the US subprime mortgage market in 2007 and quickly spread to every financial market, including equity, foreign exchange, credit, and derivatives. The impact of the financial crisis is largest for the fixed-income market. The salient features of this crisis are the rapid and severe deterioration in liquidity and credit quality of debts, and excessive volatility in the bond market. Dramatic changes in liquidity and increased dispersion in credit quality across bonds during the crisis period provide an ideal environment for examining the roles of liquidity and credit risk. A key question is whether the volatility-volume relation changes significantly in times of stress.

The subprime crisis also offers a great opportunity to examine the interactive effect of liquidity and credit risk on the relation between price volatility and trading activity. In times of financial stress, liquidity can vary considerably across bonds with different credit ratings due to the flights-to-quality effect (see Friewald et al., 2012; Dick-Nielsen et al., 2012; Acharya et al., 2013). During the subprime crisis, prices decrease and liquidity deteriorates for low-grade bonds as investors try to find a safe haven. The sudden dry-up in liquidity for risky securities could have a significant impact on prices of speculative-grade bonds when investors try to trade these risky securities. This, in turn, could affect the relation between price volatility and trading activity. In this section, we investigate the effects of liquidity, credit risk and their interactions on the relation between price volatility and trade number and size during the financial crisis.

5.1. The relation of volatility and trading variables in the financial crisis period

We estimate the volatility regression for both normal and crisis periods to examine the effect of changes in aggregate liquidity conditions. In this specification, we compare the effect of illiquidity during the normal period with that during the crisis period when aggregate liquidity shocks simultaneously affect all agents and securities. We set July 2007 as the cutoff month for the start of the subprime crisis. This definition is in line with previous studies (e.g., Dick-Nielsen, Feldhutter, and Lando, 2012). The end of the crisis period is set to the year end of 2009. The normal period is the sample period excluding the crisis period, which includes the subperiods from October 2004 to June 2007 and from January 2010 to June 2012.

Panels A and B of Table 7 report results of regressions for the crisis and normal periods, respectively. Results indicate that the impacts of trade number and size on price volatility are substantially higher during the crisis period. Tests of the differences between the mean coefficients of trade number and size in the crisis and normal periods show that the impacts of these trading variables on price volatility are all significantly higher in absolute terms (at the 1% level) during the crisis period. Results confirm that the relation between trading variables and price volatility is much stronger during the financial crisis period.

The significant increases in the impact of trading variables on price volatility are attributable to high default risk and low liquidity during the turbulent period. Conceivably, both flights-to-quality and flights-to-liquidity effects can contribute to higher volatility and trading impacts during the financial crisis. In the following, we examine effects of these factors on the volatility-volume relation.

[Insert Table 7 here]

5.2. The flights-to-liquidity effect

The increase in the impact of trades on price volatility during the financial crisis can partly be attributed to market illiquidity. Market liquidity precipitates during the financial crisis. As liquidity dries up, it becomes more difficult to find counterparties to trade with, and even if there is a trade, the impact of trading on prices will be high due to lack of market depth. Thus, liquidity may have a greater impact on the volatility-volume relation during the crisis period.

To explore the roles of both bond-level illiquidity and aggregate liquidity shocks, we run regressions for subsamples stratified by liquidity proxies for both normal and crisis periods. We sort the bond sample into quartiles by each bond-specific liquidity characteristic for the crisis period using the same procedure as described earlier. Table 8 reports results of regressions for each subsample stratified by each liquidity variable for both periods.

[Insert Table 8 here]

Panel A shows dramatic differences in the coefficients of trading variables across bonds of different volumes during the financial crisis. The impact of number of trades on price volatility for low-volume bonds is about 20 times that for high-volume bonds during the crisis period. Similarly, the impact of trade size of low-volume bonds is about 25 times that of high-volume bonds. Differences of this magnitude are unlikely to be explained by microstructure noise.

Compared with the results for the normal period, all coefficients of trading variables increase in absolute terms during the crisis period. Results indicate that liquidity becomes a more important factor in times of stress. A result that stands out is the differential impacts of the crisis on bonds with different liquidity. For bonds in the highest volume quartile, changes in the impact of trading variables on volatility are small in the crisis period. In contrast, for bonds in the lowest volume quartile, changes in the impact of trading variables are substantial. For example, the coefficient of number of trades (*NT*) is 2.64 for bonds in the high volume category during the crisis period, which is only moderately higher than that (1.88) for the normal period. In contrast, the *NT* coefficient is 52 for bonds in the low volume category, which is substantially higher than that (16) for the normal period. Similarly, trade size has a much larger impact on volatility for bonds with low volume during the crisis period.

Results for the subsamples formed by other liquidity proxies in Panels B to E exhibit a similar pattern and consistently show that illiquid bonds are much more sensitive to aggregate liquidity shocks. The relation between price volatility and number of trades increases during the financial crisis and this increase is more pronounced for illiquid bonds.

In summary, the relation between volatility and trading variables becomes much stronger for illiquid bonds during the financial crisis. The evidence strongly suggests that the flights-to-liquidity effect augments the volatility impact of trading variables during the financial crisis. This flights-to-liquidity effect hits illiquid bonds hardest.

5.3. The interactive effects of liquidity and credit risk in times of financial stress

Liquidity and default risk of fixed-income securities are correlated (see Ericsson and Renault, 2006). When market liquidity is low, default risk of bonds tends to be high, suggesting the possibility of an interactive effect of liquidity and default risk. To estimate the separate and interactive impacts of liquidity and credit risk on the relation between trading variables and price volatility, we estimate the following regression:

$$\begin{aligned} VOL_{it} &= \alpha_0 + \alpha_1 NT_{it} + \alpha_2 ATS_{it} + D_L \cdot (\gamma_1 NT_{it} + \gamma_2 ATS_{it}) + D_R \cdot (\delta_1 NT_{it} + \delta_2 ATS_{it}) \\ &\quad + D_{LR}(\varphi_1 NT_{it} + \varphi_2 ATS_{it}) + \sum_{k=1}^{q} \beta_k CV_{it,k} + \varepsilon_{it}. \end{aligned} \tag{3}$$

Three dummy variables are introduced to capture the effects of liquidity, credit quality and the interaction of liquidity and credit quality. D_L is the liquidity dummy variable with a value equal to 1 when a bond is in the lowest liquidity quartile and 0 otherwise. D_R is the credit risk dummy, which equals 1 for speculative-grade bonds and 0 otherwise. D_{LR} is the interactive dummy of liquidity and credit risk, which equals 1 for speculative-grade bonds in the lowest liquidity quartile. The control variables (*CV*) are the same as in (2). An advantage of this regression specification is its ability to jointly test the individual impact of liquidity and credit risk and the interactions of these two variables. We run the regression for both normal and crisis periods.

Table 9 reports regression results for both normal and crisis periods (rows 1 and 2) and the test of the difference in the coefficients between the two periods (row 3) by bond liquidity characteristic.

Results again show that the impacts of number of trades (*NT*) and size (*ATS*) on price volatility are much higher during the financial crisis period. More importantly, the slopes of dummy variables point to significant liquidity, credit risk and interactive effects.

The liquidity dummy coefficient of trade number (*DLNT*) is highly significant in all regressions. Results confirm that illiquidity is an important factor and the relation between price volatility and trading variables is much stronger when liquidity is low. Furthermore, this relation increases sharply during the financial crisis. The difference in the *DLNT* coefficients between the normal and crisis period is significant at the one percent level in all cases. This evidence supports the hypothesis of the flights-to-liquidity effect during the turbulent period. A similar (weaker) pattern for the impact of trade size (*DLATS*) is found for illiquid bonds. Results consistently show that liquidity is an important determinant for the relation between volatility and trading variables. In times of stress, liquidity becomes more important and the impact of trading on price volatility amplifies.

The credit risk dummy coefficients of trade number (*DRNT*) and size (*DRATS*) are also quite significant, suggesting that the relations between price volatility and trading variables are much stronger for low-quality bonds. These relations for speculative-grade bonds increase sharply during the financial crisis. The coefficients of *DRNT* are significantly higher in the crisis period in all regressions stratified by liquidity characteristic. The evidence strongly supports the hypothesis of the flights-to-quality effect during the financial crisis.

Furthermore, there is a significant interaction between liquidity and credit risk. The interactive dummy coefficients of trade number (*DLRNT*) and size (*DLRATS*) are significant. Results show that the relations between price volatility and trading variables are stronger for illiquid speculative-grade bonds, and the interactive effect of liquidity and default risk affects the relations between price volatility and trading variables during the financial crisis.

[Insert Table 9 here]

Overall, there is strong evidence that the relation between the volatility of a corporate bond and its trading activity depends on liquidity and credit risk. This relation is stronger for bonds with lower liquidity and credit quality. This finding is robust to different liquidity proxies. Both liquidity and default risk factors become more important during the subprime crisis. Results strongly support Hypothesis 4 and suggest that there are significant effects of flights-to-quality and flights-to-liquidity at play in times of stress, which affect the relation between volatility and trading activity in the corporate bond market.

6. Robustness tests

In this section, we perform additional tests to check the robustness of empirical results. We first examine whether our results are robust to the control for issuer fixed effects. Each issuer can have multiple transactions in different bond issues and it is important to check if there is any persistence in volatility at the issuer level that might affect parameter estimation. Moreover, we include the time between maximum and minimum price observations as an additional explanatory variable in the regression to see if our results are robust to this inclusion. Finally, we investigate whether tax-loss selling has an effect on the relation between price volatility and trading volume.

Panels A and B of Table 10 report results of pooled regressions with and without control for the issuer fixed effects, respectively.[17] Both sets of results are similar to those of the weekly regressions reported earlier. The coefficients of number of trades and volume are positive, and that of trade size is negative when they are used as the sole trading variable. Comparing the results with and without control for issuer fixed effects, we find that the estimated coefficients for number of trades and trade size are only slightly lower in absolute terms for the regressions with control for issuer fixed effects. Results show that the relations between price volatility and these trading variables are quite robust to the control for issuer fixed effects.

We next calculate the length of time (in hours) between the trades with maximum and minimum prices and use it as an additional explanatory variable in the weekly volatility regression. Panel C of Table 10 reports the results that include the number of hours between the trades with maximum and

[17] We run pooled regressions to control issuer fixed effects because not too many firms have multiple bond observations during the same week and this causes a degree-of-freedom problem for estimating the issuer fixed effect by weekly cross-sectional regressions.

minimum prices. As shown, our results are robust to the inclusion of the number of hours in the regression. It is expected that time between max and min prices will have a positive relation with volatility as the longer length of intervals provides more time for information to arrive and assimilate. Consistent with this argument, the coefficient of time between max and min transaction prices for each week is positive, ranging from 0.13 to 0.15. However, including this variable does not increase adjusted R^2. Most importantly, our basic conclusions remain unchanged: the coefficient of number of trades continues to be significantly positive and that of trade size is significantly negative in all regressions.

Tax-loss selling at year end may affect trading and price behaviors. To check whether our results are sensitive to tax-loss selling, we run regressions for the subsamples that include only December observations and that exclude December observations, respectively. Panel D of Table 10 reports results of these regressions. As shown, the effect of number of trades is a little stronger for the subsample with only December transactions (the upper panel). The coefficient of number of trades is 2.56 for the December subsample and 1.99 for the subsample that includes the rest of our observations (the lower panel) when the regression includes both number of trades and trade size. On the other hand, the coefficient of trade size is not larger in absolute terms (-0.62 versus -0.77). Results show that tax-loss selling has only a modest impact on the relation between price volatility and number of trades. Our conclusions regarding the relations between price volatility and trading variables remain unchanged, and it does not appear that tax-loss selling is the main driver for the relation between volatility and trading activity. [18]

[Insert Table 10 here]

7. Conclusion

The recent development in the search-based models has generated a wealth of important

[18] We also run weekly cross-sectional regressions by adding financial variables such as analyst earnings forecast dispersion, the operating income to sales ratio, dividends, leverage and stock return volatility as explanatory variables. We find that adding these variables tends to increase the adjusted R-squared but our basic conclusions remain unchanged. The results with additional variables are omitted for brevity because the requirement of these variables restricts the sample to only those firms for which these financial data are available, thus making it difficult to compare with the original results based on the full sample.

implications for asset pricing, volatility and trading behavior. This paper tests some of these implications based on the well-known volatility-volume relation. As most of these models deal with the issue of search-based inefficiencies, they are particularly suited for explaining the trading phenomenon in an OTC market setting where search frictions are of a greater concern. In this paper, we choose the corporate bond market for our study, which is a prototype of the OTC market with prevalent search problems and liquidity concern. Availability of different liquidity characteristic variables and well-defined bond risk in this market make it ideal to test the implications of search-based models.

We find that the relation between trading variables and price volatility is nonlinear, which depends on information asymmetry, liquidity and risk. The finding that liquidity and risk affect the relation between volatility and volume is consistent with the predictions of the search-based models. There is strong evidence of a significant interactive effect of liquidity and credit risk. The effects of liquidity and credit quality magnify during the financial crisis period, which can be attributed to flights-to-liquidity, flights-to-quality and the interaction of these two effects.

Our empirical findings expand the understanding of price discovery in different markets. The traditional market microstructure models focus on private information, public information flow, and heterogeneous interpretations of news as primary explanations for the relation between volatility and trading variables. These models abstract from the effects of search frictions and credit quality. A major difficulty with these models is that they cannot explain the phenomena documented in this study, e.g., the negative correlation between trade size and volatility, and the strong linkage of the volatility-volume relation to search frictions and risk. On the other hand, these phenomena can be explained very well by search-based models. Our findings provide important implications for future theoretical work to refine the microstructure models. In particular, our empirical results suggest that microstructure models should be generalized to account for the effects of search frictions and riskiness of securities in order to provide more satisfactory explanations for the volatility-volume relation across different asset classes.

Appendix

In this appendix, we show how search efficiency affects trading volume, and from this effect we infer the relation between trading volume and volatility. To examine the effect of search on trading volume, we apply an order-match model analogous to Stigler (1961) to an OTC market.[19] In this setting, the order matches consummated from the search process represent bond transactions. We assume that (1) ask and bid prices of corporate bonds each follow a statistical distribution; (2) there are N_b buyers (or N_s sellers), each having an order of constant size q_b (or q_s); and (3) there is no information asymmetry.

The number of orders matched in a given period for a bond can be derived from the perspective of either the buyer or seller. For convenience, we begin with the search from the buy side. Suppose that the ask price a has a probability density function $f(a)$ whose cumulative probability distribution function is $F(a)$.[20] Denote the maximum price that the buyer is willing to pay or the reservation price as p_b and the number of asks available from dealers' quotes and limit orders to which the buyer has access as n_a. Then the probability that a buyer's order is executed at the reservation price or lower is

$$\delta_b = 1 - [1 - F(p_b)]^{n_a}. \tag{A1}$$

where $F(p_b)$ is the probability that an ask quote received by the buyer is less than or equal to the reservation price p_b; $1 - F(p_b)$ is the probability that an ask is greater than p_b; $[1 - F(p_b)]^{n_a}$ is the probability that the minimum of the ask quotes searched is greater than the reservation price, and one minus this term yields the probability that given the n_a ask quotes searched, there is at least one less than or equal to the buyer's reservation price. Multiplying this probability of match by the number of buyers N_b in the market and order size q_b gives the expected total buy volume in a given period:

$$V_b = N_b \delta_b q_b. \tag{A2}$$

The above analysis assumes that each buyer has the same order size and reservation price and has

[19] See Stigler (1961, p. 217) for an example of the match function with a uniform distribution in prices.

[20] One can obtain an analytic solution by specifying a functional form for f. For example, if f is a uniform function distributed between 0 and 1, then $F(a) = \int_0^a dx = a.$

equal access to dealers' quotes and limit order books. These assumptions can be easily relaxed by allowing for different order sizes, reservation prices and access to quotes. In such case, the probability of matches varies by individuals and the total volume is simply the sum over individual trading volumes.

The trading volume in (2) is derived from the buy side. Similarly, we can derive the trading volume from the sell side (V_s) by plugging the seller's reservation price and bid quotes into the match function. The function for matching the sell orders can be written as

$$\delta_s = 1 - F^b(p_s)^{n_b} \tag{A3}$$

where a different notation F^b is used for the cumulative frequency function to permit a possibly different bid quote distribution (e.g. due to different selling pressure), p_s denotes the seller's reservation price or the minimum price s/he is willing to accept, and n_b is the number of bid quotes to which the seller has access. $F^b(p_s)$ is the probability that a bid quote received by the seller is lower than p_s, $F^b(p_s)^{n_b}$ is the probability that each of the bids received is lower than the seller's reservation price and $1 - F^b(p_s)^{n_b}$ is the probability that among all bids received (n_b), at least one is higher than or equal to p_s. Given the probability of matching seller orders, the expected total sell volume is

$$V_s = N_s d_s q_s . \tag{A4}$$

Again, we can allow the reservation price p_s, order size q_s and access to bid quotes to vary across sellers and sum over individual matches to give the expected total sell volume.

Assuming no order imbalances, the equilibrium trading volume is $V_b = V_s = V$. More generally, if there are more buys than sells or vice versa, the difference can be made up by dealers' inventory adjustments and the market clearing trading volume will then be *max* $[V_{b,} V_s]$.[21]

The parameter n_a (or n_b from a seller's perspective) is equivalent to the number of search options in Duffie et al. (2005, 2007). The literature suggests that the value of this parameter is negatively related to credit risk (λ) and bond age (g), and positively related to the issuance amount (ν) and trade size (q). That

[21] In the dealer market, the volume statistics are often reported separately by sells to dealers and buys from dealers.

is, the number of search options or search efficiency increases with the issuance amount and trade size, and decreases with credit risk and bond age. Furthermore, higher search efficiency is associated with lower search frictions, higher liquidity, and lower price volatility.

It can be easily shown from (1)-(4) that volume is positively related to the number of search options n_j (i.e., $\partial V_k / \partial n_j > 0$ as $\partial \delta_k / \partial n_j > 0$), $j = a, b$ and $k = b, s$.[22] When the number of search options is large, liquidity is high and volume is high, suggesting that volume and liquidity are positively related. On the other hand, the search-based models predict that price volatility and liquidity are negatively related (see Duffie et al., 2005, 2007). Taken together, this implies that the effect of liquidity (illiquidity) on the volatility-volume relation is negative (positive).

[22] For example, $\partial \delta_b / \partial n_a = -[1 - F(p_b)]^{n_a} \ln[1 - F(p_b)] > 0$, and $\partial \delta_s / \partial n_b = -F^b(p_s)^{n_b} \ln F^b(p_s) > 0$.

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Figure 1. Histograms of trading activity for sample bonds

Panel A displays a histogram of the number of transactions in each bond over the sample period from October 2004 to June 2012. The vertical bar indicates the number of bonds in the sample that trade the number of times given on the horizontal axis. Panel B shows a histogram of the number of trades per week for each bond. The vertical bar indicates the number of bond-week observations where in a given week the bond trades the number of times given on the horizontal axis. As we only kept the bond-week with at least 4 trades in our final sample, the start point for the horizontal axis is 4.

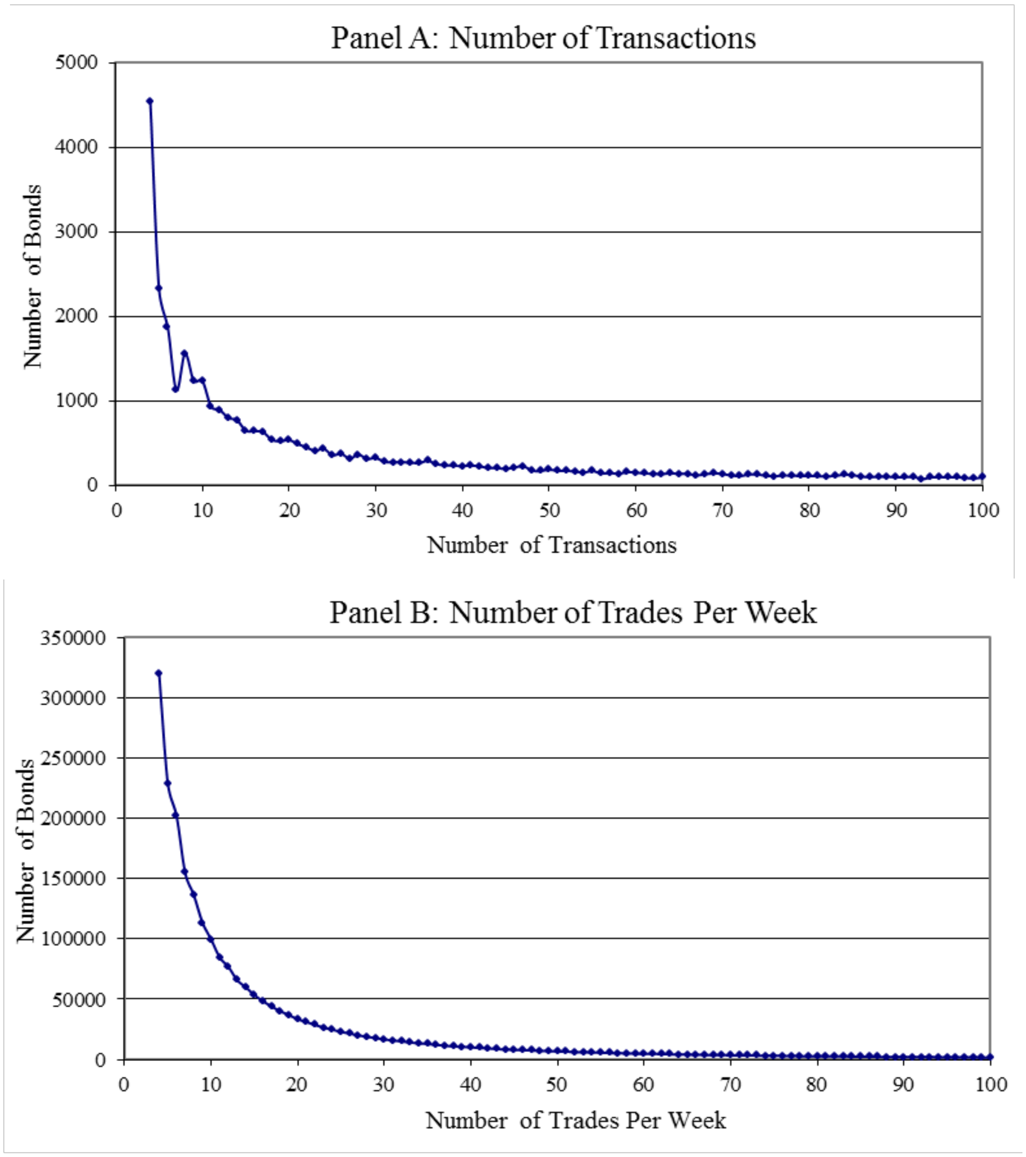
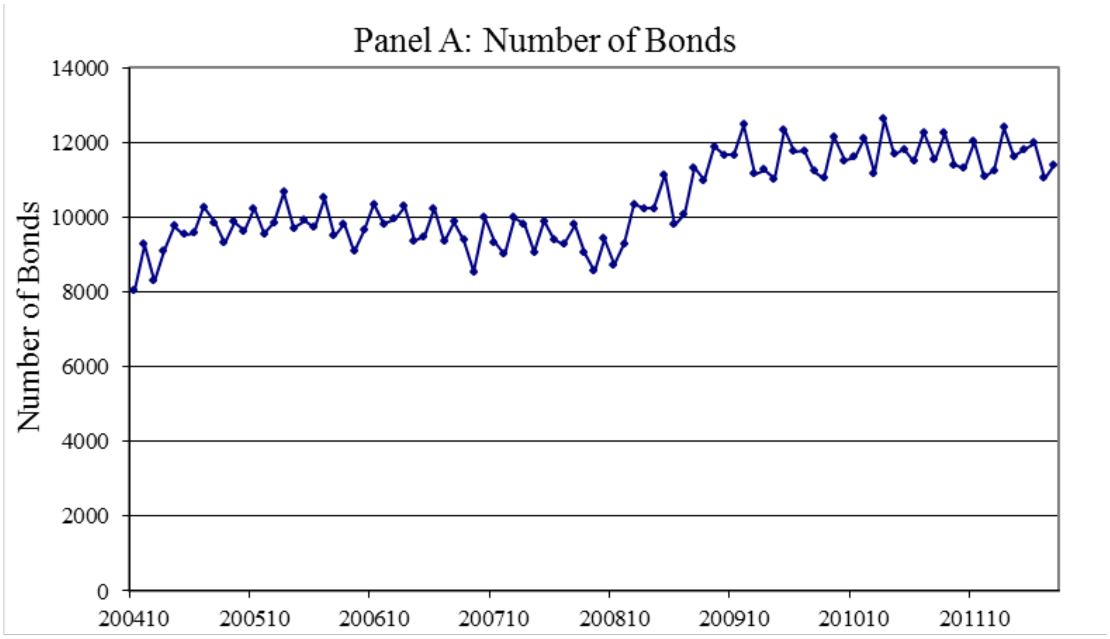


Figure 2. Distribution of bonds and transactions

Panel A displays a histogram of the number of bonds in each month over the sample period from October 2004 to June 2012. Panel B shows a distribution of the weekly number of transactions in each month over the sample period from October 2004 to June 2012.



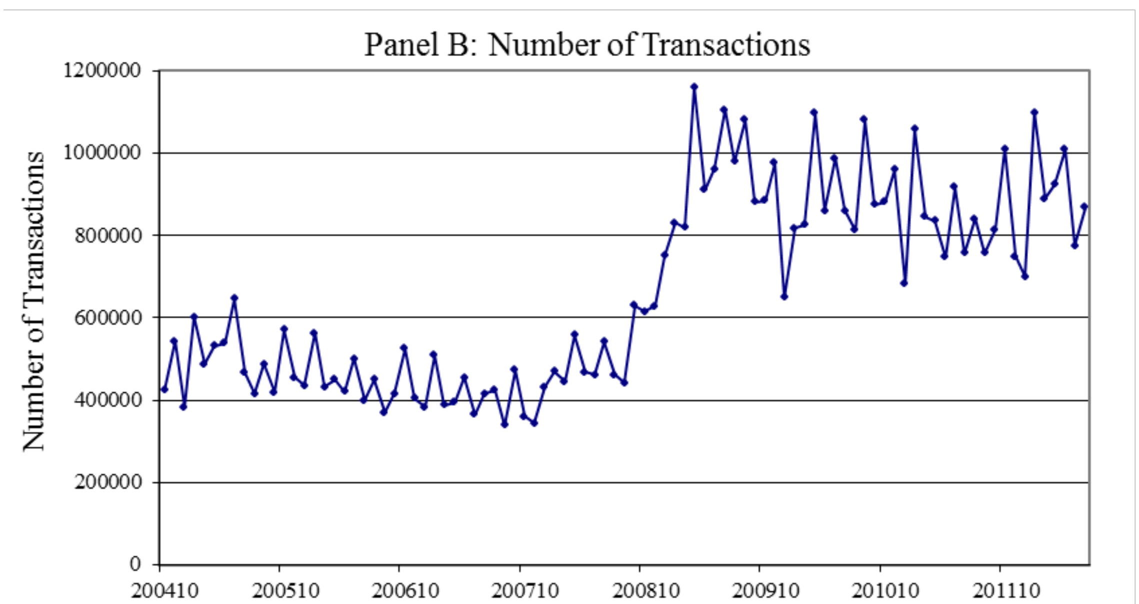


Table 1. Summary Statistics

This table summarizes the weekly variables of the corporate bond data used in empirical analysis for the sample period from October 2004 to June 2012. The mean of each variable is reported for the whole sample (All) and subsamples stratified by rating, maturity, age and provision. Bonds are divided into three maturity groups: short, medium and long, which correspond to bonds with maturities between one and seven years, maturities between seven and fifteen years, and maturities longer than fifteen years, respectively. *RVOL* denotes the range volatility estimator and *LVOL* is the log range volatility estimator (in percentage); *NT* is number of trades per week; *ATS* is average par value of trade size (per trade); *V* is the weekly par volume (in millions); *Rating* is the bond rating (AAA=0, AA+=1,…, C=20, and D=21); *Amount* represents the issue size; *Maturity* is years to maturity; *Age* denotes years since issuance; *Coupon* is the coupon rate; and *N* is the total number of observations.

Sample		*RVOL*	*LVOL*	*NT*	*ATS*	*V*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	*N*
All		2.39	4.39	24.09	0.34	8.19	7.49	0.50	9.50	4.50	5.96	1677378
Rating	AAA/AA	2.10	3.27	24.28	0.41	9.95	1.84	0.77	9.62	3.75	4.92	324420
	A	2.31	3.72	25.71	0.29	7.46	5.08	0.46	9.89	4.37	5.43	512338
	BBB	2.46	4.10	23.61	0.48	11.33	7.97	0.46	10.45	4.96	6.11	395921
	Junk	2.62	6.23	22.51	0.24	5.40	13.97	0.37	8.11	4.78	7.22	444699
Maturity	Short	2.04	3.71	27.00	0.32	8.64	7.78	0.55	3.73	4.47	5.78	914289
	Medium	2.58	4.89	21.28	0.36	7.66	7.56	0.43	9.73	3.68	6.15	402899
	Long	3.03	5.55	19.84	0.38	7.54	6.70	0.43	23.88	5.48	6.21	360190
Age	≤3M	1.76	2.69	32.07	1.40	44.90	6.12	1.18	11.04	0.12	5.66	39273
	>3M	2.40	4.43	23.90	0.32	7.65	7.53	0.48	9.46	4.60	5.97	1638105
Provisions	Callable	2.44	4.58	20.98	0.33	6.92	8.39	0.39	11.18	4.21	6.36	1097713
	Convertible	3.42	5.66	28.78	0.49	41.10	10.41	0.69	15.26	3.64	2.58	35984
	Sinking	2.10	3.37	27.23	0.27	7.35	8.87	0.56	7.96	5.02	7.42	5554
	Straight	2.28	4.01	29.96	0.37	11.09	5.71	0.69	6.30	5.06	5.22	569648

Table 2. Regression Results

This table reports the weekly regression results for the whole sample period from October 2004 to June 2012. For each week, we run the cross-sectional regression: $VOL_{it} = \alpha_0 + \sum_{j=1}^{p} \alpha_j TA_{it,j} + \sum_{k=1}^{q} \beta_k CV_{it,k} + \varepsilon_{it}$. The dependent variable (VOL_{it}) is bond price volatility, based on the range estimator (*RVOL*), log range estimator (*LVOL*) or standard deviation (*STD*); α_0 is the intercept; TA_{it} are trading variables of bonds, such as number of transactions (*NT*), average trade size (*ATS*) and volume (*V*), respectively; and CV_{it} represents corporate bond characteristic variables such as coupon, maturity, issue amount, age and the rating. To investigate the role of each trading variable and different combinations, we run five separate regressions. For each regression, we report average coefficient estimates from weekly cross-sectional regressions and Fama-MacBeth (FM) *t*-statistics (in parentheses), adjusted for the effect of serial correlation. R^2 statistics are adjusted for the degree of freedom before averaging across weekly regressions. Panels A, B and C report regression results for the three volatility measures, respectively.

Panel A: The range volatility measure (RVOL)

α_0	*NT*	*ATS*	*V*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
0.91	4.26			3.16	-1.00	0.13	0.08	-2.13	0.17
(20.94)	(42.83)			(16.11)	(-24.50)	(50.83)	(28.91)	(-13.97)	
1.29			6.13	3.17	0.05	0.12	0.10	-1.98	0.11
(26.79)			(4.47)	(16.96)	(1.83)	(55.07)	(32.31)	(-13.70)	
1.63		-1.56		3.27	0.82	0.13	0.06	-2.12	0.12
(30.60)		(-38.20)		(17.22)	(26.72)	(57.58)	(23.14)	(-14.18)	
1.11	3.96	-0.94		3.20	-0.65	0.14	0.07	-2.17	0.18
(24.66)	(40.20)	(-27.91)		(16.28)	(-15.81)	(51.51)	(25.99)	(-14.14)	
0.89	4.50		-0.91	3.16	-0.84	0.13	0.08	-2.14	0.17
(24.09)	(44.97)		(-0.79)	(16.17)	(-20.53)	(52.16)	(25.67)	(-14.13)	

Panel B: The log range volatility measure (*LVOL*)

α_0	*NT*	*ATS*	*V*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
0.83	2.20			0.45	-0.40	0.06	0.05	0.02	0.18
(29.20)	(49.29)			(24.30)	(-19.71)	(109.32)	(43.44)	(0.62)	
1.01			3.29	0.47	0.10	0.05	0.06	0.09	0.09
(34.02)			(5.48)	(26.11)	(8.02)	(100.65)	(51.37)	(2.58)	
1.18		-0.71		0.51	0.51	0.06	0.04	0.02	0.11
(37.36)		(-59.81)		(26.71)	(37.57)	(92.97)	(31.14)	(0.68)	
0.91	2.06	-0.38		0.47	-0.25	0.06	0.04	0.00	0.19
(31.43)	(48.18)	(-41.51)		(25.20)	(-13.23)	(106.65)	(36.91)	(-0.12)	
0.83	2.29		-0.10	0.45	-0.34	0.06	0.04	0.01	0.18
(29.72)	(49.10)		(-0.18)	(24.93)	(-17.60)	(106.80)	(39.43)	(0.36)	

Panel C: The standard deviation measure (*STD*)

α_0	*NT*	*ATS*	*V*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
0.67	2.83			1.79	-0.28	0.31	0.02	-0.39	0.12
(40.63)	(20.58)			(20.55)	(-31.46)	(111.02)	(38.45)	(-2.39)	
0.70			1.63	1.90	-0.17	0.31	0.02	-0.35	0.11
(42.90)			(0.52)	(21.14)	(-29.64)	(110.86)	(38.38)	(-2.22)	
0.74		-0.24		2.01	-0.13	0.33	0.02	-0.52	0.13
(44.65)		(-47.11)		(22.16)	(-27.60)	(107.37)	(29.65)	(-3.24)	
0.72	2.03	-0.22		1.90	-0.20	0.33	0.02	-0.50	0.13
(42.42)	(16.34)	(-42.49)		(21.56)	(-26.68)	(108.29)	(30.97)	(-3.08)	
0.67	3.54		-0.27	1.85	-0.24	0.32	0.02	-0.43	0.12
(40.88)	(23.30)		(-0.97)	(20.98)	(-29.59)	(107.26)	(32.38)	(-2.67)	

Table 3. Subsample Regressions

This table reports weekly regression results for subsamples stratified by risk, maturity, provision and trade side and for regressions with order imbalances. The dependent variable is bond price volatility based on the range estimator (*RVOL*). In panel A, we run regressions for subsamples stratified by different risk proxies besides the rating. Leverage is the ratio of long-term debt to total assets, dividends are on per share basis, and stock return volatility is weekly. All other variables and parameters are as defined in Table 2. For each regression, we report average coefficient estimates from weekly cross-sectional regressions and Fama-MacBeth (FM) *t*-statistics (in parentheses), adjusted for the effect of serial correlation. R^2 statistics are adjusted for the degree of freedom before averaging across weekly regressions.

Panel A: Risk

(1) by rating

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
AAA/AA	1.38	1.92	-0.57	0.46	-0.02	0.12	0.07	-0.02	0.24
	(44.97)	(61.49)	(-25.46)	(4.80)	(-1.65)	(63.18)	(20.15)	(-3.38)	
A	0.39	2.63	-0.80	3.82	-0.35	0.12	0.05	-0.10	0.21
	(4.34)	(39.20)	(-31.91)	(19.27)	(-10.72)	(88.74)	(11.84)	(-13.54)	
BBB	2.83	4.00	-0.68	0.92	-0.80	0.10	0.03	-0.20	0.23
	(10.18)	(36.08)	(-29.51)	(4.25)	(-17.76)	(52.04)	(6.57)	(-15.80)	
Below BBB	-4.01	7.93	-2.14	6.10	-1.31	0.18	0.10	-0.18	0.19
	(-11.35)	(22.28)	(-21.29)	(14.95)	(-11.98)	(25.25)	(13.31)	(-8.36)	

(2) by operating income/sales

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
High 25%	1.36	1.98	-0.75	1.64	0.09	0.12	0.09	-1.68	0.26
	(22.75)	(44.43)	(-24.26)	(18.53)	(2.69)	(45.23)	(18.82)	(-16.20)	
Middle 50%	0.40	3.25	-0.58	2.11	0.15	0.11	0.12	-1.42	0.25
	(7.55)	(40.53)	(-29.50)	(21.28)	(3.02)	(48.60)	(29.92)	(-16.30)	
Low 25%	-1.05	3.91	-0.71	3.70	0.02	0.13	0.11	-1.41	0.28
	(-8.16)	(29.56)	(-18.48)	(25.62)	(0.22)	(42.36)	(18.54)	(-11.59)	

(3) by leverage

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
Large 25%	0.22	3.80	-0.89	2.79	-0.36	0.15	0.17	-2.11	0.28
	(2.84)	(35.89)	(-23.98)	(24.91)	(-5.48)	(41.44)	(17.33)	(-19.02)	
Middle 50%	0.68	2.80	-0.61	1.86	0.03	0.11	0.08	-1.29	0.24
	(11.30)	(35.57)	(-32.54)	(23.93)	(0.93)	(66.29)	(24.37)	(-17.39)	
Small 25%	0.31	2.74	-0.62	3.27	0.04	0.09	0.07	-0.93	0.25
	(3.61)	(29.67)	(-20.86)	(21.94)	(1.01)	(43.35)	(14.87)	(-8.90)	

(4) by dividend

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
High 25%	0.84	2.72	-0.60	1.55	-0.20	0.11	0.04	-0.32	0.37
	(8.48)	(31.73)	(-13.59)	(10.27)	(-3.74)	(35.24)	(4.57)	(-1.82)	
Middle 50%	1.17	3.52	-0.64	1.23	-0.22	0.11	0.10	-1.58	0.36
	(12.98)	(39.11)	(-19.57)	(16.31)	(-4.07)	(43.73)	(21.21)	(-12.19)	
Low 25%	-1.75	4.90	-0.74	3.40	-0.04	0.12	0.15	-1.15	0.37
	(-6.59)	(25.84)	(-11.42)	(18.33)	(-0.49)	(26.34)	(11.12)	(-7.13)	

(5) by stock return volatility

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
High 25%	-0.39	3.80	-0.52	2.90	0.24	0.11	0.16	-1.90	0.30
	(-2.56)	(33.26)	(-12.89)	(19.91)	(2.54)	(35.67)	(17.40)	(-15.84)	
Middle 50%	1.20	2.72	-0.60	1.23	0.06	0.11	0.09	-1.47	0.25
	(18.11)	(50.17)	(-31.18)	(32.16)	(1.80)	(75.10)	(26.77)	(-16.58)	
Low 25%	1.19	2.29	-0.61	0.61	-0.03	0.10	0.05	-0.45	0.27
	(16.28)	(55.82)	(-26.46)	(14.05)	(-1.03)	(52.37)	(15.62)	(-4.51)	

Table 3 (cont.)

Panel B: Maturity

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
Short (1-7 years)	0.72 (14.59)	3.28 (36.33)	-0.77 (-22.35)	3.27 (17.93)	-0.39 (-10.53)	0.23 (32.38)	0.07 (15.89)	-0.23 (-14.85)	0.16
Medium (7-15 years)	0.68 (6.40)	4.74 (38.44)	-0.85 (-20.01)	2.98 (13.67)	-0.81 (-13.94)	0.28 (24.24)	0.11 (22.52)	-0.33 (-11.63)	0.23
Long (>15 years)	2.63 (25.06)	6.39 (39.61)	-0.94 (-29.84)	3.35 (14.65)	-0.68 (-15.32)	0.02 (6.95)	0.03 (4.98)	-0.13 (-9.08)	0.21

Panel C: Provisions

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
Straight bonds	1.16 (26.41)	2.27 (39.22)	-0.74 (-28.73)	3.62 (15.53)	-0.07 (-2.74)	0.14 (66.99)	-0.01 (-1.09)	-0.13 (-17.04)	0.24
Callable bonds	0.57 (8.85)	5.46 (40.53)	-1.07 (-30.47)	3.13 (16.07)	-1.42 (-20.40)	0.14 (37.22)	0.09 (28.82)	-0.17 (-10.04)	0.19
Convertible bonds	0.74 (2.46)	5.31 (29.84)	-1.37 (-16.23)	1.43 (9.14)	0.40 (3.78)	0.06 (12.67)	0.23 (10.56)	1.07 (3.37)	0.31

Panel D: Buy and sell order regressions (sample period:11/2008-6/2012)

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
Buy orders	-0.17 (-2.49)	6.63 (19.36)	-0.96 (-5.38)	2.02 (15.22)	-0.69 (-4.18)	0.07 (24.03)	0.03 (4.07)	-1.36 (-8.04)	0.18
Sell orders	-0.56 (-5.09)	9.61 (14.74)	-0.26 (-1.55)	2.26 (17.01)	1.77 (12.94)	0.06 (15.64)	0.04 (5.10)	-1.35 (-6.08)	0.20

Panel E: Order imbalances (sample period:11/2008-6/2012)

	α_0	*NT*	*OI*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
Whole Period	0.62 (15.41)	2.04 (63.18)	1.82 (4.50)	-0.30 (27.38)	2.71 (22.16)	0.02 (1.53)	0.07 (73.05)	0.07 (32.34)	-2.43 (-6.76)	0.21
Normal Period	0.27 (7.95)	1.71 (69.99)	1.40 (4.04)	-0.27 (-25.48)	1.56 (19.26)	0.02 (1.81)	0.06 (60.72)	0.07 (29.38)	-2.27 (-4.06)	0.23
Crisis Period	1.35 (17.03)	2.82 (25.72)	1.98 (5.19)	-0.34 (-12.39)	4.10 (10.75)	0.06 (0.53)	0.07 (45.07)	0.06 (14.94)	-5.88 (-5.21)	0.16

Table 4. Effects of Liquidity on the Relation between Volatility and Trading Variables

This table reports weekly regression results for subsamples sorted by each liquidity proxy into quartiles for the period from October 2004 to June 2012. Liquidity proxies are volume, trade size, age, issue size, and the Amihud measure. Regression results by these proxies are reported in Panels A to E, respectively. The dependent variable (VOL_{it}) is the range-based price volatility (*RVOL*). Variables and parameters are defined as in Table 2. For each regression, we report average coefficient estimates from weekly cross-sectional regressions and Fama-MacBeth (FM) *t*-statistics (in parentheses), corrected for the effect of serial correlation. R^2 is adjusted for the degree of freedom before averaging across weekly regressions.

Panel A: by volume

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
High 25%	0.26	2.13	-0.66	4.20	0.30	0.10	0.13	-0.20	0.21
	(3.17)	(31.41)	(-26.17)	(18.32)	(7.75)	(38.32)	(20.78)	(-13.50)	
Middle 50%	1.28	5.76	-3.90	3.22	-1.15	0.15	0.06	-0.23	0.23
	(25.15)	(44.32)	(-26.33)	(16.57)	(-19.18)	(47.07)	(18.44)	(-14.69)	
Low 25%	0.06	25.69	-16.50	2.79	-2.91	0.12	0.01	-0.16	0.20
	(1.04)	(30.51)	(-14.61)	(15.90)	(-13.62)	(46.62)	(2.07)	(-12.16)	

Panel B: by trade size

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
Large 25%	-0.21	4.85	-0.21	2.70	0.06	0.09	0.11	-0.16	0.18
	(-3.75)	(39.57)	(-13.77)	(18.91)	(2.74)	(41.62)	(27.40)	(-15.87)	
Middle 50%	1.09	3.17	-3.89	3.65	-0.51	0.14	0.06	-0.21	0.20
	(21.70)	(35.78)	(-16.08)	(16.87)	(-10.78)	(50.34)	(18.88)	(-12.54)	
Small 25%	0.80	13.04	-32.15	3.38	-2.92	0.13	0.01	-0.18	0.25
	(11.92)	(39.54)	(-10.38)	(16.75)	(-12.24)	(43.62)	(1.95)	(-11.06)	

Panel C: by age

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
Age ≤ 3	0.15	1.79	-0.15	0.63	0.00	0.07	2.80	0.14	0.24
months	(1.44)	(27.12)	(-6.84)	(6.31)	(0.19)	(14.83)	(9.87)	(8.01)	
Low 25%	0.52	3.40	-0.80	2.16	-0.38	0.10	0.45	-0.03	0.21
	(10.05)	(32.24)	(-25.93)	(13.33)	(-8.06)	(53.49)	(18.96)	(-3.35)	
Middle 50%	0.96	4.21	-1.08	3.13	-0.96	0.15	0.10	-0.18	0.19
	(16.26)	(38.75)	(-23.18)	(15.70)	(-17.09)	(39.69)	(8.23)	(-11.85)	
High 25%	1.47	4.29	-0.96	3.93	-0.68	0.16	0.06	-0.40	0.24
	(15.81)	(45.45)	(-22.77)	(17.77)	(-16.52)	(48.96)	(10.68)	(-15.81)	

Panel D: by issue size

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
High 25%	0.92	2.01	-0.82	3.84	0.31	0.12	0.11	-0.31	0.24
	(14.04)	(41.31)	(-24.22)	(16.88)	(12.61)	(48.19)	(24.27)	(-19.45)	
Middle 50%	0.86	6.83	-0.70	3.18	-3.22	0.12	0.08	-0.19	0.21
	(18.25)	(37.59)	(-31.84)	(17.40)	(-22.83)	(49.26)	(24.14)	(-12.95)	
Low 25%	-0.17	15.47	-3.19	3.11	8.83	0.13	0.00	-0.06	0.24
	(-1.75)	(26.04)	(-5.52)	(14.48)	(5.96)	(36.04)	(0.29)	(-5.33)	

Panel E: by the Amihud measure

Subsample	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
High 25%	1.37	14.86	-0.54	1.93	-1.95	0.09	0.02	-0.88	0.23
	(22.91)	(38.62)	(-16.70)	(29.44)	(-21.63)	(64.59)	(4.13)	(-8.27)	
Middle 50%	0.87	4.90	-0.23	1.71	-0.55	0.11	0.03	-0.92	0.27
	(29.98)	(62.09)	(-9.56)	(32.30)	(-13.10)	(84.36)	(12.72)	(-17.17)	
Low 25%	0.21	2.29	-0.21	1.64	0.24	0.08	0.03	-0.75	0.27
	(4.92)	(43.89)	(-14.30)	(22.90)	(16.30)	(51.13)	(9.67)	(-10.50)	

Table 5. Controls for Information and Liquidity Effects

This table reports weekly regression results for subsamples sorted by IBES analyst forecast dispersions and the Amihud bond illiquidity measure into quartiles for the period from October 2004 to June 2012. The medium group includes the middle 50% of the sorting. The dependent variable (VOL_{it}) is the range-based price volatility (*RVOL*). Variables and parameters are defined as in Table 2. For each regression, we report average coefficient estimates from weekly cross-sectional regressions and Fama-MacBeth (FM) *t*-statistics (in parentheses) corrected for serial correlation. R^2 is adjusted for the degree of freedom before averaging across weekly regressions.

Earnings forecast dispersion	Amihud	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
High	High	1.75 (9.54)	11.91 (22.72)	-1.52 (-7.08)	1.33 (11.23)	-0.52 (-3.18)	0.07 (18.28)	0.09 (8.27)	-1.09 (-4.40)	0.42
	Medium	0.98 (6.85)	3.93 (38.90)	-0.51 (-6.77)	2.01 (22.57)	-0.25 (-4.95)	0.13 (36.85)	0.06 (8.42)	-1.50 (-9.86)	0.36
	Low	0.97 (6.30)	1.94 (25.59)	-0.43 (-7.33)	1.98 (15.77)	0.31 (4.92)	0.11 (25.59)	0.05 (3.27)	-1.87 (-8.49)	0.38
Medium	High	1.75 (17.37)	8.99 (42.34)	-0.40 (-5.67)	1.23 (14.78)	-0.22 (-2.30)	0.08 (34.25)	0.07 (12.94)	-1.38 (-8.62)	0.29
	Medium	0.80 (16.91)	3.85 (66.34)	-0.23 (-8.74)	1.34 (24.09)	-0.02 (-0.53)	0.09 (52.79)	0.04 (11.96)	-0.84 (-9.60)	0.28
	Low	0.36 (5.86)	2.15 (38.44)	-0.18 (-11.13)	0.99 (20.33)	0.26 (8.21)	0.07 (42.51)	0.01 (1.52)	-0.05 (-0.52)	0.30
Low	High	2.25 (14.97)	8.20 (27.50)	-0.80 (-7.90)	0.99 9.83	-0.69 -6.23	0.08 25.12	0.09 11.87	-1.96 -8.40	0.40
	Medium	1.27 (20.49)	3.84 (53.06)	-0.33 (-10.93)	0.73 (13.33)	-0.13 (-3.63)	0.11 (50.97)	0.05 (13.57)	-1.42 (-10.79)	0.35
	Low	1.28 (14.79)	1.78 (38.12)	-0.16 (-8.53)	0.37 (6.95)	0.30 (9.69)	0.07 (36.45)	0.00 (0.19)	-0.97 (-8.29)	0.36

Table 6. Controls for Credit Risk and Liquidity Effects

This table reports weekly regression results for subsamples sorted by credit risk and the Amihud bond illiquidity measure into quartiles for the period from October 2004 to June 2007. The medium group includes the middle 50% of the sorting. The dependent variable (VOL_{it}) is the range-based price volatility (*RVOL*). Variables and parameters are defined as in Table 2. For each regression, we report average coefficient estimates from weekly cross-sectional regressions and Fama-MacBeth (FM) *t*-statistics (in parentheses) corrected for serial correlation. R^2 is adjusted for the degree of freedom before averaging across weekly regressions.

Rating	Amihud	α_0	*NT*	*ATS*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
AAA/AA	High	1.99	9.04	-3.43	-0.04	-0.26	0.08	0.03	-1.63	0.25
		(22.09)	(48.93)	(-5.71)	(-0.25)	(-2.06)	(37.71)	(5.85)	(-11.45)	
	Medium	1.18	3.31	-0.23	-0.44	-0.11	0.09	0.02	-0.36	0.29
		(31.18)	(51.24)	(-4.56)	(-5.21)	(-3.73)	(50.97)	(5.58)	(-5.89)	
	Low	0.17	1.59	-0.12	0.62	0.09	0.08	0.01	0.77	0.42
		(3.09)	(41.88)	(-6.56)	(5.84)	(5.80)	(34.17)	(1.62)	(9.49)	
A	High	0.11	11.88	-0.54	3.33	-1.61	0.09	0.03	-1.09	0.27
		(0.73)	(38.96)	(-4.09)	(13.70)	(-16.03)	(53.10)	(4.47)	(-7.58)	
	Medium	0.28	3.84	-0.24	2.22	-0.51	0.10	0.03	-0.91	0.30
		(4.30)	(70.07)	(-8.69)	(19.65)	(-14.48)	(84.65)	(7.79)	(-10.53)	
	Low	-0.03	1.82	-0.21	1.33	0.29	0.07	0.02	-0.14	0.36
		(-0.53)	(38.91)	(-11.25)	(10.90)	(15.25)	(42.00)	(5.30)	(-1.84)	
BBB	High	1.05	10.29	-0.39	1.46	-1.86	0.08	0.02	-0.53	0.26
		(6.01)	(42.05)	(-5.88)	(7.53)	(-16.93)	(30.45)	(3.73)	(-3.07)	
	Medium	0.60	4.64	-0.28	1.26	-0.62	0.09	0.03	-0.81	0.34
		(5.92)	(57.43)	(-10.39)	(10.16)	(-12.47)	(45.26)	(6.73)	(-7.78)	
	Low	-0.11	2.61	-0.15	1.24	0.23	0.06	0.02	-0.32	0.36
		(-1.08)	(25.68)	(-9.70)	(9.53)	(7.29)	(36.74)	(4.82)	(-3.40)	
Junk	High	0.40	12.14	-2.98	1.16	-1.20	0.11	-0.01	0.49	0.27
		(2.22)	(33.26)	(-10.39)	(12.52)	(-7.94)	(30.44)	(-2.01)	(3.38)	
	Medium	-0.07	5.36	-0.47	1.62	-0.76	0.10	0.04	-0.60	0.31
		(-0.67)	(48.61)	(-5.63)	(23.25)	(-8.12)	(39.36)	(10.01)	(-8.23)	
	Low	-0.87	3.75	-0.51	1.70	0.10	0.08	0.05	-0.83	0.36
		(-6.05)	(23.25)	(-10.16)	(20.97)	(1.41)	(22.82)	(7.70)	(-9.00)	

Table 7. Regression Results for Normal and Crisis Periods

This table reports the weekly regression results for the normal and financial crisis periods. For each week, we run the cross-sectional regression $VOL_{it} = \alpha_0 + \sum_{j=1}^{p} \alpha_j TA_{it,j} + \sum_{k=1}^{q} \beta_k CV_{it,k} + \varepsilon_{it}$ The dependent variable (VOL_{it}) is bond price volatility, measured by the range-based approach (*RVOL*); α_0 is the intercept; TA_{it} are trading variables of bonds, such as number of transactions (*NT*), average trade size (*ATS*) and trading volume (*V*), respectively; and CV_{it} represents corporate bond characteristic variables such as coupon, maturity, issue amount, age and the rating. To investigate the impacts of each trading variable and different combinations of variables, we run five separate regressions. For each regression, we report average coefficient estimates from weekly cross-sectional regressions and Fama-MacBeth (FM) *t*-statistics (in parentheses), adjusted for the effect of serial correlation. R^2 statistics are adjusted for the degree of freedom before averaging across weekly regressions.

Panel A: The normal period (October 2004—June 2007, January 2010—June 2012)

α_0	*NT*	*ATS*	*V*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
0.68	3.62			1.63	-1.01	0.11	0.06	-1.00	0.18
(24.09)	(38.37)			(43.66)	(-20.80)	(83.36)	(3.73)	(-18.59)	
1.01			6.63	1.79	0.00	0.10	0.08	-0.99	0.10
(29.87)			(3.30)	(43.35)	(-0.13)	(81.53)	(40.89)	(-18.35)	
1.27		-1.36		1.86	0.69	0.11	0.05	-1.10	0.12
(39.73)		(-44.74)		(45.24)	(30.52)	(85.21)	(22.09)	(-21.18)	
0.83	3.38	-0.76		1.68	-0.71	0.11	0.05	-1.04	0.19
(28.07)	(37.99)	(-40.85)		(45.31)	(-16.99)	(85.70)	(27.23)	(-19.64)	
0.70	3.84		-0.39	1.65	-0.83	0.11	0.06	-1.03	0.19
(25.05)	(38.87)		(-0.23)	(44.08)	(-18.28)	(85.14)	(29.47)	(-19.21)	

Panel B: The financial crisis period (July 2007—December 2009)

α_0	*NT*	*ATS*	*V*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
1.44	6.03			6.34	-0.97	0.18	0.12	-4.93	0.15
(10.52)	(16.28)			(11.88)	(-11.59)	(26.24)	(15.63)	(-9.09)	
1.97			5.13	6.07	0.20	0.16	0.15	-4.50	0.10
(12.73)			(6.18)	(11.75)	(2.55)	(26.31)	(17.15)	(-8.50)	
2.55		-2.02		6.19	1.18	0.17	0.09	-4.67	0.12
(13.29)		(-17.76)		(11.79)	(10.96)	(27.14)	(11.33)	(-8.54)	
1.80	5.54	-1.34		6.39	-0.48	0.18	0.09	-4.99	0.16
(12.12)	(14.76)	(-13.74)		(11.89)	(-5.12)	(26.58)	(12.53)	(-9.13)	
1.47	6.28		-2.02	6.34	-0.82	0.18	0.11	-4.91	0.15
(10.76)	(18.44)		(-4.51)	(11.90)	(-8.88)	(26.64)	(14.20)	(-9.10)	

Table 8. Regressions by Liquidity Proxy in Normal and Crisis Periods

This table reports weekly regression results for subsamples sorted by each liquidity proxy into quartiles for the normal period and financial crisis period. The dependent variable is price volatility based on the range estimator. Liquidity proxies are volume, trade size, age, issue size, and the Amihud measure. Regression results by these proxies are reported in Panels A to E, respectively. Variables and parameters are defined as in Table 2. For each regression, we report average coefficient estimates from weekly cross-sectional regressions and Fama-MacBeth (FM) *t*-statistics (in parentheses), adjusted for the effect of serial correlation. R^2 is adjusted for the degree of freedom before averaging across weekly regressions.

Panel A: by volume

	Normal Period					*Financial Crisis Period*				
Subsample	α_0	*NT*	*ATS*	*Control*	R^2	α_0	*NT*	*ATS*	*Control*	R^2
High 25%	0.11	1.88	-0.61	Yes	0.23	0.85	2.64	-0.78	Yes	0.16
	(1.47)	(31.08)	(-22.09)			(2.76)	(14.06)	(-13.47)		
Middle 50%	0.96	4.68	-2.77	Yes	0.25	1.97	8.63	-6.00	Yes	0.20
	(30.05)	(40.98)	(-44.58)			(14.24)	(20.74)	(-17.29)		
Low 25%	0.30	16.19	-14.56	Yes	0.20	-0.39	52.04	-20.58	Yes	0.22
	(6.46)	(60.08)	(-16.41)			(-2.73)	(18.95)	(-6.38)		

Panel B: by trade size

	Normal Period					*Financial Crisis Period*				
Subsample	α_0	*NT*	*ATS*	*Control*	R^2	α_0	*NT*	*ATS*	*Control*	R^2
High 25%	-0.11	3.75	-0.26	Yes	0.20	-0.36	8.27	-0.11	Yes	0.15
	(-2.18)	(38.81)	(-16.72)			(-2.07)	(13.87)	(-2.92)		
Middle 50%	0.80	2.76	-2.38	Yes	0.22	1.74	4.11	-6.92	Yes	0.17
	(22.92)	(33.39)	(-13.99)			(11.41)	(15.82)	(-11.76)		
Low 25%	0.81	9.01	-35.02	Yes	0.25	0.79	24.41	-23.69	Yes	0.24
	(11.62)	(48.48)	(-11.49)			(5.01)	(22.07)	(-3.01)		

Panel C: by age

	Normal Period					*Financial Crisis Period*				
Subsample	α_0	*NT*	*ATS*	*Control*	R^2	α_0	*NT*	*ATS*	*Control*	R^2
Age $\leq$ 3	-0.17	1.66	-0.15	Yes	0.24	0.80	2.12	-0.13	Yes	0.25
	(-2.16)	(24.31)	(-9.04)			(2.31)	(13.82)	(-2.67)		
Low 25%	0.44	3.02	-0.72	Yes	0.23	0.73	4.13	-1.05	Yes	0.15
	(8.66)	(31.70)	(-30.02)			(5.17)	(14.80)	(-9.34)		
Middle 50%	1.01	3.37	-0.80	Yes	0.20	1.11	6.79	-1.70	Yes	0.16
	(24.27)	(39.22)	(-36.34)			(4.01)	(13.06)	(-12.03)		
High 25%	0.90	3.69	-0.82	Yes	0.25	2.71	5.83	-1.23	Yes	0.23
	(14.03)	(39.75)	(-21.15)			(10.94)	(19.46)	(-11.41)		

Panel D: by issue size

	Normal Period					*Financial Crisis Period*				
Subsample	α_0	*NT*	*ATS*	*Control*	R^2	α_0	*NT*	*ATS*	*Control*	R^2
High 25%	0.67	1.72	-0.72	Yes	0.26	1.62	2.77	-1.07	Yes	0.19
	(14.65)	(42.56)	(-23.59)			(5.55)	(15.77)	(-10.82)		
Middle 50%	0.71	5.45	-0.63	Yes	0.23	1.37	11.29	-0.87	Yes	0.18
	(16.01)	(33.05)	(-37.54)			(8.80)	(13.91)	(-13.06)		
Low 25%	0.42	9.56	-2.20	Yes	0.22	-1.43	32.72	-4.78	Yes	0.27
	(6.64)	(52.26)	(-4.71)			(-5.52)	(14.10)	(-2.75)		

Panel E: by the Amihud measure

	Normal Period					*Financial Crisis Period*				
Subsample	α_0	*NT*	*ATS*	*Control*	R^2	α_0	*NT*	*ATS*	*Control*	R^2
High 25%	1.09	11.97	-0.74	Yes	0.25	1.93	21.18	-1.07	Yes	0.21
	(19.08)	(46.11)	(-17.16)			(14.97)	(19.61)	(-7.23)		
Middle 50%	0.68	4.77	-0.27	Yes	0.30	1.26	5.46	-0.68	Yes	0.20
	(27.87)	(58.87)	(-11.60)			(17.65)	(18.98)	(-5.33)		
Low 25%	-0.01	2.35	-0.21	Yes	0.30	0.73	2.99	-0.36	Yes	0.20
	(-0.18)	(39.80)	(-12.64)			(6.44)	(20.31)	(-7.12)		

Table 9. Interactive Effects of Liquidity and Credit Risk on the Volatility-Trading Relation

This table reports estimates of the effects of liquidity and credit risk on the relation between volatility and trading variables. Weekly regression results by liquidity proxy are reported for the normal and crisis periods. The liquidity proxies are volume, trade size, age, issue size and the Amihud measure. *DL*, *DR* and *DLR* denote the dummy coefficients of liquidity, rating and the interaction of these two factors, respectively, as given in equation (3), and other variables and parameters are as defined in Table 2. Bond characteristic variables are used as controls in each regression. We report average coefficient estimates and Fama-MacBeth (FM) *t*-statistics (in parentheses), adjusted for the effect of autocorrelation. Tests of the differences in coefficients between the normal and crisis periods (*t*-statistics in parentheses) are reported in row 3. R^2 statistics are adjusted for the degree of freedom before averaging across weekly regressions.

Subsample	α_0	*NT*	*ATS*	*DLNT*	*DLATS*	*DRNT*	*DRATS*	*DLRNT*	*DLRATS*	*Issue*	*Age*	*Maturity*	*Rating*	*Coupon*	R^2
Panel A: by volume															
Normal	0.72	2.31	-0.42	7.74	-19.62	2.14	-0.24	4.20	-45.91	-1.59	0.04	0.10	1.33	-0.86	0.23
	(17.63)	(45.97)	(-21.41)	(29.99)	(-21.18)	(18.97)	(-4.61)	(6.84)	(-12.88)	(-6.85)	(15.53)	(74.33)	(25.78)	(-14.89)	
Crisis	2.14	3.62	-0.55	22.40	-42.87	8.21	-0.57	26.20	-74.79	0.48	0.02	0.15	4.93	-4.32	0.19
	(7.51)	(15.57)	(-7.38)	(17.10)	(-15.79)	(7.26)	(-2.60)	(5.02)	(-6.71)	(0.49)	(3.43)	(25.01)	(12.26)	(-7.04)	
Difference	1.42	1.31	-0.14	14.66	-23.25	6.07	-0.32	22.00	-28.89	2.07	-0.01	0.05	3.60	-3.46	
	(4.93)	(5.51)	(-1.79)	(10.98)	(-8.10)	(5.34)	(-1.44)	(4.19)	(-2.47)	(2.06)	(-1.96)	(8.23)	(8.88)	(-5.62)	
Panel B: by trade size															
Normal	0.76	3.40	-0.45	1.67	25.40	2.91	-0.77	1.55	-38.38	-3.39	0.05	0.10	1.05	-0.96	0.24
	(19.90)	(50.96)	(-26.92)	(16.24)	(14.46)	(15.86)	(-14.15)	(3.72)	(-5.75)	(-14.04)	(15.36)	(79.36)	(18.78)	(-15.18)	
Crisis	1.51	7.75	-0.39	2.70	77.43	8.38	-1.29	10.31	41.93	-5.02	0.06	0.16	4.34	-4.13	0.21
	(8.43)	(18.91)	(-6.69)	(8.23)	(10.36)	(7.92)	(-5.91)	(5.45)	(2.05)	(-6.21)	(9.14)	(24.03)	(11.56)	(-8.40)	
Difference	0.75	4.35	0.05	1.03	52.03	5.47	-0.52	8.76	80.31	-1.63	0.01	0.06	3.29	-3.17	
	(4.10)	(10.48)	(0.86)	(3.00)	(6.78)	(5.09)	(-2.31)	(4.52)	(3.74)	(-1.93)	(1.62)	(8.92)	(8.66)	(-6.39)	
Panel C: by age															
Normal	1.18	2.37	-0.70	0.24	-0.08	1.97	-0.94	0.74	0.10	-5.80	0.03	0.11	1.27	-0.97	0.21
	(38.71)	(55.15)	(-40.90)	(5.64)	(-3.27)	(20.27)	(-17.58)	(5.94)	(0.78)	(-15.72)	(9.02)	(85.49)	(34.74)	(-17.41)	
Crisis	2.31	3.61	-0.88	0.36	-0.38	9.29	-3.07	-0.48	1.07	-5.21	0.10	0.18	5.40	-4.61	0.18
	(10.67)	(23.66)	(-11.27)	(4.90)	(-6.73)	(7.14)	(-10.25)	(-0.56)	(2.92)	(-6.43)	(12.92)	(27.90)	(12.13)	(-8.85)	
Difference	1.13	1.24	-0.18	0.12	-0.30	7.31	-2.14	-1.21	0.97	0.59	0.07	0.06	4.13	-3.64	
	(5.16)	(7.79)	(-2.29)	(2.40)	(-4.95)	(5.61)	(-7.02)	(-1.41)	(2.49)	(0.67)	(7.85)	(9.93)	(9.24)	(-6.95)	
Panel D: by issue size															
Normal	0.84	1.93	-0.70	4.47	0.47	1.80	-0.88	-1.62	-2.75	0.72	0.06	0.11	1.37	-1.18	0.23
	(23.52)	(50.92)	(-27.89)	(27.05)	(2.87)	(16.50)	(-10.76)	(-3.77)	(-2.69)	(2.95)	(17.87)	(74.33)	(28.89)	(-19.22)	
Crisis	1.77	3.02	-1.06	11.08	-0.04	6.83	-1.37	37.44	-11.85	4.05	0.04	0.18	4.96	-3.40	0.23
	(7.28)	(15.80)	(-9.87)	(12.17)	(-0.19)	(6.70)	(-3.67)	(6.57)	(-3.02)	(3.90)	(2.39)	(26.66)	(12.92)	(-7.57)	
Difference	0.94	1.09	-0.35	6.61	-0.51	5.03	-0.49	39.06	-9.11	3.33	-0.02	0.06	3.59	-2.22	
	(3.81)	(5.59)	(-3.19)	(7.14)	(-1.88)	(4.91)	(-1.28)	(6.83)	(-2.25)	(3.12)	(-0.88)	(9.40)	(9.28)	(-4.90)	
Panel E: by the Amihud measure															
Normal	0.61	1.03	-0.20	5.18	-0.45	4.65	-0.17	0.25	-0.73	-0.50	0.03	0.05	0.28	-0.67	0.30
	(27.11)	(51.24)	(-33.01)	(47.15)	(-12.23)	(16.38)	(-13.82)	(1.78)	(-6.27)	(-3.46)	(20.48)	(87.55)	(18.37)	(-2.28)	
Crisis	1.40	1.17	-0.33	6.66	-0.69	8.57	-0.26	0.96	-0.44	0.48	0.04	0.06	0.48	-3.09	0.23
	(21.48)	(22.04)	(-16.36)	(29.08)	(-11.11)	(9.40)	(-5.91)	(3.18)	(-2.84)	(1.82)	(16.35)	(47.96)	(11.17)	(-4.31)	
Difference	0.79	0.15	-0.14	1.48	-0.24	3.92	-0.09	0.71	0.29	0.98	0.01	0.00	0.20	-2.42	
	(11.40)	(2.51)	(-6.11)	(5.81)	(-3.34)	(41.07)	(-1.85)	(2.11)	(1.47)	(32.54)	(2.69)	(1.58)	(4.40)	(-31.17)	

Table 10. Robustness Tests

Panels A and B report the results of pooled regressions with and without control for issuer fixed effects. Panel C reports results of regressions that include the hours between maximum and minimum transaction prices in each week. Panel D reports results for the December-only and non-December subsamples to assess the potential effect of tax-loss selling. The variables are as defined in Table 2. The *t*-statistics in parentheses are corrected for autocorrelation and the adjusted R^2 is reported.

Panel A. Pooled regressions with control for issuer fixed effects

NT	*ATS*	*V*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
3.59			4.38	-0.66	0.13	0.01	-3.52	0.13
(159.13)			(140.86)	(-2.91)	(121.86)	(0.19)	(-6.11)	
		3.32	4.50	0.88	0.11	0.03	-2.50	0.11
		(48.92)	(143.78)	(39.71)	(105.98)	(11.32)	(-4.32)	
	-1.25		4.51	1.26	0.12	-0.02	-3.31	0.11
	(-57.93)		(144.14)	(59.23)	(113.04)	(-7.17)	(-3.06)	
3.40	-0.83		4.40	0.21	0.13	-0.02	-4.87	0.13
(153.61)	(-40.63)		(141.42)	(0.72)	(124.99)	(-7.28)	(-8.44)	
3.75		-1.55	4.38	-0.38	0.13	-0.01	-3.66	0.13
(151.49)		(-7.17)	(140.75)	(-1.67)	(122.06)	(-1.08)	(-6.36)	

Panel B. Pooled regressions without control for issuer fixed effects

NT	*ATS*	*V*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	R^2
3.78			3.53	-0.80	0.14	0.03	-2.50	0.06
(206.27)			(225.44)	(-56.94)	(162.81)	(14.29)	(-59.12)	
		3.20	3.54	0.32	0.12	0.06	-2.38	0.04
		(44.48)	(223.32)	(21.99)	(145.46)	(27.65)	(-55.83)	
	-1.37		3.59	0.99	0.13	0.01	-2.42	0.05
	(-114.19)		(227.23)	(77.84)	(156.86)	(2.75)	(-56.81)	
3.50	-0.92		3.56	-0.46	0.14	0.00	-2.52	0.07
(187.56)	(-76.14)		(227.68)	(-31.07)	(167.94)	(2.38)	(-59.70)	
3.94		-1.84	3.53	-0.68	0.14	0.02	-2.49	0.06
(202.81)		(-24.45)	(225.72)	(-45.07)	(164.16)	(9.77)	(-59.12)	

Panel C. The effect of time between maximum and minimum prices

Intercept	*NT*	*ATS*	*V*	*Rating*	*Amount*	*Maturity*	*Age*	*Coupon*	*Hours*	R^2
0.92	2.16			3.05	-0.58	0.10	0.08	-1.85	0.13	0.15
(23.33)	(35.60)			(16.28)	(-15.64)	(50.11)	(27.17)	(-13.01)	(22.03)	
0.99			3.72	3.06	0.07	0.10	0.09	-1.78	0.15	0.11
(24.74)			(3.73)	(16.70)	(2.73)	(50.40)	(31.40)	(-12.72)	(23.70)	
1.25		-0.99		3.12	0.54	0.11	0.07	-1.88	0.15	0.12
(29.31)		(-38.19)		(17.00)	(20.58)	(52.85)	(24.32)	(-13.23)	(24.26)	
1.10	2.04	-0.76		3.10	-0.37	0.11	0.07	-1.90	0.13	0.16
(27.34)	(34.14)	(-33.49)		(16.49)	(-10.06)	(50.50)	(24.51)	(-13.32)	(22.73)	
0.92	2.24		0.25	3.05	-0.52	0.10	0.08	-1.85	0.13	0.16
(23.97)	(36.92)		(0.31)	(16.34)	(-14.20)	(50.72)	(25.63)	(-13.13)	(22.12)	

Panel D. Tax-loss selling effects

	Intercept	*NT*	*ATS*	*V*	*Rating*	*Amount*	*Maturit*	*Age*	*Coupon*	*Hours*	R^2
December Only	0.51	2.65			4.99	-0.56	0.13	0.07	-2.85	0.15	0.16
	(3.52)	(12.68)			(4.19)	(-4.11)	(10.16)	(7.15)	(-3.71)	(5.08)	
	0.61			3.31	5.03	0.16	0.12	0.09	-2.78	0.17	0.11
	(4.22)			(5.33)	(4.29)	(1.54)	(10.48)	(8.50)	(-3.71)	(5.53)	
	0.88		-0.86		5.05	0.59	0.13	0.07	-2.91	0.16	0.12
	(6.84)		(-7.12)		(4.32)	(5.26)	(10.75)	(7.83)	(-3.77)	(5.53)	
	0.66	2.56	-0.62		5.02	-0.40	0.13	0.06	-2.91	0.14	0.16
	(4.69)	(12.05)	(-5.50)		(4.21)	(-2.87)	(10.26)	(6.95)	(-3.74)	(5.04)	
	0.50	2.72		-0.80	4.99	-0.53	0.13	0.07	-2.84	0.15	0.16
	(3.39)	(13.24)		(-1.45)	(4.19)	(-3.97)	(10.35)	(6.77)	(-3.74)	(5.07)	
Non-December	0.96	2.11			2.88	-0.57	0.10	0.08	-1.75	0.13	0.15
	(22.59)	(33.52)			(16.53)	(-14.56)	(49.39)	(25.60)	(-12.82)	(21.00)	
	1.03			3.76	2.88	0.06	0.10	0.09	-1.68	0.15	0.11
	(24.05)			(3.46)	(17.18)	(2.21)	(50.73)	(29.24)	(-12.48)	(22.58)	
	1.28		-1.00		2.94	0.54	0.10	0.07	-1.76	0.15	0.12
	(28.30)		(-37.47)		(17.48)	(19.36)	(53.06)	(22.88)	(-13.33)	(23.10)	
	1.14	1.99	-0.77		2.93	-0.37	0.11	0.07	-1.79	0.13	0.16
	(26.27)	(32.15)	(-33.08)		(16.69)	(-9.53)	(49.91)	(23.16)	(-13.34)	(21.66)	
	0.96	2.19		0.35	2.87	-0.52	0.10	0.08	-1.76	0.13	0.16
	(23.47)	(34.73)		(0.40)	(16.81)	(-12.97)	(50.24)	(24.29)	(-12.95)	(21.08)	