The Subprime Crisis and the Efficiency of the Junk Bond Market: Evidence from the Microstructure Theory

Abstract

This paper examines the joint dynamics of volume and volatility in the high-yield corporate bond market during the subprime financial crisis that hit the financial markets in 2007-2008. Using the trading volume information as a proxy for changes in the information set available to investors when financial crises occur, we investigate the impact of the subprime crisis on the informational efficiency of the corporate bond market. There are two main findings of the study. First, the estimates of the GJR-GARCH model show that it provides a better description of volatility dynamics during the crisis period compared to the before crisis period, indicating the presence of the leverage effect during the financial crisis. Second, the results of VAR and 2SLS estimates show that 2007-2008 crisis does not have an impact on the informational efficiency of the junk bond market at least from the perspective of the market microstructure theory.

1. Introduction

Financial crises occur frequently as evidenced by at least one severe global financial crisis per recent decade – the 1987 stock market crash, the 1997 Asian financial crisis, and the 2007 credit meltdown. The recurring occurrence of financial crises during the last few decades motivated three strands of literature on the financial crises. One strand investigates the crisis transmission in terms of how financial crises lead to comovements among the international stock markets (e.g., Gerlach, Wilson, and Zurbruegg, 2006). The second strand examines the reasons behind the occurrence of the financial crises (e.g., Summers, 2000). The third category focuses on the relation between crises and market efficiency (e.g., Lim, Brooks, and Kim, 2008).

Our research interests in this study fall in the latter category. After the onset of the 2007-2008 financial crisis, there has been a debate in the finance circles on the role of the efficient market hypothesis (EMH) in the occurrences of financial crises. On one hand, financial crises can be viewed as an evidence of the failure of the efficient market hypothesis, since market should have predicted the crisis if it is efficient. On the other hand, others defend the EMH based on the argument that bubbles were present in the economic history before the evolution of the market efficiency concept in 1970s, such as the 1637 Dutch tulip, the Railway Mania in the 1840s, and the Florida Land bubble in 1926 (e.g., Ball 2009). This debate motivates my research question in this study. Specifically, my main goal is to better understand this debate by examining the impact of the recent financial crisis on the market efficiency of the high-yield (Junk) corporate bond market, an issue that is understudied in the literature.

The contribution of this study is twofold. First, to the best of our knowledge, this study fills a gap in the literature since it is the first one that examines the impact of financial crises on the informational efficiency of financial markets using data from the fixed income market. The importance of investigating the junk bond market in particular stems from the unique association between trading in the high-yield corporate bond market and financial crises. Risk-averse investors rush for quality and liquidity during the bad states of economy. As a result, they tend to replace risky securities with less risky securities during financial crises. A striking example that supports the association between crises and trading in junk bonds is the collapse of Long-Term Capital Management (LTCM). When the fear spread all over the world in August 1998 because of the Asian crisis, the spread between US B-rated bonds and high-rated corporate bonds rose from 2 percentage points before the crisis to 5.7 percentage points. This wide spread led to the collapse of the LTCM by September 1998.

The second contribution is the empirical methodology which we propose in this study. Our objective is to examine the impact of the financial crisis on the market efficiency within the context of the market microstructure theory (price-volume models). However, the empirical examination of the volume-volatility relation suffers from three main methodological problems – truncation of volume data[1], heteroscedasticity of return data, and the endogenity between volume and return variables. We propose a three-step procedure that is free from these three problems.

[1] The problem with using TRACE data is that trade size information is not reported completely, since the volume information reported by TRACE for junk bonds is truncated at one million dollars (1MM+). As a result, bond trading volume data is censored and has a truncated distribution.

First, we examine the reaction of the average daily trading volume of the junk bonds to the financial crisis, using the censored regression model that is well suited for truncated data. Second, we investigate the impact the crisis had on the junk bond return volatility, using the asymmetric Sign-GARCH model of Glosten, Jagannathan and Runkle (1993) (GJR-GARCH model) to account for the leverage effect, a well-known phenomena in the literature which refers to the asymmetric response of the return volatility series to bad and good news. Finally, we use the fitted values of volume and volatility from the estimated censored regression model and GJR-GARCH, respectively, to estimate the volume-volatility relation using two-stage least square (2SLS) methodology. By comparing the estimated volume coefficients before and during the crisis, we can examine the impact of the crisis on the market efficiency of the junk bond market. If lagged volume has no power in forecasting volatility during the crisis, but had such predictive power before the crisis, this would suggest that the crisis increased the efficiency of the junk bond market, and vice versa.

The remainder of the article is organized as follows: literature review is discussed in section two. Section three presents the methodology. Section four discusses data issues. Section five presents the empirical results. Section six concludes.

2. Literature Review

Our work links three strands of finance literature – financial crises, market microstructure, and market efficiency. In this section, we will discuss first the literature on the impact of financial crises on market microstructure and investors' trading behavior. Next, we will present the literature on relation between one of the major categories of market microstructure theory (the price – volume models) and the efficient market hypothesis. Finally, we discuss the literature on the relation between financial crises and market efficiency. Our intuition for linking the three strands of literature can be shown in the following figure:

2.1. Financial Crises and Market Microstructure

The market microstructure theory examines how information is incorporated into security market prices through trading activities. The literature on the market microstructure theory can be classified into six major categories: bid-ask spread models, price-volume models, price formation models, market structure models, non-stock market microstructure models, and optimal security market regulation models. Our interest here is in the 'Bid-Ask Models', through which we can understand the role of trading volume information in financial markets. Following the literature, the quoted bid-ask spread consists of three-components: order processing costs component, inventory control component, and adverse selection component. The latter component is the one of interest here and it is designed to compensate 'uninformed' market participants for the risk of trading with better 'informed' investors.

2.1.1. Role of Trading Information in Financial Markets: Adverse Selection Theory

The adverse selection theory introduces two components for the trading volume information – informational and liquidity components. In fact, equilibrium in financial market looks like a game between informed traders and liquidity suppliers (Kyle, 1985).

Under the ‘informational trading’ view, information is the main motive for investors to trade in the financial securities, and any increase in the trading volume is a signal of informational trading which means that there is new information reached the market. In most of the time, ‘uniformed’ traders as a group will lose money by trading against the informed investors’ private information. Consequently, uniformed investors will widen the bid-ask spread to make some money (Easely and O’hara, 1992). Alternatively, the primary trading motive for ‘liquidity or non-informational trading’ is demand for liquidity. Harris and Raviv (1993) develop a model of trading in speculative markets based on differences of opinion such that all traders receive the same public information and agree on whether it is favorable or not. However, they differ in the way in which they interpret this information regarding whether such information is important.

One of the major limitations of the EMH is that it ignores liquidity trading since it assumes continuous trading (Ball, 2009), although several studies (e.g., Chen, Lesmond, and Wei, 2007) find that liquidity is priced in corporate yield spreads. The logic for liquidity trading is that ‘uniformed’ traders will know that ‘informed’ traders have their own private information, and will therefore realize that it is not worth to trade against them. The result will be little or no trading. Liquidity trading, therefore, provides the essential missing ingredient for the existence of liquid markets.

2.1.2. Trading Behavior during Financial Crises

The above discussion explains the role of trading volume information in financial markets in general. In a normal market, investors are interested mainly in collecting fundamental information such as future investment opportunities and dividends. As the financial market shifts from normal environment to crash environment, investors' trading motive also shifts from informational trading to liquidity trading. One of the major troubling aspects of financial crashes is the drying up of supply (Bookstaber, 1999). This can be seen during the 1987 equity market crash, the 1991 junk bond crisis, the LTCM collapse, and the 2008 subprime crisis, since illiquidity was an extremely key feature in all of these crises (Ball, 2009). In addition, Dick-Nielsen, Feldhutter, and Lando (2011) find that illiquidity in corporate bond market had little contribution to the corporate bond spread before the subprime crisis, but the lack of liquidity was the key factor in widening the spreads during the crisis period compared to the credit risk component of the spread.

2.2. The Market Microstructure Theory and the Efficient Market Hypothesis

2.2.1. Price - Volume Models

There is a substantial literature that examines the joint dynamics of the volume-volatility relation, inspired by the market axiom that says *"it makes volume to make prices move"*. The literature on the volatility-volume relation can be categorized into information theories (such as the sequential information arrival hypothesis 'SEQ' (e.g., Copeland, 1976; Jennings et al., 1981; and Jennings and Bary, 1983) and the mixture of distributions hypothesis 'MDH' (e.g., Clark, 1973)); and noise theories such as the dispersion of beliefs theory (e.g., Harris and Raviv, 1993; and Shalen, 1993).

The main assumption of the SEQ models is the gradual arrival of new information to the market (i.e., the new information flows which hit the market are transmitted to investors one at a time rather than disseminated to all investors at the same time). Such sequential flow of information leads to a sequence of intermediate equilibriums until the final equilibrium is reached. In particular, the first informed trader revises his beliefs and then starts trading and the market reaches a temporary equilibrium. Once the second investor becomes informed, he alters his beliefs and retrades and the security market reaches another temporary equilibrium, and so on. Such process continues until the last trader in the market receives the information, and the final complete equilibrium occurs. Due to such sequential flow of information resulting from the asymmetric information among investors, numerous authors predicted a bi-directional causality between trading volume and return volatility of securities. Copeland (1976) stands out as one among the first studies that establish such relation under the assumption of using trading volume as a proxy for the rate of information arrival in the market. In particular, the arrival of new information to the market leads to an upward (downward) shift in the demand curve of each optimistic (pessimistic) trader by the same amount, since he assumes that the short sales is prohibited. Jennings et al. (1981) relaxed such assumption, by examining the impact of the differential cost of short sales - as a realistic restriction on short sales - on the relation between price and volume. The key innovation is that the model predicts non-perfect positive correlation between price change and volume depending on the ordering of optimists and pessimists, and the maximum volume occurs near the point of maximum disagreement. Jennings and Barry (1983) provide another extension to Copeland's model through permitting '*Speculation*' by the informed traders. They argue that investors who are informed early in the information dissemination sequence will take large speculations, which leads to a large price change and volume reaction. In contrast, those who are late in the information process take small speculative position, leading to a weak price change and volume reaction. As a result, they find a positive contemporaneous correlation between price change and volume. To sum up, the SEQ suggests a positive causal relationship running from absolute returns to trading volume and vice versa).

The sequential information hypothesis discussed above assumes that information is the only motive for trading in the financial securities. However, the price of a security reflects both the information that information traders trade on and the noise that noise traders trade on. The ‘Dispersion of Beliefs Theory’ represents another strand of literature which examines the implication of the noise trading models (e.g., Delong et al., 1990) for the volume-volatility relation. The key message from this theory is that current trading volume should dictate the intensity of future return volatility. The main idea behind such prediction is based on the assumption that traders' behavior in the market is heterogeneous, given that such disagreement among traders can arise either because traders simply interpret commonly known data differently or because they have different private information.

Harris and Raviv (1993) adopt the first approach, while Shalen (1993) investigated the second approach. Harris and Raviv (1993) develop a model of trading in speculative markets based on differences of opinion so that all traders receive the same public information and agree on whether it is favorable or not. However, they differ in the way in which they interpret this information regarding whether such information is important. They further showed that price changes are also related to changes in speculator's beliefs, and such result can be extended to forecasts. Shalen (1993) develop another version of the dispersion of beliefs models but the disagreement among traders arises because they have different private information. In his model, the hedging demand is the source of noise that prevents equilibrium prices from revealing private information, so that speculators are unable to isolate the influence of the unknown hedging demand from that of private information. He shows that the possible source of positive association between volatility and both cotemporaneous and lagged volume is the uninformed traders' dispersion of beliefs. Both models of Harris and Raviv and Shalen demonstrate that heterogeneous beliefs lead to trading only when agents' beliefs change its sign. Yan and Xiong (2010) extend such result by showing that even without agents' beliefs flipping the wealth fluctuation caused by their speculative positions will lead to trading in the bond market, and also amplifies bond yield volatility.

2.2.2. Price-Volume Models and EMH

The theory of random walk says that successive price changes are independent and occur randomly. Most of the early work related to efficient capital markets was based on the random walk hypothesis. In its weak form, the Efficient Market Hypothesis (EMH) implies that security prices adjust rapidly to the arrival of new information and, therefore, the current price of security fully reflect all historical information. If market is efficient, then it should not be possible to profit by trading on the information contained in the asset's price history. Conversely, the technical approach to investment is essentially a reflection of the idea that stock prices move in trends of hopes, fears, knowledge, optimism and pessimism. Such trends persist for long periods because information that affects supply and demand does not come to the market at one point in time, but rather enters the market over a period of time. Therefore, technicians expect a gradual price adjustment to reflect the gradual flow of information, which causes trends in the security price movements. This philosophy is in sharp contrast to the EMH, which contends that past performance has no influence on future performance.

2.3. The Efficient Market Hypothesis and Financial Crises

There is a lack of theoretical research on the impact of financial crises on the efficiency of financial markets. After the onset of the subprime crisis, the EMH has come under attack based on the claim that it is responsible for the occurrence of the housing bubble. The rationale for such argument is that people believe in the validity of market efficiency and, consequently, do not verify the fair value of securities since the market price reflects all available information. In addition, if the market is efficient, it should have predicted the crisis. Recently, Ball (2009) responds to these claims by saying that bubbles are present in the economic history before the evolution of the market efficiency concept in 1970s, such as the 1637 Dutch tulip, the Railway Mania in the 1840s, and the Florida Land bubble in 1926.

Given the significant gap in the theoretical literature, few studies examined empirically the impact of crises on market efficiency and the evidence is mixed. For example, Hoque, Kim, and Pyun (2007) examine the impact of the Asian financial crisis on the market efficiency of eight Asian markets, using variance ratio tests for the pre-crisis and post-crisis periods. Their findings show that the Asian crisis does not significantly affect the market efficiency of six Asian markets. On the other hand, Lim, Brooks, and Kim (2008) use a rolling bicorrelation test statistic as a proxy for market efficiency and they find that the Asian crisis adversely affect the market efficiency of the same eight Asian markets.

3. Methodology

Our objective is to investigate the impact of global financial crisis on the junk bond market, along three dimensions. First, we investigate the trading volume impact of the financial crisis. Second, we examine the impact of the crisis on the junk bond return volatility. Finally, we explore the impact of the crisis on the Junk bond Market Efficiency.

3.1. Modeling of Trading Volume: Censored Regression

Since our interest is to examine the impact of financial crisis on the corporate bond market efficiency within the context of the volume-volatility relation, we need to investigate first whether there is any impact of the financial crisis on the trading volume in the high yield corporate bond market. In recent years, there has been a renewed interest in the effect of financial crises on market microstructure and investors' trading behavior. Examining the trading volume of high yield corporate bonds during financial crises is of particular interest, since volume is an important measure of liquidity in literature. Financial market conditions have a great influence on bond trading, as investors rebalance their portfolios once new information reach the market. Investors focus on informational trading in a normal market, but they shift to liquidity trading once the financial market shifts to crisis environment.

Our objective now is to investigate the impact of the financial crisis on the trading activity in the junk bond market. In undertaking this exercise, it is important to bear in mind the limitations of the TRACE data set which the pooled OLS regression might suffer. The problem with using TRACE data is that trade size information is not reported completely, since the volume information reported by TRACE for junk bonds is truncated at one million dollars (1MM+). As a result, bond trading volume data (my dependent variable) is censored and has a truncated distribution. This means that using OLS to estimate the impact of the independent variables on trading volume will produce biased parameter estimates, since one of the OLS assumptions (i.e., the independence between OLS errors and explanatory variables) is violated.

To handle this truncation problem, we use a censored regression model that is a limited dependent variable approach specifically suited for estimation where the dependent variable is only partially observed over some range. The censored regression models use MLE estimation to give unbiased estimates when the dependent variable is truncated, and can be driven from an underlying latent variable model, as follows:

$$VB_{it}^{*} = \alpha_{it} \mathrm{X}_{\mathrm{it}} + \xi_{it} \qquad (1)$$

where (X_{it}) is a vector of the determinants of trading volume of junk bonds, such as bond age, price volatility, equity volume, equity return, market return, and autocorrelation in volume. The literature promotes these variables as the key determinants of trading in junk bond market (e.g., Alexander, Edwards, and Ferri, 2000 and Hotchkiss and Jostava, 2007)[2]. (VB_{it}^{*}) is an unobserved (latent) variable, but we only observe (VB_{it}) that is an indicator function as follows:

$$VB = \begin{cases} VB_{it}^{*} & \text{if } v_{it}^{*} < 1 \text{ million} \\ 1 \text{ million} & \text{if } v_{it}^{*} > 1 \text{ million} \end{cases} \qquad (2)$$

In this case, the data is right censored or top coded. This means that we know the actual value of a variable only up to a certain threshold (i.e., 1 million), but for values greater than this threshold we know only that the variable is at least as the threshold. The indicator function in equation (2) is of particular interest because large trades (with par value size above $1million) are typically institutional trades[3] carried out by well informed institutional traders with high bargaining power, given that the high-yield corporate market is largely institutional.

3.2. Modeling of Return Volatility: GJR-GARCH

After examining the impact of financial crisis on the trading volume of high yield corporate bond market, the next logical step is to investigate the volatility impact of the crisis. The evidence of the excess volatility of corporate bonds documented by Bao and Pan (2010) show that OLS assumptions are violated. The common practice to capture the heteroscedasticity of return volatility is to use the autoregressive conditional heteroskedasticity (ARCH) and generalized ARCH (GARCH) models proposed originally by Engle (1982) and Bollerslev (1986) respectively. The first generation of the GARCH model have allowed the magnitude of volatility to be predicted from past news and lagged conditional variance, as:

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[2] Other volume determinants that have been used in the literature include bond rating and issue size.

$$r_{it} = \mu + \varepsilon_{it}, \quad \varepsilon_{i,t} \sim (0, \sigma^2_{it}) \qquad (3)$$

$$\sigma^2_{it} = \beta_o + \beta_1 \, \varepsilon^2_{it-1} + \beta_2 \, \sigma^2_{it-1} \qquad (4)$$

Although it appears from literature that conditional heteroscedasticity models are among the best that are currently available, there is a major drawback of using the first generation of GARCH models in examining financial crises. The GARCH models are said to be symmetrical, due to the quadratic specification used for the conditional variance (i.e., the error term is squared). Therefore, volatility will be a function only of the innovation's magnitude, since the lagged shock will have the same effect on the present volatility whether the lagged shock is positive or negative (i.e., neutral impact).

This symmetrical nature of the traditional GARCH model makes them not well suited for capturing a well-known phenomena in the literature which is the asymmetric volatility in stock returns series or what is called asymmetric or leverage effect (e.g., French, Schwert and Stambaugh, 1987; Glosten, Jagannathan and Runkle, 1993). The asymmetric volatility phenomenon (AVP) is a market dynamic that shows that periods of crash environment (where residual is negative) cause the level of market volatility to increase more than in periods of relative calm (where residual is positive).

In order to handle the asymmetries in the conditional variance, we use the asymmetric Sign-GARCH model of Glosten, Jagannathan and Runkle (1993) (GJR-GARCH model) that allows for different reactions of volatility to the sign of past innovations. The GJR-GARCH model can be formulated as follows:

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[3] Institutional trades are defined as trade with par value size above $100,000.

$$r_{i,t} = \mu + \varepsilon_{i,t}; \quad \varepsilon_{i,t} \sim (0, \sigma_{i,t}^2) \tag{5}$$

$$\sigma_{it}^2 = \beta_0 + \beta_1\, \varepsilon_{i,t-1}^2 + \beta_2\, \sigma_{i,t-1}^2 + \beta_3\, S_{t-1}\varepsilon_{i,t-1}^2 \tag{6}$$

$$\text{Where } : S_{i,t-1} = \begin{Bmatrix} 1, \text{ if } \varepsilon_{\text{i,t-1}} < 0 \\ 0, \text{ otherwise} \end{Bmatrix} \tag{7}$$

Like any traditional GARCH model, the above model consists of two equations. The mean equation specifies returns as a constant plus an error term that has a mean of zero and a variance of (σ_{it}^2). The variance equation expresses the current volatility (measured by variance (σ_{it}^2)) as a function of four factors: the mean volatility (a), news about volatility from the previous period measured as the lag of the squared residual from the mean equation (ε_{it-1}^2) (the ARCH term), the last period's variance (σ_{it-1}^2) (the GARCH term) to control for volatility clustering, and the asymmetric volatility term $(S_{t-1}\varepsilon_{it-1}^2)$ to account for the leverage effect. A model with 'q' lags of (ε_{it-1}^2), 'p' lags of (σ_{it-1}^2) and 'r' lags of $(S_{t-1}\varepsilon_{it-1}^2)$ is labeled GJR (p, q, r), and I determine the lag structure in the conditional variance equation based on Akaike (AIC) and Bayesian (BIC) information criteria. The central feature of the above specification is that the dummy variable (S) allows the conditional variance to differ on crash days, since the effect of lagged shock on current volatility now is a function of its magnitude and its sign rather than its magnitude only, as in the original GARCH models. In particular, volatility is affected by one term (β_1) when the residual is negative (i.e., good news), while it is affected by two terms $(\beta_1 + \beta_3)$ when the residual is negative (i.e., bad news).

3.3 The EMH Test: VAR and 2SLS

After modeling corporate bond return volatility and trading volume, we turn now to our key objective in this study which is examining the impact of the global financial crisis on the informational efficiency of the high-yield corporate bond market within the context of the volatility-volume relation. The volume-volatility relation can be viewed as a test of the informational efficiency of financial markets. On one hand, the Efficient Market Hypothesis says that security prices adjust rapidly to the arrival of new information and, therefore, the current price of security fully reflects all historical information. If the market is efficient, therefore, it should not be possible to profit by trading on the information contained in the bond's trading history. On the other hand, the sequential information arrival hypothesis implies that there is a bidirectional causal relation between trading volume and return volatility.

The problem with estimating the volume-volatility relation is that we have to account for endogenity problem. Using OLS estimation to examine whether trading volume can predict return volatility will produce simultaneity bias, since one of the key OLS assumptions (that states that independent variables are orthogonal to the error term) is violated. we will handle such endogenity problem using two different methodologies – vector autoregression (VAR) and two-stage least squares (2SLS).

3.3.1 Vector Autoregressive (VAR) System

The VAR system treats all of the variables in the model as endogenous variables. Therefore, the relation between bond return volatility and trading volume can be examined by estimating the following vector autoregressive (VAR) system:

$$\hat{\sigma}^2_{i,t} = \alpha_0 + \sum_{i=1}^{I} \alpha_i \hat{\sigma}^2_{i,t-1} + \sum_{j=1}^{J} \beta_j VB_{i,t-j} + \varepsilon_t \qquad (8)$$

$$VB_{i,t} = \lambda_0 + \sum_{i=1}^{I} \lambda_i VB_{i,t-1} + \sum_{j=1}^{J} \delta_j \hat{\sigma}^2_{it-j} + e_t \qquad (9)$$

where $(\hat{\sigma}^2_{it})$ represent the fitted values of volatility from equations (6); (VB_{it}) is the average daily bond trading volume; (α_i) and (λ_i) are the coefficients for the lagged regressor of the dependent variable; and (β_j) and (δ_j) are the coefficients for the lagged explanatory variable. we estimate such VAR system for two subsamples – before and during the financial crisis. we are interested mainly in the value of the estimated (β_j) since any evidence of volatility predictability contradicts the implications of the efficient market hypothesis.

3.3.2. Two Stage-Least Square (2SLS)

Another way to account for the endogenity (or simultaneity) bias and still get unbiased estimates is to estimate a simultaneous equation model using two stage least square (2LS). The first step is to use the six determinants of bond trading volume (i.e., bond age, price volatility, equity volume, equity return, market return, and lagged bond trading volume) as instruments to predict the endogenous bond trading volume (VB_{it}), as follows:

$$VB_{it} = \alpha_0 + \alpha_1 (Age)_{it} + \alpha_2 (\Pr iceVol)_{it} + \alpha_3 (VE) + \alpha_4 (RE) + \alpha_5 (RM) + \alpha_6 (VB_{i,t-1}) + \xi_{it} \quad (10)$$

The second step is to run simple regression between the fitted values of volatility $(\hat{\sigma}_{i,t-1})$ from equation (6) and the lagged fitted values of volume $(\hat{VB}_{i,t-1})$ from equation (10), as follows:

$$\hat{\sigma}_{it}^{2} = \theta_0 + \theta_1 \hat{VB}_{i,t-1} + \varepsilon_{\text{it}} \qquad (11)$$

As a robustness test, we use alternative 2SLS specification. Instead of running a simple regression between the fitted values of volatility and volume, we incorporate the lagged fitted trading volume series $(\hat{VB}_{i,t-1})$ into the GJR-GARCH model directly to examine the effect of bond trading volume on bond return volatility, as follows:

$$r_{i,t} = \mu + \varepsilon_{i,t}; \quad \varepsilon_{i,t} \sim (0, \sigma_{i,t}^{2}) \qquad (12)$$

$$\sigma_{it}^{2} = \beta_0 + \beta_1 \varepsilon_{i,t-1}^{2} + \beta_2 \sigma_{i,t-1}^{2} + \beta_3 S_{t-1}\varepsilon_{i,t-1}^{2} + \beta_4 \hat{\text{VB}}_{\text{i,t-1}} \qquad (13)$$

$$\text{Where } : S_{i,t-1} = \begin{Bmatrix} 1, \text{ if } \varepsilon_{\text{i,t-1}} < 0 \\ 0, \text{ otherwise} \end{Bmatrix} \qquad (14)$$

4. Data and Variables Measurement

4.1. Data Requirements and Sample

The bond market in general is less transparent than equity and futures market in terms of the availability of basic information on trading activity. However, there has been increasing concern over time for such lack of transparency, especially after the collapse of Drexel Burnham Lambert which dominated the high yield bond market for decades. This led the SEC to encourage the National Association of Securities Dealers (NASD) in April 1994 to initiate the fixed income pricing system (FIPS) which is an electronic quotation system for the high-yield bonds as a source of total trading volume in corporate bonds. In July 2002, FINRA, formerly NASD, launched another source of data which is TRACE (Transaction Reporting and Compliance Engine) to increase the transparency in the corporate bond markets.

The data set is obtained from TRACE and consists of hourly prices and hourly trading volume for bonds. To be included in the sample, a bond must meet two criteria: First, our sample is biased toward the heavily traded bonds. Therefore, we focus only on the most actively traded junk bonds in terms of number of trades (i.e., TRACE 50) during 2008. TRACE 50 bonds are chosen by the NASD advisory committee and updated continuously overtime such that small trading volume were replaced with more active bonds. Second, the bond must be publicly traded since we are using data from the equity market. After these two requirements, we end up with a 19 sample bonds. Table (1) summarizes the major bond characteristics of these sample bonds.

[Insert Table (1) Here]

4.2. Sample Period

The financial crisis hit the financial markets as a result of the implosion of the US mortgage market and reversal of the housing boom. The first indications of a credit crunch appeared on July 17, 2007 when the credit spreads soar as a result of Bear Sterns announcement that two if its hedge funds with subprime exposure has released losses of $1.5 billion (more than 90% of their value). Two weeks later after the announcement, on July 31 2007, these two hedge funds filed for Chapter 15 bankruptcy. On October 25, 2007, Merrill Lynch reports the biggest quarterly loss in the company's history ($2.24 billion), resulting from its huge write downs on subprime mortgages ($7.9 billion). Merrill Lynch write down was considered the largest write down in the credit crisis so far, and it was followed by a wave of write downs in the months of

November and December by Citigroup (up to $11 billion), Bank of America ($3 billion), Barclays ($1.6 billion), UBS ($10 billion), and Morgan Stanley ($9.4 billion).

All of these events were reflected in the financial statements of the major banks in the fourth quarter of 2007. Specifically, the credit crunch gets much worse on January 15 2008 when Citigroup (the largest bank in the US) reports a $9.83 billion loss as a result of its $18.1 billion write down, followed by an announcement by Wells Fargo (the fifth largest US bank) of a 37% loss in net income and by Merrill Lynch of a $7.8 billion net loss. Although the first indications of the 2008 crisis appeared on January 15 when news of a sharp drop in profits of Citigroup, September 2008 is considered a historic month and a new phase of the crisis since it witnessed the bankruptcy of Lehman Brothers which is considered the largest bankruptcy filing in the US history. Lehman's bankruptcy in September 2008 led to profound effects on the equity and bond market. On September 15 2008 – the day the Lehman Brothers filed for bankruptcy, the DJIA witnessed the largest drop in a single day since the September 11, 2001 attack (-4.4%). Also, the price volatility of investment grade bonds reached unprecedented levels during September 2008 (Longstaff, 2010; Cox and Glapa, 2009).

Our sample runs from July 2005 till July 2009. In order to address the impact of the subprime crisis on the US high yield corporate bond market, we further subdivide the sample into two subsamples – pre crisis and crisis period. Based on the above analysis of the chronology of the subprime crisis, we divide the sample period into two sub-periods:

(1) Pre-Crisis Period: from May 15, 2006 to July 17, 2007;

(2) Crisis Period: from July 18, 2007 to September 15, 2008.

Our definition of the crisis period is similar to Santos (2011) and Longstaff (2010). we subdivide the crisis period into two phases to ensure a fair comparison, such that each period has roughly equal number of observations.

4.3. Variables Measurement

4.3.1 Measurement Issues: Survey

The interest in examining the volume-volatility relation was fueled by the recent history of financial markets that has been characterized by increased volatility accompanied by high volume. For example, volatility and trading volume reached unprecedented levels during the October crash in 1987. On Black Monday (October 19, 1987) the S&P 500 composite index dropped by 22.9% on the second highest volume ever recorded (604 million shares) and the DJIA fell by 22.6%. On the next trading day, the S&P 500 index rose by 5.2 percent accompanied with the highest volume ever recorded (608 million shares). On October 13, 1989, the index dropped 7% accompanied by a 50% increase in volume and followed by heavy two and half times the normal volume on the next trading day (Gallant et al., 1992).

The relationship between trading volume and returns volatility has been studied from different perspectives such as volume measure, volatility measure, time frequency and the financial instruments used, as follows: (1) volume measure: the total trading volume of the stock index (Lee and Rui, 2002); the number of transactions (Conrad et al., 1994); the proportion of shares traded (Brooks, 1998); the number of bonds traded (Alexander, Edwards, and Ferri, 2000), and turnover (Hotchkiss and Jostava, 2007;

Dick-Nielsen, Feldhutter, and Lando, 2009) are all have been used as a measure of security trading volume. (2) Volatility measure: the volatility has been measured by absolute price change (Copeland, 1976; and Alexander, Edwards, and Ferri, 2000); price change per se (Arrif and Lee, 1993); variance of price change (Epps and Epps, 1976); squared price change (Clark 1973); standard deviation (Grammatikos and Saunders, 1988); square of return (Brooks, 1998); the difference between high and low price (Downing and Zhang, 2004); Conditional variance based on GARCH (Lamoureux and Lastrapes 1990); Quadratic GARCH (or: QGARCH) (Campbell et al., 1993); Exponential GARCH (or: EGARCH) (Martikanien et al., 1994), and GJR-GARCH (Leeves, 2007). (3) Time frequency: transaction-level (Smirlock and Starks, 1988); quarter hour (Smith et al., 1997); half hour (Foster and Viswanathan, 1995); hourly (Hotchkiss and Ronen, 2002; and Downing, Underwood and Xing, 2009); daily (Fleming and Kirby, 2011); weekly (Downing and Zhang, 2004); and monthly data (Rogalski, 1978) have all been used in the previous studies. (5) The financial instrument used: although most of the studies used data from the stock market, Tauchen and Pitts (1983) and Chang et al. (1997) examined the relationship for futures, Rogalski (1978) for warrants, and Hanna (1978), Downing and Zhang (2004) and McKenzie, Dungey, and Frino (2008) for bonds. Table (2) summarizes all of the above differences.

[Insert Table (2) Here]

4.3.2. Bond Return

Our transaction data consists of hourly prices and hourly trading volume for bonds. Following Downing, Underwood, and Xing (2009), we use the average daily price to calculate the daily bond return. The main reason for focusing my attention on returns rather than on prices is that returns have more attractive statistical properties than prices (i.e., stationarity). Our measure for log daily return is defined as follows:

$$r_{it} = \ln\left(\frac{\mathrm{P}_{\mathrm{it}} + \mathrm{AI}_{\mathrm{it}}}{\mathrm{P}_{\mathrm{it\text{-}1}} + \mathrm{AI}_{\mathrm{it\text{-}1}}}\right) \qquad (12)$$

where P_{it} is the average daily clean price (i.e., not adjusted for accrued interests (AI_{it})).

4.3.3. Bond Trading Volume and its Determinants

As we mentioned in section three, we use the censored regression model to investigate the impact of the global financial crisis on the trading volume in high yield corporate bond market. Our dependent variable in the censored regression is the bond average daily trading volume (VB_{it}), and we follow Alexander, Edwards, and Ferri (2000) by measuring trading volume as the natural log of the number of bonds traded per day. Following literature (e.g., Hotchkiss and Jostava, 2007), we use six different determinants of trading volume: bond age, price volatility, equity volume, equity return, market return, autocorrelation in volume. Age of the bond is measured by the number of years since the bond was issued. In order to calculate the bond age, we make use of the bond issuer and bond characteristics information from the Fixed Income Security Database (FISD). Price volatility is the absolute price return. Finally, we include the lagged bond trading volume to account for the autocorrelation in trading volume.

5. Empirical Results

Table (3) sets out descriptive statistics for the sample bonds' trading volume and their returns before and during crisis period. Table (4) presents the impact of each of the explanatory variables in equation (10) - bond age, price volatility, equity volume, equity return, S&P return (RM) and autocorrelation in volume - on the trading volume of the sample bonds before and during the crisis period. In general, the volume results suggest that heavily traded bonds are associated with high contemporaneous equity volume and high lagged bond volume. The coefficients on the equity volume variable are positive and significant at 1% level. This supports the literature that says that stocks and bonds react to the firm-specific information (e.g., Hotchkiss and Ronen, 2002). The positive significant coefficients on lagged bond volume show that there is a positive autocorrelation in Junk bond trading activity. These findings are consistent with the evidence found by and Hotchkiss and Jostava (2007).

[Insert Table (3) Here]

[Insert Table (4) Here]

Table (5) sets out the results of the estimated parameters of the GJR-GARCH model for the two sub periods – before and during the financial crisis. Before the crisis, most of the estimated ARCH, GARCH and the asymmetry (GJR) parameters are small and not statistically significantly different from zero. During the crisis, most of the ARCH and GARCH estimates are statistically significant at 1% level. The magnitude of the ARCH term increases during the crisis period, and this proves that the volatility dynamics become more ‘reactive’. Moreover, the magnitude of the asymmetry parameters becomes large and highly statistical significant at 1% level, indicating the presence of the leverage effect during the financial crisis. It seems, therefore, that the

GJR-GARCH model provides a better description of volatility dynamics during the crisis period compared to the before crisis period.

[Insert Table (5) Here]

After examining the impact of the financial crisis on the trading volume and return volatility of the junk bond market, we turn to VAR and 2SLS estimates to examine the impact of the recent financial crisis on the efficiency of the junk bond market, through examining bi-directional relation between volume and volatility. Table (6) presents the results from the two VAR specifications running from volume to volatility and from volatility to volume, as implied by equations (11) and (12), respectively. In each of these two specifications, the lagged dependent regressor estimated coefficients are not statistically different from zero in both sub-periods. These results indicate that historical trading volume data does not have any impact on the junk bond return volatility whether before or during the crisis period.

[Insert Table (6) Here]

Table (7) sets out the results of estimating the volume-volatility relation using 2SLS as an alternative methodological procedure to solve the endogenity problem. Panel (A) and (B) show the results the estimated volume coefficient from equation (11) and (13), respectively. The results from both panels are consistent. Unlike the results from the VAR estimates, the estimated 2SLS parameters support the notion that trading volume data has some predictability power of the bond return volatility. In particular, most of the lagged volume coefficients, with some exceptions, are positive and highly significant at 1% level. This gives some evidence that greater trading on the prior day increases the return volatility. The magnitudes of the lagged volume coefficients, however, are small indicating that there are other factors which help in predicting bond return volatility. Moreover, the magnitude and significance of the lagged volume regressor are similar in both subsample periods. This proves that the crisis does not have an impact on the informational efficiency of the junk bond market.

[Insert Table (7) Here]

6. Conclusion

This study examines the impact of the 2007-2008 financial crisis on the market efficiency of the junk bond market. The result of such examination reveals three main findings. First, the estimates of the GJR-GARCH model provides a better description of volatility dynamics during the crisis period compared to the before crisis period, indicating the presence of the leverage effect. Second, the results of VAR and 2SLS estimates show that crisis does not have an impact on the efficiency of the junk bond market. Finally, it seems that my empirical three-step procedure gives better results than previous studies. Instead of using VAR to account for endogenity problem in the volume-volatility relation, we use the fitted values of volume and volatility from censored regression and GJR-GARCH to run 2SLS model. The results from VAR (2SLS) estimation show that volume is a insignificant (significant) predictor of bond return volatility. This empirical procedure may open directions for future research on market microstructure theory.

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Table 1: Sample Description: Top Publicly Traded Junk Bonds by Number of Trades in 2008

Symbol	Issuer Name	Offering Dates	Coupon	Maturity	Rating	Trades	Total Observations
WM.IE	WASHINGTON MUTUAL, INC.	10/27/2003	4.000	1/15/2009	D	18,497	1222
WM.HE	WASHINGTON MUTUAL, INC.	3/30/2000	8.250	4/1/2010	D	10,774	654
GM.GM	GENERAL MOTORS CORPORATION	1/4/2001	7.200	1/15/2011	C	10,551	1740
GM.HB	GENERAL MOTORS CORPORATION	6/26/2003	8.375	7/15/2033	C	10,248	1489
F.GY	FORD MOTOR COMPANY	7/9/1999	7.450	7/16/2031	CC	6,887	2137
WM.IL	WASHINGTON MUTUAL, INC.	12/13/2004	4.200	1/15/2010	D	6,152	899
RAD.GA	Rite Aid Corporation	8/13/1993	6.875	8/15/2013	CCC	5,381	1481
GT.GF	GOODYEAR TIRE & RUBBER COMPANY	8/10/2001	7.857	8/15/2011	B	4,959	1504
LEH.HF	Lehman Brothers Holdings Inc.	8/14/1997	7.200	8/15/2009	CCC	4,905	1222
GM.HC	GENERAL MOTORS CORPORATION	2/23/2001	8.250	7/15/2023	C	4,807	1487
LEH.GZJ	LEHMAN BROTHERS HOLDINGS INC	1/9/2007	5.250	2/6/2012	CCC	4,571	424
GM.HA	GENERAL MOTORS CORPORATION	6/26/2003	7.125	7/15/2013	C	4,380	1489
LEH.HQ	LEHMAN BROTHERS HOLDINGS INC.	10/27/1999	7.875	11/1/2009	CCC	4,318	1219
LEH.TZ	LEHMAN BROTHERS HOLDINGS INC.	2/18/2004	3.600	3/13/2009	CCC	4,079	978
WM.HV	WASHINGTON MUTUAL BANK	1/13/2001	6.875	6/15/2011	D	4,002	1030
CHK.HE	CHESAPEAKE ENERGY CORP	12/22/2005	6.500	8/15/2017	BB	3,789	1215
LEH.XS	LEHMAN BROTHERS HOLDINGS INC.	1/4/2005	4.250	1/27/2010	CCC	3,727	893
SFD.GG	SMITHFIELD FOODS, INC.	10/7/2004	7.000	8/1/2011	B	3,571	1352
DJTE.GA	TRUMP ENTERTAIN. RESORTS INC	3/30/2005	8.500	6/1/2015	D	3,453	839

Table 2: Volume and Volatility Measurement Issues: Survey

Article	Trading Measure	Volatility Measure	Price Definition	Time Frequency	The financial instrument used
Clark (1973)	Trading volume	Squared price change	Individual contracts	Daily	Future contracts
Epps and Epps (1975)	Trading volume	Price change	Individual stocks	Transactions	Common stock & bonds
Morgan (1976)	Turnover	Variance	Individual stocks	Monthly & 4-day interval	Common stock
Hanna (1978)	Trading volume	Price change	Individual stocks	Monthly	Bonds
Rogalski (1978)	Trading volume	Price change	Individual stocks	Monthly	Common stock & options
Tauchen and Pitts (1983)	Trading volume	Variance	Individual stocks	Daily	Common stock & future contracts
Grammatikos and Saunders (1986)	Trading volume	Standard deviation	Individual contracts	Daily	Future contracts
Jain and Joh (1988)	Turnover	Price change	Composite index	hourly	Common stock
Smirlock and Starks (1988)	No. of transactions	Absolute price change	Individual stocks	Transaction	Common stock
Lamoureux and Lastrapes (1990)	Trading volume	GARCH	Individual stocks	Daily	Common stock
Gallant et al. (1992)	Log trading volume	Log price change	Composite index	Daily	Common stock
Arrif and Lee (1993)	Trading volume	Price change	Individual stocks	weekly	Common stock
Campbell et al. (1993)	Log turnover	QGARCH	Composite index & individual stocks	Daily	Common stock
Foster and Viswanathan (1993)	Turnover	Variance	Individual stocks	Half hour	Common stock
Conrad et al. (1994)	No. of transactions	------------	Individual stocks	Weekly	Common stock
Hiemstra and Jones (1994)	Trading volume	EGARCH	Composite index	Daily	Common stock
Martikanien et al. (1994)	Trading volume	Log price change	Composite index	Daily	Common stock
Anderson (1996)	Log trading volume	Squared price change	Individual stocks	Daily	Common stock
Chan et al. (1996)	Trading volume	Squared price change	Individual stocks	Every 65 minutes	Common stock

Table 2: Continued

Chang et al. (1997)	Trading volume	Absolute volatility value	Individual contracts	Daily	Future contracts
Smith et al. (1997)	Trading volume & no. of transactions	Absolute price change	Individual stocks	Every 15 minutes	Common stock
Brooks (1998)	Proportion of shares traded	Squared price change	Composite index	Daily	Common stock
Hsu (1998)	Trading volume	GARCH	Individual stocks	Daily	Common stock
Diagler and Wiley (1999)	Trading volume	Conditional variance	Individual contracts	Daily	Future contracts
Chordia and Swaminathan (2000)	Turnover	-------------	Individual stocks	Daily	Common stock
Lee and Swaminathan (2000)	Turnover	------------	Individual stocks	monthly	Common stock
Safvenblad (2000)	Trading volume	-------------	Individual stocks	Daily	Common stock
Gervais et al. (2001)	Trading volume	-------------	Individual stocks	Daily & weekly	Common stock
Parisi and Acevedo (2001)	Trading volume	--------------	Individual stocks	Weekly	Common stock
Lee et al. (2002)	Trading volume	GARCH	Composite index	Daily	Common stock
Downing and Zhang (2004)	No. of transactions	The difference between high & low divided by average price	Individual stocks	Weekly	Bonds

Table 3: Summary Statistics for Daily Returns and Trading Volume before and during the Crisis Period

	Trading Volume Statistics				Bond Return Statistics			
	Before Crisis Period		During Crisis Period		Before Crisis Period		During Crisis Period	
Bond	Mean	SD	Mean	SD	Mean	SD	Mean	SD
WM.IE	11.47	1.56	11.25	0.96	-0.00	0.02	-0.02	0.02
WM.HE	11.03	1.94	10.91	1.23	-0.00	0.04	-0.00	0.03
GM.GM	11.44	0.77	11.81	0.81	-0.00	0.04	-0.00	0.03
GM.HB	12.61	0.61	12.55	0.64	-0.00	0.04	-0.00	0.05
F.GY	12.37	0.64	12.39	0.73	-0.00	0.04	-0.00	0.04
WM.IL	11.67	1.63	11.11	1.39	-0.00	0.03	-0.00	0.03
RAD.GA	10.65	1.14	10.41	1.08	-0.00	0.06	0.00	0.05
GT.GF	11.16	0.85	10.77	0.95	0.00	0.02	-0.00	0.03
LEH.HF	9.87	1.20	10.09	1.05	0.00	0.02	-0.00	0.06
GM.HC	11.59	0.85	11.58	1.06	-0.00	0.04	-0.00	0.05
LEH.GZJ	12.93	1.43	11.73	1.38	-0.00	0.02	-0.00	0.05
GM.HA	11.72	1.01	11.72	1.01	-0.00	0.03	-0.00	0.04
LEH.HQ	10.17	1.23	10.34	1.26	-0.00	0.11	0.06	0.25
LEH.TZ	11.95	1.78	11.25	1.39	0.00	0.01	-0.00	0.07
WM.HV	11.85	1.96	11.24	1.46	-0.00	0.03	-0.00	0.03
CHK.HE	12.33	1.52	11.10	1.36	0.00	0.02	-0.00	0.03
LEH.XS	12.43	1.70	11.69	1.54	0.00	0.02	-0.00	0.05
SFD.GG	11.67	1.65	11.32	1.33	0.00	0.02	-0.00	0.03
DJTE.GA	12.86	1.11	12.88	1.14	-0.00	0.04	-0.00	0.04

Table 4: Determinants of Trading Volume before and during the Crisis Period: Censored Regression Model

	Before Crisis Period						Crisis Period					
Bond	Age	Volatility	VE	RE	RM	AC	Age	Volatility	VE	RE	RM	AC
	-0.00	0.76	0.72***	-14.92	21.13	0.07	0.01***	-3.21	0.59***	0.44	7.09	0.28**
WM.IE	(0.00)	(5.05)	(0.08)	(10.05)	(17.06)	(0.06)	(0.00)	(2.74)	(0.08)	(0.99)	(5.25)	(0.05)
	-0.01	0.31	0.78***	-12.51	28.19	0.17**	0.01***	0.44	-0.11	0.58	1.16	0.15**
WM.HE	(0.00)	(3.68)	(0.20)	(16.01)	(25.17)	(0.07)	(0.00)	(2.49)	(0.13)	(1.24)	(6.90)	(0.06)
	-0.00**	0.48	0.65***	0.19	0.31	0.32	0.00	0.19	0.55***	2.62*	-8.38**	0.21***
GM.GM	(0.00)	(1.34)	(0.06)	(2.29)	(7.14)	(7.14)	(0.00)	(1.32)	(7.84)	(1.40)	(4.17)	(0.06)
	-5.11E-05	0.22	0.61***	-1.15	1.53	0.23***	-0.01***	-0.37	0.85***	-3.25***	3.73	0.04
GM.HB	(0.00)	(0.89)	(0.05)	(1.74)	(5.43)	(0.05)	(0.00)	(0.82)	(0.06)	(1.12)	(3.32)	0.05
	0.00	-0.76	0.45	3.86**	0.22	0.29***	-0.00	1.34	0.58***	0.022	2.26	0.23***
F.GY	(0.00)	(0.43)	(0.05)	(1.85)	(5.73)	(0.05)	(0.00)	(1.10)	(0.08)	(1.50)	(3.78)	(0.06)
	-0.00	1.68	0.76***	1.82	5.17	0.05	-0.00***	1.88	0.90***	-0.61	18.33**	0.09
WM.IL	(0.00)	(4.93)	(0.07)	(11.01)	(18.74)	(0.06)	(0.00)	(0.51)	(0.08)	(1.36)	(7.18)	(0.06)
	0.00***	0.65	0.42***	-0.01	-0.34	0.02	0.00***	0.47	0.22**	-1.18	11.61**	0.17***
RAD.GA	(0.00)	(1.11)	(0.08)	(1.01)	(3.04)	(0.05)	(0.00)	(1.34)	(0.09)	(1.09)	(4.82)	(0.06)
	-0.00	-0.87	1.60***	-5.14**	6.90	0.09*	0.00***	1.58	0.83***	-2.33	2.23	0.05
GT.GF	(0.00)	(1.84)	(0.14)	(2.58)	(8.05)	(0.05)	(0.00)	(1.71)	(0.15)	(0.30)	(5.66)	(0.06)
	-0.00	6.00**	0.66***	5.82	-13.37	0.11*	0.00**	1.40	0.19*	0.43	2.79	0.22***
LEH.HF	(0.00)	(3.06)	(0.14)	(6.56)	(17.04)	(0.07)	(0.00)	(1.29)	(0.10)	(0.99)	(5.66)	(0.06)
	0.00**	2.14*	0.50***	-0.39	4.61	0.15***	-0.00	0.12	0.68***	2.17	1.28	0.14**
GM.HC	(0.00)	(1.33)	(0.06)	(2.54)	(7.89)	(0.06)	(0.29)	(1.44)	(7.39)	(1.96)	(5.85)	(0.05)
LEH.GZJ	-0.00*	2.15	0.70***	-12.45	13.34	0.19**	-0.00***	2.15	0.71***	1.16	-0.15	0.09
	(0.00)	(5.86)	(0.08)	(10.99)	(24.87)	(0.08)	(0.00)	(1.94)	(0.05)	(1.34)	(7.48)	(0.06)
GM.HA	0.00*	-1.75	0.41***	2.70	-5.66	0.30***	0.00*	-1.75	0.41***	2.70	-5.65	0.30***
	(0.00)	(1.49)	(0.06)	(1.75)	(5.20)	(0.05)	(0.00)	(1.51)	(0.06)	(1.77)	(5.25)	(0.06)
LEH.HQ	0.00**	-2.50**	0.42***	2.85	-15.39	0.00	0.00	-0.76**	0.49***	-0.05	-1.17	0.06
	(0.00)	(1.05)	(0.11)	(6.50)	(16.71)	(0.06)	(0.00)	(0.37)	(0.13)	(1.11)	(7.36)	(0.06)
LEH.TZ	-0.00	-10.35	0.76***	-3.09	5.75	0.07	-0.00	0.09	0.62***	0.78	11.38	0.25***
	(0.00)	(7.65)	(0.09)	(9.77)	(25.90)	(0.06)	(0.00)	(1.56)	(0.09)	1.53)	(8.86)	(0.06)
WM.HV	-0.00*	-3.51	0.98***	6.50	6.62	0.12*	0.00	-5.35*	0.48***	-0.67	7.04	0.14***
	(0.00)	(4.06)	(0.17)	(13.22)	(22.61)	(0.06)	(0.00)	(2.83)	(0.14)	(1.43)	(7.59)	(0.06)
CHK.HE	-0.00	-0.39	0.77***	-6.66	14.56	0.15**	-0.00***	-0.25	0.92***	2.12	2.80	0.03
	(0.00)	(3.28)	(0.06)	(6.17)	(13.90)	(0.06)	(0.00)	(2.56)	(0.07)	(3.07)	(5.99)	(0.05)
LEH.XS	-0.00	2.42	0.81***	10.35	-8.55	0.08	-0.00***	-3.18	0.81***	-1.56	7.61	0.14**
	(0.00)	(6.30)	(0.07)	(8.56)	(22.51)	(0.06)	(0.00)	(2.31)	(0.08)	(1.59)	(8.66)	(0.05)
SFD.GG	-0.00	-3.58	0.83***	-5.11	1.13	0.12**	-0.00	-0.65	0.83***	0.06	0.75	0.04
	(0.00)	(4.05)	(0.07)	(8.60)	(16.07)	(0.06)	(0.00)	(2.61)	(0.08)	(3.05)	(6.56)	(0.06)
DJTE.GA	-0.00	0.81	0.69***	0.03	0.84	0.32***	0.00***	-0.46	0.61***	-0.05	7.49	0.24***
	(0.00)	(1.96)	(0.06)	(2.51)	(10.93)	(0.05)	(0.00)	(1.69)	(0.05)	(1.20)	(4.93)	(0.05)

Table 5: Estimates of Volatility before and during the Crisis Period: GJR-GARCH Estimates

The table presents coefficient estimates of the GJR-GARCH model: $r_{i,t} = \mu + \alpha_1 r_{i,t-1} + \varepsilon_{i,t}$, $\sigma^2_{it} = \beta_0 + \beta_1 \varepsilon^2_{i,t-1} + \beta_2 \sigma^2_{i,t-1} + \beta_3 S_{t-1}\varepsilon^2_{i,t-1}$ where $(r_{i,t})$ is the daily bond return, and $(\sigma^2_{i,t})$ is the daily conditional volatility which is regressed against a constant, the lag of the squared residual from the mean equation (ε^2_{it-1}) (ARCH term) and the last periods' forecast variance (σ^2_{it-1}) (GARCH term), and the asymmetric volatility term $(S_{t-1}\varepsilon^2_{it-1})$ to account for the leverage effect. The standard errors are in parentheses.

	During Crisis Period				Crisis Period			
	β_0	β_1	β_2	β_3	β_0	β_1	β_2	β_3
WM.IE	0.00 (0.00)	0.04 (2.35)	0.58 (0.37)	-0.05 (2.35)	0.00** (0.00)	4.81*** (0.88)	0.18*** (0.03)	4.83*** (1.10)
WM.HE	0.00 (0.00)	0.04 (0.55)	0.58* (0.34)	-0.06 (0.55)	0.00 (0.00)	-0.01*** (0.00)	0.99*** (0.00)	0.01*** (0.00)
GM.GM	0.00 (0.00)	0.02 (0.21)	0.58 (0.42)	-0.03 (0.21)	0.00 (0.41)	0.84*** (0.16)	-0.05 (0.43)	-0.84*** (0.16)
GM.HB	0.00 (0.00)	0.04** (0.02)	0.59 (0.41)	-0.05** (0.02)	0.00 (0.00)	0.08* (0.04)	0.59 (0.56)	-0.08*** (0.03)
F.GY	0.00 (0.00)	0.03*** (0.00)	0.59 (0.39)	-0.05*** (0.00)	0.00 (0.00)	-0.12*** (0.01)	1.00*** (0.00)	0.12*** (0.01)
WM.IL	0.00 (0.00)	0.05 (0.22)	0.94*** (0.01)	-0.06 (0.21)	0.00** (0.00)	4.02*** (0.45)	0.21*** (0.02)	2.56*** (0.68)
RAD.GA	0.00 (0.00)	-0.07*** (0.01)	0.98*** (0.00)	0.06*** (0.01)	0.00 (0.00)	0.45* (0.27)	0.75*** (0.10)	-0.45* (0.27)
GT.GF	0.00 (0.00)	0.04 (0.36)	0.82*** (0.13)	-0.05 (0.35)	0.00 (0.00)	0.03*** (0.00)	0.89*** (0.01)	-0.04*** (0.00)
LEH.HF	0.00 (0.00)	-0.97*** (1.33)	-0.02 (0.02)	1.67 (1.06)	0.00 (0.00)	11.09*** (0.91)	-0.00* (0.00)	-9.49*** (1.43)
GM.HC	0.00 (0.00)	0.03 (1.48)	0.59 (0.47)	-0.04 (1.48)	0.00 (0.00)	-0.03 (0.38)	0.70* (0.36)	0.02 (0.38)
LEH.GZJ	0.00 (0.00)	0.05 (0.32)	0.58 (0.62)	-0.06 (0.34)	0.00 (0.00)	7.46*** (0.37)	-0.01 (0.01)	-6.92*** (0.43)
GM.HA	0.00 (0.00)	0.02*** (0.00)	0.93*** (0.01)	-0.02*** (0.00)	0.00 (0.00)	-0.06*** (0.00)	1.02*** (0.00)	0.05*** (0.00)
LEH.HQ	0.00 (0.00)	0.87 (0.85)	-0.02 (0.03)	-1.24 (0.86)	0.00 (0.00)	0.58* (0.55)	-0.01 (0.69)	-1.53 (1.63)
LEH.TZ	0.00 (0.00)	0.04 (0.27)	0.57 (0.37)	-0.05 (0.26)	0.00 (0.00)	-0.15 (0.11)	0.54*** (0.01)	6.81*** (0.43)
WM.HV	0.00 (0.00)	0.04 (0.22)	0.57 (0.38)	-0.06 (0.22)	0.00 (0.00)	47.73*** (2.93)	0.02*** (0.00)	-46.61*** (2.96)
40CHK.HE	0.00 (0.00)	-0.08*** (0.00)	1.01*** (0.00)	0.08*** (0.00)	0.00 (0.00)	0.04*** (0.00)	0.58* (0.32)	-0.05*** (0.00)
LEH.XS	0.00 (0.00)	0.04 (0.87)	0.89*** (0.04)	-0.05 (0.87)	0.00 (0.00)	-0.40** (0.20)	-0.22** (0.08)	10.25** (4.05)
SFD.GG	0.00 (0.00)	0.03 (0.22)	0.94 (0.01)	-0.04 (0.20)	0.00 (0.00)	-0.02*** (0.00)	0.93*** (0.01)	0.00*** (0.00)
DJTE.GA	0.00 (0.00)	0.02 (0.49)	0.89*** (0.01)	-0.03 (4.89)	0.00 (0.00)	0.17 (0.13)	0.58 (0.42)	-0.18 (0.13)

Table 6: Estimates of Volume-Volatility relation before and during the Crisis Period: VAR Model Results

The table presents the coefficient estimates of VAR test running from volume to volatility as implied by equation: $\hat{\sigma}^2_{it} = \alpha_0 + \sum_{i=1}^{I} \alpha_i \hat{\sigma}^2_{it-1} + \sum_{j=1}^{J} \beta_j \hat{v}_{t-j} + \varepsilon_t$ where σ^2_{it} is the estimated daily volatility, and (v_t) is the daily bond trading volume. The results show also the results of estimating VAR test running from volatility to volume as follows: $\hat{v}_{it} = \lambda_0 + \sum_{i=1}^{I} \lambda_i \hat{v}_{i,t-1} + \sum_{j=1}^{J} \delta_j \hat{\sigma}^2_{it-j} + e_t$

	Crisis Period				During Crisis Period			
	β_1	β_2	δ_1	δ_2	β_1	β_2	δ_1	δ_2
WM.IE	4.06E-05 (8.4E-05)	6.27E-05 (8.4E-05)	100.17** (50.68)	-32.29 (50.96)	-1.11E-05 (0.00)	-4.00E-05 (0.00)	19.76 (20.16)	-35.94 (-1.7)
WM.HE	-1.57E-06 (5.7E-06)	-2.55E-06 (5.7E-06)	884.6670 (933.485)	-573.36 (934.92)	-6.84E-06 (7.2E-06)	5.35E-06 (7.1E-06)	-450.69 (563.96)	-284.72 (561.95)
GM.GM	-0.01 (0.00)	-0.01 (0.00)	-0.25 (0.57)	0.35 (0.57)	0.01 (0.00)	-0.01 (0.01)	0.22 (0.35)	0.01 (0.35)
GM.HB	3.15E-06 (3.7E-06)	-6.19E-07 (3.7E-06)	-592.79 (1100)	664.66 (1098)	3.35E-06 (5.6E-06)	3.76E-06 (5.6E-06)	-375.93 (582.57)	468.52 (583.73)
F.GY	8.14E-06** (4.7E-06)	-4.88E-06 (4.8E-06)	377.9976 (860.87)	-1287 (857.9)	-8.84E-07 (5.6E-06)	4.11E-06 (5.6E-06)	519.96 (574.462)	596.75 (577.834)
WM.IL	0.01 (0.00)	0.01 (0.00)	1.15 (2.96)	1.07 (2.96)	0.00 (0.00)	0.00 (0.00)	-1.78 (1.61)	0.05 (1.61)
RAD.GA	-1.37E-05 (9.8E-05)	-0.01 (9.8E-05)	-0.86 (35.00)	-7.14 (35.00)	-0.00 (0.00)	8.78E-05 (0.00)	35.19** (14.82)	-18.23 (14.96)
GT.GF	5.23E-07 (4.4E-06)	9.46E-07 (4.4E-06)	-359.29 (779.508)	499.68 (781.66)	5.23E-07 (4.4E-06)	9.46E-07 (4.4E-06)	-359.29 (779.5)	499.68 (781.6)
LEH.HF	0.01** (0.00)	-0.00 (0.00)	-11.98 (11.43)	-4.54 (11.43)	0.00 (0.00)	-0.00 (0.00)	-2.95 (2.59)	0.84 (2.61)
GM.HC	-3.14E-06 (2.17E-06)	-4.16E-06 (2.7E-06)	-1737.9 (1490)	-585.00 (1492.17)	3.07E-06 (3.9E-06)	-4.06E-06 (3.8E-06)	75.88 (879.68)	-903.12 (880.78)
LEH.GZJ	0.00 (0.00)	0.00 (0.00)	-12.90 (11.15)	19.69** (11.16)	-0.00 (0.00)	0.00 (0.00)	10.96** (4.48)	-5.21 (4.57)
GM.HA	-4.05E-06 (0.00)	0.00 (0.00)	0.28 (3.51)	-1.09 (3.51)	-0.00 (0.00)	0.00 (0.00)	0.48 (2.10)	2.69 (2.10)
LEH.HQ	7.32E-05 (0.00)	-0.00 (0.00)	-20.86 (35.09)	-2.06 (35.09)	-0.00 (0.00)	0.00 (0.00)	-3.21 (3.15)	4.04 (3.12)
LEH.TZ	-0.00 (0.00)	-0.00 (0.00)	-5.69** (2.86)	6.75** (2.86)	0.00 (0.00)	0.00 (0.00)	0.47* (1.86)	1.25 (2.03)
WM.HV	-0.00 (0.00)	-0.00 (0.00)	-0.91 (0.65)	-0.47 (0.65)	-0.00 (0.00)	-0.00 (0.00)	-0.15 (1.67)	-0.06 (1.67)
CHK.HE	2.14E-06 (2.5E-06)	-3.77E-06 (2.5E-06)	-291.21 (1474.48)	174.32 (1474.52)	2.05E-05** (8.4E-06)	-1.84E-06 (8.5E-06)	93.63 (410.42)	35.25 (48.58)
LEH.XS	0.00 (0.00)	0.00 (0.00)	9.79 (8.05)	-3.07 (8.07)	-0.00 (0.00)	0.00 (0.00)	3.99 (5.96)	5.97 (6.11)
SFD.GG	6.59E-07 (3.0E-06)	-1.50E-06 (3.0E-06)	-58.71 (1308.33)	-321.10 (1308.67)	-3.61E-06 (4.8E-06)	-3.60E-06 (4.8E-06)	-27.74 (790.37)	-108.85 (788.88)
DJTE.GA	-2.69E-05 (0.00)	-0.00 (0.00)	2.57 (15.93)	13.43 (15.93)	0.00 (0.00)	-0.00 (0.00)	1.99 (3.87)	1.07 (3.86)

Table 7: Estimates of Volume-Volatility relation before and during the Crisis Period: 2SLS Model Results

The table presents the coefficient 2SLS estimates of the volume - volatility before and during the crisis period. Panel (A) shows the coefficient estimates of (θ_1), as implied by equation (11): $\hat{\sigma}^2_{it} = \theta_0 + \theta_1 \hat{VB}_{i,t-1} + \varepsilon_{it}$, where $(\hat{VB}_{i,t-1})$ is the fitted values for bond trading volume from equation (10): $VB_{it} = \alpha_0 + \alpha_1 (Age)_{it} + \alpha_2 (PriceVol)_{it} + \alpha_3 (VE) + \alpha_4 (RE) + \alpha_5 (RM) + \alpha_6 (VB_{i,t-1}) + \xi_{it}$ and $(\hat{\sigma}_{i,t-1})$ is the fitted values for return volatility from GJR-GARCH model, as implied by equation (6). Panel (B) shows the coefficient estimates of (β_4), from equation (13) $\sigma^2_{it} = \beta_0 + \beta_1 \varepsilon^2_{i,t-1} + \beta_2 \sigma^2_{i,t-1} + \beta_3 S_{t-1}\varepsilon^2_{i,t-1} + \beta_4 \hat{VB}_{i,t-1}$

	Panel (A)		Panel (B)	
	Before Crisis	During Crisis	Before Crisis	During Crisis
WM.IE	6.71E-05*** (0.00)	7.34E-05 (1.24E-05)	-1.08E-05 (2.60E-05)	0.01*** (2.08E-06)
WM.HE	0.0002*** (1.39E-06)	0.0002*** (1.07E-06)	-1.82E-05 (0.00)	-5.60E-05*** (3.31E-06)
GM.GM	0.0009** (0.00)	0.0009 (0.00)	-4.72E-05*** (1.36E-05)	-1.57E-05 (0.00)
GM.HB	0.0003*** (6.75E-07)	0.0002*** (7.57E-07)	-1.90E-05 (0.00)	-4.33E-05 (0.00)
F.GY	0.0002*** (5.05E-07)	0.0002*** (5.99E-07)	8.30E-06 (0.00)	-9.16E-05*** (9.72E-07)
WM.IL	0.0004** (0.00)	0.0002** (0.00)	-1.42E-05*** (1.50E-07)	0.00*** (1.92E-06)
RAD.GA	0.0002*** (1.57E-05)	0.0004*** (4.33E-05)	-9.30E-05*** (1.69E-05)	-0.00*** (1.70E-08)
GT.GF	6.72E-05*** (1.18E-06)	7.34E-05*** (1.24E-06)	-1.87E-05 (3.20E-05)	2.24E-05 (3.66E-
LEH.HF	0.0001*** (4.86E-05)	0.0002*** (5.30E-05)	0.00** (0.00)	-0.00*** (5.56E-05)
GM.HC	0.0003*** (7.28E-07)	0.0003*** (8.79E-07)	-2.01E-05 (0.00)	-1.40E-05 (0.00)
LEH.GZJ	0.0001** (8.53E-05)	0.0004*** (9.17E-05)	-1.48E-06 (0.00)	0.00*** (3.00E-05)
GM.HA	0.0002*** (8.36E-05)	0.0003*** (0.00)	-1.89E-05 (1.75E-05)	0.00*** (2.06E-05)
LEH.HQ	0.0002*** (3.58E-05)	0.0027*** (0.00)	-0.00** (0.00)	-0.00 (0.00)
LEH.TZ	0.0005** (0.00)	0.0007*** (0.00)	-2.52E-06 (7.59E-06)	-6.78E-05*** (1.06E-05)
WM.HV	0.0006** (0.00)	0.0005** (0.00)	-3.92E-05 (3.08E-05)	3.86E-05*** (7.40E-06)
CHK.HE	7.47E-05*** (7.89E-07)	7.89E-05*** (7.55E-07)	-2.11E-05** (8.45E-06)	-4.68E-05 (8.23E-05)
LEH.XS	0.0001** (6.64E-05)	0.0002** (8.01E-05)	-1.13E-05 (1.31E-05)	-0.01*** (1.05E-05)
SFD.GG	9.51E-05*** (9.79E-07)	9.26E-05*** (1.23E-06)	-1.38E-05 (0.00)	-6.83E-06 (8.20E-05)
DJTE.GA	0.0001*** (1.85E-05)	0.0004*** (7.67E-05)	-0.00*** (1.91E-05)	-1.22E-05 (0.00)