# Financial Market Imperfections and Their Asset Pricing Implications



by

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## Abstract

This thesis consists of two studies on financial market imperfections. The first study (Chapters 2 and 3) investigates illiquidity, which is a reflection of different imperfections, and its pricing implications in the corporate bond market. The second study (Chapter 4) evaluates the impact of a short-sale ban, which is a form of financial constraints, on the equity and derivatives markets.

In Chapter 2, we propose illiquidity measures that outperform existing ones statistically and economically. We estimate various illiquidity measures in the corporate bond market, using transaction-level data from 2002 to 2010. In the cross-section, we find illiquidity measures to be related to bond characteristics often used as illiquidity proxies. In the time-series, we show commonality in the aggregate illiquidity measures, increasing during the subprime crisis and peaking in October 2008. We then identify that time variation in aggregate illiquidity measures is linked with market variables such as the VIX index.

In Chapter 3, we examine pricing implications of the illiquidity measures. We find that illiquidity level is priced both at the aggregate level and at the bond level throughout the sample period. However, the role of illiquidity risk in pricing bond yield spreads is weaker, and is driven by the 2008 financial crisis.

In Chapter 4, we study the 2008 short-sale ban. We find that the banned stocks have positive cumulative abnormal returns and become more volatile when the ban is imposed. We document greater demand and abnormalities in the futures market and option market under the short-sale ban. This evidence suggests that a short-sale ban may not stabilize a financial market in crisis.

Thesis Supervisor: Jiang Wang
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# Chapter 1

# Introduction

This thesis presents two studies under a central theme of financial market imperfections and their pricing implications. The first study examines methods of quantifying illiquidity and tests asset pricing implications of illiquidity. The second study evaluates the effects of a short-sale ban, which is considered to be the extreme case of short-sale constraints, on the financial market. These two studies are self-contained. The contributions of the thesis are summarized in this chapter, and will be explained in detail in each study. The thesis is organized as follows.

For measuring illiquidity, we first review existing illiquidity measures in the literature, and propose new measures in Chapter 2. We use corporate bond data from 2002 to 2010 to estimate these measures. The cross-sectional and time-serial characteristics of these measures are examined. Using these illiquidity measures, we empirically test their pricing implications of illiquidity level as well as illiquidity risk in Chapter 3. This study makes two contributions. First, we identify measures that are more robust in terms of statistical significance and economic significance than previously used measures in the literature. Second, we provide empirical evidence that illiquidity level, as gauged by various measures, is priced in the corporate bond market. In contrast, the relation of illiquidity risk and bond yield spreads is weaker and seems to be driven by the 2008 financial crisis.

In Chapter 4, we focus on the short-sale ban established on September 18, 2008 by SEC (the US Securities and Exchange Commission) in response to the financial crisis. We first study how the short-sale ban impacts the equity market. We show that banned stocks are overvalued relative to the four factor model, and their returns are more volatile relative to the market. In addition, the effects of the ban on the derivatives market are examined.

Empirical tests show that the short-sale ban also affects the futures market and the option market, as seen in several variables such as futures premiums and option implied volatility. These main findings provide evidence that short-sale bans may not stabilize the financial market as expected.

# Chapter 2

# Measuring Illiquidity of Corporate Bonds

## 2.1 Introduction

Liquidity of an asset is how easy it is to trade that asset without causing price movement. The lack of liquidity or illiquidity arises from various market frictions such as information asymmetry, imperfection competition, transaction costs, and others [Vayanos and Wang (2012)]. Given the recent financial crisis, the importance of understanding illiquidity can not be overstated.[1] Two questions about illiquidity are central to our study. First, how can illiquidity be measured and what are its properties? Second, what are the asset pricing implications of illiquidity in the corporate bond market?

The first question of how illiquidity can be quantified has been investigated by a number of studies. Existing solutions range from using bid-ask spreads or asset characteristics as illiquidity proxies to constructing illiquidity measures motivated by theory or empirical facts. Each set of these measures will be briefly reviewed.

The literature on bid-ask spreads as well as heuristic measures is abundant. One of the early studies that investigates the use of bid-ask spreads is Amihud and Mendelson (1986). They present a model in which expected returns should increase with illiquidity as measured by bid-ask spreads and provide supporting empirical evidence from the early stock market. Different characteristics and trading activity variables have also been used as

[1] Brunnermeier (2009) gives an overview of the 2008 financial crisis and the interaction between market liquidity and funding liquidity.

illiquidity proxies. For example, Longstaff, Mithal, and Neis (2005) use bond characteristics, namely age, maturity, issuance, and raiting, to proxy for illiquidty in studying its relation to corporate bond yield spreads. Other work includes Chen, Lesmond, and Wei (2007), who use the number of zero-return days as an illiquidity measure. Turnover and modified turnover are used in many papers, including Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008). Although these heuristic measures provide quick estimates of illiquidity, they do not perform well in gauging illiquidity compared to theoretically motivated measures as shown by recent work such as Dick-Nielsen, Feldhtter, and Lando (2012).

Theoretical measures, as explained in Vayanos and Wang (2012), include price reversal, which captures the transitory component of illiquidity, and price impact, which reflects both the permanent and transitory components. An example of price reversal measures is the minus autocovariance in Bao, Pan, and Wang (2011). This measure is shown to dominate the bid-ask spread in measuring illiquidity.[2] As for the other class of theoretical measures, the price impact in Amihud (2002), defined as the price change per unit trade, has been used in many studies. Other measures belonging to the price impact family include those in Sadka (2006) and Glosten and Harris (1988). Recent work, such as Dick-Nielsen, Feldhtter, and Lando (2012), reports that these theoretical measures dominate heuristic measures, such as turnover, and the number of zero trading days, in gauging illiquidity. Although it is clear that these theoretically motivated measures capture illiquidity better than heuristic measures or bid-ask spreads, their relative performance of them is still debated.

Our first contribution is that we identify a set of illiquidity measures that can be shown to be more robust than others. Specifically, we review existing measures as well as propose new measures. The prior measures that we examine are the price reversal measure in Bao, Pan, and Wang (2011) and the price reversal conditional on volume in Campbell, Grossman, and Wang (1993). As for the price impact measures, we study a normalized price impact measure based on that in Amihud (2002), and the coefficient of return regressed on signed volume proposed in Vayanos and Wang (2012). Our proposed measures include the variance ratio, developed in Lo and MacKinlay (1988), the residual volatility of returns, and the mean-reversion coefficient of returns. We then compare their properties and their pricing implications to arrive at a set of robust measures. With more confidence in measuring

[2]Bao, Pan, and Wang (2011) document that only a small fraction of this measure is implied by bid-ask spreads.

illiquidity, these findings should allow further studies on illiquidity in other contexts.

The second question is how illiquidity and illiquidity risk are connected to asset returns, and more importantly whether it can explain the corporate yield spread puzzle. Corporate bond yield spreads are higher than what can be explained by credit risk. Huang and Huang (2003) and Elton, Gruber, Agrawal, and Mann (2001) examine this phenomenon and suggest that other factors such as illiquidity may account for the yield spreads. To date, there is no consensus on the role of illiquidity risk in the corporate spread puzzle. For example, Lin, Wang, and Wu (2011) and Dick-Nielsen, Feldhtter, and Lando (2012) report that illiquidity risk is priced in the corporate bond market. However, Bongaerts, De Jong, and Driessen (2011) argue that the effect of illiquidity risk is small. Other related work on this question includes Acharya and Pedersen (2005), who study illiquidity and illiquidity risk in the stock market, and Acharya, Amihud, and Bharath (2010), who investigate this issue in the corporate bond market.

Our second contribution is the finding that illiquidity level explains the yield spread puzzle, while illiquidity risk is not priced except during the financial crisis. Specifically, we estimate both existing illiquidity measures and our proposed measures using transaction-level corporate bond data from 2002 to 2010. We then test the pricing implications of illiquidity gauged by these measures and their risk in various specifications to reach this conclusion.

Our study can be summarized as follows. We first construct monthly estimates of illiquidity level using heuristic measures, price reversal measures, price impact measures, and other proposed measures. In estimation, we use bond trade data at the transaction-level that spans a period of about eight years from 2002 to 2010. Among other measures that we examined are the price reversal $\gamma$ in Bao, Pan, and Wang (2011), the regression coefficient on returns on signed volume $\lambda^{VW,signed}$ in Vayanos and Wang (2012), the variance ratio $VR$, and the residual volatility $\sigma_u$ from bond returns modelled as an AR(p) process. In a cross-sectional analysis, we find connections between illiquidity measures and bond characteristics documented in the literature as proxies for illiquidity. As for their time-series properties, we show that the time variations of these measures at the aggregate level share a commonality as well as comove with market conditions. These results enable us to confirm the validity of existing measures as well as our proposed measures in quantifying illiquidity. We then address the second question of the pricing implications of illiquidity in the corporate bond market. We show that corporate bond yield spreads are explained by most measures in our study both at the aggregate level and at the bond level, using the Fama and MacBeth (1973) regressions of yield spreads on these measures at monthly frequency.[3] Among all measures, we find that the residual volatility $\sigma_u$, the variance ratio $VR$, and the regression coefficient on returns on signed volume $\lambda^{VW,signed}$ dominate other measures in the pricing tests. Specifically, their estimated coefficients are statistically significant in various specifications and also economically significant in most cases. We further test the pricing implications of illiqudity risk associated with illiquidity level as gauged by each measure. The results show that part of corporate bond yield spreads is due to illiquidity level, while illiquidity risk explains yield spreads only during the crisis with negligible economic significance.

This work is organized as follows. Chapter 2 introduces the problem of illiquidity quantification and explains our proposed techniques for measuring illiquidity. Section 2.2 describes the data and gives summary statistics of our bond sample. Section 2.3 reviews existing measures and explains how our proposed measures are constructed. In Section 2.4, we report the cross-sectional and time-series properties of the measures.

Chapter 3 addresses the important question of how illiquidity and illiquidity risk are related to corporate bond yield spreads. In Section 1, we examine how illiquidity level explains yield spreads at the bond level. The pricing implcation of illiquidity risk is investigated in Section 2. We then compare the performance of illiquidity level measures and illiquidity risk measures in Section 3. Section 4 presents the relation between yield spreads and illiquidity at the aggregate level. Section 5 concludes.

## 2.2 Data Description and Summary Statistics

We obtain bond trade data from TRACE (Trade Reporting and Compliance Engine), which is dissemination service of corporate bond trade information. It was initially created by FINRA (The Financial Industry Regulatory Authority) on July 1, 2002 to increase transparency in the over-the-counter (OTC) corporate bond market by providing close to real-time information to the public. FINRA requires firms to report information within 15

[3]In regression analysis of yield spreads on illiquidity measures in Chapter 3, we start from a baseline that is controlled for bond characteristics, credit risk, and the underlying equity volatility. We then test each measure one by one, and finally run a horse race of measures that are statistically significant in their univariate regressions.

minutes of transactions as of July 1, 2005.[4] TRACE was implemented in three phases and reached full coverage in 2005 as described in FINRA (2011). In the first phase, the available data mostly consist of large investment-grade 520 corporate bonds. The second phase, which was completed on April 14, 2003, includes approximately 4,600 investment-grade bonds and only 50 speculative-grade bonds. FINRA completed the last phase in February 2005, enabling dissemination of 99% of all public transactions. The trade information we gather from this database includes transaction price, quantity, and execution time. The par value of a transaction is truncated at \$5 million for investment-grade bonds and at \$1 million for speculative bonds.

In addition to this trade information, we collect issue information from Mergent FISD (Mergent Fixed Income Securities Database). This dataset includes bond rating, offering date, offering amount, coupon, and bond maturity. Bonds may be rated at different times and by multiple credit rating agencies, which are Moody's, *S&P* (Standard and Poor's), and Fitch. We take the average of these reported ratings to use as the bond rating.

Stock and other data are also needed in our study. We obtain stock data from CRSP (The Center of Research in Security Prices). Other data that we use include interest rates from the Federal Reserve Bank, and market indices from Datastream (Thomson Reuters) and CBOE (The Chicago Board Options Exchange). Their details will be described in Section 2.4.2, where we use these data in our analysis.

Our pre-sample consists of bonds from July 2002 to December 2010. This duration of 7.5 years can be partitioned into three periods: Pre-Crisis, Crisis, and Post-Crisis, using the business cycle expansions and contractions announced by NBER (The National Bureau of Economic Research). In cleaning the data, we remove transactions with non-regular sale conditions or with special prices. We then correct the data for cancelled and corrected transactions. Lastly, we exclude repeated inter-dealer transactions and transactions with misreported prices or yields. After cleaning the data, we apply the following filters to arrive at our sample. First, we keep only bonds that are traded for one year or longer to avoid bonds that are present for only few months in the sample. Second, we require that bonds are traded for at least 75% of their trading days to avoid bonds with no trading activity during part of their time in the sample period. Third, we restrict our sample to only investment-grade bonds determined by their ratings in each period. Fourth, the included bonds must

[4]At the beginning, in 2002, the reporting requirement was 75 minutes.

have at least five transactions per day and 10 transactions per month to allow adequate accuracy in estimation. Lastly, we drop the three-month period before bond maturity to avoid the Brownian bridge of price.

We give summary statistics of our sample from July 2002 to December 2010 in Table 2.1. There is a total of 907 bonds, and approximately 500 bonds reside in each period. The rating median for our sample is A1 before the crisis, which degrades slightly to A2 in the two following periods. As for the issuance size, our bonds are fairly large. Their median issuance size is one billion dollars. The median age of bonds in the sample stays relatively constant at two years across the entire sample period. So does the median time to maturity, which is approximately six years. On average, a bond in the sample is traded for more than five years in the Pre-Crisis and Crisis periods, while this trading length is shorter in the Post-Crisis period. The average trading frequency and turnover are higher during the subprime crisis and after, compared to the time before the onset of the crisis.[5] On the other hand, the average trade size is smaller in the Crisis period. These two observations imply that traders break their trades into smaller sizes and trade more often during the crisis.

[5]In Section 2.4, we show that the number of trades per month may be used as a heuristic measure of illiquidity and is correlated with some theoretical measures.

Table 2.1: **Summary Statistics of Bond Sample**

This table reports summary statistics of the sample of 907 bonds by period. Rating is a numerical translation with AAA=1 and D=22. Turnover is the percentage of issuance traded per month.

| | Pre-Crisis Jul 2002 - Nov 2007 | | | Crisis Dec 2007 - Jun 2009 | | | Post-Crisis Jul 2009 - Dec 2010 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Median | Mean | Std. | Median | Mean | Std. | Median | Mean | Std. |
| #Bonds | | 442 | | | 461 | | | 504 | |
| Issuance ($10^6$\$) | 1,000 | 1,170 | 1,043 | 1,000 | 1,259 | 1,278 | 1,000 | 1,199 | 1,216 |
| Rating (AAA=1, D=22) | 5.15 | 5.30 | 1.94 | 6.00 | 6.19 | 1.93 | 6.17 | 6.93 | 1.93 |
| Age (yr) | 2.19 | 2.54 | 2.06 | 2.35 | 3.20 | 2.71 | 1.94 | 2.64 | 2.41 |
| Maturity (yr) | 5.13 | 7.33 | 6.84 | 6.17 | 8.62 | 8.13 | 5.93 | 8.44 | 7.93 |
| Coupon (%) | 5.50 | 5.49 | 1.28 | 5.55 | 5.63 | 0.99 | 5.65 | 5.70 | 1.45 |
| Years traded (yr) | 5.19 | 5.79 | 1.91 | 4.64 | 5.22 | 1.97 | 3.05 | 3.61 | 2.20 |
| Turnover (% of iss./month) | 8.22 | 10.43 | 7.16 | 6.07 | 7.38 | 4.80 | 6.87 | 9.15 | 7.57 |
| Trd Size ($10^3$\$, monthly) | 442 | 587 | 486 | 214 | 318 | 343 | 285 | 420 | 414 |
| #Trades (per month) | 159 | 198 | 108 | 274 | 371 | 304 | 199 | 281 | 233 |
| Price | 100.74 | 102.31 | 5.67 | 99.18 | 98.52 | 5.29 | 105.78 | 106.87 | 5.92 |

## 2.3 Measures of Illiquidity Level

Illiquidity is a result of market frictions and has a transitory impact on asset prices. In this section, we explore various illiquidity measures in the literature and propose a few new measures. They can be categorized into four families: 1) heuristic measures, 2) price reversal measures, 3) price impact measures, and 4) other measures.

Heuristic measures are often based on observed bond characteristics such as age and maturity. Section 2.3.1 discusses related work and outlines the definitions of heuristic measures in our study.

Besides heuristic measures, most of the theoretically motivated illiquidity measures can be classified into two categories: price reversal $\gamma$ and price impact $\lambda$. According to Vayanos and Wang (2012), $\lambda$ captures both the permanent component (caused by trade information) and the transitory component (caused by risk aversion of liquidity suppliers) of trade impact. On the other hand, $\gamma$ measures only the transitory part. Examples of $\lambda$ and related measures are the return per volume of Amihud (2002) and the coefficient of return regression on signed volume of Vayanos and Wang (2012). Measures related to $\gamma$ include the bid-ask spread in Roll (1984), the minus covariance in Bao, Pan, and Wang (2011), the price reversal conditional on signed volume in Campbell, Grossman, and Wang (1993), and the estimated transaction costs in Hasbrouck (2009).

Besides the $\lambda$ and $\gamma$ measures, we propose three new measures of illiquidity. The first is the RMSE (Root Mean Squared Error) of an order-p autoregressive model or AR(p) of demeaned returns. The second is the minus sum of AR(p) coefficients estimated in the former model. The last is the variance ratio (VR), introduced by Lo and MacKinlay (1988) and examined in Richardson and Stock (1989).

To facilitate the discussion of measures in subsequent subsections, we introduce the following notation for common variables of interest. For transaction $t$,

log price, $p_t \equiv ln(\text{clean price})$

log return, $r_t \equiv \Delta p_t = p_t - p_{t-1}$

Signed volume, $V_t$, is the par value volume in \$. The sign is positive if the dealer buys bonds from the client and negative otherwise.[6]

Unsigned volume, $|V_t|$, is the par value volume in \$.

Average volume, $\overline{V}$, is the average of daily unsigned volume in the sample period (includes only traded days) in \$

Issuance size, $I$ in \$

### 2.3.1 Heuristic Measures

Researchers and practitioners have used bond characteristics and trading activity variables as proxies for bond illiquidity. While these heuristic measures do not directly quantify illiquidity and may be outperformed by theoretically motivated measures, they have some links to theoretical measures, as will be shown in Section 2.4.1. Popular heuristic measures include age, maturity, issuance size, coupon, rating, turnover, trade size, and number of trades.

An example of prior work using bond characteristics is Campbell and Taksler (2003). They control for cross-sectional liquidity differences, using issuance size, maturity, and coupon rate[7] in studying the relation between corporate bond yield spreads and equity volatility. Of these three bond characteristics, they find maturity and coupon rate to be important control variables. Longstaff, Mithal, and Neis (2005) use coupon, issuance size, age, maturity, and a rating dummy as illiquidity proxies to explain the nondefault component of corporate bond yield spreads. Significant variables are issuance size, maturity, and the rating dummy. According to them, the rating dummy represents "flight-quality" or "flight-to-liquidity" rather than liquidity level itself. We will show later that some bond characteristics are connected with theoretical measures in Section 2.4.1. For example, older bonds are associated with higher illiquidity as gauged by theoretically motivated measures.

Trading activity variables have also been used extensively in the literature as illiquidity proxies. One of the illiquidity measures in Chen, Lesmond, and Wei (2007) is the percentage of zero returns. They report that this illiquidity proxy is a significant variable in explaining corporate bond yield spreads. Covitz and Downing (2007) use the number of trades at

[6] Inter-dealer trades are excluded when we estimate signed measures.

[7] Taxes are higher for bonds with higher coupon rates.

maturity as a liquidity proxy and show that it explains the yield spreads of very short-term commercial papers. Other variables include the weighted turnover in Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008). These trading activity measures are weakly connected with theoretical measures as will be shown in later sections.

In this work, we include the following heuristic measures, study their relations with other theoretical measures, as well as use them as control variables in pricing tests.

Age $\equiv$ How long bond has lived (in years)

Maturity $\equiv$ Time to maturity (in years)

Issuance $\equiv$ Par value of debt initially issued ($)

Turnover $\equiv$ Percentage of issuance traded in a month (%)

Trd Size $\equiv$ Par value volume ($)

Num Trds $\equiv$ Number of trades in a month

### 2.3.2 Price Reversal $\gamma$ and Variants

We assume that the log price $p_t$ has two components. The permanent component, $f_t$, is the fundamental value of the bond, which follows a random walk. The transitory component, $x_t$, is caused by illiquidity and is uncorrelated with $f_t$.

$$p_t = f_t + x_t \tag{2.1}$$

$$f_t = f_{t-1} + e_t, \tag{2.2}$$

where $e_t$ is shock of the random walk. The return is then

$$\begin{aligned} r_t &= p_t - p_{t-1} \\ &= q_t + e_t, \end{aligned} \tag{2.3}$$

where $q_t$ is the difference in the transitory component of price. This model is assumed for construction of illiquidity measures in 2.3.2 and 2.3.2, and again in 2.3.4 and 2.3.4.

**Bid-Ask Spread**

The bid-ask spread is one of the earliest illiquidity measures. Its connection with illiquidity has both theoretical and empirical grounds. In the theory literature, Stoll (1978) and Ho and Stoll (1981) are among the first to establish links between the bid-ask spread and market frictions. Stoll (1978) shows that market makers raise bid-ask spreads because of holding costs and order costs. Moreover, they also increase the bid-ask spread to compensate for their losses with information traders. Ho and Stoll (1981) derive an expression of the bid-ask spread that maximizes the dealer's expected utility, and conclude that the dealer widens the bid-ask spread due to a number of factors, including his risk aversion and the asset return variance. In addition, bid-ask spreads in the OTC market are shown to be larger than those in the exchange market in Ho and Stoll (1983).

On the empirical side, Amihud and Mendelson (1986) reason that illiquidity should explain asset returns. They use the bid-ask spread to measure illiquidity and show that it is a significant determinant of stock returns, using the data from 1960-1980. Bid-ask spreads have been used as an illiquidity proxy in many studies, including Brockman, Chung, and Prignon (2009), who investigate the relation between firm liquidity and exchange liquidity. Among others, Chen, Lesmond, and Wei (2007) and Longstaff, Mithal, and Neis (2005) include the bid-ask spread as one of illiquidity proxies in studying the relation between illiquidity and yield spreads.

The bid-ask spread is related to some heuristic measures. Specifically, the spread is larger for smaller trades as reported in Edwards, Harris, and Piwowar (2007). It is shown in Chen, Lesmond, and Wei (2007) that the bid-ask spread size can be explained by the number of zero returns at an adjusted $R^2$ around 7%.

There are two shortcomings in measuring illiquidity with bid-ask spreads. First, bid-ask quote data, unlike prices, may not be available. A number of techniques have been proposed to work around this problem. In a simple price model, Roll (1984) shows that the bid-ask spread can be estimated from autocovariance with the following relation:

$$s = 2\sqrt{-Cov(r_t, r_{t-1})}, \tag{2.4}$$

where $s$ is the bid-ask estimate and $Cov(r_t, r_{t-1})$ is the first lag autocovariance of returns. However, Harris (1990) later argues that this approach results in noisy estimates of the bid-ask spread in daily or weekly data and biased estimates in small samples. Hasbrouck (2009) proposes a way to estimate bid-ask spreads or transaction costs using Gibbs sampling, and reports that these estimates are close to actual data. This technique has been used in recent work, including Bongaerts, De Jong, and Driessen (2011).

Although recent techniques and increasing computing power allow for more accurate estimation of the bid-ask spread from price data, the bid-ask spread is not an accurate measure of illiquidity. Specifically, Bao, Pan, and Wang (2011) show that the bid-ask spread accounts for a tiny fraction of a theoretically motivated measure called minus autocovariance $\gamma$, introduced in Section 2.3.2.

### Minus Autocovariance

The minus autocovariance of returns $\gamma$ is linked to illiquidity both in the theoretical and empirical literature. In this section, we define the measure $\gamma$, analyze its dynamics, and explain why the illiquidity, as measured by $\gamma$, is much greater than the bid-ask bounce.

On the theory side, Huang and Wang (2009) show that the transitory effect of illiquidity gives rise to the negative serial correlation in returns, and this effect is higher on negative returns. The price reversal $\gamma$, which captures the transitory component of price changes, is analyzed in Vayanos and Wang (2012) for its relations to various market frictions. In an earlier version of the paper, they demonstrate that the minus autocovariance $\gamma$ increases with higher participation costs, transaction costs, and leverage constraints, while its relation with other types of imperfections can be either positive or negative. In the empirical literature, Bao, Pan, and Wang (2011) estimate $\gamma$ for a corporate bond sample, and show that it is a robust measure of illiquidity that comoves with market conditions at the aggregate level. In addition, they report that illiquidity, as measured by $\gamma$, is an important determinant of corporate yield spreads.

Using the model outlined in (2.1)-(2.3), we define $\gamma$ in the same manner as in Bao, Pan, and Wang (2011). We use the minus of the autocovariance rather than the autocovariance because the returns are negatively correlated:

$$\gamma \equiv -Cov(r_t, r_{t-1}), \tag{2.5}$$

where $r_t$ denotes the return of transaction $t$. To understand how $\gamma$ is influenced by the transitory component of price $q_t$, we explore two cases of $q_t$ dynamics. First, we consider a simple scenario where $q_t$ is modelled as an autoregressive process of order one or AR(1). Then, we consider a more general case of $q_t$ following an AR(p) process[8].

Suppose the transitory component of returns is an AR(1) process with coefficient $\rho_1$ and homoskedastic uncorrelated shock $\epsilon_t$. The magnitude of $\rho_1$ determines the persistence of the transitory component. This quantity represents the long-term part of illiquidty. On the other hand, the volatility of $\epsilon_t$ represents the short-term part of illiquidity.

$$q_t = \rho_1 q_{t-1} + \epsilon_t. \tag{2.6}$$

We can show that

$$\begin{aligned}
\gamma &= -Cov(r_t, r_{t-1}) \\
&= -Cov(q_t, q_{t-1}) \\
&= -\rho_1 Var(q_{t-1}, q_{t-1}) \\
\gamma &= -\rho_1 \frac{\sigma_\epsilon^2}{1-\rho_1^2}, \text{where } \sigma_\epsilon^2 \text{ is the variance of } q_t \text{ shock.}
\end{aligned} \tag{2.7}$$

From (2.7), $\gamma$ combines both the long-term and short-term aspects of illiquidity. The magnitude of $\gamma$ increases when the instantaneous volatility of the transitory component goes up. In general, it also increases with the persistence coefficient.

We now consider a more general case of the transitory component of returns, where $q_t$ is an AR(p) process. The coefficient of lag $\tau$ is denoted by $\rho_\tau$, and the shock is denoted by $\epsilon_t$.

$$q_t = \rho_1 q_{t-1} + \rho_2 q_{t-2} + \ldots + \rho_p q_{t-p} + \epsilon_t. \tag{2.8}$$

We can show that

$$\begin{aligned}
\gamma &= -Cov(r_t, r_{t-1}) \\
&= -Cov(q_t, q_{t-1}) \\
&= -Cov(\rho_1 q_{t-1} + \rho_2 q_{t-2} + \ldots + \rho_p q_{t-p}, q_{t-1}) \\
&= -\left\{\rho_1 Cov(q_{t-1}, q_{t-1}) + \rho_2 Cov(q_{t-2}, q_{t-1}) + \ldots + \rho_p Cov(q_{t-p}, q_{t-1})\right\}.
\end{aligned} \tag{2.9}$$

[8]Any autoregressive and moving average process of order (p,q) or ARMA(p,q) can be expressed as an AR(p) process.

With a few steps of algebriac manipulation, it follows that

$$\gamma = -\frac{\rho_1 + \rho_3\rho_2 + \rho_4\rho_3 + \ldots + \rho_p\rho_{p-1}}{1 - [\rho_2 + \rho_3(\rho_1 + \rho_3) + \rho_4(\rho_2 + \rho_4) + \ldots + \rho_p(\rho_{p-2} + \rho_p)]} \frac{\sigma_\epsilon^2}{1 - \sum_{\tau=1}^{p} \rho_\tau^2}. \tag{2.10}$$

By the model assumption, $|\rho_\tau| < 1$. Empirical evidence indicates that $\rho_s\rho_\tau \ll 1$ for $s \neq \tau$ and $s, \tau \neq 1$. We can approximate the measure as follows:

$$\gamma \approx -\frac{\rho_1}{1 - \rho_2} \frac{\sigma_\epsilon^2}{1 - \sum_{\tau=1}^{p} \rho_\tau^2}.$$

By further dropping the second order term in the shock variance quantity,

$$\gamma \approx -\frac{\rho_1}{1 - \rho_2}\sigma_\epsilon^2. \tag{2.11}$$

This analysis allows us to gauge the impact of the transitory dynamics on illiquidity as measured by $\gamma$. In addition to the first lag coefficient, the longer lag coefficients, especially the second one, also affect $\gamma$. Specifically, $\gamma$ decreases as the ratio of $\rho_2$ to $\rho_1$ goes up. This relation can be seen in two ways. As the relative size of $\rho_2$ and $\rho_1$ is closer to one, the transitory component, considered during a short interval, becomes smaller. In this scenario, $\rho_2$ also partially cancels the effect of $\rho_1$ more.

One important question is whether this autocovariance measure $\gamma$ is a mere reflection of the bid-ask bounce. A connection between $\gamma$ and bid-ask spreads is studied in Roll (1984). In this work, the price model consists of a fundamental $f_t$ and noise $x_t$. The fundamental $f_t$ is a random walk, and the noise $x_t$, generated by bid-ask sequences, is i.i.d.

$$p_t = f_t + x_t \tag{2.12}$$

$$x_t = -\frac{s}{2} sign(V_t), \tag{2.13}$$

where $s$ is the percentage bid-ask spread, and $sign(V_t)$ is -1 when the dealer sells a security and 1 when the dealer buys the security. Without the presence of any market frictions, Roll (1984) shows that

$$\gamma \equiv -Cov(r_t, r_{t-1}) \tag{2.14}$$

$$\gamma = \left(\frac{s}{2}\right)^2. \tag{2.15}$$

Despite the relation between $\gamma$ and bid-ask spreads in (2.15) derived in the simplied model, Bao, Pan, and Wang (2011) show that $\gamma$ captures much more than the effect of the bid-ask bounce. They estimate implied $\gamma$ from bid-ask spread quotes for a corporate bond sample, and find that these estimates are only a small fraction of $\gamma$ estimated from bond returns.

### Price Reversal Conditional on Normalized Volume

To distinguish liquidity trades from informational trades, we include the price reversal conditional on volume proposed in Campbell, Grossman, and Wang (1993). There is evidence showing that a high volume is usually followed by rising prices more often than falling prices in the stock market. Campbell, Grossman, and Wang (1993) provide further empirical evidence that a negative serial correlation in stock returns is more pronounced with a high volume, and explain this finding with a theoretical model. They point out that noninformational or liquidity trades are associated with a large volume, while this is not the case for informational trades. They explain that market makers demand higher expected future returns in order to accommodate selling pressure from liquidity traders.

With this idea, we use the price reversal conditional on normalized volume defined as follows:

$$r_{t+1} = \alpha + (\gamma_1 + \gamma^{CGW} \frac{|V_t|}{\overline{V}}) r_t, \tag{2.16}$$

where $\gamma_1$ is the first autocorrelation of returns, and $\gamma^{CGW}$ is the regression coefficient of returns on its first lag conditional on accompanied normalized volume. $|V_t|$ denotes the par value volume of transaction $t$, and $\overline{V}$ denotes the average daily par value volume. $\alpha$ is the regression constant, which is not important for our study.

Furthermore, we take advantage of the signed volume data available during the last two years of the sample, and estimate the signed conditional price reversal $\gamma^{CGW,signed}$. The regression used to estimate $\gamma^{CGW,signed}$ is similar to $\gamma^{CGW}$ with the substitution of the signed volume:

$$r_{t+1} = \alpha + (\gamma_1 + \gamma^{CGW,signed} \frac{V_t}{\overline{V}}) r_t, \tag{2.17}$$

where $V_t$ is negative if market makers buy bonds from clients and positive if market makers sell bonds to clients. Inter-dealer trades are excluded in estimating this measure.

### 2.3.3 Price Impact $\lambda$ and Variants

While the price reversal $\gamma$ captures the transitory component of the price change, the price impact $\lambda$ captures both the permanent and transitory components, as shown in Vayanos and Wang (2012). Therefore, in theory, $\lambda$ should provide a better estimate of illiquidity, compared to $\gamma$. In this section, we review some related work, and introduce two price impact measures. As a side note, we do not rely on the price model assumptions in Section 2.3.2 for these price impact measures.

One of earliest studies estimating both parts of market frictions is Glosten and Harris (1988). Using NYSE stock data from 1981-1983, they propose an econometric model that separates the bid-ask spread into the component due to asymmetric information, or the permanent component, and the component due to inventory and order costs, or the transitory component. They find that in addition to inventory and processing costs, illiquidity is also caused by asymmetric information. More recently, Sadka (2006) builds on this model and concludes that part of momentum and post-earnings-annoucement returns is due to informational trades.

One of the most widely used measures is the Amihud price impact. Amihud (2002) proposes an illiquidity measure that does not require microstructure data such as bid-ask spreads. This measure is defined as the price change per unit volume. Using this measure, he reports that illiquidity explains excess returns in the stock market. Closely related to the Amihud measure, one of our proposed measures is explained in Section 2.3.3.

#### Normalized Amihud Price Impact $\lambda^I$

We propose a normalized price impact based on that in Amihud (2002), with a slight modification. This adjustment is due to an observation that larger bonds having the same value of price change per unit volume as smaller bonds should be considered more illiquid. The measure is defined as the price movement per normalized trade size. We estimate monthly normalized price impact $\lambda^I$ using daily price impact and transaction-level price impact.

Normalized price impact of transaction $t$,

$$\lambda_t^I \equiv \frac{|p_t - p_{t-1}|}{V_t/I}, \tag{2.18}$$

where $p_t$ is the log return of transaction $t$, $V_t$ is the par value volume of the transaction in \$, and $I$ is the issuance size of the bond in \$.

Normalized price impact of day $d$,

$$\lambda_d^I \equiv \frac{1}{N_d} \sum_{t \in \text{ day } d} \lambda_t^{I,t}, \text{where } N_d \text{ is the number of transactions day } d. \tag{2.19}$$

Monthly estimate of normalized price impact,

$$\lambda^I \equiv \frac{1}{N_m} \sum_{d \in \text{ month } m} \lambda_d^{I,t}, \text{where } N_m \text{ is the number of traded days in a month} m. \tag{2.20}$$

### Coefficient of Return Regression on Signed Volume $\lambda^{VW,signed}$

The other price impact in our study is that proposed in Vayanos and Wang (2012). It is the regression coefficient of the return on the normalized signed volume. In other words, it represents the sensitivity of the return to buy and sell demands conditional on volume. This price impact $\lambda^{VW}$ is estimated from the following regression:

$$r_t = \alpha + \lambda^{VW,signed} \frac{V_t}{\overline{\overline{V}}}, \tag{2.21}$$

where $\lambda^{VW,signed}$ is the regression coefficient. $\overline{V}$ denotes the average daily par value volume. $V_t$ denotes the signed par value volume of transaction $t$. $V_t$ is positive when investors sell bonds to market makers, and negative when investors buy bonds from market makers. Inter-dealer trades are excluded in this estimation. Since the signed volume data are available only from November 2008 to December 2010, the estimated signed measures, $\lambda^{VW,signed}$ as well as $\gamma^{CGW,signed}$ introduced in Section 2.3.2, are based on shorter period of data. Despite the limitation in sample length, we are still able to show statistical significance of this measure in pricing tests to be covered in subsequent sections. This evidence tells us that $\lambda^{VW,signed}$ is a strong illiquidity measure.

In their theoretical model, Vayanos and Wang (2012) show that this measure increases with greater volatility of the asset, greater risk aversion of the investor, and a lower number of market makers (or liquidity suppliers). $\lambda^{VW,signed}$ is also shown to capture illiquidity better than price reversal measures.

### 2.3.4 Other Measures

In this section, we introduce three measures of illiquidity that do not fall into the price reversal or price impact categories. We briefly review the related literature and motivations behind them. These measures are the variance ratio, the residual volatility of the return transitory component, and the residual volatility of the total return. The price model in Section 2.3.2 is assumed.

#### Variance Ratio

The variance ratio proposed by Lo and MacKinlay (1988) is initially used to test the random walk hypothesis of stock prices.[9] The variance ratio at horizon $\tau$ or $VR(\tau)$ is defined as follows:

$$VR(\tau) \equiv \frac{Var[r_t(\tau)]}{\tau Var[r_t(1)]}, \tag{2.22}$$

where $\tau$ is the number of trading days, and $r_t(\tau)$ is the $\tau$-day return. In our estimation, we use a horizon of 120 days or $\tau = 120$. $Var[r_t(\tau)]$ denotes the variance of the $\tau$-day return. They show that when $Cov(r_t, r_{t+1}) \approx 0$ as $\tau \to \infty$, the variance ratio approaches the asymptotic value in (2.23):

$$VR(\tau) \to 1 - \frac{Var[q_t]}{Var[r_t]}. \tag{2.23}$$

[9] A number of studies extend the original variance ratio statistic such as Ronen (1997) and Andersen, Bollerslev, and Das (2001).

If the return were a random walk, the variance ratio would be 1 at all horizons. However, because of correlations among return lags, the variance ratio is less than 1. We observe that the variance ratio reaches the steady-state limit more slowly during financial distress as shown in Figure 2.2. Based on this fact, we use the variance ratio estimates at a given horizon as an illiquidity measure. One would expect that an illiquid bond would have a higher variance ratio than a liquid bond at a horizon before their steady-state values.

We are aware of the possibility of biased estimates in the variance ratio by using overlapping observations as opposed to nonoverlapping observations as pointed out in Richardson and Stock (1989). However, our sample period is not long enough to allow us to use nonoverlapping observations. Figure 2.3 shows that the variance ratio estimates from nonoverlapping observations can be non-monotonically decreasing with the horizon. With this limitation, we use overlapping observations in our estimation.

Based on the asymptotics of the variance ratio in (2.23), we can deduce the relative size of the transitory component and the fundamental component. For the sample, the transitory component variance is about nine times larger than that of the fundamental component. This value translates to approximately threefold volatility.

### RMSE of Transitory Component Decomposed by Kalman Filter

With the price model in (2.1)-(2.3), we examine the possibility of using the Kalman filter in Kalman (1960) to decompose the return into two components. This decomposition will allow us to estimate the residual volatility of the transitory component and that of the permanent component. In this setting, the observed return is the measurement equation (2.24), and the unobserved transitory component is the state equation (2.25). We make an additional assumption that the transitory component can be captured as an AR(p) process.

$$r_t = q_t + e_t, \tag{2.24}$$

where $q_t$ is the transitory component of returns, and $e_t$ is the random walk increment of the fundamental.

$$q_t = \sum_{\sigma=1}^{p} \rho_s q_{t-s} + \epsilon_t, \tag{2.25}$$

where $\rho_s$ is the correlation coefficient of lag $s$, and $\epsilon_t$ is the noise of the transitory component.

To check the feasibility of this approach, we perform Monte Carlo simulations in a practical setting. The fundamental noise $e_t$ and the transitory noise $\epsilon_t$ are specified to be normally distributed with time varying variances $\sigma_{e,t}$ and $\sigma_{\epsilon,t}$, respectively. In addition, these two noises are correlated with time varying correlation coefficient $\rho_{e\epsilon,t}$.[10] With these parameters, the two noises are drawn from the distribution in (2.26).

$$\begin{bmatrix} e_t \\ \epsilon_t \end{bmatrix} \sim \mathcal{N}\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{e,t}^2 & \rho_{e\epsilon,t}\sigma_{e,t}\sigma_{\epsilon,t} \\ \rho_{e\epsilon,t}\sigma_{e,t}\sigma_{\epsilon,t} & \sigma_{\epsilon,t}^2 \end{bmatrix} \right) \tag{2.26}$$

It turns out that this approach is not practical for our estimation. To acheive accuracy within 10% of the true value, one would need at least approximately 5,000 observations as shown in Figure 2.4. However, the bonds in our sample have on average about 200-370 trades per month, depending on the period. Although we can not estimate the residual volatility of the transitory component of returns, we can approximate it by estimating the residual volatility of the total return because the size of the transitory component[11] is about three times larger than that of the fundamental component, as implied by the variance ratio. We explain the residual volatility estimation of the total returns in Section 2.3.4.

### RMSE and Minus Mean-Reversion Coefficient of Total Return

To distinguish the short-term illiquidity from the long-term illiquidity in returns, we propose an approach that allows for estimates of these two parts. For each bond, we model the return time series with an AR(p) process in (2.27):

$$r_t^d = \phi_1 r_{t-1}^d + \phi_2 r_{t-2} + \ldots + \phi_p r_{t-p}^d + v_t, \tag{2.27}$$

where $r_t^d$ is the demeaned return of transaction $t$, $\phi_s$ is the correlation coefficient of lag $s$, and $u_t$ is the model error. The minus sum of all lag coefficients tells us how mean-reverting the return is. Thus, the magnitude of this sum should be higher for more liquid bonds. We

[10]For each replication in the Monte Carlo simulations, parameters $\sigma_{e,t}$, $\sigma_{\epsilon,t}$, and $\rho_{e\epsilon,t}$ are first drawn from their normal distributions. Then, the fundamental noise $e_t$ and the transitory noise $\epsilon_t$ are drawn from the normal distribution in (2.26) with these parameters.

[11]As measured by volatility.

denote this long-term illiquidity estimate as $\Phi$. In contrast, the volatility model error $v_t$ is the instantaneous deviation of the return.

In estimation, we determine the number of lags with AIC (Akaike Information Criterion) and BIC (Bayesian/Schwartz Information Criterion). Using transactional-level data, we find that the optimal number of lags is about four for bonds in our sample, and the $R^2$ is around 20%. With this choice, we estimate the two measures in the following regression:

$$r_t^d = \widehat{\phi}_1 r_{t-1}^d + \widehat{\phi}_2 r_{t-2}^d + \widehat{\phi}_3 r_{t-3}^d + \widehat{\phi}_4 r_{t-4}^d + \eta_t, \tag{2.28}$$

where $\widehat{\phi}_s$ is the estimated correlation coefficient of lag $s$, and $\eta_t$ is the residual from estimation. We then collect the correlation coefficient estimates $\widehat{\phi}_s$ and the residuals $\eta_t$ for each month and define the two measures as follows.

Minus sum of mean-reversion coefficients,

$$\Phi \equiv -(\widehat{\phi}_1 + \widehat{\phi}_2 + \widehat{\phi}_3 + \widehat{\phi}_4) \tag{2.29}$$

Residual volatility,

$$\sigma_u \equiv \sqrt{\frac{1}{N_m} \sum_{t \in \text{ month } m} \eta_t^2}, \tag{2.30}$$

where $N_m$ is the number of observations in a month.

### 2.3.5 Summary Statistics and Correlations

Using transaction-level data, we estimate monthly illiquidity measures and report their summary statistics in Table 2.2. The sample period is specified in each panel for most measures, except the two signed measures whose sample period is available from November 2008 onwards. All of the measure estimates have statistically signficant means. $\gamma^{CGW,signed}$ is the exception due to a shorter sample period. Most of the estimates show an increase in illiquidity level during the crisis.

For example, the average of price reversal $\gamma$ increases more than twice as much, from 0.45 in the Non-Crisis period to 0.96 in the Crisis period. The price impact $\lambda^I$ average almost doubles in the Crisis period, while the signed price impact $\lambda^{VW,signed}$ average increases more than two times as much as its average during the normal time. Similarly, our proposed measures $\Phi$ and $\sigma_u$ have a statistically significant difference between normal times and the financial crisis. The $\Phi$ average goes down from 1.54 to 1.42, signifying that bond returns are less mean-reverting during the Crisis. The increase in $\sigma_u$ in the Crisis period shows that the short-term illiquidity is larger. Of all the measures, the variance ratio $VR$ shows the least change between regimes. Its average goes up by 0.01 during the Crisis Period, and the difference between periods is statistically indistinguishable.

We study correlations among all the measures and report them in Table 2.3. With these results, we can see some connections between measure families. The price reversal $\gamma$ is moderately correlated with those in the price impact family. For example, the correlation between $\gamma$ and $\lambda^I$ is 0.44, and that between $\gamma$ and $\lambda^{VW,signed}$ is 0.22. In addition, the price reversal $\gamma$ is highly correlated with the residual volatility $\sigma_u$, which can be expected from (2.7). This high correlation indicates that much of the short-term illiquidity is due to the transitory component in returns. The residual volatility also correlates with the measures in the price impact family. On the contary, the mean-reversion measure $\Phi$ and the variance ratio $VR$ seem to be orthogonal with other measures, showing little correlation.

Within the price reversal family, there is a weak correlation between $\gamma$ and $\gamma^{CGW}$. $\gamma^{CGW,signed}$ does not comove with $\gamma$ and $\gamma^{CGW}$. This observation implies that volume is an important factor that separates these three measures. As for the price impact family, $\lambda^{VW,signed}$ and $\lambda^I$ overlap slightly. The other three measures $\sigma_u$, $\Phi$, and $VR$ are slightly correlated although they are constructed from different bases.

As far as heuristic measures are concerned, a subset of them show small but statistically significant correlations with theoretically motivated measures. For example, $ln(TrdSize)$ and $ln(NumTrds)$ are slightly correlated with $\gamma$, with correlations of -0.14 and 0.09, respectively. *Maturity* is the best heuristic measure, with a correlation of 0.47 with $\gamma$ and with a correlation of 0.49 with $\sigma_u$. *Age*, on the other hand, does not correlate with the theoretical measures except the variance ratios. These results imply that some of bond characteristics and trading variables measure illiquidity to some extent.

Within the heuristic measure family, bond characteristics and trading activity quantities exhibit some correlations. For example, older bonds have lower turnovers and their trades occur at smaller sizes. The three heuristic measures of trading activity are connected. For example, $ln(NumTrds)$ has a correlation of -0.20 with $ln(TrdsSize)$. This statistic implies that an increasing number of trades for a bond occur at smaller trade sizes. *turnover* has correlations of 0.55 with $ln(TrdSize)$ and of 0.24 with $ln(NumTrds)$, respectively. This evidence implies that we would need only one of the three trading activity measures when performing subsequent analyses to avoid multicolinearity.

Table 2.2: **Summary Statistics of Illiquidity Level Measures**

This table reports statistics of time-serial means of illiquidity level monthly estimates for the 907 bonds in the sample. The sample period is defined in each panel except for the signed measures whose data are available from November 2008 onwards. The robust t-statistics for means in brackets account for cross-sectional and serial correlations. Top and bottom 0.5% of illiquidity level estimates are winsorized. Top and bottom 1% of monthly yield spreads and associated measure estimates are trimmed.

Panel A: Full Sample (July 2002 - December 2010)

| | $\gamma$ | $\gamma^{CGW}$ | $\gamma^{CGW,signed}$ | $\lambda^{I}$ ($\times 10^{3}$) | $\lambda^{VW,signed}$ ($\times 10^{-3}$) | $\Phi$ | $\sigma_u$ | $VR$ |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.56 | 0.33 | 0.03 | 0.81 | 6.87 | 1.51 | 0.90 | 0.09 |
| Std. Dev. | 0.46 | 0.35 | 0.38 | 0.85 | 8.94 | 0.19 | 0.39 | 0.08 |
| 95% C.I. | (0.49, 0.64) | (0.28, 0.38) | (-0.00, 0.06) | (0.66, 0.95) | (4.28, 9.47) | (1.47, 1.55) | (0.83, 0.97) | (0.08, 0.11) |
| Robust t-stat | [14.67] | [13.29] | [1.86] | [11.00] | [5.20] | [75.87] | [24.73] | [12.96] |
| 95th | 1.50 | 0.96 | 0.48 | 2.56 | 21.85 | 1.75 | 1.64 | 0.26 |
| Median | 0.44 | 0.26 | 0.03 | 0.51 | 4.28 | 1.54 | 0.84 | 0.07 |
| 5th | 0.09 | -0.08 | -0.41 | 0.10 | 0.23 | 1.16 | 0.40 | 0.02 |

Panel B: Non-Crisis (July 2002 - November 2007 and July 2009 - December 2010)

| | $\gamma$ | $\gamma^{CGW}$ | $\gamma^{CGW,signed}$ | $\lambda^{I}$ ($\times 10^{3}$) | $\lambda^{VW,signed}$ ($\times 10^{-3}$) | $\Phi$ | $\sigma_u$ | $VR$ |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.45 | 0.38 | 0.01 | 0.69 | 4.90 | 1.54 | 0.78 | 0.09 |
| Std. Dev. | 0.40 | 0.37 | 0.36 | 0.72 | 5.98 | 0.20 | 0.33 | 0.08 |
| 95% C.I. | (0.41, 0.48) | (0.33, 0.43) | (-0.05, 0.07) | (0.59, 0.79) | (3.91, 5.89) | (1.48, 1.60) | (0.75, 0.82) | (0.08, 0.10) |
| Robust t-stat | [28.14] | [16.04] | [0.40] | [13.17] | [9.70] | [50.41] | [39.91] | [14.14] |
| 95th | 1.29 | 1.05 | 0.45 | 2.19 | 17.79 | 1.78 | 1.44 | 0.25 |
| Median | 0.34 | 0.32 | 0.00 | 0.45 | 3.04 | 1.58 | 0.74 | 0.07 |
| 5th | 0.08 | -0.05 | -0.45 | 0.09 | 0.11 | 1.15 | 0.36 | 0.02 |

Panel C: Crisis (December 2007 - June 2009)

| | $\gamma$ | $\gamma^{CGW}$ | $\gamma^{CGW,signed}$ | $\lambda^{I}$ ($\times 10^{3}$) | $\lambda^{VW,signed}$ ($\times 10^{-3}$) | $\Phi$ | $\sigma_u$ | $VR$ |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.95 | 0.13 | 0.05 | 1.29 | 10.95 | 1.42 | 1.29 | 0.10 |
| Std. Dev. | 0.65 | 0.32 | 0.53 | 1.24 | 12.70 | 0.15 | 0.47 | 0.07 |
| 95% C.I. | (0.86, 1.03) | (0.07, 0.18) | (0.00, 0.10) | (1.01, 1.56) | (9.00, 12.90) | (1.39, 1.45) | (1.21, 1.36) | (0.08, 0.12) |
| Robust t-stat | [21.35] | [4.34] | [1.99] | [9.21] | [11.03] | [103.10] | [32.91] | [9.54] |
| 95th | 2.41 | 0.59 | 0.65 | 4.07 | 34.83 | 1.64 | 2.15 | 0.26 |
| Median | 0.80 | 0.12 | 0.06 | 0.83 | 7.37 | 1.44 | 1.24 | 0.07 |
| 5th | 0.19 | -0.33 | -0.53 | 0.21 | 0.26 | 1.14 | 0.61 | 0.03 |

Table 2.3: **Correlation Matrix of Illiquidity Level Measures**

The sample period is from July 2002 to December 2010 (except those signed measures whose data are from November 2008 to December 2010). P-values are shown in parentheses. Correlations with statistical significance of at least 5% level are boldfaced. Top and bottom 0.5% of illiquidity level estimates are winsorized. Top and bottom 1% of monthly yield spreads and associated measure estimates are trimmed.

| | $\gamma$ | $\gamma^{CGW}$ | $\gamma^{CGW,signed}$ | $\lambda^{I}$ | $\lambda^{VW,signed}$ | $\Phi$ | $\sigma_u$ | $VR$ | Age | Maturity | Turnover | ln(Trd Size) | ln(Nm Trds) | $\sigma_E$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\gamma$ | 1.00 | | | | | | | | | | | | | |
| $\gamma^{CGW}$ | **-0.10** | 1.00 | | | | | | | | | | | | |
| | (0.00) | | | | | | | | | | | | | |
| $\gamma^{CGW,signed}$ | **0.04** | 0.00 | 1.00 | | | | | | | | | | | |
| | (0.00) | (0.74) | | | | | | | | | | | | |
| $\lambda^{I}$ | **0.44** | **0.05** | 0.00 | 1.00 | | | | | | | | | | |
| | (0.00) | (0.00) | (0.92) | | | | | | | | | | | |
| $\lambda^{VW,signed}$ | **0.23** | **-0.03** | **0.07** | **0.15** | 1.00 | | | | | | | | | |
| | (0.00) | (0.02) | (0.00) | (0.00) | | | | | | | | | | |
| $\Phi$ | **0.02** | **0.14** | 0.02 | 0.00 | **-0.02** | 1.00 | | | | | | | | |
| | (0.01) | (0.00) | (0.14) | (0.69) | (0.05) | | | | | | | | | |
| $\sigma_u$ | **0.90** | **-0.15** | **0.03** | **0.49** | **0.27** | **-0.17** | 1.00 | | | | | | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | | | |
| $VR$ | **0.13** | 0.01 | 0.02 | **0.12** | **0.05** | **-0.12** | **0.18** | 1.00 | | | | | | |
| | (0.00) | (0.47) | (0.19) | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | | |
| Age | **-0.07** | **-0.03** | **-0.03** | **0.01** | **0.11** | **-0.07** | **-0.05** | **-0.21** | 1.00 | | | | | |
| | (0.00) | (0.00) | (0.00) | (0.04) | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | |
| Maturity | **0.47** | **-0.04** | **0.02** | **0.24** | **0.05** | **-0.11** | **0.49** | **0.32** | **-0.25** | 1.00 | | | | |
| | (0.00) | (0.00) | (0.04) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | | | | | |
| Turnover | 0.01 | 0.00 | **0.02** | **-0.14** | **-0.14** | **0.02** | -0.01 | **0.22** | **-0.34** | **0.17** | 1.00 | | | |
| | (0.26) | (0.81) | (0.05) | (0.00) | (0.00) | (0.01) | (0.40) | (0.00) | (0.00) | (0.00) | | | | |
| ln(Trd Size) | **-0.14** | **0.11** | -0.01 | **-0.06** | **-0.38** | **0.03** | **-0.18** | **0.17** | **-0.43** | **0.17** | **0.55** | 1.00 | | |
| | (0.00) | (0.00) | (0.42) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | | | |
| ln(Nm Trds) | **0.09** | **0.02** | **0.05** | **0.31** | **0.15** | **0.09** | **0.11** | **0.18** | **0.03** | **-0.01** | **0.24** | **-0.20** | 1.00 | |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.05) | (0.00) | (0.00) | | |
| $\sigma_E$ | **0.36** | **-0.14** | **0.05** | **0.23** | **0.18** | **-0.21** | **0.46** | **0.11** | **0.08** | -0.01 | 0.01 | **-0.16** | **0.26** | 1.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.28) | (0.15) | (0.00) | (0.00) | |

## 2.4 Properties of Illiquidity Level Measures

To better understand the nature of illiquidity measures, we study their properties in two ways. First, we examine their cross-sectional relations with bond characteristics. Then, we look at their connections with market conditions.

### 2.4.1 Illiquidity and Bond Characteristics

In studying how illiquidity measures are related to bond characteristics, we run the following pooled regressions for each measure. Monthly illiquidity measures are estimated using transaction-level data.

$$L_{it} = a + \sum_j b_j char^j_{it} + \varepsilon_{it}, \tag{2.31}$$

where the subscript $it$ denotes bond $i$ in month $t$. $L_{it}$ denotes the illiquidity estimate of bond $i$ in month $t$, and $b_j$ denotes the regression coefficient on bond characteristic $j$ abbreviated as $char^j$.

We report the results of this analysis in Table 2.4. The results are based on the full sample period for unsigned measures in Panel A. We can see that bond characteristics are important explanatory variables of illiquidity measures in most cases with $R^2$ of 20% or more. Panel B shows the results of the signed measures whose sample starts in November 2008. Consequently, some coefficient estimates for the signed measures are statistically insignificant although they may be significant with a longer sample. The low $R^2$ values for these signed measures are probably due to this fact as well.

There are five commonalities in the relations of illiquidity measures and bond characteristics. First, young bonds are more liquid than old bonds. This trend is consistent with the findings in Bao, Pan, and Wang (2011) and Edwards, Harris, and Piwowar (2007). This observation is true for all illiquidity measures except $VR$. For example, a bond aging one more year has an increase of 0.01 in its $\gamma$, 60 in its $\lambda^I$, and 0.02 in its $\sigma_u$. These increases are equivalent to 2%, 7%, and 2% of their full sample averages, respectively. Therefore, the $\lambda$ measures tend to be more sentitive with age than those in other families.

Second, a similar relation also holds for bond maturity. Bonds with longer time to maturity tend to be less liquid. Roughly, a bond with one year longer time to maturity sees an increase of 0.05, 40, and 0.04 in its $\gamma$, $\lambda^I$, and $\sigma_u$, respectively. These changes account for approximately 9%, 5%, and 4% of these three measure averages, respectively. Hence, cross-sectional variation in $\gamma$ and $\sigma_u$ are more associated with age than maturity. However, the opposite is true for the $\lambda$ family. Maturity also explains cross-sectional differences in other measures. For instance, bonds with one-year longer maturity, on average, have a $\Phi$ of 0.006 less and a $\gamma^{CGW}$ of 0.01 less.

Third, the bond size also has mixed connections with illiquidity measures. For some measures ($\gamma, \gamma^{CGW}, \gamma^{CGW,signed}$, and $\sigma_u$), bonds with larger issuances are more liquid. For others, the issuance size does not have a significant relation to illiquidity or has the opposite connection.

Fourth, bonds with lower ratings are sometimes more illiquid, depending on the measures considered. This relation holds for $\gamma^{CGW}, \Phi, \sigma_u$, and $VR$. However, ratings have no effect on other measures.

Lastly, bonds with higher turnover are more liquid, and bonds with a higher number of trades per month are less liquid. The former is intuitive. The latter can be explained by our observations about the number of trades and the trade size in previous sections. Table 2.3 reports a negative correlation between the number of trades and trade size. In addition, the number of trades is the highest while the trade size is the smallest during the Crisis period as shown in Table 2.2. These two facts imply that investors may break their big trades into smaller ones and trade more often during illiquid times.

Given these statistically significant relations with illiquidity measures, there are grounds for using some bond characteristics and trading activity quantities as illiquidity proxies. This observation is particularly true for age, maturity, turnover, and number of trades.

Table 2.4: **Cross-sectional Variation in Measures and Bond Characteristics**

This table reports pooled regressions of measures on bond charactersitics. T-statistics in brackets account for cross-sectional and serial correlations. The data are from July 2002 to December 2010 except the signed measures, whose period is from November 2008 to December 2010.

Panel A: Full Sample (July 2002 - December 2010)

| | $\gamma$ | | | $\gamma^{CGW}$ | | |
|---|---|---|---|---|---|---|
| Intercept | 0.52 | 0.61 | 0.19 | -0.97 | -1.01 | -0.83 |
| | [2.45] | [2.92] | [0.95] | [-5.71] | [-5.92] | [-4.46] |
| Age | 0.01 | 0.00 | 0.01 | -0.01 | -0.01 | -0.01 |
| | [2.62] | [1.08] | [2.16] | [-2.69] | [-1.96] | [-2.47] |
| Maturity | 0.05 | 0.05 | 0.05 | -0.01 | -0.01 | -0.01 |
| | [13.45] | [13.46] | [14.00] | [-3.83] | [-4.04] | [-3.97] |
| ln(Issuance) | -0.06 | -0.06 | -0.11 | 0.22 | 0.23 | 0.25 |
| | [-2.10] | [-2.36] | [-3.88] | [9.06] | [9.26] | [9.01] |
| Rating | 0.01 | 0.01 | 0.01 | -0.02 | -0.02 | -0.02 |
| | [1.42] | [1.86] | [0.81] | [-3.34] | [-3.70] | [-2.99] |
| Turnover | | -0.01 | | | 0.00 | |
| | | [-3.41] | | | [1.85] | |
| ln(Num Trds) | | | 0.14 | | | -0.06 |
| | | | [8.33] | | | [-2.60] |
| Obs | 22,046 | 22,046 | 22,046 | 21,885 | 21,885 | 21,885 |
| $R^2$(%) | 22.82 | 23.35 | 24.35 | 4.28 | 4.33 | 4.50 |
| | $\lambda^I$ ($\times 10^3$) | | | $\Phi$ ($\times 10^{-2}$) | | |
| Intercept | -6.06 | -5.80 | -6.61 | 168.70 | 166.50 | 158.27 |
| | [-13.47] | [-13.54] | [-14.68] | [26.79] | [25.32] | [24.66] |
| Age | 0.06 | 0.04 | 0.05 | -1.22 | -1.05 | -1.29 |
| | [5.74] | [3.95] | [5.42] | [-6.81] | [-5.49] | [-7.20] |
| Maturity | 0.04 | 0.04 | 0.04 | -0.57 | -0.58 | -0.55 |
| | [7.31] | [7.67] | [7.63] | [-6.58] | [-6.64] | [-6.73] |
| ln(Issuance) | 0.93 | 0.91 | 0.83 | 1.43 | 1.57 | -0.36 |
| | [14.73] | [14.92] | [12.66] | [1.80] | [1.94] | [-0.42] |
| Rating | 0.03 | 0.04 | 0.02 | -2.48 | -2.56 | -2.62 |
| | [1.95] | [2.65] | [1.39] | [-9.99] | [-10.35] | [-10.76] |
| Turnover | | -0.02 | | | 0.15 | |
| | | [-7.25] | | | [2.94] | |
| ln(Num Trds) | | | 0.23 | | | 4.34 |
| | | | [5.71] | | | [4.53] |
| Obs | 22,046 | 22,046 | 22,046 | 22,046 | 22,046 | 22,046 |
| $R^2$(%) | 32.58 | 33.92 | 34.14 | 5.29 | 5.43 | 6.04 |

| | $\sigma_u$ | | | $VR$ ($\times 10^{-2}$) | | |
|---|---|---|---|---|---|---|
| Intercept | 0.69 | 0.78 | 0.41 | -14.89 | -16.19 | -17.51 |
| | [5.19] | [6.09] | [3.13] | [-5.88] | [-6.30] | [-6.99] |
| Age | 0.02 | 0.01 | 0.01 | -0.39 | -0.30 | -0.41 |
| | [3.96] | [2.46] | [3.55] | [-4.30] | [-3.28] | [-4.60] |
| Maturity | 0.04 | 0.04 | 0.04 | 0.27 | 0.26 | 0.27 |
| | [17.51] | [17.67] | [18.29] | [6.70] | [6.72] | [6.65] |
| ln(Issuance) | -0.04 | -0.05 | -0.09 | 2.44 | 2.51 | 1.97 |
| | [-2.34] | [-2.80] | [4.64] | [7.38] | [7.64] | [5.27] |
| Rating | 0.03 | 0.03 | 0.02 | 1.05 | 0.98 | 1.02 |
| | [4.30] | [4.64] | [3.77] | [8.70] | [8.45] | [8.56] |
| Turnover | | -0.01 | | | 0.14 | |
| | | [-4.17] | | | [4.46] | |
| ln(Num Trds) | | | 0.12 | | | 1.13 |
| | | | [8.05] | | | [3.88] |
| Obs | 22,046 | 22,046 | 22,046 | 18,412 | 18,412 | 18,412 |
| $R^2$(%) | 26.47 | 27.29 | 41.78 | 24.79 | 26.29 | 25.81 |

Panel B: Signed Volume Data Available (November 2008 - December 2010)

| | $\gamma^{CGW,signed}$ | | | $\lambda^{VW,signed}$ ($\times 10^{-3}$) | | |
|---|---|---|---|---|---|---|
| Intercept | -0.38 | -0.36 | -0.54 | 8.94 | 12.49 | -0.89 |
| | [-1.83] | [-1.87] | [-2.49] | [1.96] | [2.70] | [-0.20] |
| Age | -0.00 | -0.01 | -0.01 | 0.76 | 0.56 | 0.65 |
| | [-0.66] | [-0.86] | [-0.89] | [6.29] | [4.77] | [5.52] |
| Maturity | 0.00 | 0.00 | 0.00 | 0.21 | 0.23 | 0.27 |
| | [1.26] | [1.29] | [1.67] | [4.77] | [5.37] | [6.23] |
| ln(Issuance) | 0.04 | 0.04 | 0.01 | -0.63 | -0.92 | -2.32 |
| | [2.21] | [2.26] | [0.51] | [-1.00] | [-1.47] | [-3.51] |
| Rating | 0.01 | 0.01 | 0.01 | -0.19 | -0.02 | -0.30 |
| | [1.02] | [1.03] | [0.88] | [-1.15] | [-0.13] | [-2.01] |
| Turnover | | 0.00 | | | -0.28 | |
| | | [-0.51] | | | [-6.22] | |
| ln(Num Trds) | | | 0.06 | | | 3.93 |
| | | | [2.61] | | | [8.44] |
| Obs | 8,609 | 8,609 | 8,609 | 8,317 | 8,317 | 8,317 |
| $R^2$(%) | 0.07 | 0.07 | 0.14 | 1.91 | 3.44 | 4.59 |

### 2.4.2 Aggregate Illiquidity and Market Indices

In this section, we report two important findings of illiquidity measures at the aggregate level. First, we demonstrate commonality among measures, and their time variation is strongly connected with market conditions. Second, we show significant relations between the illiquidity measures and market variables that are constructed to capture different aspects of the market.

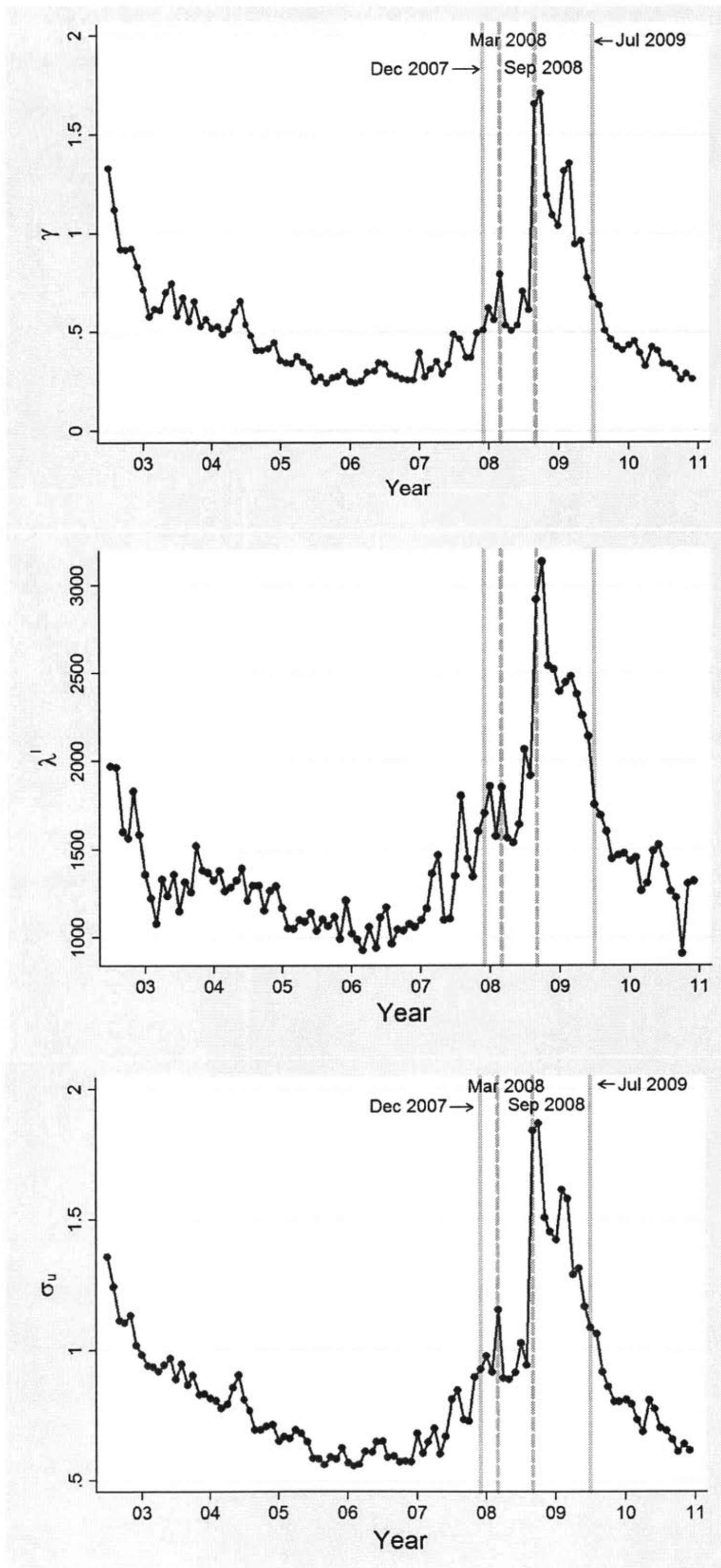
We first explore the time variation of illiquidity measures at the aggregate level. Figure 2.1 plots the time series of selected aggregate measures from July 2002 to December 2010.[12] These aggregate measures are issuance-weighted averages of measure estimates. The solid lines mark the start and end of the Crisis period, and the dotted lines indicate the bankruptcy of Bear Sterns in March 2008 and the collapse of Lehman Brothers in September 2008.

All the illiquidity measures comove in time and respond to market conditions similarly. This common pattern of measures and their strong connection with market movement show that the bond-level estimates of illiquidity share a systematic component. Price reversal $\gamma$ increases upon entering the Crisis period and peaks in October 2008 shortly after the Lehman Brothers collapse with a value as much as three times higher than its values before the crisis. The price impact $\lambda^I$ and residual volatility $\sigma_u$ behave similarly, going up at the end of 2007 and reaching its peak in October 2008. The dynamic ranges of these three measures are about the same. Their peaks in September/October 2008 peaks are about two to three times higher than their pre-crisis values. The minus sum of AR(4) coefficients $\Phi$ shows the same movement in illiquidity. It decreases during the crisis, which indicates that bond returns are less mean-reverting or more illiquid then. The variance ratio $VR$ exhibits a variation of illiquidity similar to other measures, but with a lag. This lagged comovement results from the fact that it uses the past $\tau$ days in estimation.

Next, we study the connection of aggregate illiquidity measures and market variables. We use the median as the aggregate illiquidity for each measure. The market indicators included in our analysis are: 1) CBOE Volatility Index or VIX, 2) Barclays Bond Index Volatility, 3) CDS Index, 4) Term Spread, 5) Default Spread[13], 6) Lagged Stock Market Return, and

[12] $\gamma$ represents the price reversal family, and $\lambda^I$ represents the price impact family. All the other three measures are shown.

[13] The correlation between the default spread change and the CDS index change is approximately 0.56. Although they are indicators of credit risk, both of them are included in the analysis because one provides information that supplements the other.


Mar 2008
Dec 2007
Sep 2008
Jul 2009
γ
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Mar 2008
Dec 2007
Sep 2008
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$\sigma_u$
Year

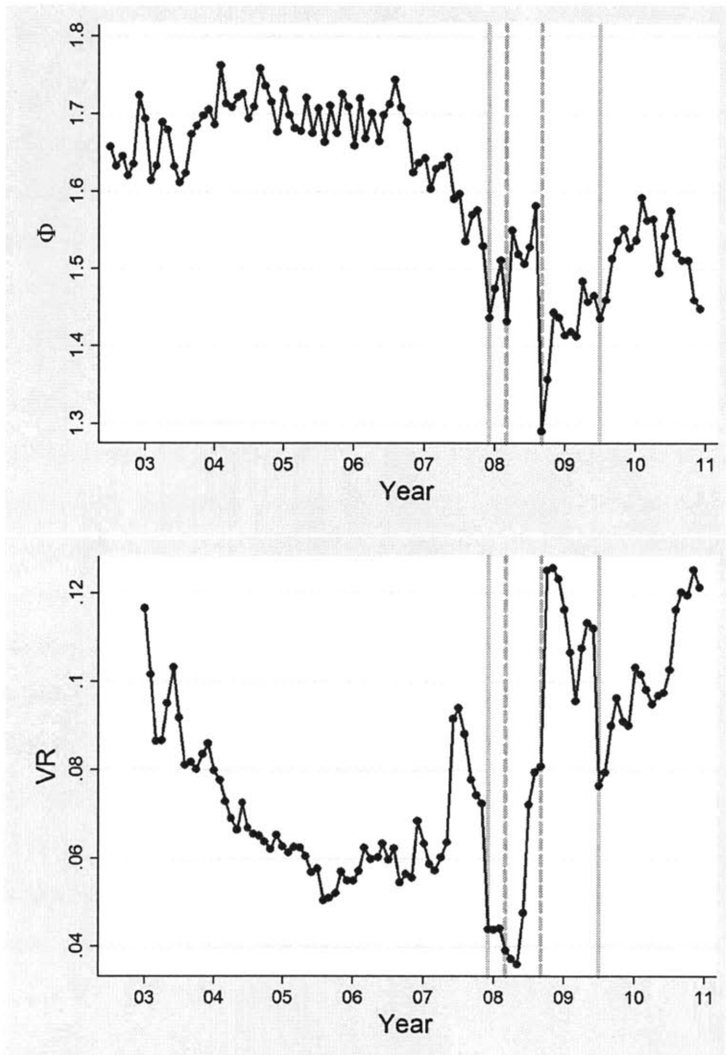


Figure 2.1: **Monthly Time-Series of Illiquidity Level Measures (Issuance-Weighted Average)**

7) Lagged Bond Market Return. We obtain VIX data from CBOE (The Chicago Board Options Exchange). The Barclays Investment Grade Corporate Bond Index and the 5-year CDS index of the financial sector are gathered from Datastream (Thomson Reuters). We obtain the 10-year government bond yield and the 3-month T-bill yield from the Federal Reserve Bank to calculate the term spread. The default spread, which is the difference between the Aaa yield and the Baa yield, is calculated from Barclays Bond Indices. Finally, the stock market return data are from CRSP (The Center for Research in Securities Prices). The summary statistics of market variables and aggregate illiquidity measures are reported in Table 2.5. The correlations among these market variables are reported in Table 2.6. The VIX index, CDS index, and default spread are highly correlated.

In the analysis, we regress monthly changes in aggregate illiquidity measures on monthly changes in market variables. The specification is as follows:

$$\begin{aligned} \Delta L_t &= a + b_1 \Delta VIX_t + b_2 \Delta BondVol_t + b_3 \Delta CDS_t \\ &\quad + b_4 \Delta TERM_t + b_5 \Delta DEF_t + b_6 R^S_{t-1} + b_7 R^B_{t-1} + \varepsilon_t, \end{aligned} \tag{2.32}$$

where $\Delta L_t$ denotes the monthly change in illiquidity measure in month $t$ from month $t-1$. $\Delta VIX_t$ denotes the monthly change in the VIX Index in month $t$ from month $t-1$. Similar notation applies to the other market variables. $\Delta BondVol_t$ denotes monthly changes in the return volatility of the Barclays Investment Grade Corporate Bond Index. $\Delta CDS_t$ denotes monthly changes in the CDS index. $\Delta TERM_t$ denotes monthly changes in the term spread. $\Delta DEF_t$ denotes changes in the default spread. $R^S_{t-1}$ is the stock market lagged monthly return, and $R^B_{t-1}$ is the bond market lagged monthly return.

The regression results are reported in Table 2.7. They lead us to conclude that the connection between the measures and market variables in normal time is different from that during the crisis. This observation is generally true for all measures, except the variance ratio $VR$, which does not have significant relation with market indices.

In the full sample period when the 2008 crisis data are included, shown in Panel A, the two market variables that have the strongest connection with illiquidity measures are the VIX index and the bond index return volatility. Monthly changes in aggregate illiquidity measures can be explained by each of these market indices with $R^2$ values ranging from 14% to 25% in univariate regressions. The movements of these measures are of approximately the same magnitude for changes in these market indicators[14]. For example, an increase of 10 percentage points in the VIX index is associated with an increase of 0.1 in $\gamma$ and $\sigma_u$, and an increase of 100 in $\lambda^I$. In other words, a VIX movement of 10 percentage points corresponds to an approximately 20% change in illiquidity as measured by $\gamma$ and $\sigma_u$, and a 10% change as measured by $\lambda^I$. When the bond index return volatility goes up by 100 percentage points, $\gamma$, $\sigma_u$, and $\lambda^I$ increase by 0.5, 0.57, and 420, respectively. The relation of changes in illiquidity measures to other market indices is weaker. For example, the variation in the CDS index and the term spread has a statistically significant relation to measure changes on their own in most cases. However, this connection is no longer significant when including the VIX index and the bond index volatility.

The results excluding the 2008 crisis in Panel B, however, show that the explanatory power of the VIX index, the bond index, and the term spread weaken. In constrast, the time variation in the CDS index, the default spread, and the lagged bond market return are more connected to changes in illiquidity measures. For example, monthly changes in measure $\gamma$ and $\sigma_u$ can be explained by the time variation in the CDS index with an $R^2$ of 17% while the time variation in the VIX index accounts for less than that. Lastly, illiquidity estimated by any measures has a stronger relation with market variables during the crisis, as judged by $R^2$.

[14]When $\lambda^I$ is expressed in $\times 10^3$

Table 2.5: **Summary Statistics of Market Indices and Aggregate Illiquidity Measures**

This table reports time-series summary statistics of monthly market indices, aggregate yield spreads, and aggregate illiquidity measures. Monthly market indices are averages of daily values over a month. Monthly aggregate yield spreads and monthly aggregate illiquidity measures are the medians of monthly yield spreads and monthly illiquidity estimates, respectively. The sample period is defined in each panel except for the CDS index, whose data start from January 2004 onwards and the signed measures, whose data start from November 2008 onwards.

Panel A: Full Sample (July 2002 - December 2010)

| | VIX (%) | Bond Ind. Ret. Volatility (%) | CDS (bps) | Term Spread (%) | Default Spread (%) | Lagged Stock Mkt Return (%) | Lagged Bond Mkt Return (%) |
|---|---|---|---|---|---|---|---|
| Mean | 21.64 | 0.34 | 267.90 | 1.98 | 1.18 | 0.52 | 0.07 |
| Std. Dev. | 10.34 | 0.12 | 326.09 | 1.31 | 0.57 | 4.72 | 1.91 |

| | Yield Spread (%) | $\gamma$ | $\gamma^{CGW}$ | $\lambda^{I}$ ($\times 10^3$) | $VR$ | $\Phi$ | $\sigma_u$ | $\gamma^{CGW,signed}$ | $\lambda^{VW,signed}$ ($\times 10^{-3}$) |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 1.25 | 0.37 | 0.32 | 0.64 | 0.07 | 1.61 | 0.79 | 0.01 | 3.54 |
| Std. Dev. | 0.92 | 0.22 | 0.13 | 0.22 | 0.02 | 0.11 | 0.25 | 0.04 | 1.86 |

Panel B: Non-Crisis (July 2002 - November 2007 and July 2009 - December 2010)

| | VIX (%) | Bond Ind. Ret. Volatility (%) | CDS (bps) | Term Spread (%) | Default Spread (%) | Lagged Stock Mkt Return (%) | Lagged Bond Mkt Return (%) |
|---|---|---|---|---|---|---|---|
| Mean | 18.79 | 0.30 | 152.85 | 1.88 | 0.98 | 1.10 | 0.14 |
| Std. Dev. | 6.71 | 0.08 | 201.25 | 1.41 | 0.20 | 3.70 | 1.45 |

| | Yield Spread (%) | $\gamma$ | $\gamma^{CGW}$ | $\lambda^{I}$ ($\times 10^3$) | $VR$ | $\Phi$ | $\sigma_u$ | $\gamma^{CGW,signed}$ | $\lambda^{VW,signed}$ ($\times 10^{-3}$) |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.90 | 0.31 | 0.37 | 0.56 | 0.07 | 1.64 | 0.71 | -0.01 | 2.40 |
| Std. Dev. | 0.44 | 0.14 | 0.09 | 0.14 | 0.02 | 0.09 | 0.15 | 0.03 | 0.58 |

Table 2.6: **Correlation Matrix of Market Indices**

The sample period is from July 2002 to December 2010 except the CDS index, whose data start from January 2004. P-values are shown in parentheses. Correlations with statistical significance of at least 5% level are boldfaced.

| | VIX Index | Bond Ind. Ret. Volatility | CDS Index | Term Spread | Default Spread | Lagged Stock Mkt Return | Lagged Bond Mkt Return |
|---|---|---|---|---|---|---|---|
| VIX Index | 1.00 | | | | | | |
| Bond Index | **0.55** | 1.00 | | | | | |
| Ret. Volatility | (0.00) | | | | | | |
| CDS Index | **0.90** | **0.58** | 1.00 | | | | |
| | (0.00) | (0.00) | | | | | |
| Term Spread | **0.45** | **0.33** | **0.55** | 1.00 | | | |
| | (0.00) | (0.00) | (0.00) | | | | |
| Default Spread | **0.86** | **0.54** | **0.91** | **0.30** | 1.00 | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | | |
| Lagged Stock | **-0.43** | -0.16 | **-0.26** | 0.01 | **-0.27** | 1.00 | |
| Mkt Return | (0.00) | (0.12) | (0.02) | (0.89) | (0.01) | | |
| Lagged Bond | -0.06 | 0.00 | 0.05 | 0.03 | 0.03 | **0.32** | 1.00 |
| Mkt Return | (0.55) | (0.96) | (0.63) | (0.77) | (0.75) | (0.00) | |

## Table 2.7: **Time Variation in Aggregate Illiquidity Measures and Market Indices**

This table reports regression of monthly changes in measures on monthly changes in market indices. The market indices are in percentage, unless otherwise noted. Newey-West t-statistics are reported in brackets. The sample period is that specified in each panel except CDS index, whose data are available from January 2004 onwards.

Panel A: Full Sample (July 2002 - December 2010)

| | $\gamma$ | | | | | | | | $\lambda^I$ $(\times 10^3)$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.00 | -0.01 | 0.00 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | 0.00 | -0.01 | 0.00 | -0.01 | -0.01 | -0.01 | 0.00 | 0.00 |
| | [-0.75] | [-0.98] | [-0.49] | [-0.80] | [-0.80] | [-0.75] | [-0.72] | [-1.14] | [-0.59] | [-0.81] | [-0.45] | [-0.67] | [-0.66] | [-0.62] | [-0.63] | [-0.59] |
| $\Delta$VIX | 0.01 | | | | | | | 0.01 | 0.01 | | | | | | | 0.01 |
| | [3.41] | | | | | | | [3.56] | [3.50] | | | | | | | [3.13] |
| $\Delta$Bond Index | | 0.50 | | | | | | 0.45 | | 0.42 | | | | | | 0.40 |
| Return Volatility | | [2.76] | | | | | | [2.54] | | [1.99] | | | | | | [1.92] |
| $\Delta$CDS Index | | | 0.04 | | | | | | | | 0.04 | | | | | 0.01 |
| | | | [1.53] | | | | | | | | [3.00] | | | | | [0.88] |
| $\Delta$Term Spread | | | | 0.11 | | | | 0.05 | | | | 0.08 | | | | |
| | | | | [2.05] | | | | [1.42] | | | | [1.61] | | | | |
| $\Delta$Default Spread | | | | | 0.14 | | | | | | | | 0.12 | | | 0.01 |
| | | | | | [1.49] | | | | | | | | [1.87] | | | [0.07] |
| Lagged Stock | | | | | | 0.00 | | | | | | | | 0.00 | | |
| Mkt Return | | | | | | [0.53] | | | | | | | | [0.11] | | |
| Lagged Bond | | | | | | | 0.00 | | | | | | | | -0.01 | |
| Mkt Return | | | | | | | [-0.72] | | | | | | | | [-1.00] | |
| $R^2(\%)$ | 24.51 | 23.03 | 12.81 | 9.06 | 5.61 | 0.50 | 0.78 | 46.25 | 13.79 | 14.61 | 14.21 | 3.89 | 3.49 | 0.02 | 1.91 | 36.90 |

| | $\sigma_u$ | | | | | | | | $VR$ $(\times 10^{-2})$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.00 | -0.01 | 0.00 | -0.01 | -0.01 | -0.01 | -0.01 | 0.00 | -0.02 | -0.02 | 0.03 | -0.02 | -0.02 | -0.02 | -0.02 | |
| | [-0.62] | [-0.89] | [-0.48] | [-0.69] | [-0.67] | [-0.64] | [-0.62] | [-0.78] | [-0.26] | [-0.26] | [0.58] | [-0.26] | [-0.26] | [-0.41] | [-0.28] | |
| $\Delta$VIX | 0.01 | | | | | | | 0.01 | 0.01 | | | | | | | |
| | [4.63] | | | | | | | [4.21] | [0.04] | | | | | | | |
| $\Delta$Bond Index | | 0.57 | | | | | | 0.57 | | -0.23 | | | | | | |
| Return Volatility | | [2.63] | | | | | | [2.46] | | [-0.51] | | | | | | |
| $\Delta$CDS Index | | | 0.04 | | | | | 0.00 | | | -0.04 | | | | | |
| | | | [2.24] | | | | | [0.27] | | | [-0.37] | | | | | |
| $\Delta$Term Spread | | | | 0.11 | | | | 0.02 | | | | -0.10 | | | | |
| | | | | [2.14] | | | | [0.46] | | | | [-0.49] | | | | |
| $\Delta$Default Spread | | | | | 0.12 | | | | | | | | 0.24 | | | |
| | | | | | [1.56] | | | | | | | | [0.57] | | | |
| Lagged Stock | | | | | | 0.01 | | | | | | | | 0.01 | | |
| Mkt Return | | | | | | [0.36] | | | | | | | | [0.84] | | |
| Lagged Bond | | | | | | | 0.00 | | | | | | | | 0.03 | |
| Mkt Return | | | | | | | [-0.72] | | | | | | | | [0.69] | |
| $R^2(\%)$ | 24.48 | 29.44 | 14.75 | 8.27 | 3.62 | 0.15 | 0.46 | 56.34 | 0.00 | 0.19 | 0.77 | 0.29 | 0.62 | 1.58 | 1.48 | |

Panel B: Non-Crisis (July 2002 - November 2007 and July 2009 - December 2010)

| | $\gamma$ | | | | | | | | $\lambda^I(\times 10^3)$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | -0.01 | -0.01 | 0.00 | -0.01 | -0.01 | -0.01 | -0.01 | 0.00 | -0.01 | -0.01 | 0.00 | -0.01 | -0.01 | -0.01 | -0.01 | |
| | [-1.98] | [-2.27] | [-0.95] | [-2.01] | [-1.71] | [-1.61] | [-2.13] | [-0.22] | [-1.06] | [-1.22] | [-0.42] | [-1.08] | [-0.96] | [-0.91] | [-1.04] | |
| ΔVIX | 0.00 | | | | | | | | 0.00 | | | | | | | |
| | [1.19] | | | | | | | | [1.17] | | | | | | | |
| ΔBond Index | | 0.14 | | | | | | 0.03 | | 0.03 | | | | | | |
| Return Volatility | | [2.98] | | | | | | [0.36] | | [0.26] | | | | | | |
| ΔCDS Index | | | 0.05 | | | | | 0.04 | | | 0.03 | | | | | |
| | | | [3.69] | | | | | [3.98] | | | [1.34] | | | | | |
| ΔTerm Spread | | | | 0.05 | | | | 0.04 | | | | 0.05 | | | | |
| | | | | [1.84] | | | | [1.37] | | | | [1.39] | | | | |
| ΔDefault Spread | | | | | 0.13 | | | 0.07 | | | | | 0.13 | | | |
| | | | | | [2.40] | | | [1.45] | | | | | [1.50] | | | |
| Lagged Stock | | | | | | 0.00 | | | | | | | | 0.00 | | |
| Mkt Return | | | | | | [-0.18] | | | | | | | | [-0.45] | | |
| Lagged Bond | | | | | | | -0.01 | -0.01 | | | | | | | -0.02 | |
| Mkt Return | | | | | | | [-2.69] | [-1.68] | | | | | | | [-2.97] | |
| $R^2$(%) | 3.49 | 4.78 | 17.23 | 5.45 | 5.02 | 0.07 | 8.76 | 33.55 | 3.34 | 0.10 | 3.55 | 2.35 | 2.19 | 0.19 | 12.80 | |

| | $\sigma_u$ | | | | | | | | $VR$ $(\times 10^{-2})$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | -0.01 | -0.01 | 0.00 | -0.01 | -0.01 | -0.01 | -0.01 | 0.00 | -0.06 | -0.05 | -0.01 | -0.07 | -0.06 | -0.10 | -0.06 | -0.07 |
| | [-1.67] | [-1.93] | [-0.75] | [-1.58] | [-1.48] | [-1.38] | [-1.75] | [-0.17] | [-0.89] | [-0.80] | [-0.19] | [-1.05] | [-0.97] | [-1.32] | [-0.99] | [-1.11] |
| ΔVIX | 0.01 | | | | | | | 0.01 | -0.03 | | | | | | | |
| | [2.77] | | | | | | | [4.59] | [-1.55] | | | | | | | |
| ΔBond Index | | 0.15 | | | | | | 0.01 | | 0.44 | | | | | | |
| Return Volatility | | [2.50] | | | | | | [0.09] | | [0.55] | | | | | | |
| ΔCDS Index | | | 0.06 | | | | | 0.04 | | | -0.06 | | | | | |
| | | | [3.37] | | | | | [3.73] | | | [-0.52] | | | | | |
| ΔTerm Spread | | | | 0.06 | | | | 0.06 | | | | -0.46 | | | | -0.24 |
| | | | | [2.35] | | | | [1.79] | | | | [-1.78] | | | | [-1.37] |
| ΔDefault Spread | | | | | 0.13 | | | 0.04 | | | | | -0.40 | | | |
| | | | | | [2.36] | | | [0.71] | | | | | [-0.42] | | | |
| Lagged Stock | | | | | | 0.00 | | | | | | | | 0.03 | | |
| Mkt Return | | | | | | [-0.50] | | | | | | | | [1.58] | | |
| Lagged Bond | | | | | | | -0.01 | -0.01 | | | | | | | 0.10 | 0.09 |
| Mkt Return | | | | | | | [-2.83] | [-1.75] | | | | | | | [1.88] | [1.73] |
| $R^2$(%) | 14.05 | 4.33 | 16.89 | 7.14 | 4.27 | 0.36 | 7.84 | 46.28 | 2.09 | 0.36 | 0.43 | 3.76 | 0.35 | 4.38 | 7.66 | 8.55 |

# 2.5 Appendix

## 2.5.1 Variance Ratio

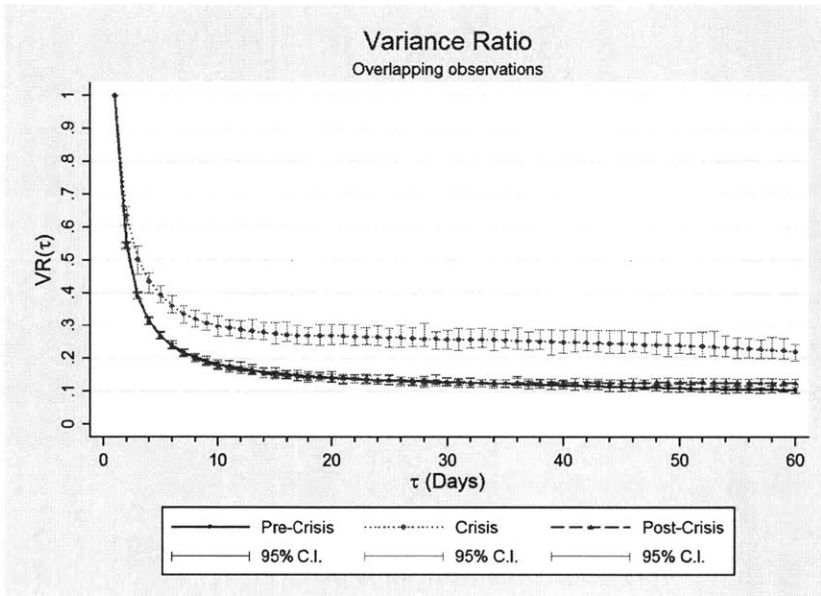


Figure 2.2: Variance Ratio using Overlapping Observations

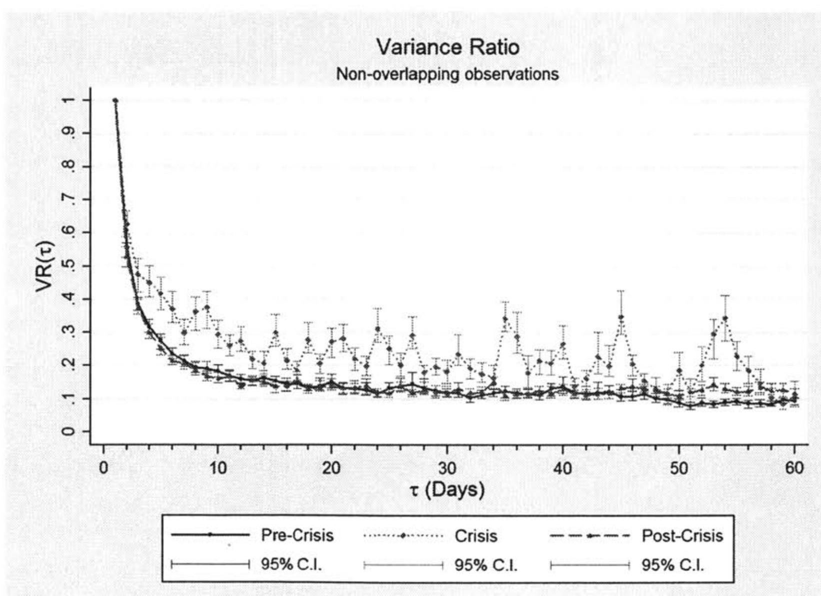


Figure 2.3: Variance Ratio using Non-overlapping Observations

### 2.5.2 Monte Carlo Simulations

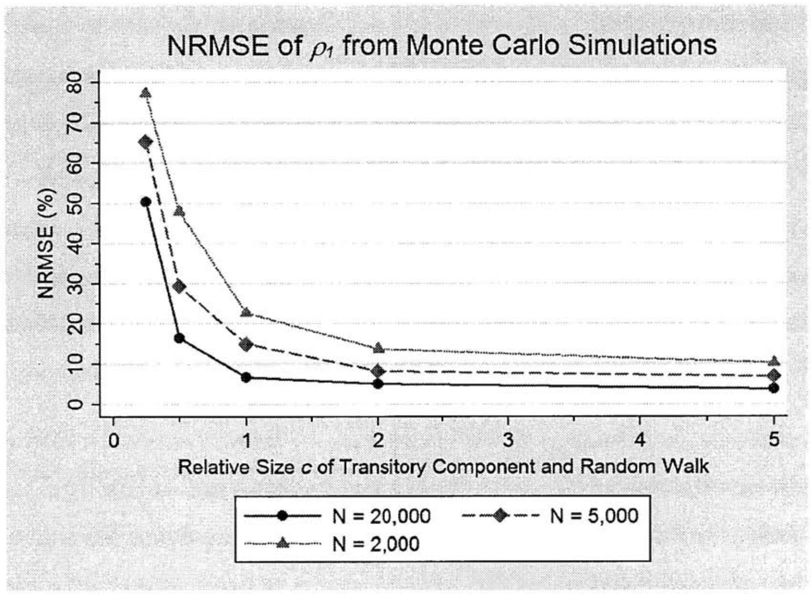


Figure 2.4: Normalized root mean squared error of AR(1) estimates $\hat{\rho}_1$ (decomposed by the Kalman filter) from Monte Carlo Simulations for $\rho_1 = -0.4$. $N$ is the number of observations used in the Kalman filter.

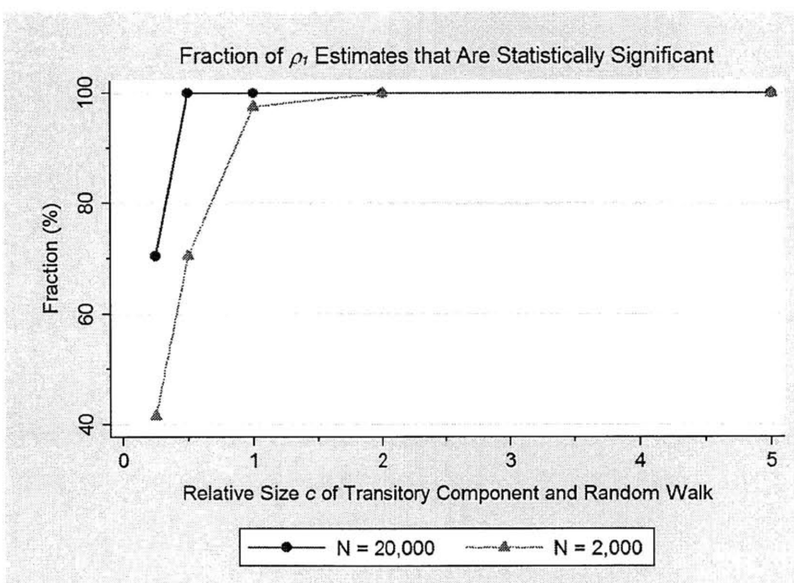


Figure 2.5: Percentage of statistically significant AR(1) estimates $\hat{\rho}_1$ (decomposed by the Kalman filter) from Monte Carlo Simulations for $\rho_1 = -0.4$. $N$ is the number of observations used in the Kalman filter.

# Chapter 3

# Corporate Bond Yields and Illiquidity

## 3.1 Bond Yields and Illiquidity Level

We investigate at the bond level, how each illiquidity measure prices corporate bonds in the cross-section, and which measures are the most robust. We find that almost all measures individually are statistically significant in explaining the yield spread, while their economic significance varies. The three most robust measures are the variance ratio $VR$, the residual volatility $\sigma_u$, and the signed price impact $\lambda^{VW,signed}$.

Prior work includes Brenner, Eldor, and Hauser (2001), who report an illiquidity premium in currency options between exchange-traded options and nontradable options. No direct illiquidity measure is used in this study, but the exchange-traded options are used to represent the liquid group, and the nontradable options are used to represent the illiquid group. Covitz and Downing (2007) document the role of illiquidity, using heuristic measures, in pricing very short-term commercial papers. More recently, Bao, Pan, and Wang (2011) show that $\gamma$ explains the bond yield spread after controlling for credit risk and bond characteristics (or heuristic measures).

We test the pricing implications of measures using monthly Fama and MacBeth (1973) regressions. We perform monthly Fama-MacBeth regression of yield spreads on illiquidity level measures and control variables.

$$y_{it} = \alpha_i + l_i{}'L_{it} + c_i^{'}Control_{it} + \varepsilon_{it}, \tag{3.1}$$

where subscript $it$ denotes bond $i$ in month $t$. $y_{it}$ is the yield spread, and $L_{it}$ is an illiquidity level measure or a vector of measures. $Control_{it}$ is a vector of control variables, i.e., bond chracteristics, credit dummies, and equity volatility.

Table 3.1 reports the results of the pricing test. To gauge the effect of illiquidity as accurately as possible, we control for credit risk using rating dummies and for fundamental risk of the bond issuers using equity volatility in the first column.[1] Bond characteristics are added as control variables in the second column, which is the baseline in determining marginal contribution of illiquidity measures in explaining yield spreads. Illiquidity measures are then tested one by one, starting in the third column, and statistically significant measures are then included in the horse races in the last three columns.

In the first column of Panel A,[2] the coefficient of equity volatility is 0.02 with a t-statistic of 5.79, i.e., bonds with 20 percentage point difference in the underlying stock volatilities show about 40 basis-point difference in their yield spreads. Similar description applies to bond characteristics variables. For example, a bond that is one year older than another is expected to have 2 bps higher in its yield spread on average.

When including illiquidity in the regression model, all of the illiquidity measures except $\gamma^{CGW}$ explain the yield spread. The most economically important measures are $\gamma$, $\sigma_u$, and $VR$, which have about 1-3 % incremental contributions on $R^2$. As for the magnitude of yield spreads explained, the yield spread is 8.7 bps, 15.6 bps, and 6.1 bps larger, on average, for a bond with one standard deviation higher in $\gamma$, $\sigma_u$, and $VR$, respectively. For other measures, the magnitude of yield spreads that are explained by illiquidity measures is smaller. A bond with one standard deviation higher in illiquidity as measured by $\lambda^I$, $\Phi$, and $\gamma^{CGW}$ is expected to have 2.6 bps, 0.8 bps, and 0.4 bps higher than others in its yield spread.

To determine the most robust measures, we run a horse race of all the measures that are statistically significant in their univariate regressions in the last two columns. The residual volatility $\sigma_u$ and the variance ratio $VR$ are the most robust measures of illiquidity level. On average, an increase of one standard deviation or 0.39 percentage points in $\sigma_u$ is associated with a 16 basis-point increase in the yield spread, while an increase of 0.08 or one standard deviation in the variance ratio explains an increase of about 7.4 bps in the yield spread. As

[1]The coefficient of the call dummy is not statistically significant. Hence, the call dummy is not included in the regression.

[2]If we include only credit dummies in the regression, the average yield spread of bonds with ratings higher than A is 93 bps. The credit rating dummies tell us that the yield spread of an A bond and that of a BAA bond are 36 bps and 107 bps larger than AA and AAA bonds, respectively.

for economic significance, these two measures jointly contribute to a 5.1% increase in $R^2$ in explaining the yield spread.

To test for robustness of the results, we examine orthogonalized measures for $\sigma_u$, $\gamma$, and $\lambda^I$. $\sigma_u - E[\sigma_u|\sigma_E]$ is the portion of $\sigma_u$ not in the projection of the equity volatility. Similarly, $\gamma - E[\gamma|\sigma_u, VR]$, and $\lambda^I - E[\lambda^I|\sigma_u, VR]$, are the part of $\gamma$ and $\lambda^I$ that is not explained by $\sigma_u$, and $VR$. The result shows that the part of $\sigma_u$ not explained by the equity volatility is also significant in explaining bond yield spreads with a similar coefficient as $\sigma_u$. The last two columns show that the part of $\gamma$ and $\lambda^I$ not implied by $\sigma_u$ and $VR$ does not play a role in determining the yield spread after including $\sigma_u$ and $VR$ in the model.

In addition to the residual volatility $\sigma_u$ and the variance ratio $VR$, the signed price impact $\lambda^{VW,signed}$ is the other robust measure. The results of the time window when signed volume data are available are reported in Table 3.6. In this period, the yield spread of bonds with one standard deviation higher in their $\lambda^{VW,signed}$ is about 5.6 bps higher than others on average. In the horse race of these three measures, $\lambda^{VW,signed}$ comes out to be significant with 2.43 t-statistic, and the marginal contribution in $R^2$ when these three measures are included is 8.1%.

Table 3.1: **Bond Yield Spread and Illiquidity Level Measures**

This table reports monthly Fama-MacBeth cross-sectional regression of bond yield spreads on illiquidity measures and control variables. The t-statistics in brackets account for serial correlation with Newey-West correction. Top and bottom 0.5% of illiquidity level estimates are winsorized. Top and bottom 1% of yield spreads are trimmed. $\sigma_E$ and Eq. Volatility denote the annualized volatility of stocks in percentage.

| Panel A: Full Sample (July 2002 - December 2010) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.38 | -0.91 | -0.85 | -0.90 | -0.83 | -0.87 | -1.05 | -0.96 | -0.78 | -1.09 | -0.96 | -0.87 |
| | [5.20] | [-4.54] | [-4.73] | [-4.50] | [-4.25] | [-4.33] | [-5.25] | [-4.93] | [-4.07] | [-4.95] | [-4.84] | [-4.53] |
| $\gamma$ | | | 0.19 | | | | | | | -0.13 | | |
| | | | [5.19] | | | | | | | [-5.69] | | |
| $\gamma^{CGW}$ | | | | -0.01 | | | | | | | | |
| | | | | [-1.22] | | | | | | | | |
| $\lambda^I$ | | | | | 0.03 | | | | | -0.03 | | |
| ($\times 10^3$) | | | | | [4.47] | | | | | [-3.17] | | |
| $\Phi$ | | | | | | -0.04 | | | | | | |
| | | | | | | [-2.21] | | | | | | |
| $\sigma_u$ | | | | | | | 0.40 | | | 0.60 | 0.42 | |
| | | | | | | | [6.30] | | | [8.34] | [7.28] | |
| $\sigma_u - E[\sigma_u \vert \sigma_E]$ | | | | | | | | 0.33 | | | | 0.33 |
| | | | | | | | | [6.00] | | | | [5.73] |
| $VR$ | | | | | | | | | 0.76 | 0.92 | 0.93 | 0.73 |
| | | | | | | | | | [5.01] | [6.22] | [6.32] | [5.00] |
| $\gamma - E[\gamma \vert \sigma_u, VR]$ | | | | | | | | | | | -0.01 | -0.01 |
| | | | | | | | | | | | [-0.77] | [-0.57] |
| $\lambda^I - E[\lambda^I \vert \sigma_u, VR]$ | | | | | | | | | | | -0.02 | -0.01 |
| ($\times 10^3$) | | | | | | | | | | | [-1.92] | [-1.13] |
| Age | | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.03 | 0.02 | 0.01 | 0.01 | 0.02 |
| | | [3.55] | [3.44] | [3.35] | [3.47] | [3.42] | [2.73] | [4.49] | [3.50] | [2.71] | [2.71] | [5.12] |
| Maturity | | 0.03 | 0.02 | 0.03 | 0.03 | 0.03 | 0.01 | 0.03 | 0.03 | 0.01 | 0.01 | 0.03 |
| | | [14.94] | [5.13] | [14.54] | [12.45] | [14.74] | [2.97] | [13.80] | [12.94] | [2.23] | [2.00] | [11.87] |
| ln(Num Trds) | | 0.20 | 0.20 | 0.20 | 0.19 | 0.21 | 0.21 | 0.21 | 0.18 | 0.20 | 0.19 | 0.19 |
| | | [7.01] | [7.29] | [6.93] | [6.55] | [7.03] | [7.20] | [7.29] | [6.08] | [5.83] | [6.22] | [6.43] |
| Eq. Volatility | 0.02 | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 | 0.01 | 0.01 | 0.02 |
| | [6.66] | [5.79] | [5.73] | [5.91] | [5.77] | [5.82] | [5.78] | [5.89] | [5.28] | [5.26] | [5.28] | [5.40] |
| A Dummy | 0.24 | 0.31 | 0.29 | 0.31 | 0.31 | 0.31 | 0.27 | 0.30 | 0.28 | 0.23 | 0.24 | 0.28 |
| | [4.26] | [5.68] | [5.98] | [5.66] | [5.73] | [5.63] | [6.05] | [5.71] | [5.14] | [5.46] | [5.38] | [5.15] |
| BAA dummy | 1.00 | 0.95 | 0.91 | 0.95 | 0.95 | 0.95 | 0.86 | 0.94 | 0.83 | 0.71 | 0.73 | 0.81 |
| | [10.07] | [9.16] | [9.97] | [9.12] | [9.10] | [9.20] | [10.28] | [9.24] | [8.00] | [8.88] | [8.63] | [7.91] |
| Avg. # bonds/month | 216 | 216 | 216 | 215 | 216 | 216 | 216 | 214 | 192 | 192 | 192 | 190 |
| $R^2$(%) | 40.66 | 58.32 | 60.17 | 58.23 | 58.65 | 58.49 | 61.40 | 59.93 | 59.19 | 63.59 | 63.38 | 61.66 |

Panel B: Non-Crisis (July 2002 - November 2007 and July 2009 - December 2010)

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.32 | -0.73 | -0.68 | -0.73 | -0.66 | -0.74 | -0.77 | -0.74 | -0.71 | -0.86 | -0.79 | -0.75 |
| | [6.73] | [-3.51] | [-3.52] | [-3.53] | [-3.15] | [-3.52] | [-3.78] | [-3.58] | [-3.32] | [-3.86] | [-3.85] | [-3.52] |
| $\gamma$ | | | 0.14 | | | | | | | -0.11 | | |
| | | | [3.75] | | | | | | | [-3.92] | | |
| $\gamma^{CGW}$ | | | | -0.01 | | | | | | | | |
| | | | | [-0.90] | | | | | | | | |
| $\lambda^I$ | | | | | 0.02 | | | | | -0.02 | | |
| $(\times 10^3)$ | | | | | [4.47] | | | | | [-2.23] | | |
| $\Phi$ | | | | | | -0.01 | | | | | | |
| | | | | | | [-0.38] | | | | | | |
| $\sigma_u$ | | | | | | | 0.30 | | | 0.51 | 0.36 | |
| | | | | | | | [4.98] | | | [7.07] | [6.17] | |
| $\sigma_u - E[\sigma_u\|\sigma_E]$ | | | | | | | | 0.21 | | | | 0.24 |
| | | | | | | | | [4.43] | | | | [4.41] |
| $VR$ | | | | | | | | | 0.74 | | 0.96 | 0.73 |
| | | | | | | | | | [5.13] | | [6.30] | [5.31] |
| $\gamma - E[\gamma\|\sigma_u, VR]$ | | | | | | | | | | | 0.00 | 0.01 |
| | | | | | | | | | | | [0.15] | [0.62] |
| $\lambda^I - E[\lambda^I\|\sigma_u, VR]$ | | | | | | | | | | | -0.02 | -0.02 |
| $(\times 10^3)$ | | | | | | | | | | | [-1.82] | [-1.55] |
| Age | | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.02 | 0.01 | 0.01 | 0.02 |
| | | [3.93] | [3.95] | [3.79] | [3.78] | [3.87] | [3.49] | [4.85] | [3.27] | [2.90] | [2.84] | [4.56] |
| Maturity | | 0.03 | 0.02 | 0.03 | 0.03 | 0.03 | 0.02 | 0.03 | 0.03 | 0.01 | 0.01 | 0.03 |
| | | [24.81] | [14.46] | [27.27] | [27.17] | [25.36] | [9.72] | [25.10] | [21.29] | [6.13] | [5.94] | [18.66] |
| ln(Num Trds) | | 0.16 | 0.15 | 0.16 | 0.14 | 0.16 | 0.15 | 0.16 | 0.16 | 0.15 | 0.15 | 0.16 |
| | | [5.25] | [5.47] | [5.34] | [4.70] | [5.43] | [5.39] | [5.26] | [4.84] | [4.74] | [5.08] | [5.04] |
| Eq. Volatility | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | [5.49] | [4.62] | [4.61] | [4.74] | [4.61] | [4.66] | [4.64] | [4.66] | [4.15] | [4.14] | [4.14] | [4.26] |
| A Dummy | 0.14 | 0.20 | 0.19 | 0.20 | 0.20 | 0.20 | 0.18 | 0.20 | 0.18 | 0.15 | 0.16 | 0.18 |
| | [3.46] | [5.26] | [5.41] | [5.19] | [5.32] | [5.25] | [5.70] | [5.37] | [4.68] | [4.93] | [4.85] | [4.68] |
| BAA dummy | 0.79 | 0.73 | 0.73 | 0.73 | 0.73 | 0.73 | 0.70 | 0.74 | 0.61 | 0.54 | 0.55 | 0.60 |
| | [13.35] | [12.01] | [12.29] | [11.79] | [11.81] | [12.14] | [12.90] | [11.90] | [11.45] | [12.87] | [11.88] | [10.92] |
| Avg. # bonds/month | 203 | 203 | 203 | 201 | 203 | 203 | 203 | 201 | 182 | 182 | 181 | 180 |
| $R^2(\%)$ | 35.66 | 53.11 | 54.50 | 53.06 | 53.34 | 53.34 | 55.45 | 54.11 | 55.65 | 59.41 | 59.44 | 57.56 |

## 3.2 Bond Yields and Illiquidity Risk

In this section, we examine the role of illiquidity risk after showing that illiquidity level, as estimated by various measures, is priced in Section 3.1. We first explain how measures of illiquidity risk are constructed in Section 3.2.1. We estimate measures of illiquidity risk associated with illiquidity level measures that are significant in determining yield spreads in Section 3.1. In addition, we include the Pastor-Stambaugh measure defined in Pastor and Stambaugh (2003) in our study. Then in Section 3.2.2, we turn to the pricing tests of these illiquidity risk measures.

Besides the role of illiquidity level in corporate bond pricing, whether illiquidity risk is priced is also central to our study. There are two strands in the literature regarding the effect of illiquidity risk. Among others in the first group, Acharya and Pedersen (2005) propose an asset pricing model adjusted for illiquidity risk. Lin, Wang, and Wu (2011) report that illiquidity risk carries a risk premium, using Amihud innovations and Pastor-Stambaugh estimates as the risk measures. In contrast, Bongaerts, De Jong, and Driessen (2011) show that illiquidity risk is not priced in the corporate bond market, using the residual of an AR(2) model for estimated transaction costs. Dick-Nielsen, Feldhtter, and Lando (2012), using Amihud risk and roundtrip cost risk measures, document mixed results on the pricing implications of illiquidity risk. Other prior work includes Li, Wang, Wu, and He (2009), Acharya, Amihud, and Bharath (2010), and Downing, Underwood, and Xing (2005).

### 3.2.1 Measures of Illiquidity Risk

We introduce the construction of illiquidity risk estimates. The illiquidity risk of an illiquidity measure is defined to be the sensitivity of its yield spread changes on changes in the aggregate illiquidity, controlled for the market, credit risk, and VIX index. We study illiquidity risk associated with each measure of illiquidity as well as a popular illiquidity risk in Pastor and Stambaugh (2003). The illiquidity risk proposed in Pastor and Stambaugh (2003) is inspired by Campbell, Grossman, and Wang (1993).

### Betas of Level Measures

For each month, each bond, and each illiquidity measure, we regress the daily change in the yield spread $y_{id}$ on the change in market illiquidity level $\Delta L_d^M$ to obtain its monthly beta or illiquidity risk estimate of illiquidity measure. We use the median illiquidity level as the market illiquidity. The regression used to estimate illiquidity risk is specified in (3.2):

$$\begin{aligned} \Delta y_{id} &= \alpha_i + \beta_i^M \Delta Y_d^M + \beta_i^{Credit} \Delta DEF_d \\ &+ \beta_i^{VIX} \Delta VIX_d + \beta_i^L \Delta L_d^M + \varepsilon_{id}, \end{aligned} \tag{3.2}$$

where subscript $id$ denotes bond $i$ and day $d$. $\Delta y_{id}$ is the daily change in the yield spread of bond $i$ on day $d$. $\Delta Y_d^M$ is the daily change in the corporate bond market yield spread on day $d$, which is calculated from the yield of the Barclays Investment Grade Bond Index and the 10-year Treasury rate.[3] $\Delta DEF_d$, which proxies for credit risk, denotes daily changes in the default spread.[4] $\Delta VIX_d$ denotes daily changes in the VIX index. $\Delta L_d^M$ denotes daily changes in the aggregate measure of illiquidity $L$. $\beta_i^L$ is the regression coefficient of yield spread changes on changes in illiquidity measure $L$ for bond $i$, which is the illiquidity risk for illiquidity measure $L$ in a month.

### Pastor-Stambaugh Measure

To estimate Pastor and Stambaugh (2003) illiquidity risk, we first estimate illiquidity measure $\gamma^{PS}$ at daily frequency from transaction-level observations in (3.3), where the excess return signs the accompanying volume. The intuition behind this equation is due to Campbell, Grossman, and Wang (1993), who explain that the return reversals are usually associated with high trading volume.

$$r_{t+1}^e = \alpha_i + \phi_1 r_t + \gamma_{id}^{PS} sign(r_{it}^e) V_{it} + \varepsilon_{it}, \tag{3.3}$$

where an individual bond is denoted by subscript $i$, a transaction is denoted by subscript $t$, and a day is denoted by subscript $d$. $r_{it}^e$ is the excess return of bond $i$, which is $r_{it} - r_{M,t}$. $r_{M,t}$ is the market return. The issuance-weighted average of bond returns is used for the

[3] The time to maturity of the bond index is approximately 10 years.

[4] The default spread is the yield difference between the BBB and AAA Barclays Bond Indices.

market return. $sign(r^e_{it})$ is -1 if the excess return is negative, and 1 otherwise. $V_{it}$ is the par value volume of the transaction. Finally, $\gamma^{PS}$ is the illiquidity cost in Pastor and Stambaugh (2003).

We then estimate innovations in the aggregate illiquidity measure, similar to Li, Wang, Wu, and He (2009), in (3.4):

$$\Delta\gamma_d^{PS} = a + b_1\Delta\gamma_{d-1}^{PS} + b_2\gamma_{d-1}^{PS} + \eta_d, \tag{3.4}$$

where $\gamma_d^{PS}$ is the median of individual illiquidity measures of on day $d$, and $\Delta\gamma_d^{PS}$ is the difference in illiquidity medians between day $d$ and day $d-1$. $\eta_d$ is the innovation of aggregate illiquidity on day $d$.

The Pastor and Stambaugh (2003) illiquidity risk is estimated at monthly frequency according to (3.5) with control factors such as the market return and the VIX index:

$$\begin{aligned} r_{id} - r_d^f &= \alpha_i + \beta_i^M \Delta Y_d^M + \beta_i^{Credit}\Delta DEF_d + \beta_i^{Term}\Delta TERM_d \\ &\quad + \beta_i^{VIX}\Delta VIX_d + \beta_i^{PS}\eta_d + \varepsilon_{id}, \end{aligned} \tag{3.5}$$

where subscript $id$ denotes bond $i$ and day $d$. $r_{id}$ is bond $i$ return on day $d$, and $r_d^f$ is the riskfree rate on day $d$. Other factors are defined in the same manner as in (3.2), and $\Delta TERM_d$ is the daily change in the term spread.

Table 3.2 reports the correlations among illiquidity risk measures and bond characteristics. $\beta^{\sigma_u}$ and $\beta^{\gamma}$ are moderately correlated with each other with a correlation coefficient of 0.45. Other illiquidity risk measures except $\beta^{PS}$ and $\beta^{VR}$ are weakly correlated. For example, the correlation between $\beta^{gamma}$ and $\beta^{\lambda^I}$ is 0.29, and that between $\beta^{\lambda^I}$ and $\sigma_u$ is 0.26. Within the same illiquidity measure family, $\beta^{\lambda^{VW,signed}}$ and $\beta^{\lambda^I}$ show a correlation of 0.33. The bond characteristics and trading activity variables have little correlation with illiquidity risk measures.

### 3.2.2 Pricing Implication of Illiquidity Risk

We empirically test the pricing implication of estimated illiquidity risk measures by performing monthly Fama-MacBeth regressions in (3.6):

$$y_{it} = \alpha_i + b_j{}'\beta_{it}^{L^j} + c_i'Control_{it} + \epsilon_{it}, \tag{3.6}$$

where subscript $it$ denotes bond $i$ and month $t$. $y_{it}$ is the yield spread, and $L^j$ denotes illiquidity measure $j$. $\beta_{it}^{L^j}$ is the illiquidity risk of illiquidity level measure $L^j$ or a vector of illiquidity risks. $Control_{it}$ is a vector of control variables.

The results are reported in Table 3.3. In Panel A when we consider the full sample period, $\beta^{\sigma_u}$ is the most statistically significant illiquidity risk with t-statistic of 2.74. Other illiquidity betas are not significant, except $\beta^{\gamma}$ and $\beta^{VR}$ that are significant at 10% level. Unlike illiquidity level measures, illiquidity risks have negligible economic significance in explaining yield spreads, i.e., their marginal contributions in $R^2$ is less than 1%. In the last column of Panel A, a horse race of $\beta^{\sigma_u}$, and orthogonalized $\beta^{\gamma}$ and $\beta^{VR}$ is shown. We find that $\beta^{\sigma_u}$ is still significant with t-statistic of 2.33.

However, when excluding the crisis period in Panel B. The illiquidity risk of $\sigma_u$ is no longer statistically significant in the horse race in the last column. In its univariate regression, $\beta^{\sigma_u}$ is significant, but with little economic importance in explaining the yield spread as in Panel A.

As far as the illiquidity risks of signed measures are concerned, $\beta^{\lambda^{VW,signed}}$ is significant in explaining bond yield spreads, while $\beta^{CGW,signed}$ is not as shown in Table 3.7 for November 2008 to December 2010. The marginal improvement in $R^2$ provided by $\beta^{\lambda^{VW,signed}}$ is about 1.6%.

Table 3.2: **Correlation Matrix of Illiquidity Risk Measures**

The sample period is from July 2002 to December 2010 (except the signed measure whose data are from November 2008 to December 2010). P-values are shown in parentheses. Correlations with statistical significance of at least 5% level are boldfaced. Top and Bottom 1% of illiquidity level estimates are winsorized. Top and bottom 1% of monthly yield spreads and associated measure estimates are trimmed.

| | $\beta^{\gamma}$ | $\beta^{\lambda^I}$ | $\beta^{\Phi}$ | $\beta^{\sigma_u}$ | $\beta^{VR}$ | $\beta^{PS}$ | $\beta^{\lambda^{VW,signed}}$ | Age | Maturity | ln(Nm Trds) | Eq. Volatility |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\beta^{\gamma}$ | 1.00 | | | | | | | | | | |
| $\beta^{\lambda^I}$ | **0.29** | 1.00 | | | | | | | | | |
| | (0.00) | | | | | | | | | | |
| $\beta^{\Phi}$ | **0.11** | **0.13** | 1.00 | | | | | | | | |
| | (0.00) | (0.00) | | | | | | | | | |
| $\beta^{\sigma_u}$ | **0.45** | **0.26** | **-0.09** | 1.00 | | | | | | | |
| | (0.00) | (0.00) | (0.00) | | | | | | | | |
| $\beta^{VR}$ | **-0.04** | **0.04** | **0.07** | **-0.06** | 1.00 | | | | | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | | |
| $\beta^{PS}$ | **0.05** | **0.05** | **0.04** | **0.05** | **0.05** | 1.00 | | | | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | |
| $\beta^{\lambda^{VW,signed}}$ | **0.00** | **0.33** | **0.18** | 0.00 | **0.04** | -0.01 | 1.00 | | | | |
| | (0.97) | (0.00) | (0.00) | (0.82) | (0.00) | (0.48) | | | | | |
| Age | **0.02** | **0.02** | **0.01** | **0.02** | **-0.02** | **0.02** | 0.00 | 1.00 | | | |
| | (0.02) | (0.00) | (0.13) | (0.00) | (0.01) | (0.02) | (0.91) | | | | |
| Maturity | **-0.02** | 0.00 | **-0.01** | **-0.02** | **0.02** | 0.00 | 0.01 | **-0.25** | 1.00 | | |
| | (0.01) | (0.50) | (0.04) | (0.02) | (0.00) | (0.50) | (0.58) | (0.00) | | | |
| ln(Nm Trds) | -0.01 | **-0.02** | 0.00 | 0.00 | -0.01 | -0.01 | -0.01 | **0.03** | **-0.01** | 1.00 | |
| | (0.18) | (0.00) | (0.72) | (0.85) | (0.05) | (0.34) | (0.33) | (0.00) | (0.04) | | |
| Eq. Volatility | **0.07** | **0.06** | **0.02** | **0.08** | **-0.03** | 0.01 | 0.01 | **0.08** | **-0.01** | **0.26** | 1.00 |
| | (0.00) | (0.00) | (0.02) | (0.00) | (0.00) | (0.33) | (0.29) | (0.00) | (0.30) | (0.00) | |

Table 3.3: **Bond Yield Spread and Illiquidity Risk Measures**

This table reports monthly Fama-MacBeth cross-sectional regression of bond yield spreads on illiquidity measures and control variables. The t-statistics in brackets account for serial correlation with Newey-West correction. Top and bottom 1% of illiquidity risk estimates are winsorized. Top and bottom 1% of yield spreads are trimmed. $\sigma_E$ and Eq. Volatility denote the annualized volatility of stocks in percentage.

| Panel A: Full Sample (July 2002 - December 2010) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.38 | -0.91 | -0.91 | -0.91 | -0.92 | -0.91 | -0.78 | -0.93 | -0.78 |
| | [5.20] | [-4.54] | [-4.53] | [-4.54] | [-4.54] | [-4.55] | [-4.00] | [-4.62] | [-4.02] |
| $\beta^{\gamma}$ | | | 0.01 | | | | | | |
| | | | [1.87] | | | | | | |
| $\beta^{\lambda^I}$ | | | | 0.60 | | | | | |
| ($\times 10^{-3}$) | | | | [1.01] | | | | | |
| $\beta^{\Phi}$ | | | | | 0.01 | | | | |
| | | | | | [0.85] | | | | |
| $\beta^{\sigma_u}$ | | | | | | 0.01 | | | 0.01 |
| | | | | | | [2.74] | | | [2.33] |
| $\beta^{VR}$ | | | | | | | -0.07 | | |
| ($\times 10^{3}$) | | | | | | | [-1.73] | | |
| $\beta^{PS}$ | | | | | | | | 0.05 | |
| | | | | | | | | [0.20] | |
| $\beta^{\gamma} - E[\beta^{\gamma}\vert\beta^{\sigma_u}]$ | | | | | | | | | 0.00 |
| | | | | | | | | | [-1.10] |
| $\beta^{VR} - E[\beta^{VR}\vert\beta^{\sigma_u}]$ | | | | | | | | | -0.04 |
| ($\times 10^{3}$) | | | | | | | | | [-0.92] |
| Age | | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.02 | 0.01 |
| | | [3.55] | [3.63] | [3.64] | [3.47] | [3.56] | [2.94] | [3.55] | [2.74] |
| Maturity | | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.0292 |
| | | [14.94] | [15.34] | [15.10] | [15.29] | [15.15] | [14.99] | [14.36] | [15.45] |
| ln(Num Trds) | | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.19 | 0.21 | 0.19 |
| | | [7.01] | [7.01] | [7.00] | [6.98] | [7.03] | [6.17] | [7.03] | [6.22] |
| Eq. Volatility | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.02 | 0.01 |
| | [6.66] | [5.79] | [5.78] | [5.80] | [5.83] | [5.79] | [5.20] | [5.77] | [5.23] |
| A Dummy | 0.24 | 0.31 | 0.30 | 0.31 | 0.31 | 0.30 | 0.30 | 0.30 | 0.30 |
| | [4.26] | [5.68] | [5.67] | [5.64] | [5.68] | [5.64] | [5.17] | [5.66] | [5.13] |
| BAA dummy | 1.00 | 0.95 | 0.95 | 0.95 | 0.95 | 0.95 | 0.87 | 0.95 | 0.87 |
| | [10.07] | [9.16] | [9.18] | [9.19] | [9.18] | [9.17] | [8.20] | [9.22] | [8.18] |
| Avg. # bonds/month | 216 | 216 | 216 | 216 | 216 | 216 | 190 | 213 | 187 |
| $R^2$(%) | 40.66 | 58.32 | 58.62 | 58.58 | 58.63 | 58.66 | 58.51 | 58.52 | 59.07 |

| Panel B: Non-Crisis (July 2002 - November 2007 and July 2009 - December 2010) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.32 | -0.73 | -0.73 | -0.73 | -0.74 | -0.73 | -0.70 | -0.74 | -0.70 |
| | [6.73] | [-3.51] | [-3.51] | [-3.50] | [-3.52] | [-3.52] | [-3.26] | [-3.51] | [-3.26] |
| $\beta^{\gamma}$ | | | 0.00 | | | | | | |
| | | | [0.90] | | | | | | |
| $\beta^{\lambda^I}$ | | | | 0.11 | | | | | |
| $(\times 10^{-3})$ | | | | [0.31] | | | | | |
| $\beta^{\Phi}$ | | | | | 0.01 | | | | |
| | | | | | [1.55] | | | | |
| $\beta^{\sigma_u}$ | | | | | | 0.01 | | | 0.00 |
| | | | | | | [2.73] | | | [1.10] |
| $\beta^{VR}$ | | | | | | | -0.07 | | |
| $(\times 10^{3})$ | | | | | | | [-1.36] | | |
| $\beta^{PS}$ | | | | | | | | 0.25 | |
| | | | | | | | | [1.23] | |
| $\beta^{\gamma} - E[\beta^{\gamma} \mid \beta^{\sigma_u}]$ | | | | | | | | | 0.00 |
| | | | | | | | | | [-1.09] |
| $\beta^{VR} - E[\beta^{VR} \mid \beta^{\sigma_u}]$ | | | | | | | | | 0.00 |
| $(\times 10^{3})$ | | | | | | | | | [-0.04] |
| Age | | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.02 | 0.01 |
| | | [3.93] | [3.90] | [3.89] | [3.86] | [3.8]] | [2.89] | [3.90] | [2.76] |
| Maturity | | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| | | [24.81] | [24.57] | [25.09] | [25.29] | [25.11] | [22.80] | [25.31] | [22.49] |
| ln(Num Trds) | | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 |
| | | [5.25] | [5.25] | [5.26] | [5.26] | [5.27] | [4.94] | [5.24] | [4.98] |
| Eq. Volatility | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | [5.49] | [4.62] | [4.62] | [4.63] | [4.64] | [4.62] | [4.08] | [4.60] | [4.13] |
| A Dummy | 0.14 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.19 | 0.20 | 0.19 |
| | [3.46] | [5.26] | [5.24] | [5.21] | [5.24] | [5.23] | [4.69] | [5.28] | [4.51] |
| BAA dummy | 0.79 | 0.73 | 0.73 | 0.73 | 0.73 | 0.73 | 0.65 | 0.73 | 1 |
| | [13.35] | [12.01] | [12.03] | [12.06] | [12.00] | [11.97] | [11.49] | [12.04] | [11.42] |
| Avg. # bonds/month | 203 | 203 | 203 | 203 | 203 | 203 | 180 | 201 | 177 |
| $R^2(\%)$ | 35.66 | 53.11 | 53.19 | 53.24 | 53.23 | 53.20 | 55.18 | 53.20 | 55.52 |

## 3.3 Horse Race of Illiquidity Levels and Illiquidity Risks

In this section, we test the relative robustness of all illiquidity measures. We include the two most robust level measures $\sigma_u$ and $VR$, and two most robust risk measures $\beta^{\sigma_u}$, and $\beta^{PS}$. This horse race is specified in (3.7). Table 3.4 reports the coefficients and other statistics from monthly Fama-MacBeth regressions of the horse race. We find that the two illiquidity level measures $\sigma_u$ and $VR$ dominate in explaining the bond yield spread in both the full sample and subsample. The illiquidity risk as proxied by $\beta^{\sigma_u}$ is priced only when the crisis period is included.

$$y_{it} = \alpha_i + l_i{}' L^j_{it} + b_j{}' \beta^{L^j}_{it} + c_i' Control_{it} + \varepsilon_{it}, \tag{3.7}$$

where subscript $it$ denotes bond $i$ and month $t$, and $L^j$ denotes illiquidity measure $j$ or a vector of measures. $y_{it}$ denotes the yield spread of bond $i$ in month $t$. $\beta^{L^j}_{it}$ is the illiquidity risk of illiquidity level measure $L^j$ or a vector of illiquidity risks. $Control_{it}$ is a vector of control variables. $l_i$ is a vector of regression coefficients on $L^j$, and $\theta_j$ is a vector of regression coefficients on illiquidity risks or illiquidity risk premiums.

Table 3.4 reports the pricing test in (3.7). In the full sample as shown in Panel A, residual volatility $\sigma_u$, variance ratio $VR$, the illiquidity risk associated with the residual volatility are statistically significant. Their marginal contribution to the $R^2$ of the model is about 4.5%. We know from Table 3.3 that the incremental contribution in $R^2$ due to $\beta^{sd_u}$ is little. Hence, this incremental contribution in $R^2$ is from the two illiquidity level measures. The coefficients on these three variables also tell us that only the two measures of illiquidity level are economically significant in terms of explaining yield spreads. If we exclude the crisis period in Panel B, the illiquidity risk no longer plays a role in determining bond yield spreads.

Considering when the signed volume data are available in Table 3.8, we find that the signed price impact $\lambda^{VW,signed}$ is also important in explaining bond yield spreads. The marginal improvement in $R^2$ from $\lambda^{VW,signed}$, $\beta^{sd_u}$, and $VR$ is 8.1% for November 2008 to December 2010 period.

Table 3.4: **Bond Yield Spread and Illiquidity Level and Risk**

This table reports monthly Fama-MacBeth cross-sectional regression of bond yield spreads on illiquidity measures and control variables. The t-statistics in brackets account for serial correlation with Newey-West correction. Top and bottom 0.5% of illiquidity level estimates are winsorized. Top and bottom 1% of illiquidity risk estimates are winsorized. Top and bottom 1% of yield spreads are trimmed. $\sigma_E$ and Eq. Volatility denote the annualized volatility of stocks in percentage.

| Panel A: Full Sample (July 2002 - December 2010) | | | |
|---|---|---|---|
| Intercept | 0.38 | -0.91 | -0.96 |
| | [5.20] | [-4.54] | [-4.86] |
| $\sigma_u$ | | | 0.41 |
| | | | [7.01] |
| $VR$ | | | 0.98 |
| | | | [6.75] |
| $\beta^{\sigma_u}$ | | | 0.01 |
| | | | [2.67] |
| Age | | 0.02 | 0.01 |
| | | [3.55] | [2.88] |
| Maturity | | 0.03 | 0.01 |
| | | [14.94] | [2.22] |
| ln(Num Trds) | | 0.20 | 0.19 |
| | | [7.01] | [6.21] |
| Eq. Volatility | 0.02 | 0.02 | 0.01 |
| | [6.66] | [5.79] | [5.30] |
| A Dummy | 0.24 | 0.31 | 0.23 |
| | [4.26] | [5.68] | [5.31] |
| BAA dummy | 1.00 | 0.95 | 0.73 |
| | [10.67] | [9.16] | [8.75] |
| Avg. # bonds/month | 216 | 216 | 192 |
| $R^2(\%)$ | 40.66 | 58.32 | 62.77 |

| Panel B: Non-Crisis (Jul 2002 - Nov 2007 and Jul 2009 - Dec 2010) | | | |
|---|---|---|---|
| Intercept | 0.32 | -0.73 | -0.78 |
| | [6.73] | [-3.51] | [-3.77] |
| $\sigma_u$ | | | 0.35 |
| | | | [5.90] |
| $VR$ | | | 0.98 |
| | | | [6.18] |
| $\beta^{\sigma_u}$ | | | 0.00 |
| | | | [1.40] |
| Age | | 0.02 | 0.01 |
| | | [3.93] | [3.02] |
| Maturity | | 0.03 | 0.01 |
| | | [24.81] | [6.07] |
| ln(Num Trds) | | 0.16 | 0.14 |
| | | [5.25] | [4.98] |
| Eq. Volatility | 0.02 | 0.01 | 0.01 |
| | [5.49] | [4.62] | [4.15] |
| A Dummy | 0.14 | 0.20 | 0.15 |
| | [3.46] | [5.26] | [4.84] |
| BAA dummy | 0.79 | 0.73 | 0.56 |
| | [13.35] | [12.01] | [12.67] |
| Avg. # bonds/month | 203 | 203 | 182 |
| $R^2(\%)$ | 35.66 | 53.11 | 58.64 |

## 3.4 Aggregate Yield Spreads and Aggregate Illiquidity

We have shown that illiquidity explains bond yield spreads at the bond level in Section 3.1. We now study how illiquidity explains the time variation in yield spreads at the aggregate level. We regress monthly changes in aggregate yield spreads on monthly changes in illiquidity measures and market variables. The specification is in (3.8). We first run a univariate regression of yield spread changes on illiquidity measure changes. Then, we include changes in all significant market variables to check for robustness of the results.

$$\begin{aligned}\Delta Y_t &= a + b_1 \Delta L_t + b_2 \Delta VIX_t + b_3 \Delta BondVol_t \\ &\quad + b_4 \Delta CDS_t + b_5 \Delta TERM_t + b_6 R^S_{t-1} + b_7 R^B_{t-1} + \varepsilon_t, \end{aligned} \tag{3.8}$$

where $\Delta Y_t$ denotes monthly changes in the aggregate yield spread in month $t$. The median of individual yield spreads is used as the aggregate yield spread. $\Delta L_t$ denotes monthly changes in illiquidity measure $L$ in month $t$. $\Delta VIX_t$ denotes monthly changes in the VIX Index in month $t$. $\Delta BondVol_t$ denotes monthly changes in the bond index return volatility. Similar notation applies to the other market variables. $R^S_{t-1}$ is the stock market lagged monthly return, and $R^B_{t-1}$ is the bond market lagged monthly return.

To calculate yield spreads of bonds in the sample, we obtain T-bill and treasury rates from the Federal Reserve Bank. We gather the rates at all maturities from 6-month maturity to 20-year maturity. We then linearly interpolate the available rates to get the treasury rates at finer maturities. The yield spread is the difference between the corporate bond yield and the treasury rate at the same maturity. We use the yield spread median as the aggregate yield spread, and the median of measures as the aggregate illiquidity.

In this analysis, we control for other market conditions to estimate the effect of aggregate illiquidity on aggregate yield spreads. We first regress changes in the aggregate yield spread on various market indices as shown in the first column of each panel in Table 3.5. We keep only market indices that are statistically significant. Of all the market indices, the VIX index is statistically and economically significant regardless of the sample window. Its changes explain about 59% and 45% of changes in the aggregate yield spread in the full sample and normal time, respectively. The lagged stock market return is included as a control variable when the crisis period is excluded in Panel B.

In the full sample, almost all measures explain the time variation in the yield spread as shown in Panel A of Table 3.5. The most important ones are $\gamma$, $\lambda^I$, and $\sigma_u$ which explain about 30% of the monthly changes in the aggregate yield spread. They also have a similar effect on the yield spread change, i.e., one standard deviation increase in illiquidity measures $\gamma$, $\lambda^I$, and $\sigma_u$ is associated with the aggregate yield spread change of 28 bps, 24 bps, and 30 bps, respectively, in the univariate regression. When controlled for market conditions by VIX, one standard deviation increase in illiquidity measures $\gamma$, $\lambda^I$, and $\sigma_u$ explains the change in the aggregate yield spread about 12 bps, 13 bps, and 13 bps, respectively. For other illiquidity measures, one standard deviation decrease in $\gamma^{CGW}$ accounts for about 13bps and 6bps increase in the univariate regression and the multivariate regression, respectively. The effect of $\Phi$ is weaker, with its coefficient being statistically insignificant when the VIX index is included. Lastly, changes in $VR$ does not explain the time variation in the aggregate yield spread.

When we consider only the normal time by excluding the Crisis period in Panel B of Table 3.5, the effect of monthly changes in the aggregate illiquidity on the time variation in the aggregate yield spread becomes smaller. In addition, the coefficients of measure changes have lower t-statistics. This result may be due to the fact that our sample includes the most liquid tier of corporate bonds[5]. Nevertheless, the monthly changes of illiquidity measures still account for a considerable portion of the yield spread. Specifically, a one standard deviation increase in illiquidity measures $\gamma$, $\lambda^I$, and $\sigma_u$ explains approximately 7 bps, 4 bps, and 6 bps of changes in the aggregate yield spread, respectively. The effect of $\gamma^{CGW}$ and $\Phi$ is not statistically significant when we exclude the crisis time. In terms of explanatory power, monthly changes in measures explain changes in the yield spread better during the bear market. For example, the change in the residual volatility $\sigma_u$ can explain the change in the aggregate yield spread better with an $R^2$ increase from 15% to 30% when including the Crisis period. This trend also holds for $\gamma$ and $\lambda^I$. The increased explanatory power of illiquidity on the yield spread during the crisis can also be seen in the incremental changes in $R^2$. Specifically, changes in measures $\gamma$, $\lambda^I$, and $\sigma_u$ have incremental contributions in $R^2$ of 3.8%, 2.9%, and 2.6%, respectively, during normal time. These incremental increases in the explanatory power are about 1-3% less than when compared to the full sample when the crisis time is included.

[5]The data filters are explained in Chapter 2. We need to restrict our sample to bonds that have enough observations for estimation purposes.

As for the signed measures, the results are not statistically significant, although $\lambda^{VW,signed}$ improves the model with about 4.6% increase in $R^2$ as shown in Panel C. This insignificance is due to the limited length of the sample period for which signed data are available.

Comparing the results of the full sample when the Crisis period is included in Panel A and the non-crisis time in Panel B, we are able to draw a conclusion. The role of illiquidity in determining the yield spread increases during the financial downturn. This fact is evident in both the increase in regression coefficients of measure changes, and the increase in incremental contribution to $R^2$ when the Crisis period is included. This finding is consistent with Bao, Pan, and Wang (2011), who report that an increasing role or $\gamma$ during the crisis. With these results, we address the corporate yield spread puzzle examined in Elton, Gruber, Agrawal, and Mann (2001) and Huang and Huang (2003). They point out the credit risk only explains only a small fraction of the yield spread, especially for high-rated bonds. We have identified that another determinant of corporate yield spreads is illiquidity.

Table 3.5: **Aggregate Yield Spread and Aggregate Illiquidity**

This table reports regression results of monthly changes in the aggregate yield spread on changes in aggregate illiquidity measures and market variables. Newey and West (1987) t-statistics are reported in brackets. The sample period is specified in each panel.

| Panel A: Full Sample (July 2002 - December 2010) | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | $\gamma$ | | $\gamma^{CGW}$ | | $VR$ | |
| Intercept | 0.007 | 0.010 | 0.010 | 0.000 | 0.007 | 0.004 | 0.008 |
| | [0.47] | [0.46] | [0.73] | [-0.00] | [0.44] | [0.13] | [0.48] |
| ΔIlliquidity | | 1.272 | 0.565 | -1.005 | -0.423 | 2.934 | 2.734 |
| | | [5.31] | [2.93] | [-1.93] | [-2.16] | [0.49] | [1.26] |
| ΔVIX | 0.037 | | 0.031 | | 0.036 | | 0.038 |
| | [8.49] | | [7.45] | | [8.64] | | [9.04] |
| $AdjR^2$(%) | 59.49 | 32.54 | 64.12 | 6.72 | 60.39 | -0.62 | 60.06 |
| | | $\lambda^I(\times 10^3)$ | | $\Phi$ | | $\sigma_u$ | |
| Intercept | 0.007 | 0.007 | 0.010 | -0.001 | 0.007 | 0.008 | 0.009 |
| | [0.47] | [0.32] | [0.70] | [-0.02] | [0.47] | [0.40] | [0.67] |
| ΔIlliquidity | | 1.102 | 0.574 | -0.770 | -0.062 | 1.219 | 0.500 |
| | | [4.72] | [5.01] | [-2.29] | [-0.22] | [7.17] | [3.67] |
| ΔVIX | 0.037 | | 0.032 | | 0.037 | | 0.032 |
| | [8.49] | | [8.00] | | [8.65] | | [6.59] |
| $AdjR^2$(%) | 59.49 | 26.47 | 65.57 | 2.03 | 59.10 | 30.08 | 63.07 |

Panel B: Non-Crisis (July 2002 - November 2007 and July 2009 - December 2010)

| | | $\gamma$ | | $\gamma^{CGW}$ | | $VR$ | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.008 | 0.001 | 0.013 | -0.007 | 0.008 | -0.005 | 0.014 |
| | [0.78] | [0.05] | [1.24] | [-0.57] | [0.81] | [-0.40] | [1.43] |
| ΔIlliquidity | | 0.773 | 0.510 | -0.310 | -0.237 | -0.041 | 3.081 |
| | | [1.74] | [2.36] | [-1.36] | [-1.47] | [-0.03] | [1.67] |
| ΔVIX | 0.023 | | 0.022 | | 0.023 | | 0.024 |
| | [4.59] | | [5.46] | | [4.93] | | [4.38] |
| Lagged Stock | -0.009 | | -0.009 | | -0.009 | | |
| Mkt Return | [-3.23] | | [-3.07] | | [-3.33] | | |
| $Adj R^2(\%)$ | 44.53 | 9.26 | 48.34 | 1.60 | 45.49 | -1.35 | 43.78 |

| | | $\lambda^I(\times 10^3)$ | | $\Phi$ | | $\sigma_u$ | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.008 | -0.003 | 0.010 | -0.008 | 0.009 | 0.001 | 0.011 |
| | [0.78] | [-0.28] | [1.06] | [-0.64] | [0.80] | [0.11] | [1.08] |
| ΔIlliquidity | | 0.474 | 0.297 | -0.368 | 0.147 | 0.874 | 0.418 |
| | | [1.94] | [2.86] | [-1.46] | [0.83] | [2.35] | [1.96] |
| ΔVIX | 0.023 | | 0.022 | | 0.024 | | 0.020 |
| | [4.59] | | [4.88] | | [4.36] | | [5.09] |
| Lagged Stock | -0.009 | | -0.009 | | -0.009 | | -0.009 |
| Mkt Return | [-3.23] | | [-3.39] | | [-3.15] | | [-3.06] |
| $Adj R^2(\%)$ | 44.53 | 8.06 | 47.44 | 0.90 | 44.13 | 15.14 | 47.12 |

Panel C: Signed Volume Data Available (November 2008 - December 2010)

| | | $\gamma^{CGW,signed}$ | | $\lambda^{VW,signed}(\times 10^{-3})$ | |
|---|---|---|---|---|---|
| Intercept | -0.053 | -0.112 | -0.052 | -0.117 | -0.029 |
| | [-2.29] | [-2.26] | [-2.39] | [-2.21] | [-1.35] |
| ΔIlliquidity | | 0.570 | -0.080 | -0.002 | 0.007 |
| | | [0.87] | [-0.15] | [-1.77] | [3.45] |
| ΔVIX | 0.016 | | 0.016 | | 0.014 |
| | [6.68] | | [6.42] | | [5.33] |
| ΔTerm Spread | -0.477 | | -0.474 | | -0.487 |
| | [-6.87] | | [-6.96] | | [-8.51] |
| Lagged Bond | -0.043 | | -0.044 | | -0.060 |
| Mkt Return | [-3.91] | | [-4.01] | | [-5.56] |
| $Adj R^2(\%)$ | 70.89 | -2.37 | 69.54 | -3.06 | 75.46 |

## 3.5 Conclusion

The two main questions in our study are how to quantify illiquidity, and what are the pricing implications of illiquidity level measures and their illiquidity risk. We review existing illiquidity measures and propose new robust measures in Chapter 2. In addition, we study their cross-sectional relations with bond characteristics and their time variation with market variables. In Chapter 3, we show how illiquidity measures and bond yields are connected at the aggregate level and individual level.

Despite differences in measures construction, we are able to establish similar connections to bond characteristics for most measures. We find that old bonds with longer maturity are more illiquid than young ones with shorter maturity. Illiquidity measures are also positively related to the number of trades. For most measures, bonds with larger issuance size are more liquid.

In addition, we show that these illiquidity measures behave similarly as the market condition changes. Their time variation is also associated with the variation in market indices such as the VIX index, the Bond Index Return Volatility, and the CDS Index.

Lastly, we empirically test the pricing implications of illiquidity level and risk in the corporate bond market. A few illiquidity measures are shown to be robust to various specifications. We establish that the illiquidity level is priced throughout the sample period, while the effect of illiquidity risk is weaker, and driven by the crisis. This finding suggests that illiquidity level dominates illiquidity risk in terms of explaining bond yield spreads.

As for future work, the measures in these studies can be applied to estimate illiquidity in other markets, possibly with minor changes. The characteristics of measures and their pricing implications may be different. However, it is expected that results should be along the same line for markets that are similar to the corporate bond market, such as the treasury market.

# 3.6 Appendix

## 3.6.1 Bond Yield Spread and Illiquidity Level (continued)

Table 3.6: **Bond Yield Spread and Illiquidity Level Measures** (continued)

This table reports monthly Fama-MacBeth cross-sectional regression of bond yield spreads on illiquidity measures and control variables. The t-statistics in brackets account for serial correlation with Newey-West correction. Top and bottom 0.5% of illiquidity level estimates are winsorized. Top and bottom 1% of yield spreads are trimmed.

| Panel A: Signed Volume Data Available (November 2008 - December 2010) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.18 | -2.02 | -2.01 | -1.94 | -2.35 | -1.82 | -2.18 |
| | [0.99] | [-7.34] | [-7.40] | [-7.29] | [-14.83] | [-6.83] | [-11.00] |
| $\gamma^{CGW,signed}$ | | | 0.00 | | | | |
| | | | [-0.33] | | | | |
| $\lambda^{VW,signed}$ | | | | 6.28 | | | 2.00 |
| | | | | [7.00] | | | [2.42] |
| $\sigma_u$ | | | | | 0.86 | | 0.86 |
| | | | | | [11.90] | | [12.78] |
| $VR$ | | | | | | 1.20 | 1.16 |
| | | | | | | [4.38] | [4.21] |
| Age | | 0.00 | 0.00 | -0.01 | -0.02 | 0.00 | -0.01 |
| | | [-0.88] | [-0.90] | [-1.66] | [-2.69] | [-0.34] | [-1.26] |
| Maturity | | 0.03 | 0.03 | 0.02 | -0.01 | 0.02 | -0.01 |
| | | [15.36] | [15.23] | [14.60] | [-1.37] | [12.59] | [-2.58] |
| ln(Num Trds) | | 0.36 | 0.36 | 0.35 | 0.39 | 0.33 | 0.35 |
| | | [9.54] | [9.66] | [9.69] | [11.01] | [7.66] | [8.90] |
| Eq. Volatility | 0.04 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| | [10.65] | [10.74] | [10.73] | [10.69] | [9.88] | [10.06] | [9.47] |
| A Dummy | 0.63 | 0.67 | 0.68 | 0.67 | 0.54 | 0.62 | 0.48 |
| | [6.16] | [6.63] | [6.64] | [6.64] | [6.11] | [5.78] | [5.04] |
| BAA dummy | 1.49 | 1.53 | 1.53 | 1.52 | 1.27 | 1.37 | 1.11 |
| | [6.36] | [6.57] | [6.58] | [6.56] | [6.60] | [5.46] | [5.18] |
| Avg. # bonds/month | 323 | 323 | 323 | 321 | 323 | 281 | 279 |
| $R^2(\%)$ | 50.67 | 58.89 | 58.90 | 59.50 | 64.69 | 60.51 | 66.99 |

### 3.6.2 Bond Yield Spread and Illiquidity Risk (continued)

Table 3.7: **Bond Yield Spread and Illiquidity Risk Measures** (continued)

This table reports monthly Fama-MacBeth cross-sectional regression of bond yield spreads on illiquidity measures and control variables. The t-statistics account for serial correlation with Newey-West correction. Top and bottom 1% of illiquidity risk estimates are winsorized. Top and bottom 1% of yield spreads are trimmed.

| Panel A: Signed Volume Data Available (November 2008 - December 2010) | | | |
|---|---|---|---|
| Intercept | 0.18 | -2.02 | -2.36 |
| | [0.99] | [-7.34] | [-6.42] |
| $\beta^{\lambda^{VW,signed}}$ | | | 0.06 |
| | | | [0.47] |
| Age | | 0.00 | -0.02 |
| | | [-0.88] | [-2.56] |
| Maturity | | 0.03 | 0.02 |
| | | [15.36] | [11.39] |
| ln(Num Trds) | | 0.36 | 0.40 |
| | | [9.54] | [7.36] |
| Eq. Volatility | 0.04 | 0.03 | 0.04 |
| | [10.65] | [10.74] | [9.48] |
| A Dummy | 0.63 | 0.67 | 0.78 |
| | [6.16] | [6.63] | [8.23] |
| BAA dummy | 1.49 | 1.53 | 1.58 |
| | [6.36] | [6.57] | [7.18] |
| Avg. # bonds/month | 323 | 323 | 230 |
| $R^2$(%) | 50.67 | 58.89 | 60.50 |

### 3.6.3 Bond Yield Spread and Illiquidity Level and Risk (continued)

Table 3.8: **Bond Yield Spread and Illiquidity Level and Risk** (continued)

This table reports monthly Fama-MacBeth cross-sectional regression of bond yield spreads on illiquidity measures and control variables. The t-statistics in brackets account for serial correlation with Newey-West correction. Top and bottom 0.5% of illiquidity level estimates are winsorized. Top and bottom 1% of illiquidity risk estimates are winsorized. Top and bottom 1% of yield spreads are trimmed.

| Panel A: Signed Volume Data Available (November 2008 - December 2010) | | | |
|---|---|---|---|
| Intercept | 0.18 | -2.02 | -2.18 |
| | [0.99] | [-7.34] | [-11.08] |
| $\sigma_u$ | | | 0.86 |
| | | | [12.80] |
| $VR$ | | | 1.17 |
| | | | [4.20] |
| $\lambda^{VW,signed}$ | | | 2.03 |
| | | | [2.47] |
| $\beta^{\sigma_u}$ | | | 0.00 |
| | | | [1.55] |
| Age | | 0.00 | -0.01 |
| | | [-0.88] | [-1.29] |
| Maturity | | 0.03 | -0.01 |
| | | [15.36] | [-2.57] |
| ln(Num Trds) | | 0.36 | 0.35 |
| | | [9.54] | [8.97] |
| Eq. Volatility | 0.04 | 0.03 | 0.03 |
| | [10.65] | [10.74] | [9.42] |
| A Dummy | 0.63 | 0.67 | 0.48 |
| | [6.16] | [6.63] | [5.02] |
| BAA dummy | 1.49 | 1.53 | 1.11 |
| | [6.36] | [6.57] | [5.16] |
| Avg. # bonds/month | 323 | 323 | 279 |
| $R^2(\%)$ | 50.67 | 58.89 | 66.98 |

# Chapter 4

# Impact of the 2008 Short-Sale Ban on the Financial Market

## 4.1 Introduction

An investor can short sell stocks at the current price by borrowing them from another party with a lending fee. At a later date, the investor needs to buy these stocks at a new price and return them to the lender. He may profit from the difference in the stock prices less the lending fee. Short-sale constraints vary in form. They range from expensive lending fees to short-sale bans. The impact of short-sale constraints on stocks as well as on their futures and options is controversial and needs to be further investigated.

One early theoretical work, Miller (1977), reasons that asset prices are optimistic under short-sale constraints when investors have heterogeneous expectations. Under such expectations, Jarrow (1980) argues that short-sale constraints can cause prices to move in either direction. Diamond and Verrecchia (1987) show that short-sale constraints prevent informative trades but do not cause overpricing under a rational expectations framework. Alternatively, Duffie, Gârleanu, and Pedersen (2002) present a model explaining that stock prices increase and then decrease under short-sale constraints. Bai, Chang, and Wang (2006) show that short-sale constraints increase asset prices for allocational trade and decrease them for informational trade. The price volatility is shown to decrease for allocational trade and increase for informational trade.

On the empirical side, Jones and Lamont (2002), using data from 1926 to 1933, document that stocks are overvalued due to expensive short selling costs. Chang, Cheng, and Yu (2007) find that short-sale constraints are likely to cause overpricing in the Hong Kong market. They also report that return volatility goes up in the presence of short selling. Bris, Goetzmann, and Zhu (2007) analyze data in 46 stock markets and document that short-sale constraints hinder price discovery in two respects: first, the amount of private information in prices; second, the speed of price adjustment. They also find market returns to be less negatively skewed under a short-sale ban.

The question being addressed in this work is how a short-sale ban, the most extreme scenario of short-sale constraints, affects the equity market as well as the derivatives market. The event in our study is the short-sale ban imposed by SEC (The US Securities and Exchange Commission) from September 19, 2008 to October 8, 2008.[1] This short-sale ban is implemented almost immediately after the collapse of Lehman Brothers on September 15, 2008, in hopes of stabilizing the financial market. Around the same time, the Emergency Economic Stabilization Act was proposed and became effective near the end of the short-sale ban period. We apply empirical tests to banned stocks and their futures and options around the ban, and report three main results.

First, the banned stocks, as measured by cumulative abnormal returns, are overvalued under the ban. Furthermore, the return volatility of those banned stocks is higher relative to the market. Second, there is evidence that implies a demand shift to the futures market to replicate short selling. Examples include addition of futures on banned stocks during the ban as well as selling pressure on these futures contracts. Third, in the option market, puts have significantly higher implied volatility relative to calls, implying puts are in greater demand. Our work contributes to the literature in two ways. First, the overvaluation of stocks during the ban confirms the prediction of a few aforementioned theoretical studies. Second, we add these results of the derivatives market to the empirical literature.

The rest of this work is organized as follows. Section 4.2 describes the short-sale ban event, related data, and the sample. Section 4.3 outlines empirical tests and reports results in the equity market. The futures and option markets are then examined in Section 4.4. Section 4.5 concludes.

[1] As of the time of this writing, there are a number of other ongoing studies examining this short-sale ban. Examples include Boehmer, Jones, and Zhang (2009), Grundy, Lim, and Verwijmeren (2009), and Battalio and Schultz (2010).

## 4.2 Event and Data

We provide background of the event and the data used in our study in this section. Section 4.2.1 outlines the ban and other related actions by policy makers. The sample is described in Section 4.2.2 with their statistics given in Section 4.2.4.

### 4.2.1 Short-sale Ban Event

The event in this study is the short-sale ban imposed in September 2008 by SEC (The US Securities and Exchange Commission). SEC decided to implement this ban shortly after Lehman Brothers had announced its bankruptcy on September 15, 2008. A number of companies such as AIG also seemed to be in critical condition. In response to this financial turmoil, SEC announced a temporary short-sale ban on 797 financial stocks on Thursday, September 18, 2008 to be effective the next day [U.S. Securities and Exchange Commission (2008a)]. The details of important events are listed in Table 4.1. Another important event during this time is the attempt to pass the Emergency Economic Stabilization Act of 2008 or the bailout bill. This bill, proposed by the Treasury Department, was rejected by The House of Representatives on September 29, 2008. The House later passed the revised bill and the President signed it on October 3, 2008.

The short-sale ban had been initially set to terminate on Thursday, October 2, 2008. However, SEC annouced on this date that the ban would extend until three business days after the President signed the Emergency Economic Stabilization Act [U.S. Securities and Exchange Commission (2008b)]. As a result, the short-sale ban ended on Wednesday, October 8, 2008, and those stocks on the ban list were protected from short selling for 13 days, starting on September 19, 2008. The initial list of stocks banned for short selling consists of 797 financial stocks. During the period of these 13 days, 10 stocks were removed from the list, and 134 were added to the list at different times as shown in Table 4.2.

### 4.2.2 Data

Our sample consists of 686 financial stocks on the ban list described in Table 4.3. We exclude a small number of stocks on the initial short-sale ban list for various reasons. For example, some stocks are delisted from the ban list, some undergo mergers, and some are delisted

Table 4.1: **Timeline of Short-Sale Ban and Related Events**

This table summarizes the short-sale ban and related events with references. The first column gives the number of trading days relative to the first day of the short-sale ban.

| Day | Date | Event | Reference |
|---|---|---|---|
| -2 | Wednesday September 17, 2008 | SEC annouced a naked short-sale ban on all stocks to begin on September 18 and end on October 1. This regulation was later extended and made permanent (SEC Release Nos. 34-58711 and 34-58773). | SEC Release No. 34-58572 |
| -1 | Thursday September 18, 2008 | After market closed, SEC announced a short-sale ban on 797 financial stocks to begin on September 19 and terminate on Thursday, October 2. Market makers were exempt from this ban for their bona fide market making and hedging until 11:59pm on September 19. | SEC Release No. 34-58592 |
| **0** | **Friday September 19, 2008** | **Short-sale ban started.** | |
| | Sunday September 21, 2008 | SEC amended Release No. 34-58592 to exempt market makers for the entire duration of the ban. SEC further specified that market makers could not short sell if they know "that the customer's or counterparty's transaction will result in the customer or counterparty establishing or increasing an economic net short position (i.e., through actual positions, derivatives, or otherwise)." | SEC Release No. 34-58611. |
| 6 | Monday September 29, 2008 | House of Representatives rejected the $700 billion bailout bill. | Treasury Department Press Release 9/29 hp1168 |
| 8 | Wednesday October 1, 2008 | Senate passed the bill. | |
| 9 | Thursday October 2, 2008 | SEC announced short-sale ban extension to be the earlier of 1) three business days from the President's signing of the Emergency Economic Stabilization Act of 2008 or 2) 11:59 p.m. on Friday, October 17, 2008. | SEC Release No. 34-58723 |
| 10 | Friday October 3, 2008 | Congress passed the bill and President Bush signed the Act. | Public Law 110-343 |
| **13** | **Wednesday October 8, 2008** | **Short-sale ban terminated.** | |

Table 4.2: **Short-Sale Banned Stocks**

| Category | Number of Stocks |
|---|---|
| Stocks on initial short-sale ban list | 797 |
| Stocks removed from short-sale ban list | 10 |
| Stocks added to short-sale ban list | 134 |
| Total stocks involved | 941 |

from the exchange.

We obtain stock data from July 2000 to December 2008 from CRSP (The Center for Research in Security Prices). We collect index data from CRSP and Datastream for the same period. The factor data are gathered from WRDS (Wharton Research Data Services), which in turn obtains the data from Kenneth French's website. These three sets of data allow us to empirically test for the impact of the short-sale ban on the equity market. In addition to studying the equity market, we examine effects of the short-sale ban on the derivatives markets. We obtain futures data from OneChicago Exchange.[2] The option data are obtained from OptionMetrics. Table 4.4 summarizes the datasets and their sources.

To facilitate subsequent discussion, we introduce symbols used for indices and factors as well as the sample in Table 4.5. For market factors, we denote the value-weighted index of CRSP by $CRSP$ and the Standard and Poor 500 index by *S&P500*. $FIN$ denotes the financial sector of *S&P500*. The size and value factors in Fama and French (1993) are denoted by $SMB$ and $HML$, respectively. Lastly, $UMD$ stands for the momentum factor in Carhart (1997). As for the sample, we denote the whole sample by $SSB$ or short-sale banned stocks. The stocks in the sample can be broken down into subsamples based on the existence of their options and futures. Subscript $O$ denotes the existence of options, and subscript $F$ denotes the existence of futures. Subscript $N$ denotes that neither futures nor options for those subsamples are available. For example, the symbol for short-sale banned stocks that have options and futures traded is $SSB_{OF}$. For some stocks, their futures were introduced for the first time during the ban. We use $F'$ and their addition dates to denote this feature. For example, $SSB_{OF'10/02}$ is the symbol for short-sale banned stocks with options and futures added on October 2, 2008.

These 686 financial stocks in the sample can be further classified based on their SIC codes (Standard Industrial Classification). Table 4.6 reports the breakdown of the sample with the percentage of market capitalization. The largest subgroup of the sample is depository institutions. Stocks in this subgroup account for about 51% of the sample by market capitialization. The second largest subgroup is insurance whose market capitialization claims about 32% of the sample. The third largest group consists of brokers and exchanges. A few stocks belong to other subgroups, such as credit institutions and holding companies.

[2]We thank two anonymous agents at the Exchange for providing futures data.

Table 4.3: **Sample Description**

| Category | Number of Stocks |
|---|---|
| Financial common stocks on initial short-sale ban list | 723 |
| Less excluded stocks (e.g., short-sale ban list delisting, mergers, exchange delisting) | 21 |
| Less stocks which were less than one year old | 16 |
| Stocks in sample | 686 |

Table 4.4: **Data Sources**

| Data | Source |
|---|---|
| Indices | CRSP |
| Stocks | CRSP and Datastream |
| Options | OptionMetrics |
| Futures | OneChicago |

Table 4.5: **Symbol Description**

This table lists symbols and their description used in this study.

**Panel A: Indices and Factors**

| Symbol | Description |
|---|---|
| $CRSP$ | CRSP value-weighted index |
| *S&P500* | *S&P* index |
| $FIN$ | Financial constituents of *S&P 500* index |
| $SMB$ | The size factor as defined in Fama and French (1993) |
| $HML$ | The value factor as defined in Fama and French (1993) |
| $UMD$ | The momentum factor as defined in Carhart (1997) and Jegadeesh and Titman (1993) |

**Panel B: Sample and Subsamples**

| Symbol | Description | Number of Stocks |
|---|---|---|
| $SSB$ : | Sample (financial stocks subject to the SEC 2008 short-sale ban) | 686 |
| $SSB_{OF}$ | $SSB$ stocks with options and futures | 77 |
| $SSB_{O}$ | $SSB$ stocks with options | 7 |
| $SSB_{N}$ | $SSB$ stocks with neither options nor futures | 361 |
| $SSB_{OF'}$ | $SSB$ stocks with options whose futures were introduced during the ban | 106 |
| $SSB_{OF'10/02}$ | $SSB$ stocks with options whose futures were introduced on October 2, 2008 | 33 |
| $SSB_{NF'}$ | $SSB$ stocks with neither options nor futures whose futures were introduced during the ban | 133 |
| $SSB_{NF'10/02}$ | $SSB$ stocks with neither options nor futures whose futures were introduced on October 2, 2008 | 36 |
| $SSB_{NO'F'}$ | $SSB$ stocks with neither options nor futures whose options and futures were introduced during on October 2, 2008 | 2 |

Table 4.6: **Composition of the Sample (*SSB*) Based on Standard Industrial Classification Codes.**

The market capitalization is the average for July 2000 to June 2008.

| SIC Codes | Description | SSB # stocks | % of total (by # stocks) | Market Cap (in \$B) | % of total (by mkt cap) |
|---|---|---|---|---|---|
| 6xxx: | Finance, insurance, and real estate | 686 | 100% | 2,133.06 | 100% |
| 60xx | Depository institutions | 495 | 72.16% | 1,082.27 | 50.74% |
| 61xx | Non-depository credit institutions | 8 | 1.17% | 11.48 | 0.54% |
| 62xx | Security and commodity brokers, dealers, exchanges, and services | 56 | 8.16% | 323.03 | 15.14% |
| 63xx | Insurance carriers | 107 | 15.60% | 690.85 | 32.39% |
| 64xx | Insurance agents, brokers, and services | 0 | 0% | 0 | 0% |
| 65xx | Real estate | 0 | 0% | 0 | 0% |
| 67xx | Holding and other investment offices | 20 | 2.92% | 25.43 | 1.19% |

### 4.2.3 Definitions and Notation

In this section, we define variables that will be used in subsequent sections. They are returns, turnovers, and their aggregates. Unless otherwise specified, subscript $i$ denotes a stock, and subcript $t$ denotes a day.

For stock $i$ at time $t$, we define the following variables:

- Return, $R_{it}$

$$R_{it} \equiv \frac{P_{it} - P_{it-1}}{P_{it-1}}, \tag{4.1}$$

where $P_{it}$ is the price of stock $i$ on day $t$.

- Market capitalization, $M_{it}$

$$M_{it} \equiv P_{it} S_{it}, \tag{4.2}$$

where $S_{it}$ is the number of shares outstanding of stock $i$ on day $t$

- Turnover, $\tau_{it}$

$$\tau_{it} \equiv \frac{X_{it}}{S_{it}}, \tag{4.3}$$

where $X_{it}$ is the share volume of stock $i$ on day $t$

The aggregate variables, i.e. the equal-weighted and value-weighted measures, are defined as follows.

- Equal-weighted return, $R_t^{EW}$

$$R_t^{EW} \equiv \frac{1}{N}\sum_{i=1}^{N} R_{it} \tag{4.4}$$

where $i$ is the index for stock, and $N$ is the total number of stocks.

- Value-weighted return, $R_t^{VW}$

$$R_t^{VW} \equiv \sum_{i=1}^{N} \frac{P_{it-1}S_{it-1}}{\sum_{j=1}^{N} P_{jt-1}S_{jt-1}} R_{it} = \sum_{i=1}^{N} \omega_{it-1}R_{it} \tag{4.5}$$

where $\omega_{it-1}$ is the weight for stock $i$ using market capitalization of time $t-1$.

- Equal-weighted turnover, $\tau_t^{EW}$

$$\tau_t^{EW} \equiv \frac{1}{N}\sum_{i=1}^{N} \frac{X_{it}}{S_{it}} = \frac{1}{N}\sum_{i=1}^{N} \tau_{it} \tag{4.6}$$

- Value-weighted turnover, $\tau_t^{VW}$

$$\tau_t^{VW} \equiv \sum_{i=1}^{N} \frac{P_{it-1}S_{it-1}}{\sum_{j=1}^{N} P_{jt-1}S_{jt-1}} \tau_{it} = \sum_{i=1}^{N} \omega_{it-1}\tau_{it} \tag{4.7}$$

The superscript $VW$ and $EW$ are also used for other variables for the value-weighted aggregate and equal-weighted aggregate, respectively.

### 4.2.4 Summary Statistics

The stocks in the sample are relatively small. More than 75% of them have the market capitalization lower than \$800 million. The median of the market capitalization is about \$200 million. There are a handful of very large stocks as shown in Table 4.7.

Table 4.7: **Market Capitalization of the Sample (*SSB*) for July 2000 to June 2008**

This table reports cross-sectional summary statistics of market capitalization averages for stocks in the sample for July 2000 to June 2008.

| | *SSB* |
|---|---|
| Observations | 686 |
| AvgCap (in million \$) | |
| Mean | 3,276.77 |
| Median | 195.99 |
| Std. Dev. | 15,381.38 |
| Percentiles: | |
| Min | 6.49 |
| p10 | 41.55 |
| p25 | 74.75 |
| p75 | 799.92 |
| p90 | 4,190.83 |
| Max | 224,686.00 |

From the daily data, we explore the distributional characteristics of the indices, portfolios, and the sample for the period of July 2000 to June 2008 which totals 2009 days. Table 4.8 reports statistics for daily returns of the indices and portfolios and their t-statistics corrected for heteroskedasticity and autocorrelation using Newey and West (1987). The median returns of the market and the financial sector are 0.05% and 0.00%, respectively. The financial sector is more volatile and has slightly fatter tails than the market for the sample period. Their first-order autocorrelation is very small and negative. The $HML$ and $UMD$ portfolios' average daily returns are approximately 0.04% and exhibit higher kurtosis than the market and the financial sector. The autocorrelations of the three portfolios are small. The $UMD$ portfolio is more persistent than the other two portfolios.

As far as the correlation is concerned, the sample $SSB$ is very highly correlated with the financial sector and is highly correlated with the market. The $HML$ and $UMD$ portfolios are negatively correlated with the market, financial sector, and the sample. The size factor

Table 4.8: **Summary Statistics of Indices' and Portfolios' Daily Returns (in %) for July 2000 to June 2008**

Newey-West t-statistics are reported in brackets.

| Statistic | *CRSP* | *FIN* | *SMB* | *HML* | *UMD* |
|---|---|---|---|---|---|
| Observations | 2009 | 2009 | 2009 | 2009 | 2009 |
| Mean | 0.006 | 0.002 | 0.013 | 0.042 | 0.039 |
| t-stat[mean] | [0.25] | [0.08] | [1.08] | [3.18] | [1.72] |
| Median | 0.049 | 0.000 | 0.03 | 0.03 | 0.07 |
| Std. Dev. | 1.090 | 1.416 | 0.525 | 0.564 | 0.891 |
| t-stat[std. dev.] | [15.67] | [13.04] | [20.41] | [9.71] | [11.87] |
| Skewness | 0.139 | 0.407 | -0.273 | -0.326 | -0.739 |
| t-stat[skewness] | [0.87] | [1.66] | [-1.76] | [-0.81] | [-1.81] |
| Kurtosis | 5.229 | 6.889 | 4.356 | 11.277 | 8.893 |
| t-stat[kurtosis] | [6.30] | [5.11] | [4.30] | [3.15] | [3.09] |
| Percentiles: | | | | | |
| Min | -5.114 | -5.363 | -3.36 | -4.90 | -7.29 |
| p10 | -1.384 | -1.582 | -0.63 | -0.48 | -0.94 |
| p25 | -0.557 | -0.677 | -0.31 | -0.21 | -0.39 |
| p75 | 0.556 | 0.660 | 0.34 | 0.27 | 0.47 |
| p90 | 1.240 | 1.538 | 0.65 | 0.63 | 1.00 |
| Max | 5.303 | 8.491 | 2.04 | 3.40 | 3.86 |
| Autocorrelations (%): | | | | | |
| $\rho_1$ | -4.41 | -4.85 | 4.31 | 4.36 | 14.11 |
| $\rho_2$ | -2.18 | 1.48 | -2.70 | -5.15 | 1.15 |
| $\rho_3$ | 0.42 | 0.24 | -2.98 | 5.80 | 1.02 |
| $\rho_4$ | 0.89 | -2.69 | -2.68 | -1.82 | 0.22 |
| $\rho_5$ | 1.12 | 2.27 | 2.85 | 1.12 | 4.56 |
| $\rho_6$ | -2.88 | -5.30 | 1.24 | 4.69 | 2.06 |
| $\rho_7$ | -2.88 | -3.55 | 4.47 | 3.05 | 1.72 |
| $\rho_8$ | -1.76 | -4.60 | -0.92 | 1.01 | 0.98 |
| $\rho_9$ | 0.72 | 1.93 | -1.19 | 3.00 | 2.71 |
| $\rho_{10}$ | -0.91 | -0.21 | -2.87 | -2.59 | -1.92 |
| Portmanteau $Q_1$ | 3.916 | 4.729 | 3.732 | 3.828 | 40.064 |
| (Prob > $Q_1$) | (0.048) | (0.030) | (0.053) | (0.050) | (0.000) |
| Portmanteau $Q_5$ | 5.321 | 7.677 | 10.074 | 16.844 | 44.750 |
| (Prob > $Q_5$) | (0.387) | (0.175) | (0.073) | (0.005) | (0.000) |
| Portmanteau $Q_{10}$ | 9.558 | 20.913 | 16.529 | 26.530 | 48.623 |
| (Prob > $Q_{10}$) | (0.480) | (0.022) | (0.086) | (0.003) | (0.000) |

is not correlated with other factors, except with the value factor, where the correlation is about -0.2. Table 4.9 summarizes these correlations.

The distributional characteristics of the sample returns are reported in Table 4.10. The value-weighted return, $R^{VW}$, has a lower median and is more volatile than the equal-weighted return, $R^{EW}$. It also has slightly higher kurtosis. $R^{VW}$ has a small negative first-order autocorrelation while there is no autocorrelation in $R^{EW}$. Table 4.11 gives the summary statistics of turnovers. The value-weighted turnover median, $\tau^{VW}$, is 0.38%. Its distribution is positively skewed and has fat tails. $\tau^{VW}$ is strongly autocorrelated with the first autocorrelation os 73% and the tenth autocorrelation of 41%. The equal-weighed counterpart, $\tau^{EW}$, has similar characteristics, with a lower median and weaker autocorrelations.

Table 4.9: **Correlation Matrix among Returns of Indices, Factors, and Sample ($SSB^{VW}$) for July 2000 to June 2008.**

Correlations shown are statistically significant at the 5% level.

| | $CRSP$ | $FIN$ | $SMB$ | $HML$ | $UMD$ | $SSB^{VW}$ |
|---|---|---|---|---|---|---|
| $CRSP$ | 1.000 | | | | | |
| $FIN$ | 0.855 | 1.000 | | | | |
| $SMB$ | 0.070 | -0.081 | 1.000 | | | |
| $HML$ | -0.499 | -0.278 | -0.202 | 1.000 | | |
| $UMD$ | -0.351 | -0.375 | 0.074 | 0.367 | 1.000 | |
| $SSB^{VW}$ | 0.869 | 0.992 | -0.055 | -0.295 | -0.363 | 1.000 |

Table 4.10: **Summary Statistics for Daily Returns (in %) of the Sample ($SSB$) for July 2000 to June 2008.**

Newey-West t-statistics are reported in brackets.

| Statistic | $R^{VW}$ | $R^{EW}$ |
|---|---|---|
| Observations (days) | 2009 | 2009 |
| Mean | 0.008 | 0.046 |
| t-stat[mean] | [0.30] | [2.88] |
| Median | 0.006 | 0.065 |
| Std. Dev. | 1.257 | 0.700 |
| t-stat[std. dev.] | [13.78] | [16.28] |
| Skewness | 0.312 | -0.056 |
| t-stat[skewness] | [1.46] | [-0.31] |
| Kurtosis | 6.276 | 5.299 |
| t-stat[kurtosis] | [5.64] | [6.27] |
| Percentiles: | | |
| Min | -5.397 | -3.227 |
| p10 | -1.425 | -0.770 |
| p25 | -0.623 | -0.358 |
| p75 | 0.618 | 0.451 |
| p90 | 1.372 | 0.840 |
| Max | 6.767 | 3.897 |
| Autocorrelations (%): | | |
| $\rho_1$ | -4.62 | -0.85 |
| $\rho_2$ | 1.13 | 1.05 |
| $\rho_3$ | 0.88 | 1.36 |
| $\rho_4$ | -2.62 | 0.78 |
| $\rho_5$ | 2.76 | 4.24 |
| $\rho_6$ | -4.63 | -2.10 |
| $\rho_7$ | -4.38 | 0.79 |
| $\rho_8$ | -3.98 | -0.53 |
| $\rho_9$ | 0.79 | 2.76 |
| $\rho_{10}$ | 0.20 | -0.70 |
| Portmanteau $Q_1$ | 4.287 | 0.145 |
| (Prob > $Q_1$) | (0.038) | (0.702) |
| Portmanteau $Q5$ | 7.620 | 4.497 |
| (Prob > $Q_5$) | (0.178) | (0.480) |
| Portmanteau $Q_{10}$ | 19.148 | 7.213 |
| (Prob > $Q_{10}$) | (0.038) | (0.705) |

Table 4.11: **Summary Statistics for Daily Turnover (in %) of the Sample** (*SSB*) **for July 2000 to June 2008.**

Newey-West t-statistics are reported in brackets.

| Statistic | $\tau^{VW}$ | $\tau^{EW}$ |
|---|---|---|
| Observations (days) | 2009 | 2009 |
| Mean | 0.464 | 0.288 |
| t-stat[mean] | [35.05] | [46.68] |
| Median | 0.382 | 0.252 |
| Std. Dev. | 0.266 | 0.133 |
| t-stat[std. dev.] | [6.86] | [7.90] |
| Skewness | 2.595 | 2.725 |
| t-stat[skewness] | [3.98] | [3.53] |
| Kurtosis | 10.787 | 15.635 |
| t-stat[kurtosis] | [3.28] | [2.30] |
| Percentiles: | | |
| Min | 0.074 | 0.057 |
| p10 | 0.278 | 0.183 |
| p25 | 0.321 | 0.209 |
| p75 | 0.481 | 0.316 |
| p90 | 0.796 | 0.447 |
| Max | 2.243 | 1.698 |
| Autocorrelations (%): | | |
| $\rho_1$ | 72.72 | 60.65 |
| $\rho_2$ | 51.45 | 43.76 |
| $\rho_3$ | 45.60 | 40.12 |
| $\rho_4$ | 44.65 | 37.87 |
| $\rho_5$ | 49.49 | 40.95 |
| $\rho_6$ | 67.09 | 54.20 |
| $\rho_7$ | 80.17 | 67.68 |
| $\rho_8$ | 64.69 | 54.22 |
| $\rho_9$ | 46.21 | 39.46 |
| $\rho_{10}$ | 41.23 | 35.45 |
| Portmanteau $Q_1$ | 1,064.1 | 740.11 |
| (Prob > $Q_1$) | (0.000) | (0.000) |
| Portmanteau $Q_5$ | 2,911.1 | 2,076.9 |
| (Prob > $Q_5$) | (0.000) | (0.000) |
| Portmanteau $Q_{10}$ | 6,735.9 | 4,756.0 |
| (Prob > $Q_{10}$) | (0.000) | (0.000) |

## 4.3 Impact on Equity Market

We now examine how the short-sale ban affects the equity market. In Section 4.3.1, we empirically test for abnormal returns during the ban, and report that the ban results in overvaluation of stocks. Then, we study the return volatility of the sample, and document higher idiosyncratic volatility of the banned stocks, compared to the market in Section 4.3.2.

### 4.3.1 Cumulative Abnormal Returns

To get an overview of the sample and market performance around the short-sale ban event, we first explore their cumulative returns. The definitions of the individual cumulative return, the equal-weighted cumulative return, and the value-weighted cumulative return are given as follows.

- Cumulative return, $CR_{it}$

$$CR_{it} = \sum_{s=t_0}^{t} R_{is}, \tag{4.8}$$

  where $s$ is the time index, and $t_0$ is the reference date (starting date).

- Equal-weighted cumulative return, $CR_t^{EW}$

$$CR_t^{EW} = \frac{1}{N}\sum_{i=1}^{N} CR_{it} \tag{4.9}$$

- Value-weighted cumulative return, $CR_t^{VW}$

$$CR_t^{VW} = \frac{1}{N}\sum_{i=1}^{N} \omega_{it-1} CR_{it} \tag{4.10}$$

Figure 4.1 shows the cumulative return of the sample and that of the market, which is the CRSP value-weighted index, around the short-sale ban. There is little difference between the sample value-weighted return and the market return before the short-sale ban starts. They begin to deviate sharply on the short-sale ban annoucement day and the first day of the ban. This difference is maintained throughout the ban.[3] The same analysis is also true when considering the equal-weighted return of the sample.

To evaluate abnormal returns (ARs) due to the short-sale ban, we use the market model similar to Brown and Warner (1985) with the size, value, and momentum portfolios as additional explanatory variables. We use daily data from July 2000 to June 2008 to estimate model coefficients in 4.11. The estimation result is summarized in Table 4.12. The median betas are 0.58, 0.26, 0.35, and -0.08 for the market factor, size factor, value factor, and momentum factor, respectively.

- Market model of the excess return for stock $i$ at time $t$,

$$R_{it}-r_t^f = \alpha_i+\beta_i^{MKT}(R_t^{MKT}-r_t^f)+\beta_i^{SMB}R_t^{SMB}+\beta_i^{HML}R_t^{HML}+\beta_i^{UMD}R_t^{UMD}+\epsilon_{it}, \quad (4.11)$$

  where $r_t^f$ is the riskfree rate at time $t$. $R_t^{MKT}$ is the market return, which we use the CRSP value-weighted index. $R^{SMB}$ and $R^{HML}$ are the returns of the size and value factors, respectively. Lastly, $R^{UMD}$ is the return of the momentum factor.

  For stock $i$ at time $t$, the abnormal return, $AR_{it}$, is the difference between its realized return and its expected return.

- Abnormal return, $AR_{it}$

$$AR_{it} = R_{it} - E[R_{it}|\mathcal{I}_t] \quad (4.12)$$

  where $\mathcal{I}_t$ is market information up to time $t$.

$$AR_{it} = R_{it} - [\hat{\alpha}_i + \hat{\beta}_i^{MKT}(R_t^{MKT} - r_t^f) + \hat{\beta}_i^{SMB}R_t^{SMB} + \hat{\beta}_i^{HML}R_t^{HML} + \hat{\beta}_i^{UMD}R_t^{UMD} + r_t^f] \quad (4.13)$$

  The sum of abnormal returns over time for stock $i$ between time $t_0$ and time $t$ is called the cumulative abnormal return, $CAR_{it}$ and their aggregate measures are given in the following definitions. We then test whether the abnormal return and cumulative return are statistically significant around the event window.

[3]After the ban, the sample cumulative return is also higher than that of the market. This evidence may be the effect of the Emergency Economic Stabilization Act.

- Cumulative abnormal return[4], $CAR_{it}$

$$CAR_{it} = \sum_{s=t_0}^{t} AR_{is} \tag{4.14}$$

- Equal-weighted cumulative abnormal return, $CAR_t^{EW}$

$$CAR_t^{EW} = \frac{1}{N}\sum_{i=1}^{N} CAR_{it} \tag{4.15}$$

- Value-weighted cumulative return, $CAR_t^{VW}$

$$CAR_t^{VW} = \frac{1}{N}\sum_{i=1}^{N} \omega_{it-1} CAR_{it} \tag{4.16}$$

Table 4.12: **Indices' and Portfolios' Betas of the Sample (*SSB*) for July 2000 to June 2008.**

| Statistic | $\hat{\beta}^{MKT}$ | $\hat{\beta}^{SMB}$ | $\hat{\beta}^{HML}$ | $\hat{\beta}^{UMD}$ |
|---|---|---|---|---|
| Observations | 686 | 686 | 686 | 686 |
| Mean | 0.587 | 0.421 | 0.394 | -0.112 |
| Median | 0.580 | 0.262 | 0.350 | -0.081 |
| Std. Dev. | 0.474 | 0.493 | 0.437 | 0.202 |
| Percentiles: | | | | |
| Min | -0.234 | -1.593 | -1.430 | -1.194 |
| p10 | 0.044 | -0.110 | -0.095 | -0.325 |
| p25 | 0.137 | 0.073 | 0.101 | -0.192 |
| p75 | 0.973 | 0.814 | 0.707 | -0.001 |
| p90 | 1.173 | 1.127 | 0.923 | 0.073 |
| Max | 2.029 | 1.872 | 1.998 | 0.643 |

The short-sale ban event starts on September 19, 2008 and ends on October 8, 2008, with government actions starting on the sixth day of the ban, as discussed in Secion 4.2.1. We consider both an event window of the first six days of the ban as well as an event window of the whole ban in evaluating the cumulative abnormal return. Doing so allows us to check the robustness of the result.

[4]For small returns, simple returns and log returns are approximately equal.

The cumulative abnormal returns (CARs) with their 95% confidence intervals for the value-weighted sample and the equal-weighted sample are plotted in Figure 4.2. On the first day of the ban, the equal-weighted AR of the sample is 2.89% and is statistically significant at the 1% level as shown in Panel A of Table 4.13. From the day before the start of the ban until five days later, the sample equal-weighted CAR is approximately 3.46% and is also statistically significant at the 1% level as reported in Panel B of Table 4.13.[5] If the whole ban period is considered, the CAR is about 6.03%.[6] Around the ban termination, the AR of banned stocks is -0.95% and -2.53% on event days 13 and 14, respectively. As for the CAR, Panel B Table 4.13 shows a CAR of -3.34% due to ban termination. Additionally, the CAR of the period well after the ban is small and statistically insignificant. With these results of the CAR increasing at the start of the ban and decreasing at the termination of the ban, it can be concluded that the short-sale ban causes overvaluation of stocks.

This finding is consistent with the argument in Miller (1977) that stock returns increase in the absence of short selling. A number of empirical studies also document similar evidence in different contexts. For example, Jones and Lamont (2002) use equity data from 1926 to 1933 and show the stocks with high short-sale costs are overvalued. Chang, Cheng, and Yu (2007) show that stocks that are shortable in the Hong Kong market have positive CARs, using data from 1994 to 2003.

[5]The short-sale ban has greater effect on larger stocks in the sample, which can be seen from larger CARs in the value-weighted sample, compared to the equal-weighted sample.

[6]Part of this CAR may be due to positive actions relating to the bailout bill starting on event day 8.

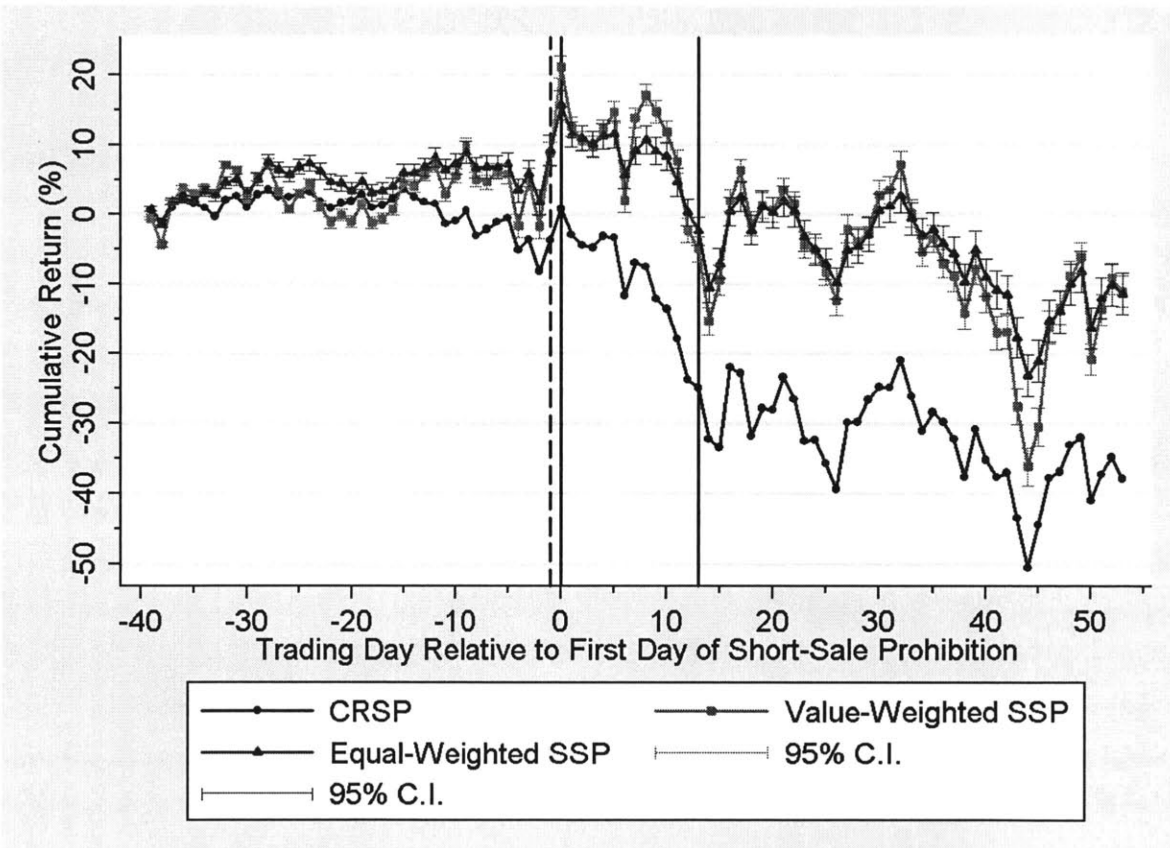


Figure 4.1: **Cumulative Returns.** The period is 40 days before and after the short-sale ban. The first and second vertical solid lines mark the start and end of the short-sale ban, respectively. The vertical dotted line marks the date when the short-sale ban is announced.

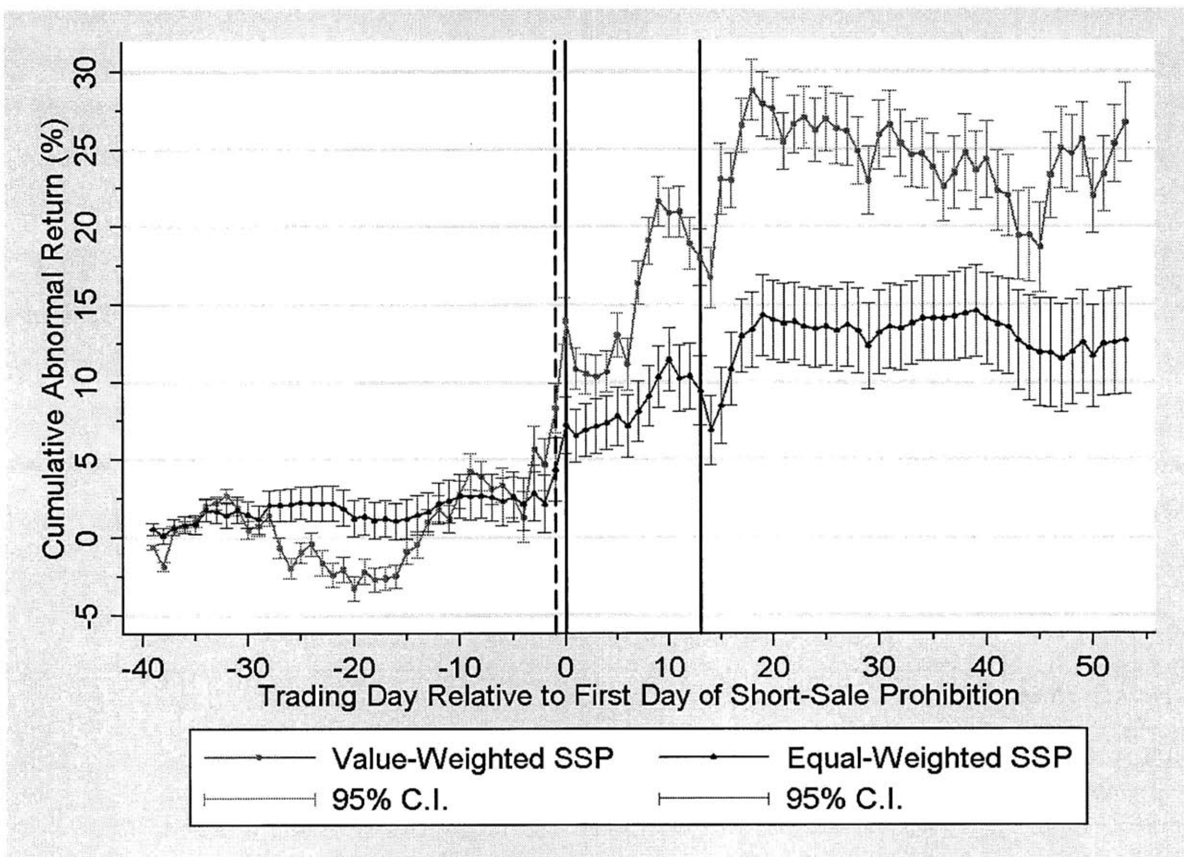


Figure 4.2: **Cumulative Abnormal Returns.** The period is 40 days before and after the short-sale ban. The first and second vertical solid lines mark the start and end of the short-sale ban, respectively. The vertical dotted line marks the date when the short-sale ban is announced.

Table 4.13: **Abnormal Returns and Cumulative Returns around Short-Sale Ban**

Abnormal returns and cumulative abnormal returns that are statistically significant at the 5% and 1% levels are marked by ** and ***, respectively.

**Panel A: Abnormal Returns (%)**

| Day | Mean | Two-Tailed p-Value | Event |
|---|---|---|---|
| $H_o : AR^i_t = 0$ | | | |
| $H_a : AR^i_t \neq 0$ | | | |
| -10 | 0.305** | (0.031) | |
| -9 | -0.027 | (0.917) | |
| -8 | 0.043 | (0.794) | |
| -7 | -0.119 | (0.507) | |
| -6 | -0.242 | (0.069) | |
| -5 | 0.287** | (0.048) | |
| -4 | -0.417 | (0.032) | |
| -3 | 0.687*** | (0.001) | |
| -2 | -0.694*** | (0.001) | SEC annouced naked short-sale ban |
| -1 | 2.178*** | (0.000) | SEC announced short-sale ban (SSB) |
| 0 | 2.885*** | (0.000) | SSB started |
| 1 | -0.698** | (0.020) | |
| 2 | 0.365 | (0.157) | |
| 3 | 0.247 | (0.258) | |
| 4 | 0.211 | (0.315) | |
| 5 | 0.444 | (0.331) | |
| 6 | -0.647 | (0.136) | House rejected bailout bill |
| 7 | 0.940** | (0.030) | |
| 8 | 1.007*** | (0.002) | Senate passed bailout bill |
| 9 | 1.212*** | (0.000) | |
| 10 | 1.132*** | (0.000) | Bailout bill passed by House and signed by President |
| 11 | -1.213*** | (0.000) | |
| 12 | 0.142 | (0.573) | |
| 13 | -0.951*** | (0.001) | SSB ended |
| 14 | -2.533*** | (0.000) | |
| 15 | 1.589*** | (0.001) | Wells Fargo acquired Wachovia |
| 16 | 2.345*** | (0.000) | |
| 17 | 2.131*** | (0.000) | TARP announced |
| 18 | 0.395 | (0.102) | |
| 19 | 0.939*** | (0.002) | |
| 20 | -0.329 | (0.168) | |
| 21 | -0.199 | (0.376) | |
| 22 | 0.118 | (0.583) | |
| 23 | -0.338 | (0.138) | |

**Panel B: Cumulative Abnormal Returns (%)**

| Window | Mean | One-Tailed p-Value | Window description |
|---|---|---|---|
| $H_o: CAR^i_{t_0,t_1} \leq 0$ | | | |
| $H_a: CAR^i_{t_0,t_1} > 0$ | | | |
| (-20,-2) | 0.278 | (0.339) | Before the ban |
| (-1,1) | 4.365*** | (0.000) | Two days around the ban initiation |
| (0,5) | 3.455*** | (0.000) | Ban period (before TARP bill) |
| (0,12) | 6.027*** | (0.000) | Ban period (after TARP bill approved) |
| (-1,14) | 4.721*** | (0.000) | Before and after the ban |
| $H_o: CAR^i_{t_0,t_1} \geq 0$ | | | |
| $H_a: CAR^i_{t_0,t_1} < 0$ | | | |
| (12,14) | -3.342*** | (0.000) | Two days around the ban termination |
| (18,53) | -0.294 | (0.394) | After the ban |

### 4.3.2 High Volatility of Banned Stocks

In addition to returns, we study idiosyncratic volatility of returns under the short-sale ban. In calculating returns, we use futures settlement prices for both the sample and the market, proxied by *S&P500.* We then adjust these returns by the market return, and use the adjusted returns to calculate idiosyncratic volatility. Using settlement prices allow us to have less noisy estimates of return volatility, compared to using high and low prices during the trading day. We compare subsample $SSB_{OF}$ or the banned stocks with traded options and futures with the *S&P500* constituents with traded futures.[7]

Table 4.14 reports the summary statistics of volatility in Panel A, and the mean comparison test in Panel B. Panel A shows that the market return volatility, as proxied by *S&P500* constituents, monotonically increases from the pre-ban period to the post-ban period. However, the subsample return volatility increases during the ban and stays approximately at that level after the ban. We then compare the return volatility among the pre-ban, ban, and post-ban periods in Panel B. We find that there is no statistical difference in return volatility between the ban and post-ban periods in the subsample. In contrast, the return volatility of the *S&P500* constituents during the ban is about 2% lower than that after the ban, and this difference is significant at the 1% level. This evidence implies that the short-sale ban causes stock returns to be more volatile.

[7]Out of 500 stocks in the index, approximately 475 stocks have futures data.

Table 4.14: **Daily Idiosyncratic Volatility**

This table reports summary statistics and two-group mean comparison tests of idiosyncratic volatility. The idiosyncratic volatility $\sigma_{\epsilon_i}$ is the volatility of $SSB_{OF}$ daily returns computed from their futures settlement prices adjusted by the market return. The futures expiration date is December 2008. Symbols ** and *** denote statistical significance at the 5% and 1% levels, respectively.

**Panel A: Summary Statistics of $\sigma_{\epsilon_i}$ (%)**

| | $SSB_{OF}$ | | |
|---|---|---|---|
| | Pre | Ban | Post |
| Obs | 77 | 77 | 77 |
| Mean | 5.697 | 10.620 | 10.266 |
| Std. Dev. | 3.866 | 8.201 | 3.968 |
| | *S&P500* constituents | | |
| | Pre | Ban | Post |
| Obs | 475 | 476 | 475 |
| Mean | 3.169 | 5.160 | 7.171 |
| Std. Dev. | 1.936 | 4.046 | 3.313 |

**Panel B: Mean Comparison Test of $\sigma_{\epsilon_i}$ (%) between Periods**

| | $SSB_{OF}$, $H_0$ : | | |
|---|---|---|---|
| | $\sigma_{\epsilon_{i,Ban}} - \sigma_{\epsilon_{i,Pre}} = 0$ | $\sigma_{\epsilon_{i,Ban}} - \sigma_{\epsilon_{i,Post}} = 0$ | $\sigma_{\epsilon_{i,Post}} - \sigma_{\epsilon_{i,Pre}} = 0$ |
| Difference (%) | 4.923*** | 0.354 | 4.570*** |
| (p-Value) | (0.000) | (0.734) | (0.000) |
| | *S&P500* constituents, $H_0$ : | | |
| | $\sigma_{\epsilon_{i,Ban}} - \sigma_{\epsilon_{i,Pre}} = 0$ | $\sigma_{\epsilon_{i,Ban}} - \sigma_{\epsilon_{i,Post}} = 0$ | $\sigma_{\epsilon_{i,Post}} - \sigma_{\epsilon_{i,Pre}} = 0$ |
| Difference (%) | 1.992*** | -2.011*** | 4.003*** |
| (p-Value) | (0.000) | (0.000) | (0.000) |

## 4.4 Impact on Derivatives Market

We investigate the effects of the short-sale ban on the futures market in Section 4.4.1, and on the option markets in Section 4.4.2.

### 4.4.1 Futures Market

The first evidence of increased activity in the futures market is the addition of futures associated with banned stocks in the OneChicago futures exchange. Figure 4.3 shows monthly futures addition in 2008. In September and October 2008, 99 futures and 258 futures are added, respectively. These numbers of added futures are higher than almost all other months in 2008. During the short-sale ban period, 284 out of the 289 futures introduced to the exchange have their underlying stocks on the ban list as shown in Figure 4.4.

Increased demand in futures also supports the argument that the trading of banned stocks shifts from the equity market to the futures market during the ban. Figure 4.5 show the normalized open interests of subsample $SSB_{OF}$ and the market, proxied by an ETF on *S&P500.* Before the ban, there is no statistical difference between the two normalized open interests. However, the normalized open interest of the subsample goes up during the ban, resulting in statistical difference with the normalized open interest of the market. This difference remains about 20 days after the ban terminates. A similar trend is also true for the normalized settlement price in Figure 4.6. While the normalized settlement price of the futures on the *S&P500* ETF generally decreases as the time gets closer to its expiration, the normalized settlement price of subsample $SSB_{OF}$ jumps up upon entering the short-sale ban period. $SSB_{OF}$ also has a higher normalized settlement price than the market during the ban and stays higher for some time after the ban. There is no difference between the two settlement prices close to their expiration.

Lastly, we find that the increased activity in the futures market is mostly due to selling pressure by looking at futures premiums. Even though the banned stocks cannot be shorted, their futures can be shorted. The payoff of shorting futures approximately replicates the payoff of shorting the underlying banned stocks. We first define the futures premium as follows.

- Futures premium of stock $i$ at time $t$, $FP_t^i$

$$FP_{i,t} = \frac{F_i(t,T) - S^*_{i,t} e^{\int_t^T r(s)\,ds}}{S^*_{i,t}}, \tag{4.17}$$

where $F_i(t,T)$ is the futures settlement price of stock $i$ at time $t$, $S^*_{i,t}$ is the adjusted stock price of stock $i$ at time $t$.

Table 4.15 reports the future premiums of banned stock and an *S&P500* ETF called $SPY$, which proxies for the market, around the short-sale ban period. As shown in Panel A, the futures premiums of all subsamples $SSB_{OF}$, $SSB_{OF'1002}$, and $SSB_{NF'1002}$ monotonically decrease as we move through the pre-ban, ban, and post-ban periods. On the other hand, the futures premiums of the market increase slightly in a monotonic manner during this time. Panel B of Table 4.15 shows that the futures premium of $SSB_{OF}$ during the ban is about 0.07 lower than that before the ban while there is no statistical difference between those times for the market. Between the ban period and the post-ban period, the futures premiums of all three subsamples, $SSB_{OF}$, $SSB_{OF'1002}$, and $SSB_{NF'1002}$, are higher during the ban, while there the market futures premium does not change. Comparing the post-ban period to the pre-ban period, the futures premium of banned stock with traded options and futures, $SSB_{OF}$, is approximately 0.11 lower after the ban. However, the futures premium of the market exhibits the opposite difference, being 0.03 higher in its futures premium before the ban.

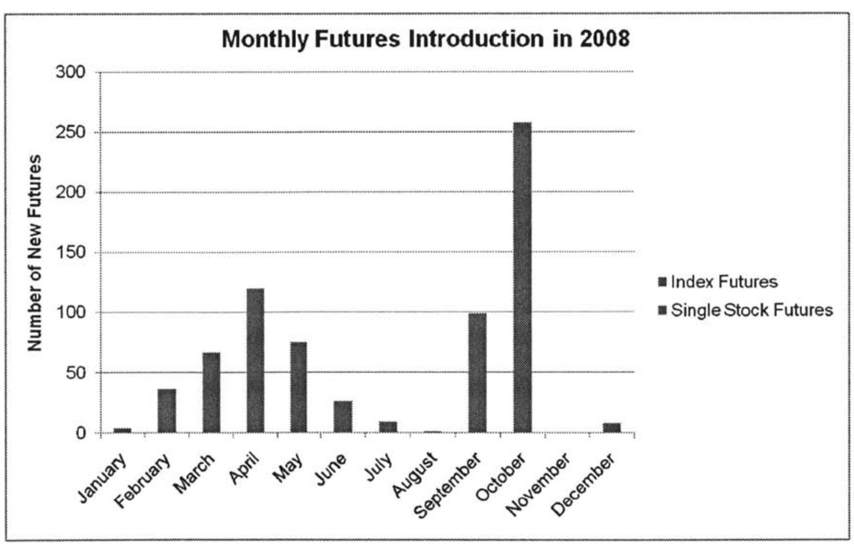


Figure 4.3: **Monthly futures introduction**

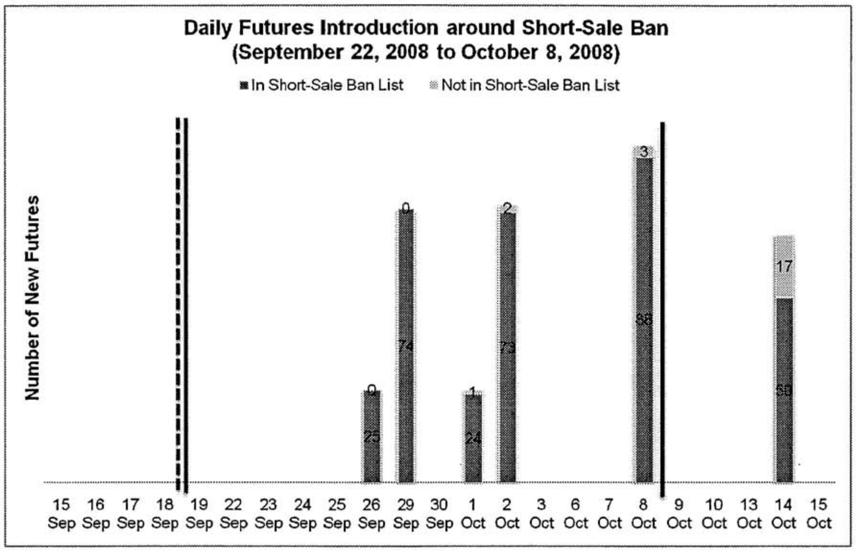


Figure 4.4: **Daily futures introduction**

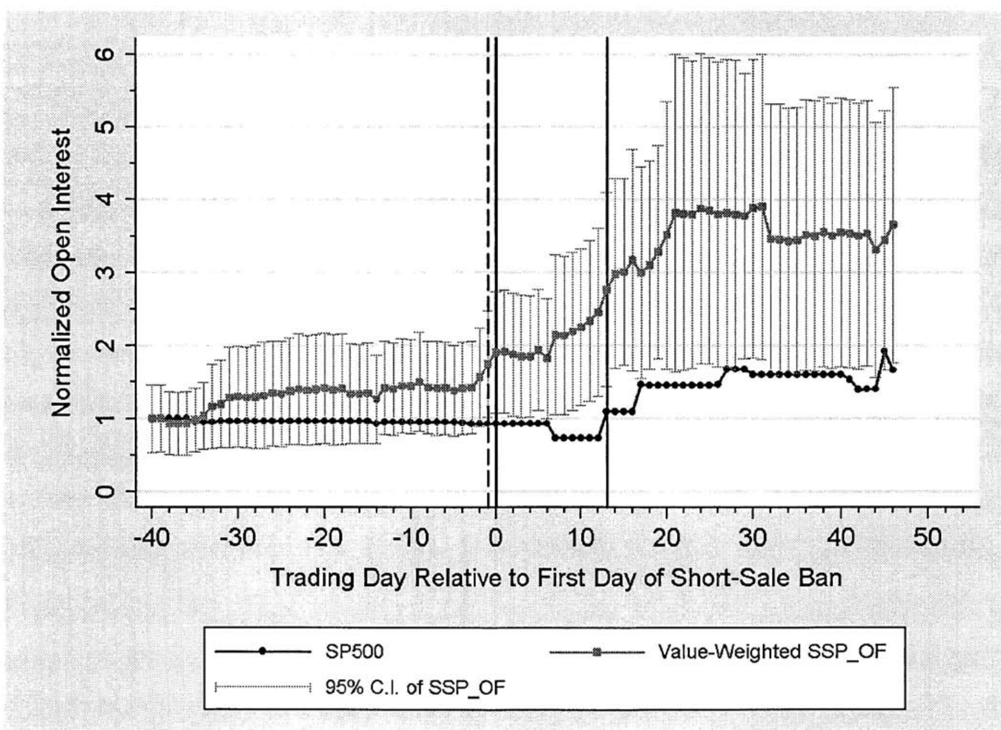


Figure 4.5: **Normalized open interest of futures expiring in December 2008**

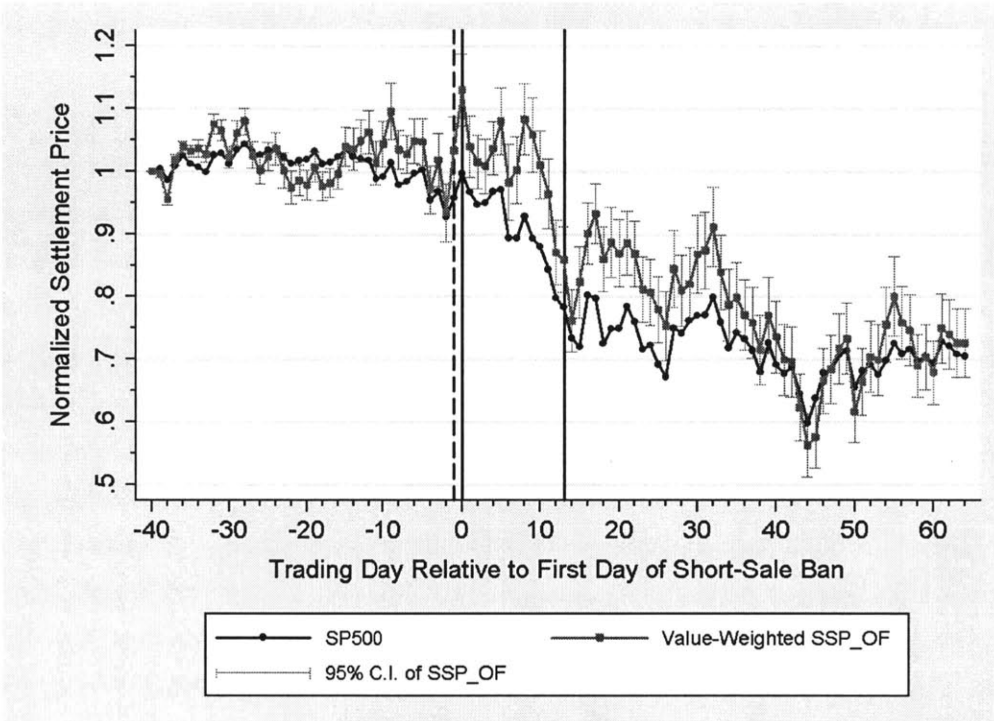


Figure 4.6: **Normalized settlement price of futures expiring in December 2008**

Table 4.15: **Futures Premiums**

This table reports statistics and mean-comparison tests of future premiums around the short-sale ban. The time window includes 40 days before the ban, during the ban, and 40 days after the ban. The sample consists of 77 $SSB_{OF}$, 33 $SSB_{OF'1002}$, and 36 $SSB_{NF'1002}$ futures contracts expiring on December 19, 2008. The statistics of *SPY* futures are also reported. (*SPY* is *SPDR S&P 500* ETF. *SPY* futures is chosen to proxy *S&P 500* due to unavailability of *S&P 500* futures data.) *Ban (ex. 9/29)* is the ban period that excludes September 29, 2008. The acronym *FI* stands for *Futures Introduction* which is applicable for $SSB_{OF'1002}$ stocks whose futures were introduced on October 2, 2008. *Futures Premium*, $FP_t$, is defined as $\frac{F_i(t,T)-S^*_{i,t}(1+r_t)^{T-t}}{S^*_{i,t}}$.

Newey-West t-statistics for means are reported in brackets. 3 lags are used for pre-ban and post-ban periods. 2 lags are used for the ban period. Symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Futures Premium Distribution**

| | $SSB_{OF}$ | | | | $SSB_{OF'1002}$ | |
|---|---|---|---|---|---|---|
| | Pre | Ban | Ban (ex. 9/29) | Post | Ban (after FI) | Post |
| No. of Days | 40 | 14 | 13 | 40 | 5 | 40 |
| Mean | -0.024*** | -0.072*** | -0.089*** | -0.135*** | 0.035*** | 0.009*** |
| [t-stat] | [-22.17] | [-3.44] | [-3.82] | [-9.88] | [3.17] | [3.62] |
| Std. Dev. | 0.007 | 0.108 | 0.091 | 0.051 | 0.030 | 0.010 |
| Min | -0.060 | -0.355 | -0.355 | -0.268 | 0.013 | -0.013 |
| p10 | -0.029 | -0.163 | -0.163 | -0.200 | 0.013 | -0.001 |
| Median | -0.024 | -0.066 | -0.067 | -0.126 | 0.023 | 0.008 |
| p90 | -0.018 | 0.005 | 0.001 | -0.068 | 0.088 | 0.024 |
| Max | -0.011 | 0.148 | 0.005 | -0.026 | 0.088 | 0.038 |
| Autocorrelations: | | | | | | |
| $\rho_1$ | -0.008 | -0.286 | 0.027 | 0.672*** | -0.137 | 0.600*** |
| (p-Value) | (0.959) | (0.236) | (0.912) | (0.000) | (0.684) | (0.000) |
| $\rho_2$ | 0.025 | -0.127 | -0.259 | 0.605*** | | 0.594*** |
| (p-Value) | (0.986) | (0.427) | (0.548) | (0.000) | | (0.000) |

| | $SPY$ | | | | $SSB_{NF'1002}$ | |
|---|---|---|---|---|---|---|
| | Pre | Ban | Ban (ex. 9/29) | Post | Ban (after FI) | Post |
| No. of Days | 40 | 14 | 13 | 40 | 5 | 40 |
| Mean | -0.010*** | 0.012 | 0.010 | 0.019* | 0.030 | -0.025*** |
| [t-stat] | [-9.57] | [1.00] | [0.76] | [1.77] | [1.85] | [-3.15] |
| Std. Dev. | 0.006 | 0.050 | 0.052 | 0.059 | 0.048 | 0.028 |
| Min | -0.022 | -0.150 | -0.150 | -0.061 | 0.005 | -0.113 |
| p10 | -0.017 | -0.004 | -0.004 | -0.048 | 0.005 | -0.059 |
| Median | -0.010 | 0.017 | 0.014 | 0.009 | 0.011 | -0.021 |
| p90 | -0.005 | 0.054 | 0.054 | 0.111 | 0.115 | 0.008 |
| Max | 0.010 | 0.064 | 0.064 | 0.164 | 0.115 | 0.014 |
| Autocorrelations: | | | | | | |
| $\rho_1$ | 0.259* | -0.128 | -0.036 | 0.324** | -0.243 | 0.776*** |
| (p-Value) | (0.089) | (0.595) | (0.885) | (0.033) | (0.473) | (0.000) |
| $\rho_2$ | 0.024 | -0.048 | -0.066 | -0.127* | | 0.698*** |
| (p-Value) | (0.232) | (0.850) | (0.952) | (0.073) | | (0.000) |

**Panel B: Futures Premium Differences Among Periods**

| | Ban (ex. 9/29) - Pre [t-stat] |
|---|---|
| $SSB_{OF}$ | -0.065*** |
| | [-2.582] |
| $SPY$ | 0.021 |
| | [1.451] |

| | Ban (ex. 9/29) - Post [t-stat] |
|---|---|
| $SSB_{OF}$ | 0.045* |
| | [1.716] |
| $SSB_{OF'10/02}$ | 0.025* |
| | [1.853] |
| $SSB_{NF'10/02}$ | 0.055*** |
| | [2.512] |
| $SPY$ | -0.009 |
| | [-0.512] |

| | Post - Pre [t-stat] |
|---|---|
| $SSB_{OF}$ | -0.110*** |
| | [13.571] |
| $SPY$ | 0.030*** |
| | [3.148] |

### 4.4.2 Option Market

In addition to changes in the futures market resulting from the short-sale ban, we document that puts are more valued relative to calls for banned stocks. An explanation of this evidence is that investors can replicate short-selling stocks in the option market by buying puts and writing calls on those banned stocks. A few studies that report put-call parity violation in the presence of short-sale constraints include Evans, Geczy, Musto, and Reed (2009), and Ofek, Richardson, and Whitelaw (2004). They have shown that short-sale constraints causes put-call parity violation, and the degree of violation is greater for more stringent short-sale constraints. Table 4.16 Panel A gives an overview of the implied volatility statistics for options associated with banned stocks and the *S&P500* options. The puts of the banned stocks in each subsample, $SSB_{OF}$, $SSB_O$, and $SSB_{OF'1002}$, have higher implied volatility (or more expensive) than calls during the ban and after the ban. The difference is most pronounced in the subsample without futures, $SSB_O$, and the subsample with new futures introduced during the ban, $SSB_{OF'1002}$. For example, the put implied volatility of $SSB_O$ is about 137% while their call implied volatility is about 97% during the ban. This observation implies that there is more demand in puts of the banned stocks relative to calls, especially when banned stocks do not have futures. In constrast, there is little difference between the implied volatility of the put and that of the call of *S&P500*. The put implied volatility of *S&P500* is 37% and its call counterpart is approximately 40% during the ban.

To empirically test for abnormality in put-call implied volatility, we define implied put-call disparity as follows.

- Implied disparity, $\Delta\sigma_t^t$

$$\Delta\sigma_t^I = \frac{\sigma_t^{I,Put} - \sigma_t^{I,Call}}{\sigma_t^{I,Put}}, \tag{4.18}$$

where $\sigma_t^I$ is the implied volatility.[8] The implied disparity is the put implied volatility subtracted by the call implied volatility, normalized by the put implied volatility. This value tells us how much more puts are valued relative to calls in a normalized term.

Panel B in Table 4.16 shows that while the implied disparity of *S&P500* is about zero

[8]The implied volatility is obtained from OptionMetrics. OptionMetrics calculate implied volatility based on the model in Cox, Ross, and Rubinstein (1979).

in all periods, subsample $SSB_O$ and $SSB_{OF'1002}$, during the ban, have implied disparity of about 0.24 and 0.12, respectively. By comparing the pre-ban period and the ban period in Panel C, the implied disparity of $SSB_O$ and $SSB_{OF'1002}$ is approximately 0.16 and 0.08 higher during the ban, respectively. This difference is significant at at least 5% level. Between these two periods, $SSB_OF$ and *S&P500* do not exhibit statistical significant difference in the disparity. Almost the same description holds when we compare the ban period with the post-ban period.[9] Comparing the ban period with the post-ban period, the implied disparity $SSB_O$ and $SSB_{OF'1002}$ is about 0.16 and 0.09 higher during the ban, respectively.

This test confirms that puts are more expensive during the ban for short-sale banned stocks, especially for banned stocks without futures, and allows us to reach two conclusions. First, investors resort to the option market to substitute their banned attempt to short sell in the equity market. Second, this substitution in the option market is stronger for banned stocks without futures.

[9]With an exception that *S&P500* disparity in the ban period is slightly lower than that in the post-ban period.

Table 4.16: **Implied Volatility and Implied Disparity**

This table reports statistics of implied volatility and implied put-call disparity in Panels A and B. Panel C reports mean-comparison tests of implied put-call disparity around the short-sale ban. The time window include 40 days before the ban, during the ban, and 40 days after the ban. The sample consists of 30-day ATM option pairs ($\Delta = 0.5$ for call and $\Delta = -0.5$ for put) of 68 $SSB_{OF}$, 7 $SSB_O$, and 33 $SSB_{OF'1002}$ stocks. The ATM option pairs of *S&P500* statistics are also reported. In Panel, *Ban (ex. 9/29)* is the ban period that excludes September 29, 2008. The acronym *FI* stands for *Futures Introduction* which is applicable for $SSB_{OF'1002}$ stocks whose futures were introduced on October 2, 2008. *Implied disparity*, $\Delta\sigma_t^I$, is defined as $\frac{\sigma_t^{I,Put} - \sigma_t^{I,Call}}{\sigma_t^{I,Put}}$.

Newey-West t-statistics for means are reported. 3 lags are used for pre-ban and post-ban periods. 2 lags are used for the ban period. In Panel C, two-sided t-tests assuming unequal variance are reported. Symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Implied Volatility (%) Distribution**

| | $SSB_{OF}$ Put | | | $SSB_{OF}$ Call | | | $SSB_O$ Put | | | $SSB_O$ Call | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pre | Ban | Post | Pre | Ban | Post | Pre | Ban | Post | Pre | Ban | Post |
| No. of Days | 40 | 14 | 40 | 40 | 14 | 40 | 40 | 14 | 40 | 40 | 14 | 40 |
| Mean | 68.74 | 104.19 | 112.94 | 65.73 | 98.83 | 107.85 | 104.49 | 136.91 | 130.77 | 91.49 | 97.40 | 112.93 |
| Std. Dev. | 9.52 | 9.35 | 12.84 | 8.50 | 18.40 | 13.60 | 18.00 | 37.37 | 27.62 | 12.56 | 48.14 | 20.74 |
| Min | 59.94 | 89.58 | 91.93 | 56.90 | 62.52 | 86.26 | 72.49 | 101.00 | 96.03 | 69.07 | 55.35 | 87.02 |
| Median | 65.50 | 105.01 | 111.10 | 63.40 | 96.62 | 105.12 | 102.42 | 125.03 | 127.40 | 89.26 | 84.94 | 107.41 |
| Max | 106.87 | 122.02 | 146.89 | 96.65 | 139.06 | 143.12 | 137.48 | 247.69 | 215.47 | 117.19 | 258.52 | 174.11 |

| | $SSB_{OF'1002}$ Put | | | | $SSB_{OF'1002}$ Call | | | | *S&P500* Put | | | *S&P500* Call | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pre | Ban (before FI) | Ban (after FI) | Post | Pre | Ban (before FI) | Ban (after FI) | Post | Pre | Ban | Post | Pre | Ban | Post |
| No. of Days | 40 | 9 | 5 | 40 | 40 | 9 | 5 | 40 | 40 | 14 | 40 | 40 | 14 | 40 |
| Mean | 69.25 | 96.08 | 96.64 | 99.85 | 65.68 | 77.95 | 78.71 | 94.40 | 22.06 | 37.47 | 57.60 | 21.89 | 39.87 | 56.70 |
| Std. Dev. | 4.87 | 8.47 | 6.96 | 7.37 | 5.61 | 11.77 | 3.91 | 6.98 | 3.39 | 6.03 | 7.77 | 3.80 | 7.90 | 7.48 |
| Min | 63.75 | 86.77 | 89.23 | 88.43 | 59.74 | 71.04 | 73.94 | 82.44 | 18.20 | 31.06 | 42.10 | 17.65 | 27.13 | 39.91 |
| Median | 67.53 | 94.55 | 93.96 | 98.79 | 64.45 | 73.00 | 79.25 | 93.39 | 20.93 | 35.39 | 58.31 | 20.81 | 37.32 | 56.82 |
| Max | 87.10 | 110.02 | 106.70 | 121.64 | 80.82 | 108.47 | 83.36 | 114.89 | 33.61 | 52.06 | 74.45 | 35.29 | 54.75 | 74.98 |

**Panel B: Implied Put-Call Disparity Distribution**

| | $SSB_{OF}$ | | | | $SSB_{O}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre | Ban | Ban (ex. 9/29) | Post | Pre | Ban | Ban (ex. 9/29) | Post |
| No. of Days | 40 | 14 | 13 | 40 | 40 | 14 | 13 | 40 |
| Mean | 0.031*** | 0.004 | 0.049 | 0.035*** | 0.084*** | 0.192*** | 0.241*** | 0.078*** |
| [t-stat] | [6.24] | [0.08] | [1.62] | [5.49] | [8.00] | [4.35] | [5.98] | [3.04] |
| Std. Dev. | 0.039 | 0.194 | 0.103 | 0.036 | 0.068 | 0.247 | 0.172 | 0.147 |
| Min | -0.066 | -0.575 | -0.024 | -0.062 | -0.108 | -0.445 | 0.014 | -0.219 |
| p10 | -0.011 | -0.024 | -0.015 | -0.011 | 0.001 | 0.014 | 0.021 | -0.094 |
| Median | 0.029 | 0.027 | 0.027 | 0.042 | 0.090 | 0.207 | 0.219 | 0.056 |
| p90 | 0.057 | 0.068 | 0.068 | 0.083 | 0.169 | 0.408 | 0.408 | 0.280 |
| Max | 0.195 | 0.379 | 0.379 | 0.109 | 0.211 | 0.626 | 0.626 | 0.470 |
| Autocorrelations: | | | | | | | | |
| $\rho_1$ | -0.257* | -0.034 | 0.048 | 0.067 | -0.012 | -0.307 | -0.175 | 0.135 |
| (p-Value) | (0.092) | (0.887) | (0.845) | (0.660) | (0.937) | (0.203) | (0.481) | (0.374) |
| $\rho_2$ | 0.182 | -0.051 | 0.063 | 0.093 | -0.028 | -0.216 | -0.078 | -0.052 |
| (p-Value) | (0.116) | (0.966) | (0.947) | (0.749) | (0.979) | (0.288) | (0.739) | (0.635) |

| | $SSB_{OF'1002}$ | | | | | *S&P500* | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Pre | Ban (before FI) | Ban (ex. 9/29 before FI) | Ban (after FI) | Post | Pre | Ban | Ban (ex. 9/29) | Post |
| No. of Days | 40 | 9 | 8 | 5 | 40 | 40 | 14 | 13 | 40 |
| Mean | 0.036*** | 0.084** | 0.119** | 0.117*** | 0.029** | 0.010 | -0.064 | -0.031 | 0.014 |
| [t-stat] | [5.63] | [2.63] | [3.27] | [7.87] | [2.29] | [0.98] | [-1.62] | [-1.37] | [1.53] |
| Std. Dev. | 0.054 | 0.138 | 0.093 | 0.046 | 0.084 | 0.049 | 0.141 | 0.070 | 0.046 |
| Min | -0.094 | -0.200 | -0.013 | 0.070 | -0.169 | -0.171 | -0.493 | -0.116 | -0.115 |
| p10 | -0.043 | -0.200 | -0.013 | 0.070 | -0.094 | -0.043 | -0.116 | -0.113 | -0.054 |
| Median | 0.053 | 0.105 | 0.123 | 0.123 | 0.060 | 0.016 | -0.041 | -0.038 | 0.019 |
| p90 | 0.094 | 0.253 | 0.253 | 0.184 | 0.127 | 0.055 | 0.036 | 0.036 | 0.048 |
| Max | 0.116 | 0.253 | 0.253 | 0.184 | 0.172 | 0.121 | 0.126 | 0.126 | 0.133 |
| Autocorrelations: | | | | | | | | | |
| $\rho_1$ | -0.330** | -0.256 | 0.136 | -0.533 | -0.036 | 0.241 | 0.100 | 0.312 | 0.287* |
| (p-Value) | (0.030) | (0.367) | (0.646) | (0.115) | (0.811) | (0.114) | (0.679) | (0.209) | (0.059) |
| $\rho_2$ | -0.070* | -0.265 | 0.065 | | -0.088 | 0.305** | -0.039 | -0.065 | 0.155* |
| (p-Value) | (0.086) | (0.405) | (0.875) | | (0.819) | (0.037) | (0.905) | (0.438) | (0.099) |

**Panel C: Implied Disparity Differences Among Periods**

| | Ban (ex. 9/29) - Pre [t-stat] | Ban (after FI) - Pre [t-stat] |
|---|---|---|
| $SSB_{OF}$ | 0.017 | - |
| | [0.598] | |
| $SSB_{O}$ | 0.157*** | - |
| | [3.201] | |
| $SSB_{OF'1002}$ | 0.084** | 0.081** |
| | [2.451] | [3.612] |
| *S&P500* | -0.041* | - |
| | [-1.946] | |

| | Ban (ex. 9/29) - Post [t-stat] | Ban (after FI) - Post [t-stat] |
|---|---|---|
| $SSB_{OF}$ | 0.014 | - |
| | [0.474] | |
| $SSB_{O}$ | 0.162*** | - |
| | [3.062] | |
| $SSB_{OF'1002}$ | 0.090** | 0.087*** |
| | [2.524] | [3.541] |
| *S&P500* | -0.045** | - |
| | [-2.187] | |

| | Post - Pre [t-stat] |
|---|---|
| $SSB_{OF}$ | 0.004 |
| | [0.434] |
| $SSB_{O}$ | -0.006 |
| | [-0.231] |
| $SSB_{OF'1002}$ | -0.006 |
| | [-0.397] |
| *S&P500* | 0.005 |
| | [0.440] |

## 4.5 Conclusion

We investigate how a short-sale ban, the most extreme form of short-sale constraints, impacts the financial markets. Using the short-sale ban imposed by SEC in 2008, we find three main abnormalities in the equity market and the derivatives market. First, the banned stocks are overvalued relative to the four factor model, and returns of banned stocks are more volatile relative to the market return. Second, we document increased trading activity, mostly selling pressure, in the futures market as reflected in settlement prices, open interests, and future premiums. Third, we find that puts associated with banned stocks are in greater demand during the ban relative to calls, resulting in higher implied volatility of puts. In addition to these three findings, there is evidence showing that futures may be a more preferable substitute for short selling, compared to options.

Our study has a policy implication. The use of short-sale ban has been a controversial subject among regulators and researchers. These results show that imposing a short-sale ban during a financial crisis may not lead to market stability as believed. Instead, banning short selling could lead to a more volatile equity market as well as more pressure on the derivatives market.

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