Intermediaries, Illiquidity and Corporate Bond Pricing

by

Zhiyi Qian

A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved April 2012 by the
Graduate Supervisory Committee:

Sunil Wahal, Chair
Sreedhar Bharath
Jeffrey Coles
Rajnish Mehra

ARIZONA STATE UNIVERSITY

May 2012

ABSTRACT

This paper examines dealers' inventory holding periods and the associated price markups on corporate bonds from 2003 to 2010. Changes in these measures explain a large part of the time series variation in aggregate corporate bond prices. In the cross-section, holding periods and markups overshadow extant liquidity measures and have significant explanatory power for individual bond prices. Both measures shed light on the credit spread puzzle: changes in credit spread are positively correlated with changes in holding periods and markups, and a large portion of credit spread changes is explained by them. The economic effects of holding periods and markups are particularly sharp during crisis periods.

ACKNOWLEDGMENTS

Qian thanks Sunil Wahal (Committee Chair), Sreedhar Bharath, Jeffrey Coles, Rajnish Mehra and seminar participants at Arizona State University for helpful comments. Qian also thanks and acknowledges Arizona State University for financial support. All errors are my own.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

INTRODUCTION

Theory predicts that liquidity is important in the pricing of assets (Amihud and Mendelson (1986), and Acharya and Pedersen (2005)). In an early important paper, Demsetz (1968) provides an intuitive framework that relates immediacy to liquidity. He argues that the asynchronous arrival of buyers and sellers generates the demand for and supply of immediacy. By providing immediacy, dealers provide liquidity to investors. In doing so, they face risk, for which they must be compensated. This risk could be through inventory effects (see Garman (1976), Stoll (1978), Amihud and Mendelson (1980), and Ho and Stoll (1981) or/and through information asymmetry (see Wang (1993), Garleanu and Pedersen (2004)). Chacko, Jurek, and Stafford (2008) build on this insight and study how such immediacy is priced when market makers provide liquidity in the presence of order imbalances.

The corporate bond market is an over-the-counter market where search frictions are particularly important (see Duffie, Garleanu, and Pedersen (2005)). It fits the Demsetz paradigm in two ways. First, for the most part, investors (both retail and institutional) cannot trade directly with themselves. Second, dealers provide immediacy through their continuous presence in the market place. These features make the corporate bond market an ideal place to study the linkages among immediacy, liquidity, and prices. While intuition and theory tell us that illiquidity should be particularly important in the pricing of corporate bonds, the existing liquidity empirical literature has had limited success, especially with respect to the so-called credit spread puzzle (Collin-Dufresne, Goldstein, and Martin (2001)): variables that should in theory determine credit spread changes have rather limited explanatory power.

Early work on liquidity in the corporate bond market focuses primarily on bid-ask spreads (Bessembinder, Maxwell and Venkataraman (2006), Chen, Lesmond and Wei (2007), Edwards, Harris and Piwowar (2007), Goldstein, Hotchkiss and Sirri (2007)). The bid-ask spread is an important indicator of liquidity, however, it does not fully capture many important aspects of liquidity such as depth (the dollar value that can be traded at the quoted bid and ask prices). More recently, Bao, Pan and Wang (2010) use the negative of the autocovariance of relative price changes as a proxy for liquidity. They find that illiquidity in corporate bonds is much greater than that captured merely by bid-ask spreads; their asset pricing regressions make considerable headway in the cross-section and time series, but they do not tackle the credit spread puzzle.

We take a slightly different approach than the existing literature. We explicitly recognize the importance of immediacy and its relation with liquidity. Our data allow us to calculate the number of days that dealers hold inventory as well as the price markup they charge in turning that inventory around. We think of the former as measuring the risk borne by dealers and the latter as the commensurate return, matching up with the elemental notions of immediacy embedded in Demsetz (1968). Together, they tell us how fast and at what cost an investor can obtain or dispose of a particular quantity of a given asset. Aside from the elegant link to theory, these two measures are model free, and possess a distinct practical advantage. Specifically, they are easily measurable for a large universe – one merely needs to ensure that trades are signed as dealer/customer buys and sells. In contrast, bid-ask spreads are subject to data and measurements issues: the corporate bond market is not centralized, and does not have mandated centralized reporting, such as the Consolidated Tape or Quote System for stocks, so that quoted spreads (where available) are at best indicative. Similarly, autocovariance based measures require frequent trading. For example, it is not uncommon to impose the requirement that bonds trade on a large fraction of the trading days in a sample. The consequence is that such measures can only be estimated for bonds in the most liquid segment of the market.

Since our data does not identify individual dealers, we treat all dealers as a group and attempt to measure bond-specific liquidity provided by the entire dealer system. We measure dealer inventory holding period as the difference between dealers' purchase date and the corresponding resale dates using a first-in-first-out (FIFO) method. Markup is the difference between dealers' purchase price and the resale price, divided by the midpoint of purchase price and the resale price. Before proceeding to formal asset pricing tests, we start with an assessment of the two measures and examine their connections with various bond characteristics. We show that older bonds with smaller issuance size and longer maturity have higher markups and longer holding periods. More interestingly, the overall explanatory power of these traditional liquidity measures is only 4% for holding periods and 10% for markup. This implies that a large portion of our measures is not explained by conventional indirect liquidity proxies. We construct monthly cross sections of individual bonds holding periods and markups and then use cross-sectional medians in time series tests. Our monthly median illiquidity measures comove strongly with the aggregate market condition variables, particularly expected volatility (as measured by VIX) and funding costs (as measured by the TED spread). Their comovement during the financial crisis is especially noteworthy. In September 2007, when the subprime industry started to collapse, our illiquidity measures almost double from their pre-crisis average. Illiquidity quadruples by October 2008, right after the Lehman bankruptcy and the bailout of AIG. Subsequent to that, illiquidity declines, coinciding with funding injections by the Federal Reserve and better market conditions. Formal regressions of bond illiquidity on the TED spread support the connection between market liquidity and funding liquidity modeled by Brunnermeier and Pedersen (2009). We also find that the liquidity of low credit rating bonds is more sensitive to worse macroeconomic conditions than is the liquidity of high credit rating bonds. This supports the "flight to quality" argument in Brunnermeier and Pedersen (2009).

Illiquidity is also an important factor in explaining the variation of the US aggregate yield spreads. Using the Barclays US corporate bond yield spread as a dependent variable, for the full sample period, a time series regression on holding period and markup alone has an adjusted R^2 of 19%. Adding an index of CDS prices, VIX, and other proxies and determinants of credit risk increases the adjusted R^2 to 46%, suggesting that illiquidity and credit risk are equally important in explaining yield spreads. We also find that the relative importance of illiquidity and credit risk changes dramatically in the crisis period. During the non-crisis period, illiquidity effects are over-shadowed by credit risk: regressions of aggregate US corporate bond yield spreads on illiquidity proxies alone have an adjusted R^2 of only 12%, and combining credit risk increases the adjusted R^2 to around 38%. In the crisis period, the adjusted R^2 for illiquidity alone triples to around 30%, larger than the combined additional explanatory power of all other factors. In addition, US aggregate yield spreads are more sensitive to illiquidity in the crisis period than in the normal periods. The coefficients of both holding period and markup double in the crisis period.

In the cross-section, we estimate monthly Fama-MacBeth regressions of individual bond yield spreads on these measures. Our regressions show that holding periods and markups together significantly explain the cross-section variation of individual bond prices in both economic and statistical terms. For the full sample period, a one standard deviation difference in holding periods (markup) leads to a difference in yield spreads of 11 (128) bps. In the crisis period, a one standard deviation difference in holding period (markup) leads to a difference in yield spreads as much as 32 (271) bps. Adjusted R^2 are also higher during the crisis period, increasing from 40% to 55%. In contrast, other conventional illiquidity proxies such as size, age, maturity are either statistically insignificant or have the wrong sign.

Finally, we assess the usefulness of these measures for the credit spread puzzle. Collin-Dufresne, Goldstein, and Martin (2001) and Huang and Huang (2003) report that credit risk determinants proposed by traditional structural models can only explain about 25% of levels of or changes in credit spreads of corporate bonds. Intriguingly, Collin-Dufresne, Goldstein, and Martin (2001) find that their regression residuals are highly cross-correlated and driven by a common systematic component. Longstaff, Mithal, and Neis (2005) suggest that illiquidity may be an additional determinant of the yield spread variation. Empirical attempts at using illiquidity proxies to explain credit spread changes have had limited success (Chen, Lesmond and Wei (2007), Driessen (2005), and Delianedis and Geske (2001)). While we cannot claim to "solve" the puzzle, our illiquidity measures make substantial progress. For B to AAA rated bonds, adding our measures to regressions of credit spread changes (while including structural determinants) increases average adjusted R^2 from 27% to over 40%.[1] This suggests that that liquidity is an important determinant of credit spread changes, beyond the pure contingent-claims framework (i.e. conventional structural models). Moreover, consistent with Huang (2003) and Acharya, Amihud, and Bharath (2010), we find that illiquidity has much larger effects on bond spread changes during crisis.

[1] For lower rated bonds (between CCC and C), structural models alone explain over 60% of credit spread changes. Adding liquidity has a negligible effect on adjusted R^2.

Chapter 2

LITERATURE REVIEW

We review the literature that studies the relationship between liquidity and asset prices in bond markets. In the literature, there are two types of models are related to this topic: inventory based model and information based model. The key question for inventory based models is how market makers deal with price and inventory uncertainty. Beginning with the pioneering paper by Garman (1976), researchers mainly studied how asset prices change given the nature of the order flow and the market-clearing protocol. Since not all investors are present in the market all of the time, market makers provide liquidity through their continuous presence in the market and thus enable continuous trading. Naturally, they face fundamental price change risk in the duration. Garman (1976) introduces a model with a monopolist market maker whose quoted prices affect the intensity of arrival of buyers and sellers. In his analysis, if quoted prices are constant, the market maker will surely be ruined. While inventory determines the market maker's viability, inventory itself plays no role in the market maker's decision problem in Garman's model, since he assumes that market makers are only allowed to set prices at the beginning of trading. This restriction severely limits the applicability of his model to actual market settings in which prices evolve continually over time. A more realistic approach to resolve the underlying problem is to consider how the market marker's prices change as the inventory position varies over time. Amihud and Mendelson (1980) take this approach. Their model explicitly incorporates inventory into the market maker's pricing problem. Using essentially the same framework as Garman (1976), they show that the market maker's quoted bid and ask prices depend on the level of his inventory position. Stoll (1978) and Ho and Stoll (1981) investigate the market maker's optimization problem. The Ho and Stoll (1981) model essentially extends the intuition of the Stoll (1978) analysis to a multi-period framework. As in Garman (1976), Ho and Stoll assume order flow is a stochastic process and depends on the market maker's pricing strategy. However, their model also assumes a risk-averse market maker who manages inventory to reduce his risk exposure. This is a significant difference from the risk neutral intertemporal models of Garman (1976) and Amihud and Mendelson (1980). Overall, the common features to all the inventory based models considered here is that: market makers essentially act as the sole provider of liquidity in the market. Inventory introduces risks for them. This risk is reflected in their pricing strategy, i.e. the quoted bid and asks prices. The bid-ask spread plays a role related to the inventory, but the extent of this role differs in the various assumptions and frameworks.

Information based models use the insights from the theory of adverse selection and focus on how prices are connected to information. Bagehot (1971) is the origin of the information models. He allows for information costs and argues it can affect bid-ask spread. In his paper, market makers know that some investors are better informed. He argues that these informed investors buy when they know that the current asset price is underpriced. They sell when they know it is overpriced. Or, they can simply choose to not trade. Since market makers must always quote prices to buy and sell, it follows that, on average, they always lose if they are trading with an informed investor. Consequently, market makers must have a pricing strategy to remain solvent. Essentially, the bid-ask spread reflects a balancing of losses to the informed investors with gains from the uninformed investors. Other early information based models include Copeland and Galai (1983) and Glosten and Milgrom (1985). They formalize this concept of information costs. Recent papers that study the effect of information asymmetry on the asset prices include Wang (1993) and Garleanu and Pedersen (2004). Wang (1993) finds that a larger fraction of less-informed investors is associated with higher required asset returns. His reasoning is that less-informed investors drive up total asset return volatility, which reduces consumption smoothing and risk sharing, therefore, raising the average risk premium. Garleanu and Pedersen (2004) model a finite number of agents trade repeatedly. Some agent might receive private information about future payoffs. They show that bid-ask spreads due to such private information are a direct trading cost if some agents are more likely to be informed than others. Trading with an informed counterparty will end up with a loss. The marginal investor does not break even on average. Therefore, the required asset return must be higher because of such expected net trading losses.

In the fixed income literature, corporate bond returns have been widely studied. Initially, conventional structural models of default provide an intuitive framework for studying corporate bond pricing factors. These models build on the original insights of Black and Scholes (1973). The key is that debt can be valued using contingent-claims analysis. In particular, from a contingent-claims standpoint, corporate bond prices are determined by a risk of default and the recovery rate in the event of default. However, empirically, Collin-Dufresne, Goldstein, and Martin (2001) and Huang and Huang (2003)) show that these credit risk determinants proposed by structural form models can only explain a limited portion of the levels of and changes in the yield spread of corporate bonds over Treasury bonds. Liquidity based studies look beyond the pure contingent-claims viewpoint and argue that liquidity may be a possible explanation for the failure of these structural models and affect corporate bond prices. Amihud and Mendelson (1986) is one of the pioneering theories on how liquidity affects required asset returns. The intuition of their argument is straightforward. Liquidity affects asset prices because investors require a compensation for bearing transaction costs, which need to be paid whenever the asset is traded. They suggest that the discounted value of this transaction cost is the proxy for the magnitude of illiquidity. There are numerous empirical studies that test these theories. For instance, Chen, Lesmond and Wei (2007) find the effect of liquidity on corporate bond prices. Their study examines about 4000 U.S. corporate bonds and finds that more illiquid bonds earn higher yield spreads. Bao, Pan, and Wang (2010) use TRACE data to study liquidity effects focusing in particular on a measure similar to the Roll measure. They find that the illiquidity in corporate bonds is much larger than what can be explained by bid-ask spreads, which is frequently used as a liquidity proxy in corporate bond market. Bongaerts, De Jong and Driessen (2012) use an asset pricing approach and find strong effects of liquidity level and liquidity risk on corporate bond prices. Dick-Nielsen, Feldhutter and Lando (2012) find that liquidity impacts are much larger during the subprime crisis for corporate bonds. Feldhutter (2012) uses price differences between small and large trades to identify liquidity crisis in the corporate bond market. Another related question is the relative importance of liquidity and credit risk in determining corporate bond pricing. The current evidence is still mixed. On the one hand, Longstaff, Mithal, and Neis (2005) use credit default swap data to provide direct measures of the size of the default and non-default components in yield spread. They find that the majority of the corporate spread is due to default risk. On the other hand, Huang and Huang (2003) report that default risk explains for only a small portion of the yield spread.

Chapter 3

DATA AND SUMMARY STATISTICS

Data

We use corporate bond transactions reported on FINRA’s Trace database. It reports key trading information, such as security identifiers, transaction dates, transaction times, transaction prices, trade direction (dealer buy, dealer sell or interdealer trade) and trade quantities. There are two different versions of Trace data. In the version of these data used by most studies (henceforth publicly disseminated Trace), trade quantities are truncated and trade direction is only available from the beginning of November 2008. Specifically, publicly disseminated Trace truncates trade quantities at $5 million and $1million in par value for investment grade and high-yield bonds, respectively. The version of Trace that we employ, however, contains precise trade quantities and trade direction for the entire period. Unfortunately, we are not able to access this version of Trace for the period after December 31 2008. Hence, we use the publicly disseminated Trace to extend our sample period to June 30 2010. We apply the data filters in Dick-Nielsen (2009), deleting duplicate trades, reversal trades, canceled trades and trades subsequently corrected by dealers. Specifically, our first filter is duplicate trades, in every business day, we delete any duplications using an intra-day unique message sequence number. Second, in TRACE, a variable called ASOF_CD indicates if the transaction being reported is an As/Of trade or Reversal from a prior business day. We delete all reports marked as reversal trades and their corresponding original reports. In our sample, there are 1,034,634 trades marked as reversal trades. Finally, there are same-day trade cancellation and trade correction in TRACE. If TRC_ST indicates it is a cancelation (1,194,369 cases in our sample), both this report and the original cancelled report are deleted. If it is a correction (874,874 cases in our sample), we delete only the original incorrect report. Obviously misreported trades (e.g. trade with negative bond prices) are also excluded even if such errors are not identified by Trace. We further exclude trades if trade prices or bond yields are missing (6,751,430 cases in our sample). Our final sample consists 68,115,697 trades.

In addition to the Trace data, we use CRSP and COMPUSTAT to obtain stock returns and leverage ratios for bond issuers. Issue and issuer specific variables such as age, maturity, issue amount, and credit ratings are from the Fixed Income Securities Database (FISD). We use Datastream to collect information on CDS prices and Barclays US Corporate Bond Indices. Treasury bond yields for a range of maturities are from the Federal Reserve website, http://www.federalreserve.gov. We obtain information on the VIX from CBOE. The 3-month LIBOR information is from the following website http://www.wsjprimerate.us/libor/index.html.

The Illiquidity of Corporate Bonds

Table 1. The Illiquidity of Corporate Bonds

Panel A: Number of Bonds within Trading Frequency									
	2002	2003	2004	2005	2006	2007	2008	2009	2010
No trade	53%	38%	35%	31%	39%	43%	47%	52%	61%
1-5 days	12%	15%	14%	16%	13%	13%	15%	8%	8%
5-50 days	24%	26%	30%	32%	28%	27%	24%	21%	19%
50-150 days	12%	14%	14%	14%	13%	11%	9%	12%	12%
150-200 days	-	3%	3%	3%	3%	2%	2%	3%	-
>200 days	-	4%	4%	4%	3%	3%	3%	4%	-
Total Issues	32,601	32,311	32,708	33,571	35,706	40,022	41,243	37,044	38,472

Panel B: Market Value of Bonds ((in Billions of $) within Trading Frequency									
	2002	2003	2004	2005	2006	2007	2008	2009	2010
No trade	39%	27%	25%	23%	29%	31%	38%	38%	59%
1-5 days	7%	9%	9%	9%	10%	11%	10%	5%	5%
5-50 days	24%	22%	27%	29%	26%	27%	23%	19%	18%
50-150 days	31%	19%	19%	20%	17%	16%	13%	15%	17%
150-200 days	-	7%	6%	6%	6%	5%	5%	7%	-
>200 days	-	16%	15%	13%	12%	9%	11%	16%	-
Total Market Value	4,471	5,005	5,320	5,578	6,364	7,032	6,556	6,463	6,511

Table 1 shows the distribution of trading for all US corporate bonds in FISD from July 2002 to June 2010. We define the frequency of trading of an issue as the number of distinct trading days in each year for that issue. In Panel A, we report the number of issues corresponding to a particular trading frequency category, as a fraction of the total number of corporate bonds. For example, in 2008, number of issues which traded for more than 200 days accounts for 3% of the FISD corporate bond population. On average, the percentage of most liquid bonds (i.e. those that trade more than 200 days in a year), constitute about 3-4%

of the bond universe. A large proportion of the bonds (about 45%) do not even trade once a year.

Panel B shows the total market value of issues corresponding to a particular trading frequency category, as a fraction of the total market value of the FISD corporate bond population. We define market value as the bond's year-end trading price times bonds outstanding. If a price is not available, we use the bond's par value as an approximation. The market value of issues which trade over 200 days in a year ranges from 9% to 16% of total corporate bond market value. This is not surprising because bonds with larger size normally trade more often. Overall, regardless of whether one uses the number of bonds or their market value as a yard-stick, it is apparent that the vast majority of the corporate bond population is highly illiquid.

Corporate bonds are be much more illiquid during the crisis period. For example, Panel A shows that from 2003 to 2006, roughly 33% of total bond population belongs to "No trade in year" group. During the post 2007 period of financial turmoil, this number jumps to about 50%. We observe similar pattern in market value from Panel B. Such variations make it particularly interesting to study how corporate bond prices respond to liquidity as economic condition changes.

Sample Summary Statistics

TRACE became available on July 1 2002, but we drop the first six months of the data due to data quality concerns. Thus, our sample period is from January 2003 to June 2010. Further, if a bond is held by dealers for a very long holding period, dealers could be thought of as long term buy-and-hold investors or perhaps engaged in proprietary trading, rather than as liquidity providers. Because we primarily focus on the trades when dealers provide immediacy/liquidity, we also drop such trades.

Table 2. Summary Statistics

	Panel A: Most Liquid Sample			Panel B: Full Sample		
	Mean	Median	SD	Mean	Median	SD
Par Value (in Millions of $)	958	792	646	216	25	312
Rating (Aaa=1,…, C=21)	5.68	5.54	1.99	6.74	6.29	3.68
Maturity (in Years)	6.59	4.42	1.89	7.32	4.25	6.00
Age (in Years)	3.07	2.61	2.86	5.29	3.51	4.03
Number of Trades Per Month	224	140	238	32	8	93
Monthly Volatility (%)	2.72	2.13	2.78	4.52	3.13	3.69
Number of bonds	792			16,928		

Given the difficulties with data availability prior to the introduction of Trace, most studies use the Fixed Income (or Warga) Database, Bloomberg Corporate Bonds Database or other proprietary databases. Such datasets typically focus on the most liquid bonds in the marketplace. Even studies that use Trace data are often forced to restrict their analysis to bonds that trade frequently. For example, Bao et al. (2010) require that a bond must trade on at least 75% of days in a calendar year to be included in their sample. In contrast, the above-described restrictions imposed in our sampling procedure are minimal. To understand the sampling differences (and their potential consequences for the results), in table 2 we provide some descriptive statistics on our sample, as well as a "most liquid bond" sample. The latter simply requires that a bond exist in Trace for at least one full year, and trade in 200 days of a year.

On average, there are 16,928 bonds every year in our sample, representing about 85% of traded corporate bonds. In the most liquid bond sample, on average, there are only 792 bonds every year, accounting for 4% of traded corporate bonds. The bonds in our sample are much smaller, with a median issuance size of $25 million. In contrast, the median issuance size of a typical bond in the most liquid sample is $792 million. Bonds in our sample are also about 2 years older. The average (median) age of bonds in our sample is 5.3 (3.5) years. For the most liquid bond sample, the average (median) age of bonds is 3.1 (2.6) years. This is expected since younger bonds are typically more liquid. We do not see significant difference in maturity and bond rating between these two samples. Perhaps most obviously, and unsurprisingly, the median number of trades per month of bonds in our sample is 8, compared to 140 for the most liquid sample. Finally table 2 shows that the returns of bonds in our sample are more volatile, with a median monthly volatility of 3.13%, compared to 2.13% for the most liquid bond sample. Broadly speaking, our sample is representative of the US corporate bond market, in terms of the number of issues, bond characteristics and trading characteristics. For the most liquid sample, there is a bias towards more liquid, larger, younger, and less volatile bonds.

Chapter 4

ILLIQUIDITY MEASURES AND PROPERTIES

Illiquidity Measures

It is difficult to define a single measure to capture all aspects of liquidity. In this subsection, we first describe a number of commonly used liquidity measures.

For bond i, Volume_i is one of the simplest measures of liquidity, which is defined as the total trading volumes in certain period for this bond. $\text{Volume}_{i,t}$ is the trading volume for the t*th* trade in this period. There are n trades in this period.

$$\text{Volume}_i = \sum_{t=1}^{n} \text{Volume}_{i,t}$$

The Amihud (2002) liquidity measure follows Kyle (1984)'s concept of liquidity, the response of price to order flow. For bond i, Amihud_i is defined as the average ratio of the absolute return to the trading volume in certain period. There are n+1 trades in this period, $\text{Return}_{i,t}$ and $\text{Volume}_{i,t}$ are the return and trading volume for bond i and t*th* trade respectively.

$$\text{Amihud}_i = \frac{1}{n} \sum_{t=2}^{n+1} \frac{|\text{Return}_{i,t}|}{\text{Volume}_{i,t}}$$

Waiting time between subsequent trades is another commonly used liquidity proxy. Intuitively, longer waiting time implies less liquid. For bond i,

Waitingtime_i is defined as the average waiting time in certain period. There are n+1 trades in this period, $\text{tradetime}_{i,t}$ is the trading time for bond i and t*th* trade.

$$\text{Waitingtime}_i = \frac{1}{n}\sum_{t=2}^{n+1}(\text{Tradetime}_{i,t} - \text{Tradetime}_{i,t-1})$$

Flow ratio essentially combines quantity and time aspects of liquidity. Larger flow ratio implies the asset is more liquid. For bond i, Flowratio_i is defined as the average trading volume divided by the waiting time between two consequent trades in certain period. There are n+1 trades in this period, $\text{tradetime}_{i,t}$ and $\text{Volume}_{i,t}$ are the trading time and trading volume for bond i and t*th* trade.

$$\text{Flowratio}_i = \frac{1}{n}\sum_{t=2}^{n+1}\frac{\text{Volume}_{i,t}}{(\text{Tradetime}_{i,t} - \text{Tradetime}_{i,t-1})}$$

Bao, Pan and Wang (2010) use the negative of the autocovariance of relative price changes as a proxy for liquidity, λ. Their measure is based on Roll (1984). Under certain assumptions, transitory price movements reflect bid-ask bounces or the round trip costs, therefore, essentially, their measure can be interpreted as another version of effective bid-ask spread. More precisely, their measure is defined as the following formula.

$$\lambda_i = -\text{COV}(\Delta\text{Price}_{i,t}, \Delta\text{Price}_{i,t+1})$$

In our paper, we propose two simple and robust measures of liquidity: dealers inventory holding period and the associated price markup. We measure dealer inventory holding period as the difference between dealers' purchase date and the corresponding resale date using a first-in-first-out (FIFO) method. Markup is the difference between dealers' purchase price and the resale price, divided by the midpoint of purchase price and the resale price. More formally, for each day, we calculate the holding period and markup of bond i by:

$$HP_i = ResaleDate_i - PurchaseDate_i + 1$$

$$MU_i = \frac{ResalePrice_i - PurchasePrice_i}{\left(\frac{ResalePrice_i + PurchasePrice_i}{2}\right)}$$

$PurchaseDate_i$ represents dealers' purchase date of bond i, $ResaleDate_i$ is the corresponding resale date. Similarly, $PurchasePrice_i$ and $ResalePrice_i$ refer to dealers' purchase price and matched resale price of bond i respectively.

An example helps illustrate the intuition behind the measures. On Feb. 04, 2003, dealers bought 4,000,000 shares of Bond "A.GB" from investors at a price of $ 96.106, and then sold 3,543,000 shares on the same day at a price of $ 96.142, and 457,000 shares on the next day at a price of $ 97.111. For the first sale, on Feb. 04, 2003, the daily holding period is 1 day and the corresponding daily markup is 0.04%. For the second sale, on Feb. 05, 2003, the daily holding period is 2 days and the corresponding daily markup is 1.04%. We define monthly liquidity measures for any bond i as the value weighted-average of daily holding periods and markups within the month. For instance, if there is no other trades in the month, the monthly markup and holding period for Bond "A.GB" in Feb. 2003 should be 0.15% and 1.11 days.

Table 3. Measures of Illiquidity

Panel A: Dealers' Holding Period (in days)

	2003	2004	2005	2006	2007	2008	2009	2010	Full
Mean	9.49	11.89	12.01	11.78	12.27	13.78	13.69	10.79	11.79
Median	2.27	1.83	2.16	2.35	2.76	2.64	2.88	2.04	2.49
SD	18.93	21.35	21.50	21.08	21.51	23.14	24.08	7.47	18.67

Panel B: Dealer Markup(%)

	2003	2004	2005	2006	2007	2008	2009	2010	Full
Mean	1.51	1.16	1.09	1.24	1.17	1.56	2.47	1.92	1.50
Median	0.91	0.74	0.64	0.75	0.80	1.19	1.41	0.75	0.91
SD	5.91	4.86	3.23	2.69	2.76	5.82	7.29	3.87	4.76

Panel C: Illiquidity Measures and Bond Characteristics

	Holding Period		Markup	
	Liquid Sample	Full sample	Liquid Sample	Full sample
Constant	5.43	7.13	1.52	1.47
	2.74	10.41	6.86	8.25
Size	-0.49	-0.82	-0.23	-0.29
	-2.43	-5.24	-6.87	-17.05
Rating	0.08	0.31	-0.01	0.06
	0.37	0.42	-0.81	3.52
Maturity	0.79	0.32	0.04	0.04
	4.78	6.16	5.81	4.28
Age	0.51	0.69	0.03	0.01
	2.71	19.26	3.33	3.21
Number of Trades	-0.011	-0.032	-0.002	0.001
	-2.44	-8.13	-2.98	1.08
Adj. R^2	4.14	4.08	10.07	10.22

Panel D: Correlation

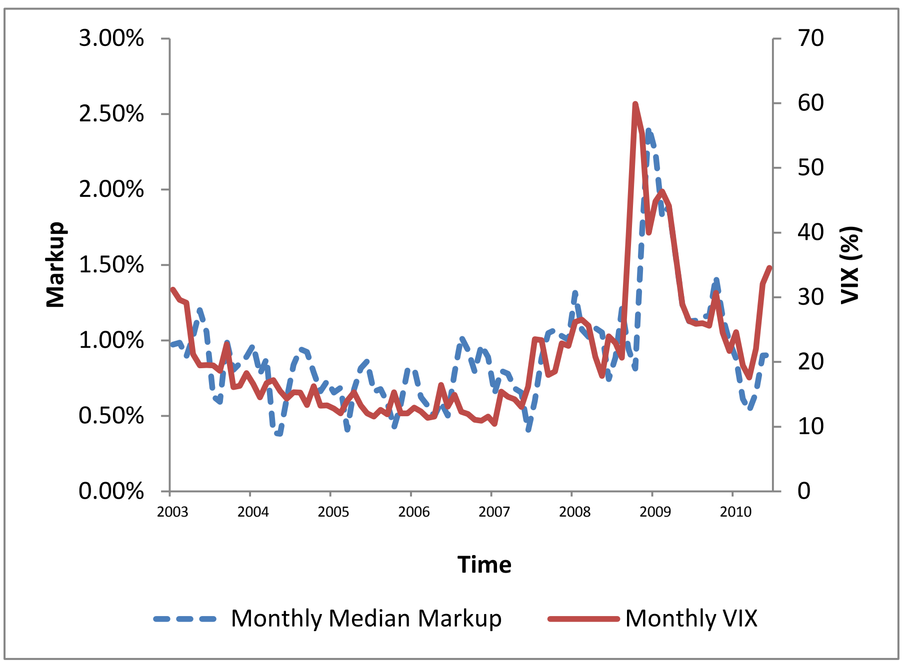
	HP	MU	Volume	Amihud	Wating Time	Flow Ratio	λ	ID Trades	ID Volume
HP	1.000	0.344	-0.065	0.463	-0.360	-0.151	0.582	0.151	-0.225
MU		1.000	0.042	0.727	-0.463	0.080	0.703	0.457	-0.165
Volume			1.000	0.083	0.607	0.227	-0.004	0.074	0.701
Amihud				1.000	-0.471	0.115	0.936	0.663	-0.167
Wating Time					1.000	-0.233	-0.561	-0.503	0.799
Flow Ratio						1.000	-0.004	0.739	-0.061
λ							1.000	0.736	-0.235
ID Trades								1.000	-0.189
ID Volume									1.000

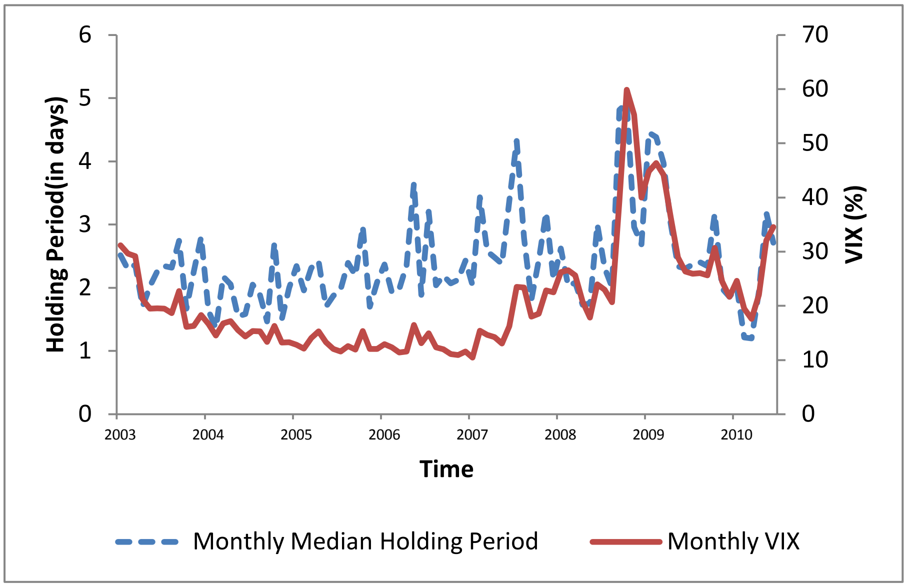
Table 3 summarizes our illiquidity measures. In each year, we report mean, median, and standard deviation as the time-series averages of the cross-sectional means, medians and standard deviations. Focusing first on Panel A, which reports descriptive statistics of holding period, the median (mean) dealer holding period is between 1.83 (9.49) days to 2.88 (13.78) days from 2003 through 2010. Interestingly, the median holding period during the crisis period (2007-2009) is much larger than it is in the non-crisis period, jumping from 2.1 days to 2.8 days. Panel B reports descriptive statistics on markup. The median (mean) markup is between 0.64% (1.09%) and 1.41% (2.47%) for the entire sample period. As a point of comparison, Green, Hollifield, and Schurhoff (2006) find that median markups are between 1.3% and 2% in municipal bond market between 2000 and 2003. One potential reason that markup is higher in municipal bond market is that municipal bonds are even more illiquid. For example, they report that, from March 1998 to May 1999, 71% of the outstanding issues did not trade at all. The median markup also jumps from 0.7% in the non-crisis period to about 1.2% in the crisis period. Standard deviations are much larger in crisis periods as well, indicating that the effects of liquidity are very different during the crisis period.

Illiquidity, Bond Characteristics, and Market Conditions

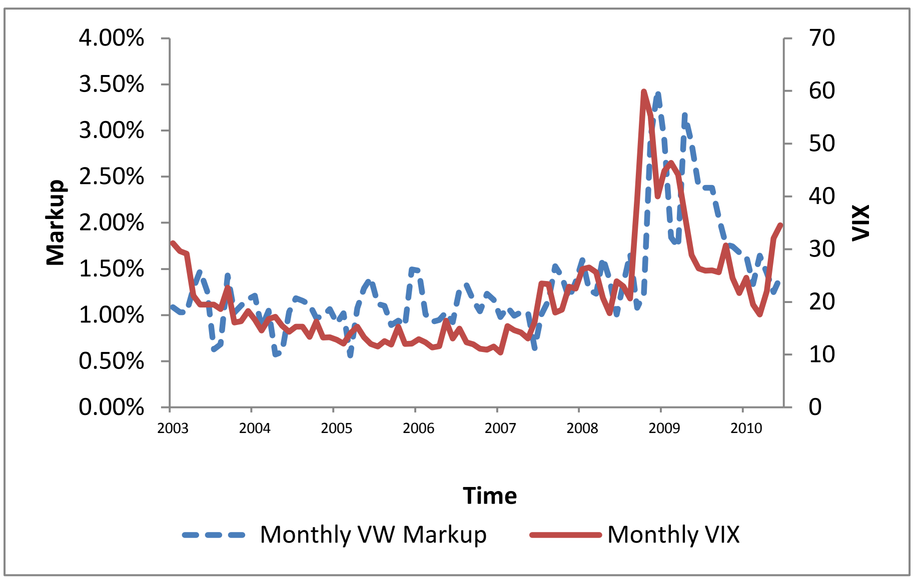
We start with an assessment of the two measures and examine their connections with key bond characteristics. Age, maturity, size, credit rating, and number of trades are often linked to bond liquidity (for example, Houweling, Mentink, and Vorst (2005)). Table 3 Panel C reports monthly Fama-MacBeth cross-sectional regressions with holding period and markup as the dependent variables on the most liquid sample, and full sample. In both samples, older bonds with smaller issuance size and longer maturity have higher markups and longer holding periods. The relationship between credit rating and our measures is almost insignificant for all regressions, implying that our illiquidity measures are not correlated with individual bond credit risks. More interestingly, the overall explanatory power of these traditional liquidity measures is rather low, only 4% for holding period and 10% for markup. This implies that a large portion of our measures is not explained by conventional liquidity proxies. Table 3 Panel D reports the correlations of our measures, other commonly used liquidity measures and inter dealer trading information. We find that our measures are positively correlated with Amihud measure, the λ measure and the number of inter-dealer trades (ID trades) and negatively correlated with inter-dealer trading volume (ID Volume). More inter-dealer trades are associated with more transaction costs, therefore markup is larger. ID trades and ID Volume are negatively correlated. There are several possibilities, for instance, higher ID trades might imply that the buying dealer cannot lay off inventory on his own, so he has to push it to other dealers because of illiquidity.

We also examine the time series variation in these liquidity measures. We are particularly interested in this because systematic component of bond illiquidity emerges when many bonds become illiquid at the same time. If bond-level illiquidity is driven by a systematic component, rather than purely idiosyncratic noise, this should be reflected in the time series.





6
5
4
3
2
1
0
70
60
50
40
30
20
10
0
Holding Period(in days)
VIX (%)
2003
2004
2005
2006
2007
2008
2009
2010
Time
Monthly Median Holding Period
Monthly VIX



4.00%
3.50%
3.00%
2.50%
2.00%
1.50%
1.00%
0.50%
0.00%
70
60
50
40
30
20
10
0
Markup
VIX
2003
2004
2005
2006
2007
2008
2009
2010
Time
Monthly VW Markup
Monthly VIX

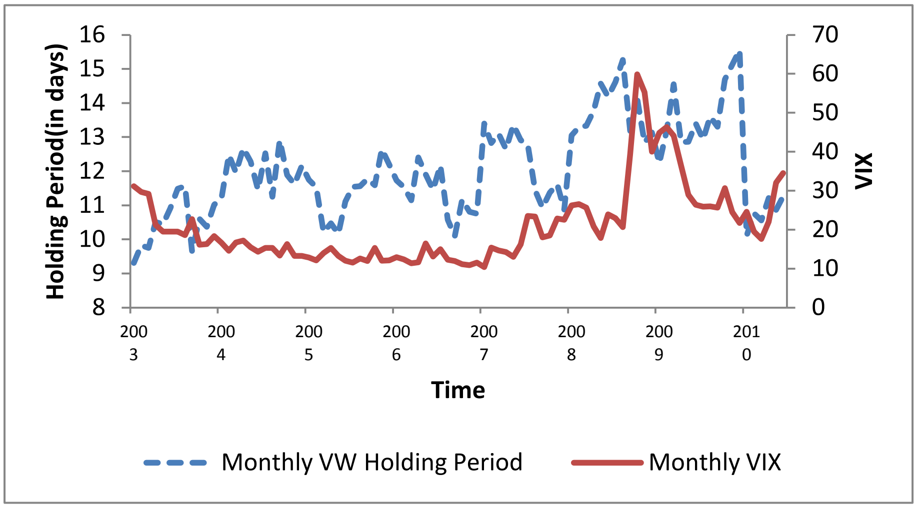


Figure 1: Monthly Time-Series of Illiquidity Measures

We first construct monthly cross sections of individual bonds holding periods and markups and then calculate cross-sectional medians and value weighted means. Figure 1 shows that in the time series our illiquidity measures comove strongly with the aggregate market condition variables, particularly expected volatility (as measured by VIX). Their comovement during the 2008 financial crisis is especially noteworthy. Focusing first on markup, we see that in September 2007, when the subprime industry started collapse, markups almost doubled from their pre-crisis average, from around 0.64% to 1.05%. In October 2008, right after the Lehman bankruptcy and the bailout of AIG, markups quadrupled and reached 2.42%. We find similar pattern for holding period in the same period. Subsequent to that, both measures decline, coinciding with funding injections by the Federal Reserve and better market conditions.

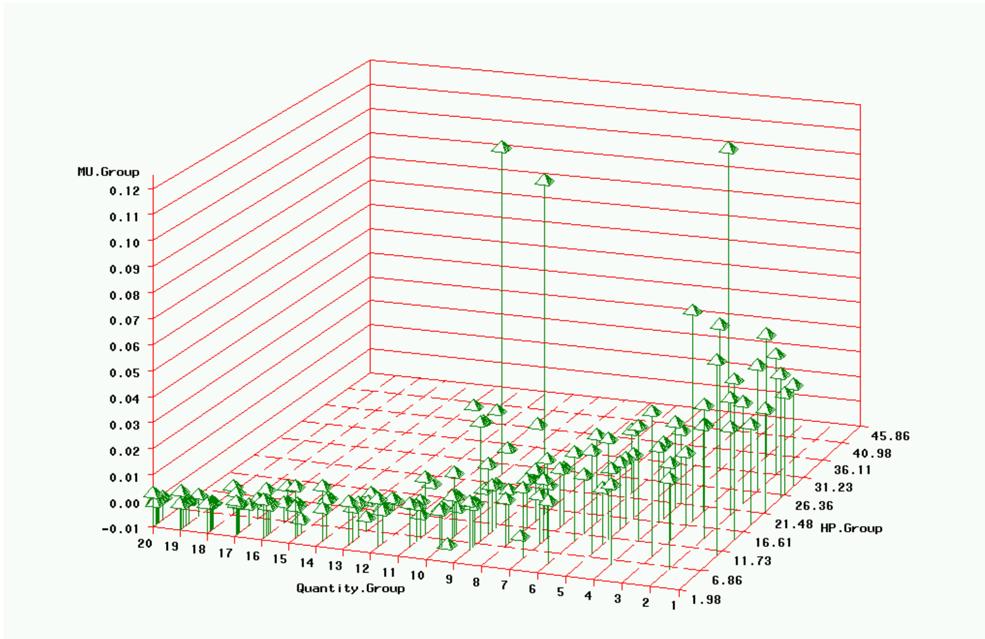


Figure 2: Trading Volume, Markup and Holding Period

Trading quantity, price and time are the three very basic elements of all trading. They have captured the interest and attention of researchers. In our study, markup and holding period essentially measure the price and time aspects of a trade. Quantity can be measured by trading volume. Figure 2 reports their relationship . In every year, we divide all trades into 20 groups based on dealer resale trading volume. Then, we calculate the value weighted average markup and holding period for each group. Overall, we can see that larger trading volume is associated with smaller markup. Negotiation power of institutional investors for large trades might contribute to such negative relation between trade size and markup. Also, we can see that longer inventory holding period is associated with larger markup. This is consistent with the view that dealers require higher return for taking more risks. There are 2 outliers with high markup. One potential explanation is that some factors that directly determine markup of these bonds play a role here. For instance, these bonds might share some particular bond characteristics which are different with bonds of other groups.

Table 4. Illiquidity, Market Conditional Variables and Flight to Quality

Panel A: Putting VIX into regression

	∆ Holding Period$_t$				∆ Markup$_t$			
	High Quality	Mid Quality	Low Quality	Full	High Quality	Mid Quality	Low Quality	Full
Constant	4.81	5.58	4.61	4.97	0.20	0.39	0.79	0.31
	15.92	18.56	9.44	25.53	2.63	3.63	6.13	5.59
∆ VIX$_t$	0.05	0.06	0.11	0.10	0.02	0.03	0.04	0.03
	2.13	2.51	5.18	3.65	8.44	4.23	3.03	4.47
∆ CDS index$_t$	0.01	0.04	0.04	0.02	0.03	0.01	0.03	0.02
	0.82	1.01	0.05	0.72	1.18	1.84	0.61	0.67
∆ Term Spread$_t$	-0.38	-0.50	0.20	-0.64	-0.13	-0.05	-0.30	-0.10
	-2.27	-3.05	0.73	-6.64	-3.18	-0.78	-4.17	-3.36
SP500 Return$_t$	-8.54	-7.08	-6.07	-3.74	-2.15	-1.61	-5.07	-2.96
	-2.24	-1.87	-0.99	-1.53	-2.21	-1.19	-3.11	-4.20
Adj. R^2	28.50	32.09	29.18	29.46	58.30	46.69	40.59	45.64

Panel B: Putting TED spread into regression

	∆ Holding Period$_t$				∆ Markup$_t$			
	High Quality	Mid Quality	Low Quality	Full	High Quality	Mid Quality	Low Quality	Full
Constant	4.23	5.03	4.26	4.70	0.53	0.63	0.94	0.58
	19.85	23.94	13.44	36.29	8.96	8.27	11.07	15.09
∆ TED spread$_t$	0.05	0.15	1.01	0.66	0.26	0.31	0.38	0.35
	3.84	4.30	7.18	6.72	6.26	3.29	3.53	8.83
∆ CDS index$_t$	0.04	0.04	0.01	0.02	0.03	0.01	-0.03	-0.01
	1.51	1.46	0.81	0.88	1.41	0.39	-1.22	-1.24
∆ Term Spread$_t$	-0.64	-0.73	0.19	-0.68	0.06	0.09	-0.19	0.06
	-4.49	-5.21	0.91	-7.86	1.40	1.73	-3.25	2.34
SP500 Return$_t$	-3.32	-1.98	-0.51	-1.05	-0.08	-0.04	-0.44	-0.22
	-0.95	-0.57	-0.87	-1.30	-1.08	-1.03	-3.17	-1.93
Adj. R^2	21.38	26.41	27.60	25.19	45.80	40.14	43.81	41.65

Table 4 panel A reports the connection between these measures and broader market conditions more formally. We regress monthly changes in holding period and markup on contemporaneous changes in the VIX, a CDS index, and the term spread and the S&P500 index return. We define the CDS index as the equally weight average of five-year corporate CDS spreads covered in Datastream. We compute the term spread as the difference between the rates of the 10 year Treasury bond and the 90-day T-bill. For the full sample, VIX has a slope coefficient of 0.10 (0.03) with a t-stat of 3.65(4.47) for holding period (markup). This connection is not driven just by bond quality: the positive relation remains even if we divide the bonds into 3 groups based on their credit ratings. Our results suggest that illiquidity in the corporate bond market and shocks to stock market risk and/or risk appetite are tightly connected. We do not see a significant positive relation between changes in our illiquidity measures and changes in the CDS index, echoing earlier results that our measures do not contain much credit information.

In panel B, regressions of bond illiquidity on TED spread provide the direct evidence of the connection between market liquidity and funding liquidity in the corporate bond market. Brunnermeier and Pedersen (2009) predict that the ability of liquidity-suppliers to provide liquidity depends on their financing constraints. The slope of the TED spread coefficient is indeed positive and significant in all specifications after controlling various other market condition variables. This suggests that funding costs, as proxied by the TED spread, explain time variation in the liquidity that dealers provide. Another important testable prediction of Brunnermeier and Pedersen (2009) is that when funding becomes scarce, liquidity provision is especially reduced for more risky assets. They use the term “flight to quality” to refer to such phenomena. We test this prediction by examining the relation between funding constraints and the liquidity of bonds with different credit ratings. We find that the slope coefficients of TED spread are positive and statistically significant, and, more importantly, monotonically increasing from high quality bonds to low quality bonds. For holding period, the F-value for a joint test of significance confirms that coefficients differ across three groups (F-value 3.83). For markup, regression coefficients between low quality bonds and high quality bonds are statistically different (F-value is 2.47). Overall, our results here suggest that the liquidity of low credit rating bonds is more sensitive to borrowing costs than is the liquidity of high credit rating bonds.

Overall, our analysis shows the existence of substantial commonality in the time series variation of corporate bond illiquidity. This variation is correlated with overall market conditions, particularly VIX and TED spread. Further, the significance of such correlation changes systematically cross bonds with different credit ratings. These findings provide direct and strong evidence that supports links between liquidity supplier behavior, capital limitations, and liquidity modeled by Brunnermeier and Pedersen (2009).

Chapter 5

ASSET PRICING IMPLICATIONS OF ILLIQUIDITY

Aggregate Corporate Bond Prices and Illiquidity

Table 5. Time Series Regression of Changes in Aggregate Bond Yield on Changes in Illiquidity Measures

	Full Sample Period				Non-Crisis Sample Period				Crisis Sample Period			
Constant	0.92	0.04	0.98	0.12	0.79	0.12	0.93	0.11	0.43	0.04	0.41	0.08
	6.23	2.98	7.87	3.96	6.03	2.05	7.46	2.16	5.62	1.83	6.06	2.53
Δ Holding Period	0.02	0.02			0.01	0.01			0.04	0.03		
	2.49	1.97			2.27	1.11			2.62	2.79		
Δ Markup	0.35	0.37			0.23	0.21			0.61	0.43		
	5.72	6.62			4.85	4.49			7.03	6.80		
Δ Composite illiquidity			0.04	0.03			0.03	0.02			0.06	0.05
			4.14	2.91			4.41	2.43			4.30	3.71
Δ λ		0.73		0.71		0.69		0.59		0.77		1.20
		10.30		8.09		5.29		4.92		4.11		4.23
Δ CDS Index		0.28		0.28		0.24		0.19		0.29		0.41
		4.89		3.93		4.40		3.64		4.04		4.11
Δ Slope		-0.38		-0.25		-0.25		-0.23		-0.22		-0.29
		-4.08		-2.52		-2.44		-2.17		-9.56		-2.05
Δ VIX		0.00		0.01		0.00		0.00		0.00		0.00
		-0.29		0.30		1.66		1.49		-0.01		0.79
SP500 Return		-0.02		-0.02		-0.01		-0.01		-0.03		-0.02
		-7.13		-5.19		-2.44		-2.17		-2.94		-3.33
ΔTreasury rate		-0.15		-0.10		-0.13		-0.08		-0.13		-0.11
		-2.89		-3.09		-3.10		-2.13		-2.15		-2.08
ΔConvexity		0.01		0.00		0.12		0.15		0.09		0.10
		0.66		0.47		0.17		0.06		0.14		0.12
Adj. R^2	18.96	46.82	18.33	44.86	11.61	38.24	5.15	33.13	29.30	55.85	24.52	55.83

Now we examine whether our liquidity measures are relevant for bond pricing in the time series and cross-section. Table 5 reports time series regressions with monthly changes in aggregate US corporate bond yield spreads as the dependent variable. Yield spreads are defined as the difference between the yield of Barclay Intermediate U.S. Corporate Bond index (formerly known as the Lehman Index) and the yield of the 5-year treasury constant maturity series. We regress monthly yield spread changes on monthly changes in the illiquidity measures, market condition variables and other control variables. We also divide the sample into non-crisis periods and crisis periods to examine if illiquidity has larger effects on bond spread changes during the crisis period. We control for the illiquidity measure used in Bao, Pan and Wang (2010), the negative autocovariance of price changes (λ). We follow Collin-Dufresne, Goldstein, and Martin (2001) in using slope and convexity as additional explanatory variables, where the slope of the yield curve is the difference between yields of 10-year and 2-year treasury constant maturity series, and convexity is the squared level of the yield of 10-year treasury constant maturity series. Finally, to speed up a trade, sellers can always give substantially price concessions, or vice verse, hence holding period and markup might be jointly determined, we construct a composite illiquidity measure that is the sum of z-scores of holding period and markup.

Time series regressions show that illiquidity is an important factor in explaining the variation of the US aggregate yield spreads. For the full sample period, a regression on holding period and markup alone has an adjusted R^2 of 19%. Adding an index of CDS prices, VIX, and other proxies and determinants of credit risk increases the adjusted R^2 to 46%, suggesting that illiquidity and credit risk are equally important in explaining yield spreads. The coefficient on holding period (markup) is 0.02 (0.35) with a t-stat of 2.49 (5.72). This implies that an increase of holding period (markup) by 1 day (100 bps) is associated with an increase of 2 bps (35 bps) of aggregate yield spread. Among the non-liquidity variables, the CDS index, slope, S&P500 index return, and treasury rate all play important roles with significant coefficients. On the other hand, VIX is statistically insignificant. This implies that despite the strong correlation between VIX and our liquidity measures evident from table 4, our illiquidity measures contain important information about bond yield spreads beyond VIX. Further, we do not see potential nonlinear effects due to convexity since the coefficient on the convexity variable is statistically insignificant. Finally, consistent with the findings of Bao, Pan and Wang (2010), we find that λ is also significant in the time series regression.

Separating the full sample period into crisis period and non-crisis period, we find that the relative importance of illiquidity and credit risk changes dramatically in the crisis period. During the non-crisis period, illiquidity effects are over-shadowed by credit risk: regressions of aggregate US corporate bond yield spreads on illiquidity proxies alone have an adjusted R^2 of 12% and combining credit risk increases the adjusted R^2 to around 38%. In the crisis period, adjusted R^2 for illiquidity alone triple to around 30%, larger than the combined additional explanatory power (25%) of all other factors. In addition, US aggregate yield spreads are more sensitive to illiquidity in the crisis period than in the normal periods. The coefficients of both holding period and markup double in the crisis period. These results are similar whether we use holding period and markup as illiquidity proxies, or use the composite illiquidity proxy.

Bond-Level Illiquidity and Individual Bond Prices

We now study the extent to which bond-level illiquidity measures affect individual bond prices. We focus on the yield spread of individual bonds, the difference between the corporate bond yield and the Treasury bond yield of the same maturity. We perform monthly Fama-MacBeth regressions of individual bond yield spreads on illiquidity proxies, along with a set of control variables. The t-values are calculated with Newey-West adjustments (3 lags).

Table 6. Fama-MacBeth Regressions of Bond Yield Spreads on Illiquidity Measures

	Full		Crisis		Non-Crisis		Full		Crisis		Non-Crisis	
Constant	5.53	3.65	2.68	0.88	5.97	4.08	6.87	-1.43	4.90	1.09	7.17	-1.82
	6.27	0.57	2.02	1.62	6.61	2.49	3.74	-0.69	2.02	1.33	4.00	-1.38
Holding Period	0.008	0.004	0.025	0.017	0.005	0.002						
	4.78	0.86	3.39	2.53	4.96	0.09						
Markup	0.51	0.27	0.95	0.57	0.44	0.22						
	5.04	4.36	2.94	3.06	5.08	4.56						
Composite illiquidity							0.13	0.08	0.25	0.16	0.11	0.07
							3.11	2.70	2.53	2.41	3.20	4.27
Size		-0.65		-1.74		-0.48		-0.96		-1.59		-0.87
		-1.89		-1.34		-0.13		-1.96		-1.72		-0.92
Rating		0.64		1.48		0.51		0.62		1.21		0.53
		3.37		2.48		3.76		3.44		2.49		3.75

Maturity		-0.37		-0.79		-0.30		-0.24		-0.66		-0.18
		-0.70		-0.32		-2.62		-0.25		-0.81		-0.18
Age		-0.12		-0.81		-0.02		-0.11		-0.80		-0.01
		-0.67		-0.74		-1.06		-0.05		-0.11		-0.94
# of Trades		-0.003		-0.011		-0.002		-0.005		-0.018		-0.003
		-2.74		-2.60		-3.44		-1.03		-1.09		-0.34
# of Months		90		12		78		90		12		78
Adj. R^2	19.44	41.67	27.59	55.32	18.19	39.57	14.12	40.34	24.21	56.77	12.57	37.81
# of bonds		13356		13645		13312		13356		13645		13312

Table 6 shows the regression results. The average number of bonds in each month is over 13,000. The regressions show that holding periods and markups together significantly explain the cross-section variation of individual bond prices in both economic and statistical terms. For the full sample period, the coefficient on holding period (markup) is around 0.01 (0.51) with a t-stat of 4.78 (5.04). This implies that if one bond has a holding period (markup) that is higher than another bond by 1 day (100 bps), the yield spread of this bond is on average 1 bp (51bps) higher. To put an increase of 1 day (100 bps) in holding period (markup) in context, a one standard deviation difference in holding periods (markup) implies a difference in yield spreads of 11 (128) bps. In the crisis period, the coefficient on holding period (markup) jumps to 0.025 (0.95) with a t-stat of 3.39 (2.94). In economic terms, during the crisis period, a one standard deviation difference in holding period (markup) leads to a difference in yield spreads as much as 32 (271) bps. Adjusted R^2 are also higher during the crisis period, increasing from 40% to 55%.

We also use credit ratings to control for the fundamental risk of a bond. Credit ratings are important in explaining yield spreads for all regression specifications. As shown in Table 6, the slope coefficient on credit rating is 0.51 (1.48) with a t-stat of 3.76 (2.48) in non-crisis period (crisis period). Since some bond characteristics, such as age, issuance size, and maturity, are known to be linked to bond liquidity, we include them as control variables. The overall positive and significant connection between our measures and bond yield spreads is unchanged despite the inclusion of these variables. Moreover, many of these conventional illiquidity proxies are either statistically insignificant or have the wrong sign. Our results remain robust if we use the composite illiquidity proxy. Table 6 shows that the coefficient on it is statistically significant across all the sample periods and model specifications.

Chapter 6

THE CREDIT SPREAD PUZZLE

Collin-Dufresne, Goldstein, and Martin (2001) and Huang and Huang (2003) report that credit risk determinants proposed by traditional structural models can only explain about 25% of levels of or changes in credit spreads of corporate bonds. Intriguingly, Collin-Dufresne et al. (2001) find the regression residuals are highly cross-correlated and driven by a common systematic component. Longstaff, Mithal, and Neis (2005) suggest that illiquidity may be an additional determinant of the credit spread variation. Empirical attempts at using illiquidity proxies to explain credit spread changes have had limited success. For example, Chen, Lesmond and Wei (2007) find that changes in their three liquidity proxies, bid-ask spreads, percentage of zero returns and the LOT (Lesmond et al. (1999)) liquidity estimate, are significantly and positively related to changes in the credit spread.[2] However, their combined adjusted R^2s of the full regression models are rather low, about 15% for investment grade bonds.

We start by simply replicating the original regressions of Collin-Dufresne, Goldstein and Martin (2001):

$$\Delta \text{Credit.Spread}^i = \alpha + \beta_1^i \text{ret}^i + \beta_2^i \Delta r^{10} + \beta_3^i (\Delta r^{10})^2 + \beta_4^i \Delta \text{Slope}$$

[2] LOT liquidity estimate is based on the limited dependent variable model proposed by Lesmond et al. (1999). They argue that a liquidity cost threshold exists because bond prices will reflect new information only if the information value of the marginal trader exceeds the total liquidity costs. The model estimated upper and lower liquidity thresholds represent round-trip liquidity costs.

$$+\beta_5^i \Delta VIX + \beta_6^i S\&P + \beta_7^i \Delta Jump + \varepsilon^i$$

Credit.Spread is the difference between the yield of bond and the associated yield of the Treasury curve at the same maturity. Ret is the issuer's monthly equity return. r^{10} is the monthly series of 10-year treasury rate, and the square of this, $(r^{10})^2$, proxies for convexity. Slope is the difference between 10-year and 2-year treasury constant maturity yields. VIX is the VIX index. Jump refers to the probability and magnitude of a large negative jump in firm value, and is constructed from S&P 500 futures options following the procedure in Collin-Dufresne, Goldstein and Martin (2001). Collin-Dufresne, Goldstein and Martin (2001) also apply several data filters. They use only noncallable and nonputtable industrial corporate bonds with more than four years to maturity. Additionally, they require a bond to have at least 25 monthly observations in order to enter the sample. These data filters dramatically reduce the number of bonds available to measure credit spread changes.

Table 7. Determinants of Credit Spread Changes by Rating Group

Panel A: Structural Model Determinants of Credit Spread Changes

	AAA	AA	A	BBB	BB	B	CCC	CC	C
Constant	0.045	-0.158	0.364	0.190	-0.404	-0.190	0.081	0.995	-8.924
	1.21	-1.15	2.61	2.41	-2.55	-1.79	0.42	2.33	-2.86
Stock Return	-0.008	0.000	-0.037	-0.057	-0.064	-0.077	-0.069	-0.256	-0.118
	-0.60	-1.72	-1.84	-1.90	-3.93	-2.38	-2.20	-2.99	-3.21
ΔTreasury rate	-0.012	-0.345	-0.590	-0.086	-0.295	-0.261	-0.144	-1.737	-1.948
	-1.95	-2.10	-2.08	-3.04	-3.59	-3.52	-3.23	-5.91	-6.76
ΔConvexity	0.047	-0.768	-0.240	-0.592	-1.265	-0.492	0.765	-0.833	-1.352
	0.41	-1.18	-0.82	-0.51	-1.11	-1.20	0.82	-2.03	-0.19
ΔSlope	-0.024	-0.124	-0.159	-0.132	-0.066	-0.084	-0.129	0.003	-0.098

	-0.99	-2.70	-2.53	-2.48	-2.26	-0.59	-0.76	0.40	-0.70
ΔVolatility	0.004	0.075	0.004	0.019	0.022	0.005	0.002	0.004	0.049
	2.93	2.38	2.56	2.69	3.02	0.56	1.28	1.32	1.58
S&P 500	-0.032	-0.274	-0.144	-0.043	-0.051	-0.143	-0.506	-0.169	0.291
	-2.15	-1.94	-2.23	-2.67	-2.20	-1.88	-6.21	-2.67	1.66
ΔJump	0.001	0.016	0.004	0.001	0.009	0.003	0.144	0.057	0.015
	3.18	1.96	2.21	3.98	4.43	2.75	2.89	3.23	2.84
N	14	175	434	295	129	75	58	33	24
Adj. R^2	25%	31%	26%	30%	24%	23%	48%	76%	61%

Panel B: Adding Individual Illiquidity Measures

	AAA	AA	A	BBB	BB	B	CCC	CC	C
ΔMU	0.282	0.302	0.231	0.220	0.292	0.205	0.776	0.181	0.478
	2.28	2.36	2.65	2.40	1.82	0.57	2.79	1.07	1.27
ΔHP	0.007	0.091	0.022	0.113	0.123	0.066	0.261	0.025	0.059
	0.76	2.82	1.55	2.64	0.86	2.44	2.24	0.81	1.49
Adj. R^2	32%	45%	36%	41%	40%	44%	59%	68%	56%

Panel C: Adding Composite Illiquidity Measure

	AAA	AA	A	BBB	BB	B	CCC	CC	C
Δ Composite Illiquidity	0.012	0.015	0.009	0.079	0.014	0.006	0.015	0.003	0.014
	2.08	2.83	2.15	2.70	2.27	2.37	2.82	1.12	1.70
Adj. R^2	33%	40%	36%	39%	41%	44%	59%	67%	51%

Panel D: Percentage improvement in Adj. R^2

	AAA	AA	A	BBB	BB	B	CCC	CC	C
HP+MU	27%	46%	39%	36%	66%	89%	22%	-10%	-8%
Composite Illiquidity	32%	31%	38%	29%	68%	90%	23%	-12%	-17%

Table 7 panel A reports regression results of the original Collin-Dufresne, Goldstein and Martin (2001) model with bonds grouped by credit rating. For each of the bonds within a group, we estimate a time series regression and report cross-sectional averages of estimated coefficients within the group. Collin-Dufresne, Goldstein and Martin (2001) only study bonds rated from B to AAA because of data availability. Our data allows us to extend sample coverage to bond rating groups of CCC, CC, and C. Focusing first on bonds rated from B to AAA, which are covered in Collin-Dufresne, Goldstein and Martin (2001), we find results similar to theirs. The variables suggested by structure models are significant both economically and statistically in explaining changes in individual bond credit spreads. However, they have rather limited explanatory power, with an adjusted R^2 of about 27%. For low-rated (CCC through C) bonds, structural models alone explain over 60% of credit spread changes, suggesting that for this rating group, the "puzzle" is less of a puzzle.

We now expand their original regression model to include contemporaneous changes in holding period and markup. Table 7 Panel B reports the regression results. For B to AAA rated bonds, changes in holding period and markup are generally positively associated with changes in credit spreads. The coefficient on markup ranges from about 0.21 to 0.30. It is statistically significant for all bond groups except B rated bonds. In economic term, an increase of markup by 100 bps is associated with an increase of about 25 bps of credit spread. The coefficient on holding period is statistically significant for AA, BBB, and B rated bonds. It is economically significant for these groups, so that a one day increase in holding period is associated with an increase of about 9 bps in the credit spread. More importantly, adding our measures increases average adjusted

R^2 from 27% to 40%.[3] This suggests that that liquidity is an important determinant of credit spread changes, beyond the pure contingent-claims framework (i.e. conventional structural models). While we cannot claim to "solve" the puzzle, our illiquidity measures make substantial progress. In Panel C, we combine holding period and markup into a composite illiquidity measure. For B to AAA rated bonds, we can see that our composite liquidity proxy is significant for all bond groups. Adding the composite illiquidity measure increases average adjusted R^2 to about 40%.

Collin-Dufresne, Goldstein and Martin (2001) find that their regression residuals are highly cross-correlated. Their principal components analysis suggests the 75.9% of the residual variation is driven by the first component. They also report that including a list of additional independent variables (e.g. Fama and French factors, on-the-run minus off-the-run 30-year Treasury yields, leading effects of stocks on bonds and economic state variables) reduces the explanatory power of the first principal component to 58.5%. We study how much of the regression residuals are driven by the principal components after we add our liquidity proxies. Essentially, we ask if liquidity can explain this common systematic component in the CGM specifications. For each rating group, we calculate an average residual, and then undertake the principal components

[3] For lower rated bonds (between CCC and C), adding liquidity has a negligible effect on adjusted R^2. Also, liquidity measures are statistically insignificant in most cases.

analysis and extract the principal components of the covariance matrix of these residuals. For bonds rated above B, we find that the first principal component accounts for 58.8% of the residual variance. Results here suggest that our liquidity proxies to some extent contribute to credit spread changes.

In Panel D, we report percentage improvement in adjustment R^2 after adding holding period and markup, or composite illiquidity measure respectively. For bonds rated from B to AAA, the percentage improvement in adjusted R^2 is substantial. It ranges from around 30% to 90%, depending on rating groups. For credit spreads changes in B, BB, and AA groups, the corresponding percentage improvement in adjustment R^2 is 89%, 66% and 46% respectively. For bond rated from CCC to C, our liquidity proxies do not provide additional explanatory power.

Table 8. Crisis Effects on the Determinants of Credit Spread Changes by Rating Group

Panel A: Additional Determinants of Credit Spread Changes-HP, MU, and Crisis									
	AAA	AA	A	BBB	BB	B	CCC	CC	C
ΔMU	0.238	0.256	0.193	0.182	0.247	0.169	0.682	0.148	0.414
	2.03	2.11	2.36	2.14	1.62	0.27	2.50	0.94	1.07
ΔHP	-0.009	0.066	0.012	0.085	0.095	0.044	0.219	0.007	0.037
	-0.10	2.52	1.37	1.93	0.06	1.86	1.99	0.35	0.63
Crisis*ΔMU	0.141	0.143	0.080	0.135	0.142	0.054	0.190	0.051	0.081
	2.34	1.87	1.90	1.87	2.62	1.21	2.72	0.14	0.16
Crisis*ΔHP	0.019	0.044	0.021	0.038	0.031	0.033	0.053	0.029	0.024
	0.89	2.30	1.77	1.88	1.30	2.66	1.84	1.14	1.77
Crisis	0.180	-0.005	0.139	0.056	0.012	0.015	0.263	0.198	0.238
	0.98	-1.15	2.68	2.52	3.23	4.77	2.97	2.43	1.99
Adj. R^2	35%	47%	41%	45%	47%	51%	62%	75%	62%
Crisis*ΔMU/ΔMU	59%	56%	41%	74%	57%	32%	28%	34%	20%
Crisis*ΔHP/ΔHP	-	67%	175%	45%	33%	75%	24%	414%	65%

Panel B: Additional Determinants of Credit Spread Changes-Composite Illiquidity, and Crisis									
	AAA	AA	A	BBB	BB	B	CCC	CC	C
Δ Composite Illiquidity	0.009	0.012	0.006	0.062	0.011	0.004	0.010	0.001	0.009
	1.78	2.58	2.72	1.89	0.52	2.67	2.46	1.32	1.12
Crisis*Δ Composite Illiquidity	0.005	0.006	0.005	0.029	0.005	0.003	0.006	0.004	0.006
	2.84	2.14	1.64	1.80	2.72	2.09	2.45	1.68	1.08
Crisis	0.006	-0.034	0.076	0.069	0.019	0.027	0.245	0.040	0.001
	0.89	-0.62	4.10	2.74	2.83	2.92	3.72	2.88	1.86
Adj. R^2	35%	45%	39%	41%	44%	50%	62%	68%	54%
Additional Impact	56%	51%	83%	47%	45%	75%	61%	402%	67%

Huang (2003) predicts that illiquidity has larger effects on asset returns when agents face liquidity shocks and borrowing constraints. In a recent paper, Acharya, Amihud, and Bharath (2010) suggest a regime-switching pattern in the response of bond returns to liquidity. Their model implies that the impact of illiquidity might increase dramatically during the crisis period (their “stress” regime). We test the implications of these models and relate them to the credit spread puzzle. Particularly, we examine the crisis effects on the credit spread changes by expanding the regression model with interaction term of crisis and illiquidity measures, and crisis dummy. Table 8 Panel A and Panel B reports regression results using holding period and markup, and composite illiquidity measure respectively.

Panel A shows that the crisis dummy is positively associated with changes of credit spread and statistically significant for all bonds rated below AA. Other things equal, the increase in credit spreads during the crisis period (over 20 bps) is much bigger for bonds rated from CCC to C than it is for bonds rated above CCC (around 4 bps). More importantly, consistent with the predictions of Huang (2003) and Acharya, Amihud, and Bharath (2010), there is a positive correlation between the interaction term of crisis and our illiquidity measures, and credit spread changes for bonds across all rating groups. Statistically, most of these interaction terms are significant at 10% significance level or above. They are also economically important because overall, the sensitivity of credit spread changes to liquidity changes is about 60% larger during crisis period. In panel B, we repeat the analysis using the composite illiquidity measure instead of holding period and markup. The results are largely similar.

Table 9. Determinants of Credit Spread Changes by Leverage Group

Panel A: Structural Model Determinants of Credit Spread Changes

	<15%	15-25%	25-35%	35-45%	45-55%	>55%
Intercept	0.042	0.024	0.016	0.011	0.032	0.020
	5.99	5.93	5.62	5.25	5.91	6.39
Δleverage	0.007	0.003	0.015	0.007	0.010	0.011
	2.40	2.32	2.26	2.66	2.55	2.80
ΔTreasury rate	-0.168	-0.187	-0.186	-0.416	-0.418	-0.402
	-4.93	-4.90	-5.03	-5.55	-5.17	-4.80
ΔConvexity	0.014	0.167	-0.005	-0.013	0.082	0.094
	0.09	0.14	-0.33	-0.65	0.09	0.13
ΔSlope	0.008	-0.015	0.010	-0.009	0.026	-0.010
	0.25	-0.13	0.37	-2.33	0.26	-1.63
ΔVolatility	0.008	0.012	0.002	0.003	0.005	0.005
	2.11	2.62	0.87	1.59	2.06	2.68
S&P 500	-0.014	-0.028	-0.010	-0.034	-0.040	-0.026
	-5.08	-5.38	-5.17	-4.94	-5.24	-4.77
ΔJump	0.003	0.002	0.005	0.004	0.005	0.003
	5.46	5.20	5.61	5.79	5.69	5.83
N	130	167	181	147	199	386
Adj. R^2	23%	22%	34%	30%	25%	26%

Panel B: Adding Individual Illiquidity Measures						
	<15%	15-25%	25-35%	35-45%	45-55%	>55%
Δ MU	0.132	0.343	0.155	0.511	0.194	-0.033
	2.04	3.154	1.766	2.456	2.532	-0.506
ΔHP	0.025	0.022	0.022	0.034	0.014	-0.008
	1.64	2.88	1.69	2.55	1.17	-1.04
Adj. R^2	30%	44%	36%	49%	40%	36%

Panel C: Adding Composite Illiquidity						
	<15%	15-25%	25-35%	35-45%	45-55%	>55%
Δ Composite Illiquidity	0.015	0.022	0.015	0.023	0.018	0.007
	2.14	3.31	2.168	3.164	2.44	1.64
Adj. R^2	33%	41%	35%	43%	37%	37%

Panel D: Percentage improvement in Adj. R^2						
	<15%	15-25%	25-35%	35-45%	45-55%	>55%
HP+MU	29%	93%	5%	62%	58%	39%
Δ Composite Illiquidity	44%	78%	3%	42%	49%	42%

Table 10. Crisis Effects on the Determinants of Credit Spread Changes by Leverage Group

Panel A: Additional Determinants of Credit Spread Changes-MU, HP, and Crisis						
	<15%	15-25%	25-35%	35-45%	45-55%	>55%
Δ MU	0.104	0.293	0.119	0.444	0.159	0.044
	1.82	3.14	1.66	2.20	2.27	0.68
ΔHP	0.020	0.017	0.018	0.028	0.011	0.005
	1.476	2.592	1.514	2.297	1.051	0.935
Crisis*Δ MU	0.081	0.147	0.071	0.146	0.065	0.019
	2.70	2.14	2.24	2.17	3.16	0.43
Crisis*Δ HP	0.010	0.011	0.009	0.010	0.008	0.005
	2.66	2.57	1.98	2.07	1.57	1.74
Crisis	0.035	0.059	0.001	0.002	0.041	0.113
	2.55	2.04	1.04	1.65	2.36	3.61
Adj. R^2	37%	51%	39%	51%	47%	44%
Crisis*Δ MU/Δ MU	78%	50%	60%	33%	41%	43%
Crisis*Δ HP/ΔHP	51%	65%	49%	36%	73%	99%

Panel B: Additional Determinants of Credit Spread Changes-Composite Illiquidity, and Crisis						
	<15%	15-25%	25-35%	35-45%	45-55%	>55%
Δ Composite Illiquidity	0.012	0.018	0.012	0.019	0.014	0.007
	1.92	3.14	1.99	2.84	2.19	1.34
Crisis*Δ Composite Illiquidity	0.01	0.01	0.008	0.008	0.007	0.001
	2.75	2.41	2.36	2.43	2.31	0.87
Crisis	0.002	0.011	0.001	0.001	0.008	0.021
	2.09	2.58	1.39	1.53	3.09	2.93
Adj. R^2	34%	49%	37%	48%	44%	38%
Additional Impact	81%	57%	67%	43%	49%	14%

Finally, as noted in Collin-Dufresne, Goldstein and Martin (2001), the structural framework implies that credit spreads should increase with leverage since default is triggered when the leverage ratio approaches unity. Also, changes in leverage have often been used to proxy for changes in the firm's health. Hence, for robustness, we also use changes of leverage, instead of firm's stock return, as an explanatory variable. In table 9 and table 10, we use this approach and repeat the analysis in table 7 and table 8, grouping bonds by firms' leverage ratios rather than credit ratings. Table 9 panel A shows that the adjusted R^2 of the original model without our liquidity proxies is about 25%. Table 9 panels B and C show that adding our liquidity measures increases the adjusted R^2 to around 40%. In table 9, panel D shows that leverage group of 15-25% has the biggest adjusted R^2 improvement, almost doubling from 22% to 44%. Regression results in table 10 again support the predictions of Huang (2003) and Acharya, Amihud, and Bharath (2010).

Chapter 7

CONCLUSION

Building on the insights of Demsetz (1968) and Chacko, Jurek, and Stafford (2008), we link immediacy, liquidity, and prices in the corporate bond market. We construct dealers' inventory holding periods and the associated price markups as liquidity proxies. Our measures allow us to cover a relatively comprehensive sample of over 16,000 bonds. While our liquidity proxies are related to some bond characteristics (e.g. size, age, and maturity etc.) and market variables (VIX, TED spread etc.), our tests suggest that they contain new information.

The main objective of our paper is to examine the association between corporate bond liquidity and yield spreads. Our pricing regressions show a strong link between them, both in time series and in the cross section. Changes in our measures explain a large part of the time series variation in aggregate corporate bond prices. In the cross-section, holding periods and markups overshadow extant liquidity measures and have significant explanatory power for individual bond prices. More importantly, we find our liquidity measures can be helpful in attempts to explain the credit yield puzzle. Changes in holding periods and markup are significant both economically and statistically in explaining variation in individual bond's credit spreads changes. In particular, adding our measures to regressions of credit spread changes increases average adjusted R^2 from 27% to

40%. Finally, consistent with Huang (2003) and Acharya, Amihud, and Bharath (2010), we show that the effects of holding periods and markups are particularly sharp during crisis periods.

Overall, our findings help us better understand how corporate bonds are priced, in other words, what are the determinants of bond price. These are issues of fundamental importance to academics, practitioners, and regulators. For academics, exploring the role of liquidity in corporate bond pricing is important and a necessary step toward a unified theory of asset pricing. It is a common practice for practitioners to draw conclusions regarding default probabilities/recovery rate from corporate yield spreads, or vice verse. Our findings imply that this approach is inappropriate for high rated bonds, and especially in crisis periods. For regulators, our study provides policy making implication, particularly in crisis periods.

REFERENCES

Acharya, Viral, Amihud, Yakov, and Bharath, Sreedhar. 2010. Liquidity risk of corporate bond returns. *Working Paper.*

Acharya, Viral, and Pedersen, Lasse. 2005. Asset pricing with liquidity risk. *Journal of Financial Economics* 77(2): 375-410.

Amihud, Yakov, and Mendelson, Haim. 1980. Dealership markets: market making with inventory. *Journal of Financial Economics* 8: 21-53.

Amihud, Yakov, and Mendelson, Haim. 1986. Asset pricing and the Bid-Ask spread. *Journal of Financial Economics* 17(2): 223-249.

Amihud, Yakov, and Mendelson, Haim. 1991. Liquidity, maturity, and the yields on U.S. Treasury securities. *Journal of Finance* 46(4): 1411-1425.

Bagehot, Webster pseud. for Jack Treynor. 1971. The only game in town. *Financial Analysts Journal* 27: 12-17.

Bao, Jack, Pan, Jun and Wang, Jiang. 2011. The illiquidity of corporate bonds *Journal of Finance* 66: 911-946

Bessembinder, Hendrick, Maxwell, William and Venkataraman, Kumar. 2006. Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. *Journal of Financial Economics* 82: 251-288.

Black, Fischer, and Scholes, Myron. 1973. The pricing of options and corporate liabilities.*Journal of Political Economy* 81: 637-654.

Bongaerts, Dion, De Jong, Frank and Driessen Joost. 2012. An asset pricing approach to liquidity effects in corporate bond markets. *Working Paper.*

Brunnermeier, Markus, and Pedersen, Lasse. 2009. Market liquidity and funding liquidity. *Review of Financial Studies* 22: 2201-2238.

Chacko, George, Jurek, Jakub and Stafford, Erik. 2008. The price of immediacy. *Journal of Finance* 63(3): 1253-1290.

Chen, Long, Lesmond, David and Wei, Jason. 2007. Corporate yield spreads and bond liquidity. *Journal of Finance* 62: 119-149.

Collin-Dufresne, Pierre, Goldstein, Robert and Martin, Spencer. 2001. The determinants of credit spread changes. *Journal of Finance* 56: 2177-2207.

Copeland, Thomas and Galai, Dan. 1983. Information effects on the Bid-Ask spread. *Journal of Finance* 38: 1457-1469

Demsetz, Harold. 1968. The cost of transacting. *Quarterly Journal of Economics* 82: 33-53.

Dick-Nielsen, Jense. 2009. Liquidity biases in TRACE. *Journal of Fixed Income* 19 (2): 43-55.

Dick-Nielsen, Jense, Feldhutter, Peter and Lando, David. 2012. Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics* 103: 471-492.

Driessen, Joost. 2005. Is default event risk priced in corporate bonds? *Review of Financial Studies* 18(1): 165-195.

Duffie, Darrell, Garleanu, Nicolae and Pedersen, Lasse. 2005. Over-the-counter markets. *Econometrica* 73: 1815-1847.

Edwards, Amy, Harris, Lawrence and Piwowar, Michael. 2007. Corporate bond market transaction costs and transparency. *Journal of Finance* 62: 1421-1451.

Feldhutter, Peter. 2012. The same bond at different prices: identifying search frictions and selling pressures. *Review of Financial Studies* 25: 1155-1206.

Garman, Mark. 1976. Market microstructure. *Journal of Financial Economics* 3: 257-275.

Glosten, Lawrence and Milgrom, Paul. 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14(1): 71-100.

Goldstein, Michael, Hotchkiss, Edith and Sirri, Erik. 2007. Transparency and liquidity: A controlled experiment on corporate bonds. *Review of Financial Studies* 20: 235-273.

Green, Richard, Hollifield, Burton and Schurhoff, Norman. 2006. Financial intermediation and the costs of trading in an opaque market. *Review of*

Financial Studies (20) 2: 275-314.

Ho, Thomas, and Stoll, Hans. 1981. Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics* 9: 47-73.

Houweling, Patrick, Mentink, Albert and Vorst, Ton. 2005. Comparing possible proxies of corporate bond liquidity. *Journal of Banking and Finance* 29: 1331-1358.

Huang, Ming. 2003. Liquidity shocks and equilibrium liquidity premia. *Journal of Economic Theory* 109: 104-129.

Huang, Jingzhi, and Huang, Ming. 2003. How much of the corporate-Treasury yield spread is due to credit risk? *Working Paper*.

Lesmond, David, Ogden, Joseph and Trzcinka, Charles. 1999. A new estimate of Transaction costs. *Review of Financial Studies* 12: 1113-1141.

Longstaff, Francis, Mithal, Sanjay and Neis, Eric. 2005. Corporate yield spreads: default risk or liquidity: New evidence from the Credit-Default Swap market. *Journal of Finance* 60: 2213-2253.

Stoll, Hans. 1978. The supply of dealer services in securities markets. *Journal of Finance* 33: 1133-1151.

Wang, Jiang. 1993. A model of intertemporal asset prices under asymmetric information. *Review of Economic Studies* 60: 249-282.