

Liquidity and Credit Default Swap Spreads^{*}

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ABSTRACT

This paper examines the market microstructure and asset pricing of the credit derivatives market. We present an empirical study of the pricing effect of liquidity in the credit default swaps (CDS) market. We construct liquidity proxies to capture various facets of CDS liquidity including adverse selection, search frictions, and inventory costs. We show that the liquidity effect on CDS spreads is significant with an estimated liquidity premium on par with those of Treasury bonds and corporate bonds. Our finding of cross-sectional variations in the liquidity effect highlights the structure of the search-based over-the-counter market and the interplay between search friction and adverse selection in CDS trading. Using liquidity betas and volume respectively to measure liquidity risk, we find supporting evidence for liquidity risk being priced beyond liquidity level in the CDS market.

Keywords: Credit Default Swaps; Credit Spreads; Liquidity; Liquidity Risk

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This paper examines the market microstructure and asset pricing of the credit derivatives market. We present an empirical study of the pricing effect of liquidity in the credit default swaps (CDS) market. We construct liquidity proxies to capture various facets of CDS liquidity including adverse selection, search frictions, and inventory costs. We show that the liquidity effect on CDS spreads is significant with an estimated liquidity premium on par with those of Treasury bonds and corporate bonds. Our finding of cross-sectional variations in the liquidity effect highlights the structure of the search-based over-the-counter market and the interplay between search friction and adverse selection in CDS trading. Using liquidity betas and volume respectively to measure liquidity risk, we find supporting evidence for liquidity risk being priced beyond liquidity level in the CDS market.

JEL Classification: G12; G13; E43; E44

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I. Introduction

Credit derivative innovations play a significant role in the ongoing subprime crisis. This crisis is in large part driven by the illiquidity of those credit derivative products, particularly collateralized debt obligations (CDO). A building block for the credit derivative market, and the essence of the CDOs, is credit default swaps (CDS). In this paper, we explore the CDS market microstructure and study liquidity effects in CDS pricing.

A credit default swap (CDS) is a type of insurance contract against corporate default that is traded in the over-the-counter market. Over the last decade, the CDS market has grown rapidly to more than \$17 trillion in notional value. Much of this development has been driven by the demand from banks and insurance companies to hedge their underlying bond and loan exposures and by the need of hedge funds and investment banks' proprietary trading desks for more liquid instruments to speculate on credit risk. Given the tremendous growth and the formidable size of the market, trading in CDS contracts can have a pervasive market-wide impact, as demonstrated by the GM/Ford credit debacle in 2005.¹ The rapid growth and the lax regulatory supervision of the CDS market have raised a number of policy concerns about market stability and risk of adverse selection, both of which would influence investors' propensity to trade in the market and hence the liquidity of CDS contracts.²

There are a number of indications that liquidity may play a crucial role in the further growth of credit derivatives markets and in the pricing of these derivatives contracts. For instance, even with the tremendous size of the CDS market, the usage of CDS contracts by banks is still surprisingly low despite its hedging advantage. Minton, Stulz, and Williamson (2005) find that only 5% (19 out of 345) of large banks in their sample use credit derivatives. They argue that "the use of credit derivatives by banks is limited because adverse selection and moral hazard problems make the market for credit derivatives illiquid for the typical credit exposure of banks." Parlour and Plantin (2007) show in a theoretical model that the liquidity effect can arise endogenously in the credit derivative market when banks are net protection buyers. Because banks may utilize CDS contracts either for managing their balance sheet obligations or for trading on their private information about the underlying firm, their

¹Bonds of General Motors and Ford were downgraded to the junk status in May, 2005, causing turmoil in the credit markets that also unsettled the equity and options markets and resulted in heavy losses for some hedge funds that had sold a large amount of CDS contracts.

²See, for instance, International Monetary Fund (2006) for a discussion of market stability. Reports in the financial press, such as "Can Anyone Police the Swap" in *The Wall Street Journal* on August 31, 2006, highlight possible informed trading in the CDS market.

presence in the market may increase the risk of adverse selection and affect the liquidity of CDS contracts. Acharya and Johnson (2007) provide evidence of informed trading in CDS contracts that highlights this risk of adverse selection in the CDS market. In addition, several papers have documented that CDS spreads seem too high to be accounted for by default risk alone, and some have suggested that liquidity may be a factor determining CDS prices.³

In this paper, we investigate the impact of liquidity characteristics and liquidity risk on CDS spreads. Our analysis reveals multiple facets of liquidity in the CDS market that have significant effects on CDS spreads. We find that the interplay between search frictions and adverse selection results in cross-sectional variations in the impact of different liquidity measures on CDS prices. We show that while CDS spreads generally decrease with market depth and increase with dealers' inventory constraints, the impact of matching intensity in the search process and bid-ask spreads on CDS spreads is quite different in the cross section. For infrequently quoted contracts, the CDS spread is lower with a higher matching intensity or a lower bid-ask spread, *ceteris paribus*. For actively quoted contracts, however, neither matching intensity nor bid-ask spread seems to have a significant impact on CDS prices. The differential effect of the matching intensity is consistent with the implications of a search model of Duffie, Garleanu and Pedersen (2005, 2006) for over-the-counter markets. Our result with the bid-ask spread also sheds more light on the findings of Acharya and Johnson (2007), who uncover the evidence of informed trading in contracts with the most active trading without finding a link between CDS spreads and bid-ask spreads among these contracts.

To further examine the role of adverse selection, we classify samples by a measure of likelihood of informed trading, or PIN, following its construction by Easley *et al* (1997). We find that for contracts with a small PIN, CDS spreads decrease with matching intensity and increase with bid-ask spread. For contracts with a large PIN, however, higher matching intensity increases CDS spreads, implying that improved liquidity for these contracts facilitates informed trading, and hence the risk of adverse selection is priced in the CDS price. Moreover, for these high PIN names, large bid-ask spreads actually reduce CDS spreads. We argue that this observation implies that the risk of adverse selection is reflected in the widened bid-ask spread while CDS spreads do not fully incorporate inside information, as most of the informed trading seems to have come from buyers of credit protection.

Our analysis suggests that sellers of CDS contracts provide not only insurance against credit risk, but also liquidity service in the market. This is indicated by evidence that when

³See, e.g., Berndt, Douglas, Duffie, Ferguson, and Schranz (2005), Blanco, Brennan, and Marshall (2005), Pan and Singleton (2005), and Saita (2006).

the supply of a particular contract outstrips its demand, sellers are offering discounts for a better matching intensity and charging a premium when they have the pricing power. If the demand exceeds supply, sellers are charging a premium for faster matching, *ceteris paribus*, as they are liquidity providers. Overall, with measures of various facets of liquidity, we demonstrate the significant effect of liquidity on CDS spreads. Indeed, our estimated mean liquidity premium across all liquidity proxies is 13.2 basis points, comparable with the prior estimate of liquidity premium from Treasury bonds (Longstaff, 2004) and with the non-default component of corporate bond spreads (Longstaff, Mithal and Neis, 2005).

While the effect of liquidity characteristics captures the impact of liquidity for trading today, the variation of liquidity measures over time can pose liquidity risk that may affect future trading, and hence this liquidity risk should also be priced in CDS spreads. To verify this intuition, we examine the effect of liquidity risk – measured by liquidity betas following the framework of Acharya and Pedersen (2005) – on CDS spreads, controlling for liquidity levels. We find that CDS spreads are significantly positively related to the sensitivity of individual liquidity shocks to market-wide liquidity shocks, and negatively related to the sensitivity of shocks to individual CDS spreads to market-wide liquidity shocks, consistent with the prediction of Acharya and Pedersen (2005). To mitigate the concern over the impact of measurement errors in betas on our analysis of liquidity risk premium, we follow the argument of Johnson (2007) by using the volume measure as an alternative proxy for liquidity risk. Our results confirm an overall positive liquidity premium in the CDS market.

Although the liquidity effects for traditional securities, such as stocks and bonds, have been studied extensively in the literature,⁴ relatively little is known about the liquidity effects for derivative contracts, as the contractual nature of these instruments and their zero net supply in the market distinguish them from stocks and bonds. Several recent papers have explored the role of liquidity in pricing options. For instance, Bollen and Whaley (2004), Cetin, Jarrow, Protter, and Warachka (2006), and Garleanu, Pedersen, and Poteshman (2007) illustrate the effect of supply/demand imbalance on equity option prices. Brenner, Eldor, and Hauser (2001) find a significant illiquidity discount in the prices of non-tradable currency options compared to their exchange-traded counterparts. Deuskar, Gupta and Subrahmanyam (2006) argue that there are liquidity discounts in interest rate options markets. Thus far, to our best knowledge, no other paper has systematically investigated the liquidity effect in the fast growing CDS market which has important implications for financial market stability.

⁴See Amihud, Mendelson, and Pedersen (2005) for an excellent review.

The contribution of our paper is two-fold. First, we provide the first comprehensive evidence of significant liquidity effects on CDS spreads. Our analysis illustrates that both search frictions and adverse selection play important and differentiated roles in affecting the liquidity and, in turn, the prices of CDS contracts. As such, ours is among the first empirical studies to specifically examine the role of search frictions in OTC markets. Second, we demonstrate empirically for the first time that liquidity risk is positively priced in the CDS market. Our finding thus lends further support to the liquidity-augmented asset pricing framework of Acharya and Pedersen (2005).

The rest of this paper is organized as follows: Section II provides some background information on the CDS market and develops our research hypotheses regarding the roles of liquidity characteristics and liquidity risk. Section III describes the CDS data, the econometric procedure, the control variables and the proxies we use in our empirical work. Section IV discusses the empirical results on the effect of liquidity characteristics in the CDS market. Section V presents the evidence on liquidity risk. Section VI concludes.

II. The Impact of Liquidity on CDS Spreads: Hypothesis Development

A. The CDS Market

Credit derivatives markets have been growing rapidly. The notional amount traded in global credit derivatives markets has increased from \$180 billion in 1997 to \$34.4 trillion in 2006.⁵ Most credit derivatives are unfunded, i.e., they do not require lumpy capital investments upfront. Banks, securities houses and insurance companies constitute the majority of market participants. Recently, hedge funds have emerged as important players in credit derivatives markets. Enhanced standardization of contracts and trading procedures, increased participation of hedge funds in the market, and improved market liquidity have all been instrumental in the rapid growth of global markets in credit derivatives.

Nearly half of the instruments traded in credit derivatives markets are related to credit

⁵The International Swaps and Derivatives Association (ISDA) 2006 Year-End Market Survey reports that the notional amount of CDS on single-names, baskets and portfolios of credits and index trades reached \$34.4 trillion by December 31, 2006. The figures from the Bank of International Settlements (BIS) show the notional amount of \$28.8 trillion for credit derivatives by the end of 2006, of which \$18.9 trillion is for single-name CDS contracts.

default swap contracts. Credit default swaps are over-the-counter contracts for credit protection. CDS contracts were initially developed by banks in order to reduce their credit risk exposure and better satisfy regulatory requirements. In a CDS contract, the two parties, the protection buyer and the seller, agree to swap the credit risk of a bond issuer or loan debtor (“reference entity” or “name”). The credit protection buyer pays a periodic fee (as a percentage of the face value of the debt) – alternately called CDS premium, spread, or price – to the protection seller until the contract matures or a credit event occurs. When a credit event takes place, either the buyer of the protection delivers defaulted bonds or loans (“reference issue”) to the seller in exchange for the face value of the issue in cash (“physical settlement”), or the seller directly pays the difference between the market value and the face value of the reference issue to the protection buyer (“cash settlement”). Credit events and deliverable obligations are specified in the contract. Credit events generally include bankruptcy, failure to pay, and restructuring. Along with the development of the CDS market, the International Swaps and Derivatives Association (ISDA) has given definitions to four types of restructuring: full restructuring; modified restructuring (only bonds with maturity shorter than 30 months can be delivered); modified-modified restructuring (restructured obligations with maturity shorter than 60 months and other obligations with maturity shorter than 30 months can be delivered); and no restructuring.

The typical maturity of a CDS contract is five years. The typical notional amount is \$5-10 million for investment-grade credits and \$2-5 million for high-yield credits. CDS trading is concentrated in London and New York, each accounting for about 40% of the total market. Most transactions (86%) use physical settlement, according to the 2003/2004 Credit Derivatives Report by the British Bankers’ Association.

B. Default Risk and CDS Spreads

CDS spreads are the required periodic payment for providing insurance for default risk of the underlying firm. Therefore, theoretical determination of CDS spreads should capture the risk of default and the potential loss upon default, similar to that of credit spreads for corporate bonds.⁶ Recent empirical studies, including Blanco, Brennan, and Marshall (2005), Houweling and Vorst (2005), Hull, Predescu and White (2004), and Zhu (2006), have confirmed an approximate parity between the CDS spreads and bond spreads. Berndt *et al* (2005) find that default probabilities, measured by Moody’s KMV’s Expected Default

⁶See, e.g., Duffie (1999) and Hull and White (2000).

Frequencies (EDF), can account for a large portion of CDS spreads. While these results imply that CDS spreads reflect well the underlying credit risk, Blanco *et al* (2005), Hull *et al* (2004) and Zhu (2006) also document that the CDS market is more likely to lead the bond market in price discovery as CDS spreads are more responsive to new information.

A number of empirical studies of corporate bond spreads have shown that a large component of corporate bond yield spreads may be attributed to the effects of taxes and liquidity (see, e.g., Elton, Gruber, Agrawal, and Mann (2001), Ericsson and Renault (2006) and Chen, Lesmond, and Wei (2007)). In contrast, Longstaff, Mithal and Neis (2005) argue that prices of CDS contracts may not be significantly affected by liquidity because of their contractual nature that affords relative ease of transacting large notional amounts compared to the corporate bond market, and hence CDS spreads may better reflect default risk premium. This argument has led a few studies to use CDS spreads as a benchmark to control for credit risk in order to study liquidity effects in bond markets (Han and Zhou (2007), Nashikkar and Subrahmanyam (2006), etc.). However, Berndt, Douglas, Duffie, Ferguson, and Schranz (2005) and Pan and Singleton (2005) have documented that CDS spreads seem too high to be accounted for by default risk alone and suggested a liquidity factor as a possible mechanism for filling the gap. We discuss the role of liquidity in the CDS market in the next subsection.

C. CDS Trading and Liquidity

CDS contracts are traded over the counter.⁷ In this market, an interested party searches through a broker or a dealer to find a counter-party. The two parties negotiate the terms of a contract. Information about the trade is then passed along through the back office and sent to a clearing house. Because the entire process has not been sufficiently standardized, there may be delays in clearing the trades.⁸ Recently, inter-dealer brokerages (IDB) have gained popularity. A dealer can register with an IDB and use either an online trading platform or a voice quoting system. An IDB maintains a limit order book, which substantially facilitates both the quoting and trading processes. Traders can also remain anonymous until the order is filled. Presently, CDS trading is done through a hybrid of voice-brokered and electronic platforms.

⁷In 2007, binary CDS contracts started trading on exchanges.

⁸The backlog in the clearing of CDS contracts has been a focus of attention by the New York Fed in recent years. See, e.g., “Fed, Banks Will Meet over Derivatives”, *The Wall Street Journal*, August 25, 2005; “Fed Looks to Improve Derivatives Infrastructure”, *The Wall Street Journal*, September 16, 2005; and “Wall Street Is Cleaning Derivatives Mess”, *The Wall Street Journal*, February 16, 2006.

Credit default swaps allow for the transfer of credit risk from one party to another. For investors who only want the exposure for a limited period of time, such as hedge funds, the ability to take or remove the exposure with relative ease and at a fair price, i.e., an adequate level of liquidity in the CDS market, is an important consideration of using CDS contracts. Liquidity is an important issue for securities traded on more transparent and centralized exchanges, and it is a particularly acute concern for CDS contracts because of their over-the-counter, nonstandardized trading mechanics.

In general, liquidity is vaguely defined as the degree to which an asset or security can be bought or sold in the market quickly without affecting the asset's price. Liquidity has multiple facets and cannot be described by a sufficient statistic. Usually, a security is said to be liquid if its bid-ask spread is small (tightness), if a large amount of the security can be traded without affecting the price (depth), and if price recovers quickly after a demand or supply shock (resiliency).⁹ Compared to other established markets, the CDS market is relatively illiquid. The bid-ask spread is high – at 23% on average – with a sizable fixed component. The market is not continuous, as one trader has to search for another trader who can match his trade. Generally speaking, the aspects that affect liquidity of stocks and bonds should also affect liquidity of CDS contracts. These aspects include: adverse selection, inventory costs, search costs, and order handling costs.

Acharya and Johnson (2007) find evidence indicating informed trading in the CDS market. This finding implies that uninformed traders in the market face the risk of adverse selection. Consequently, they will seek to pay less when they buy protections and demand more when they sell protections in order to compensate for the risk of trading against informed traders. This situation may also deter potential liquidity providers from participating in the market and hence increase search frictions and transaction costs.

Inventory costs matter for risk-averse dealers who also face funding constraints (Brunermeier and Pedersen, 2007). Dealers with excessive inventory will worry about the risk of front-running and the costs of dynamic hedging. Cao, Evans, and Lyons (2006) show that inventory information can have a significant impact on prices even in the absence of changes in fundamental risk, and Hendershott and Seasholes (2007) illustrate how specialists' inventory influences stock prices. In the CDS market, inventory can become restrictive for dealers with

⁹Fischer Black (1971) stated that "... a liquid market is a continuous market, in the sense that almost any amount of stock can be bought or sold immediately, and an efficient market, in the sense that small amounts of stock can always be bought and sold very near the current market price, and in the sense that large amounts can be bought or sold over long periods of time at prices that, on average, are very near the current market price."

funding constraints, which will in turn affect the supply of contracts in the market.

Order handling costs can be substantial for CDS contracts, which may be reflected in bid-ask spreads. Credit derivatives deals have so far largely been processed manually. The market is opaque and a substantial backlog is suspected. Of particular concern is the post-trade clearing and settlement process. The Federal Reserve Bank of New York has requested major CDS participants in the U.S. to clean up their processing of derivatives trades.¹⁰ A survey by the International Securities and Derivatives Association (ISDA) shows that one in five credit derivatives trades by large dealers in 2005 contained mistakes.¹¹ Even though virtually all market participants are sophisticated institutional investors, the opacity of the trading mechanics in the CDS market has raised concerns about its vulnerability at the time of crisis (see, e.g., IMF (2005)).

A salient feature of opaque and decentralized markets is search frictions. CDS dealers can only fill an order through a match with a counter-party. Even with IDBs, CDS dealers will have to wait for the next trader to appear because IDBs do not take positions themselves. Search costs therefore directly affect market liquidity and market prices, as indicated in a theoretical model of OTC markets by Duffie, Garleanu and Pedersen (2005, 2006). Market makers in this search-based market may also have pricing power (Chacko, Jurek, and Stafford, 2007). The over-the-counter market in which CDS contracts are traded thus provides a good laboratory for investigating the effect of search frictions on asset valuation and the impact of the interaction between adverse selection and matching intensity on liquidity.

D. Research Hypotheses

We have delineated above various factors that can affect the liquidity of CDS contracts in the CDS market. Given that the seller bears the credit risk and faces the constraints in hedging his exposures and making the market, it is conceivable that, *ceteris paribus*, the seller would charge a higher price for a CDS contract with inferior liquidity characteristics. Therefore, we can articulate the potential impact of these aspects of liquidity on CDS spreads into the following hypothesis that can be tested with data.

HYPOTHESIS 1 *CDS spreads are higher for less liquid contracts, ceteris paribus. These include contracts with higher search costs, higher price sensitivity to trading, higher level of*

¹⁰See footnote 8.

¹¹ISDA 2005 Operations Benchmarking Survey and FpML Use Survey.

adverse selection, and higher level of inventory constraints.

If liquidity characteristics vary over time and there are common liquidity shocks across securities, investors may worry about systematic liquidity risk (see, e.g, Pástor and Stambaugh (2003)). Acharya and Pedersen (2005) propose that liquidity risk be represented by three components: (1) the sensitivity of the liquidity of individual securities to market-wide liquidity shocks (β^2); (2) the sensitivity of the return of individual securities to market-wide liquidity shocks (β^3); and (3) the sensitivity of the liquidity of individual securities to the market return (β^4). Their unconditional liquidity-adjusted CAPM relates the expected excess return of a security at time t , $E(r_t - r_t^f)$, to the expected level of liquidity, $E(c_t)$, the market beta (β^1) and the three liquidity sensitivities in the following form:

$$E(r_t - r_t^f) = E(c_t) + \lambda\beta^1 + \lambda\beta^2 - \lambda\beta^3 - \lambda\beta^4 \quad (1)$$

where $\lambda = E(\lambda_t) = E(r_t^M - c_t^M - r^f)$ is the market risk premium, with r_t^M and C_t^M being the market return and liquidity measure at time t , respectively.

While liquidity risk in derivatives has not been explored in this context so far, the pricing framework of Acharya and Pedersen (2005) should be generally applicable and can be similarly applied to the CDS market. Liquidity risk and liquidity levels are conceptually distinct from each other, even though they are often highly correlated with each other. In order to distinguish the effect of liquidity risk from the effect of liquidity characteristics, we propose to test the following hypothesis derived from this framework:

HYPOTHESIS 2 All else being equal, CDS spreads are positively related to the sensitivity of individual liquidity shocks to market-wide liquidity shocks (β^2), negatively related to both the sensitivity of shocks in individual CDS spreads to market-wide liquidity shocks (β^3) and the sensitivity of individual liquidity shocks to shocks in aggregate CDS spreads (β^4).

We note that in this hypothesis we use CDS spreads in place of the expected return in Acharya and Pedersen's framework. Because of the nature of swaps, such as CDS contracts, which do not have initial costs at the inception of the contract, the concept of percentage returns is not well-defined. Even though CDS spreads are sometimes called CDS prices, they do have the role of a value as in a true price. Valuation of CDS swaps may be done based on CDS spreads in terms of the present value of future payments such as in Duffie (1999). In this regard, as shown in Jarrow (1978), the expected percentage change of such values moves closely with the rate, which for CDS contracts is the CDS spread.

Tests of traditional CAPM models are prone to measurement errors in betas, both due to the proxy problem for the market portfolio (Roll (1977)) and the error-in-variable problem (Shanken (1992)). It is possible that this problem may be exacerbated in our test of the effect of liquidity risk in the CDS market. There is, however, an alternative way of measuring liquidity risk proposed by Johnson (2007) who argues that volume is positively related to liquidity risk because volume is determined by the varying flux of participation in trading by heterogeneous investors and thus captures the risk of shocks to the balance of demand and supply in the market. Because volume is relatively easy to measure, its role as a proxy for liquidity risk provides an independent means to confirm the effect of liquidity risk in the market. Therefore, we also set out to test the following hypothesis:

HYPOTHESIS 3 All else being equal, CDS spreads are positively related to the volume of trade in the underlying contracts.

Having developed these hypotheses, our next task is to find appropriate proxies for liquidity and liquidity risk. We will discuss our choices in the next section after we describe our CDS data set and empirical methodology used in our tests.

III. Data and Empirical Methodology

A. CDS Data

Our CDS dataset is compiled by CreditTrade and spans from June 1997 to March 2006.¹² It has information on all intraday quotes and trades, including transaction date, reference entity (bond issuer), seniority of the reference issue, maturity, notional amount and currency denomination of a CDS contract, restructuring code, and quote or trade price. In this study, we focus on CDS contracts for non-Sovereign U.S. bond issuers denominated in U.S. dollars with reference issues ranked senior and CDS maturities between 4.5 and 5.5 years. Monthly data are obtained by averaging over the month. All together, in our sample, there are 12,984 issuer-month CDS spread observations.

Average CDS spreads are plotted in Figure 1. There is a significant time-series variation

¹²Acharya and Johnson (2007), Blanco, Brennan, and Marshall (2005), Ericsson, Jacobs, and Oviedo (2007), Houweling and Vorst (2005), Norden and Weber (2004), and Zhu (2006), among others, have used the same data source.

in average CDS spreads. CDS spreads peaked in the second half of year 2002 due to the credit market turbulence at the time. CDS spreads subsequently declined afterwards possibly due to (1) improving macroeconomic conditions that lead to lower market-wide credit risk; (2) greater dominance of high quality issuers in the market; (3) increased competition in the market such that CDS sellers could not overprice CDS contracts.

Table I provides year-by-year summary statistics for our data sample. In our sample, average CDS spreads over the entire sample is 119.75 basis points. The majority of CDS contracts are for A and BBB ratings. Two observations from the summary table are noteworthy. First, the average spread for AAA bonds is about 30 basis points, which is still much higher than the predicted value of most structural models. Second, CDS spreads for AAA bonds are not always smaller than CDS spreads for AA bonds, which suggests that CDS spreads may contain components other than credit risk. Other factors such as liquidity may also be at work. Alternatively, CDS spreads may react to news more promptly than credit ratings. As shown by Hull, Predescu, and White (2004) and Norden and Weber (2004), CDS market anticipates rating announcements, especially negative rating events. For AAA bonds, the only possible rating change is downgrading. Therefore, the market could incorporate information into CDS spreads before rating agencies adjust the ratings of the corresponding reference entities.

In order to have a first glimpse of the measure of liquidity in the CDS market and its evolution over the years in our data sample, we plot in Figure 2 the time series of average bid-ask spreads, in both level and percentage terms. The graphs demonstrate that in early years, bid-ask spreads were quite high, both in terms of basis points and as a percentage of CDS spreads, indicating the lack of liquidity in the market in its development stage. In recent years, liquidity in the CDS market has improved significantly. The average bid-ask spread has dropped from the neighborhood of 40 basis points in early years to the neighborhood of 15 basis points, despite the dramatic rise in the number of contracts for reference names with less stellar credit ratings (BBB and below). Even in percentage terms, the bid-ask spread has on average narrowed substantially, from as high as 35% in January 2001 to about 17% in early 2006.

One caveat with our data is that our dataset does not cover the entire CDS market. How well our data represent the market depends on the market share of our data source and the distribution of industries in our dataset. As long as our data have a stable representation of industries over time similar to the overall market, we should be confident that the lack of comprehensive coverage of the entire market, which is not feasible due to the opaque nature

of the market, is not a concern of the first-order for our results. Our examination of the distribution of industries over the years in our data sample shows that our dataset spreads out to 28 industries overall and their respective proportions in our data seem to reflect the relative market size of debt across industries. On the other hand, anecdotal evidence seems to suggest that CreditTrade had lost significant market share to its competitors after 2004.¹³ To mitigate this concern about the data coverage, we carry out our robustness check by focusing on the subsample between 2001 and 2004, which is least prone to the data limitation. This subperiod analysis yields qualitatively the same results as the ones we report in this paper.

B. Empirical Methodology

Our objective in this paper is to examine the cross-sectional effects of liquidity characteristics and liquidity risk on CDS spreads. Our dataset is a pooled time-series and cross-section unbalanced panel. Extra care needs to be taken to analyze such a panel dataset.¹⁴ Two types of correlations need to be considered in panel data: (1) Observations from the same issuer cannot be treated as independent of each other, therefore we need to control for the issuer effect; (2) Firms in the aggregate may be affected by the same macroeconomic conditions, therefore we need to control for the time effect. Petersen (2007) provides a detailed analysis on the performance of various approaches for this type of analysis. He shows that when the firm effect exists, adjusting for firm clustering is the preferred approach, while if the time effect is important, the Fama-MacBeth approach should be applied. When both firm and time effects are present, one may consider controlling time effect in a parametric form using time dummies with firm clustering.

Petersen (2007) points out that when the standard errors clustered by firm are much larger than the White standard errors (i.e., three to four times larger), a firm effect may be present in the data. If the standard errors clustered by time are much larger than the White standard errors, then the presence of a time effect is implied in the data. Using this diagnosis, we find both firm and time effects present in our panel data, although the time effect is somewhat weak. Hence, we follow Petersen’s suggestion and conduct our regression analysis by adjusting for issuer-clustering and by controlling for the time effect with monthly time dummies. Because of the use of time dummies, we do not include any other macroeconomic

¹³CreditTrade was acquired by the Creditex in December 2006.

¹⁴Fama and French (2002) have expressed their concern about obtaining robust econometric inferences from panel data, stating that “the most serious problem in the empirical leverage literature is understated standard errors that cloud inferences.”

variables in our analysis.

The specification we use in our regression analysis is then:

$$CDSSpread_{it} = a + b \times CDSLiquidity_{it} + c \times CreditRisk_{it} + Controls + \epsilon_{it}, \quad (2)$$

with issuer-clustered t -statistics for the coefficients. Proxies for CDS liquidity characteristics and measures of liquidity risk will be discussed in the next two sections. The controls variable, in addition to the time dummy, will be described in the next subsection.

We have also entertained other approaches to obtain robust cross-sectional results. We first considered firm fixed effect rather than issuer-clustering. For the second alternative approach, we calculated the time-series average for each issuer, and then ran one cross-sectional regression. This approach suppressed any time-series variations. For the third approach, we ran a cross-sectional regression for each month. The average coefficient and its t value were then calculated by aggregating over all the months. This was the standard Fama-MacBeth approach. The results obtained from these other approaches were consistent with our issuer clustering-adjusted results. Therefore, we will only report the results based on the issuer-clustered panel regression as discussed earlier.

In addition, we also run robustness checks regarding our methodology. First, our credit risk and other control variables, even though carefully selected as discussed below, may not capture all fundamental determinants of CDS spreads. Therefore, we first regress CDS spreads on stock returns and firm credit risk characteristics to take out the fundamental portion of CDS spreads. The regression residuals are then regressed on liquidity and liquidity risk measures. The pricing role of liquidity found in this exercise is similar to the one we will discuss later in this paper, hence we will not report these results to save space.

C. Control Variables: Credit Risk and Others

In order to isolate the effects of liquidity and liquidity risk on CDS spreads, we need to control for the fundamental determinants of credit risk. We identify the set of credit risk factors that are commonly studied in the literature (see, among others, Collin-Dufresne, Goldstein, and Martin (2001), Campbell and Taskler (2003), Eom, Helwege, and Huang (2004) and Tang and Yan (2006)). Those factors affect credit spreads either through default probabilities or through expected recovery rates.

The Merton (1974) model suggests leverage ratio and asset volatility as important cross-sectional determinants of default probabilities. Leland (2004) argues that in order to better match historical default probabilities, a jump component is needed for the asset value process. Driessen (2005) estimates a reduced form model and uncovers a significant jump risk premium. Therefore, our first set of credit risk factors include leverage, asset volatility, and jump component in asset value. In theory, credit spreads should increase with leverage, asset volatility, and jump magnitude.

Leverage: We measure leverage using the book value of debt and the market value of equity in the following form:

$$\text{Leverage} = \frac{\text{Book Value of Debt}}{\text{Market Value of Equity} + \text{Book Value of Debt}}. \quad (3)$$

The market value of equity is calculated as stock price multiplied by the number of shares outstanding based on the data from CRSP. The book value of debt is the sum of short-term debt (Compustat quarterly file data item 45) and long-term debt (item 51). Note that debt level is only available at quarterly frequency. Following Collin-Dufresne, Goldstein, and Martin (2001), we use linear interpolation to obtain monthly debt levels based on quarterly data.¹⁵ We replace missing value with the previous debt level.

Option-Implied Volatility: Asset volatility is not directly observable. In a simplified framework, asset volatility should be approximately proportional to stock volatility (and leverage). Therefore, we use instead stock return volatility measured by the average monthly at-the-money stock option implied volatility calculated based on option data from Option-Metrics. Option-implied volatility measures total equity volatility, including idiosyncratic volatility. Campbell and Taskler (2003) show that idiosyncratic volatility can explain the cross-sectional variation in credit spreads as much as can credit ratings. We find option-implied stock volatility have more explanatory power than historical volatility. Cremers, Driessen, Maenhout, and Weinbaum (2006) argue that option prices contain information for credit spreads. These results further bolster the use of stock volatility as one of the fundamental control variables. Moreover, in practice, trades in credit derivatives are often carried out in concert with trades in equity derivatives in strategies to take advantage of new information about or to arbitrage among different securities of the same underlying entities.

¹⁵All of our results are not affected by this interpolation. Using quarterly leverage produces almost identical results.

Option-Implied Jump: Asset value jump size is proxied by the monthly average slope of the option-implied volatility curve. Specifically, it is the difference between the implied volatility measured at the strike-to-spot ratio of 0.9 and the implied volatility measured at the money. The idea is that the skewness of the volatility curve is mainly caused by the jump component. Similar measures of jump size are used by Collin-Dufresne, Goldstein, and Martin (2001), and Cremers, Driessen, Maenhout, and Weinbaum (2006).

Additionally, we also control for the variables below suggested by the literature. We do not control for firm balance sheet financial ratios such as profitability, cash flow volatility, asset tangibility, etc. because the data on those variables contain many missing values and the effect of these variables should be reflected in the ones we consider below.

Credit Rating: Although credit rating does not directly enter into any structural credit risk model, we include credit rating for two reasons. First, credit rating has been shown to affect credit spreads even after controlling for leverage, volatility, and other factors. Second, Molina (2005) shows that, when leverage ratio is endogenized, the effect of leverage on credit risk is much larger than in the case of exogenous leverage choice. Leverage ratio could also be chosen to target a certain credit rating (Kisgen, 2006). Therefore, credit rating should have additional explanatory power as part of the fundamental control variables. The credit rating data we use are included in our CDS database. Missing values are filled in by the data in Compustat or the Fixed Income Securities Database (FISD). Letter ratings are converted into numerical values as 37 minus the numerical number in Compustat, with AAA corresponding to 35, AA+ to 33, and D to 10, etc.

Size and Book-to-Market: We control for a firm's equity size and book-to-market equity ratio. Size and book-to-market ratio have long been argued to be associated with firm distress. Campbell, Hilscher, and Szilagyi (2007) show that book-to-market ratio and firm size are strong predictors of long-run default probability. Size and book-to-market ratios may also affect firms expected recovery rates.

Accounting Transparency: In addition, we control for accounting transparency. Duffie and Lando (2001) show in a theoretical model that accounting transparency affects credit spreads, and supporting evidence is provided by Yu (2005). We use analysts' earnings forecast dispersion as a proxy for accounting transparency. Accounting transparency helps reduce parameter uncertainty and ultimately leads to smaller forecast dispersion.

Number of Bond Issues Outstanding: A main feature of CDS contracts prior to 2004 is the dominance of physical settlement, in contrast to the cash settlement for other OTC contracts. Since firms usually have multiple bonds outstanding, physical settlement embeds a cheapest-to-deliver option in CDS contracts for CDS buyers. Therefore, the more valuable this option, the higher the CDS spread. We use the number of senior unsecured bonds outstanding issued by the same issuer as a proxy for the magnitude of the cheapest-to-deliver option, similar to the practice in the prior literature.

Table II provides descriptive statistics and a correlation matrix of our control variables. We observe the highest correlation between market capitalization and credit rating (0.553). However, other pairwise correlations among these control variables are moderate so that multi-collinearity problems should not be of a concern in our regression analysis.

D. Proxies for CDS Liquidity

Liquidity in the CDS market reflects the ease with which traders can initiate a contract at an agreeable price. It is difficult to find a single summary measure to capture the various facets of liquidity as we discussed before. In this subsection, we describe a number of variables constructed from our data set that are designed to reflect different aspects of liquidity and discuss their respective roles in our tests.

D.1. Liquidity Measures

Volatility-to-Volume Ratio (V2V): One aspect of liquidity is the depth, namely, the price sensitivity to the amount of market activity, usually indicated by volume. This is the essence of the Amihud (2002) illiquidity measure for stocks. We measure price sensitivity by the volatility of spreads. We measure the level of market activities using the total number of quotes and trades (NQT). We include quotes because these quotes are binding prices in response to market interest. Since our database contains only a subset of the CDS market and dealers can quote and trade in different segments of the market, using NQT can better capture the true level of market interest and alleviate data constraints. As CDS contracts selected in our sample mostly have \$10 million notional amount per contract, this measure is conceptually similar to trading volume. Therefore, the ratio of spread volatility over NQT should capture the notion of market depth reasonably well. We constructed this measure on

a monthly basis.

Number of Contracts Outstanding (NOC): In the inter-dealer market of CDS contracts, inventory control may be a major concern for dealers who face funding constraints. When funding constraints become binding, the capacity for dealers to take sides in additional contracts is severely impaired, and this will consequently affect the liquidity of the related contracts (Brunnermeier and Pedersen, 2007). To proxy for the overall inventory of specific contracts, we use the total number of outstanding contracts for a reference entity. Because our sample covers five-year contracts, we count the number of outstanding contracts at any point in time as the sum of CDS trades during the past five years.

Trade-to-Quote Ratio (T2Q): In a search-based market, such as the CDS market, the likelihood of finding a trading counter-party is a measure of liquidity that directly affects the price at which the asset is traded, as shown in Duffie, Garleanu and Pedersen (2005, 2006) and Chacko, Jurek, and Stafford (2007). We use the ratio of trades over quotes for a CDS contract as a measure of *matching intensity*. A higher matching intensity implies a more speedy trade, consistent with the operational measure of liquidity proposed by Lippman and McCall (1986). An increasing matching intensity, however, may come from either a demand shock or a supply shock which will have different implications for pricing. The measure is constructed on a monthly basis.

Bid-Ask Spread (BAS): Bid-ask spread is arguably the most widely used liquidity proxy in the equity market and its importance for asset prices has been established since Amihud and Mendelson (1986). We calculate bid-ask spreads on a daily basis, then average them over a month. In order to avoid artificial level effects, we measure the bid-ask spread as a percentage of the mid-quote. One caveat is that because of the data limitation, the bid-ask spreads we obtain in our dataset may not always be the narrowest in the CDS market at any point in time. However, there is no reason to believe that this should introduce any systematic bias in our findings.

Table III provides a descriptive analysis of these CDS liquidity measures. The liquidity measures have large time-series and cross-sectional variations, as demonstrated in Panel A. In general, CDS prices are sensitive to trading activities. Roughly speaking, on average each quote or trade in our data set moves the CDS spread by 2.4 basis points (mean V2V is 2.41). The mean (median) number of outstanding contracts (NOC) is 58 (25) contracts. If each contract's notional size is \$10 million, then this implies that the average firm in our sample

has CDS contracts in it covering about \$580 million credit exposure, which is a relatively small amount compared to the total debt amount of the average firm. On average, every 14 quotes would result in one trade (mean T2Q is 0.07). This low matching intensity implies that market participants often submit rather conservative quotes. Percentage bid-ask spreads are high, with a mean (median) of 23% (19%). The skewness and kurtosis of those liquidity measures are notably large.

In order to understand why some CDS contracts are more liquid than others, we regress our measures of CDS liquidity on firm characteristics and present the results in Panel B of Table IV. It appears that larger firms with higher equity volatility and lower credit ratings tend to have higher levels of interest in credit protection. This in turn helps reduce bid-ask spreads of corresponding contracts. CDS prices are more sensitive to trading when option-implied volatility is higher. Matching intensity is lower when the firm's accounting transparency is worse, suggesting information quality matters for trading execution. The relatively low R^2 s imply that liquidity is not driven by fundamentals, therefore using these fundamental explanatory variables together with the liquidity variables will not introduce collinearity in multivariate regressions.

Panel C shows that all liquidity proxies are moderately correlated. More trading (higher NOC) generally reduces the bid-ask spread (BAS), with a high correlation of -0.35 . Higher price sensitivity and lower matching intensity are associated with less trading. The bid-ask spread increases with price sensitivity and matching difficulty. Price sensitivity is higher when matching is more difficult.

D.2. Auxiliary Measures of Liquidity Environment

We observe in the summary statistics Table III that the distributions of our three liquidity proxies have substantial amount of skewness and kurtosis. This observation indicates that the CDS market could consist of groups with distinctive liquidity features. We use a number of auxiliary measures to characterize markets with different levels of search intensity, likelihood for informed trading, and supply-demand imbalance, respectively. While these are not direct measures of liquidity, they could affect the liquidity effect in various ways.

Number of Quotes (NQ): Traders express their willingness to trade and search the market for a potential counter-party by submitting a quote. The quote may or may not result in a trade. We use total number of quotes over the month as a measure of search intensity. Trades

are more likely to be completed in markets with higher search intensities. However, higher search intensity may also indicate the demand for immediacy (from either informed or uninformed traders) and attract more informed trading because information may be camouflaged more easily.

Probability of Informed Trading (PIN): Information asymmetry or adverse selection can be a major concern in the CDS market, as evidenced by the findings of Archarya and Johnson (2007). To measure the likelihood of informed trading, we adopt the methodology of Easley, Kiefer, O'Hara, and Paperman (EKOP 1997) and calculate the probability of informed trading (PIN) using intraday buys and sells. In order to obtain more accurate PIN measures, we follow EKOP and estimate PIN on an annual basis.

Order Imbalance (OIB): Different markets may have different latent liquidity demand. High trading volume does not necessarily correspond to a high level of liquidity. For instance, some record volume dates in the stock market (e.g., October 29, 1929 and October 19, 1987) experienced the least amount of market liquidity. Excess demand in the market may have a different impact on asset prices than excess supply. Order imbalance measures this variation in the demand-supply dynamics and has been used often in recent asset pricing literature as a liquidity measure (e.g, Bollen and Whaley (2004) and Chordia, Roll and Subrahmanyam (2002)). We use the Lee-Ready (1991) algorithm to identify order direction and measure order imbalance as the difference between buyer initiated orders and seller initiated orders, aggregated on the monthly basis. Therefore, this measure is also an indicator of buying pressure, as it represents the net demand for specific contracts.

Our unreported correlation analysis shows that bid-ask spread (BAS) is negatively related to order imbalance (OIB), number of outstanding contracts (NOC), and PIN. NQ is positively correlated with OIB and NOC. The positive correlation between NQ and PIN indicates that the risk of adverse selection is likely to be higher when search intensity is stronger. This finding is consistent with the intuition that informed traders are likely to seek out liquid trading venues to realize the value of their information (see, e.g., Admati and Pfleiderer (1988)).

IV. Liquidity Characteristics and CDS Spreads

We first investigate how liquidity characteristics as measured by our proxies affect CDS spreads. In our analysis, we regress CDS spreads on individual CDS liquidity measures while controlling for the fundamental variables associated with credit risk. We first perform our analysis using the full sample. To further delineate the nature of the liquidity effect, we then investigate the cross-sectional variations of the liquidity effect in different trading segments.

A. The Overall Liquidity Effect

Table IV presents the results of the effect of liquidity characteristics on CDS spreads obtained in the full sample.¹⁶ The first column shows that CDS spreads increase in V2V, namely, the higher the price sensitivity to the amount of market activity, the higher the CDS spread, *ceteris paribus*. This is consistent with the notion that a premium is demanded for a security with a thin market depth, as V2V corresponds to the inverse of the market depth. This result indicates that CDS sellers capture the liquidity premium because they provide liquidity in the CDS markets as the buyers of credit risk.

The second column of the table reveals that a higher number of contracts outstanding causes a higher CDS spreads, holding all else the same. If one considers a higher number of outstanding contracts as an indication of a higher level of liquidity, this result seems to suggest a liquidity discount. While this appears to be consistent with Deuskar, Gupta and Subrahmanyam's (2006) findings in the interest rate derivatives market, it is contrary to the results from equity markets. However, this discrepancy may be reconciled if we argue that higher numbers of outstanding contracts in a specific name increase the likelihood that dealers' funding constraints become binding, and thus raise their inventory costs and subsequently the CDS spreads, in the same mechanism articulated in Brunnermeier and Pedersen (2007). If the number of contracts outstanding is a measure of illiquidity, then our finding suggests again that CDS sellers are compensated for providing liquidity services.

In contrast, CDS spreads are generally negatively associated with T2Q, a measure of

¹⁶In all regressions, we maintain the control for the fundamental variables that capture default risk, recovery risk and information risk. Their effects on CDS spreads are all consistent with the findings in the prior literature. The number of bonds issued by reference entities is also important, indicating both the demand for protection and the cross-market liquidity spillover, which is left for future research. Table IV also indicates that CDS spreads are well explained by these fundamental variables and liquidity, as R^2 's of these regression are around 60%.

search frictions in terms of matching intensity in the market for a particular contract, as shown in the third column of Table IV. This association is consistent with the notion that increasing matching intensity may signal increased liquidity, and hence reduce the premium for illiquidity. However, as we mentioned earlier, the relative ease of trading in underlying contracts may exacerbate the funding constraints for dealers, or invite informed traders in the presence of information asymmetry. These aspects may adversely affect liquidity in the face of improving matching intensity and induce a cross-sectional variation of the impact of matching intensity on CDS spreads. This potential cross-section variation may account for the lack of statistic significance in the coefficient. We will further investigate this claim in the next subsection.

Bid-ask spread is a commonly used measure of liquidity, as it embodies various components such as adverse selection, inventory costs, and search frictions that affect liquidity and capture directly the associated trading costs. Indeed, as demonstrated in the fourth column of Table IV, all else being equal, CDS spreads in general increase with bid-ask spreads, consistent with our expectation. The statistical significance of the coefficient is at the 10% level, which is not as strong as that found in other markets. In fact, using a sample of most actively traded benchmark names, Acharya and Johnson (2007) fail to find a significant relationship between CDS spreads and bid-ask spreads, despite the evidence of informed trading in the market. This again calls for attention on possible cross-sectional variations in the relative importance of various aspects of liquidity in this over-the-counter search markets of insurance contracts.

In summary, we find strong evidence for illiquidity premium in the CDS market. Moreover, the premium seems to be captured by CDS sellers. Although we do not have a structural model for liquidity pricing in the CDS market, we attempt to quantify the magnitude of illiquidity premium by multiplying the coefficient estimate by the standard deviation of the corresponding liquidity proxy, following Acharya and Pedersen (2005). We find that the illiquidity premia associated with the four liquidity proxies – price sensitivity of trading, inventory constraint, matching intensity, and bid-ask spread – are 32.5, 17.8, 0.4, and 2.4 basis points, respectively. The average of these estimates is 13.2 basis points. Given the average level of the CDS spread at 120 basis points, the liquidity premium represents a substantial portion of the CDS spread.

The range of CDS liquidity premium estimates is comparable to the estimate of the 5-year Treasury bond liquidity premium (9.99 basis points) provided by Longstaff (2004), as well as to the average size of the non-default component of corporate bond spreads (8.6 basis points)

estimated by Longstaff, Mithal, and Neis (2005) using swap curves. Moreover, to illustrate the economic significance of the liquidity effect in the CDS market, we multiply 13.2 basis points by the CDS market nominal amount of \$12.43 trillion at the end of our sample period according to ISDA 2006 Mid-Year Market Survey, resulting in a total liquidity premium of \$16.4 billion contained in CDS contracts over the entire development stage of the CDS market (1997-2006). In other words, market making in the CDS market over the last decade may have yielded a significant premium on the order of \$10 billion. This large premium captured by liquidity providers may help explain the flourish of the credit derivatives market. Our estimates represent the first quantitative evidence for the importance of liquidity in the CDS market.

Probably surprisingly, even though the CDS market is an OTC market with substantial search costs, our results on the effect of matching intensity and bid-ask spread are rather weak. Our intuition is that adverse selection and matching intensity are positively correlated due to strategic trading. In other words, when trading is relatively more fluid, informed trading may be more intense. In the next subsection, we formally investigate this conjecture that may shed some light on the driving forces of the liquidity effect in the CDS market.

B. Cross-sectional Variations in the Liquidity Effect

There are several reasons for cross-sectional variations in the liquidity effect on CDS spreads. For sparsely traded contracts, search frictions may be the dominant aspect of liquidity, while for actively traded names, the risk of adverse selection and funding constraints can be overriding concerns. Moreover, imbalance of supply and demand in the CDS market can also impact the character of the liquidity effect, as discussed in Garleanu, Pedersen, and Poteshman (2007). Therefore, we use three auxiliary measures described before, NQ , PIN and OIB , to cut the sample so that we can study if and how the impact of liquidity characteristics represented by the four measures above differs across subsamples. The results are reported in Table V, where we omit the coefficients on the same set of control variables that are qualitatively same as in Table IV.

In Panel A, the sample is divided into a subsample of contracts with no more than 30 quotes ($NQ \leq 30$) per month and another subsample of contracts with more than 30 quotes in the month. We intend to separate out the most intensively searched contracts from the rest. We have conducted robustness checks with various cutoff points and found similar results as

long as the most active subsample is isolated. The results in this panel show that the effect of market depth as measured by V2V is approximately the same across the two subsamples, so is the effect of NOC. However, for the measure of matching intensity, T2Q, the sparsely traded sample shows a negatively relationship between CDS spreads and T2Q, same as for the full sample, with improved statistical significance (at the 10% level). This relationship implies that among sparsely traded names, search and matching frictions in the market are an important component of liquidity and command an illiquidity premium. This is not the case for actively traded names, for which the coefficient on T2Q turns positive and is statistically insignificant. This result could imply either that among these names, the ease of trading has reached the level with which search frictions are no longer a major concern, or that there might still be further cross-sectional variations among these names due to their different levels of information asymmetry or supply-demand balance.

When we examine the effect of the bid-ask spread on CDS spreads in the two subsamples, we find CDS spreads are positively associated with bid-ask spreads very strongly among sparsely traded names, with the point estimate of the coefficient 2.5 times of the coefficient obtained for the full sample and its t-statistic improved from 1.88 to 2.28. For actively traded names, however, there is no discernible impact of the bid-ask spread on CDS spreads. This is exactly what Acharya and Johnson (2007) have documented using the benchmark names that by design are the most actively traded in the market. Nevertheless, this result alone can not imply that liquidity is not priced in the CDS market, as our earlier results have clearly established an affirmative conclusion. What this result does indicate is still further possibilities that other factors may affect the liquidity effect in the market.

As Acharya and Johnson (2007) have shown, one of the factors is informed trading due to asymmetric information. In order to examine the impact of the likelihood of informed trading on the liquidity effect, we divide the full sample into a subsample of contracts with PIN below the eightieth percentile (0.25) and another sample with PIN above the eightieth percentile. Again, robustness checks assure that the results are not due to the specific breakpoint for the sample. The results presented in Panel B show that while in both samples, CDS spreads is positively associated with V2V, the effect is weaker when PIN is higher. This is interesting because the notion of market depth is indeed first developed with the informed trading in Kyle (1985). Because V2V is related to the inverse of market depth, the positive association actually implies a discount for a deep market in a particular contract. When PIN is large, the reduced sensitivity of CDS spreads to V2V indicates a smaller discount for market depth. This effect is consistent with the idea that a deep market attracts informed trading, and hence in

equilibrium, the price responds less strongly to market depth (Admati and Pfleiderer, 1988).

Other notable differences between the two subsamples are for T2Q and BAS, as demonstrated in Panel B. For names with small PINs, their CDS spreads decrease in T2Q, the matching intensity, with a stronger t-statistic than the full sample. For names with large PINs, however, their CDS spreads actually increase with T2Q. The sign difference is also statistically significant. This implies that for these names, search frictions are no longer of the primary concern, as the ease of trading actually facilitates informed trading, and thus increases the risk of adverse selection for traders. Therefore, CDS spreads are increased to account for this additional dimension of risk that affects the liquidity of the contracts. The other surprising finding is that for names with large PINs, CDS spreads decrease with bid-ask spreads, reversing the relationship in the full sample and among names with small PINs. One possible scenario consistent with this result is to postulate that informed trading is mostly from CDS buyers, which is consistent with the observation of the data. When this happens, the bid-ask spread will widen to reflect the increased risk of adverse selection, especially for the seller, yet the traded price may not fully reflect the true information of the informed traders, i.e., below its *ex post* true value. *ceteris paribus*, this may induce the observed negative association between CDS spreads and bid-ask spreads among names with high levels of information asymmetry.

Like any other derivatives markets, it is a zero-sum game in the CDS market. Therefore the shifting balance of supply and demand in the market will also have an important impact on the liquidity effect in the market. We separate the sample into one with a positive order imbalance (OIB), i.e., with excessive demand, and one with a negative OIB, i.e., with excessive supply. The important differences across the two subsamples again come from the effects of T2Q and BAS. For the excess supply sample, a higher matching intensity (higher T2Q) leads to a larger discount in CDS spreads, consistent with, but stronger than, the result in the full sample. For the excess demand sample, however, a higher T2Q leads to a higher premium in CDS spreads. Sellers offer discounts in contracts with high matching intensities and excess supplies and extract extra compensations for the risk of adverse selection and binding funding constraints on contracts with high matching intensities and excess demand. Hence, these results reinforce the earlier indication that sellers, as liquidity providers, have the pricing power in the CDS market. Since informed traders tend to be buyers of credit protection, the argument at the end of the last paragraph may be used to understand the negative, albeit statistically insignificant, coefficient on bid-ask spread for contracts with excess demand in the last column of Table V.

Our cross-sectional analysis reveals that different aspects of liquidity manifest themselves differently among securities with different levels of market activities. For thinly traded contracts, search frictions dominate the liquidity effect, while for actively traded names, adverse selection becomes an important concern. The strategic trading of informed participants in the market leads to an interesting interplay between adverse selection and matching intensities that endogenously affect the character of the liquidity of the related contracts and hence their prices. The rich cross-sectional variations we discuss here demonstrate the complexity of the liquidity effect in security markets.

V. Liquidity Risk and CDS Spreads

We have observed in Figure 2 that there are substantial time-series variations in CDS liquidity, as measured by the bid-ask spread. If liquidity varies over time and there are common liquidity shocks across securities, investors may worry about systematic liquidity risk. We use two approaches to test whether liquidity risk is priced in CDS spreads beyond liquidity levels. First, we directly construct CDS liquidity betas and run asset pricing tests in the framework of Acharya and Pedersen (2005). Second, we adopt a measure of volume in the CDS market as an aggregate proxy for liquidity risk following the argument in Johnson (2007).

A. Liquidity Betas

In this section, we estimate CDS liquidity betas and test the liquidity-adjusted CAPM as specified in Equation (1). As we discussed previously, among the four measures of liquidity, bid-ask spread is the composite measure of liquidity capturing the costs associated with adverse selection, funding constraint, and search frictions. Therefore, we use the bid-ask spread to conduct our analysis of liquidity risk. We follow Acharya and Pedersen (2005) to perform the pricing tests of liquidity risk in the following steps:

- (i) We estimate, in each month t , a measure of illiquidity, c_t^i , for each CDS contract i . Specifically, c is the percentage bid-ask spread. We estimate the illiquidity shock or innovation $c_t^i - E_{t-1}(c_t^i)$ as the residual of the following AR(2) process for illiquidity:

$$ILLIQ_t = a_0 + a_1 \times ILLIQ_{t-1} + a_2 \times ILLIQ_{t-2} + u_t. \quad (4)$$

That is, $ILLIQ_t = c_t^i$, and $c_t^i - E_{t-1}(c_t^i) = u_t$. The AR(2) process is used to filter out the persistence in illiquidity. We estimate the innovation in CDS spreads, $r_t^i - E_{t-1}(r_t^i)$, in the same way.

- (ii) We form a “market portfolio” as an equal-weighted aggregate of the CDS contracts in our data set in each month. The innovations to the market-wide illiquidity $c_t^M - E_{t-1}(c_t^M)$ and innovations to market CDS spreads $r_t^M - E_{t-1}(r_t^M)$ are estimated in the same way as for the innovations of individual contracts above.
- (iii) Using these individual and market innovations in both CDS illiquidity measures and CDS spreads, we estimate the liquidity betas for each CDS reference entity i as the following:

$$\beta^{1i} = \frac{\text{cov}(r_t^i, r_t^M - E_{t-1}(r_t^M))}{\text{var}(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}, \quad (5)$$

$$\beta^{2i} = \frac{\text{cov}(c_t^i - E_{t-1}(c_t^i), c_t^M - E_{t-1}(c_t^M))}{\text{var}(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}, \quad (6)$$

$$\beta^{3i} = \frac{\text{cov}(r_t^i, c_t^M - E_{t-1}(c_t^M))}{\text{var}(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}, \quad (7)$$

$$\beta^{4i} = \frac{\text{cov}(c_t^i - E_{t-1}(c_t^i), r_t^M - E_{t-1}(r_t^M))}{\text{var}(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}. \quad (8)$$

This estimation is conducted over the entire sample, resulting in one set of liquidity betas per CDS name. We do not consider time-varying liquidity-betas to mitigate estimation risk due to the short span of the sample time-series.

- (iv) Finally, we consider the empirical fit of the (unconditional) liquidity-adjusted CAPM by running cross-sectional regressions. Namely, we regress the monthly average of CDS spreads for each reference entity on their respective betas as measured above and on the corresponding liquidity measure, while maintaining the other control variables for credit risk, recovery and information uncertainty. We also estimate the regression coefficient of $\beta^{net} = \beta^1 + \beta^2 - \beta^3 - \beta^4$, similar to Acharya and Pedersen (2005). To check the robustness of our results, we carry out an analysis with a number of different specifications.

The results of our analysis are presented in Table VI with the bid-ask spread (BAS) as the (il)liquidity measure. In the first regression model presented in the first column of the table, we include both the liquidity measure and the composite liquidity beta, β^{net} . The result shows that both the liquidity measure and the liquidity risk (in the form of β^{net}) are positively priced in CDS spreads. One standard deviation change in the composite beta is

associated with 10.9 basis points change in CDS spreads. In comparison, the same regression yields a premium of 3.7 basis points for the liquidity level. The second model is designed to investigate the effect of β^1 , which should represent the systematic default risk on CDS spreads. The result shows no impact of β^1 on CDS spreads. This is not surprising because we have already included a number of variables controlling for default risk in our regression, and there may not be much residual systematic default risk not captured by these variables. Specification (3) is consistent with specification (2) in showing that the net beta effect mostly comes from the aggregate of the three liquidity betas.

In the last model, we examine the separate effects of various betas. We observe a positive and significant coefficient on β^2 , which measures the sensitivity of individual liquidity shocks to market-wide liquidity shocks, consistent with the prediction in equation (1). The coefficient on β^3 , which measures the sensitivity of shocks to individual CDS spreads to market-wide liquidity shocks, is negative and marginally significant. This is also consistent with the prediction of the Acharya-Pedersen model. The coefficient on β^4 , however, is insignificant. As β^4 measures the sensitivity of individual liquidity shocks to market-wide CDS spread shocks, it implies that the impact of shocks to aggregate CDS spreads on the liquidity of individual names appears to be minimal.

Generally speaking, our results confirm the qualitative impact of liquidity betas, especially β^2 and β^3 , on CDS spreads as predicted in the Acharya-Pedersen specification of a liquidity-based CAPM. We do not attempt a quantitative assessment here because of the issue of the benchmark portfolio and the error-in-variable problem in the estimation of betas and their use in the second stage of cross-sectional regressions. This is the problem that has plagued tests of traditional CAPM models, and our estimation framework cannot escape from that issue, either. Given the relatively short time-series of our dataset, these measurement problems are not likely to be resolved.

B. Liquidity Risk Proxied by Volume

Given the practical problems involving the measurement of liquidity betas, an alternative scheme of assessing the effect of liquidity risk would be a welcome addition. In an interesting recent paper, Johnson (2007) argues that the volume of trade is driven by the degree of rearrangement, or flux, of the trading population. While higher trading volume does not necessarily signal better liquidity (i.e., the 87' market crash), it is indicative of a higher

population flux that leads to liquidity changes. Therefore, volume is associated with the second moment of liquidity changes, i.e., the liquidity risk. Therefore, volume may serve as a proxy for liquidity risk. Since volume can be directly observed, the lack of an estimation problem with this proxy is an added advantage.

Our volume measure in the CDS market is the aggregate notional amount of all quoted and traded contracts over the month. (Notional CDS contract size usually ranges from \$1 million to \$20 million.) We investigate the explanatory power of CDS volume for CDS spreads after controlling for liquidity characteristics and other credit factors in the following regression:

$$CDS\text{Spread}_{it} = a + \lambda\text{Volume} + b \times CDSLiquidity_{it} + c \times CreditRisk_{it} + Controls + \epsilon_{it}. \quad (9)$$

Table VII presents the results of our estimation with different methods of controlling for liquidity characteristics. In the first model, we include only the volume measure, in addition to the control variables, to assess if this measure can capture some variations in CDS spreads. Indeed, we find a significantly positive association between CDS spreads and volume, consistent with the notion that liquidity risk earns a positive risk premium. Model 2 adds three liquidity measures, V2V, NOC and T2Q, into the regression as they capture different aspects of liquidity. The result shows that these variables and the volume measure retain their own statistical significance, signaling the importance of various aspects of liquidity measures and liquidity risk in accounting for the overall liquidity effect on CDS spreads. Because the bid-ask spread typically embodies various aspects of liquidity, we specify Model 3 by including only BAS as the liquidity measure to size up its effect in the presence of volume. The result again shows that both volume and bid-ask spreads retain their own importance in the regression.

Finally, we include all liquidity measures and the volume measure in Model 4 and demonstrate that all these variables play a significant role in accounting for the liquidity effect on CDS spreads. It is worth pointing out that after controlling for volume and the other three measures of liquidity, bid-ask spread becomes negatively associated with CDS spread. Note that by including NOC, we have to filter out many contracts with almost no trading; therefore, the sample may be dominated by actively traded names. The negative sign on BAS in Model 4 may reflect the same force that was discussed for the results in the last column of Table V in the previous section.

In summary, the results in this section demonstrate that liquidity risk is positively priced

in the CDS beyond the effect of liquidity characteristics. In fact, our findings suggest that the effects of liquidity characteristics and liquidity risk are complements, rather than substitutes.

VI. Concluding Remarks

In this paper, we present an empirical study of the pricing effect of liquidity and liquidity risk in the credit default swaps market. Using a rich data set of credit default swaps (CDS) transactions, we construct liquidity proxies to capture various facets of CDS liquidity and examine the impact of different aspects of liquidity in this search market with adverse selection and inventory constraints. We find that both liquidity level and liquidity risk are significant factors in determining CDS spreads. We estimate the average liquidity premium using different liquidity proxies to be 13.2 basis points in CDS spreads, on par with the Treasury bond liquidity premium and the nondefault component of corporate bond yield spreads. Liquidity risk is positively priced beyond liquidity levels, with an estimated liquidity risk premium of around 10.9 basis points. On average, liquidity and liquidity risk together could account for about 20% of CDS spreads. Moreover, we document cross-sectional variations in the liquidity effect as the consequence of the search-based over-the-counter market structure and the interplay between search friction and adverse selection in CDS trading.

Our findings highlight the need for a CDS pricing model that explicitly takes liquidity effects into account. In an over-the-counter market of derivatives contracts that are in zero net supply, the supply curve for CDS contracts may be a function of order flows. The demand-supply dynamics are affected by search frictions, the market maker's pricing power, hedging costs and the risk of adverse selection that endogenously determine the liquidity of the securities and, in turn, their prices. While some recent studies have provided insights into this new aspect of asset pricing dynamics,¹⁷ more theoretical and empirical research on this subject is certainly warranted.

¹⁷See, e.g., Bollen and Whaley (2004), Cetin, Jarrow, Protter, and Warachka (2006), Chacko, Jurek, and Stafford (2007), and Garleanu, Pedersen, and Poteshman (2007).

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Table I
CDS Data Summary Statistics

This table reports pooled time-series and cross-sectional year-by-year summary statistics of monthly average CDS spreads in basis points from June 1997 to March 2006. Data is from a major CDS broker CreditTrade. This sample selects only non-sovereign US bond issuers denominated in US dollars with reference issue ranked senior unsecured and maturity around five years. Intradaily quotes and trades are aggregated to obtain monthly average CDS spreads.

		Rating Groups						
		AAA	AA	A	BBB	BB	B	NR
1997	N	2	5	19	12	3	1	7
(from June)	Mean	32.50	23.00	41.05	38.04	66.67	120.00	38.24
	Std	3.54	20.53	42.74	12.04	40.41	.	34.21
1998	N	4	32	101	49	9	8	25
	Mean	50.42	41.92	33.02	51.88	68.50	28.73	40.21
	Std	20.43	35.00	19.20	37.56	46.70	7.26	22.01
1999	N	8	64	221	133	13	12	37
	Mean	38.86	31.69	35.85	66.56	55.06	34.31	53.32
	Std	25.16	16.27	20.89	40.30	36.11	16.48	46.38
2000	N	12	75	298	343	62	25	60
	Mean	49.72	41.28	57.99	125.18	205.26	196.84	132.47
	Std	30.38	27.73	48.35	109.29	130.55	188.34	112.15
2001	N	17	122	490	551	104	60	112
	Mean	49.89	50.99	84.21	163.36	331.83	372.16	216.06
	Std	29.28	27.72	57.67	100.48	170.50	274.64	165.25
2002	N	34	170	765	1041	204	64	58
	Mean	56.15	60.20	107.09	209.67	422.03	401.15	216.55
	Std	42.90	49.23	87.44	179.41	231.25	268.91	180.62
2003	N	53	104	706	1214	238	99	36
	Mean	28.00	31.65	59.35	122.13	344.17	508.78	127.52
	Std	24.36	23.84	56.26	102.61	197.48	279.47	122.97
2004	N	47	72	518	899	248	79	176
	Mean	15.42	23.56	41.66	72.05	195.01	289.90	116.04
	Std	9.35	9.53	38.15	44.34	118.59	171.30	114.53
2005	N	31	88	541	1054	360	111	315
	Mean	10.60	18.90	32.55	57.70	151.30	301.94	136.91
	Std	4.75	8.21	27.47	41.16	95.47	134.19	155.46
2006	N	13	26	114	207	71	22	86
(till March)	Mean	7.57	16.38	32.73	61.08	143.61	353.84	98.49
	Std	3.15	6.96	28.37	54.25	131.57	182.52	118.64
All	N	221	758	3773	5503	1312	481	912
	Mean	29.72	39.73	62.90	118.04	251.38	349.81	136.58
	Std	29.49	33.67	62.30	118.52	189.43	243.16	145.09
	Min	3.88	4.68	2.00	7.88	15.00	24.00	7.36
	Max	250.00	382.22	558.60	1500.00	1400.00	1350.00	917.86

Table II
Sample Firm Characteristics

This table shows the summary statistics of our sample firm characteristics which will be used as control variables in our regressions. OIV is monthly average at-the-money option implied volatility. Jump is option implied jump risk (at-the-money OIV - 10% in-the-money OIV). Credit rating is numerical ratings, with 35 given to AAA and 10 given to D. Leverage is the ratio of book debt over the sum of book debt and market equity. B/M is book to market ratio. ME is market equity capitalization. Forecast Disp is analysts forecast dispersion (standard deviation over mean) over annual earnings. NBonds is total number of senior unsecured bonds issued by the firm.

Panel A: Summary Statistics					
	Obs	Mean	Std. Dev.	Min	Max
OIV	10466	0.37	0.15	0.03	1.43
Jump ($\times 100$)	10466	0.22	0.87	-12.97	14.01
Credit Rating	12075	26.88	2.86	10.00	35.00
Leverage	11047	0.31	0.23	0.00	0.99
B/M	11357	0.49	0.36	0.00	7.58
Ln(ME)	11735	9.39	1.26	3.96	12.86
Forecast Disp.	10854	0.09	0.46	0.00	11.00
NBonds	9544	9.34	10.81	1.00	108.00

Panel B: Correlation Matrix							
	OIV	Jump	Rating	Leverage	B/M	Ln(ME)	Disp.
OIV	1.000						
Jump	0.002	1.000					
Credit Rating	-0.228	-0.089	1.000				
Leverage	0.167	0.073	-0.131	1.000			
B/M	0.314	0.111	-0.261	0.348	1.000		
Ln(ME)	-0.181	-0.118	0.553	-0.189	-0.375	1.000	
Forecast Disp.	0.092	0.017	-0.129	0.066	0.156	-0.076	1.000
NBonds	0.019	-0.023	0.167	0.435	0.021	0.243	-0.001

Table III
CDS Liquidity Proxies

This table describes liquidity proxies for individual CDS names. V2V is the ratio of monthly CDS spread volatility over total number of quotes and trades over the month. NOC is the total number of CDS contracts traded during the past 60 months, or total number of CDS contracts outstanding. T2Q is the ratio of number of trades over number of quotes per month. BAS is the monthly average percentage bid-ask spread. Data spans from June 1997 to March 2006 from a major CDS broker CreditTrade. Panel A provides the summary statistics. Panel B shows results regressing liquidity proxies on firm characteristics and monthly dummies. Robust t values in parenthesis (absolute number) are adjusted by firm clustering. Panel C shows the correlations among five liquidity proxies.

	CDS Liquidity Proxied by:			
	V2V	NOC	T2Q	BAS
Panel A: Summary Statistics				
Mean	2.41	57.71	0.07	0.23
Std	7.94	80.69	0.31	0.16
Skewness	17.08	2.78	13.17	2.22
Kurtosis	509.29	10.93	298.42	9.20
1st	0.00	1	0.00	0.03
5th	0.00	2	0.00	0.07
25th	0.19	8	0.00	0.12
50th	0.60	25	0.00	0.19
75th	1.81	76	0.00	0.29
95th	9.95	228	0.36	0.53
99th	31.81	348	1.15	0.80
Panel B: Determinants of CDS Liquidity				
Const	13.57 (9.19)	-44.32 (0.79)	-0.03 (0.65)	0.22 (2.86)
OIV	4.96 (3.55)	39.49 (1.35)	0.02 (0.43)	-0.15 (5.40)
Jump	29.83 (1.59)	-124.38 (0.88)	-0.47 (0.80)	-0.03 (0.16)
Credit Rating	-0.15 (2.99)	-7.00 (4.46)	-0.01 (2.55)	0.02 (7.37)
Leverage	-0.51 (1.05)	74.91 (2.95)	0.02 (1.34)	-0.19 (13.69)
B/M	0.61 (1.29)	4.53 (0.41)	0.02 (1.39)	-0.04 (3.87)
Ln(ME)	-0.57 (4.85)	23.87 (5.59)	0.02 (4.55)	-0.04 (8.13)
Forecast Disp.	0.14 (0.57)	0.03 (0.01)	-0.01 (1.68)	-0.01 (1.91)
Adj. R^2	0.112	0.295	0.075	0.248
Panel C: Correlation Matrix				
V2V	1.00			
NOC	-0.17	1.00		
T2Q	0.26	-0.16	1.00	
BAS	0.22	-0.35	0.08	1.00

Table IV
CDS Illiquidity and CDS Spreads

This table shows the effects of CDS illiquidity on CDS spreads using four liquidity proxies. Shown in the table are panel regression results. The dependent variable is monthly average CDS spreads. CDS data spans from June 1997 to March 2006 from a major CDS broker CreditTrade. The four liquidity proxies are V2V (the ratio of monthly CDS spread volatility over total number of quotes and trades over the month), NOC (the total number of CDS contracts traded during the past 60 months, or total number of CDS contracts outstanding), T2Q (the ratio of number of trades over number of quotes per month), and BAS (the monthly average percentage bid-ask spread). OIV is monthly average at-the-money option implied volatility. Jump is option implied jump risk (at-the-money OIV - 10% in-the-money OIV). Credit rating is numerical ratings, with 35 given to AAA and 10 given to D. Leverage is the ratio of book debt over the sum of book debt and market equity. B/M is book to market ratio. ME is market equity capitalization. Forecast Disp is analysts forecast dispersion (standard deviation over mean) over annual earnings. NBonds is total number of senior unsecured bonds issued by the firm. Monthly dummies (not shown) are also included in the regressions. Issuer-clustering is adjusted to obtain robust t-values.

	CDS Liquidity Proxied by:							
	V2V		NOC		T2Q		BAS	
	Coef.	<i>t</i>	Coef.	<i>t</i>	Coef.	<i>t</i>	Coef.	<i>t</i>
Const ($\times 10^2$)	1.82	4.05	1.86	3.41	2.13	4.68	1.95	3.67
OIV ($\times 10^2$)	4.64	11.57	4.61	10.08	4.83	12.07	4.90	10.74
Jump ($\times 10^2$)	6.31	3.05	6.53	2.08	8.22	3.37	9.63	3.84
Credit Rating	-13.26	-8.64	-12.35	-6.81	-13.74	-8.49	-15.11	-8.70
Leverage	49.18	2.69	47.17	1.94	50.27	2.76	57.56	2.97
B/M	34.80	2.45	29.45	1.93	40.15	2.80	31.05	1.97
Ln(ME)	2.85	0.85	-5.25	-1.04	1.21	0.34	3.03	0.79
NBonds	-0.53	-1.89	-0.68	-1.77	-0.64	-2.24	-0.62	-2.04
Forecast Disp	10.11	1.78	5.33	1.43	9.35	1.50	11.94	1.63
CDS Liquidity	4.09	6.96	0.22	4.46	-1.11	-1.41	14.71	1.88
<i>N</i>	6462		2109		7292		5447	
Clusters	364		261		371		345	
Adj. R^2	0.617		0.605		0.581		0.590	

Table V
CDS Illiquidity and CDS Spreads: Cross-sectional Variations

This table shows subsample results of the effects of CDS illiquidity on CDS spreads using four liquidity proxies. Shown in the table are panel regression results. The dependent variable is monthly average CDS spreads. CDS data spans from June 1997 to March 2006 from a major CDS broker CreditTrade. The four liquidity proxies are V2V (the ratio of monthly CDS spread volatility over total number of quotes and trades over the month), NOC (the total number of CDS contracts traded during the past 60 months, or total number of CDS contracts outstanding), T2Q (the ratio of number of trades over number of quotes per month), and BAS (the monthly average percentage bid-ask spread). The set of independent variables are the same as in Table IV. Only the coefficient estimates and t-values for the liquidity proxies (and their difference) across subsamples are shown. The subsample separators are NQ, PIN and OIB. NQ is the total number of quotes per month, as a proxy for search intensity of the CDS market. PIN is the probability of informed trading estimated using intradaily quotes and trades, following EKOP (1997). PIN is estimated annually. OIB is the difference between number of buyer-initiated orders and seller-initiated orders per month, as a proxy for liquidity demand. Monthly dummies (not shown) are also included in the regressions. Issuer-clustering is adjusted to obtain robust t-values.

	CDS Liquidity Proxied by:							
	V2V		NOC		T2Q		BAS	
	Coef.	<i>t</i>	Coef.	<i>t</i>	Coef.	<i>t</i>	Coef.	<i>t</i>
	Panel A: By Search Intensity							
NQ \leq 30	4.25	6.95	0.25	3.62	-1.59	-1.58	35.78	2.28
NQ $>$ 30	4.55	7.65	0.18	3.35	19.42	1.11	-29.47	-0.52
	Panel B: By Information Asymmetry							
PIN \leq 0.25	4.74	8.60	0.23	4.64	-7.90	-1.73	19.09	1.69
PIN $>$ 0.25	2.60	2.52	0.34	3.14	6.99	2.00	-53.95	-1.79
	Panel C: By Liquidity Demand							
OIB $<$ 0	3.97	2.36	0.20	3.89	-14.41	-2.34	39.27	2.23
OIB $>$ 0	5.41	4.59	0.24	4.14	6.62	2.13	-29.94	-1.35

Table VI
CDS Illiquidity Risk and CDS Spreads: Liquidity Beta Approach

This table shows the effects of CDS illiquidity risk measured by liquidity betas on CDS spreads. Shown in the table are panel regression results. The dependent variable is monthly average CDS spreads. CDS data spans from June 1997 to March 2006 from a major CDS broker CreditTrade. OIV is monthly average at-the-money option implied volatility. Jump is option implied jump risk (at-the-money OIV - 10% in-the-money OIV). Credit rating is numerical ratings, with 35 given to AAA and 10 given to D. Leverage is the ratio of book debt over the sum of book debt and market equity. B/M is book to market ratio. ME is market equity capitalization. Forecast Disp is analysts forecast dispersion (standard deviation over mean) over annual earnings. NBonds is total number of senior unsecured bonds issued by the firm. CDS illiquidity is proxied by the monthly average percentage bid-ask spread. Betas $\beta^1, \beta^2, \beta^3, \beta^4$ are constructed according to equations (5)-(8). $\beta^{net} = \beta^1 + \beta^2 - \beta^3 - \beta^4$. Monthly dummies (not shown) are also included in the regressions. Issuer-clustering is adjusted to obtain robust t-values.

	Models:							
	(1)		(2)		(3)		(4)	
	Coef.	<i>t</i>	Coef.	<i>t</i>	Coef.	<i>t</i>	Coef.	<i>t</i>
Const ($\times 10^2$)	1.99	3.74	1.90	3.54	1.98	3.73	1.97	3.72
OIV ($\times 10^2$)	4.86	10.71	4.86	10.39	4.83	10.48	4.85	10.49
Jump ($\times 10^2$)	10.01	3.95	9.64	3.86	10.04	3.98	10.04	4.00
Credit Rating	-14.88	-8.48	-15.10	-8.65	-14.90	-8.49	-14.92	-8.50
Leverage	54.94	2.88	59.38	3.11	56.56	3.01	56.75	3.01
B/M	30.51	1.95	29.89	1.93	29.58	1.91	29.31	1.90
Ln(ME)	1.92	0.48	2.93	0.76	1.91	0.48	1.95	0.49
NBonds	-0.56	-1.84	-0.62	-2.04	-0.56	-1.84	-0.57	-1.85
Forecast Disp	10.52	1.56	11.59	1.59	10.27	1.52	10.26	1.53
CDS Liquidity	22.92	1.81	16.42	1.90	24.41	1.62	26.33	1.64
β^1			1.52	0.66	1.29	0.45	2.43	0.89
β^2							0.31	2.74
β^3							-1.24	-1.79
β^4							6.84	1.08
β^{net}	1.27	1.89			1.22	1.77		
<i>N</i>	5365		5447		5365		5365	
Clusters	312		345		312		312	
Adj. <i>R</i> ²	0.598		0.590		0.598		0.599	

Table VII
CDS Illiquidity Risk and CDS Spreads: Volume Proxy for Liquidity Risk

This table shows the effects of CDS illiquidity risk measured by CDS volume on CDS spreads. Shown in the table are panel regression results. The dependent variable is monthly average CDS spreads. CDS data spans from June 1997 to March 2006 from a major CDS broker CreditTrade. OIV is monthly average at-the-money option implied volatility. Jump is option implied jump risk (at-the-money OIV - 10% in-the-money OIV). Credit rating is numerical ratings, with 35 given to AAA and 10 given to D. Leverage is the ratio of book debt over the sum of book debt and market equity. B/M is book to market ratio. ME is market equity capitalization. Forecast Disp is analysts forecast dispersion (standard deviation over mean) over annual earnings. NBonds is total number of senior unsecured bonds issued by the firm. Volume is the total notional amount of CDS contracts quoted and traded, as a proxy for liquidity risk. Other control variables are CDS liquidity proxies V2V (the ratio of monthly CDS spread volatility over total number of quotes and trades over the month), NOC (the total number of CDS contracts traded during the past 60 months, or total number of CDS contracts outstanding), T2Q (the ratio of number of trades over number of quotes per month), and BAS (the monthly average percentage bid-ask spread). Monthly dummies (not shown) are also included in the regressions. Issuer-clustering is adjusted to obtain robust t-values.

	Models:							
	(1)		(2)		(3)		(4)	
	Coef.	<i>t</i>	Coef.	<i>t</i>	Coef.	<i>t</i>	Coef.	<i>t</i>
Const ($\times 10^2$)	2.18	4.71	1.64	3.36	2.00	3.77	2.46	4.70
OIV ($\times 10^2$)	4.77	11.55	4.11	9.15	4.83	10.21	3.75	8.84
Jump ($\times 10^2$)	7.86	3.24	5.97	2.37	9.41	3.75	5.21	2.26
Credit Rating	-13.69	-8.46	-11.17	-6.92	-15.07	-8.63	-10.14	-5.95
Leverage	49.31	2.70	45.46	2.00	57.18	2.99	41.21	1.93
B/M	40.22	2.83	25.65	1.75	31.28	2.00	25.54	1.86
Ln(ME)	0.66	0.19	-4.79	-0.95	2.37	0.61	-2.97	-0.65
NBonds	-0.60	-2.07	-0.58	-1.69	-0.58	-1.92	-0.56	-1.62
Forecast Disp	9.89	1.57	3.30	1.03	11.62	1.57	3.48	1.19
Volume	1.37	2.02	2.89	3.89	1.58	2.36	3.36	4.27
V2V			23.41	3.28			48.67	6.81
NOC			0.17	3.79			0.16	3.43
T2Q			-7.96	-1.45			-15.41	-2.69
BAS					21.11	1.78	-80.48	-2.30
<i>N</i>	7343		2058		5447		2005	
Clusters	371		258		345		256	
Adj. R^2	0.581		0.645		0.591		0.661	

Figure 1. Market average CDS spreads

The figure reports the time series of the cross-sectional average of CDS spreads in the data sample. The sample includes only U.S. dollar denominated contracts for U.S. corporations with reference issues being senior unsecured bonds and maturity around 5 years, from CreditTrade.

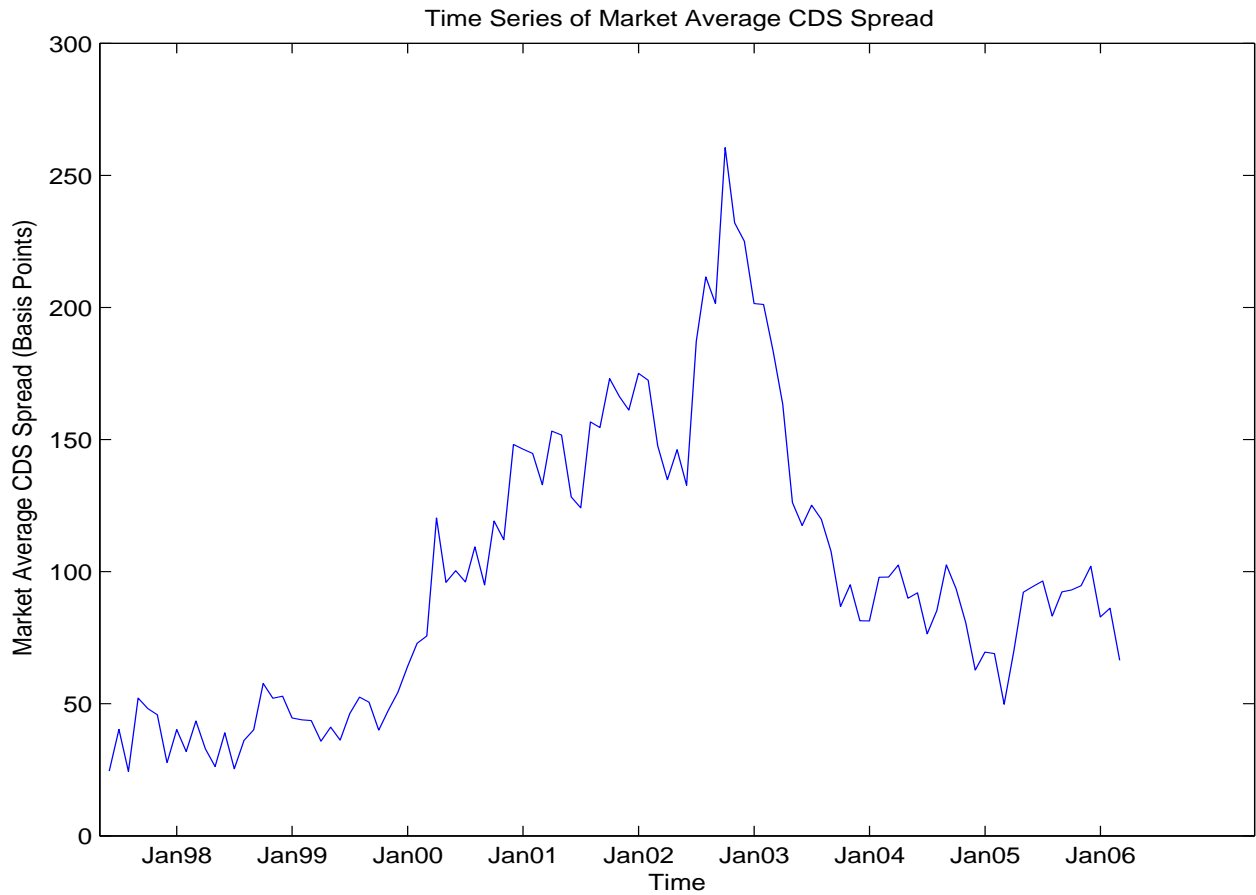
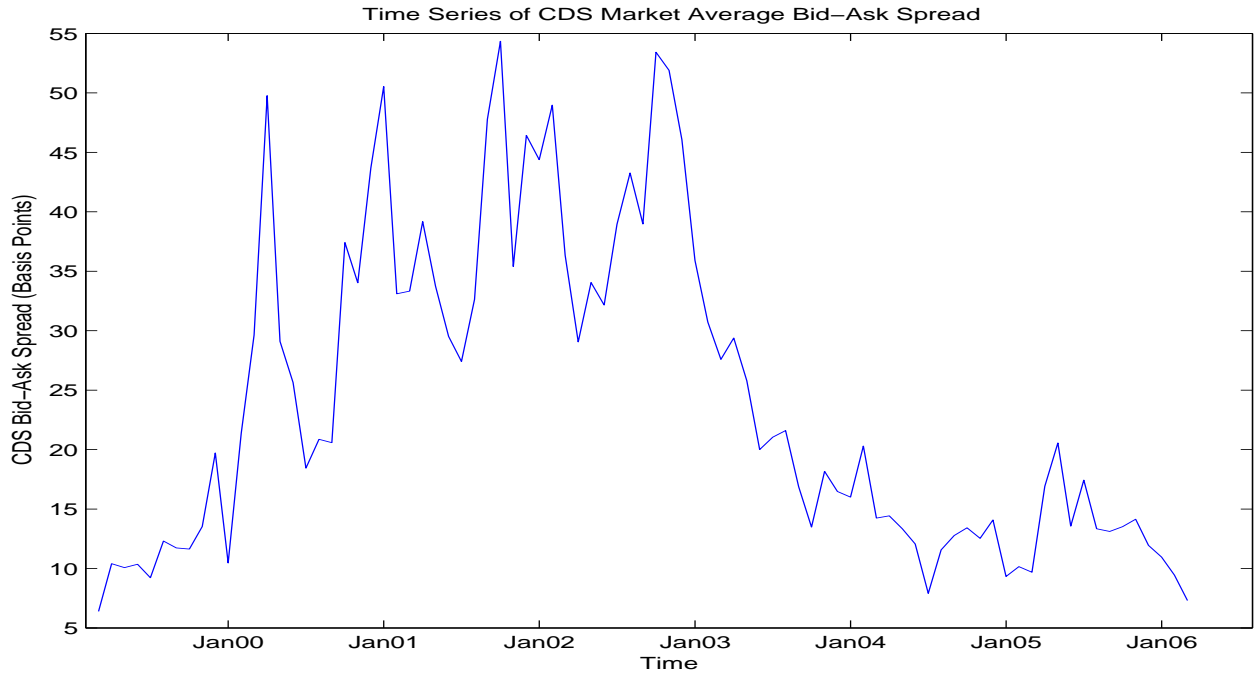


Figure 2. Time-series plots of average bid-ask spreads in the CDS market

The figure reports the time series plots of the cross-sectional average of bid-ask spreads in the CDS market. Bid-ask spread is calculated as the difference between daily average offer and daily average bid. Monthly average is then obtained for individual CDS names. Reported is the cross-sectional mean for each month. Panel A shows the level of bid-ask spreads in basis points. Panel B shows the percentage bid-ask spread, which is the ratio of bid-ask spread over the average of bid and offer prices.

Panel A: Level of bid-ask spread



Panel B: Percentage bid-ask spread

