Hedging Credit:
Equity Liquidity Matters [*]

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Abstract

Credit default swap (CDS) spreads are directly related to equity market liquidity in the Merton (1974) model via hedging. Empirical tests confirm this relationship. This relationship is monotone increasing when credit quality worsens. We theorize and confirm this new channel by means of which liquidity costs are embedded in CDS spreads.

1 Introduction

This paper makes explicit the link between illiquidity in the equity markets and spreads in the credit default swap (CDS) market in the context of Merton (1974)'s structural model. Empirical analysis of the link shows that the theory is well supported.

A growing literature documents that illiquidity is a component of bond and CDS spreads. This component has been extracted from the CDS-bond basis (the difference between the CDS spread and the bond yield) by Longstaff, Mithal and Neis (2005) who provide evidence that the basis is related to liquidity proxies. Mahanti, Nashikkar and Subrahmanyam (2007) use a "latent liquidity" measure, based on the accessibility of a bond, developed by Mahanti, et al. (2007), to explain why liquid bonds trade at a premium relative to corresponding CDS contracts with similar default risk. de Jong and Driessen (2005) present evidence that overall market illiquidity is related to liquidity premia in corporate bond spreads.

The CDS-bond basis is treated as a catch-all proxy for the non-default components of a bond yield. This entails an implicit assumption that CDS spreads contain minimal or no components of liquidity, taxes and other non-default priced systematic risks. Our empirical results show however that CDS spreads do contain a liquidity component.

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There is an inherent dissimilarity between corporate bond and CDS liquidity based on differences in the use of these instruments. Whereas the average corporate bond does not trade frequently[1], and is held for portfolio reasons, CDS contracts are derivatives used widely in credit arbitrage, construction of CDOs, and risk management. The sellers of CDS contracts actively hedge their exposures through the equity markets. When liquidity in the equity markets dries up, it becomes more expensive for sellers of CDS contracts to delta hedge their short credit positions by taking short positions in equity or long positions in put options. These hedging costs are recovered through higher CDS spreads, even when illiquidity is not systematic. Indeed, our empirical results will show that equity market illiquidity remains a strong explanatory variable for CDS spreads even after controlling for other default related factors.

The literature that examines the CDS-bond basis is primarily focused on corporate bond liquidity, whereas our attention in this paper is directed toward liquidity embedded in CDS spreads. Mahanti, Nashikkar and Subrahmanyam (2007) find that the CDS-bond basis is contaminated by several firm-level default-related variables, and we find that after controlling for default risk, there is a distinct remaining liquidity component. Further, our use of equity market liquidity to explain CDS spreads provides a degree of separation from bond market default factors.

Much of the past literature has shown that the CDS-bond basis is related to a systematic liquidity factor. In contrast, our empirical analysis focuses on individual firm CDS liquidity. (Chen, Lesmond and Wei (2007) examine bond-specific illiquidity as well, but do not consider equity market linkages.) Since CDS contracts are actively hedged, unlike bonds, and because hedging costs are incurred whether or not liquidity risk is systematic, we should anticipate that illiquidity costs from the equity markets are transmitted into CDS spreads. Using standard measures of illiquidity and transactions costs in the *equity* markets, such as the ILLIQ measure of Amihud (2002), the LOT measure of Lesmond, Ogden and Trzcinka (1999), and bid-ask spreads, regressions show that individual variations in illiquidity across firms explain the cross-section of CDS spreads even after controlling for default and other explanatory variables. By controlling for common time-series effects across firms, we isolate the firm-specific component of the impact of equity market illiqidity on CDS spreads.

The model in the following section posits that the impact of illiquidity in the equity markets on CDS spreads will increase when credit quality worsens. This relationship is monotone, and is found in the data. Next, we present the framework and hypotheses.

2 Hedging CDS in a Structural Model

Ericsson and Renault (2002) develop a structural model to connect bond market liquidity with default risk. In their model, bond spreads are related to costs of having to trade when it is not optimal to do so. Our model here is a simpler one, relating CDS spreads to illiquidity-induced hedging costs.

We begin by positing the standard Merton (1974) framework for default risk, in that firm

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[1] The median bond trades only once a year.

value V is assumed to follow a geometric Brownian motion under the risk-neutral measure:

$$dV = rV\ dt + \sigma V\ dW \tag{1}$$

where r is the risk free rate and σ is the volatility of the firm's assets; dW is the standard Wiener increment. It is well-known that in this framework, stock value S is determined as a call option on the firm's value V, with strike price equal to the face value F of zero-coupon debt (of maturity T) issued by the firm. Hence,

$$\begin{aligned} S &= V\ \Phi(d_1) - Fe^{-rT}\ \Phi(d_2) && (2) \\ d_1 &= \frac{\ln(V/F) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} && (3) \\ d_2 &= \frac{\ln(V/F) + (r - \sigma^2/2)T}{\sigma\sqrt{T}} && (4) \end{aligned}$$

where $\Phi(x)$ is the cumulative normal distribution value for x.

We consider a very simple insurance contract where the seller is obligated to make good a pre-specified loss amount on default of the firm. For simplicity, assume that the maturity of the insurance contract is T, the same as that of the firm's debt. This is analogous to a very simple CDS contract where the buyer pays only an upfront premium in return for a fixed contingent payment on default. Denoting the price of the contract as C, the price is proportional to the risk-neutral probability of default, which in the Merton model is simply $\Phi(-d_2)$.

The seller of this CDS hedges credit risk by taking a short equity position, either by selling stocks or buying put options, because the value of the CDS contract declines when the stock price rises, i.e. the hedge ratio is negative, $\Delta = \frac{\partial C}{\partial S} \leq 0$. Note also that as Δ changes, the seller adjusts the amount of equity shorted as a hedge. Instantiation of the initial hedge, changes in the hedge ratio, and the close out of the hedge, all result in hedging costs emanating from frictions in the equity markets. Hedging costs are proportional to the size of Δ, which may be computed in closed-form as follows:

$$\begin{aligned} \Delta &= \frac{\partial C}{\partial S} \\ &= \frac{\partial C}{\partial V} \times \frac{\partial V}{\partial S} \\ &= \frac{\partial}{\partial V}\Phi(-d_2) \times \frac{1}{\Phi(d_1)} \\ &= -\phi(-d_2)\frac{\partial d_2}{\partial V} \times \frac{1}{\Phi(d_1)} \\ &= \frac{-\phi(d_2)}{\Phi(d_1)}\ \frac{1}{V\sigma\sqrt{T}} \quad \leq 0 && (5) \end{aligned}$$

where $\phi(x)$ is the normal density of x. We can also see that this confirms that the relationship of CDS to equity (or firm value) is an inverse one. Using the equation above, Figure 1 shows that as the stock price falls, the absolute hedge ratio rises, thereby increasing hedging costs proportionately.

Hedging costs, proportional to Δ, may arise from various frictions in the equity markets. We examine three well-known liquidity frictions here. *First*, price impact from illiquidity, which we proxy with the ILLIQ measure of Amihud (2002). The greater the hedging need, it is likely to create a larger price impact, making this proxy for illiquidity a good candidate variable for explaining CDS spreads. *Second*, lack of immediacy (see Chacko and Stafford (2007)) or non-tradability of the stock, proxied by the zero-return (LOT) measure of Lesmond, Ogden and Trzcinka (1999). Here, hedging costs arise from the fact that this form of illiquidity might result in slippage in the dynamic hedging program, either through delayed hedging or partial hedging. *Third*, bid-ask spreads. The wider the bid-ask spreads, the greater the round trip cost of putting on the hedge and taking it off when the credit position is closed out. We note that all three measures of illiquidity impact the costs of the dynamic hedging strategy, albeit through different channels. There are two other aspects of dynamic hedging that impact running a CDS book irrespective of which illiquidity channel we consider most impacting. One, dynamic hedging incurs greater costs when markets are volatile as the hedge ratio changes more rapidly. Since changes in volatility are likely to be systematic, it is hard to diversify this component of hedging risk. Two, when credit quality changes, even for a single issuer, re-hedging across positions in the market occurs on one side of the bid-ask spread, and hence, the costs of adverse selection are exacerbated. Both these effects enhance the impact of equity market illiquidity on CDS spreads.

In the next section, we provide an empirical analysis that demonstrates that CDS spreads are explained by equity market liquidity frictions, and that this component increases as credit quality worsens.

3 Empirical Testing

3.1 Data

Our sample of credit default swap spreads is obtained from Bloomberg. It consists of 2,860 quarterly credit default swap spreads over the period 2001-2005. This sample was further restricted to include only CDS securities where the notional value is dollar denominated and where the reference entity is a publicly traded firm. Financial information on the reference entity is then obtained from COMPUSTAT and CRSP. Berndt, et al. (2003) find that a large portion of the variation in CDS spreads can be explained by the distance-to-default and the T-bill rate. In addition, Das, Hanouna and Sarin (2006) find that certain accounting ratios can explain CDS spread variation above and beyond the distance-to-default metric and the T-bill rate. We use both sets of variables to control for default risk and then include the liquidity variables to ascertain their influence.

In the following subsections we explain how we proxy for liquidity, how we calculate the distance-to-default and finally, the computation of the accounting ratios used as explanatory variables in our cross-sectional regressions explaining CDS spreads.

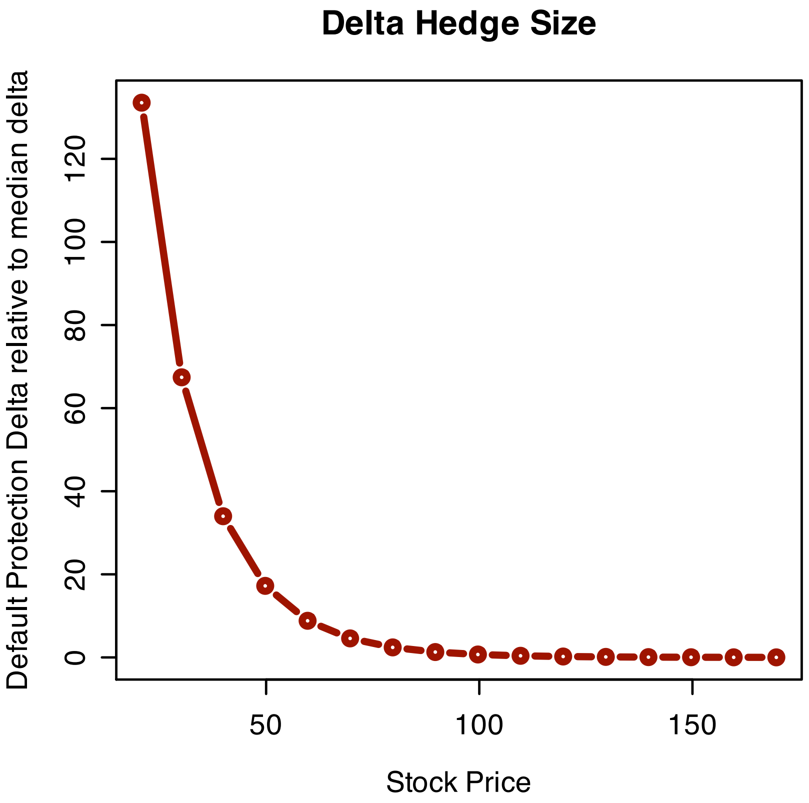

Figure 1: Delta of the CDS. The plot shows how the delta of the CDS contract changes when the stock price changes. This plot was generated by varying firm value from 50 to 200, and computing the stock price and the delta of the CDS. We plot the delta divided by the median delta for this range of firm value, based on equation (5). The parameters of the Merton model were set to: debt face value $F = 50$, debt maturity $T = 5$ years, risk-free rate $r = 10\%$, and firm asset volatility $\sigma = 20\%$. Since CDS hedging costs are proportional to the delta of the CDS with respect to the stock price, we see that delta increases rapidly as the stock price declines, implying that poor quality firms' CDS spreads will be more sensitive to equity market illiquidity.

3.1.1 Liquidity Variables

We construct three variables to proxy for liquidity: the Amihud illiquidity measure, the number of zero return trading days in the year, and bid-ask spreads.

The Amihud illiquidity measure is calculated as in Amihud (2002) using the following equation:

$$ILLIQ_{it} = \frac{1}{DAYS_{it}} \sum_{t=1}^{DAYS_{it}} \frac{|r_{it}|}{PRC_{it} \times VOL_{it}} \times 10^6,$$

where r_{it} is the ith stock's return for day t, PRC_{it} is closing price, and VOL_{it} is daily trading volume, that is, the number of shares traded for a firm. $DAYS_{it}$ is the number of trading days for stock i in year t. This proxy for liquidity is used by Acharya and Pedersen (2005) who develop a liquidity-extended CAPM and Avramov, Chordia and Goyal (2006) who examine the relationship of liquidity to autocorrelation in stock returns.

The number of zero return trading days in the year is a measure developed by Lesmond, Ogden and Trzcinka (1999) to measure transaction costs and is often referred to as the LOT measure. Das and Hanouna (2007) find that the LOT also measures liquidity. Whether LOT measures transaction costs or liquidity is not crucial in our context since we view illiquidity as a hedging cost in managing default risk exposure. We calculate the number of zero return trading days in the year using CRSP. However, on days where no trade occurs (reported volume is zero) CRSP calculates returns from the average of the bid and ask prices. This can create circumstances where there are non-zero returns on days with no volume. To correct for this we set zero volume days to also have zero return.

The bid-ask spread is calculated following Amihud and Mendelson (1986) as the difference between the ask and bid prices on CRSP divided by the average of the two.

3.1.2 Distance-to-Default

As presented in equations (1), (2), (3) and (4), the stock S of a firm is a call option on it's underlying value V with an exercise price equal to the face value of debt F and a time to maturity of T. We recall the result here.

$$S = V\Phi(d_1) - e^{-rT}F\Phi(d_2) \tag{6}$$

where $\Phi(.)$ is the cumulative normal distribution function with d_1 and d_2 given by:

$$d_1 = \frac{\log(V/F) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}, \quad d_2 = d_1 - \sigma\sqrt{T} \tag{7}$$

Since stock $S(V)$ is function of firm value, application of Ito's lemma allows us to express stock volatility in terms of firm volatility as follows:

$$\sigma_S = \left(\frac{V}{S}\right) \frac{\partial S}{\partial V} \sigma \tag{8}$$

The Merton (1974) model uses equations (6) and (8) solve for V and σ where σ_S, r, S, F, and r are obtained exogenously. T is assumed to be one year following standard practice. σ_S is the annualized standard deviation of returns and is estimated from the prior 100 trading days of stock price returns. Similar to Bharath and Shumway (2005), we require that at least 50 trading days be available for these computations. The market value of equity S is computed as the number of shares outstanding times the end of quarter closing stock price. As in Vassalou and Xing (2004), we take the face value of debt F to be debt in current liabilities (COMPUSTAT item 45) plus one-half of long-term debt (COMPUSTAT item 51). The risk-free rate r is the 3-month treasury constant maturity rate from the Federal Reserve Bank following Duffie, Saita and Wang (2007). We numerically solve the system of simultaneous equations in the Merton model to obtain the firm value V and the volatility of the firm σ. Then distance to default is computed as:

$$DD = \frac{\log{(V/F)} + (\mu - \sigma^2/2)T}{\sigma\sqrt{T}} \tag{9}$$

where μ is estimated as the annualized mean equity returns on the prior 100 trading days.

3.1.3 Accounting Ratios

We measure firm size as the value of total assets (COMPUSTAT-Quarterly item 44) divided by the Consumer Price Index for all-urban consumers, all items (Series CUUR0000SA0) with a base of 100 in the period 1982-1984. ROA is constructed as net income (item 69) divided by total assets. Interest coverage is taken as pretax income (item 23) plus interest expense (item 22) divided by interest expense, the cash-to-asset ratio is cash and equivalents (item 36) over total assets. We proxy for differences in capital structure by calculating the ratio of total liabilities (item 54) to total assets.

We account for seasonal effects by taking the trailing four-quarter average of ROA and interest coverage. The relationship between CDS spreads and interest coverage is usually monotonically increasing. When interest coverage is ample, the effect of small changes in interest coverage will be negligible. Sometimes, interest coverage is negative, and then the ratio is not meaningful since the relative magnitude of pretax income to interest expense is blurred. As undertaken by Blume, Lim, and MacKinlay (1998) we adjust the interest coverage ratio in two ways. One, before taking the trailing four quarter average, negative quarterly interest coverage ratios are set to zero. Two, trailing 4 quarter average interest coverage ratios are capped at 100, and such censoring is undertaken on the assumption that further increases in value convey no additional information. As in Blume, Lim, and MacKinlay (1998) we allow the data to determine the shape of the nonlinearity. Assume that IC_{it} is the interest coverage for firm i in quarter t, then the interest coverage ratio in the regression model is:

$$IC_{it} = \sum_{j=1}^{4} \kappa_j c_{jit} \tag{10}$$

where c_{jit} is defined in the following table as:

	c_{1it}	c_{2it}	c_{3it}	c_{4it}
$IC_{it} \in [0,5)$	IC_{it}	0	0	0
$IC_{it} \in [5,10)$	5	$IC_{it} - 5$	0	0
$IC_{it} \in [10,20)$	5	5	$IC_{it} - 10$	0
$IC_{it} \in [20,100]$	5	5	10	$IC_{it} - 20$

The result is that the regression model determines the form of the non-linearity between the dependent variable and the interest coverage ratio.

3.1.4 Other Control Variables

To account for differences in industry performance we include the prior year return on the industry associated with the firm. Industries are defined using the Fama and French (1997) 17-industry classification. We also include the volatility of equity used in the distance to default separately since volatility is strongly related to credit risk (Duffie, Saita and Wang (2007) include the VIX in addition to the Distance to Default measure). Note also that the Moody's Public Firm model (see Sobehart, Stein, Mikityanskaya and Li (2000)) includes equity volatility as a measure of market sensitivity.

3.2 Empirical Results

In Table 1 we report the descriptive statistics of the data. The variables relate to measures of both, credit and liquidity risk for individual firms.

We next estimate four models of multivariate regressions. In the first three, we examine the relationship between the log of CDS spreads (in basis points) and our three measures of liquidity individually.[2] In the fourth model, we also regressed the log of CDS spreads on all three measures of liquidity in the same pooled panel regression. The results are presented in Table 2. All three metrics of illiquidity are highly significant. We used time dummies to remove time-series effects and thereby isolate the firm-specific effects. We also used firm clustered standard errors. These corrections are imposed in all subsequent analyses as well.

We then augmented the basic regressions with a credit variable and a macro-economic variable to examine the impact on the liquidity variables. The credit variable chosen was the standard measure of distance to default (DD) and the macro-economic one is the level of the three-month Treasury rate (TBILL). Both variables were successfully used in prior work by Duffie, Saita and Wang (2007). In Table 3 we see that distance to default greatly increases the explanatory power of the regression but that the Treasury rate does not. Injection of these additional variables does not render the liquidity variables insignificant at all. Only in the regression with all three variables taken together, is bid-ask spread insignificant. However, these regressions make it clear that equity market liquidity matters in explaining the cross-section of CDS spreads.

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[2] We use the logarithm of CDS spreads as the dependent variable because spreads are exponential functions of the state variables in the popular class of affine models. For a theoretical analysis of this, see Das, Hanouna and Sarin (2006).

Table 1: Descriptive statistics. The data is taken from Bloomberg, Inc. It consists of 2,860 quarterly credit default swap spreads over the period 2001-2005. This sample was restricted to include only CDS securities where the notional value is dollar denominated and where the reference entity is a publicly traded firm. Financial information on the reference entity is then obtained from COMPUSTAT and CRSP. After filtering the data, we obtained a total of 1452 observations coming from 195 distinct firms.

VARIABLE	MNEMONIC	MEAN	MEDIAN	Q1	Q3
3 MONTH TBILL	TBILL	0.01	0.01	0.01	0.02
AMIHUD ILLIQUIDITY	ILLIQ $\times 10^4$	3.64	1.99	1.14	4.14
ZERO RETURN DAYS	LOT	2.92	2	1	4
BID-ASK SPREADS	BASPREAD $\times 10^3$	2.54	1.55	0.72	3.31
CASH/ASSET	CASH	0.06	0.04	0.01	0.08
DISTANCE TO DEFAULT	DD	9.94	9.9	6.69	13.13
EQUITY VOLATILITY	EQVOL	0.28	0.26	0.2	0.34
INTEREST COVERAGE 1	C1	3.41	3.72	2.14	5
INTEREST COVERAGE 2	C2	1.25	0	0	2.1
INTEREST COVERAGE 3	C3	1.01	0	0	0
INTEREST COVERAGE 4	C4	1.46	0	0	0
INVESTMENT GRADE DUMMY	INVGRADE	0.91	1	1	1
LIABILITIES TO ASSET	LTOA	0.67	0.68	0.58	0.77
LOG OF ASSETS	LOGASSET	4.51	4.43	3.84	5.03
LOG OF CDS SPREAD	LOGCDS	4.14	3.98	3.53	4.64
INDUSTRY RETURNS	INDRET	0	0.01	-0.02	0.03
RETURN ON ASSETS	ROA	0.01	0.01	0	0.02

Table 2: Explaining CDS spreads with liquidity variables only. In this set of regressions the dependent variable is the log of CDS spreads. The independent variables are our three measures of liquidity: Amihud (2002)'s ILLIQ metric, Lesmond, Ogden and Trzcinka (1999)'s LOT metric, and bid-ask spreads (BASPREAD). T-statistics are provided below the estimated parameters and are based on clustered standard errors. The liquidity variables are shown in bold font if they are statistically significant.

	MODEL1	MODEL2	MODEL3	MODEL4
INT	3.48	3.37	3.53	3.34
	19.93	15.14	17.58	17.38
ILLIQ	**648.08**			**457.25**
	4.85			2.88
LOT		**0.09**		**0.05**
		5.35		2.95
BASPREAD			**146.27**	**56.54**
			6.99	1.97
R-SQUARE	0.16	0.04	0.18	0.24
N	1452	1452	1452	1452

Table 3: Explaining CDS spreads with liquidity variables augmented by primary credit and macroeconomic variables. In this set of regressions the dependent variable is the log of CDS spreads. The independent variables are our three measures of liquidity: Amihud (2002)'s ILLIQ metric, Lesmond, Ogden and Trzcinka (1999)'s LOT metric, and bid-ask spreads (BASPREAD). The set of dependent variables is augmented with distance to default (DD) as a credit proxy and the 3-month Treasury rate (TBILL) as a macro-economic proxy. These variables were chosen based on the work of Duffie, Saita and Wang (2007). T-statistics are provided below the estimated parameters, and are based on clustered standard errors. The liquidity variables are shown in bold font if they are statistically significant.

	MODEL1	MODEL2	MODEL3	MODEL4
INT	4.97	5.03	5.04	4.82
	48.10	56.86	50.6	51.53
DD	-0.09	-0.1	-0.09	-0.09
	-17.21	-19.53	-16.25	-17.48
TBILL	-3.49	-4.73	-4.6	-2.77
	-1.09	-1.39	-1.38	-0.88
ILLIQ	**426.76**			**332.32**
	4.43			3.09
LOT		**0.07**		**0.05**
		5.25		3.82
BASPREAD			**39.13**	9.48
			4.18	0.88
R-SQUARE	0.47	0.46	0.43	0.49
N	1452	1452	1452	1452
CLUSTERS	195	195	195	195

In Table 4 we provide the kitchen sink regression that contains all major credit and illiquidity variables we consider in this paper, as listed in Table 1. In the initial three models, we use each of our three liquidity metrics individually. Despite the inclusion of many credit variables, the three illiquidity variables remain strongly significant. In the fourth model, we include all three illiquidity variables together, and now bid-ask spreads are not significant, though the other two (ILLIQ and LOT) are. Therefore, there is strong statistical evidence for the impact of equity market liquidity on CDS spreads.

Using the estimates in Table 4 we computed the percentage change in CDS spreads for a one standard-deviation change in equity market liquidity in the cross-section of firms. The impact of this magnitude of change on spreads is 5.86%, 9.48% and 16.84% respectively across the three models. If the average (across firms) time-series standard deviation is used instead of the cross-sectional standard deviation this effect on spreads is 3.30%, 4.38% and 9.82% respectively.

Finally, we consider if the impact of illiquidity on CDS spreads is greater for lower quality firms. In order to examine this, we interacted distance to default with our three liquidity variables. Firms with smaller distance to default are of poorer credit quality. Hence, a significant negative coefficient on the interaction variable will imply that liquidity impacts credit spreads more for lower credit quality firms. The results are shown in Table 5. We can see that the interaction term is significant only in Model 1 (for Amihud's ILLIQ measure) and the sign is negative as required. It is insignificant in the case of the other two models. The drop in significance might be the result of constraining the model coefficients to be the same for high and low DD firms, though ILLIQ is more widely used in the liquidity literature since it is known to be a robust measure. In Model 4 in Table 5 we used all three liquidity measures and interaction terms together. Here, the ILLIQ measure swamps the others, and the interaction term is still significant. Hence, there is confirmation of the proposition that CDS spreads for low DD firms will be more impacted by equity liquidity than the spreads of high DD firms.

4 Conclusion

After positing theoretically that equity market illiquidity should be a component of CDS spreads at the individual firm level, empirical analysis shows that this is indeed so at high levels of statistical significance. We further find that the illiquidity component will increase as the credit quality of the firm declines. Using equity market proxies for liquidity has the practical benefit that plentiful data is available, which is not the case with bond market proxies. Our results imply a growing connnection between the credit and equity markets, and suggest that cross-market liquidity linkages may be a good avenue for further research.

Table 4: Explaining CDS spreads with liquidity variables augmented by all credit and macro-economic variables. In this set of regressions the dependent variable is the log of CDS spreads. The independent variables are our three measures of liquidity: Amihud (2002)'s ILLIQ metric, Lesmond, Ogden and Trzcinka (1999)'s LOT metric, and bid-ask spreads (BASPREAD). The set of dependent variables is augmented with all the variables from Table 1. Time dummies are used in the regressions to remove effects that are not firm-specific. T-statistics are provided below the estimated parameters and are based on clustered standard errors. The liquidity estimates are shown in bold font if they are statistically significant.

	MODEL1	MODEL2	MODEL3	MODEL4
INT	4.00	4.19	4.31	3.93
	9.68	10.72	11.31	9.27
DD	-0.03	-0.04	-0.03	-0.03
	-4.67	-4.92	-5.07	-4.88
LTOA	0.78	0.87	0.85	0.79
	3.05	3.24	3.18	3.10
CASH	0.04	-0.09	0.00	0.00
	0.09	-0.22	0.00	0.00
ROA	-1.93	-1.96	-1.83	-1.86
	-3.40	-3.50	-3.30	-3.43
EQVOL	1.90	2.02	1.81	1.88
	6.90	6.82	6.16	6.86
C1	-0.10	-0.11	-0.12	-0.10
	-4.41	-4.96	-5.43	-4.37
C2	0.00	0.01	0.01	0.01
	0.11	0.50	0.35	0.33
C3	0.00	0.00	0.00	0.00
	0.04	-0.41	0.16	-0.20
C4	-0.01	-0.01	-0.01	-0.01
	-2.35	-2.05	-2.14	-2.35
INVGRADE	-0.84	-0.84	-0.86	-0.85
	-10.68	-10.79	-11.69	-10.82
LOGASSET	0.05	-0.01	0.00	0.04
	0.98	-0.24	0.03	0.82
INDRET	0.87	0.84	0.84	0.78
	1.73	1.62	1.61	1.58
ILLIQ	**284.90**	.	.	**193.11**
	3.90			2.42
LOT	.	**0.04**	.	**0.03**
		3.73		2.54
BASPREAD	.	.	**55.58**	22.19
			4.41	1.46
RSQUARE	0.69	0.69	0.69	0.70
N	1452	1452	1452	1452
CLUSTERS	195	195	195	195

Table 5: Impact of liquidity on spreads based on varying credit quality. Low distance to default firms are of poorer quality than firms with high distance to default. We interacted DD with the illiquidity variable to see if it was significant. T-statistics are presented below the estimates and are based on clustered standard errors and time dummies are used to isolate the firm-specific effect from time-series effects. The ILLIQ variables is Amihud's illiquidity for Model 1, the LOT measure for Model 2, and bid-ask spreads for Model 3. Model 4 puts all the illiquidity measures in one regression with individual interaction terms. Significant illiquidity coefficients are highlighted in bold font.

	MODEL 1	MODEL 2	MODEL 3	MODEL 4
INT	4.01	4.17	4.28	3.91
	9.68	10.76	11.27	9.44
DD	-0.03	-0.03	-0.04	-0.04
	-4.20	-4.06	-5.17	-4.60
LTOA	0.78	0.86	0.86	0.81
	3.04	3.20	3.21	3.15
CASH	0.06	-0.09	-0.01	0.02
	0.14	-0.20	-0.02	0.04
ROA	-1.96	-1.97	-1.84	-1.93
	-3.46	-3.51	-3.29	-3.55
EQVOL	1.85	2.01	1.87	1.94
	6.78	6.81	6.46	7.27
C1	-0.10	-0.11	-0.12	-0.10
	-4.33	-4.92	-5.41	-4.22
C2	0.00	0.01	0.01	0.01
	0.05	0.47	0.38	0.29
C3	0.00	0.00	0.00	0.00
	0.09	-0.40	0.18	-0.13
C4	-0.01	-0.01	-0.01	-0.01
	-2.52	-2.04	-2.09	-2.52
INVGRADE	-0.84	-0.84	-0.85	-0.84
	-10.84	-10.79	-11.26	-10.70
LOGASSET	0.05	-0.01	0.00	0.04
	0.88	-0.25	0.09	0.79
INDRET	0.94	0.84	0.77	0.79
	1.88	1.62	1.43	1.60
ILLIQ	**367.91**			**343.35**
	4.97			3.64
LOT		**0.05**		0.02
		2.22		0.79
BASPREAD			**49.17**	4.22
			3.93	0.27
DD*ILLIQ	**-12.86**			**-19.95**
	-1.92			-3.02
DD*LOT		0.00		0.00
		-0.53		0.81
DD*BASPREAD			2.22	3.16
			1.26	1.78
R-SQUARE	0.70	0.69	0.69	0.70
N	1452	1452	1452	1452
CLUSTERS	195	195	195	195

References

Acharya, Viral., and Lasse Pedersen (2005). Asset Pricing with Liquidity Risk, *Journal of Financial Economics* 77(2), 375-410.

Amihud, Yakov (2002). Illiquidity and stock returns: cross-section and time series effects, *Journal of Financial Markets* 5, 31-56.

Amihud, Yakov., and Haim Mendelson (1986). Asset Pricing and the Bid-Ask Spread, *Journal of Financial Economics* 17, 223-249.

Avramov, Doron., Tarun Chordia, and Amit Goyal (2006). Liquidity and Autocorrelations in Individual Stock Returns, *Journal of Finance* 61(5), 2365-2394.

Berndt, Antje, Rohan Douglas, Darrell Duffie, Mark Ferguson, and David Schranz, 2003, Measuring Default-Risk Premia from Default Swap Rates and EDFs, Working paper, Graduate School of Business, Stanford University.

Bharath, Sreedhar, and Tyler Shumway, 2005, Forecasting Default with the KMV-Merton Model, Working paper, University of Michigan.

Blume, Marshall, Felix Lim, and A. Craig MacKinlay, 1998, The Declining Credit Quality of U.S. Corporate Debt: Myth or Reality?, *Journal of Finance* 53, 1389-1413.

Chacko, George., and Eric Stafford (2007). Pricing Immediacy, forthcoming *Journal of Finance*.

Chen, L., D. Lesmond, and J. Wei, 2007, Corporate yield spreads and bond liquidity, forthcoming *Journal of Finance*.

Das, Sanjiv., Paul Hanouna and Atulya Sarin (2006). Back to Basics: Fundamentals-Based versus Market-Based Cross-Sectional Models of CDS Spreads, Working paper, Santa Clara University.

Das, Sanjiv., and Paul Hanouna (2007). Run Length and Liquidity, Working paper, Santa Clara University.

de Jong, Frank., and Joost Driessen (2005). Liquidity Risk Premia in Corporate Bond Markets, Working paper, University of Amsterdam.

Duffie, Darrell, Leandro Saita, and Ke Wang (2007). Multiperiod Corporate Default Probabilities with Stochastic Covariates, *Journal of Financial Economics* 83, 635-665.

Ericsson, Jan., and Oliver Renault (2002). Liquidity and Credit Risk, Working paper, McGill University.

Fama, Eugene F., Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153-193.

Lesmond, David., Joseph Ogden, and Charles Trzcinka (1999). A New Estimate of Transaction Costs, *Review of Financial Studies* 12(5), 1113-1141.

Longstaff, Francis., Sanjay Mithal and Eric Neis (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market, *Journal of Finance* LX, 2213-2253.

Mahanti, Sriketan., Amrut Nashikkar and Marti Subrahmanyam (2007). Latent Liquidity and Corporate Bond Spreads, Working paper, NYU Stern School of Business.

Mahanti, Sriketan., Amrut Nashikkar, Marti Subrahmanyam, George Chacko and G. Mallick (2007). Latent Liquidity: A New Measure of Liquidity with an Application to Corporate Bonds, forthcoming *Journal of Financial Economics*.

Merton, Robert, C (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *Journal of Finance*, v29, 449-470.

Sobehart, Jorge., Roger Stein, Victoriya Mikityanskaya, and Li Li (2000). Moody's Public Firm Risk Model: A Hybrid Approach to Modeling Short Term Default Risk, Global Credit Research, *Moody's Investors Service*.

Vassalou, Maria, and Yuhang Xing, 2004, Default risk in equity returns, *Journal of Finance* 59, 831-868