Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market[*]

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Abstract

We derive a theoretical asset-pricing model for derivative contracts that allows for expected liquidity and liquidity risk, and estimate this model for the market of credit default swaps (CDS). Our model extends the LCAPM of Acharya and Pedersen (2005) to a setting with derivative instruments and shows that the sign of the liquidity effects depends on investor heterogeneity in non-traded risk exposure, risk aversion and wealth. Empirically, the model is estimated by applying the standard two-pass regression approach to CDS portfolios, for which we construct liquidity and return time series using a repeated sales methodology. Expected CDS returns are calculated by correcting CDS spreads for the expected loss. We find evidence for an economically and statistically significant expected liquidity premium earned by the protection seller. In line with our theoretical predictions, we do not find strong evidence that liquidity risk is priced.

Keywords: CDS, Liquidity, Liquidity Risk

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1 Introduction

The relation between liquidity and asset prices has received considerable attention recently. However, much less is known about liquidity effects in derivative markets. This paper provides a theoretical model of liquidity effects in derivative markets and estimates this model for the credit default swap market. Recent market developments suggest that the credit default swap (CDS) market is subject to shocks in liquidity. In the subprime crisis of summer 2007, not only credit spreads increased substantially, but liquidity also dropped dramatically.

Our paper makes three contributions. Our first contribution is a theoretical asset pricing model for derivatives that incorporates liquidity risk. This model extends the 'Liquidity-CAPM' of Acharya and Pedersen (2005), who only consider investors with long positions in assets that are in positive net supply, in which case illiquidity always leads to lower asset prices. For derivative securities, which are in zero net supply, the effect of liquidity is much more complicated and can be zero, positive or negative. We propose an equilibrium framework where heterogenous investors use derivatives to hedge a fixed (credit) risk exposure. Transaction costs for derivatives vary systematically over time. We derive that under fairly mild conditions, the expected return on the derivative asset can be decomposed into market risk premia, an expected liquidity component, and one liquidity risk premium. This result differs from the result for a positive net supply market as in Acharya and Pedersen (2005) where there are three liquidity risk premia. In particular, our model predicts that the liquidity exposure of a derivative to derivative-market liquidity is not priced. We show that sign of the liquidity effects depends on heterogeneity in investors' risk exposures, risk aversion and wealth. Our model is related to work on hedging pressures in futures markets (De Roon, Nijman and Veld, 2000) and option markets (Garleanu, Pedersen and Poteshman, 2006).

Our second contribution is an empirical test of this theoretical framework for an important class of derivative assets, credit default swaps (CDS). By now, the market for CDS contracts is one of the largest derivative markets (approximately 45.5 trillion USD around June 2007 according to Baird (2007)). The CDS market has become much more liquid than the corporate bond market. This has induced researchers and practitioners to use CDS spreads as pure measures of default risk (for example, Longstaff, Mithal and Neis (2005) and Blanco, Brennan and Marsh (2005)). However, using a standard two-pass regression approach to estimate the asset pricing model, our empirical results show that part of the CDS spread reflects a compensation for expected liquidity. Sellers of credit protection thus receive an illiquidity compensation on top of the compensation for default risk. There is no strong evidence for an effect of market-wide CDS liquidity risk on expected CDS returns, which is line with predictions from our theoretical model.

Third, we make several methodological contributions. We derive expressions for realized and expected excess returns on CDS positions. In particular, we show how to construct the expected excess returns from the CDS spread level, corrected for the expected loss. As argued by Campello, Chen and Zhang (2008) and De Jong and Driessen (2005), this procedure gives much more precise estimates of expected returns than averaged realized returns. On the econometric side, we use a repeated sales methodology to construct portfolio CDS returns and bid-ask spreads from the unbalanced panel of individual CDS quotes. Since our data are rather sparse, and because the sample composition varies substantially from one day to another, a repeated sales methodology makes much more efficient use of the information in the data than simple averaging of quotes over daily or weekly intervals.

For the empirical analysis we use a representative dataset of CDS bid and ask quote data for US firms and banks over a relatively long period (2000-2006). We only rely on the most standard and most liquid 5-year contracts. By taking raw quote data we avoid the use of pre-manipulated data. Applying the repeated sales method to these data, we construct excess CDS returns and bid-ask spreads for portfolios sorted on rating and quote activity. The level and variation of the bid-ask spreads is used to measure liquidity and liquidity risk.

We estimate the asset pricing model in two steps. In the first stage, realized CDS excess returns and unexpected liquidity shocks are regressed on market risk factors. In the second stage, expected excess returns are regressed on a measure of expected liquidity and on the risk exposure coefficients obtained in the first step. As discussed above, the expected excess returns are obtained from CDS spread levels, corrected for expected loss. Here, including both portfolios sorted on rating and quote activity helps to disentangle the effects of credit risk and liquidity.

The first-step time series regressions provide evidence for systematic equity risk and credit risk exposure of CDS returns. Moreover liquidity shocks also seem to exhibit a factor structure, but to a systematic liquidity factor rather than to a systematic market risk factors. In the second stage, we find a significant premium on expected liquidity, earned by the protection seller. Survey data for the CDS market in 2006 from the British

Bankers Asscoiation[1] show that long-term investors such as insurance companies and hedge funds are net protection sellers, while banks are net buyers. The expected liquidity premium for the protection sellers is in line with the theoretical model if protection sellers (long-term funds) are less risk averse and/or have more wealth than protection buyers (banks).

Specification tests on the empirical model reveal that the effect of liquidity on CDS prices feeds through the channel of expected liquidity and that the systematic liquidity factor does not play a role in CDS pricing, which is in line with the theoretical predictions.

Two recent papers estimate the impact of liquidity on CDS spreads, Tang and Yan (2006) and Chen, Cheng and Wu (2005). Our paper contributes to this work by developing a theoretical framework for liquidity effects on derivative prices and by explicitly estimating an asset pricing model for expected CDS returns. The asset pricing model allows for an immediate interpretation of our results as liquidity and liquidity risk premia. Tang and Yan (2006) regress CDS spreads on variables that capture expected liquidity and liquidity risk, and find that illiquidity leads to higher spreads. Chen et al. (2005) estimate the impact of liquidity and other factors on CDS spreads using a term structure approach. For estimation, they use term structures of CDS spreads over a sample period of slightly less than one year, much shorter than our sample period. They find that premia for liquidity risk and expected liquidity premium are earned by the CDS buyer. The identification of the liquidity risk premium comes from the term structure of CDS spreads, whereas our method follows the standard procedure of identifying risk premia from expected excess returns. Another recent paper by Das and Hanouna (2007) develops a framework in which lower equity market liquidity leads to higher CDS prices and confirms this mechanism empirically.

More generally, our paper builds on the literature on asset pricing and liquidity.[2] For derivative markets, the literature on liquidity is very scarce and often starts from a somewhat different viewpoint, see for example Çetin, Jarrow, Protter and Warachka (2006) who add liquidity to the standard Black-Scholes framework and Brenner and Eldor (2001) who investigate the effect of non-tradability on currency derivatives. Deuskar,

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[1] Reported in Mengle (2007)

[2] For the equity market, the pricing of liquidity risk has been studied by Amihud (2002), Acharya and Pedersen (2005), Pastor and Stambaugh (2003), and Korajczyk and Sadka (2007), amongst others. De Jong and Driessen (2005), Downing, Underwood and Xing (2005) and Nashikkar and Subrahmanyam (2006) study the pricing of liquidity in corporate bond markets.

Gupta and Subrahmanyam (2006) find empirically that illiquid interest rate options trade at higher prices than liquid options, and also find evidence for commonality in liquidity of different options.

The remainder of this paper is structured as follows. In section 2 we introduce our theoretical model. In section 3 we discuss the definition and construction of our model variables in detail. A brief description of the data and the filters applied to these data is presented in Section 4. The results of the empirical analysis are presented in Section 5. Section 6 concludes.

2 A model for pricing liquidity in derivative markets

2.1 Motivation

In this section we derive an asset pricing model in a setting with transaction costs, heterogeneous agents and multiple assets. The model has two key ingredients that differentiate it from the liquidity CAPM of Acharya and Pedersen (2005) (henceforth AP). First of all, agents have exposure to a non-traded risk factor. Second, whereas AP assume that all agents hold long positions in all assets, we allow agents to optimally hold short positions in some of the assets. This setting is natural when some of the assets are derivative contracts that are in zero net supply. For example, agents may take short positions in the derivative contracts in order to partially hedge the non-traded risk exposure. In our empirical analysis we apply this model to a setting where agents have a non-traded exposure to credit risk. Specifically, commercial banks have exposure to non-traded bank loans and illiquid corporate bonds, which they can partially hedge using credit derivatives (e.g. credit default swaps). Other agents, such as hedge funds or insurance companies, do not have exposure to non-traded credit risk and sell credit default swaps to commercial banks, thus earning a credit risk premium.

Even though we apply our model to derivative markets, the theory developed below applies more generally to asset markets with positive supply. The liquidity CAPM of AP is a special case of our model, since in AP all investors only hold long positions and have no non-traded risk exposure.

2.2 Assumptions and notation

1. *AGENTS.* The economy has N agents with mean-variance preferences. Agents live for one period, invest at time $t-1$ and consume at t. We allow for heterogeneity in absolute risk aversion A_i and initial wealth w_i (w_i is agent i's wealth as a fraction of aggregate wealth). Assumption 1 is shared with Acharya and Pedersen (2005). We thus abstract from intertemporal hedging demands in our model.

2. *TRADED ASSETS.* There are K traded assets, divided into two subsets without loss of generality. For the first subset of K_b assets all agents optimally hold long positions in these assets. These assets thus should have positive risk premia and sufficiently small cross-correlations and correlation with the non-traded risk exposure. We refer to these assets as non-hedge assets or basic assets. The second subset has K_h assets, and some agents optimally hold short positions in these assets. We refer to these assets as hedge assets. For simplicity, it is assumed that for each investor the sign of the position in hedge assets is the same across all hedge assets.[3] We denote $\delta_i = 1$ when investor i has a long position in these hedge assets and $\delta_i = -1$ in case of a short position.[4] Aggregate supply, as a fraction of aggregate wealth across all agents, is denoted S_b for non-hedge assets and S_h for hedge assets. Obviously, for non-hedge assets supply has to be positive. For hedge assets, aggregate supply could be zero, in which case these are derivative assets, but it can also be positive or negative.

3. *NON-TRADED RISK EXPOSURE.* Agent i has exposure q_i to a single non-traded risk factor with return R_t. This is a key assumption. As shown below, if the exposure q_i varies across agents, they will hold different hedge positions in the hedge assets. For example, agents with large positive q_i may hold short positions in hedge assets, while agents with zero or negative non-traded exposure take long positions in the hedge assets. We think of R_t as the return on a diversified portfolio of very illiquid assets that are not traded in equilibrium. For the credit risk application, these can be illiquid corporate bonds or bank loans.

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[3] The assumption that an investor either buys or sells all hedge assets is somewhat restrictive, but in the setting of the CDS market not completely unrealistic: an investor is either a seller of CDS contracts or a buyer. For example, long-term investors like hedge funds and pension funds will typically take on credit risk while commercial banks will try to hedge their credit exposure with CDS contracts. To make sure that agents indeed either buy or sell all hedge assets in equilibrium, restrictions on the parameters of the model are required.

[4] Of course, the sign of the optimal portfolio weights is determined in equilibrium. The two subsets of assets are thus determined endogeneously.

4. *TRANSACTION COSTS.* Following Acharya and Pedersen (2005), agents pay proportional transaction costs when closing the position at time t. The percentage costs are denoted by the K_b-dimensional vector $c_{b,t}$ for non-hedge assets and K_h-dimensional vector $c_{h,t}$ for hedge assets. Both long and short holders pay transaction costs. Transaction costs here represent both the bid-ask spread and search costs, which are relevant in over-the-counter markets (see Duffie, Gârleanu and Pedersen (2005)). We assume that there are (implicit) market makers who only play a role as intermediary, that is they earn the bid-ask spread and hold net zero positions in the hedge assets. The net returns of the agents (in excess of the risk-free rate) are then given by the vectors $r_{b,t} - c_{b,t}$ and $r_{h,t} - \delta_i c_{h,t}$.

2.3 Asset pricing implications

We now derive the main asset pricing implications for our economy. We focus on the implications for the hedge asset returns, since these are the assets that are relevant for our empirical analysis. Investor i maximizes the mean-variance utility function over nonnegative positions x_i in non-hedge assets and positions y_i in hedge assets

$$U_i = x_i' E(r_b - c_b) + y_i' E(r_h - \delta_i c_h) - \frac{1}{2} A_i Var(x_i'(r_b - c_b) + y_i'(r_h - \delta_i c_h) + q_i R) \qquad (1)$$

To simplify notation, we drop all time subscripts. In particular, the expectation and variance in equation (1) are conditional upon the information set at time $t-1$. Imposing the market clearing condition and the optimality conditions for each investor, appendix A derives the following result for the asset pricing equation for the hedge assets.

Theorem I. *Given assumptions 1 to 4, the expected return on the hedge assets satisfies in equilibrium*

$$\begin{aligned} \mathrm{E}(r_h) \;=\; & \beta_r \mathrm{E}(r_b - c_b) + \left(\gamma_1 V_{r-c}^{-1} + \gamma_2 V_{r+c}^{-1}\right)^{-1} \Big[S_h + \left(\gamma_1 V_{r-c}^{-1} - \gamma_2 V_{r+c}^{-1}\right) \mathrm{E}(\widehat{c}_h) \\ & + \left(\gamma_3 V_{r-c}^{-1} + \gamma_4 V_{r+c}^{-1}\right) \mathrm{Cov}(\widehat{r}_h, R) + \left(\gamma_4 V_{r+c}^{-1} - \gamma_3 V_{r-c}^{-1}\right) \mathrm{Cov}(\widehat{c}_h, R) \Big] \qquad (2) \end{aligned}$$

where $\widehat{r}_h = r_h - \beta_r(r_b - c_b)$ *and* $\widehat{c}_h = c_h - \beta_c(r_b - c_b)$ *with* $\beta_r = Var(r_b - c_b)^{-1} Cov(r_h, r_b - c_b)$ *and* $\beta_c = Var(r_b - c_b)^{-1} Cov(c_h, r_b - c_b)$, $V_{r-c} = Var(\widehat{r}_h - \widehat{c}_h)$, $V_{r+c} = Var(\widehat{r}_h + \widehat{c}_h)$, $\gamma_1 = \sum_{i:\delta_i=1} w_i A_i^{-1}$, $\gamma_2 = \sum_{i:\delta_i=-1} w_i A_i^{-1}$, $\gamma_3 = \sum_{i:\delta_i=1} w_i q_i$, and $\gamma_4 = \sum_{i:\delta_i=-1} w_i q_i$.

Proof: Appendix A.

This theorem shows that expected returns on the hedge assets are determined by (i) their covariance with the net return on the non-hedge assets, (ii) aggregate supply S_h

(this term is zero for derivatives with zero net supply), (iii) expected transaction costs, (iii) the covariance of hedge asset returns (orthogonalized for non-hedge asset returns) with the non-traded risk factor R, and (iv) the covariance of hedge asset transaction costs (orthogonalized for non-hedge asset returns) with R.[5]

Theorem I shows that the N agents can be aggregated into two representative agents. The first representative agent is long in the hedge assets and has risk aversion equal to $A_{r1}^{-1} = \sum_{i:\delta_i=1} w_i A_i^{-1} / \sum_{i:\delta_i=1} w_i$ while the second representative agent is short in all hedge assets and has risk aversion $A_{r2}^{-1} = \sum_{i:\delta_i=-1} w_i A_i^{-1} / \sum_{i:\delta_i=-1} w_i$. Similarly, the non-traded risk exposure of these two representative agents is a wealth-weighted average of the risk exposures of the underlying agents.

The four parameters $\gamma_1, .., \gamma_4$ in the system of equations (2) can be estimated using the Generalized Method of Moments (replacing the first and second moments on the right hand side by sample counterparts).

For our empirical application, it is important to note that we cannot reject that $\mathrm{Cov}(\widehat{c}_h, \widehat{r}_h) = 0$ for almost all hedge assets. Imposing this restriction simplifies the asset pricing equation (2) considerably and gives a linear asset pricing model.

Theorem II. *If* $\mathrm{Cov}(\widehat{c}_h, \widehat{r}_h) = 0$, *equation (2) can be written as*

$$\begin{aligned} \mathrm{E}(r_h) &= \beta_r \mathrm{E}(r_b - c_b) + (\gamma_1 + \gamma_2)^{-1} \mathrm{Cov}(\widehat{r}_h - \widehat{c}_h, \widehat{r}_m - \widehat{c}_m) + \frac{\gamma_1 - \gamma_2}{\gamma_1 + \gamma_2} \mathrm{E}(\widehat{c}_h) \\ &\quad + \frac{\gamma_3 + \gamma_4}{\gamma_1 + \gamma_2} \mathrm{Cov}(\widehat{r}_h, R) + \frac{\gamma_4 - \gamma_3}{\gamma_1 + \gamma_2} \mathrm{Cov}(\widehat{c}_h, R) \end{aligned} \tag{3}$$

where the market-wide hedge asset return and cost are defined as $\widehat{r}_m = S_h{}' \widehat{r}_h$ and $\widehat{c}_m = S_h' \widehat{c}_h$.

Proof: Appendix A.

Given that $\gamma_1 + \gamma_2 > 0$, the sign of the expected liquidity effect depends on the sign of $\gamma_1 - \gamma_2 = \sum_{i:\delta_i=1} w_i A_i^{-1} - \sum_{i:\delta_i=-1} w_i A_i^{-1}$. The model implies that if the more wealthy or less risk averse investors have long positions in the assets, the coefficient on the transaction costs is positive and the 'long' holders earn an expected liquidity premium. In the next subsection, we illustrate this in a simple example.

The sign of the coefficient on $\mathrm{Cov}(\widehat{r}_h, R)$ depends on the sign of $\gamma_3 + \gamma_4 = \sum w_i q_i$.

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[5] It is straightforward to show that equation (2) reduces to AP's Liquidity CAPM if $S_h > 0$, $K_b = 0$ and $q_i = 0$ and $\delta_i = 1$ for all agents, using that $V_{r-c} S_h = Cov(r_h - c_h, S_h' r_h - S_h' c_h)$. In this case $\gamma_2 = \gamma_3 = \gamma_4 = 0$.

For example, if aggregate exposure to non-traded risk is positive we obtain the intuitive result that assets that have positive covariance with the non-traded exposure have high expected returns. The coefficient on $\mathrm{Cov}(\widehat{c}_h, R)$ depends on the hedge exposure of the long versus short agents. For example, if the 'short' agents have positive hedge exposure $\gamma_4 > 0$ while the 'long' agents have zero hedge exposure, $\gamma_3 = 0$, the coefficient on $\mathrm{Cov}(\widehat{c}_h, R)$ or $\beta_{\widehat{c}R}$ is positive. In this case, only the 'short' agents care about covariance with R. Because the return on their short position equals $-r_h - c_h$, positive covariance between costs c_h and R hedges part of the non-traded risk, which decreases the expected return on shorting the hedge asset $(-\mathrm{E}(r_h) - \mathrm{E}(c_h))$, thus increasing $\mathrm{E}(r_h)$.

In Theorem II, the coefficients on the covariances and expected costs are constant across assets, and we obtain a linear asset pricing model for the expected return on the hedge assets. Substituting back the definition of $\widehat{c}_h$, we can write asset pricing equation (3) for the expected hedge portfolio returns as:

$$\mathrm{E}(r_h) = \beta_r \mathrm{E}(r_b - c_b) + \lambda_{net}\beta_{net} + \zeta \mathrm{E}(c_h - \beta_c \mathrm{E}(r_b - c_b)) + \lambda_{\widehat{r}R}\beta_{\widehat{r}R} + \lambda_{\widehat{c}R}\beta_{\widehat{c}R} \tag{4}$$

with

$$\beta_{net} = Cov(\widehat{r}_h - \widehat{c}_h, \widehat{r}_m - \widehat{c}_m)/Var(\widehat{r}_m - \widehat{c}_m),$$

$$\beta_{\widehat{r}R} = Cov(\widehat{r}_h, R)/Var(R),$$

$$\beta_{\widehat{c}R} = Cov(\widehat{c}_h, R)/Var(R).$$

The first two terms of this equation are very intuitive: covariance with the non-hedge asset returns is priced, and if aggregate supply S_h is positive, covariance with the net market-wide return of hedge assets is also priced. This term vanishes if the hedge assets are in zero net supply ($S_h = 0$). The third term is the price of expected liquidity (corrected for the exposure of the asset's liquidity to the non-hedge asset returns). The final two terms price the exposure of the returns and liquidity to the background risk. Equation (4) can be estimated using standard two-pass linear regression methods.

2.4 A two-investor example

We now provide some more intuition for the expected liquidity effect by a simple example with constant transaction costs c. Let there be two (representative) investors, one with a positive initial exposure to the risk factor (agent 1) and one without, hence $q_1 > 0$ and $q_2 = 0$. Let there be one hedge asset with return r, with $\sigma^2 = V(r)$. There are no other assets. If $c = 0$, the asset demands (as a fraction of wealth) of investor 1 and 2 are

$$\begin{aligned} y_1 &= \frac{E(r)}{A_1\sigma^2} - cov(r,R)q_1/\sigma^2 \\ y_2 &= \frac{E(r)}{A_2\sigma^2} \end{aligned} \tag{5}$$

In a zero net supply market, the wealth-weighted demands have to add up to zero

$$0 = w_1y_1 + w_2y_2 = \frac{1}{\sigma^2}\left[(w_1A_1^{-1} + w_2A_2^{-1})E(r) - cov(r,R)w_1q_1\right] \tag{6}$$

which gives the equilibrium expected return

$$E(r) = \frac{cov(r,R)w_1q_1}{(w_1A_1^{-1} + w_2A_2^{-1})} \equiv \gamma \tag{7}$$

The portfolio holdings of the agents then can be shown to satisfy $y_1 < 0$ and $y_2 > 0$.

We now turn to the case where there are transaction costs. With constant transaction costs, the asset demands are

$$\begin{aligned} y_1 &= \frac{(E(r)+c)}{A_1\sigma^2} - cov(r,R)q_1/\sigma^2 \\ y_2 &= \frac{(E(r)-c)}{A_2\sigma^2} \end{aligned} \tag{8}$$

The equilibrium return then follows from

$$0 = w_1y_1 + w_2y_2 = \frac{1}{\sigma^2}\left[(w_1A_1^{-1} + w_2A_2^{-1})E(r) + (w_1A_1^{-1} - w_2A_2^{-1})c - cov(r,R)w_1q_1\right] \tag{9}$$

with solution

$$E(r) = \frac{cov(r,R)w_1q_1}{w_1A_1^{-1} + w_2A_2^{-1}} + \frac{w_2A_2^{-1} - w_1A_1^{-1}}{w_1A_1^{-1} + w_2A_2^{-1}}c = \gamma + \zeta c \tag{10}$$

with the compensation for transaction costs determined by the coefficient

$$\zeta = (w_2A_2^{-1} - w_1A_1^{-1})/(w_1A_1^{-1} + w_2A_2^{-1}) \tag{11}$$

Equation (11) is indeed a special case of equation (3), as it should be. For this equilibrium to hold, we need to make sure that $y_1 < 0$ and $y_2 > 0$ in equilibrium. These inequalities are satisfied if $cov(r,R)q_1A_1 > 2c$, implying that the hedge demand has to be sufficiently large relative to the costs c and the speculative demand (which depends on A_1).

Figure 1 illustrates the equilibrium. It shows minus the asset demand of agent 1 (w_1y_1) and the asset demand of agent 2 (w_2y_2), and is drawn such that agent 2 is the less risk averse or more wealthy ($w_2A_2^{-1} > w_1A_1^{-1}$), hence her speculative asset demand is steeper than that of agent 1. The solid lines indicate the asset demand in the case of no transaction cost. The equilibrium expected return γ is obtained at the point where the two lines cross, ie $-w_1y_1 = w_2y_2$ or $w_1y_1 + w_2y_2 = 0$. The dashed lines show the asset demand in the case with transaction costs. Both lines now shift downward as transaction costs make the investors want to invest less (in absolute value). The lines now cross at a different point, where the expected return is higher by ζc. Due to higher wealth and/or lower risk aversion, the demand of agent 2 is more sensitive to transaction costs than agent 1. Therefore, when transaction costs increase, the asset demand of agent 2 goes down more strongly than for agent 1. Then, to persuade agent 2 to invest a sufficient amount in the risky asset, the expected return needs to increase so that ζc is positive.

Extending this example to a case where c is stochastic and correlated with r, it can be used to understand the expression $\gamma_1 V_{r-c}^{-1} - \gamma_2 V_{r+c}^{-1}$ for the coefficient on expected liquidity in equation (2), which equals $\frac{w_2A_2^{-1}}{V(r)+V(c)-2Cov(c,r)} - \frac{w_1A_1^{-1}}{V(r)+V(c)+2Cov(c,r)}$ in this example. If $\text{Cov}(c, r) > 0$, the speculative demand of agent 2 will be higher, since a positive covariance decreases the variance of her net return $r - c$, while it decreases the speculative demand of agent 1, since the return on her short position is $-r - c$. The demand of agent 2 will thus be more sensitive to transaction costs if $\text{Cov}(c, r) > 0$, and a similar effect as in figure 1 occurs, leading to a higher coefficient on $E(c)$ and thus a higher expected return for agent 2 even when both agents have the same wealth and risk aversion.

3 Empirical model for CDS contracts

We apply the theory developed above to the market for credit default swaps. Table 1 is a summary of figures reported by Mengle (2007), providing an overview of buyers and sellers in the CDS market. It shows that insurance companies and funds (pension funds, hedge funds and mutual funds) are net protection sellers in the CDS market, while banks are net protection buyers for their loan portfolio. This suggests that banks use the CDS market to hedge credit exposure, while long-term investors buy credit risk to earn a credit risk premium. Table 1 also shows that the net position of banks for their trading portfolio is close to zero, even though they have large long and short positions in CDS contracts. This suggests that investment banks act as market makers in the CDS market, in the sense that they do not take directional exposure but bring demand and supply together. Given that the CDS market is an OTC market with counterparty default risk, a market maker cannot simply sell through a CDS contract, so that the market maker ends up with large long and short positions.

In the empirical model, we define the background risk R as a general credit index. Empirically we construct this as the first principal component extracted from returns on corporate bond portfolios and CDS portfolios, with the idea that this return captures the pure credit risk of illiquid corporate bonds and bank loans. The hedge assets are credit default swaps, for which we will form portfolios based on different characteristics (rating and quote activity). The CDS market has zero net supply. We include as non-hedge asset the US equity market. This market has positive net supply. We thus assume that investors mainly use CDS contracts to hedge credit risk, and take long positions in equity. For CDS contracts, the liquidity costs c are measured by the relative bid-ask spread on the CDS portfolios. For the equity market, we follow Acharya and Pedersen (2005) and construct liquidity costs as a function of the ILLIQ measure of Amihud (2001). We discuss this below in more detail. As a specification test of the model, we also include other risk factors. In particular, it is interesting to see whether systematic liquidity risks in the CDS market are priced or not.

3.1 Two step estimation

We estimate the model with a two stage regression analogous to Black, Jensen and Scholes (1972). First, we notice that the betas in the model are defined as the ratio of conditional covariances and variances, i.e. the (co)variances of the unpredictable shocks (innovations) in returns and costs. We assume that returns have no serial correlation and correct for persistence in the liquidity level by taking the residuals of an autoregressive model as the liquidity innovations (see section 5 for more details). Following the theory in section 2, we then orthogonalize the return and unexpected transaction costs on the CDS portfolios (denoted by the vectors r_{CDS} and c_{CDS}) for the net equity market return

$$r_{CDS,t} = a_{1r} + \beta_{rEQ}(r_{EQ,t} - [c_{EQ,t} - E_{t-1}(c_{EQ,t})]) + e_{r,t} \qquad (12)$$

$$c_{CDS,t} - E_{t-1}(c_{CDS,t}) = a_{1c} + \beta_{cEQ}(r_{EQ,t} - [c_{EQ,t} - E_{t-1}(c_{EQ,t})]) + e_{c,t} \qquad (13)$$

where the equity returns are in excess of the risk-free rate.[6] We then estimate the time-series regressions to estimate the exposure of the orthogonalized CDS returns and liquidity shocks to the credit risk factor R. In order to generate a specification test,

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[6] As discussed below, the CDS returns are also constructed as excess returns.

we also include an additional risk factor: the CDS market liquidity innovation $\bar{c}_{CDS,t}$ (constructed as a weighted average of all orthogonalized CDS cost innovations $e_{c,t}$):

$$e_{r,t} = a_{2r} + \beta_{\hat{r}R} R_t + \beta_{\widehat{r\bar{c}}} \bar{c}_{CDS,t} + \epsilon_t \tag{14}$$

$$e_{c,t} = a_{2c} + \beta_{\hat{c}R} R_t + \beta_{\widehat{c\bar{c}}} \bar{c}_{CDS,t} + \upsilon_t \tag{15}$$

In the second stage, we estimate the asset pricing model for the unconditional expected CDS returns, equation (4), extended with the exposures of returns and costs to the additional risk factor $\bar{c}$:

$$\begin{aligned} \mathrm{E}(r_{CDS,t}) &= \beta_{rEQ}\mathrm{E}(r_{EQ,t} - c_{EQ,t}) + \zeta \mathrm{E}(c_{CDS,t} - \beta_{cEQ}\mathrm{E}(r_{EQ,t} - c_{EQ,t})) \\ &\quad + \lambda_{\hat{r}R}\beta_{\hat{r}R} + \lambda_{\widehat{r\bar{c}}}\beta_{\widehat{r\bar{c}}} + \lambda_{\hat{c}R}\beta_{\hat{c}R} + \lambda_{\widehat{c\bar{c}}}\beta_{\widehat{c\bar{c}}} \end{aligned} \tag{16}$$

The coefficient ζ captures the impact of expected liquidity, $\lambda_{\hat{r}R}$ the price of the exposure to systematic non-traded risk, while the coefficient $\lambda_{\hat{c}R}$ reflects the liquidity risk premium. According to theoretical model the other risk premia should equal zero, i.e. $\lambda_{\widehat{r\bar{c}}} = \lambda_{\widehat{c\bar{c}}} = 0$.

Typically, the left hand side of the second stage equation is the sample average of all realized excess returns. However, given the short sample period this will likely give noisy estimates of expected returns. Instead, following Campello et al. (2008) and De Jong and Driessen (2005), we use an ex-ante measure of expected returns by correcting CDS spread levels for the expected default losses (the exact procedure is discussed in detail below). For a similar reason, and to reduce the number of parameters in the estimation, we impose specific values for the net equity premium $\mathrm{E}(r_{EQ,t} - c_{EQ,t})$. This procedure has the advantage that we can use additional information about the equity premium.

3.2 CDS returns

In this subsection, we describe how the (expected) CDS returns used in our model are constructed.

To estimate the factor and liquidity exposures (betas), we construct time series of excess returns of CDS contracts at a portfolio level. We first transform CDS spreads to excess returns. To derive the excess holding returns, consider an investor at time $t - \Delta t$ who sells protection using a CDS contract on one of the n underlyings in the market, say k, at a spread $CDS_{k,t}$ paid in quarterly periods. Next, at time t the investor buys an offsetting contract and pockets $-\frac{1}{4}\Delta CDS_{k,t}$ each quarter until default or maturity. The value of this stream at time t is the value of a portfolio of defaultable zero coupon bonds each with a face value of $-\frac{1}{4}\Delta CDS_{i,t}$, which gives the holding return[7]

$$R^{e,CDS}_{k,t} = \frac{\Delta t}{4} CDS_{k,t-\Delta t} - \frac{1}{4}\Delta CDS_{k,t} \sum_{j=1}^{(T-t)} B_t(t+j)\mathbb{Q}^{SV}_{k,t}(t+j), \tag{17}$$

where $\mathbb{Q}^{SV}_{k,t}(t+j)$ is the risk-neutral survival probability up to time $t+j$ and $B_t(t+j)$ is the price of a risk-free zero-coupon bond maturing at time $t+j$. Time is measured in quarters (the payment frequency). Since we initiated the contract at zero cost, our excess return is equal to the value of this stream. Of course, when default occurs between $t-\Delta t$ and t, the excess return on the CDS is equal to (minus) the loss given default (LGD). However, if we assume that these individual jumps-to-default are not priced, we can ignore these cases for estimating portfolio betas.[8][9]

To calculate the expected excess return at time t, we calculate the expectation under the real world measure of all cash flows resulting from the CDS contract when held till maturity, discounted at the risk free rate:

$$\begin{aligned} \mathrm{E}_t(\text{total CDS payoff}_k) = \frac{1}{4} CDS_{k,t} \sum_{j=1}^{(T-t)} B_t(t+j)\mathbb{P}^{SV}_{k,t}(t+j) - \\ (1-\rho)\sum_{j=1}^{(T-t)} B_t(t+j)\mathbb{P}^{SV}_{k,t}(t+j-1)\mathbb{P}^{def|SV}_{k,t}(t+j), \end{aligned} \tag{18}$$

where ρ is the expected recovery rate, $\mathbb{P}^{SV}_{k,t}(t+j)$ is the real world survival probability up to time $t+j$ and $\mathbb{P}^{def|SV}_{k,t}(t+j)$ is the probability of a default in period $t+j$ conditional on survival up to time $t+j-1$. Notice that this formula gives the excess return over the five-year holding period of the CDS contract.

We then obtain an estimate of the unconditional expected excess return by averaging these expected excess returns to maturity over all weeks in our sample. These

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[7] This method is very close to the one used by Duffie, Longstaff, Pan and Singleton (2007). The only difference is that they discount each cash flow with the risk-free rate plus CDS spread, whereas we discount with the risk-free rate and multiply with the risk neutral survival probability of each cash flow.

[8] Note that we do not use these excess returns to construct expected excess returns, where which we do correct for possible defaults (as shown in equation 18).

[9] In our sample the time to maturity of the CDS contracts varies between 4.5 and 5.5 years. Therefore, we scale the excess returns such that they are defined on a maturity of exactly five years, assuming that the term structure of default probabilities and risk free rates around the five year point is flat.

unconditional expected returns are used as the left-hand-side variable in the second step of the two-pass regression method. Constructing expected excess returns in this way rather than averaging realized excess returns allows us to achieve much more accurate estimates and thus achieve much lower standard errors for risk premia. Since we use the expected return to maturity for this calculation, the underlying assumption we make here is that the term structure of expected CDS returns is flat.

3.3 Risk-free rates and default probabilities

To construct excess returns from CDS spread changes, we need risk-free discount rates. Lando and Feldhütter (2005) argue that despite the AA default risk premium present in LIBOR rates, the best estimates of risk-free rates are obtained from swap rates. Therefore, we use daily data on the 3-month LIBOR based swap curve with a maturity of 1 up to 6 years. Swap rates are obtained from Datastream. To construct zero-coupon rates, we assume that these are piece-wise constant per year and subsequently bootstrap these rates from the observed term structure of swap rates.

To obtain the risk-neutral default probabilities, also needed to construct excess returns, we assume for simplicity that CDS prices only reflect default risk, that the risk-neutral default intensity is constant over the maturity period and that there is a deterministic recovery rate $\rho = 40\%$. We then solve the CDS pricing equation under these assumptions to obtain the default intensity and compute the risk-neutral probabilities (Duffie and Singleton (2003)):

$$CDS_{k,t} = 4\frac{(1-\rho)\sum_{j=1}^{(T-t)} \mathbb{Q}_{k,t}^{def|SV}(t+j)B_t(t+j)}{\sum_{j=1}^{(T-t)} \mathbb{Q}_{k,t}^{SV}(t+j)B(t,t+j)}, \tag{19}$$

$$\mathbb{Q}_{k,t}^{SV}(t+j) = \exp(-\lambda_{k,t}(t+j)), \tag{20}$$

where $\mathbb{Q}_{k,t}^{def|SV}(t+j)$ is the risk neutral probability of a default in period $t+j$ conditional on survival up to time $t+j-1$. We calculate these probabilities at each day and for each CDS portfolio used in the empirical analysis.[10]

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[10] Naturally, there is an inconsistency in assuming that CDS prices are only driven by default risk where the goal is to identify a non-default component. However, the relative sensitivity of $\mathbb{Q}^{SV}$ with respect to λ is very small since λ is small and $\mathbb{Q}^{SV}$ close to one. If we iterate our estimation procedure, by correcting the CDS spread and λ for the estimated liquidity effect and re-estimating the model, we find results that are extremely close to the results reported here.

Real world default probability estimates, needed to construct expected excess returns, are obtained from S&P annual default studies from 2001 up to 2005. These reports specify average cumulative default frequencies per rating category starting from 1983 up to the reporting year, ordered by notched rating class and tenor (in whole years). For non-rated companies we used the average of all rated companies, also reported by S&P in these reports. For a given year (say 2003), we used the average cumulative default probabilities calculated up to the year before (i.e. 1983 until 2002).

Our empirical analysis is performed using portfolios of CDS contracts. We thus require default probabilities (PDs) at the portfolio level. The aggregation of PDs to the rating sorted portfolios is trivial. For the portfolios sorted on quote activity, we take weighted averages of all rating implied PDs, where the weight of every issuer is the number of daily quotes for this issuer relative to the total number of daily quotes in its portfolio.

4 Data

We use a database of CDS quotes compiled by CreditTrade. They keep track of all CDSs quoted and traded on their trading platform. Our sample starts in July 2000 and runs until end of June 2006. Since the merger with Creditex, CreditTrade no longer provides these data. We can therefore not extend the sample to incorporate the credit crisis.

The sample contains bid and ask quotes of CDS spreads on US corporates and banks. The sample period contains many important events like the Ford and GM downgrade, the WorldCom collapse and the 9/11 terrorist attacks. We explicitly asked for the terms of use of the trading platform and the typical end-users. The platform offers only access to large financial institutions. Moreover, one cannot withdraw a quote once it is hit and the issuer is obliged to trade at his quote. Therefore, we consider the issuance of off-market quotes unlikely since they will be useless for the quote issuer.

4.1 Detailed data description

The data include fields that indicate the date, name of underlying, the seniority of the underlying, the maturity, the currency, the amount underlying, either the quoted bid or the ask price (occasionally both), the ICB level 2 industry of the underlying, the country the underlying is in, the Moody's and/or S&P rating and the restructuring clause. In this sample, the typical contract is a five year maturity (90%) contract on a senior (98.5%) unsecured loan in USD (99.9%) with a Modified Restructuring (MR) (96.7%) restructuring clause. Since Credit Trade provides incomplete rating data, we match our data to S&P ratings from Compustat NA Quarterly. These ratings are then used in our analysis.

We look at the distribution of quotes across industries and rating categories in Figure 2, where we aggregated industries to ICB level 1. We see that in general, telecom and healthcare companies have many CDSs written on their debt as well as the two much broader categories of consumer goods and consumer services. With respect to credit rating we see a strong presence of quotes in the lower categories of investment grade debt.

By comparing different quotes of identical underlyings within the same week, we identified several data problems (mainly typos or voice misinterpretations) and either corrected them where possible or removed them when not. Restricting our sample to senior contracts with a time to maturity of approximately (+/- 6 months) 5 years in USD with US standard MR restructuring clause leaves us with 339904 intra-day quotes. This will be the base sample for our data construction. We then go from intra-day quotes to daily quotes, to avoid intra-day market microstructure issues. Within each day, we take the average bid and the average ask for each CDS that we observe that day. After doing this, we end up with roughly 100,000 daily averages of bid and offer quotes on 918 entities.

To get an idea about patterns in the CDS market and the characteristics of different variables, we present graphs of our data averaged over all companies available every week. Figure 3 shows a time series plot of the CDS spread (average bid or average offer) in our sample. We see that the average CDS spread rises throughout the burst of the ICT bubble to peak mid 2002. In 2003 we see a sharp decline in the average spread and it remains low the rest of the sample period.

In Figure 4 we plot the weekly median bid-offer spread averaged over all issuers in our sample. The average bid-offer spread is relatively high and very volatile during the first period of the sample and then drops together with the average CDS spreads in the second half of 2002 to a much lower and stable level. In the second part of the sample we then observe one peak at the Ford/GM downgrade in May 2005.

4.2 CDS portfolio return and cost estimation

As is usual in the asset pricing literature, we test the model specified above on different test portfolios rather than on individual assets. This approach helps us to reduce the effect of the outliers due to idiosyncratic shocks. We define portfolios based on rating and quote activity. As shown below, there is a relation between our liquidity measure (bid-ask spread) and quote activity. Hence, our portfolios thus capture both variation in risk (rating) and liquidity (quote activity). Figure 2 shows that there is no clear monotonic relation between quote activity and rating, which should help in disentangling the effects of liquidity and credit risk in the two-step regression procedure.

For the rating portfolios, we use notched S&P ratings. We pool the high quality (AAA to AA) and speculative grade (BB+ and lower) to have enough observations in each portfolio. Additionally, we construct a non-rated class since we were unable to find S&P ratings for all issuers. The non-rated returns turn out to be noisier than the other portfolios, indicating a lack of homogeneity in this portfolio.

For the activity based portfolios we allow the composition of the portfolios to change by calendar year. Each calendar year we sort portfolios by the number of quotes that were recorded in the previous calendar year, imposing a maximum on the number of issuers in each portfolio. This way we ensure that we have on the one hand a proper sort, and on the other hand also have enough different contracts in the most active portfolio. All issuers that were not traded during the previous year are put in a separate portfolio called 'New'.

The construction of portfolio returns and transaction costs in this setting is nontrivial. For some CDS contracts we observe several quotes per day, while for other contracts less than one quote per week is observed. As a result, we have to deal with missing observations. Therefore, we adopt a technique called weighted repeated sales that originates from the real estate literature (for example Bailey, Muth and Nourse (1963) and Case and Shiller (1987)) and extend it to incorporate liquidity effects. This method calculates a return and cost index for all CDS contracts in a specific portfolio. The method assumes that individual contract returns are the sum of the portfolio return and an uncorrelated idiosyncratic term. The method employs regression analysis to estimate the value of the index and the transaction costs at different points in time as regression coefficients.

Formally the model is set up as follows. Let $k(i)$ be the portfolio that contains constituent i and let T the number of periods in our sample. For constituent i, we assume that the spread quote of a five years CDS contract $p_{i,t}$ is given by

$$p_{i,t} = CDS_{k(i),t} + c_{k(i),t}\delta_{i,t} + u_{i,t}, \tag{21}$$

where $CDS_{k(i),t}$ is the portfolio spread level (which is to be estimated), $c_{k(i),t}$ is half the portfolio bid-ask spread, δ is a dummy that indicates whether $p_{i,t}$ is a bid (-1) or ask (+1) quote and $u_{i,t}$ is a quote specific error term.[11] $u_{i,t}$ has mean zero and constant variance of σ_u and is uncorrelated with the other variables and its own lags. To illustrate the approach, suppose we have three transactions in constituent i, say at times s, s' and s'' and $s < s' < s''$. We can then specify spread innovations

$$\Delta p_{i,ss'} = p_{i,s'} - p_{i,s} = \sum_{j=2}^{T} x_{i,j,ss'}\Delta CDS_{k(i),j} + (\delta_{i,s'}c_{k(i),s'} - \delta_{i,s}c_{k(i),s}) + (u_{i,s'} - u_{i,s})$$

$$\Delta p_{i,s's''} = p_{i,s''} - p_{i,s'} = \sum_{j=2}^{T} x_{i,j,s's''}\Delta CDS_{k(i),j} + (\delta_{i,s''}c_{k(i),s''} - \delta_{i,s'}c_{k(i),s'}) + (u_{i,s''} - u_{i,s'})$$

where $x_{i,j,ss'}$ is a dummy that defines whether $j \in [s, s']$. The error covariance matrix is given by

$$\operatorname{var}(\Delta p_{i,ss'}) = 2\sigma_u^2 \tag{22}$$

$$\operatorname{var}(\Delta p_{i,s's''}) = 2\sigma_u^2 \tag{23}$$

$$\operatorname{cov}(\Delta p_{i,ss'}, \Delta p_{i,s's''}) = -\sigma_u^2. \tag{24}$$

We can write our spread innovation equations for all constituents of $k(i)$ up to time T in matrix form as

$$\Delta p = x\Delta CDS_{k(i)} + (\Delta\delta)c_{k(i)} + v \tag{25}$$

where $v = \Delta u$. The best linear unbiased estimators of $\Delta CDS_{k(i)}$ and $c_{k(i)}$ are given by

$$\begin{pmatrix} \widehat{\Delta CDS}_{k(i)} \\ \widehat{c}_{k(i)} \end{pmatrix} = (y'M^{-1}y)^{-1}y'M^{-1}r, \tag{26}$$

where $y = [x'\Delta\delta']'$, and M is the (sparse, block diagonal) covariance matrix of v. Empirically, σ_u is unknown. However, because M is known up to a scalar which drops out, it turns out to be possible to consistently estimate $\Delta CDS_{k(i)}$ and $c_{k(i)}$ without knowledge of σ_u by estimating $\Delta CDS_{k(i)}$ and $c_{k(i)}$ using regression.

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[11] Notice that we here implicitly assume that the mid-price is equal to the true price.

The CDS spread index is calculated on a daily basis, but in order to achieve identification and accurate estimates, we restrict the bid-ask spread to be constant within a week.[12] Then, we aggregate the daily returns to weekly returns. The final outcome of this procedure is weekly series of CDS spread changes and bid-ask spread levels for nine rating portfolios and seven activity portfolios. We also estimate the market-wide bid-ask spread and market-wide CDS spread changes by applying the method to the full sample. In line with the aggregate market behavior, for almost all portfolios the level and volatility of both CDS spreads and bid-ask spreads was rather high during the first part of the sample (even increasing at the burst of the ICT bubble and the attacks of 9/11). After 2002, the levels and volatility of CDS spreads and their bid-ask spreads decreased. Later on, we see for some portfolios a temporary peak around the Ford/GM downgrade that is relatively quickly reversed.

In order to estimate the risk neutral default and survival probabilities and expected excess returns, we need portfolio CDS spread *levels* rather than *innovations*. To construct the levels we perform the following regression

$$m_{k(i),t} I_{k(i),t} = CDS_{k(i),0} + \epsilon_{k(i),t}, \tag{27}$$

$$m_{k(i),t} = \frac{1}{n_{k(i),t}} \sum_{j \in k(i)} p_{j,t}, \qquad I_{k(i),t} = \sum_{j=1}^{t} \Delta CDS_{k(i),j}, \tag{28}$$

where $m_{k(i),t}$ and $n_{k(i),t}$ are the average and the number of all CDS quotes in portfolio $k(i)$ on day t respectively, $I_{k(i),t}$ the accumulated spread change and $CDS_{k(i),0}$ the level of the portfolio spread at the start of our sample. We estimate $CDS_{k(i),0}$ by regressing $m_{k(i)} - I_{k(i)}$ on a constant and then construct the time series of spread levels using $CDS_{k(i),t} = CDS_{k(i),0} + I_{k(i),t}$. We redo this for each calendar year, because our sample is not fully homogeneous over time. Once we have done this, we construct excess CDS returns and expected CDS returns as described in section 3.

4.3 Equity data

Returns on the market-wide CRSP equity index are obtained from Ken French's website. Equity liquidity costs are obtained analogous to Acharya and Pedersen (2005). That is, we calculate daily Amihud (2002) ILLIQs for all equities in CRSP. Following Acharya

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[12] Occasionally, there are days for which the data do not allow estimation of a spread change. In such a case, a multiple-day spread change is calculated.

and Pedersen (2005), we then apply the following transformation to get the average costs per trade:

$$c_t = \min(0.25 + 0.30 ILLIQ_t P^M_{t-1}, 30.00) \tag{29}$$

where P^M_{t-1} is the ratio of the market capitalization in year $t-1$ relative to the base year (to correct for inflation). We then take a value-weighted cross-sectional average and average those over each week to get weekly market-wide liquidity costs. This leads to an effective half spread of 33 bps per per dollar traded. Since each dollar invested in the equity market turns over approximately 1.5 times per year (aggregate annual volume over average market cap) and the costs are incurred both at the purchase as well as at the sale, this leads to trading costs of approximately 1% per dollar invested per annum.

4.4 Systematic credit risk factor

For our empirical analysis, we also need to measure the return on the non-traded credit risk factor R. As mentioned above, we think of R as the return on bank loans and illiquid corporate bonds. Since these returns are, by their very nature, not observable, we construct a proxy for this systematic credit risk using returns on corporate bond indices and CDS portfolios. Bond index excess returns are obtained by collecting weekly holding returns on intermediate maturity Lehman Brothers US Corporate Bond Indices per credit rating. The average life of all indices is approximately five years. Five year benchmark treasury returns are downloaded from Datastream and subtracted from the corporate bond returns to construct excess returns.

In order to capture the most important systematic credit risk factor in these indices and portfolios, we perform a principal component analysis (PCA). We take the holding returns of all our CDS portfolios and the holding returns on Lehman corporate bond indices for the ratings AAA up to CCC and calculate the first principal component in these returns. Since all these instruments have exposure to systematic credit risk, we would expect the first principal component to be a good measure for systematic credit risk.

For some CDS portfolios the return variance is much higher than the corporate bond return variance, suggesting that part of the CDS return variation is noise caused by infrequent observations. Performing a PCA on the covariance matrix would then lead to a very high weight on these high-variance CDS portfolios. Therefore, we use the correlation matrix rather than the covariance matrix for our principal component analysis where we follow Lindskog (2000) and use a correlation estimator based on a transformation of Kendall's τ rank correlation estimator.[13] Both CDS and corporate bond returns load positively on the first principal component with stable weights across all portfolios and indices, except for the AAA and AA bond indices which have negative but small loadings on the first factor.

5 Empirical Results

5.1 General setup

As mentioned before, we estimate the risk premia using a two-stage regression approach as in Black et al. (1972). When we estimate the time series regressions in equations (14) and (15) with all factors included, we find that several factor betas are not significantly different from zero: for the cost-equity beta β_{cEQ} we only find a significant estimate for 5 out 16 portfolios (at the 5% level), for the cost-return beta $\beta_{\widehat{c}R}$ we only find a significant estimate for 6 out 16 portfolios (but fewer in both sub-samples), and for the return-cost beta $\beta_{\widehat{r}\widehat{c}}$ none of the 16 estimates are significant.

This leads to a benchmark model where we only include the factors which have significant betas for a significant portion of the portfolios. These are the betas of the CDS returns with respect to the equity market return β_{rEQ}, the betas of the CDS returns with respect to the non-traded risk factor R, $\beta_{\widehat{r}R}$, and the betas of the CDS portfolio liquidity innovations with respect to the CDS market liquidity innovations $\beta_{\widehat{c}\widehat{c}}$. Our final pricing model is therefore given by

$$\mathrm{E}(r_{CDS,t}) = \beta_{rEQ}\mathrm{E}(r_{EQ,t} - c_{EQ,t}) + \zeta\mathrm{E}(c_{CDS,t}) + \lambda_{\widehat{r}R}\beta_{\widehat{r}R} + \lambda_{\widehat{c}\widehat{c}}\beta_{\widehat{c}\widehat{c}}. \tag{30}$$

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[13] Several of our series have missing values. We therefore calculate pairwise correlations since many observations are lost if the correlation matrix is estimated on the common sample. In this case, the correlation matrix is not guaranteed to be positive definite anymore. We follow the suggestion in Lindskog (2000) and replace negative eigenvalues by small positive numbers and then use the eigenvectors to get a positive definite approximation of the correlation matrix. Further, when constructing the principal component, a missing value in any of the series will give a missing value in the principal component. To construct the factors when we have missing values at a timepoint t, we do the following. First, we identify which series have missing values at time t. Next, for each of the series with missing values, we regress this series on all the series that do not have missing values and then fill in a fitted value for the missing series.

5.2 Benchmark model: First stage regression results

We first specify AR-models for the equity and CDS liquidity costs in order to construct innovations in these costs (needed for equations (12) and (13)). For the equity costs, an AR(2) model turns out be most appropriate, while for CDS liquidity costs an AR(4) model is used for all portfolios. Acharya and Pedersen (2005) correct for persistence in transaction costs in a similar way.

We then orthogonalize the CDS returns with respect to the equity market return (net of costs), following equation (12).[14] Table 2 reports the estimated betas β_{rEQ}, which are positive except for one case. Since we use the return for a CDS seller, which is proportional to minus the change in the CDS spread, a positive sign for β_{rEQ} can be expected: when equity prices increase, CDS spreads go down. As expected, almost all betas are below one, since especially high-rated bonds only have small market risk (see for example Elton, Gruber, Agrawal and Mann (2001). Only the speculative-grade portfolio and the non-rated portfolio have high betas of respectively 0.89 and 0.36. These betas are significant (at 5% level) in 6 out of 16 cases. As discussed above, some portfolios are not fully homogenous over time and have missing observations, which explains the high standard errors for these portfolios.

Next, we follow equation (14) and regress the orthogonalized CDS returns on our proxy for the non-traded risk factor constructed using PCA. Table 2 reports the resulting regression coefficients $\beta_{\widehat{r}R}$ and shows that these coefficients are always positive, and statistically significant for all portfolios. As expected, the return on selling CDS contracts is positively related to our proxy for systematic credit risk. Also, given that our credit risk factor represents an average of entire rating spectrum, we find the intuitive result that high-rated CDS portfolios have an exposure $\beta_{\widehat{r}R}$ smaller than one, while low-rated CDS portfolios have betas larger than one.

Finally, we estimate the time series regression of CDS portfolio liquidity innovations $c_{CDS,t} - E_{t-1}(c_{CDS,t})$ on the market-wide CDS liquidity innovation $\overline{c}_{CDS,t}$. Note that we do not orthogonalize these innovations for the equity market return because the equity market betas for the liquidity innovations were not significantly different from zero. Table 2 reports the liquidity-liquidity betas $\beta_{\widehat{c\overline{c}}}$ (equation (15)) and provides evidence for significant commonality of liquidity shocks in the CDS market. Liquidity

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[14] In the entire analysis, we aggregate our weekly return data to overlapping 4-weekly return series, in order to average out the measurement error that is present in some of the CDS portfolio returns.

shocks of all portfolios have positive exposure to the market-wide CDS liquidity shocks and the exposures are strongly significant for 15 out 16 portfolios. The CDS market therefore exhibits a systematic liquidity risk factor. For the equity market, existing work has provided evidence for systematic liquidity risk (for example, Chordia, Roll and Subrahmanyam (2000)). We see that low-rated CDS portfolios have a larger exposure to systematic liquidity than high-rated portfolios. Also, the two portfolios with lowest 'cross-sectional' liquidity, measured by quote frequency, have the highest exposure to liquidity risk. The same we see for expected liquidity in Figure 5: liquid portfolios have lower expected liquidity costs than illiquid portfolios. This shows that there is a relation between our two measures of liquidity, the bid-ask spread and the number of quotes per contract (quote activity). The portfolios based on quote activity thus capture variation expected liquidity and liquidity risk exposure, which is important to disentangle the effects of credit risk and liquidity on expected CDS returns.

5.3 Benchmark model: Second stage regression results

Given the estimated betas, we estimate the second-stage regression for expected CDS returns (16). To minimize the number of parameters to be estimated, we fix the annual equity risk premium $\mathrm{E}(r_{EQ,t} - c_{EQ,t})$ at 3% net of costs. Given the short time series, using realized equity returns will not generate a precise estimate of the equity premium. Using corporate bond price data and inverting the Merton (1974) model to obtain equity price implications, Campello et al. (2008) provide an ex-ante estimate of the equity premium of 3.80% before costs. Fama and French (1992) use postwar dividend yield information to obtain an ex-ante estimate of 4.91% before costs. As discussed above, annual expected transaction costs are around 1% so that the net-of-cost estimates of Fama and French (1992) and Campello et al. (2008) are close to our value of 3%. As a robustness check, we consider a higher value for the equity premium of 4%.

All the regressors in the second stage show substantial pairwise correlation. This leads to multi-collinearity issues. Since the aim of the paper is to see whether the CDS spread (expected excess returns) is affected by liquidity, we take a conservative approach and first orthogonalize the expected liquidity with respect to systematic credit risk exposure, and then orthogonalize the systematic liquidity exposure with respect to both systematic credit risk exposure and expected liquidity.

The results of our benchmark second stage regression can be found in Table 3.

Table 4 presents the cross-sectional R^2 when we step-by-step add expected liquidity and liquidity risk to the second-step regression. The effect of the systematic credit risk exposure is strongly significant and, as expected, the credit risk premium is positive. It explains 39.2% of the cross-sectional variation of the expected CDS returns (corrected for the exposure to the equity market). When we add expected liquidity, we find a positive and strongly significant coefficient ζ for expected liquidity which implies that the protection seller earns an expected liquidity premium. The cross-sectional R^2 increases to 70.5% after including expected liquidity, which shows the economic significance of expected liquidity. When we finally add liquidity risk exposure to the cross-sectional regression, we find an insignificant coefficient for liquidity risk and the R^2 only increases marginally to 70.7%. We therefore do not find evidence that liquidity risk is priced in the cross-section of CDS returns.

As a robustness check, we use a higher equity risk premium of 4%. Results can be found in Table 3. Since almost equity betas are positive, this drives down the expected excess returns after compensation for equity risk premium, and thus drives down the risk premium on systematic credit risk, although it is still marginally significant. Most importantly, the coefficient on expected liquidity remains economically and statistically significant, and even increases slightly. The liquidity risk premium is also statistically significant in this case, but the economic effect of liquidity risk remains small: the R^2 increases from 48.9% to 49.5% when we add liquidity risk exposure to the model (not reported). Since the R^2's are lower at the 4% equity risk premium, the data seem to favour a lower value for the equity risk premium.

We have also estimated the benchmark model for the first half of the sample and second half separately. The first-step regression results for the first and second half of the sample (not reported) are very similar to the full-sample results. Turning to the second-step regression results, we find that the coefficients for the credit risk premium and liquidity risk premium vary somewhat over the two subsamples, but the coefficient for expected liquidity is very stable and always significant. Overall, the results for the two subsamples support our main findings that an expected liquidity is earned by the protection seller and that the economic effect of liquidity risk is small.

5.4 Decomposing the CDS spread

The second stage regression results can be used to decompose the observed CDS spreads (corrected for expected loss) into components due to exposure to equity risk, credit risk and an expected liquidity premium. The base case results are as follows. The average equity beta across the sixteen test portfolios is 0.17. Multiplied by the assumed 3% annual equity risk premium this yields a 50 basis point risk premium. The exposure to credit risk is on average 1.063. Multiplied with the estimated price of risk 0.0177 this implies a credit risk premium of 38 basis points per year for the average CDS portfolio.[15] Finally, the orthogonalized expected liquidity multiplied by its regression coefficient implies a 13 basis points annualized liquidity premium. Notice that this is a lower bound on the effect of expected liquidity, as the expected liquidity was orthogonalized with respect to the credit risk exposure. We estimate the upper bound for the liquidity premium as follows: we run a second stage regression with (non-orthogonalized) expected liquidity as the only explanatory variable. The coefficient of this regression (15.5938 for the full sample, with a t-statistic of 4.42) implies a liquidity premium of 48 basis points per year for the average CDS portfolio. In summary, we find a significant effect of expected liquidity on the prices of CDS contracts. The liquidity premium is between 13 and 48 basis points per annum, depending on the order of orthogonalization between credit risk exposure and expected liquidity.

6 Conclusion

We introduce an asset pricing model for CDS contracts which includes credit risk and liquidity risk premia. In contrast to positive net-supply markets, the sign of liquidity effects on CDS contracts is not clear a priori. We develop a theoretical asset pricing model for derivatives with heterogeneous investors, and derive a linear asset pricing equation for the expected return on a derivative asset, similar to Acharya and Pedersen (2005). We test this model using CDS bid and ask quotes over a 2000 to 2006 sample period, and apply a repeated sales methodology to construct CDS spreads and bid-ask spreads at a portfolio level. We find evidence for a systematic credit risk and liquidity factor in the CDS market, which affects the liquidity of CDS portfolios based on rating and quote activity sorts. Expected liquidity affects expected CDS returns,

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[15] Notice that we measure the expected returns in the regressions over a five year holding period; for the ease of exposition we transform all expected returns in this paragraph to basis point per annum.

with a liquidity premium for the protection seller. Liquidity risk however, seems not to be priced, which is in line with the predictions from our theoretical model. Our results thus suggest that CDS spreads cannot be used as frictionless measures of default risk, as is often done in the recent literature.

A Proof of Theorems I and II

Orthogonalize the hedge asset returns for the net return on the other non-hedge assets, and optimize with respect to $\widehat{x}_i$ and y_i with $\widehat{x}_i = x_i - \beta_r' y_i + \delta_i \beta_c' y_i$. The utility function can then be rewritten as

$$U_i = \widehat{x}_i' \mathrm{E}(r_b - c_b) + y_i{}' \mathrm{E}(\widehat{r}_h - \delta_i \widehat{c}_h) - \frac{1}{2} A_i \mathrm{Var}(\widehat{x}_i{}'(r_b - c_b) + y_i'(\widehat{r}_h - \delta_i \widehat{c}_h) + q_i R) \quad (31)$$

Writing out the variance and omitting terms that don't involve $\widehat{x}_i$ gives

$$U_i = y_i'(\mathrm{E}(\widehat{r}_h) - \delta_i \mathrm{E}(\widehat{c}_h)) - \frac{1}{2} A_i \left[y_i' \left(V_r - \delta_i (C + C') + V_c \right) y_i + 2 y_i' \mathrm{Cov}(\widehat{r} - \delta_i \widehat{c}, R) q_i \right] \quad (32)$$

with V_r =Var$(\widehat{r}_h)$, $V_c = \mathrm{Var}(\widehat{c}_h)$ and $C = \mathrm{Cov}(\widehat{c}_h, \widehat{r}_h)$. Taking derivatives with respect to y_i gives the first order condition for investor i

$$\mathrm{E}(\widehat{r}_h) - \delta_i \mathrm{E}(\widehat{c}_h) - A_i \left(V_r - \delta_i (C + C') + V_c \right) y_i - A_i \mathrm{Cov}(\widehat{r}_h - \delta_i \widehat{c}_h, R) q_i = 0 \quad (33)$$

with solution for the optimal portfolio weights

$$y_i = A_i^{-1} \left(V_r - \delta_i (C + C') + V_c \right)^{-1} \left[\mathrm{E}(\widehat{r}_h) - \delta_i \mathrm{E}(\widehat{c}_h) - A_i \mathrm{Cov}(\widehat{r}_h - \delta_i \widehat{c}_h, R) q_i \right] \quad (34)$$

Pre-multiplying by the wealth-weights gives the equilibrium pricing condition:

$$\sum_i w_i y_i = \sum_i w_i A_i^{-1} \left(V(\delta_i)^{-1} \right) \left[\mathrm{E}(\widehat{r}_h) - \delta_i \mathrm{E}(\widehat{c}_h) - A_i \mathrm{Cov}(\widehat{r}_h - \delta_i \widehat{c}_h, R) q_i \right] = S_h \quad (35)$$

where $V(\delta_i) = V(\widehat{r}_h - \widehat{c}_h) = V_{r-c}$ if $\delta_i = 1$ and $V(\delta_i) = V(\widehat{r}_h + \widehat{c}_h) = V_{r+c}$ if $\delta_i = -1$. Collecting terms we get

$$\begin{aligned} & \left[\sum_{i:\delta_i=1} w_i A_i^{-1} V_{r-c}^{-1} + \sum_{i:\delta_i=-1} w_i A_i^{-1} V_{r+c}^{-1} \right] E(\widehat{r}_h) - \\ & \left[\sum_{i:\delta_i=1} w_i A_i^{-1} \delta_i V_{r-c}^{-1} + \sum_{i:\delta_i=-1} w_i A_i^{-1} \delta_i V_{r+c}^{-1} \right] E(\widehat{c}_h) - \\ & \left[\sum_{i:\delta_i=1} w_i q_i V_{r-c}^{-1} + \sum_{i:\delta_i=-1} w_i q_i V_{r+c}^{-1} \right] Cov(\widehat{r}_h, R) + \\ & \left[\sum_{i:\delta_i=1} w_i q_i \delta_i V_{r-c}^{-1} + \sum_{i:\delta_i=-1} w_i q_i \delta_i V_{r+c}^{-1} \right] Cov(\widehat{r}_h, R) \\ = \; & S_h \end{aligned} \quad (36)$$

Using the definition of δ_i and defining $\gamma_1 = \sum_{i:\delta_i=1} w_i A_i^{-1}$, $\gamma_2 = \sum_{i:\delta_i=-1} w_i A_i^{-1}$, $\gamma_3 = \sum_{i:\delta_i=1} w_i q_i$, and $\gamma_4 = \sum_{i:\delta_i=-1} w_i q_i$, we get equilibrium expected returns

$$\begin{aligned} \mathrm{E}(\widehat{r}_h) &= \left(\gamma_1 V_{r-c}^{-1} + \gamma_2 V_{r+c}^{-1}\right)^{-1} \left[S_2 + \left(\gamma_1 V_{r-c}^{-1} - \gamma_2 V_{r+c}^{-1}\right) \mathrm{E}(\widehat{c}_h) \right. \\ &\quad \left. + \left(\gamma_3 V_{r-c}^{-1} + \gamma_4 V_{r+c}^{-1}\right) \mathrm{Cov}(\widehat{r}_h, R) - \left(\gamma_3 V_{r-c}^{-1} - \gamma_4 V_{r+c}^{-1}\right) \mathrm{Cov}(\widehat{c}_h, R)\right] \end{aligned} \tag{37}$$

If $C = Cov(\widehat{r}_h, \widehat{c}_h) = 0$, we have $V(\widehat{r}_h - \widehat{c}_h) = V(\widehat{r}_h + \widehat{c}_h) = V(\widehat{r}_h) + V(\widehat{c}_h) = V_r + V_c$, and this simplifies to

$$\begin{aligned} \mathrm{E}(\widehat{r}_h) &= (\gamma_1 + \gamma_2)^{-1} (V_r + V_c) S_2 + \frac{\gamma_1 - \gamma_2}{\gamma_1 + \gamma_2} \mathrm{E}(\widehat{c}_h) \\ &\quad + \frac{\gamma_3 + \gamma_4}{\gamma_1 + \gamma_2} \mathrm{Cov}(\widehat{r}_h, R) - \frac{\gamma_3 - \gamma_4}{\gamma_1 + \gamma_2} \mathrm{Cov}(\widehat{c}_h, R) \end{aligned} \tag{38}$$

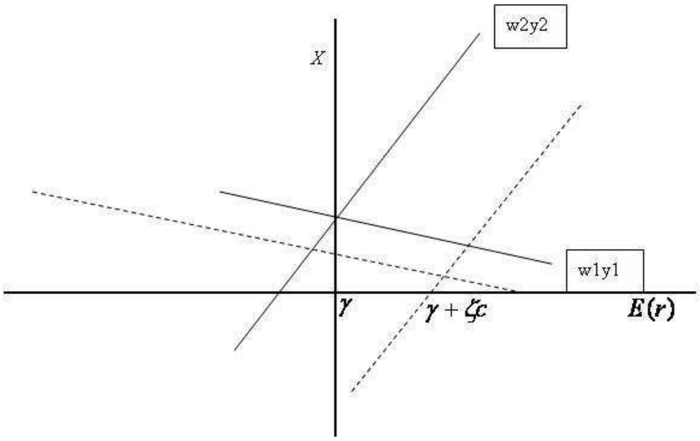


Figure 1: Graphical illustration of the asst pricing equilibrium with liquidity costs

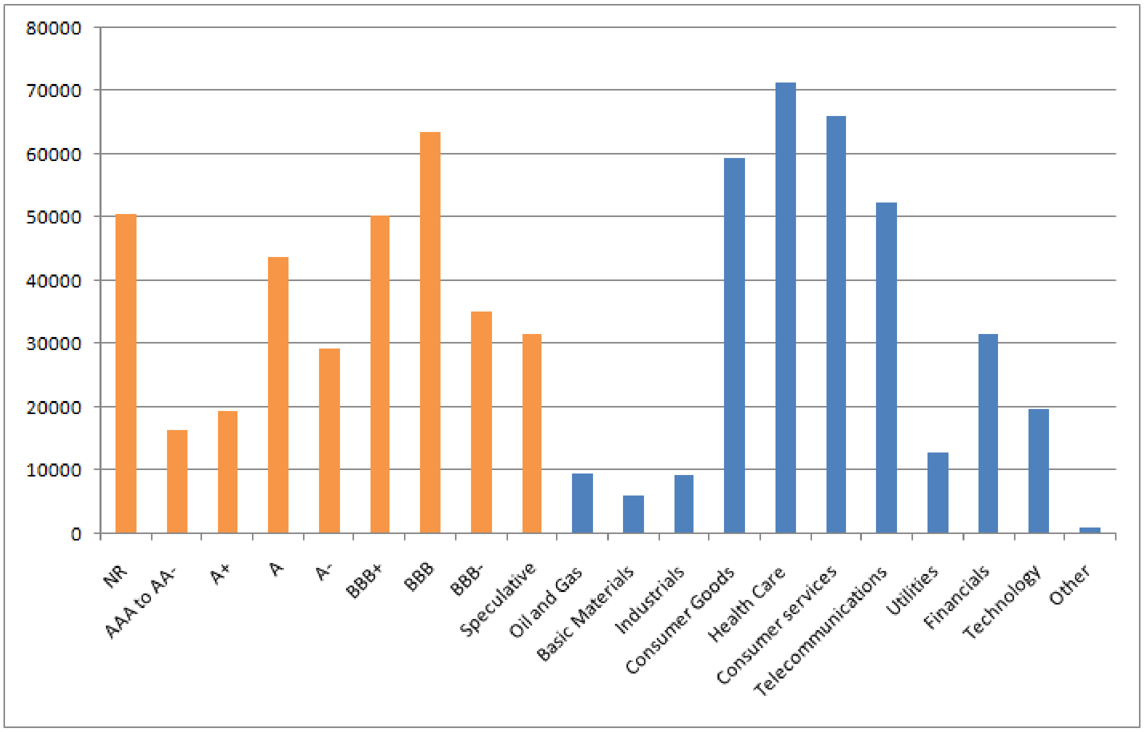


Figure 2: Number of quotes per industry and S&P rating category

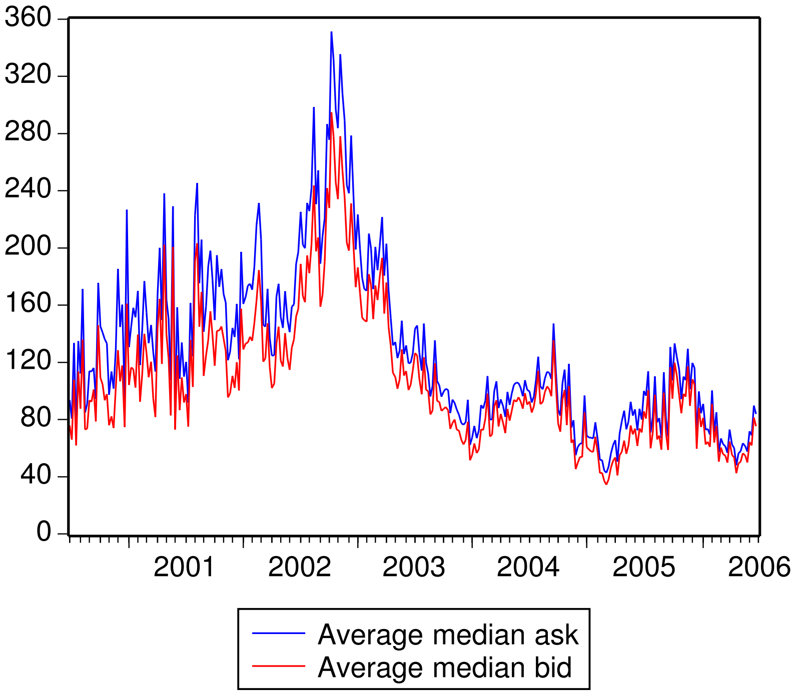


Figure 3: Weekly median bid and offer quotes averaged over issuers

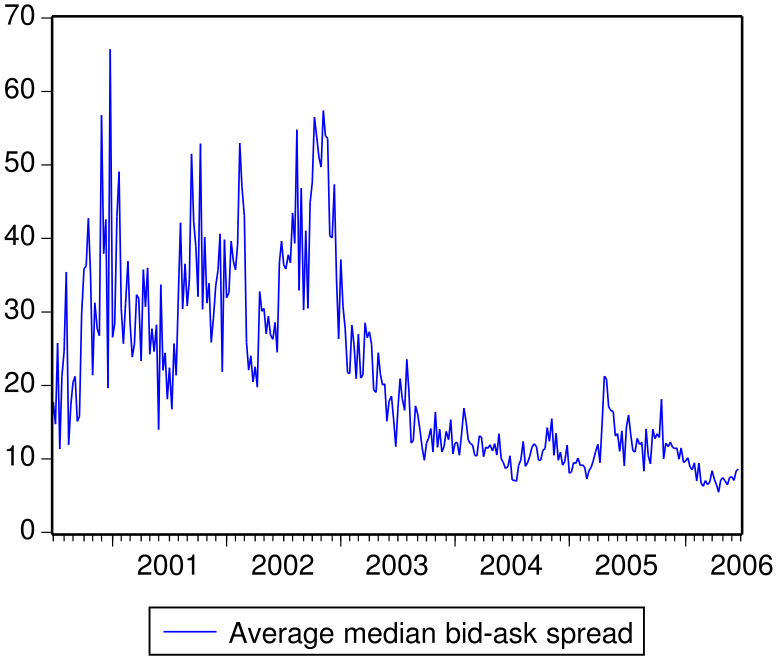
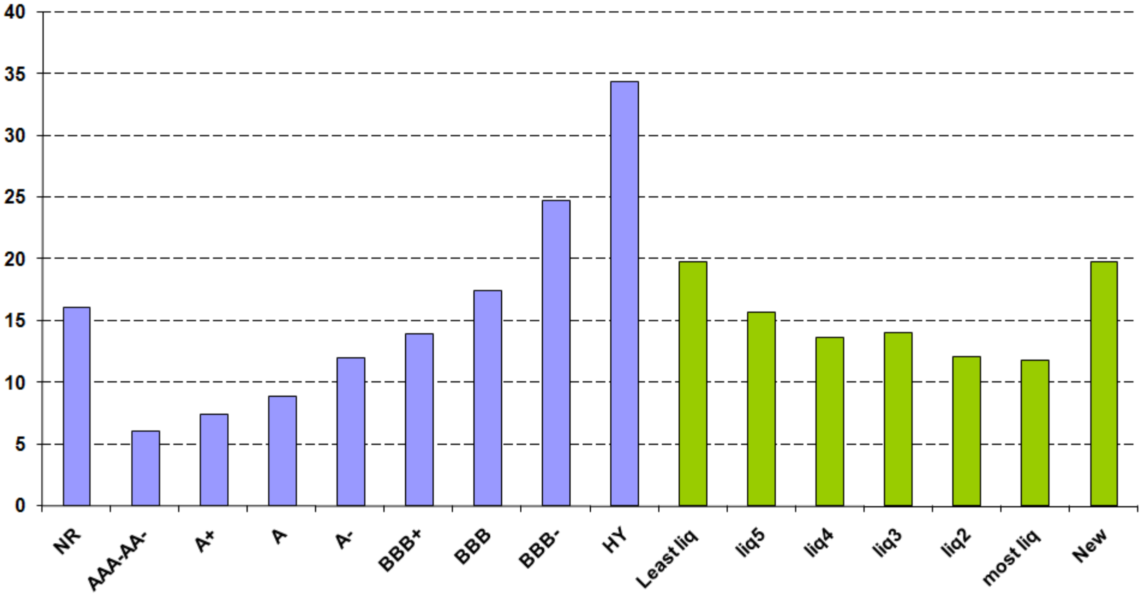


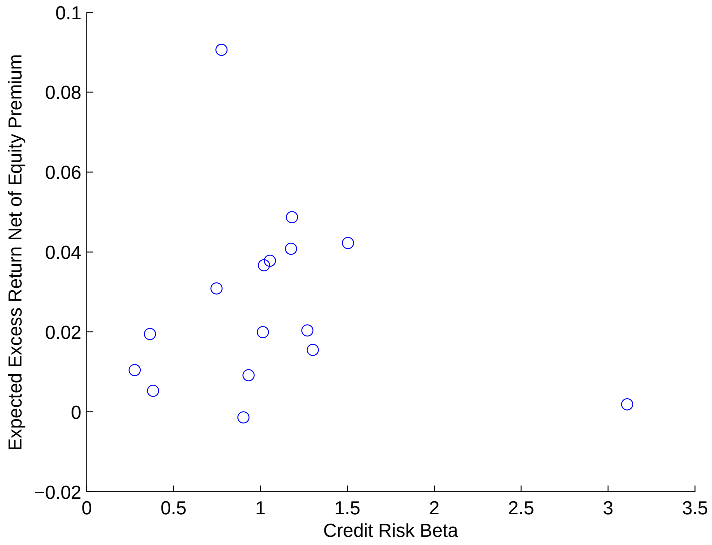
Figure 4: Weekly median bid-offer spread averaged over issuers

Figure 5: Expected liquidity per portfolio



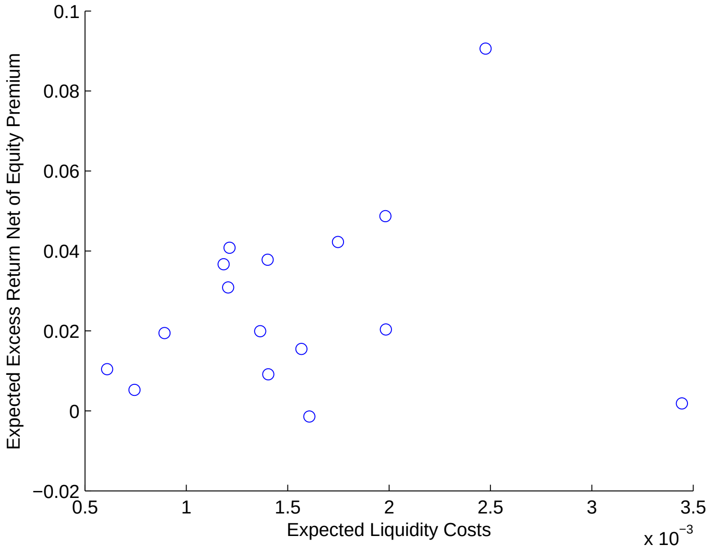
The figure displays the expected liquidity cost per portfolio for the full sample period. Liquidity costs are measured as half the quoted portfolio bid-ask spread (in bp) generated by the repeated sales procedure.

Figure 6: Scatterplot of credit risk betas and expected excess return residuals



The figure displays a scatterplot of portfolio expected excess returns minus portfolio equity betas times the equity market risk premium to expected liquidity costs over the full sample period. Betas are obtained from a first stage regression of CDS excess holding returns orthogonal to equity market returns on corporate bond index excess holding returns. Expected excess returns are measured as five year cumulative excess return per dollar of underlying.

Figure 7: Scatterplot of expected liquidity and expected excess return residuals



The figure displays a scatterplot of expected excess returns minus portfolio equity betas times the equity market risk premium to expected liquidity costs over the full sample period. Liquidity costs are measured as half the quoted portfolio bid-ask spread (in bp) generated by the repeated sales procedure. Expected excess returns are measured as five year cumulative excess return per dollar of underlying.

Table 1: Buyers and sellers in the CDS market

Source: 2006 Survey of the British Bankers Association, reported in Mengle (2007).

	Buy protection	Sell protection	Net position
Banks - Loan portfolio	20%	9%	11%
Banks - Trading activity	39%	35%	4%
Insurers	6%	17%	-11%
Funds	32%	39%	-7%
Hedge funds	28%	32%	-4%
Pension funds	2%	4%	-2%
Mutual Funds	2%	3%	-1%
Corporates & other	3%	2%	1%

Table 2: First stage regression results

We present regression coefficients for the first stage rolling window excess return and liquidity innovation regressions

$$r_{CDS,t} = a_{1r} + \beta_{rEQ}(r_{EQ,t} - [c_{EQ,t} - E_{t-1}(c_{EQ,t})]) + e_{r,t} \tag{39}$$

$$c_{CDS,t} - E_{t-1}(c_{CDS,t}) = a_{2c} + \beta_{\hat{c}\bar{c}}\bar{c}_{CDS,t} + \upsilon_t \tag{40}$$

$$e_{r,t} = a_{2r} + \beta_{\hat{r}R}R_t + \epsilon_t \tag{41}$$

on portfolios sorted on quote-activity and rating for our full sample running from July 2000 to June 2006. Standard errors are corrected for autocorrelation resulting from the rolling window approach using Newey-West. One, two and three stars indicate statistical significance at the 10%, 5% and 1% level respectively.

Full sample						
Portfolio	$\beta_{r,EQ}$	t-stat	$\beta_{\hat{r}R}$	t-stat	$\beta_{\hat{c}\bar{c}}$	t-stat
NR	0.361	3.118 ***	0.902	5.367 ***	1.157	6.538 ***
HQ	0.039	1.051	0.276	4.886 ***	0.241	3.476 ***
A+	0.103	2.344 **	0.382	5.909 ***	0.351	3.810 ***
A	0.069	1.719 *	0.364	6.318 ***	0.384	4.929 ***
A-	0.022	0.296	0.747	7.148 ***	0.187	1.517
BBB+	0.078	0.874	1.054	8.175 ***	1.300	8.653 ***
BBB	0.093	0.861	1.503	11.252 ***	0.973	5.423 ***
BBB-	-0.107	-1.029	0.776	5.039 ***	1.419	6.088 ***
HY	0.893	3.533 ***	3.110	9.054 ***	1.667	3.658 ***
least	0.216	2.301 **	1.270	11.058 ***	1.467	5.240 ***
liq2	0.220	1.419	1.301	5.742 ***	1.602	8.509 ***
liq3	0.192	2.398 **	1.014	8.528 ***	0.531	2.170 **
liq4	0.268	3.118 ***	0.931	7.824 ***	0.966	6.403 ***
liq5	0.035	0.270	1.176	6.354 ***	1.003	5.187 ***
most	0.123	1.483	1.020	9.671 ***	0.531	5.474 ***
new	0.044	0.423	1.181	9.497 ***	1.433	8.889 ***

Table 3: Second stage regression results

This table shows the results of the second stage regressions

$$\mathrm{E}(r_{CDS,t}) - \beta_{rEQ}\mathrm{E}(r_{EQ,t} - c_{EQ,t}) = \lambda_{\hat{r}R}\beta_{\hat{r}R} + \zeta\mathrm{E}(c_{CDS,t}) + \lambda_{\hat{c}\bar{c}}\beta_{\hat{c}\bar{c}}$$

where the regressors are orthogonalized in the order of appearance in this equation. Results are based on the full sample running from July 2000 to June 2006. Sub-samples 1 and 2 run from July 2000 to June 2003 and from July 2003 to June 2006 respectively. Standard errors are corrected for autocorrelation using Newey-West with 20 lags. One, two and three stars indicate statistical significance at the 10%, 5% and 1% level respectively.

	$\lambda_{\hat{r}R}$	t-stat	ζ	t-stat	$\lambda_{\hat{c}\bar{c}}$	t-stat	R^2
$\mathrm{E}(r_{EQ} - c_{EQ}) = 3\%$							
Full, 3%	0.0177	3.7244 ***	41.2045	12.1872 ***	0.0047	1.4404	0.7067
SS1, 3%	0.0704	13.0622 ***	29.5878	16.0861 ***	0.0089	1.7118 *	0.9259
SS2, 3%	0.0123	3.2082 ***	34.6764	18.4439 ***	-0.0014	-1.6342	0.4540
$\mathrm{E}(r_{EQ} - c_{EQ}) = 4\%$							
Full, 4%	0.0083	1.7549 *	47.5823	14.0736 ***	0.0090	2.7655 ***	0.4947
SS1, 4%	0.0682	12.6507 ***	31.4981	17.1247 ***	0.0146	2.8082 ***	0.8734
SS2, 4%	0.0009	0.2280	37.7494	20.0784 ***	-0.0010	-1.1743	0.2577

Table 4: Partial R^2s by subsample

This table presents R^2s for the second stage regressions for the different (sub)samples. The equity risk premium is fixed at 3%. Expected liquidity is orthogonalized with respect to systematic credit risk and liquidity risk is orthogonalized with respect to systematic credit risk and expected liquidity.

	Full Sample	Sub-Sample 1	Sub-Sample 2
Systematic Credit Risk (SCR)	0.392	0.803	0.205
SCR + Expected Liquidity (EL)	0.705	0.924	0.453
SCR + EL + Liquidity Risk	0.707	0.926	0.454

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