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Dion Bongaerts

Frank de Jong

Joost Driessen

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Dion Bongaerts[†] Frank de Jong[‡] Joost Driessen[§]

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[†]Finance Group, University of Amsterdam. E-mail: d.g.j.bongaerts@uva.nl.

[‡]Department of Finance, Tilburg University and Netspar. E-mail: f.dejong@uvt.nl.

[§]Finance Group, University of Amsterdam and Netspar. E-mail: j.j.a.g.driessen@uva.nl.

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Abstract

We derive a theoretical asset pricing model for derivative contracts that allows for expected liquidity and liquidity risk. Our model extends the LCAPM of Acharya and Pedersen (2005) to a setting with derivative instruments. The sign of the liquidity effect depends on investor heterogeneity in non-traded risk exposure, risk aversion and wealth. We estimate this model for the market of credit default swaps using a two pass regression approach. We find evidence for an economically and statistically significant expected liquidity premium earned by the protection seller. We do not find strong evidence that liquidity risk is priced.

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, and transaction costs for derivatives vary systematically over time. In the current sub-prime crisis we have witnessed a sharp decrease in the liquidity of CDS contracts, along with an increase of CDS spreads.

Our paper makes three contributions. Our first contribution is a theoretical asset pricing model for derivatives that incorporates expected liquidity and 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. We derive that 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 exposure of the liquidity of a derivative to the common 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 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 (2007), 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 5-year contracts. 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 portfolio returns and unexpected liquidity shocks are regressed on market and liquidity risk factors. In the second stage cross-sectional regression, expected CDS portfolio 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 CDS 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.

Our main empirical findings are as follows. The first-step time series regressions provide evidence that CDS returns are exposed to systematic equity risk and credit risk. Moreover we find commonality in the liquidity shocks of the CDS portfolios, which implies the existence of a systematic liquidity factor for the CDS market. Most importantly, the second stage results show a significant premium on expected liquidity, earned by the protection seller. Specification tests on the empirical model reveal that the effect of liquidity on CDS returns feeds through the channel of expected liquidity and that the systematic CDS 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 (2007) 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 (2007) 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. 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.[1] For derivative markets, the literature on liquidity is very scarce and often starts from a some-

[1]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 (2008), amongst others. De Jong and Driessen (2007), Downing, Underwood and Xing (2005) and Nashikkar and Subrahmanyam (2007) study the pricing of liquidity in corporate bond markets.

what 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, Gupta and Subrahmanyam (2008) 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 1 we introduce our theoretical model. In section 2 we discuss in detail how the model can be implemented empirically for the CDS market. The results of the empirical analysis are presented in section 3. Section 4 concludes.

1 A model for pricing liquidity in derivative markets

1.1 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, some of the assets are in zero net supply. This setting is natural when some of the assets are derivative contracts. An implication of this assumption is that in equilibrium, a fraction of the agents optimally hold short positions in the derivative contracts in order to hedge the non-traded risk exposure. This contrasts with AP whose assumptions imply that all agents hold long positions in equilibrium.

In our empirical analysis we apply this model to a setting where agents have a non-traded exposure to credit risk. For example, 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 may 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 assets are in positive net supply and agents have no non-traded risk exposure.

1.2 Assumptions and notation

1. *AGENTS.* The economy has N agents with mean-variance preferences (as in Acharya and Pedersen (2005)). 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). 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 small 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.[2] 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.[3] 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 non-zero.

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 (if the hedge asset returns correlate with R). 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.

[2] 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. As discussed earlier, 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.

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

For our credit risk application, these can be illiquid corporate bonds or bank loans.

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. 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)). Both long and short holders pay transaction costs, and 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 zero net 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 $r_{h,t} - \delta_i c_{h,t}$.

1.3 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 positions x_i in non-hedge assets and positions y_i in hedge assets

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

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 excess return on the hedge assets satisfies in equilibrium*

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

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 excess returns on the hedge assets are determined by (i) their covariance with the net excess 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.[4]

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

[4] It is straightforward to show that equation (2) reduces to AP's Liquidity CAPM if $S_h > 0$, $K_b = 0$, $q_i = 0$ 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 $\gamma_2 = \gamma_3 = \gamma_4 = 0$.

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 in equation (2) 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.

We now provide an interpretation for each term in equation (3). The intuition for the first two terms of this equation is straightforward: 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 ($S_h = 0$).

Given that $\gamma_1 + \gamma_2 > 0$, the sign of the expected liquidity effect (the third term) 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 thus 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 $\gamma_3 + \gamma_4 = \sum w_i q_i$. 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. If, for example, the 'short' agents have positive hedge exposure $\gamma_4 > 0$ while the 'long' agents have zero hedge exposure, $\gamma_3 = 0$, the coefficient on $\mathrm{Cov}(\widehat{c}_h, R)$ 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:

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

with

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

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

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

and where the λ's and ζ are functions of the underlying γ-parameters. Equation (4) can be estimated using standard two-pass linear regression methods.

1.4 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

$$0 = w_1 y_1 + w_2 y_2 = \frac{1}{\sigma^2}\left[(w_1 A_1^{-1} + w_2 A_2^{-1})E(r) - cov(r, R)w_1 q_1\right] \tag{6}$$

which gives the equilibrium expected return

$$E(r) = \frac{cov(r, R)w_1 q_1}{(w_1 A_1^{-1} + w_2 A_2^{-1})} \equiv \gamma \tag{7}$$

The portfolio holdings of the agents then can be shown to satisfy $y_1 < 0$ and $y_2 > 0$ if $cov(r, R) > 0$.

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

$$0 = w_1 y_1 + w_2 y_2 = \frac{1}{\sigma^2}\left[(w_1 A_1^{-1} + w_2 A_2^{-1})E(r) + (w_1 A_1^{-1} - w_2 A_2^{-1})c - cov(r,R)w_1 q_1\right] \tag{9}$$

with solution

$$E(r) = \frac{cov(r,R)w_1 q_1}{w_1 A_1^{-1} + w_2 A_2^{-1}} + \frac{w_2 A_2^{-1} - w_1 A_1^{-1}}{w_1 A_1^{-1} + w_2 A_2^{-1}} c = \gamma + \zeta c \tag{10}$$

with the compensation for transaction costs determined by the coefficient

$$\zeta = (w_2 A_2^{-1} - w_1 A_1^{-1})/(w_1 A_1^{-1} + w_2 A_2^{-1}) \tag{11}$$

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 $cov(r,R)q_1 A_1 > 2c$, 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 ($-w_1 y_1$) and the asset demand of agent 2 ($w_2 y_2$), and is drawn such that agent 2 is the less risk averse or more wealthy ($w_2 A_2^{-1} > w_1 A_1^{-1}$), 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 $-w_1 y_1 = w_2 y_2$ or $w_1 y_1 + w_2 y_2 = 0$. 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 has to be 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 would equal $\frac{w_2 A_2^{-1}}{V(r)+V(c)-2Cov(c,r)} - \frac{w_1 A_1^{-1}}{V(r)+V(c)+2Cov(c,r)}$ in this example. If $\mathrm{Cov}(c,r) > 0$, 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 $\mathrm{Cov}(c,r) > 0$, 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.

2 Empirical model for CDS contracts

We apply the theory developed above to the market for credit risk. In this market, the background risk is the pure credit risk of illiquid corporate bonds and bank loans. Credit default swap (CDS) contracts can be used to hedge this risk. 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.

Linking this market to our theoretical model, the background credit risk is proxied by a general credit index. Credit default swap (CDS) contracts are the hedge assets in zero net supply. We include as non-hedge asset the US equity market index. This market has positive net supply. We thus assume that investors use CDS contracts to hedge or take on credit risk, and take long positions in equity.

Our empirical approach follows the standard two-pass asset pricing test methodology of Black, Jensen and Scholes (1972). In the first step, the exposures of CDS returns and unexpected liquidity shocks to common return and liquidity factors are estimated. In the second step, the expected returns on the CDS portfolios are regressed on the factor exposures which gives estimates of premia on equity risk, credit risk and liquidity.

Typically, the left hand side of the second stage equation is the sample average of realized excess returns. However, given the short sample period this will give noisy estimates of expected returns. Instead, following Campello et al. (2008) and De Jong and Driessen (2007), 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).

In order to estimate the model, several steps have to be taken:

1. Construct portfolios of CDS contracts based on different characteristics, in particular the creditworthiness and the liquidity of the CDS contract.

2. For each CDS portfolio, estimate weekly holding returns and bid-ask spreads (a measure of the portfolio's liquidity).

3. Construct the background risk return R as the first principal component extracted from returns on corporate bond portfolios and CDS portfolios.

4. Collect data on equity index returns and construct a measure of equity liquidity.

5. Construct unexpected liquidity shocks for the CDS portfolios and the equity market and perform the first step regressions.

6. Construct expected returns on CDS contracts from the observed CDS spreads and historic default frequencies.

7. Finally, perform the second step estimation with the expected returns constructed in the previous step as the dependent variable and the liquidity estimates and exposure coefficients as explanatory variables.

We now discuss each step of the empirical procedure in detail.

Step 1: CDS data and portfolio selection

Detailed data description

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.

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. The platform offers only access to large institutions. Moreover, one cannot withdraw a quote once it is hit and the issuer is obliged to trade at his quote.[5]

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 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%) clause. Since Credit Trade provides incomplete rating data, we match our data to S&P ratings from Compustat North America Quarterly. These ratings are then used in our analysis. We look at the distribution of quotes across rating categories in Figure 4. With respect to credit rating we see a hump-shaped pattern: the most actively quoted CDS contracts are those around a BBB rating. Higher-rated and lower-rated CDS contracts are traded relatively less frequently.

Restricting our sample to senior contracts with a time to maturity between 4.5 and 5.5 years in US dollars with US standard Modified Restructuring clause leaves us with 339904 intra-day quotes. 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

[5]By comparing different quotes of identical underlyings within the same week, we identified several data problems (mainly typos or voice misinterpretations); we corrected obvious errors like missing digits, and removed erroneous data otherwise.

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 ask quotes on 918 entities. This will be the base sample for our portfolio construction.

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 2 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.

Figure 3 plots the weekly median bid-ask spread averaged over all issuers in our sample. The average bid-ask 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.

Portfolio selection

As is usual in the asset pricing literature, we fit the model to different test portfolios rather than to individual assets. 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. Our portfolios thus capture both variation in risk (rating) and liquidity (quote activity). Figure 4 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'.

Step 2: CDS portfolio return and cost estimation

In this step, we calculate weekly estimates of the CDS returns and bid-ask spreads at the portfolio level. The construction of portfolio CDS returns and bid-ask spreads for our data is nontrivial. For some CDS contracts we observe quotes almost every 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 CDS spread index and a bid-ask spread for all CDS contracts in a specific portfolio. The method assumes that individual CDS spread quote is the sum of the portfolio spread level, a term that captures whether the quote is bid or ask, and an uncorrelated idiosyncratic term.

Specifically, let $k(i)$ be the portfolio that contains constituent $i.$, for which we assume that the spread quote of a five-year CDS contract $p_{i,t}$ is given by

$$p_{i,t} = CDS_{k(i),t} + c_{k(i),t}\delta_{i,t} + u_{i,t}, \tag{12}$$

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 ($\delta = -1$) or ask ($\delta = +1$) quote and $u_{i,t}$ is a quote specific error term. The repeated sales method employs regression analysis to estimate the value of the portfolio CDS spread and the bid-ask spread at different points in time as regression coefficients. Appendix B details the procedure.

To construct time series of excess returns of CDS contracts at a portfolio level, we transform the portfolio 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 excess holding return (also including the 'accrued' spread)[6]

$$r_{k,t} = \frac{\Delta t}{4} CDS_{k,t-\Delta t} - \frac{1}{4} \Delta CDS_{k,t} \sum_{j=1}^{(T-t)} B_t(t+j) \mathbb{Q}_{k,t}^{SV}(t+j), \tag{13}$$

where $\mathbb{Q}_{k,t}^{SV}(t+j)$ 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 $t+j$.[7] 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.

Step 3: 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

[6]Of course, if 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.

[7]This method is very close to the one used by Longstaff, Pan, Pedersen and Singleton (2008). 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. Appendix C provides the details on the risk free rate data and the construction of the risk neutral default probabilities.

corporate bond returns to construct excess returns.

In order to capture the most important systematic credit risk factor in these bond indices and CDS 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.

We use the correlation 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. 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.

Step 4: Equity market returns and liquidity

Returns on the market-wide CRSP equity index are obtained from Kenneth 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 and Pedersen (2005), we then apply the following transformation to get the average costs per trade:

$$c_{EQ,t} = \min(0.25 + 0.30 ILLIQ_t P^M_{t-1}, 30.00) \tag{14}$$

where P_{t-1}^{M} 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 basis points. 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 annum.

Step 5: First step estimation

We estimate the model with a two stage regression analogous to Black et al. (1972). The first step of this procedure estimates the exposures of CDS returns and transaction costs to the common risk factors. The estimation of these exposures proceeds in several sub-steps.

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. For the equity costs, $c_{EQ,t}$, an AR(2) model turns out be most appropriate, while for CDS liquidity costs c_t an AR(4) model is used for all portfolios. Acharya and Pedersen (2005) correct for persistence in transaction costs in a similar way.

Following the theory in section 1, we then orthogonalize the return and unexpected transaction costs on the CDS portfolios (denoted by the vectors r and c) for the net equity market return

$$r_t = a_{1r} + \beta_{rEQ}(r_{EQ,t} - [c_{EQ,t} - E_{t-1}(c_{EQ,t})]) + \hat{r}_t \tag{15}$$

$$c_t - E_{t-1}(c_t) = a_{1c} + \beta_{cEQ}(r_{EQ,t} - [c_{EQ,t} - E_{t-1}(c_{EQ,t})]) + \hat{c}_t \tag{16}$$

where the equity returns are in excess of the risk-free rate.

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, we also include an additional risk factor: the CDS market liquidity innovation $\overline{c}_t$, constructed by applying the repeated sales procedure to the entire universe of CDS contracts:

$$\hat{r}_t = a_{2r} + \beta_{\hat{r}R} R_t + \beta_{\hat{r}\overline{c}}[\overline{c}_t - E_{t-1}(\overline{c}_t)] + \epsilon_t \tag{17}$$

$$\hat{c}_t = a_{2c} + \beta_{\hat{c}R} R_t + \beta_{\hat{c}\overline{c}}[\overline{c}_t - E_{t-1}(\overline{c}_t)] + \upsilon_t \tag{18}$$

In all first step regressions, 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.

Step 6: Expected CDS returns

To calculate the expected excess return of a CDS contract (or portfolio) 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:

$$\begin{aligned}\mathrm{E}_t(\text{total CDS payoff}_k) = \frac{1}{4} CDS_{k,t} \sum_{j=1}^{(T-t)} B_t(t+j)\mathbb{P}^{SV}_{k,t}(t+j) - \\ (1-\rho)\sum_{j=1}^{(T-t)} B_t(t+j)\mathbb{P}^{SV}_{k,t}(t+j-1)\mathbb{P}^{def|SV}_{k,t}(t+j), \quad (19)\end{aligned}$$

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 for every week in the sample. 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.

Real world default probability estimates, needed to construct the 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.

Step 7: Second step estimation

For the second stage estimation, we obtain an estimate of the unconditional expected excess return by averaging expected CDS returns from equation (19) over all weeks in our sample. These unconditional expected returns are then used as the left-hand-side variable in the second step of the two-pass regression method. We then 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 $\overline{c}$

$$\begin{aligned} \mathrm{E}(r) &= \beta_{rEQ}\mathrm{E}(r_{EQ,t} - c_{EQ,t}) + \zeta\mathrm{E}(c - \beta_{cEQ}\mathrm{E}(r_{EQ,t} - c_{EQ,t})) \\ &\quad + \lambda_{\widehat{r}R}\beta_{\widehat{r}R} + \lambda_{\widehat{c}R}\beta_{\widehat{c}R} + \lambda_{\widehat{r}\widehat{\overline{c}}}\beta_{\widehat{r}R} + \lambda_{\widehat{c}\widehat{\overline{c}}}\beta_{\widehat{c}R} \end{aligned} \tag{20}$$

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

To assess whether there is time variation in the risk premia, we also estimate equation (20) using a rolling window of 12 weeks for the expected CDS returns and bid-ask spread. We still use the full-sample estimates of the risk exposures in this case, since these are hard to estimate over short windows due to missing observations. This procedure gives us a time series of estimated premia on expected liquidity and the different risk factors.

3 Empirical Results

3.1 First stage regression results

When we estimate the first step series regressions in equations (17) and (18) 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 $\beta_{\hat{c}R}$ we only find a significant estimate for 6 out 16 portfolios (but fewer in both sub-samples), and for the return-cost beta $\beta_{\widehat{r\overline{c}}}$ none of the 16 estimates are significant.

We therefore exclude these three mostly insignificant betas. Our final first-stage regression is then given by

$$r_t = a_{1r} + \beta_{rEQ}(r_{EQ,t} - [c_{EQ,t} - E_{t-1}(c_{EQ,t})]) + \hat{r}_t \tag{21}$$

$$\hat{r}_t = a_{2r} + \beta_{\hat{r}R} R_t + \epsilon_t \tag{22}$$

$$c_t - E_{t-1}(c_t) = a_{2c} + \beta_{\widehat{c\overline{c}}}[\overline{c}_t - E_{t-1}(\overline{c}_t)] + \upsilon_t \tag{23}$$

Table 2 reports the estimated first stage equity 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 (22) 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 $\beta_{\hat{r}R}$ 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 $\beta_{\hat{r}R}$ 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 $c_t - E_{t-1}(c_t)$ on the market-wide CDS liquidity innovation $\overline{c}_t - E_{t-1}(\overline{c}_t)$ as in equation (23). 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 $\beta_{\widetilde{c}\widetilde{\overline{c}}}$ and provides evidence for significant commonality of liquidity shocks in the CDS market. Liquidity 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: portfolios with high quote activity have lower expected liquidity costs than portfolios with low quote activity. 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 in expected liquidity and liquidity risk exposure, which is important to disentangle the effects of credit risk and liquidity on expected CDS returns.

3.2 Second stage regression results

Given the estimated betas, we estimate the second-stage regression for expected CDS returns (20). As discussed above, we only include the factors which have significant betas for a significant portion of the portfolios. Our final pricing model is therefore given by

$$\mathrm{E}(r) = \lambda_{EQ}\beta_{rEQ} + \lambda_{\widehat{r}R}\beta_{\widehat{r}R} + \zeta \mathrm{E}(c) + \lambda_{\widehat{cc}}\beta_{\widehat{cc}} + u. \tag{24}$$

where $\lambda_{EQ} = \mathrm{E}(r_{EQ} - c_{EQ})$ is equity risk premium net of transaction costs. The regressors in the second stage show substantial pairwise correlation, which may lead to multi-collinearity problems. 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 step-by-step orthogonalize the regressors. More precisely, we first orthogonalize the credit risk betas across portfolios ($\beta_{\widehat{r}R}$) with respect to the equity betas β_{rEQ}, we orthogonalize expected liquidity with respect to credit risk betas and equity betas, and finally orthogonalize the systematic liquidity risk exposure with respect to equity betas, credit risk betas, and expected liquidity. This is conservative in the sense that we allow equity risk and credit risk to explain as much as possible of the expected CDS return. Only if there is an orthogonal component in expected liquidity or liquidity risk that explains part of the CDS returns, we will conclude that liquidity or liquidity risk matters for CDS prices. This procedure also implies that, for example, the level of the equity premium does not affect the estimates for the other premia, since the regressors are all orthogonal to each other. Hence, we could impose any value for the equity premium without affecting the estimated effects for the other premia.

The results of our second stage regressions can be found in Table 3. This table also presents the cross-sectional R^2 when we step-by-step add regressors to the second-step regression. The effect of the systematic equity risk and credit risk exposures is strongly significant and, as expected, these risk premia are positive. The estimated net equity premium is about 17% over a 5-year period, so roughly 3.4% per year. 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 estimated net equity premium.

The equity and credit risk premia together explain 95.7% of the cross-sectional variation of the expected CDS returns. 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

98.9% after including expected liquidity, which shows its economic significance. When we finally add liquidity risk exposure to the cross-sectional regression, we find a very small (but statistically significant) coefficient for liquidity risk; the R^2 only increases marginally to 99.0%. We therefore do not find strong evidence that liquidity risk is priced in the cross-section of CDS returns.

The result that CDS sellers earn an expected liquidity premium can be interpreted using our theory in section 1, combined with the survey data for the CDS market in 2006 from the British Bankers Association in Table 1. These data 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).

We also estimate the 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 similar to the full-sample results. Turning to the second-step regression results, we find that the coefficients for the equity premium, credit risk premium and liquidity risk premium vary somewhat over the two sub-samples, but the coefficient for expected liquidity is very stable and always significant. Moreover, the economic significance of the premium on liquidity risk is very small. Overall, the results for the two sub-samples support our main findings that an expected liquidity is earned by the protection seller and that the liquidity risk premium is close to zero.

Finally, we look at time varying estimates of the risk premia. These are obtained by running the second step regression (24) on rolling 12 week averages of the expected CDS returns and expected liquidity, but using the full sample estimates of the risk exposures. The results are graphed in Figure 8. The results show that the equity risk premium and the credit risk premium are quite large in the first half of the sample, and decline over time but remain positive. This declining pattern over the 2000-2006 period suggests that investors accepted low risk premia in the period before the credit crisis. The expected liquidity risk premium follows a different pattern with cyclical variations, but is almost always positive. The liquidity premium is time varying around zero, but generally small especially at the end of the sample. These results confirm that our estimates are robust over time, and again point at the relevance of equity market risk, credit risk and expected liquidity as the dominant factors in pricing CDS contracts. This is consistent with our theoretical model.

3.3 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 estimated 3.4% annual equity risk premium this yields a 56 basis point risk premium. The exposure to credit risk is on average 0.430. Multiplied with the estimated price of risk 0.0488 this implies a credit risk premium of 42 basis points per year for the average CDS portfolio.[8]

[8]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.

Finally, the orthogonalized expected liquidity multiplied by its regression coefficient implies a 5 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 equity risk and credit risk exposures. 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 implies a liquidity premium of 38 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 5 and 38 basis points per annum, depending on the order of orthogonalization between the equity risk and credit risk exposures and expected liquidity.

4 Conclusion

We develop a theoretical asset pricing model for derivatives with heterogeneous investors and liquidity effects. This is an extension of the model of Acharya and Pedersen (2005) who focus on positive net-supply assets only. Compared to the case of positive net-supply assets, our theory highlights a different role for liquidity premia for zero net-supply assets (derivatives), where the sign of liquidity effects on derivative prices is not clear a priori.

We test this model using credit default swap (CDS) bid and ask quotes over a 2000 to 2006 sample period. We apply a repeated sales methodology to construct CDS spreads and bid-ask spreads at a portfolio level and then estimate the asset pricing model using a standard two-pass regression approach. 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. Our main empirical finding is that expected liquidity affects expected CDS returns, 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

$$U_i = \widehat{x}_i' \mathrm{E}(r_b - c_b) + y_i{}' \mathrm{E}(\widehat{r}_h - \delta_i \widehat{c}_h) - \frac{1}{2} A_i \mathrm{Var}(\widehat{x}_i{}'(r_b - c_b) + y_i'(\widehat{r}_h - \delta_i \widehat{c}_h) + q_i R) \quad (25)$$

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

$$U_i = y_i'(\mathrm{E}(\widehat{r}_h) - \delta_i \mathrm{E}(\widehat{c}_h)) - \frac{1}{2} A_i \left[y_i' \left(V_r - \delta_i (C + C') + V_c \right) y_i + 2 y_i' \mathrm{Cov}(\widehat{r} - \delta_i \widehat{c}, R) q_i \right] \quad (26)$$

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

$$\mathrm{E}(\widehat{r}_h) - \delta_i \mathrm{E}(\widehat{c}_h) - A_i \left(V_r - \delta_i (C + C') + V_c \right) y_i - A_i \mathrm{Cov}(\widehat{r}_h - \delta_i \widehat{c}_h, R) q_i = 0 \quad (27)$$

with solution for the optimal portfolio weights

$$y_i = A_i^{-1} \left(V_r - \delta_i (C + C') + V_c \right)^{-1} \left[\mathrm{E}(\widehat{r}_h) - \delta_i \mathrm{E}(\widehat{c}_h) - A_i \mathrm{Cov}(\widehat{r}_h - \delta_i \widehat{c}_h, R) q_i \right] \quad (28)$$

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

$$\sum_i w_i y_i = \sum_i w_i A_i^{-1} \left(V(\delta_i)^{-1}\right) \left[\mathrm{E}(\widehat{r}_h) - \delta_i \mathrm{E}(\widehat{c}_h) - A_i \mathrm{Cov}(\widehat{r}_h - \delta_i \widehat{c}_h, R) q_i\right] = S_h \quad (29)$$

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

$$\begin{aligned}
& \left[\sum_{i:\delta_i=1} w_i A_i^{-1} V_{r-c}^{-1} + \sum_{i:\delta_i=-1} w_i A_i^{-1} V_{r+c}^{-1}\right] E(\widehat{r}_h) - \\
& \left[\sum_{i:\delta_i=1} w_i A_i^{-1} \delta_i V_{r-c}^{-1} + \sum_{i:\delta_i=-1} w_i A_i^{-1} \delta_i V_{r+c}^{-1}\right] E(\widehat{c}_h) - \\
& \left[\sum_{i:\delta_i=1} w_i q_i V_{r-c}^{-1} + \sum_{i:\delta_i=-1} w_i q_i V_{r+c}^{-1}\right] Cov(\widehat{r}_h, R) + \\
& \left[\sum_{i:\delta_i=1} w_i q_i \delta_i V_{r-c}^{-1} + \sum_{i:\delta_i=-1} w_i q_i \delta_i V_{r+c}^{-1}\right] Cov(\widehat{r}_h, R) \\
= \; & S_h
\end{aligned} \quad (30)$$

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

$$\begin{aligned}
\mathrm{E}(\widehat{r}_h) &= \left(\gamma_1 V_{r-c}^{-1} + \gamma_2 V_{r+c}^{-1}\right)^{-1} \left[S_2 + \left(\gamma_1 V_{r-c}^{-1} - \gamma_2 V_{r+c}^{-1}\right) \mathrm{E}(\widehat{c}_h)\right. \\
& \left. + \left(\gamma_3 V_{r-c}^{-1} + \gamma_4 V_{r+c}^{-1}\right) \mathrm{Cov}(\widehat{r}_h, R) - \left(\gamma_3 V_{r-c}^{-1} - \gamma_4 V_{r+c}^{-1}\right) \mathrm{Cov}(\widehat{c}_h, R)\right]
\end{aligned} \quad (31)$$

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

$$\begin{aligned}
\mathrm{E}(\widehat{r}_h) &= (\gamma_1 + \gamma_2)^{-1} (V_r + V_c) S_2 + \frac{\gamma_1 - \gamma_2}{\gamma_1 + \gamma_2} \mathrm{E}(\widehat{c}_h) \\
& + \frac{\gamma_3 + \gamma_4}{\gamma_1 + \gamma_2} \mathrm{Cov}(\widehat{r}_h, R) - \frac{\gamma_3 - \gamma_4}{\gamma_1 + \gamma_2} \mathrm{Cov}(\widehat{c}_h, R)
\end{aligned} \quad (32)$$

B Repeat sales method

This appendix contains details on the repeat sales method used to form returns on CDS portfolios. 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

$$p_{i,t} = CDS_{k(i),t} + c_{k(i),t}\delta_{i,t} + u_{i,t}, \tag{33}$$

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.[9] $u_{i,t}$ 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

$$\mathrm{Var}(\Delta p_{i,ss'}) = 2\sigma_u^2 \tag{34}$$

$$\mathrm{Var}(\Delta p_{i,s's''}) = 2\sigma_u^2 \tag{35}$$

$$\mathrm{Cov}(\Delta p_{i,ss'}, \Delta p_{i,s's''}) = -\sigma_u^2. \tag{36}$$

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

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

$$\Delta p = x\Delta CDS_{k(i)} + (\Delta\delta)c_{k(i)} + v \tag{37}$$

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

$$\begin{pmatrix} \widehat{\Delta CDS}_{k(i)} \\ \\ \widehat{c}_{k(i)} \end{pmatrix} = (y'M^{-1}y)^{-1}y'M^{-1}r, \tag{38}$$

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.

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.[10] 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

[10]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.

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

$$m_{k(i),t} - I_{k(i),t} = CDS_{k(i),0} + \epsilon_{k(i),t}, \tag{39}$$

$$m_{k(i),t} = \frac{1}{n_{k(i),t}} \sum_{j \in k(i)} p_{j,t}, \qquad I_{k(i),t} = \sum_{j=1}^{t} \Delta CDS_{k(i),j}, \tag{40}$$

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 2.

C Risk-free rates and default probabilities

To construct excess returns from CDS spread changes, we need risk-free discount rates. Lando and Feldhütter (2008) 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)):

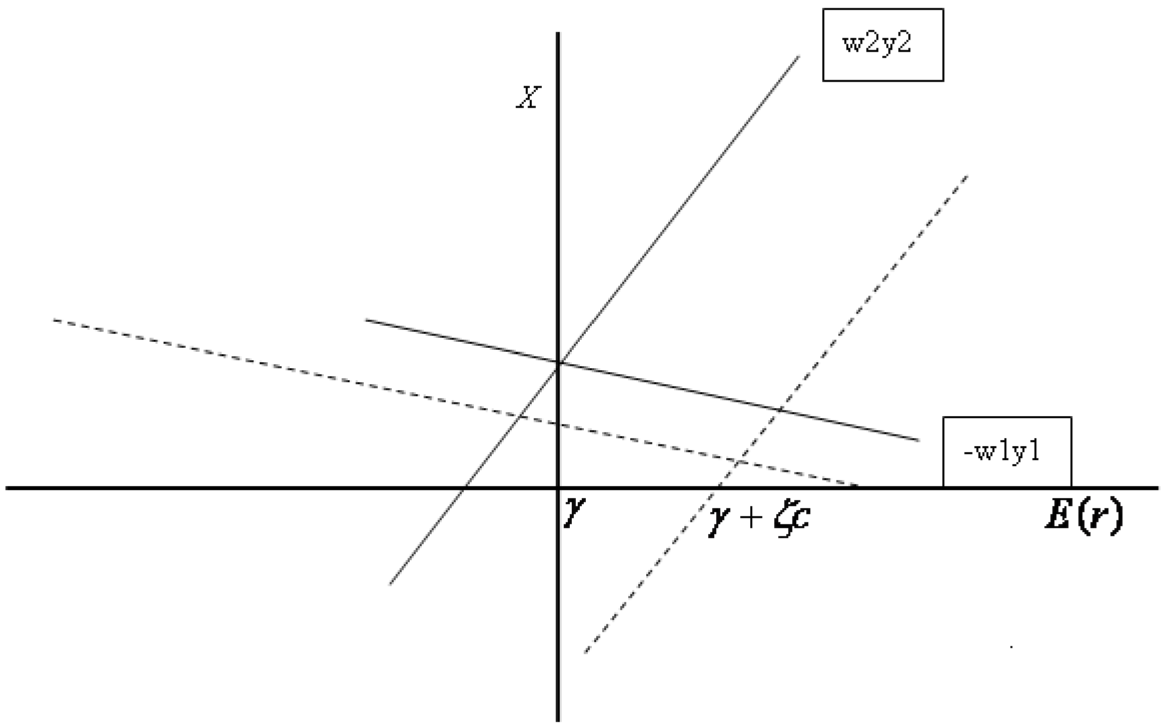
$$CDS_{k,t} = 4\frac{(1-\rho)\sum_{j=1}^{(T-t)} \mathbb{Q}_{k,t}^{def|SV}(t+j)B_t(t+j)}{\sum_{j=1}^{(T-t)} \mathbb{Q}_{k,t}^{SV}(t+j)B(t,t+j)}, \tag{41}$$

$$\mathbb{Q}_{k,t}^{SV}(t+j) = \exp(-\lambda_{k,t}(t+j)), \tag{42}$$

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.

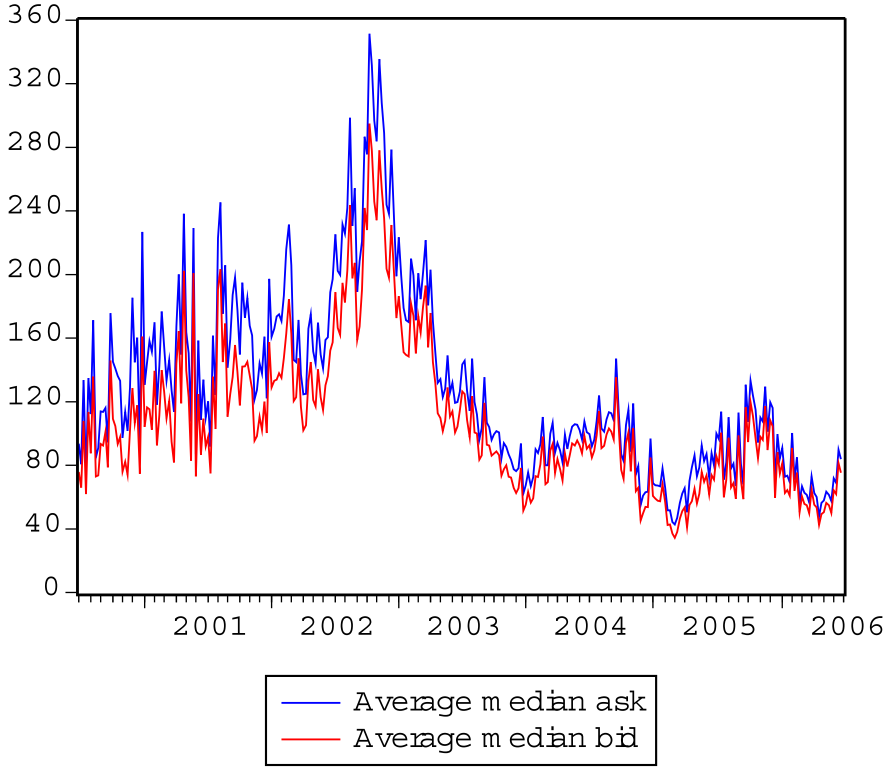
Naturally, there is an inconsistency in assuming that CDS prices are only driven by default risk where the goal is to identify a non-default component. However, the relative sensitivity of $\mathbb{Q}^{SV}$ with respect to λ is very small since λ is small and $\mathbb{Q}^{SV}$ close to one. If we iterate 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. Note that we only need $\mathbb{Q}^{SV}$ to estimate the first-step exposures.

Figure 1: Asset pricing equilibrium with transaction costs



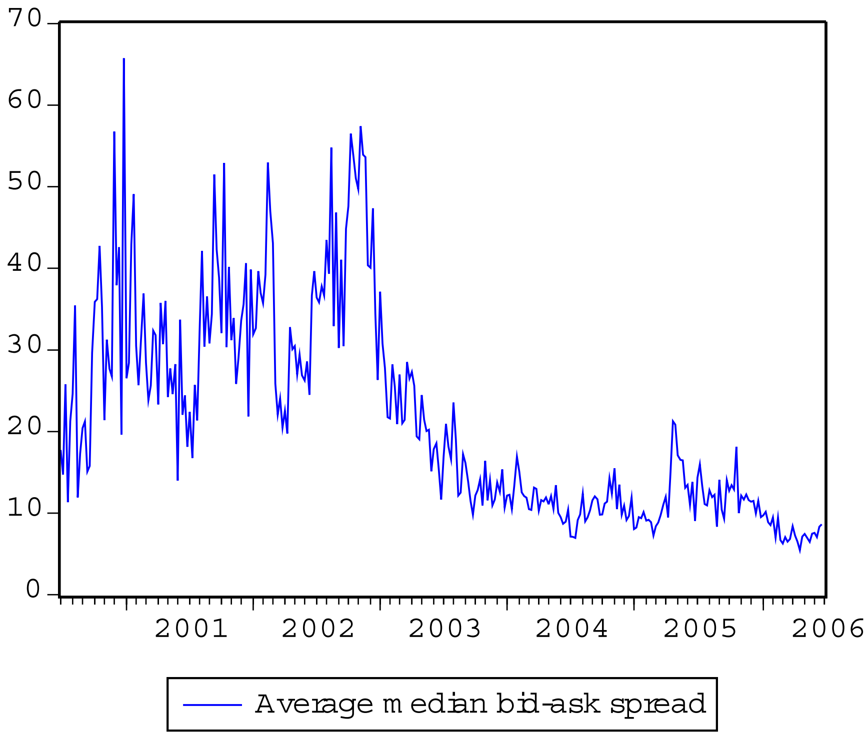
The figure illustrates the asset pricing equilibrium with constant liquidity costs, as in the example of Section 2.4. The figure graphs the asset demand and supply of an investor with hedging needs ($-w_1y_1$) and a less risk averse investor with no hedging demand (w_2y_2). The solid lines reflect the situation without transaction costs, the dashed lines reflect the situation with transaction costs c. γ is the equilibrium expected return without transaction costs, $\gamma+\zeta c$ is the equilibrium expected return with transaction costs.

Figure 2: Weekly median bid and offer quotes averaged over issuers



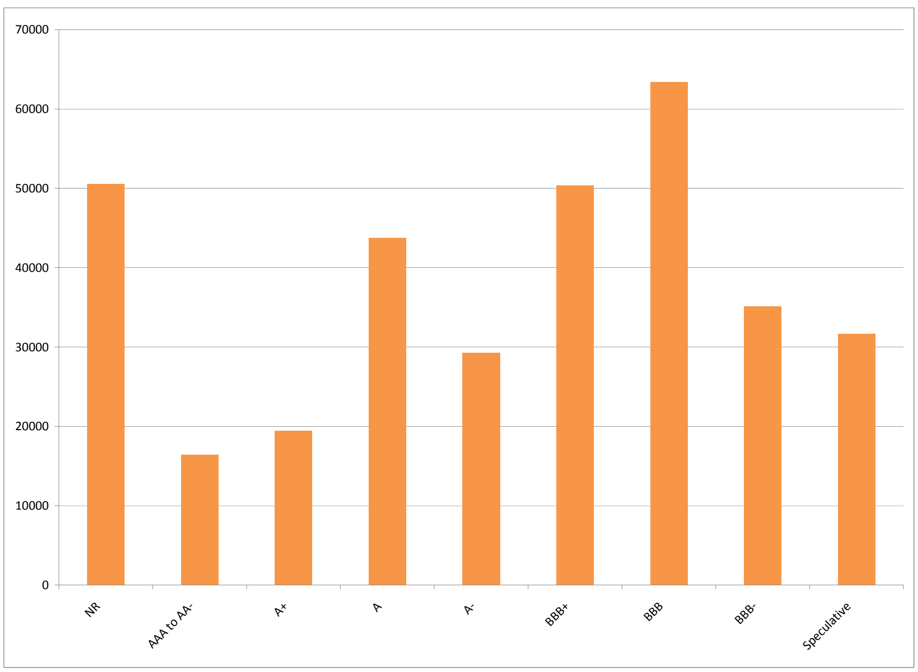
The figure displays the median of the CDS spread over all CDS contracts in our data set, averaged per week.

Figure 3: Weekly median bid-offer spread averaged over issuers



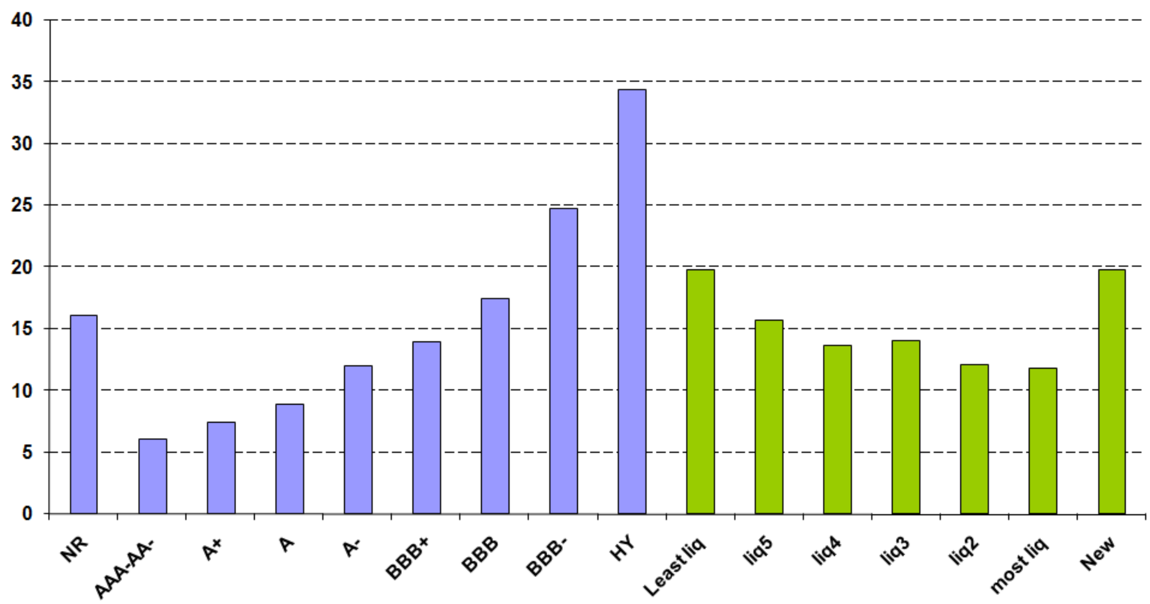
The figure displays the median of the bid-ask spread over all CDS contracts in our data set, averaged per week.

Figure 4: Number of quotes per S&P rating category



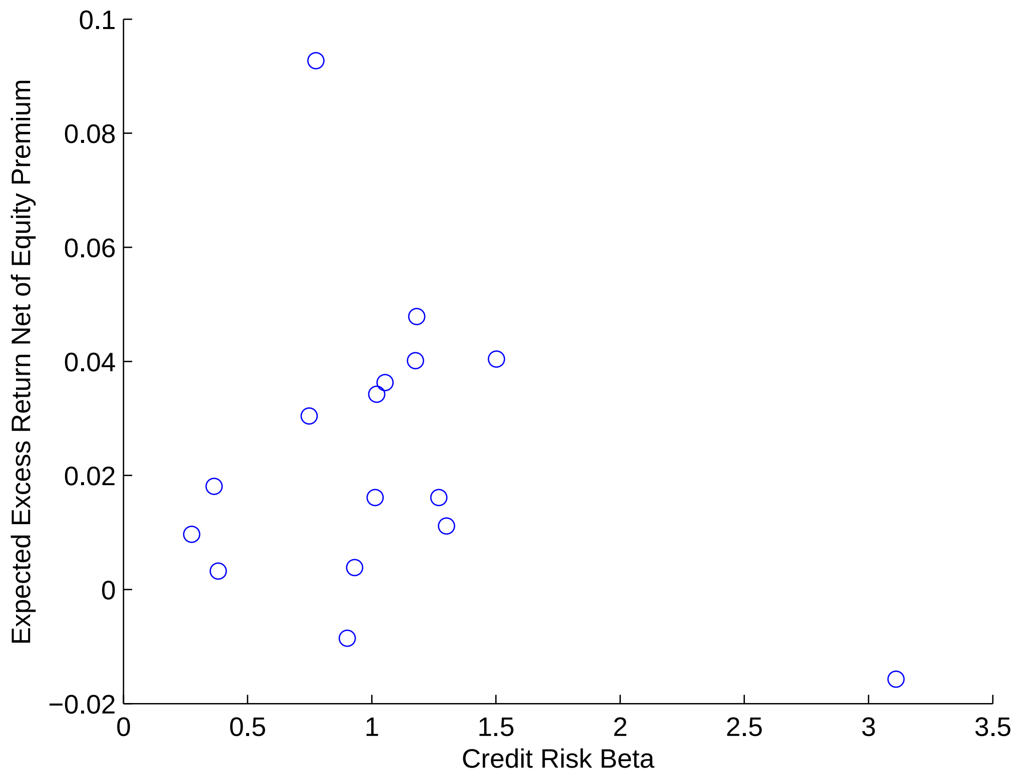
The figure shows the number of bid-ask quotes in the sample per rating portfolio.

Figure 5: Expected liquidity per portfolio



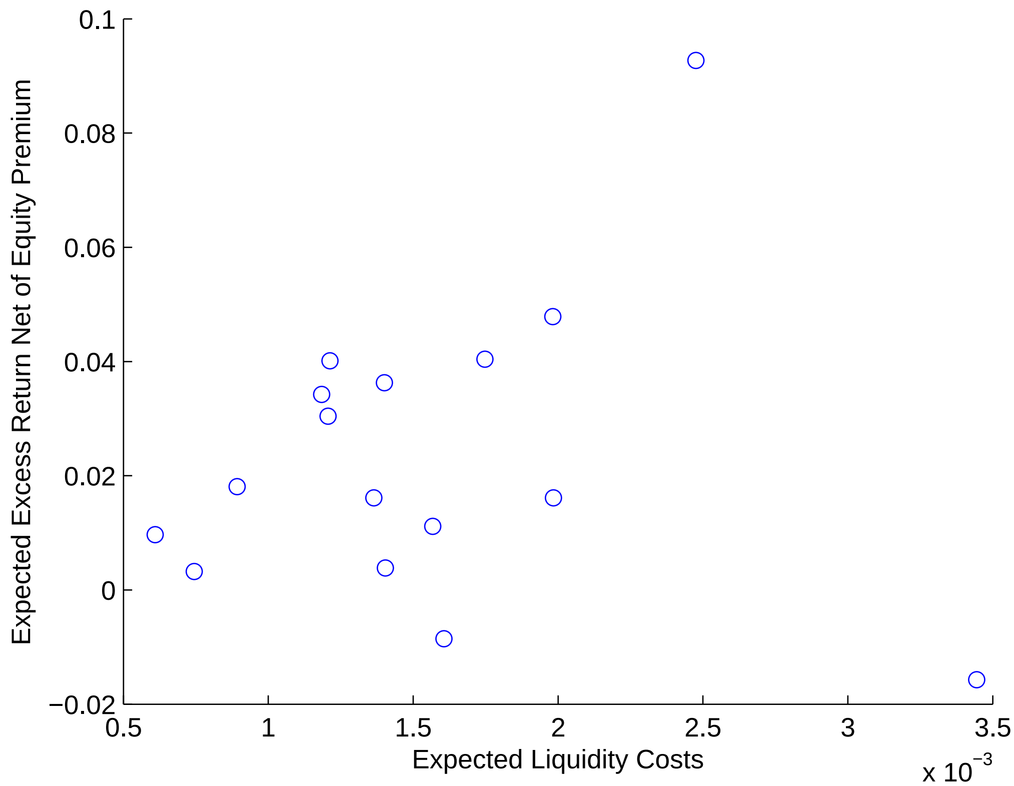
The figure displays the expected liquidity cost per portfolio for the full sample period. Liquidity costs are measured as half the quoted portfolio bid-ask spread (in bp) generated by the repeated sales procedure.

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



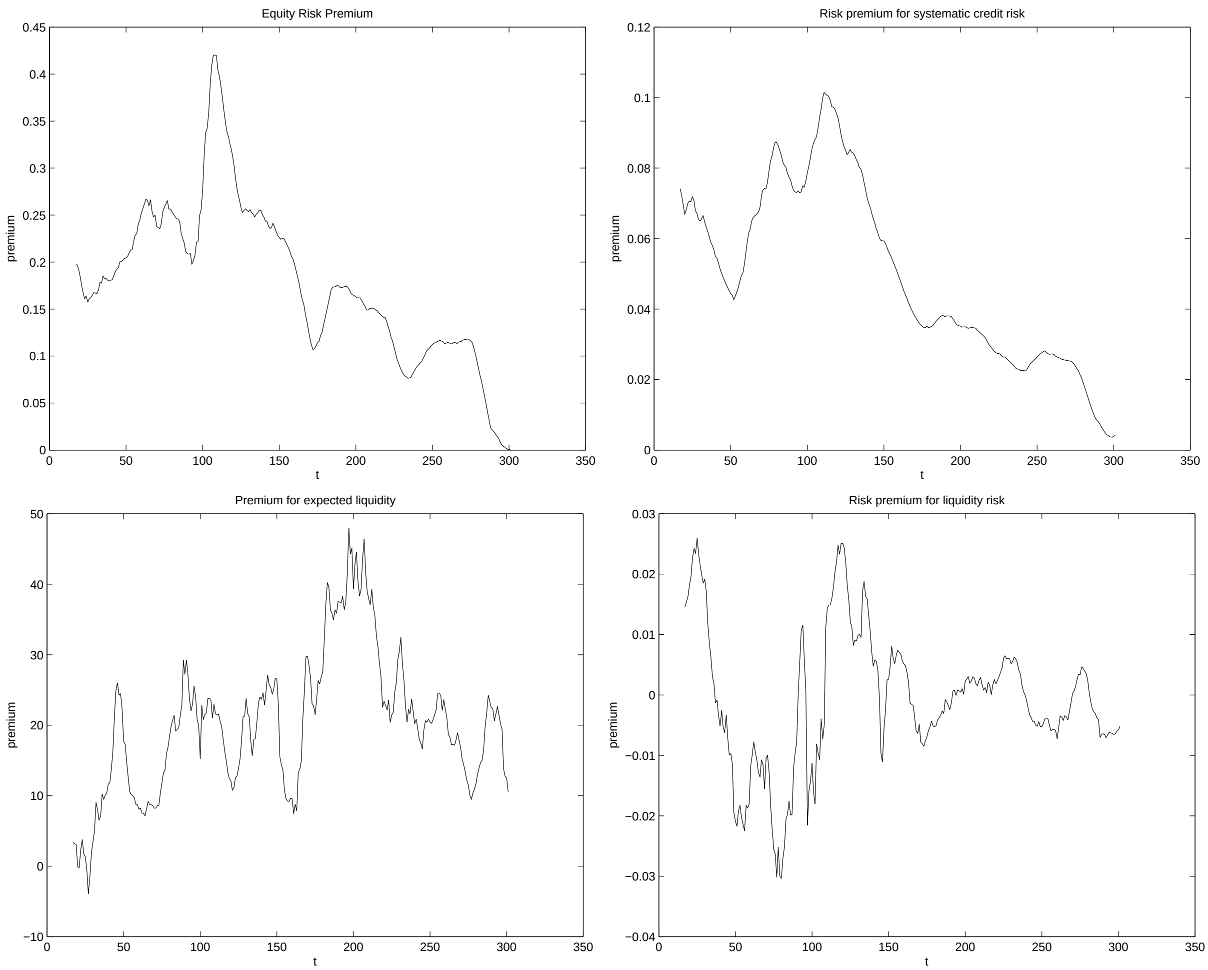
The figure displays on the y-axis the expected CDS portfolio return minus the equity betas times the estimated equity market risk premium. On the x-axis we display the credit risk beta of each CDS portfolio. Betas are obtained from a first stage regression of CDS excess returns (orthogonal to equity market returns) on our proxy for non-traded systematic credit risk. Expected excess returns are measured over a 5-year holding period.

Figure 7: Scatter plot of expected liquidity and expected excess return residuals



The figure displays on the y-axis the expected CDS portfolio return minus the equity betas times the estimated equity market risk premium. On the x-axis we display the expected liquidity costs of each CDS portfolio. 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 over a 5-year holding period.

Figure 8: Time-varying risk premium estimates



The figure displays the estimates of risk premia over time, obtained by running the second step regression (24) on rolling 12 week averages of the expected CDS returns.

Table 1: Buyers and sellers in the CDS market

This table shows the fraction of CDS contracts held by various parties. 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 return and liquidity innovation regressions

$$r_{CDS,t} = a_{1r} + \beta_{rEQ}(r_{EQ,t} - [c_{EQ,t} - E_{t-1}(c_{EQ,t})]) + \hat{r}$$
$$\hat{r} = a_{2r} + \beta_{\hat{r}R} R_t + \epsilon_t$$
$$c_{CDS,t} - E_{t-1}(c_{CDS,t}) = a_{2c} + \beta_{\hat{c}\overline{c}}[\overline{c}_t - E_{t-1}(\overline{c}_t)] + \upsilon_t$$

on portfolios sorted on quote-activity and rating for our full sample running from July 2000 to June 2006. We use 4-weekly overlapping returns. Standard errors are corrected for auto-correlation due to overlapping returns 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	$\beta_{\hat{c}\overline{c}}$	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

$$\mathrm{E}(r) = \lambda_{EQ}\beta_{r,EQ} + \lambda_{\widehat{r}R}\beta_{\widehat{r}R} + \zeta\mathrm{E}(c) + \lambda_{\widetilde{cc}}\beta_{\widetilde{cc}} + u$$

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. The second panel presents partial R^2s for the second stage regressions.

Panel A: regression coefficients

	λ_{EQ}	t-stat	$\lambda_{\hat{r}R}$	t-stat	$\zeta/100$	t-stat	$\lambda_{\hat{c}\bar{c}}$	t-stat
Full sample	0.1697	10.02	0.0488	8.28	0.2401	8.37	-0.0072	-2.39
Sub-sample 1	0.1161	8.58	0.0778	14.27	0.2451	13.92	-0.0007	-1.42
Sub-sample 2	0.1579	12.34	0.0582	11.07	0.2355	13.61	-0.0028	-3.33

Panel B: partial R^2's

	Full sample	Sub-sample 1	Sub-sample 2
Equity risk (ER)	0.644	0.054	0.684
ER and Systematic Credit Risk (SCR)	0.957	0.916	0.946
ER, SCR and Expected Liquidity (EL)	0.989	0.990	0.981
ER, SCR, EL and Liquidity Risk	0.990	0.991	0.982

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