Liquidity and liquidity risk premia in the CDS market*

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

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Abstract

In this paper, we develop a framework to study the effect of liquidity on prices of credit default swaps (CDS). We derive a theoretical asset-pricing model for derivative contracts that allows for expected liquidity and liquidity risk. This extends the LCAPM of Acharya and Pedersen (2005) to a setting with derivative instruments. This model is tested by applying the standard two-pass regression approach to CDS portfolios, for which we construct time series of excess returns and liquidity costs using a repeated sales methodology. The first-step time series regressions provide evidence for systematic credit and liquidity factors. In a second step, we explain expected excess CDS returns which are estimated from CDS spreads, corrected for the expected loss. We find that the exposure to credit risk is priced and provide evidence of an economically and statistically significant expected liquidity premium attributable to the protection seller. Liquidity risk seems not to be priced. Our results thus suggest that CDS spreads cannot be used as frictionless measures of default risk, as is often done in the recent literature.

Keywords: CDS, Liquidity, Liquidity Risk

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

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

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

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 studies the impact of liquidity on the prices of credit default swaps, both theoretically and empirically. Recent market developments suggest that the credit default swap (CDS) market is subject to shocks in liquidity. In the sub-prime crisis of summer 2007, not only credit spreads increased substantially, but liquidity also dropped dramatically.

This 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 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 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 a market risk premium, 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. We show that sign of the liquidity effect depends on heterogeneity in investors' risk exposures and wealth. Our model builds on existing 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 a considerable 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 seems to be no effect of liquidity risk on expected CDS returns.

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), 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 rating, liquidity and industry portfolios. 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.

The first-step time series regressions provide evidence for a systematic credit risk factor in CDS returns. Moreover liquidity shocks also seem to exhibit a factor structure, but to a systematic liquidity factor rather than to a systematic credit factor. In the second stage, we find a positive and significant premium on expected liquidity, implying that the exposures to this are priced for the protection seller. Specification tests on the model reveal that the effect of liquidity on CDS prices feeds through the channel of expected liquidity as our model predicts and that the detected systematic liquidity factor does not play a role in CDS pricing. These results are robust to the apparent trend break in CDS quotes that can be seen at the moment that the standardized ISDA contract was introduced, errors-in-variable problems and restrictions on risk premia.

To our knowledge, 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.[1] When we shift our attention to derivative markets, we see that 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, 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 methodology of our empirical analysis is presented in Section 5, followed by the results and robustness checks in Section 6. Section 7 concludes.

[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 (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.

2 Pricing of liquidity risk in derivatives

Our starting point is the liquidity CAPM of Acharya and Pedersen (2005), henceforth AP. Let there be K risky assets, and let r be the vector of excess returns and c the vector of transaction costs on these assets. The asset pricing of AP equation is

$$\mathrm{E}(r) = \mathrm{E}(c) + \lambda \mathrm{Cov}(r - c, r_m - c_m) \tag{1}$$

AP write their result also as

$$\mathrm{E}(r) = \pi \mathrm{E}(c) + \lambda_1 \mathrm{Cov}(r, r_m) - \lambda_2 \mathrm{Cov}(r, c_m) - \lambda_3 \mathrm{Cov}(c, r_m) + \lambda_4 \mathrm{Cov}(c, c_m) \tag{2}$$

The AP model is derived in a setting where all assets are in positive net supply and (in equilibrium) all investors hold long positions in the assets. In this section, we extend the AP model to a setting where agents use the assets to hedge background risk, as in the models of de Roon et al. (2000) and Garleanu et al. (2006). We have two versions of this model, one for a positive net supply market and one for assets that are in zero net supply. The latter model is appropriate for a derivatives market such as the CDS market.

2.1 Positive net supply

We first derive an extension of the AP model with initial non-traded exposures to a risk factor R. Following de Roon et al. (2000), we assume that investor i maximizes the mean-variance utility function

$$U_i = x_i' \mathrm{E}(r - c) - \frac{1}{2} A_i \mathrm{Var}(x_i'(r - c) + q_i R) \tag{3}$$

where x_i is the vector of portfolio weights, r the vector of returns, and c the vector of transaction costs (incurred when liquidating the position) for the K assets.[2] The scalar R denotes the return on the risk factor and q_i the investor's exogenous exposure to the risk factor. Finally, A_i is the coefficient of absolute risk aversion. Maximizing the utility function with respect to x_i, the solution for optimal portfolio weight is

$$x_i = A_i^{-1} V_{r-c}^{-1} \left[\mathrm{E}(r) - \mathrm{E}(c) - A_i \mathrm{Cov}(r - c, R) q_i\right] \tag{4}$$

[2] Like in Acharya and Pedersen (2005), we assume for this example that all portfolio weights are positive. If there is a single representative investor, this is obviously the case in equilibrium.

with $V_{r-c} = \text{Var}(r - c)$. Then, summing over all investors with wealth weights w_i, the aggregate first order condition is

$$\sum_i w_i x_i = V_{r-c}^{-1} \left[\sum_i w_i A_i^{-1} (\text{E}(r) - \text{E}(c)) - \text{Cov}(r - c, R) \sum_i w_i q_i \right] \tag{5}$$

Solving this for $\text{E}(r)$ gives

$$\text{E}(r) = \text{E}(c) + \frac{\bar{x}}{\theta_1} V_{r-c} + \frac{\theta_2}{\theta_1} \text{Cov}(r - c, R) \tag{6}$$

with $\bar{x} = \sum_i w_i x_i$, $\theta_1 = \sum_i w_i A_i^{-1}$, and $\theta_2 = \sum_i w_i q_i$. Defining the net market return $r_m - c_m = (r - c)'\bar{x}$, this can be written as

$$\text{E}(r) = \text{E}(c) + \frac{1}{\theta_1} \text{Cov}(r - c, r_m - c_m) + \frac{\theta_2}{\theta_1} \text{Cov}(r - c, R) \tag{7}$$

This is a straightforward extension of the AP pricing equation (1). Their model is a special case with $q_i = 0$ for all i and hence $\theta_2 = 0$.

2.2 Zero net supply

We now extend this model to a zero-net supply case. 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 CDS contracts. In reality, investment banks often act as market makers.

In equilibrium some investors hold long positions ($\delta_i = 1$) and other investors hold short positions ($\delta_i = -1$) in the assets. For each investor, it is assumed that the 'sign' of the position (long or short) is the same for all assets. This is somewhat restrictive, but in the setting of the CDS market not 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.

Investor i maximizes the mean-variance utility function

$$U_i = x_i' \text{E}(r - \delta_i c) - \frac{1}{2} A_i \text{Var}(x_i'(r - \delta_i c) + q_i R) \tag{8}$$

Writing out the variance and omitting terms that don't involve x_i gives

$$U_i = x_i'(\text{E}(r) - \delta_i \text{E}(c)) - \frac{1}{2} A_i \left[x_i' \left(V_r - \delta_i (C + C') + V_c \right) x_i + 2 x_i' \text{Cov}(r - \delta_i c, R) q_i \right] \tag{9}$$

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

$$\mathrm{E}(r) - \delta_i \mathrm{E}(c) - A_i \left(V_r - \delta_i (C + C') + V_c\right) x_i - A_i \mathrm{Cov}(r - \delta_i c, R) q_i = 0_K \tag{10}$$

where 0_K is a K-dimensional zero vector, with solution for the optimal portfolio weights

$$x_i = A_i^{-1} \left(V_r - \delta_i (C + C') + V_c\right)^{-1} \left[\mathrm{E}(r) - \delta_i \mathrm{E}(c) - A_i \mathrm{Cov}(r - \delta_i c, R) q_i\right] \tag{11}$$

This asset demand function is nonlinear in δ_i and can therefore not be aggregated in an easy way over all individuals. However, if the transaction costs are small relative to the returns, we can do a Taylor expansion to linearize the asset demand (see Appendix A). This gives

$$x_i = A_i^{-1} \left(V_r^{-1} + \delta_i W\right) \left[\mathrm{E}(r) - \delta_i \mathrm{E}(c) - A_i \mathrm{Cov}(r - \delta_i c, R) q_i\right] \tag{12}$$

with $W = V_r^{-1}(C + C')V_r^{-1}$. Pre-multiplying by the wealth-weights w_i and imposing the zero-net supply condition $\sum_i w_i x_i = 0_K$ gives the equilibrium pricing condition:

$$0_K = \sum_i w_i A_i^{-1} \left(V_r^{-1} + \delta_i W\right) \left[\mathrm{E}(r) - \delta_i \mathrm{E}(c) - A_i \mathrm{Cov}(r - \delta_i c, R) q_i\right] \tag{13}$$

Solving this equation for $\mathrm{E}(r)$ gives the equilibrium expected returns

$$\begin{aligned} \mathrm{E}(r) \;&=\; \left(\theta_1 V_r^{-1} + \theta_3 W\right)^{-1} \Big[\left(\theta_3 V_r^{-1} + \theta_1 W\right) \mathrm{E}(c) \\ &\quad + \left(\theta_2 V_r^{-1} + \theta_4 W\right) \mathrm{Cov}(r, R) - \left(\theta_4 V_r^{-1} + \theta_2 W\right) \mathrm{Cov}(c, R)\Big] \end{aligned} \tag{14}$$

with $\theta_1 = \sum w_i A_i^{-1}$, $\theta_2 = \sum w_i q_i$, $\theta_3 = \sum w_i A_i^{-1} \delta_i$ and $\theta_4 = \sum w_i q_i \delta_i$. The four parameters in this system of equations can be estimated using the Generalized Method of Moments (replacing the first and second moments by sample equivalents). For our purpose, we consider two special cases that lead to a linear asset pricing equation that can be estimated more easily.

The first case assumes that $C = \mathrm{Cov}(c, r)$ is equal to zero so that $W = 0$. For our empirical application to CDS contracts we cannot reject that these covariances differ significantly from zero. In this case, equation (14) can be rewritten into the following linear asset pricing equation

$$\mathrm{E}(r) = \frac{\theta_3}{\theta_1} \mathrm{E}(c) + \frac{\theta_2}{\theta_1} \mathrm{Cov}(r, R) - \frac{\theta_4}{\theta_1} \mathrm{Cov}(c, R) \tag{15}$$

where θ_i / θ_1, $i = 2, 3, 4$, are scalars. In this case, expected returns are determined by an expected liquidity component a market risk premium component (if we take R to be a market index), and a premium for the covariance between costs and the market return. Given that $\theta_1 > 0$, the sign of the expected liquidity effect depends on the sign of $\theta_3 = \sum w_i A_i^{-1} \delta_i$. For example, this effect is positive if the long positions are held by investors with small risk aversion and/or high wealth, in which case the 'long' holders pocket the liquidity premium. The model in (15) turns out to be the empirically most relevant model in our empirical analysis.

The second case allows for some degree of covariation between returns and transaction costs. Specifically, we assume in this case that $CV_r^{-1} = \mathrm{Cov}(c, r)\mathrm{Var}(r)^{-1} = \frac{1}{2}\rho I$, where ρ is a scalar. The matrix $\mathrm{Cov}(c, r)\mathrm{Var}(r)^{-1}$ is the matrix of slope coefficients in a regression of c on r: $c = a + Br + e$. The assumption made is that this matrix is diagonal and that all diagonal elements are the same, i.e. $B = \rho I$. As B has the interpretation as hedge coefficients, this assumption implies that for each asset, the own returns are the best hedge of transaction costs, and moreover the hedge ratio is the same for all assets. With this assumption, we get $W = \rho V_r^{-1}$ and equation (14) simplifies to

$$\mathrm{E}(r) = \frac{\theta_3 + \theta_1 \rho}{\theta_1 + \theta_3 \rho} \mathrm{E}(c) + \frac{\theta_2 + \theta_4 \rho}{\theta_1 + \theta_3 \rho} \mathrm{Cov}(r, R) - \frac{\theta_4 + \theta_2 \rho}{\theta_1 + \theta_3 \rho} \mathrm{Cov}(c, R) \tag{16}$$

The coefficient on the transaction costs depends on the wealth and risk aversion weighted sign of the asset holdings (δ_i). 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 a liquidity premium. Notice that in the CDS market, the way that we define the CDS return means that a long position in the (credit) risk factor implies providing (selling) credit protection. Equation (16) also shows that, even if the 'first order effect' on expected liquidity, θ_3, is equal to zero, the expected liquidity effect can still be nonzero if ρ differs from zero. For example, if $\rho > 0$ and $\theta_3 = 0$, the 'long' holders earn an expected liquidity compensation equal to $\rho \mathrm{E}(c)$.

Comparing the risk premiums in equations (15) and (16) to the pricing equation of the positive net supply model of AP in equation (2), we see that the risk factor R takes the role of the market return. The coefficient of the covariance of the transaction costs with the risk factor again can take any sign, depending on the balance of long and short positions and initial exposures to the risk factor. In contrast to the AP model, there is only one liquidity risk factor, rather than three as in equation (2). However, in some of our empirical models, we estimate the betas as they appear in AP and add them in as a robustness test.

3 Empirical model

In the empirical model, we define the background risk R as a general credit index, constructed as the return on a broad portfolio of CDS contracts. The excess returns r_k are returns on portfolios of similar (in terms of credit rating, industry or liquidity) CDS contacts. The liquidity variable c_k is the relative bid-ask spread on these portfolios.

3.1 Two step estimation

As is often done with linear asset pricing models, we recast our theoretical asset pricing model into a form that allows for standard two step estimation. For our first step, we specify the sensitivity equations

$$r_{k,t} = \alpha_{r,k} + \beta_{rR,k} R_t + \epsilon_{k,t} \tag{17}$$

$$c_{k,t} - E_{t-1}(c_{k,t}) = \alpha_{c,k} + \beta_{cR,k} R_t + \upsilon_{k,t} \tag{18}$$

where $c_{k,t} - E_{t-1}(c_{k,t})$ are the unexpected changes in transaction costs. In addition, we specify an unconditional asset pricing model

$$\mathrm{E}(r_{k,t}) = \zeta \mathrm{E}(c_{k,t}) + \lambda_{rR}\beta_{rR,k} + \lambda_{cR}\beta_{cR,k} + e_k \tag{19}$$

The coefficient ζ captures the impact of expected liquidity, while the coefficient λ_{cR} reflects the liquidity risk premium. The coefficient λ_{rR} captures the risk premium on systematic credit risk in the CDS market.

We did however notice that the liquidity costs exhibit a factor structure with the market average bid-ask spread as driving factor. As a specification test, we therefore also estimate a version of the model that is in line with the positive net supply model of Acharya and Pedersen (2005). That is, we estimate the sensitivity equations

$$r_{k,t} = \alpha_{r,k} + \beta_{rC,k}\left(C_t - E_{t-1}(C_t)\right) + \beta_{rR,k} R_t + \epsilon_{k,t} \tag{20}$$

$$c_{k,t} - E_{t-1}(c_{k,t}) = \alpha_{c,k} + \beta_{cC,k}\left(C_t - E_{t-1}(C_t)\right) + \beta_{cR,k} R_t + \upsilon_{k,t} \tag{21}$$

and the asset pricing equation

$$\mathrm{E}(r_{k,t}) = \zeta \mathrm{E}(c_{k,t}) + \lambda_{rR}\beta_{rR,k} + \lambda_{rC}\beta_{rR,k} + \lambda_{cR}\beta_{cR,k} + \lambda_{cC}\beta_{cC,k} + e_k \tag{22}$$

where C are the market-wide transaction costs (the average costs across all assets). We estimate the model with a two stage regression analogous to Black, Jensen and Scholes

(1972). In the first stage we estimate the betas of the excess return equation (17) and the liquidity equation (18) and in the second stage we regress the expected excess returns on the betas from the first stage. The point estimates are obtained by simple OLS, but the standard errors of the second stage estimates are harder to obtain. Typically, the left hand side of the second stage equation is the sample average of all excess returns and the covariance matrix of the second stage error terms is given by a linear combination of first stage error and factor covariances. However, as discussed in detail below, we construct estimates of the expected CDS returns by correcting CDS spread levels for the expected loss, instead of using the average of the realized returns (used in the first step regression). Therefore, rather than using error and factor covariance matrices, we calculated the second stage error covariance matrix as the expected excess return covariance matrix corrected for autocorrelation and heteroscedasticity using the method presented in Newey and West (1987) with lag order 20. Moreover, we correct our second stage standard errors for the errors in variables problem by modifying the procedure of Shanken (1992) to incorporate the use of expected returns implied by CDS spreads, as described in the appendix.

3.2 CDS returns

In this section, we describe how the 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. To estimate risk premia, we use the fact that the CDS spread level, corrected for the expected loss, gives a direct estimate of the expected return. This gives a much more accurate estimates of $\mathrm{E}(R_i^{e,CDS})$ than sample averages of realized excess returns. This is especially relevant as we have a short sample period of six years.

We first transform CDS spreads to excess returns. To derive the excess holding returns, consider an investor at time $t-1$ 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 period 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[3]

$$R_{k,t}^{e,CDS} = -\frac{1}{4}\Delta CDS_{k,t} \sum_{j=1}^{4(T-t)} B(t,t+j)\mathbb{Q}_{k,t}^{SV}(t+j), \tag{23}$$

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 $t+j$. 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 $t-1$ and t, the excess return on the CDS is equal to minus one times the loss given default (LGD). However, if we assume that the individual jumps are not priced, we can ignore these cases for estimating portfolio betas.[4] The excess returns defined in equation (23) are the realized excess returns. However, in our sample the time to maturity of the CDS contracts is not fully constant. 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 and risk free rates around the five year point is flat.

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:

$$\begin{aligned} \mathrm{E}_t(\text{total CDS pay-off}_k) = \frac{1}{4}CDS_{k,t} \sum_{j=1}^{4(T-t)} B(t,t+j)\mathbb{P}_{k,t}^{SV}(t+j) - \\ (1-\rho)\sum_{j=1}^{4(T-t)} B(t,t+j)\mathbb{P}_{k,t}^{SV}(t+j-1)\mathbb{P}_{k,t}^{def|SV}(t+j), \end{aligned} \tag{24}$$

where ρ is the expected recovery rate, $\mathbb{P}_{k,t}^{SV}(t+j)$ is the real world survival probability up to time $t+j$ and $\mathbb{P}_{k,t}^{def|SV}(t+j)$ 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 returns 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 time. These unconditional expected returns are used as the left-hand-side variable in the second step of the two-pass regression

[3]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 $r_f + CDS$, whereas we discount with r_f and multiply with the risk neutral survival probability of each cash flow

[4]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 24).

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.

To construct excess returns from our 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, 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)):

$$S_t = 4\frac{(1-\rho)\sum_{j=1}^{4(T-t)} \mathbb{Q}^{def|SV}(t+j)B(t,t+j)}{\sum_{j=1}^{4(T-t)} \mathbb{Q}^{SV}(t+j)B(t,t+j)}, \tag{25}$$

$$\mathbb{Q}^{SV}(t+j) = \exp(-\lambda(t+j)), \tag{26}$$

where $\mathbb{Q}^{def|SV}(t+j)$ 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. [5]

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

[5] 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.

in these reports. For a given year, we used the average cumulative default probabilities calculated up to the year before. For quarterly periods, we use linear interpolation.

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 industry and liquidity sorted portfolios, 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. It 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 either useless or dangerous 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 or maturity date, the currency, the amount underlying, either the bid or the ask price (occasionally both), the ICB level 2 industry of the underlying, whether it is a bank or corporate, the country the underlying is in, whether the record is a trade or a quote, the Moody's and/or S&P rating and the restructuring clause. Since Credit Trade provide incomplete rating data, we match our data to S&P ratings from Compustat NA Quarterly. These ratings are then used in our analysis.

When we look at the different characteristics in our sample, we can identify the typical characteristics of a US contract. 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.

Something that is striking is the distribution of quotes over the years (Graph 1). Since the peak in 2003 this number seems to go down every year, whereas the recent literature reports an increase in liquidity and volume of the CDS market. Graph 1 also shows a split with respect to the months of every year, to show that this is not an artefact of excessive trading during one month. This graph also shows us that in general, we see a decline in activity in December. Moreover, we see a very sharp decline in activity around the Ford/GM downgrade in May 2005. The decreasing number of quotes can be due to several factors. It can be that Credit Trade is losing market share and simply gets less inflow. Another cause can be that the market has grown to a better understanding and that unrealistic quotes are not posted anymore. Finally, a better transparency might have led to a shorter track of price discovery.

We can also look at the distribution across industries and rating categories (Graph 2; here we aggregated industries to ICB level 1 consistent with our portfolio formation basis later on). 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 preference for the lower categories of investment grade debt.

4.2 Filters

By comparing different quotes of identical underlyings within the same week, we identified 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 every day, we take the average bid and the average ask for every CDS that we observe that day. After doing this, we end up with roughly 100,000 daily average bid and offer quotes on 918 entities.

4.3 Preliminary Data Analysis

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. Note that these data represent an unbalanced panel and therefore will by construction be noisy.

Figure 3 shows a time series plot of the average bid and average offer in our sample. We see that the average CDS spread rises throughout the burst of the ICT bubble to peak mid 2002. Hereafter, we see a sharp decline in average spreads, which coincides with the introduction of the standardized ISDA contract.

In Figure 4 we see 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 latter part of the sample we then see one peak at the Ford/GM downgrade in May 2005. What is interesting is that although the bid-offer spread widens immensely at the Ford/GM downgrade, the spread of the CDS market as a whole did not increase dramatically.

5 Portfolios

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. However, portfolio construction in this setting leads to problems. Contrary to equity markets in which reliable prices are available even on intra-day basis for almost the whole spectrum of stocks, not every CDS has a price quote in every week. 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 and extend it to incorporate liquidity effects. A short description is given below. For a more thorough coverage of this method, refer to Bailey, Muth and Nourse (1963) and Case and Shiller (1987).

5.1 The Repeated Sales Method

The repeated sales method originates from the real estate literature and generates a house price index from data on individual house sales. The method employs regression analysis to estimate the value of the index 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. For constituent i, we assume that the spread quote of a five years CDS contract $p_{i,t}$ is given by

$$p_{i,t} = CDS_{k(i),t} + c_{k(i),t}\delta_{i,t} + u_{i,t}, \tag{27}$$

where $CDS_{k(i),t}$ is the portfolio (or index) 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.[6] $u_{i,t}$ 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

$$\mathrm{var}(\Delta p_{i,ss'}) = 2\sigma_u^2 \tag{28}$$

$$\mathrm{var}(\Delta p_{i,s's''}) = 2\sigma_u^2 \tag{29}$$

$$\mathrm{cov}(\Delta p_{i,ss'}, \Delta p_{i,s's''}) = -\sigma_u^2. \tag{30}$$

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

$$\Delta p = x\Delta CDS_{k(i)} + (\Delta\delta)c_{k(i)} + v \tag{31}$$

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

$$\begin{pmatrix} \widehat{\Delta CDS}_{k(i)} \\ \widehat{c}_{k(i)} \end{pmatrix} = (y'M^{-1}y)^{-1}y'M^{-1}r, \tag{32}$$

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

where $y = [x'\Delta\delta']'$, 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.[7] In the appendix we discuss in detail how we deal with missing observations and how we aggregate to weekly data. The final outcome of this procedure is weekly series of CDS spread changes and bid-ask spread levels at the portfolio level.

In order to estimate the risk neutral default and survival probabilities and expected excess returns, we need portfolio CDS spread levels rather than innovations. We can estimate the CDS spread level at any time up to a constant by simply summing the innovations. We have

$$m_{k(i),t} = CDS_{k(i),0} + I_{k(i),t} + \epsilon_{k(i),t}, \tag{33}$$

$$m_{k(i),t} = \frac{1}{n_{k(i),t}} \sum_{j \in k(i)} p_{j,t}, \tag{34}$$

$$I_{k(i),t} = \sum_{j=1}^{t} \Delta CDS_{k(i),j}, \tag{35}$$

$$CDS_{k(i),t} = CDS_{k(i),0} + I_{k(i),t}, \tag{36}$$

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. We redo this for every calendar year, because our sample is not fully homogeneous over time. Once we have done this, we construct excess returns and expected excess returns from the portfolio returns and levels that are obtained by repeated sales as described in section 4.

5.2 Portfolio Descriptions

First of all, we estimate the market-wide bid-ask spread and market-wide CDS spread changes. Additionally, we estimate the same quantities for ten industry portfolios, nine rating portfolios and seven liquidity portfolios.

For the industry portfolios, we use the ICB level one classification. The portfolios obtained this way vary substantially in the number of quotes per portfolio. The estimated

[7]we can do this because M is known up to a scalar which drops out

portfolio return and bid-ask spread series for the sparse industries are rather noisy, whereas those for the dense industries are much more precise.

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 every portfolio. Additionally, we construct a non-rated class since we were unable to find S&P ratings for all issuers. The non-rated returns however turn out to be rather noisy compared to the other portfolios, indicating a lack of homogeneity in this portfolio.

The liquidity based portfolios are constructed as follows. We allow the composition of the portfolios to change by calendar year. Each calender year we sort portfolios by the number of quotes that were recorded in the previous calendar year, but we impose 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 liquid portfolio. All issuers that were not traded during the previous year are put in a separate portfolio called 'New'.

As for the market averages, for almost all portfolios, levels and volatility of both CDS spreads and bid-ask spreads were rather high during the first part of the sample (even increasing at the burst of the ICT bubble and the attacks of 9/11). Then somewhere halfway, around the introduction of the standardized ISDA contract, 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. Note that our market average spreads seem to stabilize after 2004, whereas market participants generally indicate that CDS spreads have only gone down ever since. However, one needs to realize that the number of high yields in our sample has increased from 10% in 2004 to 23% in 2006. For most rating portfolios, spreads indeed go down between 2004 and 2006.

6 Empirical Results

As mentioned before, we estimate the risk premia using a two-stage regression approach as in Black et al. (1972). We observe that the market became much less volatile in the second half of the sample and that the average spread level decreased substantially around the mid-point of the sample. The introduction of a standardized contract for CDSs early 2003 may be one of the factors driving this behavior. Therefore, we also split the sample in two at the mid-point of our sample period (July 1st 2003) and present the results for both sub-samples.

6.1 First stage regression results

We estimate equations (20) and (21). For both the excess return and the liquidity first stage regression equations, we initially include only the market CDS excess returns as a factor as predicted by our theoretical model[8]. In this case, only the return-market betas β_{rR} are significant.

Turning to the full specification, we find generally that the return-market betas β_{rR} and the cost-cost betas β_{cC} are statistically significant, while the other betas (β_{rC} and β_{cR}) are almost always insignificant. We therefore set $\beta_{rC} = 0$ and $\beta_{cR} = 0$ for all portfolios in the rest of the analysis.

Results for the first stage excess return and liquidity regressions of the different portfolio splits can be found in Tables 1 and 2. Each table displays the estimation results of the full sample and the two sub-samples each spanning half the sample period. To avoid outliers driving the regressions, we excluded the top and bottom 1% of every (sub-)sample[9]. The results for the rating portfolios have in general the most explanatory power. We see as expected that almost all excess returns load up positively on the CDS market excess returns, which is evidence for a common credit risk factor in CDS returns. This is in line with existing evidence of common factors in credit spreads (Driessen (2005) and Lando and Feldhütter (2005)). We also see that low-rated portfolios have more exposure to this credit factor than high-rated portfolios, which is intuitive and also in line with existing work on corporate bonds. In the BAS equations, we mainly see positive significant loadings on liquidity risk especially for the lower rating categories, giving a pronounced source of liquidity risk.

For the liquidity sorted portfolios, constructed by sorting on the number of quotes per contract, the picture is similar. The fact that the liquidity innovation of most portfolios loads significantly on the market-wide liquidity factor provides evidence for the existence

[8]We also estimated a specification where we added equity market returns orthogonal to CDS market returns, but betas on this factor were insignificant.

[9]We also investigated the effects of this filter; in general the results are quite robust to the inclusion of outliers. However, for some less homogeneous portfolios like the 'New' portfolio of the liquidity split, the inclusion of outliers did fundamentally change the results.

of 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)). The excess portfolio returns tend to load up on CDS market excess returns with a beta that is decreasing as liquidity increases, whereas the portfolio BAS changes tend to load up on the market BAS innovations. We see that liquidity betas are higher for low liquidity than for high liquidity portfolios. 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.

The industry portfolios tend to be the most noisy ones. This we see for example in the loadings on the CDS market factor. These are almost all positive and most often (border) line significant, but the point estimates of the betas differ widely from sample to sample. For the industry portfolios, the only driver in the BAS equations is again the market BAS factor.

6.2 Second stage regression results

We pool the different portfolio splits to increase the number of observations. We estimate several versions of the asset pricing model. First, we estimate the model without expected liquidity and with unrestricted risk premia. Next, we add expected liquidity while leaving the risk premia unrestricted. Finally, we estimate the model with and without expected liquidity in which we restrict the systematic credit risk premium (the 'return-return' premium) to be the average expected excess market return over the sample under investigation. The restriction on the market beta coefficient is due to the critique on asset pricing models by Lewellen and Nagel (2006) and Lewellen, Nagel and Shanken (2006). Moreover, it mitigates any collinearity between CDS market betas and liquidity betas and/or expected liquidity. Also, restricting that the market risk premium is equal to the expected CDS market return is likely to render a conservative estimate of the liquidity (risk) premium. Since we find that part of the expected CDS return is due to liquidity in the unrestricted regressions, imposing that the market risk premium captures the full expected CDS return will lead to a smaller role for liquidity effects.

The second stage regression results can be found in Table 7. We see that for the whole sample, the portfolio expected excess returns load significantly on the market beta and also on β_{cC}. In the conservative case where we fix the CDS market risk premium at its average level over the sample, the premium on liquidity risk becomes only slightly smaller. When we add expected liquidity to the specification, we see that it is priced (positive) and that the risk premium for liquidity risk changes sign.

For sub-sample 1, the results are similar to those of the complete sample, except for the fact that liquidity risk becomes insignificant once expected liquidity is included. Moreover, the risk premia are somewhat larger in size, whereas the premia on expected liquidity are smaller in size. For sub-sample 2 the result is slightly different. First, liquidity risk seems to play a role even beyond expected liquidity, when the risk premium on market wide default risk is not restricted. In view of the severe decline in risk premium of market wide default risk, this is likely to be caused by collinearity between expected liquidity and liquidity risk (see also our discussion below). Even in the conservative case where we restrict the market risk premium on market wide default risk again, we see the same pattern as in the full sample. With respect to the size of the coefficients, we see a higher premium on expected liquidity and lower risk premia on credit and liquidity risk.

Since there is a cross-sectional correlation of about 75% between the expected liquidity and β_{cC}, the fact that the risk premium on β_{cC} shows up significant in some cases can be due to collinearity. Indeed, once we orthogonalize liquidity risk with respect to expected liquidity, its risk premium becomes insignificant for both sub-samples but stays significantly negative for the full sample. However, the economic impact of liquidity risk is quite small. This can be seen from the last column of Table 7, where we present the root mean squared pricing error (RMSE) of the second stage regression. We see that the addition of liquidity risk only marginally lowers the RMSE. We do however, see a large decrease in RMSE once we add expected liquidity to our pricing model. This effect seems to be robust for all sub-samples. In view of this evidence and since our two sub-samples are much more homogeneous than the full sample, we conclude that there is little evidence that exposure to liquidity risk (as captured by β_{cC}) is priced, in line with the predictions from our theoretical model.

To check that the strong effect of expected liquidity on CDS returns is not driven by outliers, we draw a scatterplot with expected liquidity on the x-axis and expected excess returns on the y-axis in Figure 6 (for the full sample). We see a strong positive upward sloping pattern, not driven by any outliers. Even if we report on the y-axis the expected CDS return in excess of the return predicted by a one-factor model with the CDS market as factor, a clear and stable positive relation between expected liquidity and expected excess CDS returns is found (Figure 7).

Figure 9 shows the economic significance and the fit of the model. This graph presents the fitted expected excess returns (area graph) as well as the 'empirical' expected excess returns (bars) for the full sample. The lower part of the area graph shows the risk premium due to systematic credit risk, whereas the upper part shows the premium due to expected liquidity. These graphs illustrate that first the model fit is rather good since the fitted values track the empirical values rather well. Moreover, the economic significance is also substantial; expected liquidity accounts for 42% of the fitted expected excess return. This percentage however is higher than the percentage of spreads since spreads also include an expected loss component.[10]

7 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 more than 300.000 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. Empirically, we show that liquidity cannot simply be assumed away when considering CDS spreads. We find evidence for a systematic liquidity factor in the CDS market, which affects the liquidity of CDS portfolios based on industry, rating and liquidity sorts. Expected liquidity also 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.

[10] Our results here are opposite to what Chen et al. (2005) find. From an unreported analysis of summary statistics over different sample periods, we conclude that their findings are very likely to be driven by the short sample period they consider.

Appendices

A Taylor approximation

The aim is to find the inverse of $X = V_r - \delta_i(C + C') + V_c$. Now let $c = \sigma\bar{c}$ with σ a scalar. Then we can write

$$X(\sigma) = V_r - \sigma\delta_i(\bar{C} + \bar{C}'^2 V_{\bar{c}}$$

Then take a first order Taylor expansion of $X(\sigma)^{-1}$ around $\sigma = 0$. This is

$$X(\sigma)^{-1} \approx X(0)^{-1} + \frac{dX(\sigma)^{-1}}{d\sigma}_{|\sigma=0}\sigma$$

and use from Amemiya (p.461, expression 21.(iv))

$$\frac{dX(\sigma)^{-1}}{d\sigma} = -X(\sigma)^{-1}\frac{dX(\sigma)}{d\sigma}X(\sigma)^{-1}$$

with

$$\frac{dX(\sigma)}{d\sigma} = -\delta_i(\bar{C} + \bar{C}') + 2\sigma V_{\bar{c}}$$

Now $X(0) = V_r^{-1}$ and

$$\frac{dX(\sigma)}{d\sigma}_{|\sigma=0} = -\delta_i(\bar{C} + \bar{C}')$$

Notice that $\mathrm{Var}(c)$ is of order σ^2 and therefore vanishes in the first order Taylor expansion. Substituting all these expressions, we find

$$X(\sigma)^{-1} \approx V_r^{-1} + V_r^{-1}\left[\delta_i(\bar{C} + \bar{C}')\right]V_r^{-1}\sigma = V_r^{-1} + \delta_i V_r^{-1}(C + C')V_r^{-1}$$

In summary, we find

$$[V_r - \delta_i(C + C') + V_c]^{-1} \approx V_r^{-1} + \delta_i V_r^{-1}(C + C')V_r^{-1}$$

which is the expression used in equation (12).

B The repeated sales method in practice

This appendix discusses how we deal with missing observations and sampling frequency for the repeated sales method (section 7). When creating the different portfolios using the repeated sales method, we found that for the market as a whole, when ignoring bid-ask spread effects we were able to estimate market spread innovations on a daily basis. When we tried to estimate the bid-ask spread on a daily basis, we did not achieve full identification, since on some days, the quotes were too sparse (for example only bids or only asks). However, when bid-ask spreads were constrained to be piecewise constant per week, we achieved full identification.

At the portfolio level, we also restrict the bid-ask spread to be constant within a week. Then, for some days we failed to achieve identification of the spread innovations and for some weeks the per week constant bid-ask spread. Moreover, in weeks were quotes were relatively sparse, it happened occasionally that column of $\delta(w_i)$, the delta of week i was a linear combination of the columns x_j where $j \in w_i$. This led to a singular data matrix. To solve these problems, we dropped all days on which we did not have any quotes. Moreover, for every week, we tried to solve the system $Az = \delta(w_i)$, where A consists out of all columns x_j such that $j \in w_i$. If this system could be solved, we had a singularity and therefore we dropped the $\delta(w_i)$ column. Naturally, we kept track of which days and weeks were dropped, because now some spread innovations were estimated over a period of two days rather than one. With these modifications, we were able to estimate the spread innovations and bid-ask spreads of all but the most sparse portfolios that we constructed. Our spread innovation estimates however turned out to be somewhat noisy since they had been estimated on a daily basis. Therefore, we aggregated them to a weekly basis. This also allowed us to mitigate the effect of spread innovations estimated over multiple days.

C Derivation Shanken Correction

In our second step regression, we have:

$$E(R^{e,CDS}) = \zeta E(liq) + \beta\lambda \tag{37}$$

$$\overline{E(R^{e,CDS})} = \zeta\overline{liq} + \beta\lambda + \eta \tag{38}$$

$$= \zeta\overline{liq} + \hat{\beta}\lambda + (\beta - \hat{\beta})\lambda + \eta \tag{39}$$

$$E(\eta\eta') = \Omega \tag{40}$$

where a bar denotes the sample average, η is a vector of pricing errors and the $\hat{\beta}_i$s are the (OLS) estimates of the regression equation [11]

$$y_i = X\beta_i + \nu_i \tag{41}$$

where

$$y_i = \begin{bmatrix} R^{e,CDS}_{i,1} \\ R^{e,CDS}_{i,2} \\ \vdots \\ R^{e,CDS}_{i,T} \\ \Delta liq_{i,1} \\ \Delta liq_{i,2} \\ \vdots \\ \Delta liq_{i,T} \end{bmatrix} \qquad X = \begin{bmatrix} R^{e,CDS}_{m,1} & 0 \\ R^{e,CDS}_{m,2} & 0 \\ \vdots & \vdots \\ R^{e,CDS}_{m,T} & 0 \\ 0 & \Delta liq_{m,1} \\ 0 & \Delta liq_{m,2} \\ \vdots & \vdots \\ 0 & \Delta liq_{m,T} \end{bmatrix} \qquad \nu_i = \begin{bmatrix} \epsilon_{i,1} \\ \epsilon_{i,2} \\ \vdots \\ \epsilon_{i,T} \\ \upsilon_{i,1} \\ \upsilon_{i,2} \\ \vdots \\ \upsilon_{i,T} \end{bmatrix} \tag{42}$$

Since we use the beta estimates from the first stage as explanatory variables in the second stage, we have an error-in-variables problem. To calculate standard errors of our risk premia, we have to take this into account and therefore need to calculate

$$\begin{aligned} &E(((\beta - \hat{\beta})\lambda + \eta)((\beta - \hat{\beta})\lambda + \eta)') = \\ &\qquad \Omega + E((\beta - \hat{\beta})\lambda\lambda'(\beta - \hat{\beta})') + E((\beta - \hat{\beta})\lambda\eta') + E(\eta\lambda'(\beta - \hat{\beta})') \end{aligned} \tag{43}$$

Now we realize that for every portfolio i

$$(\hat{\beta}_i - \beta_i) = (X'X)^{-1}X'\nu_i \tag{44}$$

So that we have

$$(\hat{\beta} - \beta) = \begin{bmatrix} (\hat{\beta}_i - \beta_1)' \\ (\hat{\beta}_i - \beta_2)' \\ \vdots \\ (\hat{\beta}_i - \beta_n)' \end{bmatrix} = \begin{bmatrix} \nu_1' X(X'X)^{-1} \\ \nu_2' X(X'X)^{-1} \\ \vdots \\ \nu_n' X(X'X)^{-1} \end{bmatrix} \tag{45}$$

And thus, element i,j of $E\left((\beta - \hat{\beta})\lambda\lambda'(\beta - \hat{\beta})'\right)$ matrices should look like

$$\begin{aligned} E\left((\beta - \hat{\beta})\lambda\lambda'(\beta - \hat{\beta})'\right)_{i,j} &= E(\nu_i' X(X'X)^{-1}\lambda\lambda'(X'X)^{-1}X'\nu_j) && (46) \\ &= E(\lambda'(X'X)^{-1}X'\nu_i\nu_j' X(X'X)^{-1}\lambda) && (47) \end{aligned}$$

[11]Since only β_{retret} and β_{liqliq} are significant.

since $\lambda'(X'X)^{-1}X'\nu_i$ is a scalar. Thus, we can obtain $E\left((\beta - \hat{\beta})\lambda\lambda'(\beta - \hat{\beta})'\right)$ by

$$E\left((\beta - \hat{\beta})\lambda\lambda'(\beta - \hat{\beta})'\right) = (\lambda'(X'X)^{-1} \otimes I_N)B(I_N \otimes (X'X)^{-1}\lambda') \tag{48}$$

where $B_{ij} = E(X'\nu_i\nu_j'X)$ and is calculated by the Newey-West procedure. The calculation of the covariance matrices $E((\beta - \hat{\beta})\lambda\eta')$ and $E(\eta\lambda'(\beta - \hat{\beta})')$ goes analogous.
The standard errors of the regression estimates are then given by the square roots of the diagonal elements of:

$$\sigma_{est}^2 = (Z'Z)^{-1}Z'E(((\beta - \hat{\beta})\lambda + \eta)((\beta - \hat{\beta})\lambda + \eta)')Z(Z'Z)^{-1} \tag{49}$$

$$Z = \left[\begin{array}{cc} \overline{liq} & \hat{\beta} \end{array} \right] \tag{50}$$

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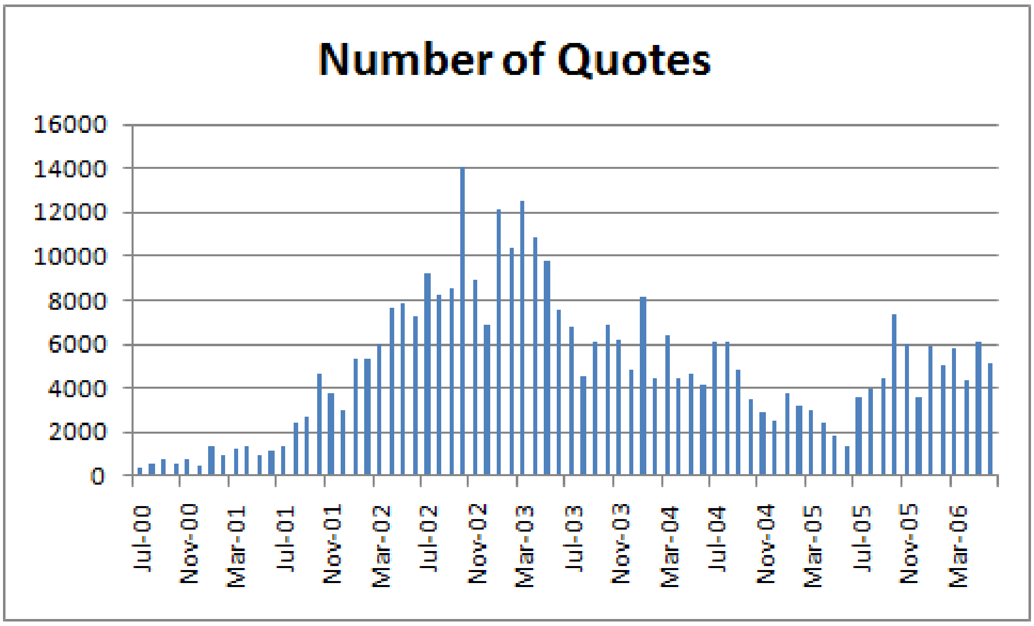

Figure 1: Number of quotes per month

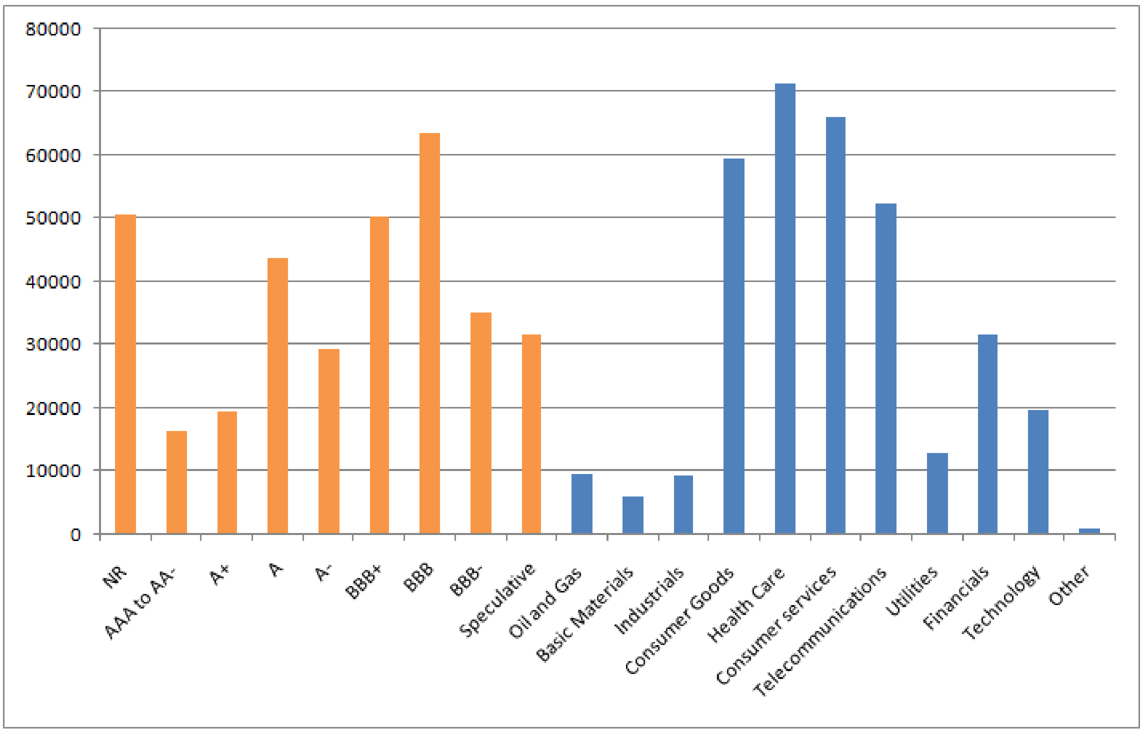

Figure 2: Number of quotes per industry and S&P rating category

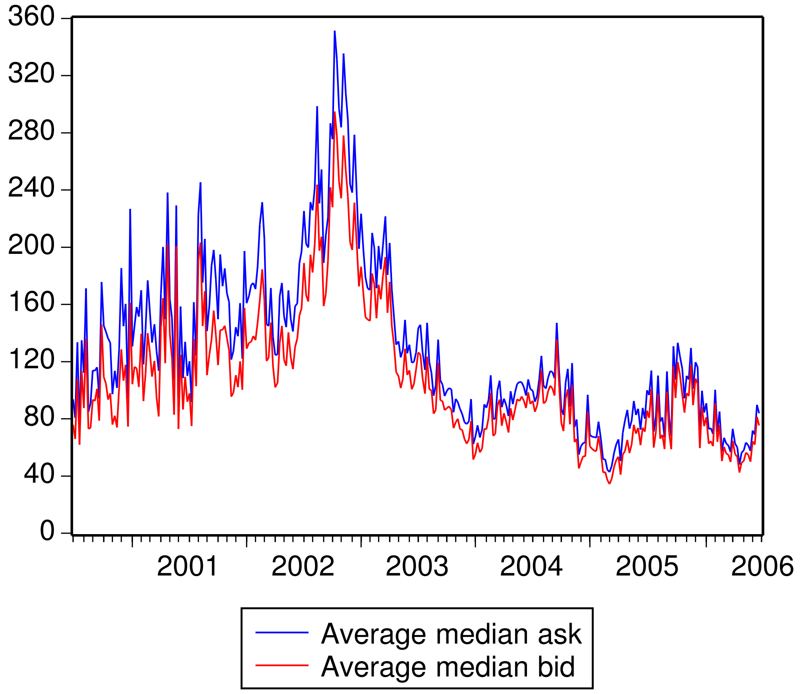

Figure 3: Weekly median bid and offer quotes averaged over issuers

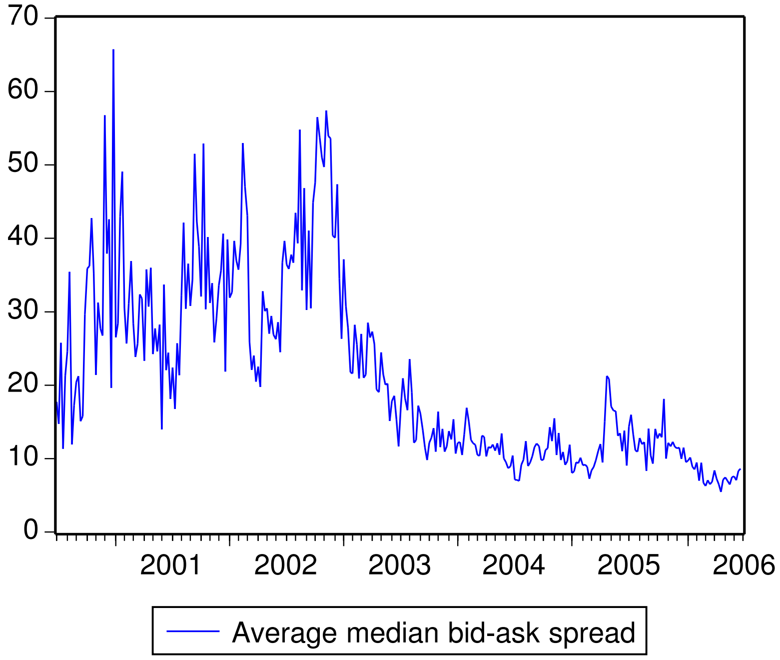

Figure 4: Weekly median bid-offer spread averaged over issuers

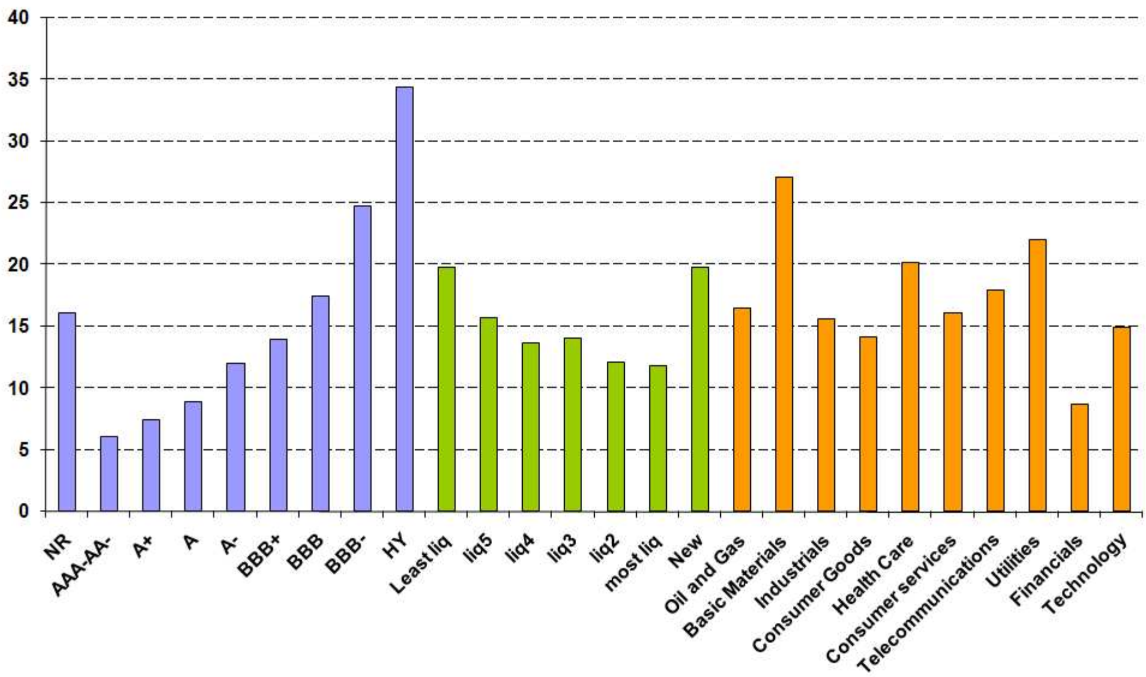

Figure 5: Expected liquidity per portfolio

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.

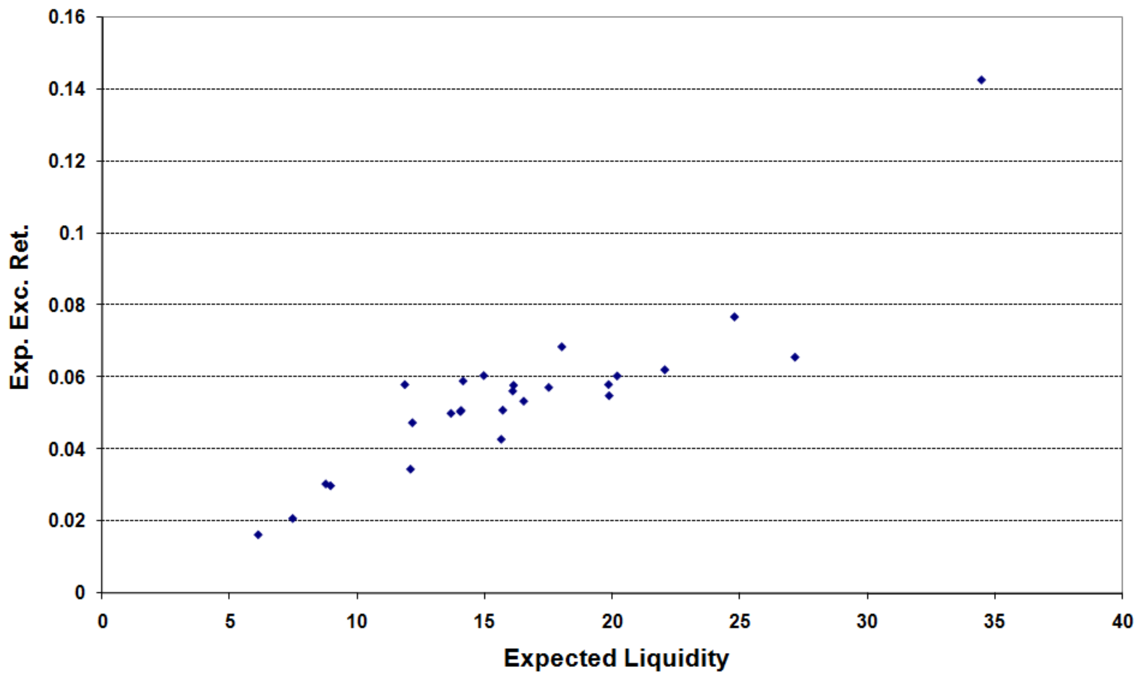

Figure 6: Scatterplot of expected liquidity and expected excess returns

The figure displays a scatterplot of expected excess returns 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.

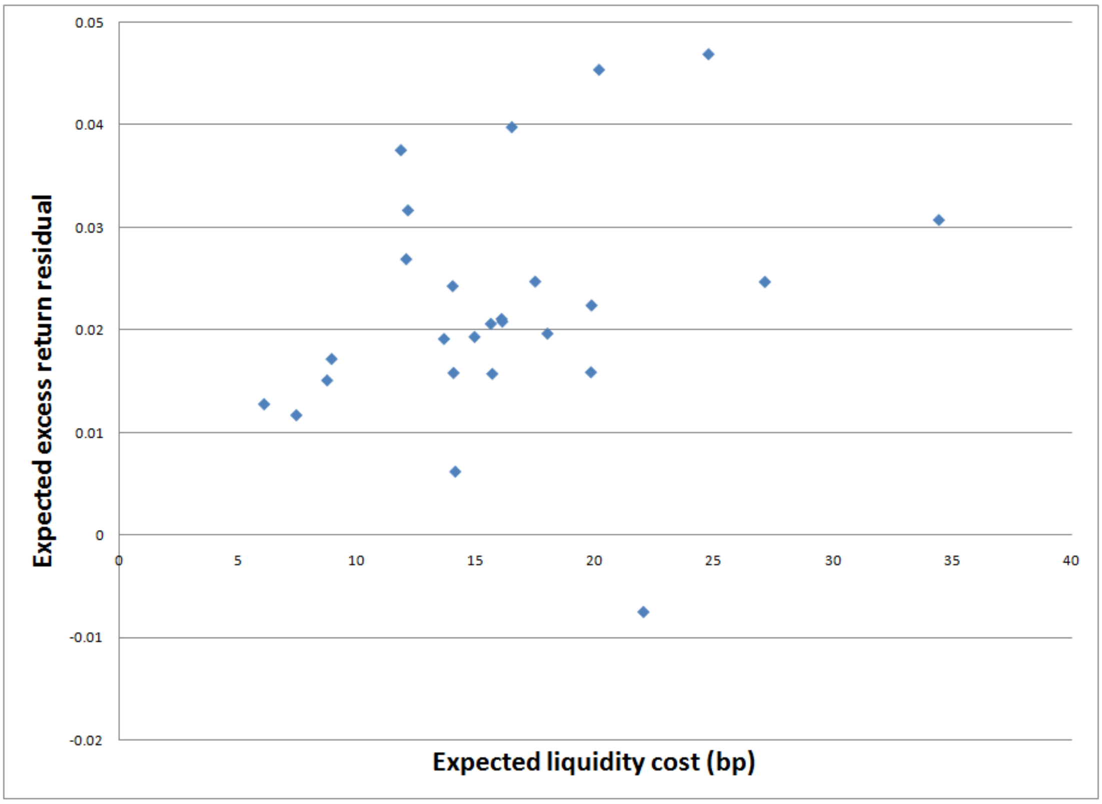

Figure 7: Scatterplot of expected liquidity and expected excess return residuals
The figure displays a scatterplot of portfolio expected excess returns minus portfolio betas times average excess return on market portfolio to expected liquidity costs over the full sample period. Liquidity costs are measured 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.

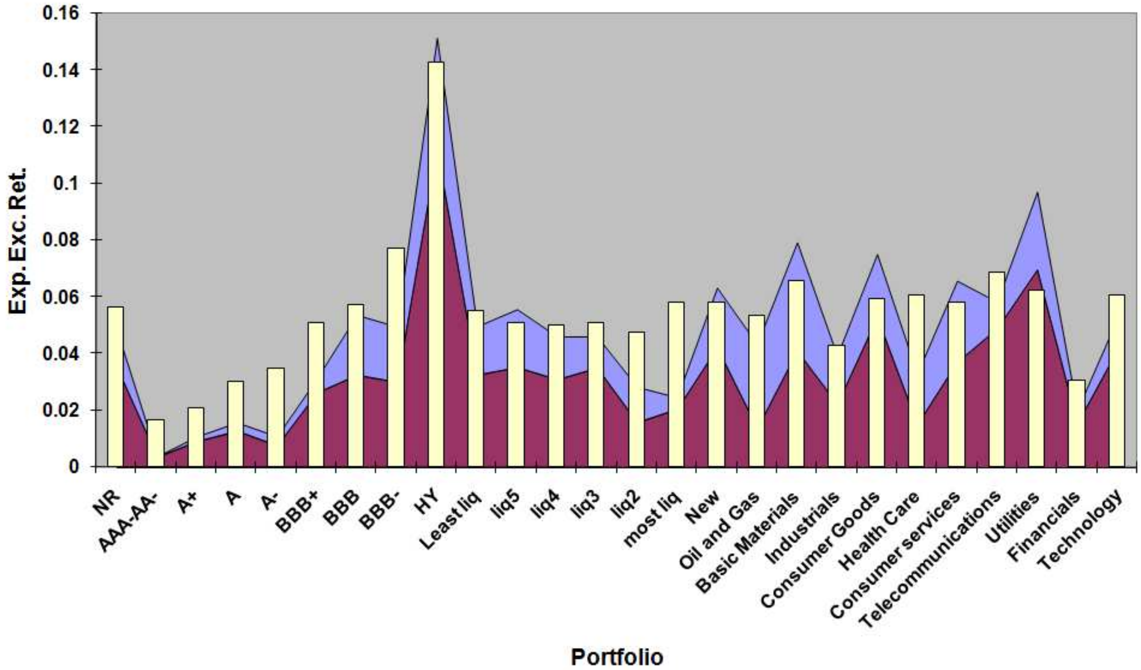

Figure 8: Fitted Expected Excess Returns with Liquidity Risk

The figure displays observed and fitted expected excess returns, split up by credit risk and liquidity risk contribution for the full sample period. Expected excess returns are measured as five year cumulative excess return per dollar of underlying.

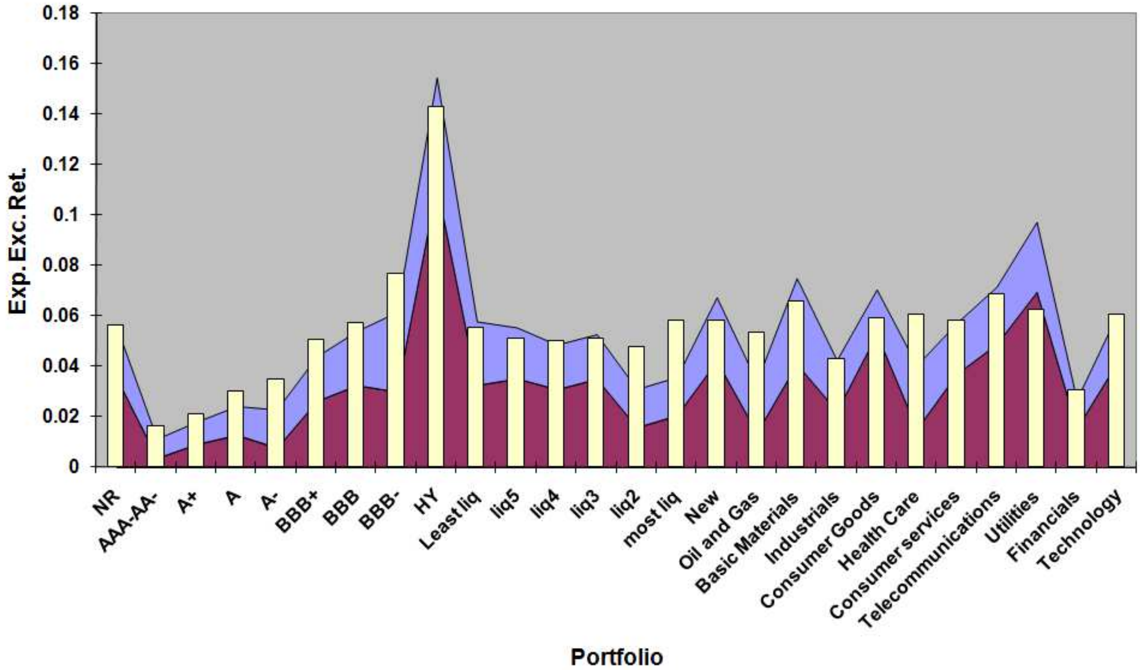

Figure 9: Fitted Expected Excess Returns with Expected Liquidity

The figure displays observed and fitted expected excess returns, split up by credit risk and expected liquidity contribution for the full sample period. Expected excess returns are measured as five year cumulative excess return per dollar of underlying.

Return Equation			
Full Sample			
Portfolio	β_{retret}	t-value	R^2
NR	0.6562***	6.40	11.89 %
AAA-AA-	0.0678**	1.99	1.35 %
A+	0.1715***	4.07	5.32 %
A	0.239***	5.14	8.02 %
A-	0.1436*	1.82	1.16 %
BBB+	0.4904***	7.18	14.53 %
BBB	0.6069***	7.18	14.70 %
BBB-	0.5594***	4.62	6.70 %
HY	2.0855***	7.00	15.15 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
NR	0.5589***	3.51	7.58 %
AAA-AA-	0.0556	0.88	0.56 %
A+	0.1889***	3.38	7.27 %
A	0.2213***	3.41	7.29 %
A-	0.22*	1.64	1.96 %
BBB+	0.5709***	4.94	14.18 %
BBB	0.6834***	5.03	14.57 %
BBB-	0.6035***	3.09	6.23 %
HY	2.4193***	4.51	14.59 %
Sub-sample 2			
Portfolio	β_{retret}	t-value	R^2
NR	0.7563***	6.56	22.17 %
AAA-AA-	0.1168***	3.25	6.56 %
A+	0.1255*	1.80	2.16 %
A	0.2652***	4.12	10.02 %
A-	0.0636	1.02	0.70 %
BBB+	0.1526**	2.47	3.85 %
BBB	0.4794***	7.66	28.19 %
BBB-	0.6065***	6.68	22.88 %
HY	1.8181***	7.47	26.79 %

Table 1: First stage excess return regressions of rating portfolios

This table reports the β_{retret}s and R^2s of the excess return regression $R^{e,CDS}_{i,t} = a_{s,i} + \beta_{retret,i} R^{e,CDS}_{m,t} + \epsilon_i, t$ of rating portfolios for the whole sample period and the two sub-samples July 2000 to June 2003 and July 2003 to June 2006.

Return Equation			
Full Sample			
Portfolio	β_{retret}	t-value	R^2
NR	0.5841***	5.16	8.24 %
AAA-AA-	0.0032	0.07	0.00 %
A+	0.0713	1.24	0.56 %
A	0.1294***	2.93	2.79 %
A-	0.1389	1.48	0.83 %
BBB+	0.2248**	2.45	2.01 %
BBB	0.9477***	7.98	18.41 %
BBB-	0.8764***	5.61	9.96 %
HY	1.774***	5.83	12.47 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
NR	0.6108***	3.64	8.41 %
AAA-AA-	0.0241	0.37	0.11 %
A+	0.1345*	1.66	1.98 %
A	0.1462**	2.49	4.05 %
A-	0.1532	1.00	0.88 %
BBB+	0.2533	1.54	1.69 %
BBB	1.1306***	5.43	17.92 %
BBB-	0.8737***	3.29	7.46 %
HY	1.7613***	2.76	7.51 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
NR	0.982***	6.76	23.44 %
AAA-AA-	0.023	0.35	0.08 %
A+	0.1165	1.16	0.94 %
A	-0.0288	-0.36	0.08 %
A-	0.0813	0.83	0.46 %
BBB+	0.1009	1.12	0.82 %
BBB	0.4539***	5.22	15.70 %
BBB-	0.5986***	3.79	8.80 %
HY	2.2108***	6.07	20.38 %

Table 2: First stage liquidity regressions of rating portfolios

This table reports the β_{retret}s and R^2s of the liquidity innovation regression $\Delta liq_{i,t} = a_{l,i} + \beta_{liqliq,i}\Delta liq_{m,t} + \upsilon_i, t$ of rating portfolios for the whole sample period and the two sub-samples July 2000 to June 2003 and July 2003 to June 2006.

Return Equation			
Full Sample			
Portfolio	β_{retret}	t-value	R^2
Least liq	0.6073^{***}	6.00	11.75 %
liq5	0.657^{***}	8.20	19.67 %
liq4	0.5769^{***}	6.10	12.28 %
liq3	0.6535^{***}	7.22	16.03 %
liq2	0.2951^{***}	3.67	4.69 %
most liq	0.3834^{***}	7.22	15.93 %
New	0.7864^{***}	7.57	17.39 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
Least liq	$0.644^{***}1$	4.17	12.39 %
liq5	0.5896^{***}	3.17	7.46 %
liq4	0.7312^{***}	4.72	15.76 %
liq3	0.6654^{***}	4.67	14.94 %
liq2	0.3636^{***}	2.72	5.58 %
most liq	0.4531^{***}	5.16	17.8 %
New	0.857^{***}	6.31	24.48 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
Least liq	0.8511^{***}	6.78	23.95 %
liq5	0.5213^{***}	6.80	23.71 %
liq4	0.3834^{***}	3.16	6.38 %
liq3	0.5245^{***}	4.22	10.71 %
liq2	0.2851^{***}	3.87	9.29 %
most liq	0.2766^{***}	3.81	8.76 %
New	0.6445^{***}	3.83	8.99 %

Table 3: First stage excess return regressions of liquidity portfolios

This table reports the β_{retret}s and R^2s of the excess return regression $R^{e,CDS}_{i,t} = a_{s,i} + \beta_{retret,i} R^{e,CDS}_{m,t} + \epsilon_i, t$ of liquidity portfolios for the whole sample period and the two sub-samples July 2000 to June 2003 and July 2003 to June 2006.

Return Equation			
Full Sample			
Portfolio	β_{retret}	t-value	R^2
Least liq	0.7659***	4.44	6.88 %
liq5	0.9173***	6.37	13.09 %
liq4	0.6796***	4.79	7.85 %
liq3	0.4926***	4.86	7.98 %
liq2	0.5585***	5.38	9.58 %
most liq	0.1785***	3.08	3.33 %
New	0.9456***	7.46	16.92 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
Least liq	0.626***	2.28	4.27 %
liq5	1.0133***	3.67	10.15 %
liq4	0.772***	3.12	7.58 %
liq3	0.4883***	3.31	8.17 %
liq2	0.5751***	2.64	5.49 %
most liq	0.2062*	1.93	2.97 %
New	0.9078***	4.90	15.98 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
Least liq	1.1399***	6.44	21.78 %
liq5	0.5129***	3.60	8.01 %
liq4	0.826***	5.26	15.65 %
liq3	0.3461**	2.09	2.83 %
liq2	0.2003***	3.30	6.69 %
most liq	0.1697***	2.63	4.35 %
New	1.1438***	5.28	16.04 %

Table 4: First stage liquidity regressions of liquidity portfolios

This table reports the β_{retret}s and R^2s of the liquidity innovation regression $\Delta liq_{i,t} = a_{l,i} + \beta_{liqliq,i}\Delta liq_{m,t} + \upsilon_i, t$ of liquidity portfolios for the whole sample period and the two sub-samples July 2000 to June 2003 and July 2003 to June 2006.

Return Equation			
Full Sample			
Portfolio	β_{retret}	t-value	R^2
Oil and Gas	0.256	1.27	0.81 %
Basic Materials	0.764**	2.04	2.11 %
Industrials	0.4155**	2.37	2.4 %
Consumer Goods	0.9853***	11.27	29.39 %
Health Care	0.2822***	2.60	2.29 %
Consumer services	0.6907***	6.86	13.43 %
Telecommunications	0.9118***	6.36	12.08 %
Utilities	1.2977***	6.06	13.62 %
Financials	0.2871***	3.29	3.65 %
Technology	0.7688***	4.08	5.93 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
Oil and Gas	0.2637	0.92	0.88 %
Basic Materials	0.9472*	1.87	3.26 %
Industrials	0.4903*	1.88	2.65 %
Consumer Goods	0.9931***	8.63	33.15 %
Health Care	0.1199	0.57	0.24 %
Consumer services	0.6488***	4.30	10.96 %
Telecommunications	0.841***	3.73	8.85 %
Utilities	1.3075***	3.96	11.46 %
Financials	0.3539***	4.07	9.91 %
Technology	1.1029***	4.08	11.35 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
Oil and Gas	0.2244	0.77	0.58 %
Basic Materials	0.7758	1.27	1.81 %
Industrials	0.5342	1.59	2.46 %
Consumer Goods	0.9168***	5.85	18.33 %
Health Care	0.3835***	4.17	10.22 %
Consumer services	0.5939***	5.01	14.26 %
Telecommunications	0.5548***	4.59	12.34 %
Utilities	1.1675***	5.28	19.78 %
Financials	-0.1653	-0.53	0.2 %
Technology	1.0534***	2.92	5.92 %

Table 5: First stage excess return regressions of industry portfolios

This table reports the β_{retret}s and R^2s of the excess return regression $R^{e,CDS}_{i,t} = a_{s,i} + \beta_{retret,i} R^{e,CDS}_{m,t} + \epsilon_i, t$ of industry portfolios for the whole sample period and the two sub-samples July 2000 to June 2003 and July 2003 to June 2006.

Return Equation			
Full Sample			
Portfolio	β_{retret}	t-value	R^2
Oil and Gas	1.3325***	4.57	13.05 %
Basic Materials	1.7217	1.55	2.4 %
Industrials	0.7641***	3.37	6.23 %
Consumer Goods	0.9989***	9.93	24.62 %
Health Care	0.7991***	5.73	11.16 %
Consumer services	1.287***	8.83	21 %
Telecommunications	0.4185***	2.64	2.43 %
Utilities	1.2331***	3.52	6.27 %
Financials	0.2071***	3.03	3.32 %
Technology	0.491	1.62	1.14 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
Oil and Gas	1.9151***	3.47	17.94 %
Basic Materials	1.2232	0.95	1.42 %
Industrials	0.7819***	2.74	6.92 %
Consumer Goods	0.9809***	8.98	34.96 %
Health Care	0.9244***	3.72	10.93 %
Consumer services	1.8134***	8.17	31.8 %
Telecommunications	0.5605**	2.16	3.38 %
Utilities	1.0628*	1.82	3.61 %
Financials	0.2404***	3.34	7.04 %
Technology	0.1368	0.38	0.15 %
Sub-sample 1			
Portfolio	β_{retret}	t-value	R^2
Oil and Gas	0.1193	0.66	0.53 %
Basic Materials	1.1693	0.40	0.47 %
Industrials	0.617	1.39	2.72 %
Consumer Goods	0.9292***	3.77	8.72 %
Health Care	0.4131***	3.27	6.83 %
Consumer services	0.3867***	2.97	5.57 %
Telecommunications	0.2046	1.53	1.59 %
Utilities	-0.1406	-0.39	0.15 %
Financials	-0.1319	-0.59	0.29 %
Technology	1.4163***	2.67	5.39 %

Table 6: First stage liquidity regressions of industry portfolios

This table reports the β_{retret}s and R^2s of the liquidity innovation regression $\Delta liq_{i,t} = a_{l,i} + \beta_{liqliq,i}\Delta liq_{m,t} + \upsilon_i, t$ of industry portfolios for the whole sample period and the two sub-samples July 2000 to June 2003 and July 2003 to June 2006.

Table 7: Second stage regressions pooled portfolios

Full Sample						
No restriction on market risk premium						
λ_{retret}	t-value	λ_{liqliq}	t-value	ζ	t-value	RMSE
0.0771***	10.4612					0.0184
0.0218***	5.8586			25.0643***	8.5803	0.0083
0.0527***	9.3642	0.023***	7.7966			0.0162
0.0238***	6.2066	-0.0095***	-3.0742	28.7007***	7.9279	0.0079
Restricted market risk premium						
0.0537***	10.1481					0.0288
0.0537***	10.1481			12.6355***	3.9122	0.0121
0.0537***	10.1481	0.0222***	3.6954			0.0162
0.0537***	10.1481	-0.015***	-5.0506	19.6525***	4.9824	0.0113

Sub-Sample 1						
No restriction on market risk premium						
λ_{retret}	t-value	λ_{liqliq}	t-value	ζ	t-value	RMSE
0.0919***	14.1755					0.0279
0.0197***	4.3060			24.23***	15.0578	0.0093
0.061***	10.1809	0.0332***	18.2365			0.0220
0.0196***	4.3105	-0.0008	-0.3166	24.5001***	11.0099	0.0093
Restricted market risk premium						
0.07***	12.0426					0.0330
0.07***	12.0426			10.2378***	5.0988	0.0191
0.07***	12.0426	0.0267***	5.3850			0.0223
0.07***	12.0426	-0.0002	-0.0715	10.2989***	3.9424	0.0191

Table 7 continued

Sub-Sample 2						
No restriction on market risk premium						
λ_{retret}	t-value	λ_{liqliq}	t-value	ζ	t-value	RMSE
0.0569***	19.7538					0.0152
0.0168***	7.5144			31.5899***	23.1379	0.0089
0.0447***	13.0899	0.023***	8.7862			0.0146
0.0145***	5.6160	-0.0095**	1.9912	30.9064***	19.8985	0.0088
Restricted market risk premium						
0.0376***	19.3728					0.0198
0.0376***	19.3728			18.0536***	8.8785	0.0106
0.0376***	19.3728	0.0222***	7.8822			0.0148
0.0376***	19.3728	-0.015***	-4.1195	21.9917***	10.4558	0.0104

[1]This table presents the estimated risk premia and t-values for the different specifications of the second stage regression

$$E(R_k^{e,CDS}) = \zeta E(liq_{k,t}) + \lambda_{retret}\beta_{retret,k} + \lambda_{liqliq}\beta_{liqliq,k} + e_k,$$

for the pool of rating, liquidity and industry portfolios. Moreover, it gives the root mean squared pricing errors (RMSE) for every specification. The excess returns are calculated over a five-year holding period, as in equation 24