Liquidity Tail Risk and Credit Default Swap Spreads

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ABSTRACT

We show that liquidity tail risk in credit default swap (CDS) spreads is time-varying and explains variation in CDS spreads. We capture the liquidity tail risk of a CDS contract written on a firm by estimating the tail dependence, i.e., the asymptotic probability of a joint surge in the bid-ask spread of the firm's CDS and the illiquidity of a CDS market index. Our results show that protection sellers earn a statistically and economically significant premium for bearing the risk of joint extreme downwards movements in the liquidity of individual CDS contracts and the CDS market. This effect holds in various robustness checks such as instrumental variable regressions and alternative liquidity measures and is particularly pronounced during the financial crisis.

Keywords: Finance, credit default swaps, liquidity risk, copula, liquidity tail beta.
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1 Introduction

Over the past decades, the emergence and growth of credit derivatives markets have provided market participants with additional ways to invest in credit risk. Especially insurers, mutual funds, and pension funds entered these markets as net protection sellers as credit derivatives provided them with previously unattainable risk-return profiles. During the financial crisis, however, investments in credit derivatives markets exposed several insurers to extreme tail risk when both prices and illiquidity in the market for credit default swaps (CDS) as the most widely used credit derivative surged during the height of the crisis. In the case of the most prominent example of such an insurer, American International Group (AIG) faced bankruptcy and had to be bailed out as the U.S. government deemed AIG to be systemically important due to its involvement in the CDS market. Consequently, economists and regulators alike have taken a strong interest in investigating the role crash and liquidity risk play for investors in the CDS market.

In this study, we try to answer the question whether liquidity tail risk is a significant driver of CDS spreads. We define a firm's CDS contract's liquidity tail risk as the propensity of the contract to experience a joint crash in its liquidity together with the liquidity of the CDS market. To measure this propensity, we propose the use of a dynamic copula model to estimate the asymptotic probability of both spread series jointly being in their extreme upper tail (i.e., their upper tail dependence). As a first result, we find average liquidity tail risk to be of small magnitude (about 0.2%) before the financial crisis. During the crisis, however, average liquidity tail risk almost doubled after the bailout of AIG and tripled at the start of 2009. We then estimate panel regressions of monthly CDS spreads on several proxies of liquidity tail risk in the CDS market and various controls. Our results confirm that the risk of a joint liquidity crash in the CDS market is significantly related to CDS spreads with sellers of credit protection demanding a premium for bearing liquidity tail risk.

The empirical evidence that we find adds to a rich and growing literature on the role of liquidity and liquidity risk in financial markets. For example, Lesplingart et al. (2012) argue that investors in the CDS market that are crash-averse with regard to liquidity should demand a premium for holding liquidity-crash-sensitive CDS contracts. Whereas investors may generally disregard the liquidity of assets during normal market circumstances, it can become a main issue in extreme market crashes when liquidity is fragile and can suddenly dry up (see Brunnermeier and Pedersen, 2009). The role liquidity risk (and liquidity tail risk in particular) plays for prices of CDS contracts, however, is far from being obvious. While the Liquidity Capital Asset Pricing Model (LCAPM) of Acharya and Pedersen (2005) shows that liquidity and liquidity risk should always be priced in assets that are in positive net supply, the role of liquidity risk for derivatives prices is much less clear with empirical studies on this subject yielding only contradicting findings: Whereas Bongaerts et al. (2011) show that prices of derivatives should not carry a premium for liquidity risk, Junge and Trolle (2015) find the exact opposite result by using a different proxy for the liquidity risk of CDS contracts.

Perhaps most importantly for our analysis, the model of Brunnermeier and Pedersen (2009) predicts that initial shocks to investors' funding liquidity can lead to reinforcing spirals of both market and funding liquidity, and ultimately, falling asset prices. They posit that traders react to initial losses (and reduced capital) by reducing their positions thus in turn reducing market liquidity and inducing further asset losses.

In this scenario, traders would first reduce the positions whose individual liquidity is highest and thus least affected by the decreases in overall market liquidity. As Brunnermeier and Pedersen (2009) point out, this effect could be negligible during normal times but could become significant when market illiquidity spikes. As such, CDS liquidity tail risk could increase CDS prices even though linear CDS liquidity risk does not. Moreover, the causality of this relation is testable in case of exogenous shocks to CDS market liquidity.

We test these predictions and show that an important facet of liquidity risk, the probability of *extreme* joint surges in idiosyncratic and market illiquidity, indeed explains CDS spreads. A one standard deviation increase in our proxy for CDS liquidity tail risk is associated with an increase in a firm's monthly CDS spread of about 16 basis points (bps). Together with an average yearly CDS spread of 152 bps in our sample, this shows that the effect we find is not only statistically, but also economically highly significant. Moreover, this effect holds even when controlling for individual CDS liquidity, known drivers of credit risk taken from the structural model of Merton (1974), crash risk in the CDS market (see Meine et al., 2016), and linear CDS liquidity risk (i.e., correlations).

Consequently, our findings are of significant importance to risk managers and traders as our results stress the importance of accounting for liquidity tail risk in the pricing of CDS contracts. Moreover, our results should be of particular interest to long-term investors like insurers and pension funds which predominantly enter the CDS market as net protection sellers (see, e.g., Mengle, 2007; Bongaerts et al., 2011; Hilscher et al., 2015). For these investors, offsetting short positions in CDS contracts could become dangerously costly when liquidity tail risk increases and market liquidity deteriorates. We confirm that liquidity tail risk in the CDS market indeed spiked during the financial crisis - a time when the adverse effects of extreme CDS liquidity risk were accompanied by steep increases in overall default risk.

Our paper contributes to the operational research literature by being the first to propose the use of dynamic copula models to estimate the time-varying nonlinear dependence between contract-specific and market liquidity in the CDS market. While copulas have been used extensively, e.g., in the study of stock prices and banking crises (see, e.g., Grundke and Polle, 2012; Ye et al., 2012; Jayech, 2016; Calabrese et al., 2017), this study is the first that employs these dependence models in the context of CDS liquidity. Our modeling approach allows us to capture facets of liquidity risk that have so far been neglected in studies on CDS market liquidity but which appear to be of significant importance to investors. By doing so, our paper complements and extends several studies on the determinants of corporate bond credit spreads and CDS spreads. To start with, Collin-Dufresne et al. (2001) use variables from a structural model of credit spreads and employ these in regressions of changes in bond credit spreads. As their main result, they find the explanatory power of the variables that should in theory drive default risk to be low. In a related study, Campbell and Taksler (2003) find that levels of corporate credit spreads are driven by idiosyncratic equity volatility.[1] In contrast to these studies, however, we employ CDS spreads rather than bond spreads. A critical advantage of using swaps over bonds is that swaps do not require the specification of a risk-free yield curve to extract the credit spreads. Our paper is also related to the studies of Ericsson et al. (2009) and Meine et al. (2016) who study the determinants of changes in CDS spreads. While the former again finds the result that variables from structural models of credit risk possess only little explanatory power, the latter

[1]Cremers et al. (2008) confirm this result using option-based rather than historical volatility.

study finds CDS tail risk to be a strong driver of banks' CDS during the crisis.

Next, our paper is also related to several studies on the ambiguous role liquidity risk plays in CDS markets. While several studies clearly show that CDS spreads increase with contract-specific illiquidity (see, e.g., Tang and Yan, 2008; Bühler and Trapp, 2009; Lesplingart et al., 2012), the question whether liquidity risk is also priced in CDS spreads remains controversial. For example, Bongaerts et al. (2011) show in their work theoretically and empirically that liquidity risk should not matter for CDS spreads. In contrast, recent studies by Tang and Yan (2008), Meine et al. (2015), and Junge and Trolle (2015) all find the opposite result that liquidity risk measured via linear relations between idiosyncratic and market liquidity does indeed drive CDS spreads. Extending their work, we focus in this paper on the explanatory power of liquidity *tail* risk proxied by the tail dependence between contract-specific and market CDS liquidity. Finally, our study is also related to work on the potentially systemic role of insurers in the CDS market. As noted by, e.g., Harrington (2009) and Chen et al. (2014), involvement in the CDS market turned out to be a major source of risk for several insurers during the financial crisis. Our results suggest that one source of this risk exposure to protection sellers in CDS contracts could be sudden and extreme co-movements in illiquidity leading to a sudden (and costly) dry-up in contract-specific liquidity.

The paper proceeds as follows: Section 2 describes the construction of our CDS liquidity tail risk proxies, Section 3 presents the data used in this study, Section 4 investigates the pricing of liquidity tail risk, while Section 5 reports results of robustness tests. Section 6 concludes.

2 Methodology

This section deals with the estimation of the proxies for extreme CDS liquidity risk. First, the univariate modeling of CDS spreads and CDS bid-ask spreads is described. Next, we present the copula model that we use to estimate the tail betas of CDS liquidity in the spirit of the linear liquidity betas of Acharya and Pedersen (2005).

Our econometric modeling is based on log-differenced CDS spreads and log differences of the spreads of a CDS market index. The log-differenced CDS spreads, $R_{i,t}$, are given by

$$R_{i,t} = log\left(\text{CDS}_{i,t}\right) - log\left(\text{CDS}_{i,t-1}\right) \tag{1}$$

with $\text{CDS}_{i,t}$ being the CDS spread of company i at time t $(i = 1, \ldots, N, t = 1, \ldots, T)$.

Next, the CDS market spreads are estimated as the equally-weighted average of all individual spreads across all sample companies. Thus, the CDS market spread, $\text{CDS}_{M,t}$, at time t is defined as

$$\text{CDS}_{M,t} = \frac{1}{N}\sum_{i=1}^{N}\text{CDS}_{i,t}, \tag{2}$$

and the log differences of the CDS market spread, $R_{M,t}$, as

$$R_{M,t} = log\left(\text{CDS}_{M,t}\right) - log\left(\text{CDS}_{M,t-1}\right). \tag{3}$$

To eliminate the artificial correlation between $R_{i,t}$ and itself if it were included in the index $R_{M,t}$, we estimate different market spreads for each bivariate analysis of the market index and a company i by aggregating all companies excluding the respective company i. In addition to levels and log differences of CDS spreads, we also model contract-specific and CDS market liquidity. We measure a CDS contract's liquidity by the use of the contract's absolute bid-ask spread as the most widely used liquidity proxy in the literature (see, e.g., Amihud and Mendelson, 1986).[2] We compute the absolute bid-ask spread BAS as

$$\text{BAS}_t = \text{Ask quote}_t - \text{Bid quote}_t. \tag{4}$$

As for the CDS market spreads, we calculate the market liquidity measures as the daily equally-weighted averages of the bid-ask spread across all sample firms excluding firm i for which we intend to measure CDS liquidity risk.

For derivatives markets, the effect of liquidity on prices is not clear since derivatives are in zero net supply. Therefore, liquidity can have a positive, negative, or zero impact on CDS spreads depending on whether the supply- or the demand-side predominates. However, the unanimous empirical evidence is that liquidity exerts a decreasing effect on the level of CDS spreads with protection sellers acting as liquidity providers (see, e.g., Bongaerts et al., 2011; Corò et al., 2013). Consequently, we also expect a positive relation between spreads and bid-ask spreads of CDS contracts in our later regression analyses.

2.1 Univariate modeling of CDS data

In this subsection, we model the univariate marginal models for a CDS contract's idiosyncratic liquidity and the CDS market's bid-ask spread. These models will be used later together with a copula model to yield a bivariate model of the distribution of a contract's liquidity tail risk. We start our univariate modeling by describing the mean dynamics of our liquidity proxies.

2.1.1 Mean dynamics

Following the empirical literature (see, e.g., Acharya and Pedersen, 2005; Bongaerts et al., 2011), we first correct for persistence in the levels of CDS liquidity. Therefore, for each time period t and for each firm i including the CDS market spread $i = M$, we calculate the innovations in the liquidity time series. To obtain the liquidity innovations, we fit ARMA(r, s) models $(r, s \in \{1, \dots, 10\})$ to the bid-ask spreads:

$$BAS_t^i = \phi_0^i + \sum_{k=1}^{r} \phi_k^i BAS_{t-k}^i + e_t^i - \sum_{k=1}^{s} \theta_k^i e_{t-k}^i \tag{5}$$

[2] The vast majority of studies on CDS markets employ bid-ask spreads to measure liquidity, see, e.g., Bongaerts et al. (2011), Lesplingart et al. (2012), Corò et al. (2013), and Meine et al. (2015, 2016).

with $\{e_t^i\}$ being a white noise series and $r, s > 0$ (see, e.g., Tsay, 2005). Consequently, the conditional mean, μ_t^i, follows the dynamics

$$\mu_t^i = \phi_0^i + \sum_{k=1}^{r} \phi_k^i BAS_{t-k}^i - \sum_{k=1}^{s} \theta_k^i e_{t-k}^i. \tag{6}$$

The ARMA(r, s) model is estimated via Maximum Likelihood. To choose the proper orders r and s in the ARMA(r, s) processes, we employ the Ljung-Box test with the number of lags equal to 20 to the corresponding ARMA residuals and select the orders $r, s \in \{1, \ldots, 10\}$ so that the null of the Ljung-Box test cannot be rejected at the 10% significance level. If this is true for more than one model, we will choose the model with the lowest value of Akaike's Information Criterion (AIC).[3]

In the same way, the ARMA residuals of the log-differenced CDS spreads are estimated by substituting R_t^i for BAS_t^i $(t \in 1, \ldots, T, i \in 1, \ldots, N, M))$ in equation (5) and (6), since empirical studies have also revealed that log differences of CDS spreads are characterized by autocorrelation (see Meine et al., 2016; Oh and Patton, 2017). In the next step, the residuals, $e_t^i = BAS_t^i - \mu_t^i$ and $e_t^{i,R} = R_t^i - \mu_t^{i,R}$, of the ARMA($r, s$) models of the CDS bid-ask spreads and the log-differenced CDS spreads, respectively, are used for modeling the variance dynamics.

2.1.2 Volatility dynamics

According to the econometrics literature as well as the empirical results presented in the following Sections 3 and 4, the time series of the log-differences of CDS spreads as well as the CDS bid-ask spreads are stationary, autocorrelated, and conditionally heteroskedastic (see, e.g., Oh and Patton, 2017). Therefore, we test several variants of the original GARCH model to capture the variance dynamics of our data and for each company and each time series we select the model that fits the data best.

In our empirical study, we also account for skewness and fat tails in the time series of the log-differenced CDS spreads and CDS bid-ask spreads. Hence, we use the skewed t distribution of Fernández and Steel (1998) with the degrees of freedom parameter $\nu_i \in (2, \infty)$ and the skewness parameter $\gamma_i \in (0, \infty)$ to account for skewness and fat tails in the marginal distributions (see also Christoffersen et al., 2012, 2017). The probability density function (pdf) of the skewed student t distribution, t_{ν_i,γ_i}, is given by

$$t_{\nu_i,\gamma_i}(x) = \frac{2}{\gamma_i + \frac{1}{\gamma_i}} \left[f_t\left(\frac{x}{\gamma_i}\right) 1_{[0,\infty)}(x) + f_t(\gamma_i x)\, 1_{(-\infty,0)}(x) \right] \tag{7}$$

with f_t the pdf of a univariate standard t distribution and $i \in \{1, \ldots, N\}$ (see Fernández and Steel, 1998). For $\gamma_i = 1$ we get the standard t distribution and for $\gamma_i \neq 1$ a skewed t distribution.

As we do not employ one specific GARCH model for all CDS time series, we give a generic definition of the models here. More precisely, we fit the so-called *family GARCH* model of Hentschel (1995) to the

[3] In an unreported robustness test, we alternatively employ the Bayes Information Criterion (BIC) to select the best-fitting marginal model. Using BIC for model selection does not change our results.

ARMA(r, s) residuals $e_t^{i,j}$.[4] Hence, the conditional volatility follows the dynamics

$$e_t^{i,j} = \sqrt[\lambda]{\sigma_{i,j,t}^{\lambda}}\epsilon_t^{i,j}, \ \epsilon_t^{i,j}|\mathcal{F}_{t-1}^{i,j} \sim t_{\nu_i,\gamma_i}, \tag{8}$$

$$\sigma_{i,j,t}^{\lambda} = \omega^{i,j} + \sum_{k=1}^{q} \alpha_{i,j,k}\sigma_{i,j,t-k}^{\lambda}\left(|e_{t-k}^{i,j} - \eta_{i,j,2k}| - \eta_{i,j,1k}\left(e_{t-j}^{i,j} - \eta_{i,j,2k}\right)\right)^{\delta} + \sum_{k=1}^{p} \beta_{i,j,k}\sigma_{i,j,t-k}^{\lambda} \tag{9}$$

where $\mathcal{F}_{t-1}^{i,j}$ is the information available on the time series R^i as well as BAS^i up to and including time t with $i \in \{1, \dots, N\}, j \in \{R, BAS\}$ and $p, q > 0$.[5] Here, equation (9) is a Box-Cox transformation for the conditional standard deviation, in which λ is the shape parameter, δ transforms the absolute value function and η_{1k} as well as η_{2k} allow for rotation and shifts. If we choose $\lambda = \delta = 2$ and $\eta_{1k} = \eta_{2k} = 0$, we obtain the standard GARCH model of Bollerslev (1986) and for $\lambda = \delta = 2$ and $\eta_{2k} = 0$ we get the GJR-GARCH model of Glosten et al. (1993). All GARCH models are estimated via Maximum Likelihood.[6]

We choose the appropriate GARCH model by the following procedure: First, we select a number of suitable GARCH models that are most likely to fit the given time series well and fit these models to the ARMA residuals $e_t^{i,j}$. Then, we compute the ARMA-GARCH residuals of the chosen GARCH models for the orders $p, q \in \{1, 2\}$ and select the model, for which the null of the Ljung-Box test with lag 5 cannot be rejected for the squared ARMA-GARCH residuals and the Engle (1982) Lagrange multiplier test for ARCH effects with lag 5 cannot be rejected for the ARMA-GARCH residuals at the 10% significance level. Again, if this is true for more than one model, we will choose the model with the lowest AIC value. The possible models for the log-differences of CDS spreads and the CDS bid-ask spreads are the GARCH model of Bollerslev (1986) and the Integrated GARCH (I-GARCH) model of Engle and Bollerslev (1986). The GARCH model is most commonly used in the empirical literature and it accounts for all the stylized facts documented for financial market data. Other popular asymmetric models like the GJR-GARCH model or the E-GARCH model are not considered for the CDS data, since these models incorporate a leverage effect. More precisely, they account for the fact that negative returns lead to higher volatility and positive returns to lower volatility, which is not adequate for our time series of CDS data as they exhibit a reversed pattern (see also Daníelsson, 2011). Finally, we generate white-noise residuals, $\epsilon_t^{i,j}$, which we will use in our joint distributional model to estimate extreme CDS liquidity risk together with CDS tail betas.

2.2 Bivariate modeling of CDS spreads and CDS liquidity

In this subsection, we construct proxies for CDS liquidity tail risk based by focusing on the joint extreme movements in individual and market CDS spreads and bid-ask spreads. However, instead of using simple covariances to estimate the dependence between the different variables like it is done by, e.g.,

[4]The family GARCH model is an omnibus model that encompasses some of the most popular GARCH models (see Hentschel (1995)).

[5]For a detailed definition of the family GARCH model see Hentschel (1995). Furthermore, we note that while the distribution of shocks in log-differenced CDS spreads or in the CDS bid-ask spread, $\epsilon_t^{i,j}$, differs across the individual sample firms, but is constant over time, the distribution of the log differences does vary through time due to the dynamics of the conditional means and variances.

[6]In addition to the GARCH models, we also consider the stochastic volatility model of Heston and Nandi (2000) as a candidate model for the marginals.

Acharya and Pedersen (2005), Tang and Yan (2008), and Lesplingart et al. (2012), we estimate upper tail dependence coefficients between the variables instead using copula models.We use the dynamic t-copula of Patton (2006a,b) to account for time dynamics in the dependence of our variables asChristoffersen et al. (2012) have shown that copula correlations are highly time-varying and persistent. Then, the evolution of the correlation parameter of the dynamic t-copula follows an ARMA(1,10)-like process (see equation (11)).

To be precise, the (standard) t-copula is defined as

$$C_{\nu,\rho}\left(u_1,u_2\right)=t_{\nu,\rho}\left(t_\nu^{-1}(u_1),t_\nu^{-1}(u_2)\right) \tag{10}$$

where $t_{\nu,\rho}$ is the (standard) bivariate Student t distribution with the degree of freedom parameter ν and the correlation parameter ρ, t_ν^{-1} is the inverse of the standard univariate t distribution and $u_1,u_2\in[0,1]$. Then, the time variation of the dynamic t-copula of Patton (2006a) is modeled by the following evolution process for $\rho_t, t\in\{1,\ldots,T\}$:

$$\rho_t=\tilde{\Lambda}\left(c+b\rho_{t-1}+a\frac{1}{10}\sum_{i=1}^{10}t_\nu^{-1}\left(u_{1,t-i}\right)t_\nu^{-1}\left(u_{2,t-i}\right)\right) \tag{11}$$

where $\tilde{\Lambda}(x):=(1-e^{-x})(1+e^{-x})^{-1}$ is the modified logistic transformation in order to keep ρ_t in $(-1,1)$ at all times. Consequently, this dynamic process captures persistence in the dependence parameters by including ρ_{t-1} and variation in the dependence by the mean of the product of the last ten observations of the transformed variables $t_\nu^{-1}\left(u_{1,t-i}\right)$ and $t_\nu^{-1}\left(u_{2,t-i}\right)$.

Now, the coefficients of the lower and upper tail dependence, $\lambda_{L,t}$ and $\lambda_{U,t}$, are given by

$$\begin{aligned}\lambda_{L,t}\left(X_{1,t},X_{2,t}\right) &:= \lim_{q\searrow 0}P\left[X_{2,t}\leq F_2^{-1}(q)\mid X_{1,t}\leq F_1^{(-1)}(q)\right]\\ \lambda_{U,t}\left(X_{1,t},X_{2,t}\right) &:= \lim_{q\nearrow 1}P\left[X_{2,t}> F_2^{-1}(q)\mid X_{1,t}> F_1^{(-1)}(q)\right]\end{aligned}$$

with q being the q-quantile and F_1^{-1} and F_2^{-1} being the inverse marginal distribution functions of X_1 and X_2, respectively. As the t-copula is symmetric, the coefficients can be written as

$$\lambda_{U,t}\left(X_{1,t},X_{2,t}\right)=\lambda_{L,t}\left(X_{1,t},X_{2,t}\right)=2t_{\nu+1}\left(-\sqrt{\frac{(\nu+1)(1-\rho_t)}{1+\rho_t}}\right). \tag{12}$$

The log-likelihood function of the dynamic t-copula is given by

$$\mathcal{L}_{\nu,\boldsymbol{\rho}}\left(\boldsymbol{u_1},\boldsymbol{u_2}\right)=\sum_{t=1}^{T}log\left(f_{\nu,\rho_t}\left(t_\nu^{-1}\left(u_{1,t}\right),t_\nu^{-1}\left(u_{2,t}\right)\right)\right)-log\left(f_\nu\left(t_\nu^{-1}\left(u_{1,t}\right)\right),f_\nu\left(t_\nu^{-1}\left(u_{2,t}\right)\right)\right), \tag{13}$$

with f_{ν,ρ_t} and f_ν being the density of a $t_{\nu,\rho}$ and a t_ν distribution, respectively, and $\boldsymbol{\rho}=\left(\rho_1,\ldots,\rho_T\right)^T$, $\boldsymbol{u_1}=\left(u_{1,1},\ldots,u_{1,T}\right)^T$ as well as $\boldsymbol{u_2}=\left(u_{2,1},\ldots,u_{2,T}\right)^T$. Using this log-likelihood function, the copula parameters are then estimated via Maximum Likelihood.

We use the described dynamic copula model to estimate the following tail betas:

$$\text{Tail beta}_{i,t}^{BAS,BASM} = \lambda_{U,t}\left(BAS_t^i, BAS_t^M\right) \quad (14)$$

$$\text{Tail beta}_{i,t}^{CDS,CDSM} = \lambda_{U,t}\left(R_{i,t}, R_{M,t}\right) \quad (15)$$

where the estimation of the copula and the tail dependence coefficients are done based on the pseudo-observations $u_{i,t}^R$, $u_{M,t}^R$, $u_{i,t}^{BAS}$, and $u_{M,t}^{BAS}$ of the corresponding ARMA(r, s)-GARCH(p, q) residuals $\epsilon_t^{i,j}$ for $j \in \{R, BAS\}$ that are computed as the ranks of these residuals. CDS and BAS refer to a contract's spread and bid-ask spreads, respectively, while $CDSM$ and $BASM$ are the corresponding market spread and bid-ask-spread, respectively.

The interpretation of each tail beta is as follows. Tail beta$_{i,t}^{BAS,BASM}$ specifies the upper right tail of the bivariate distribution between the individual liquidity of a CDS of company i and the CDS market liquidity. As a consequence, this tail beta captures a contract's risk of experiencing a joint surge in its illiquidity together with liquidity in the CDS market. In addition to the *liquidity tail beta*, we denote the CDS tail beta as Tail beta$_{i,t}^{CDS,CDSM}$, which describes the dependence between the log differences of CDS spreads of company i and the log differences of the CDS market spreads in the upper-right tail of their joint distribution. We expect that the protection seller of the CDS contract demands a premium for bearing the risk of a joint increase in the firm's and market CDS spreads. As Meine et al. (2016) show in their empirical study, this CDS tail beta was a significant driver of banks' CDS premia during the financial and we thus include it as a control variable in our study.[7]

3 Data and Variables

This section presents the data used in our empirical analysis. First, we present the CDS data set and, second, introduce the determinants of CDS spreads. We further discuss alternative CDS liquidity measures.

3.1 Sample construction

The CDS data set is constructed from all available single-name CDS time series for U.S. firms that have traded CDS contracts on their debt. Our sample consists of 228 financial and non-financial companies for the time period from January 1, 2004 to September 30, 2010.[8] The available daily five-year CDS mid, bid,

[7] In robustness tests, we also employ the upper tail dependence between the individual log-differences of CDS spreads and the CDS market liquidity, Tail beta$_{i,t}^{CDS,BASM}$. Diminishing opportunities for hedging default risk via a CDS contract due to market-wide illiquidity could not only affect the contract's liquidity, but also the reference unit's default risk itself. As shown by Subrahmanyam et al. (2014), the default risk of reference firms increases upon the inception of CDS trading due to the empty creditor problem. Accordingly, extreme dry-ups of CDS market liquidity and thus diminished CDS trading could affect default risk reflected in CDS spreads as well. Also, Tail beta$_{i,t}^{BAS,CDSM}$ describes the dependence between a company's CDS liquidity and the log-differences of the CDS market spreads in the upper-right tail of their joint distribution. We expect that this tail beta is positively correlated with CDS spreads since protection sellers will demand a premium for the risk that a company's CDS liquidity drops at the same time when the average default risk of the market increases. In times of market crashes, financial intermediaries sometimes withdraw from providing liquidity or investors withdraw funds, hence, causing potential problems in fulfilling the payment obligations of the protection buyer (see Coval and Stafford, 2007; Brunnermeier and Pedersen, 2009).

[8] A list of all sample companies is reported in the Internet Appendix.

and ask quotes are downloaded from *Credit Market Analysis* (CMA) via *Thomson Reuters' Datastream*.[9] Moreover, we filter our data by using several criteria. We start by considering all U.S. companies with traded CDS contracts. Next, we delete from our sample all entities that refer to U.S. sovereign debt issues and all companies without a stock market listing. Since we are also interested in the associated equity data of the companies, we extract the equity symbol and match it with the Thomson Reuters' CDS symbol after which we end up with 228 entities. We assign each firm to one of the 19 different industrial sectors based on the Industry Classification Benchmark (ICB) Level 3 Supersector Codes, which are taken from *Datastream* based on the equity symbols of the companies.[10].

3.2 Determinants of CDS spreads

In our empirical analysis, we control for known determinants of CDS spreads suggested by the structural model of Merton (1974) and previous empirical literature.

VOLATILITY: According to Merton (1974), debt is equivalent to a risk-free loan combined with a short put-option on the firm's assets. Thus, a higher equity volatility, implying a higher asset volatility, will increase the probability of default and eventually CDS spreads. We estimate asset volatility as the annualized monthly stock return volatility.

LEVERAGE AND FIRM VALUE: Higher leverage reveals a shorter distance to default barrier, since default occurs when the leverage ratio nears unity. Hence, the probability of default increases and the CDS spreads will also increase. As we perform our empirical analysis on monthly data, it is difficult to measure the leverage ratio based on balance sheet data. Therefore, we follow, e.g., Collin-Dufresne et al. (2001) as well as Annaert et al. (2013) and use the firm's arithmetic stock return as a proxy for leverage, since decreasing stock returns will increase leverage, which leads to higher credit spreads.[11]

INTEREST RATE: The impact of the risk-free rate on CDS spreads is not obvious. On the one hand, Longstaff and Schwartz (1995) emphasize that a higher risk-free rate increases the risk-neutral drift of the firm value process, which reduces the probability of default and, thus, decreases CDS spreads (see Longstaff and Schwartz, 1995; Collin-Dufresne et al., 2001). On the other hand, higher risk-free rates may reflect that the stance of monetary policy is tightened, which would increase the probability of default and, thus, the CDS spreads (see, e.g., Zhang et al., 2009; Meine et al., 2016). We use the two-year U.S. Treasury benchmark yield as a proxy for the risk-free interest rate.

Empirical evidence shows that default probabilities and recovery rates are also influenced by economic cycles (see, e.g., Bruche and González Aguado, 2010). Also, Ericsson et al. (2009) reveal that the explana-

[9] There are several reasons for using CMA data. First, Mayordomo et al. (2014) find that CMA quoted CDS spreads are more preferable than those from other databases regarding the price discovery process. Furthermore, CMA data capture quotes from intra-day CDS market activity, which are reported only if there are a sufficient number of quotes available. Hence, the data account for the actual daily market situation and for low levels of liquidity, which suggests that they are reliable and appropriate for the use of investigating tail risks.

[10] Our sample firms are distributed across all 19 industrial sectors. While most of the companies are in the Industrial Goods & Services sector (a total of 32 companies), only one company is in the Telecommunications sector.

[11] In addition, arithmetic stock returns are also a proxy for changes in firm value (see Meine et al., 2015). The model of Merton (1974) also provides a connection between the firm value and the probability of default. A higher firm value will decrease the probability of default, since it is less likely that the default barrier is reached. Therefore, CDS spreads will decrease as well. Hence, we expect a negative relation between CDS spreads and firm value.

tory power of the variables suggested by the structural model is very low. Therefore, we include some further control variables that reflect global macro-economic and financial conditions.

BUSINESS CLIMATE: One indicator of the market condition is the business climate, which influences the probability of default and the expected recovery rates (see Altman and Kishore, 1996; Zhang et al., 2009; Ericsson et al., 2009). We proxy for the business climate using monthly values of the S&P 500 index and expect a negative relation between the index and CDS spreads.

MARKET-WIDE VOLATILITY: As an additional explanatory variable, we include the option-implied volatility index of the S&P500 (VIX) as a proxy for market-wide volatility. Similar to equity volatility, we expect a positive sign of the coefficient in our regression analyses.

SLOPE OF THE YIELD CURVE: The slope of the yield curve serves as a control variable for overall economic health in our empirical analysis. The effect of this variable on CDS spreads is undetermined (see Collin-Dufresne et al., 2001).[12] We calculate the slope of the yield curve as the difference between the ten-year and the two-year U.S. Treasury benchmark yield.

GDP GROWTH: As another determinant of CDS spreads that proxies for the overall stance of the economy is the growth of the economy. Therefore, we follow Meine et al. (2016) and include the GPD growth rate of the U.S. obtained from the OECD as a control variable in our empirical study. We expect GDP growth to be negatively related to CDS spreads, since an increase in economic growth will increase the firm-level growth rate which implies a decrease of default probabilities and lower CDS spreads (see Tang and Yan, 2010).

SYSTEMIC RISK: Motivated by the fact that systemic risk can also emerge from liquidity squeezes as seen in the financial crisis of 2008 (see, e.g., International Monetary Fund, 2009), we employ a measure of systemic risk proposed by Giglio et al. (2016) as additional control. The Partial Quantile Regression (PQR) measure combines 19 individual systemic risk measures into one and has shown to have strong predictive power for future macroeconomic shocks.

3.3 Alternative measures of CDS (il)liquidity

Our main analysis is based on CDS bid-ask spreads to construct our proxy of liquidity tail risk in the CDS market. This is most suitable as bid-ask spreads are available on a daily basis and thus, allow us to model the time-series and tail dependence as outlined above.[13] Furthermore, we employ two alternative measures of liquidity to ensure the robustness of our main results. First, we adapt the 'P-zero' measure introduced in Lesmond et al. (1999) to CDS contracts which counts the number of 'zero-return days', the number of days the CDS price did not change over a given time frame. We calculate the p-zero measure on a daily basis

[12] On the one hand, a negative relation with CDS spreads is expected, since according to Fama and French (1989) a steeper slope indicates a better economic growth or future economic activity. This also increases the recovery rates, which reduces CDS spreads. On the other hand, an increase of the slope may also predict a tightening of monetary policy and an increasing inflation rate, which would increase CDS spreads (see Zhang et al., 2009; Meine et al., 2016).

[13] Junge and Trolle (2015) capture CDS market illiquidity by comparing CDS-implied and actual index levels and thus, require the CDS contract to be part of a credit index. As contract-specific illiquidity measures, they also use bid-ask spreads. Other measures of illiquidity such as in Amihud (2002) for equities or respective measures for bonds cannot be easily adapted to CDS contracts due to the lack of volume data. Data providers such as The Depository Trust & Clearing Corporation (DTCC) provide information on notionals and (average) number of trades, which could serve as a substitute for transaction volume. However, this data are only available on a quarterly frequency and cannot be used to estimate tail dependence measures. Also, the data provided do not cover the time period investigated in this study.

using a 30 day rolling window (see Schestag et al., 2016) as follows:

$$\text{P-zero}_{t,\text{daily}} = \frac{\text{\#zero return days}}{30}. \tag{16}$$

Second, we use the P-zero measure of CDS illiquidity and further compute P-zero FHT as suggested in Fong et al. (2017) which is derived from comparing the theoretical probability of experiencing zero-return days with its empirical frequency:

$$\text{P-zero FHT}_{t,\text{daily}} = 2 \cdot \sigma(\text{CDS}) \cdot \Phi^{-1}\left(\frac{1 + \text{P-zero}_{t,\text{daily}}}{2}\right), \tag{17}$$

where $\sigma(\text{CDS})$ is the standard deviation of CDS spreads over a 30 day rolling window and Φ^{-1} is the inverse function of the standard normal distribution. Daily values of (16) and (17) are later used to model alternative liquidity tail betas used for additional regressions.

4 Empirical results

4.1 Descriptive statistics and stylized facts of CDS spreads

Figure 1 presents the time-variation of the CDS mid quotes and of the log-differenced CDS spreads by plotting the corresponding equally-weighted cross-sectional averages (black line) and the range between their cross-sectional 5th and 95th percentiles (gray-shaded area).

Panel (a) illustrates that average CDS premia are relatively low, less than 100 bps, from 2004 until mid-2007. However, during the financial crisis, starting with the sub-prime crisis in August 2007, CDS spreads rise dramatically, thus, indicating the great change in the market's perception and valuation of credit risk. After the maximum is reached at the beginning of 2009, premia decrease. Besides, the cross-sectional variation is also low during the pre-crisis period and it widens significantly after the mid of 2007. However, we find an overall large cross-sectional variation in CDS spreads within the full sample period.[14]

We perform several tests to obtain stylyzed facts of our time series of interest. First, we find that the time series of log differences of CDS spreads are stationary.[15] Second, a Ljung-Box (LB) test (with 20 lags) for the log differences of CDS spreads is rejected at the 1% level for about one quarter of our sample CDS contracts and thus, we conclude that most of the time series exhibit linear serial dependence. Further, we employ the Lagrange multiplier (LM) test from Engle (1982) to test for ARCH effects.[16] The hypothesis that there is no ARCH effect is rejected at the 5% and 10% level for about 91% of our time series. Finally, we check for non-normality in the log-differences of the CDS spreads, which we find by applying several

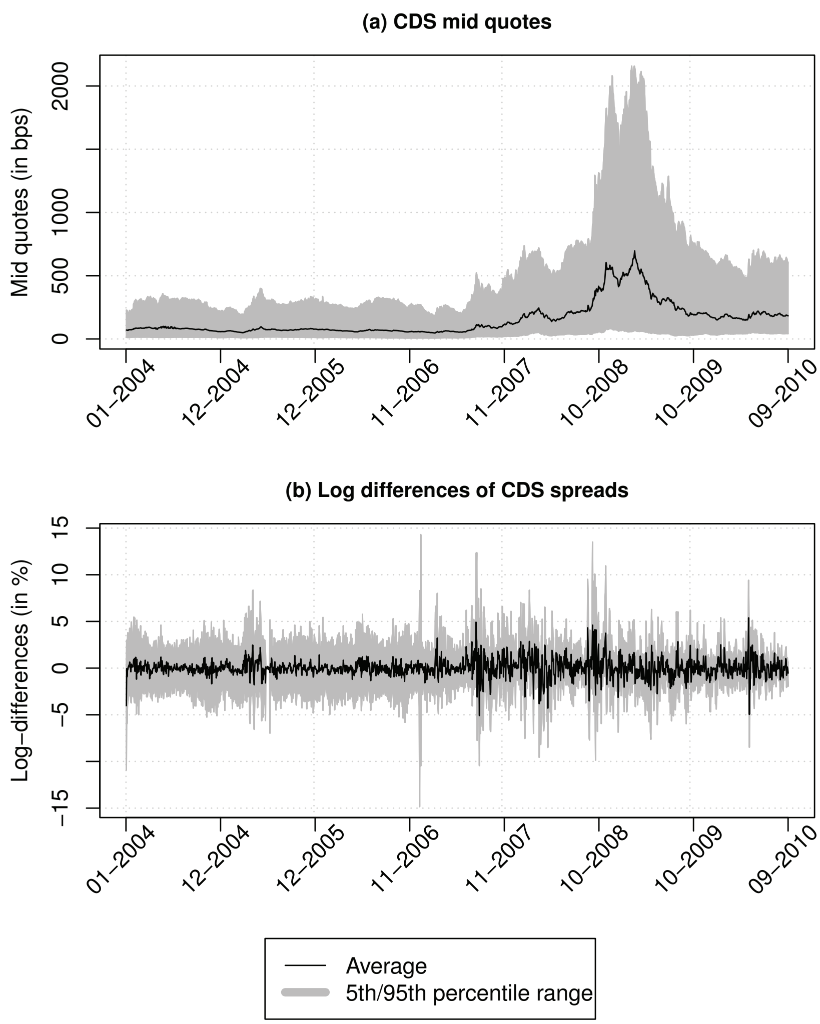
[14]Additional descriptive statistics on the percentiles and moments of CDS spreads (by year) that are available from the authors upon request suggest that most of the data are located in the lower tail of the distribution and that CDS mid quotes exhibit a significant autocorrelation of about 97%.

[15]We employ the Augmented-Dickey-Fuller (ADF) test (see Said and Dickey, 1984), the Phillips-Perron (PP) test, and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test.

[16]We estimate an AR model for each series in order to manage linear serial dependence and then follow Meine et al. (2016) and choose the orders of the AR model so that the null of the LB test (with 20 lags) cannot be rejected at the 10% significance level. Afterwards, we use the AR residuals for the LM test.

Figure 1: Time evolution of CDS spreads and log differences of CDS spreads

This figure depicts the time evolution of CDS mid quotes in Panel (a) and the time-series variation of log differences of CDS spreads in Panel (b). In each panel, we plot the equally weighted cross-sectional averages of the mid quotes or the log-differenced CDS spreads (black line) and the range between their cross-sectional 5th and 95th percentiles (shaded area). CDS mid quotes are denoted in basis points (bps) and log differences of CDS spreads are measured in %. Our sample consists of daily data of 228 financial and non-financial companies for the period of January 2004 to September 2010.



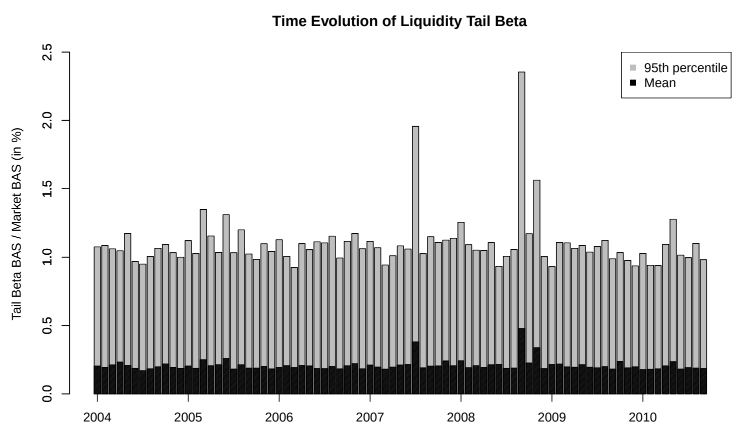
statistical tests.[17] Bringing the same set of tests to CDS (absolute) bid-ask-spreads, we also find evidence for stationarity, linear serial dependence, and ARCH effects in most of the time series.

For reasons of efficiency and due to previous findings in the empirical literature, we first fit AR(r) models to all CDS spread and CDS liquidity time series by choosing the order of the model according to the Ljung-Box test described in Section 2.1. If the AR(r) models are not adequate, we filter the data by ARMA(r, s) processes.[18] Estimation results suggest that AR models of order up to five are sufficient to model the persistence in the data.[19] GARCH model orders vary between one and two. The parameter estimates of the degrees of freedom, ν, suggest fat tails in the conditional distribution. Lastly, the estimates for parameter γ indicates positive skewness. Altogether, we have generated white-noise residuals for all data which is necessary for our dynamic copula model.

In the following, we present the estimates for the liquidity tail beta using the dynamic t-copula ofPatton (2006a).[20] Figure 2 plots the time evolution of the liquidity tail beta based on CDS bid-ask spreads.

Figure 2: Time evolution CDS liquidity tail betas

This figure shows the time evolution of liquidity tail betas based on CDS (market) bid-ask spreads. We plot the equally weighted cross-sectional averages of the liquidity tail beta (black bars) and their 95th percentiles (grey area). Our sample consists of daily data of 228 financial and non-financial companies for the period of January 2004 to September 2010. The tail betas are estimated from the dynamic t-copula of Patton (2006a) and the definition of each tail beta is reported in Appendix I. All tail betas are denominated in %.



[17] Overall, we employ three tests: the Jarque-Bera (JB), the Kolmogorov-Smirnov (KS), and the Shapiro-Wilk (SW) test.

[18] Furthermore, the procedure of fitting the volatility models described in Section 2.1 is not always sufficient for all time series so that we need to employ further methods. First, if the suggested GARCH models generate residuals for which the Ljung Box test and the ARCH-LM test with lag 5 cannot be rejected at the 10% significance level, we fit all these GARCH models up to lag $p = q = 4$. If this is not adequate as well, we fit other GARCH models such as the Integrated GARCH, the Exponential GARCH, the GJR-GARCH, the Asymmetric Power ARCH, the Absolute Value GARCH, the Threshold GARCH, the Nonlinear ARCH, the Nonlinear Asymmetric GARCH, the Component GARCH and the ALLGARCH model. In a last step, we would increase the number of lags to 10, 12, 15 and 20 in the Ljung Box test and to 12 in the ARCH-LM test until there is one model for which both tests on the corresponding residuals cannot be rejected at the 10% significance level.

[19] The CDS market spreads, however, require a slightly higher order.

[20] We also compare the dynamic copula model with a different time-varying model of the standard (static) t-copula. This copula is computed on a daily basis as the standard t-copula defined in equation (10) over a rolling window of 100 data points. We compare the two models using Akaike's Information Criterion (AIC) and find that the dynamic copula model is chosen much more often than the static approach.

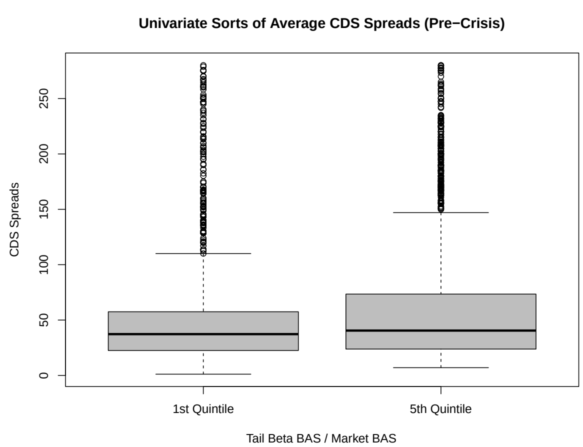
Black bars represent average values of tail betas and the 95th percentiles are given by grey-shaded areas. The dynamic liquidity tail beta varies between 0% and 3% during the sample period. Average tail dependence stays flat, especially during the pre-crisis period where the values are about 0.2%. However, the average tail beta spikes several times with the maximum values being reached at a little less than 0.5% during the financial crisis. The highest value of the 95th percentile of the liquidity tail beta is higher than 2% in September 2008. During the crisis, the cross-sectional variation increases slightly as well, most likely depending on whether the firm's industry was immediately affected by the crisis.

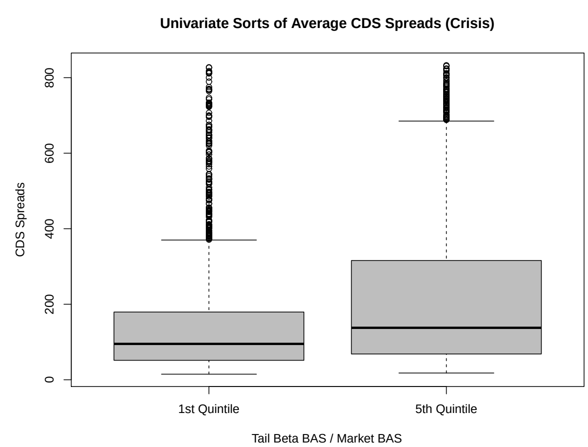
4.2 Univariate sorts

We continue our empirical analysis by presenting the results of univariate sorts of CDS spreads according to the liquidity tail risk measure. To investigate the relation between the liquidity tail risk variables and CDS spreads, we calculate average CDS spreads for observations that are in the first and fifth quintiles of the CDS liquidity tail betas. We divide our sample in two periods, the pre-crisis and the crisis period.[21] For each sub-sample we compute quintiles of the liquidity tail beta across all sample firms. We then rank the observations for CDS spreads according to these quintiles and calculate the average CDS spread in each quintile for each sub-sample. The results using the basic CDS tail betas are shown by boxplots in Figure3.

Figure 3: Univariate sorts of average CDS spreads

This figure shows boxplots of CDS spreads in the pre-crisis (left panel) and crisis period of observations that are in the 20th or 80th percentile of liquidity tail betas for each subsample period. Our sample consists of daily data of 228 financial and non-financial companies for the period of January 2004 to September 2010. The pre-crisis period lasts from January 1, 2004 to August 8, 2007 and the crisis period comprises August 9, 2007 to September 30, 2010. For illustration purposes, CDS spreads are winsorized at the 95% level. The tail betas are estimated from the dynamic t-copula of Patton (2006a) and the definition of each tail beta is reported in Appendix I.





We first observe that the distribution of CDS spreads differs significantly both across observations ranked by quintiles of the liquidity tail beta and between crisis versus pre-crisis periods. Observations in the fifth quintile of the liquidity tail beta exhibit a wider range of values in the middle part, i.e., between the 25th and

[21] We employ August 9, 2007 as our cut-off date for the beginning of the financial crisis (see, e.g., `http://news.bbc.co.uk/2/hi/business/7521250.stm`=.

75th percentile of CDS spreads, with all values being higher than their counterpart where observations are in the first quintile of the tail betas. This is true for both pre-crisis and crisis period although the magnitude of this difference is much higher in the latter period. The difference in averages of the CDS spreads in the high and the low tail beta quintile is significant and is higher in the crisis period than in the pre-crisis period. Before the crisis, the difference between average CDS spreads in the first versus the fifth quintile is only about 10.3 bps while in the crisis subsample the difference is 62.9 bps.[22]

4.3 Baseline panel regressions

We continue our main empirical analysis by performing a set of OLS panel regressions using our full sample of observations. We regress CDS spreads on our main variable of interest, the (lagged) liquidity tail beta, and various lagged controls. All regressions include industry-fixed effects with standard errors being adjusted for heteroskedasticity. Hence, we account for the variation of our sample companies across several industrial sectors so that market downturns in the U.S economy can have different effects in each sector. First, we start with the results of our benchmark industry-fixed effects regressions of the CDS spreads. The results are presented in Table I. For an easy interpretation, all coefficients are standardized.

In Panel A of Table I, results for our full sample are shown. The estimated coefficient of the liquidity tail beta is positive and significant, which is consistent with our expectations that protection sellers earn a premium when writing a CDS contract that carries a higher liquidity tail risk. A one standard deviation increase in the liquidity tail beta is associated with an increase in monthly CDS spreads of 26.9 bps. The regression of which the results are shown in column (2) further include time-fixed effects and reduce the impact of the liquidity tail beta to 23.4 bps.

Next, we include our full set of lagged control variables. The liquidity tail beta remains a statistically significant determinant of CDS spreads with a coefficient estimate of 15.79 bps per month. Given that the average annual CDS spread in our sample is 152 bps, we find that the effect of CDS liquidity tail risk on spreads is highly economically significant.

The Merton-type variables enter the regressions with the expected sign as in other empirical studies (see, e.g., Ericsson et al., 2009). When additionally controlling for the slope of the yield curve, GDP growth rate, business climate, market-wide volatility, and systemic risk, we find that our main variable of interest remains significant. One could argue that the regression model in column (3) exhibits multicollinearity as some of the firm-invariant variables proxy for certain aspects of the current economic environment.[23] In order to mitigate this concern, we drop all macroeconomic control variables in column (4) and replace them with time-fixed effects that would absorb any omitted time-varying effects influencing CDS spreads. Our variable of interest is still significant and remains at a coefficient estimate of about 16 bps per month. Further, as expected, the level of CDS bid-ask spreads is an important determinant of CDS spreads as shown by other empirical studies (e.g. Tang and Yan, 2008; Bühler and Trapp, 2009).

[22]Both differences are statistically different from zero, which is confirmed by Welch Two Sample t-tests that yield t-statistics of 5.82 and 9.82, respectively.

[23]For example, the interest rate and the value of the S&P 500 exhibit a high correlation of about 72.6%. However, the CDS tail beta and liquidity tail beta exhibit a positive correlation of about 9.4%. Generally, the absolute pairwise correlation of the liquidity tail beta and other covariates is less than 10% and correlations among other firm-specific variables are also low.

Table I: Panel benchmark regressions

The table presents results from the panel regressions of monthly sampled CDS mid quotes on the CDS liquidity tail beta, variables suggested by theory, and further controls. We estimate the following regression model for each firm i in sector j for the period from January 2004 to September 2010 on a monthly basis:

$$\text{CDS}_{i,t} = \alpha + \beta \cdot \text{Liquidity tail beta}_{i,t-1} + \gamma \cdot X_{i,t-1} + \omega_j + \mu_t + \epsilon_{i,t},$$

where $X_{i,t-1}$ describes lagged control variables. In Panel B, we run the same regressions as in column (2) and (4) of Panel A but split our sample into a pre-crisis and crisis period. The pre-crisis period lasts from January 1, 2004 to August 8, 2007 and the crisis period comprises August 9, 2007 to September 30, 2010. We run all regressions with industry-fixed effects, ω_j, based on the ICB Level 3 Supersector Codes. Monthly-fixed effects are denoted as μ_t. Variable definitions and data sources are outlined in AppendixI. Standard errors are adjusted for heteroskedasticity. We present the standardized coefficients and the corresponding t-statistics are reported in parentheses. ***, ** and * indicate that the coefficients are significantly different from zero at the 1%, 5% and 10% level, respectively.

Panel A: Baseline Regressions	(1)	(2)	(3)	(4)
Dependent variable:	CDS spreads			
(Tail beta BAS / Market BAS)$_{t-1}$	**26.8821*** **	**23.4269*** **	**15.7898*** **	**15.9748*** **
	(10.83)	**(10.59)**	**(8.08)**	**(8.49)**
Lagged controls:				
Tail beta CDS / Market CDS			**-4.6259** **	-3.6754
			(-2.02)	(-1.57)
Firm value			**-27.3911*** **	**-22.0732*** **
			(-4.18)	**(-2.70)**
Volatility			**96.1519*** **	**102.4506*** **
			(10.08)	**(9.98)**
BAS			**168.8815*** **	**168.3621*** **
			(6.13)	**(6.14)**
Interest rate			**-68.0426*** **	
			(-5.22)	
GDP growth			**-22.5189*** **	
			(-6.14)	
Business climate			-4.0384	
			(-1.27)	
Slope			**-39.6150*** **	
			(-3.05)	
VIX			**-19.7865*** **	
			(-3.04)	
Systemic Risk			-3.4071	
			(-0.52)	
N	18,240	18,240	18,120	18,120
Adjusted R^2	0.071	0.195	0.500	0.508
Industry FE	YES	YES	YES	YES
Time FE	NO	YES	NO	YES

Panel B: Crisis Subsample Regressions	(1)	(2)	(3)	(4)
Dependent variable:	CDS spreads			
	Pre-Crisis		Crisis	
(Tail beta BAS / Market BAS)$_{t-1}$	**11.9298*** **	**11.9452*** **	**17.8462*** **	**17.8003*** **
	(9.49)	**(9.68)**	**(4.93)**	**(5.03)**
N	9,491	9,491	8,629	8,629
Adjusted R^2	0.575	0.583	0.482	0.487
Lagged controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Time FE	NO	YES	NO	YES

In summary, the panel regressions yield strong evidence that investors in the CDS market are crash-averse regarding liquidity as they demand a premium for liquidity tail risk, i.e., the risk of a joint extreme co-movement of a company's CDS illiquidity with the CDS market illiquidity. As we include the CDS tail beta and the liquidity tail beta in the same regression and find that both coefficients remain significant, we find that an investor's liquidity crash aversion is different from a general crash aversion regarding default risk.

4.4 Sub-sample analysis

So far, the panel regressions have strongly supported the notion that liquidity tail risk is an important determinant of CDS spreads. In the following, we check the explanatory power of the liquidity tail beta in different regimes and whether the impact of liquidity tail risk increases during the financial crisis. Therefore, we split our data set into two sub-samples associated with two different regimes: the pre-crisis and crisis period.

We expect that the CDS protection sellers and buyers are less concerned about liquidity crashes and, therefore, about liquidity tail risks in the pre-crisis period. The reason is that an asset's liquidity might not be as important during normal market conditions as it is during extreme market crashes. Indeed, the dramatic fall of liquidity during the financial crisis has shown how fragile liquidity is (see International Monetary Fund, 2008). Hence, protection sellers should be more sensitive to higher illiquidity during extreme market downturns since it can cause increased default risk and lower recovery rates. The International Monetary Fund (2008) reported rising default risks as well as systemic risk in the global financial system since the beginning of the financial crisis. On the other hand, protection buyers will also be more concerned about illiquidity during financial distress as counterparty credit risk rose in the CDS market during the financial crisis.

We use the same sub-samples as in the univariate sorts in Figure 3 and split the sample on August 9, 2007, so that the crisis period reflects the recent financial crisis. Regarding the CDS liquidity tail betas, we repeat the benchmark panel regression of Panel A in Table I for each sub-sample and report the results in Panel B of the table. We observe that the liquidity tail beta is statistically highly significant in both periods. However, the economic effect of this variable on CDS spreads is larger in the crisis period with the standardized estimated coefficient increasing from 11.9 bps in the pre-crisis period to 17.8 bps in the crisis period. Thus, we do find evidence in line with Brunnermeier and Pedersen (2009) that the effect of illiquidity spirals during crisis times are more pronounced for contracts that have a higher CDS liquidity crash sensitivity, i.e., a higher liquidity tail beta.

4.5 Instrumental variable and system GMM regressions

The OLS estimates given above could be biased due to endogeneity problems. First, extremely high CDS spreads might also affect the propensity to experience liquidity tail risk so that estimates are biased because of reversed causality. Second, although we lag all independent variables by one month, some endogeneity concerns are still present as omitted variables can influence both liquidity tail risk and CDS spreads simultaneously. To mitigate some of these concerns, we perform two-stage least squares (2SLS) regressions in which we instrument the liquidity tail beta as our endogenous variable. As instrument we employ a firm's extreme equity exposure to changes in the market capitalization of the group of 14 major credit derivatives dealers during our sample period (see Junge and Trolle, 2015).[24] Since we instrument tail liquidity risk, we construct our instrument to measure the sensitivity of a firm to extreme downturns in the G14-Dealers' market capitalization. This is motivated by empirical evidence given in Junge and Trolle (2015), who show that the G14-Dealers' market capitalization as a proxy of risk-bearing capacity of the intermediary sector is strongly correlated with CDS (market) liquidity). We define 'G14-Dealer Sensitivity' as the average return of a firm's equity on the days the returns on the aggregate market capitalization of G14 are below the 5%-quantile (multiplied by minus one so that higher values indicate higher exposure). In this way, we ensure that our instrument satisfies the relevance condition (which is also confirmed by respective statistics). While we cannot directly test whether the exclusion restriction is fulfilled (see Roberts and Whited, 2013), we argue that this is likely to be the case. If extreme exposure to the group of major CDS dealers influenced CDS spreads directly, it would require firms to have direct business links to all of these major dealers in the cross-section, a situation that is highly unlikely given the diversity of firm sizes and industries in our sample. Finally, our instrument is directly linked with the theoretical model of Brunnermeier and Pedersen (2009) as it measures a drop in funding liquidity and its subsequent effect on (CDS) market liquidity.

As an alternative to the 2SLS approach based on our instrument, we also run system GMM regressions in which the lagged endogenous variables are instrumented using their second lag. In Table II we report results of the two different regression analyses.

Panel A of Table II shows results of the 2SLS estimation. In the first stage, the liquidity tail beta is regressed on the lagged instrument and other control variables as well as industry- and time-fixed effects. Second stage regressions employ CDS spreads as dependent variable and use the instrumented liquidity tail beta as main explanatory variable. We first notice that the Kleibergen-Paap rank test on underidentification and the Wald test on weak identification both reject the null hypothesis at statistically relevant levels. Thus, we can infer that our chosen instrument is relevant and our model is well identified. Higher values of G14-Dealers Sensitivity result in higher liquidity tail betas as expected. The second stage results presented in column (2) further confirm that our variable of interest is highly relevant when explaining the variation of CDS spreads.

Panel B of Table II shows the main results of a dynamic system GMM panel regression of CDS spreads on the first lag of the dependent variable, the liquidity tail beta, and the same set of lagged controls as in Panel A. The system GMM regression further includes firm-fixed and time-fixed effects and thus, controls for further omitted firm-specific variables. The first lag of CDS spreads, liquidity tail beta, and CDS tail beta are instrumented using their respective second lag. The AR(2) test and Hansen test are both insignificant at conventional levels and validate our model choice. The estimated coefficient of the liquidity tail beta is positive and statistically significant at the 10% level. This confirms our main result even after controlling for persistence in the dependent variable and only looking at within-firm variation.

[24]The G14-Dealers are Bank of America, Barclays, Bear Stearns, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, J.P. Morgan, Lehman Brothers, Merrill Lynch, Morgan Stanley, UBS, and Wachovia (see Junge and Trolle, 2015, p.38).

Table II: Instrumental variable and system GMM regressions

The table presents results from two-stage least squares (2SLS) and system GMM panel regressions of monthly sampled CDS mid quotes on the CDS liquidity tail betas and lagged controls. In Panel A, we report results of 2SLS regressions where in the first stage we regress the liquidity tail beta on an instrumental variable and lagged controls such as firm value, volatility, CDS bid-ask spreads, CDS tail beta, as well as time- and industry-fixed effects. The instrument used is 'G14-Dealer Sensitivity' which is the average return of a firm's equity on the days the returns on the aggregate market capitalization of G14 are below the 5%-quantile multiplied by minus one. In the second stage, CDS spreads are then regressed on the instrumented liquidity tail beta and the same set of control variables and fixed effects. Panel B shows the main results of a dynamic system GMM panel regression of CDS spreads on the first lag of the dependent variable, the liquidity tail beta, and the same set of lagged controls as in Panel A. The system GMM regression further includes firm-fixed and time-fixed effects. The first lag of CDS spreads, liquidity tail beta, and CDS tail beta are instrumented using their respective second lag. We report corresponding AR(2) tests and Hansen test results. Variable definitions and data sources are outlined in Appendix I. Standard errors are adjusted for heteroskedasticity and corresponding t-statistics are reported in parentheses. ***, ** and * indicate that the coefficients are significantly different from zero at the 1%, 5% and 10% level, respectively.

Panel A: Instrumental Variable Regressions (2SLS)	(1)	(2)
Stage:	1st	2nd
(G14-Dealers Sensitivity)$_{t-2}$	**0.0124*** **	
	(5.31)	
Tail Beta $\widehat{\text{BAS / Market BAS}}_{t-1}$		**219,588.8*** **
		(4.82)
N	16,886	
Kleibergen-Paap rk LM test (underidentification)	31.38***	
Kleibergen-Paap Wald test (weak identification)	28.22***	
Lagged controls	YES	YES
Industry FE	YES	YES
Time FE	YES	YES

Panel B: System GMM Regression	(1)
Dependent variable:	CDS spreads
(CDS spreads)$_{t-1}$	**0.0956*** **
	(6.87)
(Tail Beta BAS / Market BAS)$_{t-1}$	**1,541.218***
	(1.81)
(Tail Beta CDS / Market CDS)$_{t-1}$	99.5781
	(-1.03)
N	18,120
AR(2) test	-1.58
Hansen	167.35
Lagged controls	YES
Firm FE	YES
Time FE	YES

5 Robustness and further analyses

The purpose of this section is to convey the robustness our main findings in the presence of other types of (CDS) risk measures, alternative measures of CDS liquidity, and the possibility that CDS spreads might be affected not by CDS liquidity tail risk, but by extreme spillovers from the equity market.

5.1 Alternative measures of (systemic) risk

As our first robustness test, we control for various additional (systemic) risk measures that might serve as an alternative explanation of the effects of liquidity tail betas on CDS spreads. Motivated by the fact that systemic risk can also emerge from liquidity squeezes as seen in the financial crisis of 2008 (see, e.g., International Monetary Fund, 2009), we employ the Marginal Expected Shortfall (MES) from Acharya et al. (2017) based on equity log returns and test if MES is different from the CDS liquidity tail beta in explaining CDS spreads.[25] As an additional measure, we consider the CoVaR measure introduced in Adrian and Brunnermeier (2016) which measures an individual equity's contribution to distress in the market. It is calculated as the equity market beta times the difference in value at risks of the firm's stock returns at the 95% and 50% percentile, i.e., the firm being in distress versus in a median state.

We also consider three measures that capture linear co-movement risk: the regular liquidity beta, the upside liquidity beta, and the liquidity cokurtosis. Further, we control for these risk measures based on CDS spreads rather than bid-ask spreads. We estimate our baseline regression including time-fixed effects and include the linear measures of co-movement risk as further covariates. TableIII shows results of regressions that include these alternative risk measures as control variables.

We find no significant change in the significance of the CDS liquidity tail beta which enters all regressions with a significant positive coefficient. Altogether, our estimation results indicate that the CDS liquidity tail beta is not simply another proxy for a company's contribution to systemic risk, but has a different impact on CDS spreads than the MES and ΔCoVaR. MES is positively correlated to CDS spreads indicating that investors require a premium for bearing the exposure of the underlying equity to extreme equity market movements. The effects of the systematic risk measures on CDS spreads that we find are in line with the literature (see, e.g., Tang and Yan, 2008; Lesplingart et al., 2012). In particular, this confirms that the impact of CDS liquidity tail beta on CDS spredas is not explained by liquidity risk calculated as regular beta, upside beta, or cokurtosis.

5.2 Alternative measures of CDS liquidity

We now employ the two additional CDS liquidity measures introduced in Section3, P-zero and P-zero FHT, to ensure that our results are not driven by the specific choice of bid-ask spreads as a proxy for CDS liquidity. For both the P-zero and P-zero FHT time series, we again consider ARMA-GARCH specifications and select the best fitting model via BIC. The tail dependence coefficients are then again estimated via pseudo-

[25]Acharya et al. (2017) find evidence that a financial firm's MES as a proxy for systemic relevance is a significant driver in explaining CDS spreads of financial institutions during the recent financial crisis. In particular, they consider the MES, which is defined as the average return of a firm when the market is collapsing, based on equity returns and on changes of CDS spreads.

Table III: Alternatives measures of (systemic) risk

The table presents results from the panel regressions of monthly sampled CDS mid quotes on the basic CDS liquidity tail betas, alternative (systemic risk) measures, and further controls. We estimate the following regression model for each firm i in sector j for the period from January 2004 to September 2010 on a monthly basis:

$$\text{CDS}_{i,t} = \alpha + \beta \cdot \text{Liquidity tail beta}_{i,t-1} + \gamma \cdot X_{i,t-1} + \delta \cdot \text{RISK}_{i,t-1} + \omega_j + \mu_t + \epsilon_{i,t},$$

where $X_{i,t-1}$ describes lagged control variables. $\text{RISK}_{i,t-1}$ represents various alternative measures of (systemic) risk such as an equity's marginal expected shortfall (MES), ΔCoVaR, beta, upside beta, and cokurtosis based on either CDS or equity market data. We run all regressions with industry-fixed effects, ω_j, based on the ICB Level 3 Supersector Codes. Monthly-fixed effects are denoted as μ_t. Variable definitions and data sources are outlined in AppendixI. Standard errors are adjusted for heteroskedasticity. We present the standardized coefficients and the corresponding t-statistics are reported in parentheses. ***, ** and * indicate that the coefficients are significantly different from zero at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	CDS spreads							
Tail beta BAS / Market BAS_{t-1}	**13.2916*** (6.80)**	**16.3892*** (8.50)**	**16.1811*** (8.29)**	**16.1578*** (8.27)**	**16.1802*** (8.29)**	**16.1661*** (8.28)**	**17.9094*** (9.23)**	**16.8109*** (8.69)**
MES_{t-1}	**102.9871*** (9.69)**							
ΔCoVaR_{t-1}		**73.2125*** (4.12)**						
Beta $(\text{CDS})_{t-1}$			0.7861 (1.40)					
Beta $(\text{BAS})_{t-1}$				**-5.1549*** (-3.95)**				
Upside Beta $(\text{CDS})_{t-1}$					-0.2876 (-1.10)			
Upside Beta $(\text{BAS})_{t-1}$						**-2.5772*** (-3.05)**		
Cokurtosis $(\text{CDS})_{t-1}$							**-19.4731*** (-4.37)**	
Cokurtosis $(\text{BAS})_{t-1}$								**-12.0956*** (-3.86)**
N	17,212	17,211	17,219	17,219	17,219	17,219	17,177	17,186
Adjusted R^2	0.530	0.514	0.508	0.508	0.508	0.508	0.509	0.509
Lagged controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

maximum likelihood using the dynamic Student's t copula. The time evolution of liquidity tail betas yield a comparable pattern to those based on CDS bid-ask spreads. Also, the distribution of CDS spreads after univariate sorting according to the alternative liquidity tail betas in the (pre-)crisis period is very similar to our main analysis.[26] We repeat our baseline regressions of Table I for the two alternative CDS liquidity measures and report OLS estimation results in Table IV.[27]

Both alternative liquidity tail betas exhibit positive coefficient estimates that are statistically significantly different from zero at the 1% level, regardless of the specification chosen. The economic impact of changes in liquidity tail risk using the alternative liquidity measures is even more pronounced than in the case of CDS bid-ask spreads. For example, a one standard deviation increase in the liquidity tail beta based on P-zero results in CDS spreads increasing by 27.83 bps on average (column (4) of Panel A). Not surprisingly, this effect is much stronger in the crisis period where the coefficient estimate is 51.02 bps. Interestingly, the magnitude of the impact of liquidity tail risk on CDS spreads is extremely small in the pre-crisis period (ca. 9 bps), compared to the average effect measured over the whole sample period. Thus, we find that there is a higher variation in the effect of the liquidity tail beta on CDS spreads when using P-zero as CDS illiquidity measure (compared to bid-ask spreads). This variation is lower for the regressions shown in Panel D of Table IV, where P-zero FHT is used, but is still higher than for our baseline case. Finally, both P-zero and P-zero FHT are significantly positively related to CDS spreads as higher values of those measures proxy for more illiquid CDS contracts.

5.3 Liquidity spillover from the equity market to the CDS market

CDS contracts are often traded together with equity securities, for example, in the context of capital structure arbitrage.[28] Therefore, equity liquidity complements CDS liquidity and affects CDS spreads, because, for instance, an illiquid equity market leads to more expensive hedging costs for sellers of CDS contracts, which then are recovered through higher CDS spreads (see, e.g., Tang and Yan, 2006; Das and Hanouna, 2012; Lesplingart et al., 2012).

Some of the empirical studies on the pricing of CDS have already focused on potential liquidity spillover effects between the equity and the CDS market (see, e.g., Tang and Yan, 2006; Lesplingart et al., 2012; Meine et al., 2015; Junge and Trolle, 2015). Most of them show that an increase in equity liquidity significantly reduces CDS spreads, whereas Lesplingart et al. (2012) find an insignificant relation. Furthermore, considering the fact that there is a strong commonality in liquidity across the bond and the CDS market, it has also been found that stock liquidity is priced in the cross-section of corporate bond returns.[29] Moreover, Ruenzi et al. (2016) show that equity returns contain a premium for liquidity tail risk in the equity market. Thus, it can be argued that sellers of credit protection such as capital structure arbitrageurs also want to be compensated for liquidity tail risk in the equity market and not only in the CDS market. This is because they

[26] Respective figures are provided in the Internet Appendix.

[27] We also rerun our instrumental variable and system GMM regressions using both alternative CDS liquidity measures and again refer to the Internet Appendix for respective estimation results.

[28] The strategy of capital structure arbitrage is to sell or buy credit protection and delta-hedge it by taking short or long positions in equity depending on the relation between the stock price and the CDS spread.

[29] For the pricing of stock liquidity in the bond market see Lin et al. (2011), Acharya et al. (2013), or Bongaerts et al. (2017) and for the commonality between CDS and bond market see Pu (2009).

Table IV: Alternative measures of CDS liquidity

The table presents regressions of monthly sampled CDS spreads on liquidity tail betas based on the P-zero (Panel A & B) and P-zero FHT (Panel C & D) (il)liquidity measures as defined in Lesmond et al. (1999) and Fong et al. (2017), respectively. We estimate the following regression model for each firm i in sector j for the period from January 2004 to September 2010 on a monthly basis:

$$\text{CDS}_{i,t} = \alpha + \beta \cdot \text{Alternative liquidity tail betas}_{i,t-1} + \gamma \cdot X_{i,t-1} + \omega_j + \mu_t + \epsilon_{i,t},$$

where $X_{i,t-1}$ describes lagged control variables. Panel A and C show results for the full sample period whereas Panel B and D show regressions where the sample is split into pre-crisis and crisis periods. The pre-crisis period lasts from January 1, 2004 to August 8, 2007 and the crisis period comprises August 9, 2007 to September 30, 2010. We run all regressions with industry-fixed effects, ω_j, based on the ICB Level 3 Supersector Codes. Monthly-fixed effects are denoted as μ_t. Variable definitions and data sources are outlined in Appendix I. Standard errors are adjusted for heteroskedasticity. We present the standardized coefficients and the corresponding t-statistics are reported in parentheses. ***, ** and * indicate that the coefficients are significantly different from zero at the 1%, 5% and 10% level, respectively.

P-zero as CDS illiquidity measure

Panel A: Baseline regressions	(1)	(2)	(3)	(4)
Dependent variable:	CDS spreads			
(Tail Beta P-zero / Market P-zero)$_{t-1}$	**42.4409*****	**38.0871*****	**28.6180*****	**27.8312*****
	(15.20)	**(15.42)**	**(11.84)**	**(11.61)**
(P-zero)$_{t-1}$			**4.5958****	**4.5379****
			(2.16)	**(2.04)**
N	18,012	18,012	17,897	17,897
Adjusted R^2	0.078	0.201	0.315	0.328
Lagged controls	NO	NO	YES	YES
Industry FE	YES	YES	YES	YES
Time FE	NO	YES	NO	YES

Panel B: Crisis subsample regressions	(1)	(2)	(3)	(4)
Dependent variable:	CDS spreads			
	Pre-crisis		Crisis	
(Tail Beta P-zero / Market P-zero)$_{t-1}$	**9.9500*****	**9.5315*****	**53.7861*****	**51.0210*****
	(10.40)	**(9.97)**	**(11.30)**	**(10.19)**
(P-zero)$_{t-1}$	**-11.8046*****	**-12.3129*****	**22.1294*****	**18.0543*****
	(-14.73)	**(-14.51)**	**(4.74)**	**(3.86)**
N	9,268	9,268	8,629	8,629
Adjusted R^2	0.222	0.235	0.310	0.319
Lagged controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Time FE	NO	YES	NO	YES

P-zero FHT as CDS illiquidity measure

Panel C: Baseline regressions	(1)	(2)	(3)	(4)
Dependent variable:	CDS spreads			
(Tail Beta P-zero FHT / Market P-zero FHT)$_{t-1}$	**27.7612*****	**25.7172*****	**22.4219*****	**21.7288*****
	(9.02)	**(9.10)**	**(9.56)**	**(9.19)**
(P-zero FHT)$_{t-1}$			**93.3460*****	**91.4695*****
			(6.37)	**(6.33)**
N	18,012	18,012	17,618	17,618
Adjusted R^2	0.071	0.196	0.376	0.386
Lagged controls	NO	NO	YES	YES
Industry FE	YES	YES	YES	YES
Time FE	NO	YES	NO	YES

Panel D: Crisis subsample regressions	(5)	(6)	(7)	(8)
Dependent variable:	CDS spreads			
	Pre-crisis		Crisis	
(Tail Beta P-zero FHT / Market P-zero FHT)$_{t-1}$	**5.9279*****	**5.9489*****	**40.7831*****	**39.3489*****
	(5.75)	**(5.70)**	**(8.98)**	**(8.59)**
(P-zero FHT)$_{t-1}$	**22.9619*****	**23.3853*****	**131.1253*****	**127.7621*****
	(5.19)	**(5.14)**	**(6.21)**	**(6.17)**
N	9,161	9,161	8,457	8,457
Adjusted R^2	0.245	0.258	0.372	0.377
Lagged controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Time FE	NO	YES	NO	YES

need to hedge their credit protection in the equity market at the same time when the market is extremely illiquid, which should result in higher hedging costs. Hence, investors in the CDS market might be more crash-sensitive to liquidity shocks in the equity market than in the CDS market itself.

To control for liquidity tail risk in the equity market, we follow Ruenzi et al. (2016) and repeat our benchmark regression by using tail dependence coefficients associated with the equity market.[30] To be precise, we compute the following tail dependence coefficients:

$$\text{Tail beta}_{i,t}^{EQ,EQM} = \lambda_L \left(R_{i,t}^{EQ}, R_{M,t}^{EQ} \right) \tag{18}$$

$$\text{Tail beta}_{i,t}^{EQBAS,EQBASM} = \lambda_U \left(BAS_{i,t}^{EQ}, BAS_{M,t}^{EQ} \right) \tag{19}$$

where $R_{i,t}^{EQ}$ and $BAS_{i,t}^{EQ}$ are the equity returns and the equity bid-ask spread, respectively, of each company and the market $i = M$.[31] Again, the estimation of the tail dependence coefficients is done via pseudo-maximum likelihood estimation using pseudo-observations based on the ARMA(r, s)-GARCH(p, q) residuals of the marginal equity returns/spreads time series. We apply the same procedure as in Section 2 to calculate the tail dependence coefficients.[32]

It could be argued that the risk premium for holding CDS spreads that are illiquid when the CDS market is extremely illiquid results from the fact that the equity market is extremely illiquid. As investors like capital structure arbitrageurs need to hedge their CDS contract on the equity market, the liquidity in the equity market affects the CDS market. Thus, a seller of credit protection may not price a firm's exposure to liquidity in the CDS market but in the equity market. To model this dependence in extreme market situations,

[30] As pointed out by a referee, the spillover effects could also manifest themselves in other forms of dependence. For example, the equity spillover effects could be characterized by weaker forms of quantile dependence like, e.g., intermediate tail dependence (see Coles et al., 1999; Heffernan, 2000; Bernard and Czado, 2015). The use of intermediate tail dependence, however, does not yield any new conclusions in our case as all available models suffer from significant drawbacks compared to our baseline model (e.g., the coefficients of intermediate tail dependence are equal to one for the Student's t copula and alternative Archimedean copulas are outperformed by our dynamic t-copula).

[31] For empirical studies using equity bid-ask spreads see, e.g., Amihud and Mendelson (1986), Chordia et al. (2000) as well as Meine et al. (2015). We note that we cannot use the Amihud (2002) measure for the equity liquidity factor due to the lack of volume data.

[32] First, we fit ARMA(r, s) models to the equity data (that are the equity bid-ask spreads and the equity log returns) of the individual firms and of the market since previous empirical analyses have shown that stock returns and equity bid-ask spreads are autocorrelated (see, e.g., Amihud and Mendelson, 1986; Fama and French, 1989; Acharya and Pedersen, 2005; Ruenzi et al., 2016). The market indexes are calculated as daily equally-weighted averages of the corresponding individual measures across all sample companies which is line with the computation of the CDS market spreads in equation (2). Then, these residuals are filtered by an appropriate GARCH(p, q) model ($p, q \in \{1, 2\}$), so that we obtain white-noise residuals for the joint distribution model. In this context, we use the following GARCH models: GARCH, GJR-GARCH and E-GARCH, as empirical studies have shown that stock returns are asymmetric in volatility, skewed, and fat tailed (see, e.g., Christoffersen et al., 2017). Besides, the time-series analysis of our equity data confirms that our equity bid-ask spreads are also stationary, autocorrelated, conditionally heteroskedastic as well as skewed and fat tailed. When calculating the tail dependence coefficients from equity returns, we need to take into account that stock returns decrease during extreme market downturns in contrast to CDS spreads or bid-ask spreads. This phenomenon is important when estimating the dependence structure between equity returns and equity bid-ask spreads because tail dependence coefficients can only model tail dependencies either in the lower or in the upper tail of both variables. To solve this problem, we follow Ruenzi et al. (2016) and convert the algebraic sign of the equity returns. For simplicity, we filter these new measures by individually chosen ARMA models and by employing the same GARCH models that we used for the positive equity returns. The GARCH models mostly fit very well. Hence, we apply the method of choosing an adequate GARCH model explained in section 2.1 only for the negative returns, for which the GARCH models of the positive equity returns are inappropriate.

we estimate the upper tail dependence between a company's CDS liquidity and the equity market liquidity using the dynamic t-copula of Patton (2006a) and call this coefficient the *spillover liquidity tail beta* (Tail beta^{BAS,EQBASM}).[33] The results of our additional regressions using various tail betas that are related to equity markets are shown in Table V.

Table V: Liquidity spillover from the equity market to the CDS market

The table presents results from panel regressions of monthly sampled CDS mid quotes on the liquidity tail betas, lagged control variables, and an equity liquidity spillover tail beta or equity-based tail betas. We estimate the following regression model for each firm i in sector j for the period from January 2004 to September 2010:

$$\text{CDS}_{i,t} = \alpha + \beta \cdot \text{CDS tail beta}_{i,t-1} + \gamma \cdot X_{i,t-1} + \zeta \cdot \text{Spillover Tail beta}_{i,t-1} + \kappa \cdot \text{EQ Tail beta}_{i,t-1} + \omega_j + \mu_t + \epsilon_{i,t}$$

where $X_{i,t-1}$ describes lagged control variables. We run all regressions with industry-fixed effects, ω_j, based on the ICB Level 3 Supersector Codes. Monthly-fixed effects are denoted as μ_t. Column (1) and (4) use the full sample period while the other columns report results from subsample regressions where the sample is split into pre-crisis and crisis periods. The pre-crisis period lasts from January 1, 2004 to August 8, 2007 and the crisis period comprises August 9, 2007 to September 30, 2010. Variable definitions and data sources are outlined in AppendixI. Standard errors are adjusted for heteroskedasticity. We present the standardized coefficients and the corresponding t-statistics are reported in parentheses. ***, ** and * indicate that the coefficients are significantly different from zero at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	CDS spreads					
	Full	Pre-crisis	Crisis	Full	Pre-crisis	Crisis
(Tail Beta BAS / Market BAS)$_{t-1}$	**16.2214*****	**11.9740*****	**18.4662*****	**12.8965*****	**15.3992*****	**12.9081*****
	(8.73)	**(9.72)**	**(5.32)**	**(4.77)**	**(7.89)**	**(3.25)**
Lagged equity (spillover) tail betas:						
(Spillover Tail Beta BAS / Market EQ)$_{t-1}$	**-6.4707*****	-1.0351	**-15.9695*****			
	(-3.56)	(-1.43)	**(-4.15)**			
(Tail beta EQBAS / Market EQBAS)$_{t-1}$				**11.1836*****	**2.9500****	**12.9081*****
				(4.40)	**(2.11)**	**(3.53)**
(Tail beta EQ / Market EQ)$_{t-1}$				**-78.6962*****	**-14.3066*****	**-99.1865*****
				(-12.55)	**(-8.72)**	**(-12.08)**
N	18,120	9,491	8,629	11,789	3,328	8,461
Adjusted R^2	0.509	0.583	0.488	0.522	0.642	0.513
Lagged controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

In columns (1) - (3) of Table V, we report the results of the panel regressions including the basic CDS liquidity tail betas and the tail beta for liquidity spillover effects between the CDS and equity markets. We find our main finding to be robust to the inclusion of the proxy for these liquidity spillover effects. For both our full sample and the crisis/pre-crisis sub-periods, the liquidity tail beta remains statistically and economically significant. In contrast, the spillover tail beta is significant only in the regression based on the crisis sub-sample.

Next, in columns (4) - (6), we repeat our main regressions using the basic CDS liquidity tail beta and the equity tail betas of equations (18) and (19). Our main findings regarding the CDS liquidity tail beta and the CDS tail beta are robust to the inclusion of the company's equity tail betas. In addition, *Tail beta EQ / Market EQ* is highly significantly and negatively correlated with changes in CDS spreads during the crisis. In contrast, the Tail beta EQBAS / Market EQBAS which is the counterpart of the CDS liquidity tail beta in

[33]The copula is estimated on the basis of the ARMA(r, s)-GARCH(p, q) filtered CDS bid-ask spreads of a company and the equity market bid-ask spreads as described above.

the equity market, is significantly positively related to CDS spreads both before and during the crisis.[34]

In summary, we can deduce that the CDS liquidity tail beta is different from liquidity tail risks that arise from the equity market. However, we note that in theory it is ambiguous, in which direction the link between the CDS and the equity market goes. On the one hand, we have stated reasons for a spillover effect from the equity to the CDS market. On the other hand, there also exist arguments for a spillover from the CDS to the equity market. For instance, Boehmer et al. (2015) deal with the effect of CDS markets on equity market quality categorized by liquidity and price efficiency. They argue that in the context of capital structure arbitrage the corresponding hedging strategies can decrease equity liquidity because these trades are in the same direction of overall order flow.

5.4 Other robustness checks

We also run additional robustness tests the results of which we summarize in this section.[35]

A possible problem with our main findings could be that the significance of our tail betas are simply due to the omission of a simpler non-linear liquidity effect. In fact, it could simply be that liquidity (rather than liquidity risk) exerts both a linear and non-linear effect on CDS spreads. To control for this source of a potential bias, we estimate additional regressions in which we include squared CDS bid-ask spread or the exponential function of bid-ask spreads as additional control variables. While the former non-linear proxy is statistically significant, the latter is not. In neither of the two cases does the inclusion of these non-linear terms alter our main insight as the liquidity tail beta coefficient estimate is still positive and highly significant.

Our main independent variables of interest are liquidity tail betas, which we estimate using various statistical models. Therefore, our independent variables could suffer from errors-in-variables biases (EIV biases). To account for such measurement errors, we run EIV regressions in levels of CDS spreads assuming a reliability of 95%, 75%, and 50%. However, our results do not change.

In our baseline regressions, we control for various (macroeconomic) variables from the empirical literature that have been found to explain CDS spreads. To make sure our first results do not suffer from choosing the wrong indices for economic growth and business climate, we employ different indices such as the seasonally adjusted *Industrial Production Index* and the *Coincident Economic Activity Index*, respectively (see Appendix I for detailed definitions). Also, we include additional tail dependence coefficients that proxy for the probability of joint surges in CDS (market) spreads and CDS (market) illiquidity (see also subsection 2.2). All our main results are robust to including these additional and alternative control variables.[36]

[34]Note that the observation size drops in column (5) due to missing values for the equity tail betas.

[35]Respective regression results can be found in the Internet Appendix.

[36]In unreported regressions, we also employ a different approach to proxy for equity volatility: instead of calculating annualized stock return volatility from 'raw' returns, we take the volatility estimates from GARCH models that were used to estimate equity tail betas. Subsequent regression results, however, are unaffected by this change.

6 Conclusion

In this paper, we show that liquidity tail risk in the CDS market significantly comoves with CDS spreads. We make use of a dynamic copula model to estimate the upper tail dependence between a CDS contract's idiosyncratic bid-ask spreads and illiquidity in the CDS market (i.e., liquidity tail betas). In panel regressions, we then regress the CDS spreads of our sample firms on the contracts' liquidity tail betas and various controls for the firms' default risk.

The results that we find have important implications for risk managers and investors that enter the CDS market as net protection sellers like insurers and pension funds. Our results provide ample evidence for the presence of time-varying liquidity tail risk in the CDS market. Liquidity tail risk spiked across our full sample during the financial crisis with peaks in liquidity tail risk appearing shortly after the bailout of AIG and at the start of 2009. Moreover, monthly CDS spreads comove significantly with liquidity tail betas with protection sellers demanding a premium for bearing liquidity tail risk.

Our empirical finding that liquidity tail risk matters for CDS investors is intuitive and in line with experiences made during the financial crisis. Writing a CDS contract is more costly in case the contract's liquidity could suddenly dry up with the market's liquidity thereby diminishing the opportunity to hedge the position. However, given the fact that the related literature on the pricing of liquidity risk in derivative markets is divided the correlation we find between CDS spreads and liquidity tail betas is particularly surprising.

Our findings also have several important implications for risk managers and investors alike. Sudden downward comovements in idiosyncratic and market CDS liquidity are not always of a linear nature, but tend to exhibit significant upper tail dependence and thus non-linear dependence. For insurers and funds that are usually net short invested in CDS markets, hedging their positions can become costly for contracts with higher liquidity tail betas. Finally, such investors face additional risk from two sides. First, liquidity tail betas exhibit considerable time-variation making their pricing a challenging task for risk managers. Second, and more importantly, liquidity tail risk makes hedging CDS positions more costly when investors need hedging the most: during a crisis.

A topic not covered in our analysis is the question, whether liquidity tail risk also exists in other markets like, e.g., the bond market. We intend to explore this in the future.

Appendix I: Variable definitions and data sources

This table presents the definitions of all dependent and independent variables used in the study as well as their data sources. The data are downloaded from Thomson Reuter's Datastream (DS), Credit Market Analysis (CMA), and the OECD statistics Database (OECD Stat). The sample consists of 228 financial and non-financial companies from January 2004 to September 2010. Moreover, *own calc.* indicates that we have estimated or calculated the variable ourselves based on the data from the corresponding data source.

Variable	Description	Data source
CDS and CDS liquidity variables		
(Market) CDS	End-of-month (market) CDS mid quote, denoted in basis points (bps). The CDS market spread and is calculated as the cross-sectional average of the CDS spreads across all sample firms excluding the current firm.	CMA (own calc.)
(Market) BAS	End-of-month absolute (market) bid-ask spread, calculated as ask minus bid price, denoted in bps. The CDS market bid-ask spreads and is calculated as the cross-sectional average of BAS across all sample firms excluding the current firm.	CMA (own calc.)
(Market) P-zero	End-of-month value of the fraction of number of zero return days of CDS mid quotes over a 30 day rolling window (see Lesmond et al., 1999). Market P-zero is calculated as the cross-sectional average of P-zero across all sample firms excluding the current firm.	CMA (own calc.)
(Market) P-zero FHT	P-zero FHT is calculated as in Fong et al. (2017), i.e., P-zero FHT = $2 \cdot \sigma\,(\text{CDS}) \cdot \Phi^{-1}\left(\frac{1+\text{P-zero}}{2}\right)$, where $\sigma(\text{CDS})$ is the standard deviation of CDS spreads over a 30 day rolling window and Φ^{-1} is the inverse function of the standard normal distribution. Market P-zero FHT is calculated as the cross-sectional average of P-zero across all sample firms excluding the current firm.	CMA (own calc.)
Equity and equity liquidity variable		
(Market) EQ	End-of-month firm's (market) stock log returns, denoted in %. EQM denotes the equity market return and is calculated as the cross-sectional average of the equity log returns across all sample firms excluding the current firm.	DS (own calc.)
(Market) EQBAS	End-of-month absolute bid-ask spread of the firm's (market) stock price, calculated as daily ask minus bid price, denoted in bps. EQBASM denotes the absolute equity market bid-ask spread and is calculated as the cross-sectional average of EQBAS across all sample firms excluding the current firm.	DS (own calc.)
Tail dependence variables		
Tail Beta CDS / Market CDS	End-of-month upper tail dependence (UTD) coefficients between the log differences of the company's CDS spreads and the log differences of the CDS market spreads. The UTD coefficients are computed from the dynamic t-copula of Patton (2006a).	CMA (own calc.)
Tail Beta BAS / Market BAS	End-of-month upper tail dependence (UTD) coefficients between the company's CDS bid-ask spreads and the CDS market bid-ask spreads. The UTD coefficients are computed from the dynamic t-copula of Patton (2006a).	CMA (own calc.)
Tail Beta P-zero / Market P-zero	End-of-month upper tail dependence (UTD) coefficients between the company's P-zero measure and the market P-zero. The UTD coefficients are computed from the dynamic t-copula of Patton (2006a).	CMA (own calc.)
Tail Beta P-zero FHT / Market P-zero FHT	End-of-month upper tail dependence (UTD) coefficients between the company's P-zero FHT and the market P-zero FHT. The UTD coefficients are computed from the dynamic t-copula of Patton (2006a).	CMA (own calc.)
Tail Beta EQ / Market EQ	End-of-month lower tail dependence (LTD) coefficients between the company's equity log returns and the equity market log returns. The LTD coefficients are computed from the dynamic t-copula of Patton (2006a).	DS (own calc.)
Tail Beta EQBAS / Market EQBAS	End-of-month upper tail dependence (UTD) coefficients between the company's absolute equity bid-ask spreads and the equity market bid-ask spreads. The UTD coefficients are computed from the dynamic t-copula of Patton (2006a).	DS (own calc.)
Spillover Tail Beta BAS / Market EQBAS	End-of-month upper tail dependence (UTD) coefficients between the company's absolute CDS bid-ask spreads and the absolute equity market bid-ask spreads. The UTD coefficients are computed from the dynamic t-copula of Patton (2006a).	DS, CMA, (own calc.)

Appendix I: Variable definitions and data sources (continued)

Variable	Description	Data source
Main control variables		
Firm value	Monthly arithmetic average of a firm's stock returns.	DS (own calc.)
Volatility	Annualized monthly stock return volatility.	DS (own calc.)
Interest rate	End-of-month two-year U.S. Treasury Benchmark yield, denoted in %.	DS
Slope	End-of-month ten-year minus two-year U.S. Treasury Benchmark yield, denoted in %.	DS
VIX	End-of-month values of the option-implied volatility index of the S&P500.	DS
Business climate	End-of-month values of the S&P 500 index.	DS
GPD growth	U.S. GDP growth rate in comparison to previous quarter, linearly interpolated to estimate monthly growth figures (denoted in %).	OECD Stat, (own calc.)
Systemic Risk	Partial Quantile Regression (PQR) measure as introduced in Giglio et al. (2016), which combines 19 individual systemic risk measures into one.	Giglio et al. (2016)
Measures of (systemic risk) and instrumental variable		
G14-Dealers Sensitivity (IV)	G14-Dealers Sensitivity is the average return of a firm's equity on the days the returns on the aggregate market capitalization of G14 are below the 5%-quantile. Daily values are calculated on the basis of a 100 day rolling window and are multiplied by minus one so that higher values represent higher sensitivity.	DS, (own calc.)
Beta (CDS or BAS)	Realized regular beta is computed on the basis of the ARMA(r, s)-GARCH(p, q) residuals of the company's log-differenced CDS (bid-ask) spreads, $\epsilon_t^{i,R}$, and of the log-differenced CDS (bid-ask) market spreads, $\epsilon_t^{M,R}$, from rolling windows of 100 data points: Beta $:= \frac{cov\left(\epsilon_t^{i,R}, \epsilon_t^{M,R}\right)}{var\left(\epsilon_t^{M,R}\right)}$.	CMA (own calc.)
U90beta (CDS or BAS)	Realized upside beta as the regular beta conditional on the ARMA(r, s)-GARCH(p, q) residuals of the log-differenced CDS (bid-ask) market spreads being above its 90% quantile. The computation is based on the ARMA(r, s)-GARCH(p, q) residuals of the the company's log-differenced CDS (bid-ask) spreads and on rolling windows of 100 data points: U90beta $:= \frac{cov\left(\epsilon_t^{i,R}, \epsilon_t^{M,R} \mid \epsilon_t^{M,R} > \alpha_{90\%}\right)}{\left(\epsilon_t^{M,R} \mid \epsilon_t^{M,R} > \alpha_{90\%}\right)}$, where $\alpha_{90\%}$ denotes the 90% quantile of the ARMA(r, s)-GARCH(p, q) residuals of the log-differenced CDS (bid-ask) market spreads.	CMA (own calc.)
Cokurtosis (CDS or BAS)	Realized cokurtosis of the ARMA(r, s)-GARCH(p, q) residuals of the company's log-differenced CDS (bid-ask) spreads and of the log-differenced CDS (bid-ask) market spreads based on rolling windows of 100 data points is defined as: Cokurtosis $:= \frac{E\left[\left(\epsilon_t^{i,R} - \mu_{i,R}\right)\left(\epsilon_t^{M,R} - \mu_{M,R}\right)^3\right]}{\sqrt{var\left(\epsilon_t^{i,R}\right)} var\left(\epsilon_t^{M,R}\right)^{3/2}}$.	CMA (own calc.)
MES	The Marginal Expected Shortfall (MES) according to Acharya et al. (2017), which is calculated from rolling windows of 100 data points. The MES is computed as the daily average equity log returns of a firm on the 5% worst days of the equity market log returns.	DS (own calc.)
ΔCoVaR	Unconditional ΔCoVaR as defined in Adrian and Brunnermeier (2016). It is calculated on the basis of a 100 day rolling window as the equity market beta times the difference in value at risks of the firm's stock returns at the 95% and 50% percentile.	DS (own calc.)
Variables used in robustness checks		
Business climate (alternative index)	Monthly values of the *Coincident Economic Activity Index* for the United States, which includes four indices on nonfarm payroll employment, the unemployment rate, average hours worked in manufacturing and wages and salaries.	FRED
Industrial Production Index	Monthly values of the seasonally adjusted *Industrial Production Index* as economic indicator that measures real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities (excluding those in U.S. territories).	FRED
Tail beta CDS / Market BAS	End-of-month upper tail dependence (UTD) coefficients between the log differences of the company's CDS spreads and the CDS market bid-ask spreads. The UTD coefficients are computed from the dynamic t-copula of Patton (2006a).	CMA (own calc.)
Tail beta BAS / Market CDS	End-of-month upper tail dependence (UTD) coefficients between the company's CDS bid-ask spreads and the log differences of the CDS market spreads. The UTD coefficients are computed from the dynamic t-copula of Patton (2006a).	CMA (own calc.)

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