# Liquidity Risk in Credit Default Swap Markets*

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**Abstract**

We analyze whether liquidity risk, in addition to expected illiquidity, affects expected returns on credit default swaps (CDSs). First, we construct a measure of CDS market illiquidity from divergences between published credit index levels and their theoretical counterparts, the so called index-to-theoretical bases. Non-zero and time-varying bases are observed across credit indices referencing North American and European names of both the investment grade and high-yield universes, and the aggregate measure can be viewed as a summary statistic of the impact of all the different dimensions of illiquidity that are present in the CDS market. Consistent with this, the measure correlates with transaction costs, funding costs, and other commonly used illiquidity proxies. Then, we construct a tradable liquidity factor highly correlated with innovations to the CDS market illiquidity measure and estimate a factor pricing model, which accounts for market risk and default risk in addition to liquidity risk and expected illiquidity. Liquidity risk is priced in the cross-section of single-name CDS returns and has a larger contribution to expected returns than expected illiquidity.

*JEL classification: G12*

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## 1 Introduction

In this paper, we analyze whether liquidity risk, in addition to expected illiquidity, affects expected returns on credit default swaps (CDSs). First, we construct a measure of CDS market illiquidity from divergences between published credit index levels and their theoretical counterparts. Then, we construct a tradable liquidity factor and investigate the extent to which exposure to this factor is priced in the cross-section of single-name CDS returns.

Studying the impact of liquidity risk on CDSs is important for several reasons. From a theoretical perspective, CDSs are interesting as these derivatives trade in a relatively

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opaque, dealer dominated, decentralized market and as such are subject to numerous sources from which illiquidity may arise. From a practical perspective, the issue is important for the trading, pricing, hedging, and risk-management of CDSs. This is underscored by the recent five billion dollar trading loss at J.P. Morgan associated with relatively illiquid CDS market strategies (see 'London whale' rattles debt market, *Wall Street Journal*, April 6, 2012). From a regulatory perspective, liquidity risk is important given the potential systemic nature of the CDS market.

Since CDSs trade in over-the-counter (OTC) markets with no readily available transaction data, it is very difficult to apply standard measures of liquidity. Instead, in this paper we capture illiquidity by the extent to which market prices deviate from fundamental values. In particular, we consider a law of one price type relation between the published level of a credit index and the theoretical level inferred from a basket of single-name CDSs which replicates the cash flows of the index.[1] We denote the difference between the two levels as *the index-to-theoretical basis* and refer to an index-to-theoretical basis in percent of the current index level as the percentage index-to-theoretical basis.[2] The CDS market illiquidity measure is constructed as a weighted average (by number of index constituents) of the absolute value of percentage index-to-theoretical bases. The average is taken over ten credit indices referencing the most liquid North American and European names of both the investment grade and high-yield universes which cover a substantial part of the overall CDS market.

The rationale behind the construction of the illiquidity measure is index arbitrage. Hedge funds and trading desks at investment banks or other large financial institutions usually engage in relative value trades that keep the published and theoretical index levels in line. Deviations between the two levels indicate that market participants are temporarily unable or unwilling to execute relative value trades. Reasons for this relate to financial frictions (e.g. transaction costs and margin constraints), institutional obstacles (e.g. access to investment funds and slow moving capital), the form of organization of the market (e.g. search costs and execution risk), and other sources of illiquidity.[3] In other words, we view our illiquidity measure as a summary statistic of the impact of all the different dimensions of illiquidity that are present in the CDS market.

We find non-zero index-to-theoretical bases across all ten credit indices that we include in the construction of the CDS market illiquidity measure. Index-to-theoretical bases are usually of moderate size, but widen considerably during the 2007–2009 financial crisis and in its aftermath. At the peak of the crisis, index-to-theoretical bases of credit indices referencing investment grade and high-yield names reach, respectively, up to 60 and 300 basis points (bps) in absolute value, and the CDS market illiquidity measure reaches 25%. Consistent with interpreting our aggregate measure as capturing illiquidity, we show that it correlates with transaction costs, funding costs, and measures of Treasury market illiquidity.

We then investigate if liquidity risk is priced in the cross-section of single-name CDS returns. For this purpose, we set up a factor pricing model which accounts for market

[1] A number of recent papers document violations of the law of one price, e.g., for TIPS and a replicating portfolio consisting of inflation swaps and a Treasury bond (Fleckenstein, Longstaff, and Lustig (2012)), for spot and forward exchange rates (Mancini-Griffoli and Ranaldo (2011)), and for sovereign bonds issued in domestic and foreign currencies (Buraschi, Sener, and Menguturk (2012)).

[2] Practitioners and the financial press usually refer to the index-to-theoretical basis as the index skew.

[3] Sources of illiquidity can be found in the surveys of the liquidity literature by Amihud, Mendelson, and Pedersen (2005) and Vayanos and Wang (2012). See also the survey of the limits to arbitrage literature by Gromb and Vayanos (2010) and Duffie's (2010) presidential address on slow moving capital.

risk and default risk in addition to liquidity risk and expected illiquidity.[4] We construct a tradable liquidity factor based on a simple index arbitrage strategy that trades credit indices against their replicating baskets so as to systematically exploit non-zero index-to-theoretical bases. This liquidity factor is highly correlated with innovations to the CDS market illiquidity measure. In the model expected illiquidity reflects the expected transaction cost, which in turn is given by the expected costs, conditional on a trade occurring, times the likelihood of trading. We capture the former as the average of weekly round-trip transaction costs, while the latter is calibrated to average weekly turnover of CDSs at the reference entity level, which is inferred from CDS volume data from the Depository Trust & Clearing Corporation (DTCC).

We estimate the factor pricing model on a large data set of single-name CDS contracts referencing 663 North American and European entities and covering the period June 1, 2006, to February 1, 2012. The CDS contracts are sorted into portfolios that exhibit variation in credit quality and the level of illiquidity. Special attention is paid to the computation of expected returns on CDSs. Average realized excess returns on CDSs are very noisy estimates of expected excess returns. This is due to both the short sample period and the peso problem that arises in the return computation of securities subject to default risk because of the rare occurrence of defaults and the extreme returns associated with default. Instead, we follow Bongaerts, de Jong, and Driessen (2011) in obtaining forward-looking estimates of expected excess returns by using Moody's KMV Expected Default Frequencies (EDFs) to calculate expected default losses. Across all portfolios, the unconditional expected excess returns are positive from the perspective of sellers of CDS protection, ranging from 0.37% per annum for a portfolio of the most liquid high-credit-quality CDSs to 5.04% per annum for a portfolio of the most illiquid low-credit-quality CDSs.

The model is estimated in two steps. In the first step, we estimate factor loadings. All CDS portfolios have significant loadings on the market, default, and liquidity factors, which together explain between 44% and 67% of the time-series variation in CDS portfolio returns. Sellers of CDS protection tend to realize negative returns, when the equity market drops, default risk increases, and CDS market illiquidity increases. In the second step, we estimate factor prices of risk from a cross-sectional regression of expected excess returns net of expected transaction costs on the factor loadings. We find that liquidity risk is both a statistically and economically significant determinant of expected excess returns. For instance, considering the difference between the expected excess returns on the portfolio of the most illiquid low-credit-quality CDSs and the portfolio of the most liquid high-credit-quality CDSs, 1.49% is due to liquidity risk, while 0.96%, 0.21%, and 2.10% of the difference is due to expected illiquidity, market risk, and default risk, respectively. Alternatively, considering the average expected excess returns across test portfolios, 0.43% is due to liquidity risk, while 0.29%, 0.07%, and 0.90% of the average is due to expected illiquidity, market risk, and default risk, respectively. Not only is the compensation for liquidity risk significant, it appears to be larger than the expected illiquidity component.

We also conduct a series of robustness checks and find that our results are robust to changes in the methodological setup, the use of alternative liquidity and default factors, and the inclusion of additional factors, amongst others, liquidity factors from other markets. In particular, we find only weak evidence for exposure to equity market liquidity being

[4] In principle, counterparty risk could also be a determinant of CDS returns. However, Arora, Gandhi, and Longstaff (2012) find that the effect of counterparty risk on CDS spreads is negligible, which is consistent with the widespread use of collateralization and netting agreements. Hence, we do not take counterparty risk into account in our factor pricing model.

priced on top of exposure to CDS market liquidity. Statistically, but not economically, there is some evidence for exposure to Treasury market liquidity being priced.

The analysis of liquidity effects in the cross-section of single-name CDS returns is related to that by Bongaerts et al. (2011). They consider an equilibrium asset pricing model with liquidity effects that arise from stochastic transaction costs. Agents are exposed to a non-traded risk factor, which creates a demand for hedge assets. In equilibrium, expected returns on hedge assets are related to both expected illiquidity and liquidity risk as captured by covariation between transaction cost innovations and the non-traded risk factor. However, in their empirical analysis of the CDS market, Bongaerts et al. (2011) only find a significant premium for expected illiquidity, while the liquidity risk premium is negligible. In contrast, using a novel measure of CDS market illiquidity and a different notion of liquidity risk, we find strong evidence for a significant liquidity risk premium.[5]

Using pre-crisis data, Tang and Yan (2007) and Bühler and Trapp (2009) also study liquidity risk in CDS markets. Tang and Yan (2007) regress CDS spreads on expected illiquidity and liquidity betas inspired by Acharya and Pedersen's (2005) liquidity-adjusted CAPM. They find suggestive evidence that liquidity risk affects CDS spreads. In contrast, we estimate a formal factor pricing model using returns and a forward-looking estimate of expected returns instead of CDS spreads. Bühler and Trapp (2009) estimate a reduced-form model which allows CDS spreads to be affected by the liquidity of the underlying bonds. In contrast, our focus is on the effect of exposure to market-wide liquidity risk.

Finally, our paper is also related to Fontaine and Garcia (2012), Hu, Pan, and Wang (2012), and Pasquariello (2011) in how we construct the CDS market illiquidity measure. Both Fontaine and Garcia (2012) and Hu et al. (2012) consider the U.S. Treasury market and derive illiquidity measures based, respectively, on price and yield deviations from a fitted term structure model. Pasquariello (2011) considers three different parity relations to infer a "market-dislocation index." Similar to our results, Hu et al. (2012) find that liquidity risk is priced in the cross-section of returns on hedge funds and currency carry strategies and Pasquariello (2011) shows that exposure to his index is priced in the cross-section of stock returns.

The paper proceeds as follows: Section 2 presents the construction of the CDS market illiquidity measure and Section 3 describes its time series properties. Asset pricing implications are discussed Section 4 and Section 5 concludes.

# 2 Construction of CDS Market Illiquidity Measure

This section presents the construction of the CDS market illiquidity measure and the data used. Furthermore, it briefly describes credit indices and the replication argument on which index arbitrage is based.

## 2.1 Credit Indices

Credit indices are standardized credit derivatives that provide insurance against any defaults among its constituents. They allow investors to gain or reduce credit risk exposure in certain segments of the market. Due to their widespread use and standardized terms, they

[5] A similar notion of liquidity risk (covariation between returns and a market-wide liquidity factor) has been used, amongst others, by Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) in the equity market and by Lin, Wang, and Wu (2011) and Bongaerts, de Jong, and Driessen (2012) in the corporate bond market.

trade with lower costs and higher liquidity than most single-name CDSs or cash bonds.[6] Credit indices trade in OTC markets for maturities between one and ten years. The five-year maturity is typically the most liquid and is the focus of our empirical analysis.[7]

Each credit index is a separate CDS contract with a specified maturity, fixed spread, and underlying basket of reference entities. Over the life of the contract, the seller of protection on the index provides default protection on each index constituent, with the notional amount of the contract divided evenly among the index constituents. In return, the seller of index protection earns the fixed spread. In case of default, the seller of index protection pays the loss-given-default and the notional amount of the contract is reduced accordingly. If the quoted level of the index differs from its fixed spread, counterparties initially exchange an upfront payments equal to the contract's present value.

As a clarifying example, suppose that on September 21, 2007, an investor sells a 10 million USD notional amount of protection on the main North American investment grade credit index (CDX.NA.IG 9) with a maturity of five years and a fixed spread of 60 bps.[8] On that date the index trades at 49.92 bps which translates into an 46,183.13 USD upfront charge for the seller of protection. Over the next three quarters he receives quarterly spread payments each being approximately equal to $1/4\times0.0060\times10{,}000{,}000 = 15{,}000$ USD.[9] On September 7, 2008, Fannie Mae and Freddy Mac, both reference names of the CDX.NA.IG 9, were placed into conservatorship by their regulator. Creditors recovered 91.51 and 94 cents per dollar of senior unsecured debt issued by Fannie Mae and Freddy Mac, respectively. Thus, the seller of index protection has to compensate losses incurred, paying $1/125\times(1\text{-}0.9151)\times10{,}000{,}000+1/125\times(1\text{-}0.94)\times10{,}000{,}000 = 11{,}592$ USD.[10] Due to the credit events, the spread payment on September 20, 2008, is reduced to $1/4\times123/125\times0.0060\times10{,}000{,}000 = 14{,}760$ USD. Until expiry of the index on December 20, 2012, another two credit events occur: First, the default of Washington Mutual on September 27, 2008, triggers a $1/125\times(1\text{-}0.57)\times10{,}000{,}000 = 34{,}400$ USD payout and reduces subsequent spread payments to $1/4\times122/125\times0.0060\times10{,}000{,}000 = 14{,}640$ USD. Second, the Chapter 11 filing of CIT Group on November 1, 2009, triggers a $1/125\times(1\text{-}0.68125)\times10{,}000{,}000 = 25{,}500$ USD payout and reduces successive spread payments to $1/4\times121/125\times0.0060\times10{,}000{,}000 = 14{,}520$ USD.

Twice a year, on the so-called index roll dates in March and September, a new series of each credit index is launched, with the basket of reference entities revised according to credit rating and liquidity criteria. Entities that fail to maintain a rating within a specified range, due to either an upgrade or downgrade, and entities whose CDS contracts have significantly deteriorated in terms of their liquidity are replaced by the most liquid reference names meeting the rating requirements. Liquidity is typically concentrated in the most recently launched series, which are referred to as the on-the-run series. Consequently,

[6] Market activity reports published by the DTCC show that the average daily notional amount of trades is 37.6 million USD, on average, across the 1000 most actively traded single-name CDSs for the three-month period from June 20, 2011, to September 19, 2011. In contrast, the average daily notional amount of untranched index transactions is approximately 1.01 billion USD. Furthermore, the average number of trades per day in untranched indices is 25 compared to 5 trades per day for the average single-name CDS contract.

[7] Using a representative three-month sample of CDS transaction data, Chen, Fleming, Jackson, Li, and Sarkar (2011) find that 84% of all index transactions are in the five-year maturity.

[8] The number following the index name is referred to as the index's series and uniquely identifies the underlying basket of reference names.

[9] In practice the actual number of days during the quarter is determined by ACT/360 daycount convention.

[10] Here and in the sequel of this example we assume that cash settlement, the standard settlement method of credit index transactions, applies. Furthermore, we neglect accrual payments on default and the fact that recovery values are determined in credit event auctions that usually do not take place on the default date.

these are the subject of our empirical analysis.

In case of a credit event for one of the reference names, a new version of the index series starts trading. In the new version, the entity that triggered the event no longer contributes to the index level because its weight in the basket of reference names is set to zero. Otherwise weights remain fixed over the life of the contract. Since triggered CDSs usually continue to trade in the market until the recovery value is determined, multiple versions of the same index series can trade at the same time. In such cases, we focus on the most liquid version.

Credit indices are maintained by an administrator which, in case of most indices, is Markit. The index administrator sets the rules and procedures that govern revision of entities on the roll dates. In addition, it determines a group of licensed dealers. These dealers actively make markets for credit indices and, based on their spread quotes, the administrator computes index levels that are published on a daily basis.

The most liquid credit indices currently traded are the ones that belong to the CDX North American and iTraxx Europe family. The two index families differ in the region from which reference entities are eligible for inclusion, in the currency in which they trade, in the rules that govern revision of entities, and in some technicalities of the contract terms, e.g., documentation clauses. Table 1 briefly summarizes index rules and provides additional information concerning the major indices of the CDX North American and iTraxx Europe families.

[Table 1 about here.]

## 2.2 Index Arbitrage

In this section we present the replication argument on which index arbitrage is based. A detailed account of the actual implementation can be found in Appendix A.

Investors can gain credit risk exposure either by selling index protection or by selling protection on a basket of single-name CDSs that replicates the cash flows of the index contract. Thus, besides the published index level, a theoretical index level can be inferred from single-name CDS quotes on the index constituents. This gives rise to the notion of an index-to-theoretical basis, defined as the difference between the published and theoretical index levels. In perfect capital markets, index arbitrage will keep the index-to-theoretical bases close to zero.

Suppose that at time $t$ an investor wants to sell index protection with maturity $T$, fixed spread $C$, and notional $N$. This involves an initial upfront payments equal to the contract's present value.[11] Instead of selling index protection, the investor can sell protection on the index constituents via single-name CDSs. In particular, to replicate the payments in the index contract, the investor must sell protection on each of the $I_t$ index constituents that, prior to the inception of trade, have not triggered a credit event. Each single-name CDS must have maturity $T$, fixed spread $C$, and notional $N/I$, where $I$ denotes the number of reference entities at the launch of the index's series. As in the credit index trade, upfront payments are necessary when trading single-name CDSs at off-par spreads. Hence, the investor faces costs equal to the aggregate amount of all upfront charges from the single-name CDS transactions.

[11] In addition, there will be an accrual payment. The seller of index protection is entitled to a full spread payment on the first payment date after inception of trade, regardless of the actual time of opening his position. Therefore, he has to compensate the buyer of protection for the fixed spread accrued between the last spread payment date and the inception of trade. We abstract from these accrual payments in our discussion of the index arbitrage strategy.

Both trades generate the following contingent payments: Until the earlier of the maturity date and the first credit event by one of the remaining index constituents, the seller of index protection earns quarterly spread payments of $A/360 \times C \times I_t/I \times N$, while the seller of protection via single-name CDSs receives quarterly spread payments of $\sum_{i=1}^{I_t} A/360 \times C \times N/I$. Here $I_t/I \times N$ is the index's adjusted notional amount and $A/360$ denotes the accrual time during a given quarter, determined by ACT/360 daycount convention. Obviously both payment streams are identical.

In case of a default prior to maturity by one of the remaining reference names, say $i^*$, a payment of $1/I \times (1 - R_{i^*}) \times N$ by the seller of index protection becomes due, where $R_{i^*}$ is the recovery per dollar of notional on $i^*$'s debt. This payment coincides with the one the seller of protection via single-name CDSs has to make.[12]

Following the credit event, the notional amount of the index is adjusted to $(I_t - 1)/I \times N$ and quarterly spread payments earned by the seller of index protection reduce to $A/360 \times C \times (I_t - 1)/I \times N$. Since there is also one single-name CDS less in the basket, the seller of protection via single-name CDSs collects quarterly spread payments of $\sum_{i=1}^{I_t-1} A/360 \times C \times N/I$. Thus, payments coincide in this case as well.

Applying the same argument to any possible credit event that may occur prior to maturity establishes identical payoffs for the seller of index protection and the seller of protection via single-name CDSs. The theoretical index level, $C^*(t,T)$, is now obtained as that fixed spread on the single-name CDSs that makes the replicating basket have zero net present value. The index-to-theoretical basis $B(t,T)$ of a credit index is then defined as $B(t,T) = C(t,T) - C^*(t,T)$, where $C(t,T)$ denotes the index's published level as of time $t$.

### 2.3 Data

The credit index data are obtained from Markit, which administrates most commonly traded credit indices. This data set comprises daily published index levels and the corresponding price quotations for virtually all credit indices. In addition, the number of licensed dealers that submit spread quotes for the computation of the published index level is reported.[13] We conduct our analysis on ten credit indices that belong to either the CDX North American or the iTraxx Europe family. From the individual series of each of these indices, we get daily levels of a continuous on-the-run index at the five-year maturity for the period from September 20, 2006, to February 1, 2012. Whenever multiple versions of the on-the-run series trade simultaneously, we choose the version with the largest number of contributing dealers.

Single-name CDS data are from Markit as well. They cover the same sample period and consist of daily par spread quotes for up to eleven maturities, ranging from six months to possibly 30 years. For the latest version of a given on-the-run series of a credit index we collect, on a daily basis, the quoted term-structure up to the seven-year maturity for each

[12] Upon default, both the seller of index protection and the seller of protection via single-name CDSs will receive an accrual payment. The accrual compensates for the protection they provided on the defaulted reference name since the last premium payment date prior to the credit event.

[13] We find the number of contributors to be a reliable indicator of trading activity. Trading activity usually concentrates in the latest version of the on-the-run series. However, following a credit event, trading activity frequently does not shift to the version of the credit index that is launched on the trading day following the default date. Instead, it remains with the version including the defaulted name until the recovery value is set in a credit event auction. The reason for the non-immediate shift is related to the trading of index tranches. Attachment and detachment points of a new version of a tranche can only be set once the final auction results are known. As dealers hedge tranche positions using the index itself, they prefer to continue trading the version including the defaulted name.

entity in the basket of reference names.[14] The collected spreads are for single-name CDS denominated in the index's currency and written on instruments matching the index's seniority. Unfortunately, we cannot always locate CDSs with matching documentation clauses.[15] Thus, whenever spreads of an entity are not available for the index's documentation clause, those for a more valuable clause are used.[16]

In addition to the credit index and CDS data, daily interest rate data over the sample period are retrieved from the Bloomberg system. We obtain USD LIBOR and EURIBOR rates (generically referred to as LIBOR rates) with maturities 1M, 2M, 3M, 6M, 9M, and 1Y. For maturities longer than one year, we collect swap rates of USD and EUR denominated interest rate swaps with maturities of 2Y, 3Y, . . . , 8Y. Following a convention that emerged upon standardization of CDS markets, we construct zero rates from "locked-in" LIBOR rates, i.e., rates fixed on the previous day. These zero rates are used for discounting throughout the paper.[17]

The ten credit indices considered in the construction of the CDS market illiquidity measure can be briefly described as follows: The CDX.NA.IG and the iTraxx Eur (Main) are broad-based indices that, respectively, reflect the credit risk of North American an European investment grade entities. Both indices comprise 125 reference names. Among those, the thirty reference names with the widest five-year CDS spreads constitute the CDX.NA.IG.HVOL and iTraxx Eur HiVol sub-indices. The 25 financial sector reference names included in the iTraxx Eur form a separate sub-index, the iTraxx Eur Sr Finls. The iTraxx Eur Sub Finls is composed of the same reference names as the iTraxx Eur Sr Finls, however, reference obligations are subordinated. The CDX.NA.HY is comprised of 100 non-investment-grade entities domiciled in North America and its European counterpart, the iTraxx Eur Xover, counts up to 50 non-investment-grade reference names. BB and

[14] Note that theoretical index levels are those of the latest version of the on-the-run index, while the index level itself is that of the most liquid version of the on-the-run index. The two usually coincide. However, in case a credit event occurs the two usually differ until a credit event auction is held. This is because on the one hand index data for the latest on-the-run series are in general unavailable for that time period, see footnote 13, on the other hand we cannot replicate the most liquid on-the-run series because single-name CDS data for the defaulted name are unavailable as well.

[15] In the sample, we are able to match documentation clauses in 85% of all cases. This percentage ranges from 0.8% to 100% across the individual series of the credit indices.

[16] Here more valuable refers to the fact that par spreads increase as the documentation clause changes from no restructuring to modified restructuring, from modified restructuring to modified modified restructuring, and from modified modified restructuring to full restructuring. Index-to-theoretical basis will be downward biased whenever a large number of entity single-name CDSs trade with more valuable documentation clauses than the index. This can be the case for some indices of the CDX North America family prior to early 2009, because almost all single-name CDSs on North American investment grade names traded with modified restructuring during this period. With the inception of trading standardized contracts (as part of the changes to CDS contract specifications and trading conventions in the CDS market due to the implementation of the International Swaps and Derivatives Association's (ISDA's) 'Big Bang' Protocol) this problem is eliminated. The bias due to mismatching documentation clauses is a small fraction of the published index level. The median restructuring premium of modified restructuring over no restructuring reported in Berndt, Jarrow, and Kang (2007) is 5% of the CDS spread with no restructuring clause. For instance, for the CDX.NA.IG, this suggests a bias of similar magnitude in case that all reference names of the index trade with modified restructuring instead of no restructuring. Despite the fact that restructuring premia in Berndt et al. (2007) are quite volatile, the bias due to mismatching restructuring clauses is presumably fairly constant over time because it is the cross-sectional average of restructuring premia that contributes to fluctuations of the bias. Therefore, the bias does not matter for innovations of bases which are important for our analysis of asset pricing implications of liquidity risk.

[17] We recognize that LIBOR rates are not risk free. Using them appears reasonable to us, because the administrator of most credit indices, Markit, uses "locked-in" LIBOR rates in the conversion procedure between upfront charges and index levels which is, e.g., used to determine theoretical index levels given the upfront charge on the replicating basket of single-name CDSs.

B rated entities of the CDX.NA.HY comprises the CDX.NA.HY.BB and CDX.NA.HY.B sub-indices, respectively.

Descriptive statistics of the credit index data are reported in Panel A of Table 2. Both the average and the standard deviation of index levels increase as we consider indices referencing names with progressively lower credit quality and there is a 0.98 cross-sectional correlation between the two.

[Table 2 about here.]

Figure 1 displays the time series of continuous on-the-run index levels (gray line in each panel) for the ten credit indices. Each of the indices increases shortly before the 2008 March role date, when Bear Stearns was on the brink of bankruptcy, and after a short period of relief, peaks in the aftermath of the September 2008 events; the credit events of Fannie Mae, Freddy Mac, Lehman Brothers, and Washington Mutual.

[Figure 1 about here.]

### 2.4 CDS Market Illiquidity Measure

In addition to published index levels, the panels in Figure 1 also display the theoretical index levels (black dashed line in each panel) and the corresponding index-to-theoretical bases (light gray shaded area in each panel). The panels reveal that non-zero index-to-theoretical bases frequently arise. In particular, between the September 2008 index roll and the next index roll in March 2009, i.e., at the height of the 2007–2009 financial crisis, bases are wide and very volatile. For instance, bases of the main indices of North American and European investment grade credit risk, the CDX.NA.IG and the iTraxx Eur, drop to -66.91 and -58.64 bps, respectively. These are extreme moves compared to the standard deviations of these bases which are 12.42 and 9.07 bps, respectively. Among indices of high-yield credit risk, the widening of index-to-theoretical bases is even more extreme. For instance, bases of the CDX.NA.HY and the iTraxx Eur Xover reach -301.86 and -105.65 bps, respectively, at the height of the crisis.

The negative sign on the bases at the height of the crisis is related to different trading conventions of credit indices and single-name CDSs at that time. While credit indices traded with fixed spreads, most single-name CDS transactions were settled at par spreads.[18] Since credit index levels, in general, exceeded fixed spreads during this period, sellers of index protection would receive upfront payments in a transaction, while sellers of single-name CDS protection would not. This made selling of index protection relatively more attractive for funding-constrained dealers pushing the index below its theoretical level.

Descriptive statistics of index-to-theoretical bases are reported in Panel B of Table 2. For both index families, bases of investment grade indices are negative, on average, while bases of those indices referencing lower-quality credits are positive, on average. Basis volatility is higher within the CDX North American family than within the iTraxx Europe family. Within both index families, basis volatility is highest for those indices referencing the names with the lowest credit quality. The cross-sectional correlation between the

[18] Some single-name CDSs traded with fixed spreads even prior to the implementation of the ISDA's 'Big Bang' Protocol. According to Mitchell and Pulvino (2012), transactions in single-name CDSs with par spreads of less than 1000 bps were settled at par spread, while those in single-name CDSs with par spreads above 1000 bps were settled with a fixed spread of 500 bps and an upfront payment. With the implementation of the 'Big Bang' Protocol in April 2009, all single-name CDSs trade with fixed spreads.

average index level and the basis volatility is particularly strong within the CDX North American family.

Figure 1 suggests that, for most indices, the basis is negatively correlated with the index level. The time-series correlation between the index level and the absolute value of the basis is reported in the sixth row of Table 2, Panel B, and varies between 0.35 (for iTraxx Eur Sr Finls and iTraxx Eur Sub Finls) and 0.80 (for CDX.NA.IG.HVOL). On average, across indices, this time-series correlation is 0.57.

The time-series correlation between the index level and the absolute value of the basis and the cross-sectional correlation between the average index level and the basis volatility suggest that percentage index-to-theoretical bases, i.e., bases in percent of index levels, are more meaningful when comparing deviations from fundamental values across time and across indices. Therefore, we construct a CDS market illiquidity measure, denoted by $\text{CDSILLIQ}_t$, as a weighted average (by number of index constituents) of absolute index-to-theoretical bases in percent of current index levels, i.e.,

$$\text{CDSILLIQ}_t = \sum_{i=1}^{n_t} w_{i,t} \frac{|B_i(t, 5Y)|}{C_i(t, 5Y)},$$

where $w_{i,t}$ is the fraction of the number of constituents of index $i$, $i = 1, \ldots, n_t$, relative to the aggregate number of constituents of the $n_t$ indices with available data on date $t$. Absolute values of bases rather than the bases themselves are used in the computation because we are more interested in the magnitude of divergences from fundamentals than in their direction.[19] The CDS market illiquidity measure peaks at 25.49% on December 12, 2008, i.e., during the market turmoil that followed the collapse of Lehman Brothers. The upper panel of Figure 2 displays weekly observations of the measure. It reveals, that the CDS market illiquidity measure is strongly persistent which is confirmed by its 0.94 first order autocorrelation at the daily frequency.

[Figure 2 about here.]

# 3 Time Series Properties of CDS Market Illiquidity

This section explores time series properties of the CDS market illiquidity measure. In particular, we investigate its relation to other illiquidity measures, funding cost measures, and market volatility.

## 3.1 Illiquidity Measures

We focus on proxies for illiquidity specific to credit index contracts as well as broader measures of Treasury market illiquidity conventionally used in the empirical literature.

Credit index illiquidity is measured in three ways. First, it is measured by the average of bid-ask spreads for single-name CDSs referencing credit index constituents (Bid-Ask).[20]

[19] As bases can be both positive and negative, in an extreme case it could happen that the individual bases are non-zero while their average is zero. This can be circumvented by the use of absolute bases in the computation of the CDS market illiquidity measure.

[20] The construction of Bid-Ask proceeds as follows: Each date and for each credit index, indicative bid and ask quotes for single-name CDSs on the index's current reference names are retrieved from Bloomberg. Then, in order to arrive at a bid-ask spread at the index level, bid-ask spreads are averaged across current reference names, whenever they are available for at least 50% of them. Equal weights are chosen because this parallels the practice of equally weighting reference names in the construction of credit indices. Finally, Bid-Ask is inferred as a weighted average (by number of index constituents) of index level bid-ask spreads.

When average bid-ask spreads are wider, index arbitrage is more expensive, and we expect less arbitrage activity and a wider CDS market illiquidity measure. Second, credit index illiquidity is measured by minus the number of contributors to a composite quote on a credit index (Depth-1).[21] Assuming that designated market makers also engage in index arbitrage, we conjecture a tighter CDS market illiquidity measure, the larger the number of dealers that actively quote index contracts and monitor index-to-theoretical bases. Third, credit index illiquidity is measured by minus the average number of contributors to composite quotes for single-name CDSs referencing credit index constituents (Depth-2).[22] Naturally, we expect lower CDS market illiquidity, the higher the average number of contributors.[23]

We use two proxies for Treasury market illiquidity. The first is the yield spread between Resolution Funding Corporation and U.S. Treasury bonds (Refco).[24] As pointed out by Longstaff (2004) both securities have literally identical credit risk and differences in taxation or transaction costs are too small to explain the observed spread. Therefore, the spread constitutes a relatively clean illiquidity proxy. The second proxy for Treasury market illiquidity is the Hu et al. (2012) noise measure (Noise).[25] It captures deviations of U.S. Treasury yields from the respective points on a fitted smooth yield curve. Hu et al. (2012) argue that deviations from fair-values are wider, whenever risk capital is scarcer. In such circumstances, we expect also less activity by index arbitrage traders and a wider CDS market illiquidity measure.

It is well known that liquidity exhibits commonality within and across markets. We, therefore, perform a principal component analysis on the pairwise correlation matrix of the five illiquidity measures. The first principal component is able to explain 56% of the common variation of illiquidity measures and, collectively, the first three principal components explain 95% of the variation. Consistent with considering the CDS market illiquidity measure as a summary statistic of illiquidity measured in various ways, we find a strong correlation of 0.77 with the first principal component. Moreover, in a time series regression, the first three principal components are able to explain 62% of the time variation of the CDS market illiquidity measure. The last column of Panel B in Table 3 shows the correlation between the illiquidity measures with the CDS market illiquidity measure. Given the low correlation between the average number of contributors to single-name composite quotes (Depth-2) and the CDS market illiquidity measure, it is not surprising that Doshi et al. (2013), who capture liquidity at the contract level by the number of contributors to a quote, do not observe a strong role of liquidity as an observable covariate for the pricing of CDSs.

[21] We construct Depth-1 by collecting the number of contributors to the five-year continuous on-the-run series of the credit indices from the Markit database and then aggregate the negative of weighted (by number of index constituents) numbers of contributors across indices.

[22] The construction of Depth-2 proceeds in the same manner as that of Bid-Ask but using the number of contributors to the composite quote on the five-year contract of a constituent instead of the bid-ask spread.

[23] Despite not being a direct liquidity measure, Tang and Yan (2007) argue that the number of contributors to a quote affects liquidity through a component related to matching and search frictions, which is particularly relevant in the CDS market. Kapadia and Pu (2012), Qiu and Yu (2012), and Doshi, Jacobs, Ericsson, and Turnbull (2013) also use the number of contributors to a quote on a single-name CDS contract as a measure of its liquidity.

[24] We follow Longstaff (2004) in the construction of the spread, namely, we use Bloomberg fair value curves (fitted to either Resolution Funding Corporation or U.S. Treasury coupon strips) to obtain Resolution Funding Corporation and U.S. Treasury constant maturity yields. Refco is the average yield spread for maturities between three months and ten years.

[25] Jun Pan makes data of the noise measure available on her website `http://www.mit.edu/~junpan/`.

### 3.2 Funding Cost Measures

As explained in Section 2.2, index arbitrage requires capital to make upfront payments and mark-to-market CDSs. Given that arbitrage traders (as, e.g., hedge fund managers and proprietary traders at investment banks) are typically highly leveraged, the cost of short-term debt financing may be an important determinant of illiquidity in the CDS market. There are several ways through which short-term funding can be obtained. For instance, market participants can raise funds on unsecured terms in interbank markets or on secured terms in repo markets. We use the three-month LIBOR-OIS spread (LIB-OIS) and the spread between Agency MBS and Treasury general collateral, henceforth GC, repo rates (MBS-Tsy) to, respectively, capture the costs associated with unsecured and secured financing.[26] The three-month LIBOR-OIS spread is a commonly used measure of risk in (unsecured) interbank markets (see, e.g., Filipovic and Trolle (2012)), while the GC repo spread reflects differential collateral values of Agency MBS and Treasury securities (see, e.g., Bartolini, Hilton, Sundaresan, and Tonetti (2011)). We expect the CDS market illiquidity measure to widen when funding becomes more expensive.

### 3.3 Market Volatility

Market volatility is captured by the VIX index (VIX), which is an option implied estimate of expected variance to be realized over the next thirty calendar days.[27] Brunnermeier and Pedersen (2009) predict that market illiquidity and market volatility are positively correlated, and we expect the CDS market illiquidity measure to widen when market volatility increases.

In Figure 3, the time series dynamics of the different illiquidity measures, the funding cost measures, and market volatility are depicted against the value of the CDS market illiquidity measure.

[Figure 3 about here.]

### 3.4 Results

We estimate both univariate and multivariate specifications of the following time series regression from weekly observations between September 20, 2006, and December 28, 2011:[28]

$$\text{CDSILLIQ}_t = a + b'x_t + c\,\text{CDSILLIQ}_{t-1} + e_t, \tag{1}$$

where $x_t$ is a vector of explanatory variables depending on the specification under consideration. Since we use absolute values of index-to-theoretical bases in the construction of the CDS market illiquidity measure, a positive coefficient in the above regression always indicates a widening of the latter as the explanatory variable increases. In order to avoid identifying spurious relationships and mitigate autocorrelation in the residual we include a lagged dependent variable in regression (1).

Results for univariate and multivariate specifications are exhibited in Panels A1 and A2 of Table 3, respectively. Overall, the specifications seem to be meaningful in the sense that

[26] LIB-OIS denotes the spread between three-month USD LIBOR and OIS rates. MBS-Tsy denotes the average spread between Agency MBS and Treasury GC repo rates for maturities between one day and three months. USD LIBOR, OIS, and GC repo rates are retrieved from the Bloomberg system.

[27] VIX index data are obtained from the Bloomberg system.

[28] The sample period is shortened slightly because the Hu et al. (2012) noise measure is available only up to the end of 2011.

autoregressive coefficients are well below one, implying covariance stationarity and mean-reversion of the CDS market illiquidity measure, and that signs of significant coefficient estimates mostly correspond to those intuitively expected.

[Table 3 about here.]

Considering the univariate specifications first, we find statistically significant relations of the CDS market illiquidity measure with respect to the illiquidity measures (except Depth-2), the LIB-OIS, and VIX. Among those, only Depth-1 and Noise turn out to be significant in a multivariate specification including all explanatory variables. The large number of insignificant variables in this specification and counterintuitive signs for the funding cost measures indicate multicollinearity among regressors, which is confirmed by the regressor correlation matrix reported in Panel B of Table 3. Bid-Ask, Refco, Noise, LIB-OIS, and VIX are strongly correlated, with correlation coefficients between 0.56 and 0.86. To mitigate confounding effects of multicollinearity, we report results of five additional multivariate specifications in which only one of the strongly correlated variables is included. The results of these multivariate regression show that the statistically significant relations of the univariate specifications are robust to the inclusion of additional explanatory variables.

Overall our analysis reveals that the CDS market illiquidity measure correlates with other illiquidity measures and funding cost proxies.

# 4 Asset Pricing Implications

This section investigates whether liquidity risk is priced in the cross-section of single-name CDS returns. As in Pástor and Stambaugh (2003), we focus on liquidity risk captured as return covariation with respect to a market-wide liquidity factor. As discussed in Acharya and Pedersen (2005), there are other dimensions of liquidity risk, but it is difficult to empirically disentangle their individual effects; consequently, we focus on a single dimension of liquidity risk. In addition to liquidity risk, we also control for the effect of expected illiquidity.

## 4.1 Asset Pricing Model

For our analysis, we consider one-week excess returns from a CDS protection seller's perspective. We rely on a factor pricing model in the spirit of the one used by Bongaerts et al. (2012) to study liquidity effects in corporate bond markets. In the model, factor loadings of the excess return on a CDS contract referencing entity $i$, $r^e_{i,t}$, are the slope coefficients $\beta_i$ in the regression

$$r^e_{i,t} = \alpha_i + \beta_i^{\mathrm{MKT}}\,\mathrm{MKT}_t + \beta_i^{\mathrm{DEF}}\,\mathrm{DEF}_t + \beta_i^{\mathrm{LIQ}}\,\mathrm{LIQ}_t + \epsilon_{i,t}, \tag{2}$$

where $\mathrm{MKT}_t$, $\mathrm{DEF}_t$, and $\mathrm{LIQ}_t$ denote the market, default, and liquidity factors, respectively. As in Fama and French (1993), $\mathrm{MKT}_t$ and $\mathrm{DEF}_t$ are given by the excess returns on a stock and corporate bond index, respectively. $\mathrm{LIQ}_t$ is given by the excess return on a tradable liquidity factor that is highly correlated with innovations to the CDS market illiquidity measure and whose construction is outlined below. The choice of the first two factors is motivated by Bongaerts et al. (2011), who, in the context of their equilibrium asset pricing model, find evidence for priced equity and credit risk in the cross-section of CDS returns.

Since CDSs have zero net present value at inception of trade, it is not obvious how to compute their excess returns. As shown by Duffie (1999) CDSs can be replicated by portfolios of par floating rate notes and it has become standard practice (see, e.g., Berndt and Obreja (2010), Bongaerts et al. (2011), Bao and Pan (2012)) to compute (excess) returns on CDSs based on this relation. We adopt this practice to compute excess returns and leave additional details to Appendix B.

In the cross-section, the model relates expected excess returns to expected illiquidity, factor loadings, and factor prices of risk. Expected illiquidity is captured by the expected transaction cost, which in turn is given by the expected costs, conditional on a trade occurring, times the likelihood of trading. Specifically, expected excess returns are given by

$$E[r^e_{i,t}] = E[c_{i,t}]\zeta + \beta_i^{\text{MKT}}\lambda_{\text{MKT}} + \beta_i^{\text{DEF}}\lambda_{\text{DEF}} + \beta_i^{\text{LIQ}}\lambda_{\text{LIQ}}, \tag{3}$$

where $\lambda$s denote factor prices of risk, $c_{i,t}$ denotes weekly round-trip transaction costs per dollar notional amount of a contract referencing entity $i$, and $\zeta$ is denotes the unconditional likelihood of exiting a CDS contract after one week.[29] For our empirical analysis, we calibrate $\zeta$ to the average weekly turnover of CDSs in our sample.

The factor pricing model is estimated in two steps. In the first step, we determine factor loadings as ordinary least squares (OLS) estimates, $\widehat{\beta}_i$, of the slope coefficients in regression (2). In the second step, we estimate factor prices of risk from a cross-sectional OLS regression of expected CDS returns net of expected transaction cost on first-step factor loadings, i.e.,

$$\widehat{E}[r^e_{i,t}] - \widehat{E}[c_{i,t}]\widehat{\zeta} = \lambda_0 + \widehat{\beta}_i^{\text{MKT}}\lambda_{\text{MKT}} + \widehat{\beta}_i^{\text{DEF}}\lambda_{\text{DEF}} + \widehat{\beta}_i^{\text{LIQ}}\lambda_{\text{LIQ}} + u_i, \tag{4}$$

where $\widehat{\zeta}$ is the calibrated value of $\zeta$ and $\widehat{E}[r^e_{i,t}]$ and $\widehat{E}[c_{i,t}]$ are estimates of expected excess returns and expected weekly transaction costs, respectively. Since returns on CDSs are already in excess of the risk free rate, so are returns net of transaction costs, and therefore no constant term appears in the model (Equation (3)).[30] Due to potential differences between true and calibrated $\zeta$ coefficients, we, nevertheless, include an intercept in regression (4). If the asset pricing model is true and if our calibration is reasonable, $\lambda_0$ will be insignificantly different from zero and by means of a test of this hypothesis the asset pricing model and/or the calibration can be rejected.

In the empirical asset pricing literature, expected returns are typically estimated by time series averages of realized returns. Average realized excess returns on CDSs, however, are very imprecise estimates of expected excess returns. This is because of the rare occurrence of credit events and the extreme returns associated. As noted by Bongaerts et al. (2011), CDS spreads and physical survival probabilities can be used to construct forward-looking estimates of conditional expected $h$-week excess returns on CDSs, $\widehat{E}_t[r^e_{i,t+h}]$, that exhibit smaller standard errors than realized returns. Therefore, their average gives a more precise estimate of unconditional expected excess returns than average realized returns. Since weekly transaction costs are less noisy than realized returns, expected weekly

[29] An alternative way of interpretation is the following: Suppose that investors' holding periods were known to be $X$ weeks, then the holding period return is approximately the sum of $X$ one-week returns, while transaction costs are only incurred once. Consequently, over the holding period the coefficient on $E[c_{i,t}]$ is one, while over a one-week period the coefficient is $\zeta \approx 1/X$. Amihud and Mendelson (1986) show that for an asset with perpetual cash flow and given appropriate assumptions, $\zeta$ can indeed be interpreted as the reciprocal of the expected holding period.

[30] If the model is true, a contract that is not systematically exposed to any of the factors should not be expected to earn a return that, after taking into account transaction costs, exceeds the risk free rate.

transaction costs can be estimated with satisfactory precision by their time series averages. Thus, $\widehat{E}[r^e_{i,t}]$ and $\widehat{E}[c_{i,t}]$ in regression (4) are given by

$$\widehat{E}[r^e_{i,t}] = \frac{1}{T}\sum_{s=1}^{T}\widehat{E}_s[r^e_{i,s+1}] \qquad \text{and} \qquad \widehat{E}[c_{i,t}] = \frac{1}{T}\sum_{s=1}^{T} c_{i,s},$$

where $T$ denotes sample size.

Due to estimation error in first-step factor loadings, standard errors of coefficient estimates in regression (4) have to be adjusted for errors-in-variables (EIV). We account for EIV by use of asymptotic GMM standard errors (see pp. 240–243 in Cochrane (2001)).

### 4.2 Data

The daily data we use in the construction of our sample come from Markit, Bloomberg, and Moody's Analytics and extend from June 1, 2006, to February 1, 2012. From Markit, we collect five-year composite mid CDS spreads, the corresponding recovery rates, and the average rating by Moody's and Standard & Poor's (S&P) for all companies domiciled in North America and Europe.[31] Spreads are obtained for CDS contracts written on senior unsecured debt and denominated in either EUR or USD.[32] From Bloomberg, we collect five-year bid and ask spreads for all EUR and USD denominated senior CDS contracts. We match CDS contracts from the two sources based on the denominated currency and the reference entities' six-digit Reference Entity Database (RED) codes. From Moody's Analytics, we obtain one-year and five-year EDFs for all public companies that are contained in the Markit database. Thus, our sample consists of North American and European reference names with data coverage by each of the three providers.

Since the key ingredients to our asset pricing tests, namely CDS returns and estimates of their conditional expectations, are inferred from mid CDS spreads, we filter those for stale quotes. A quote is classified as stale, once it does not change over five or more consecutive trading days. In this case, only the spread quotation on the first of the consecutive days is retained in the sample, while the remaining ones are excluded.

From the collected data, we compute realized excess returns on CDSs over distinct one-week periods and construct weekly observations of conditional expected one-week excess return estimates and weekly round-trip transaction costs; details of the numerical implementation are deferred to Appendix B. Weekly observations are sampled on Wednesdays of the one-week periods. In order to mitigate the impact of outliers, we Winsorize the top and bottom 0.5% of the realized and conditional return distributions and the top 1% of the transaction cost distribution.[33] Furthermore, we exclude all companies with less than fifty joint observations of conditional expected returns, realized returns, and transaction costs. This leaves a sample of 663 companies, of which 424 are domiciled in North America and 239 in Europe, and a total of 141,262 joint observations of conditional expected returns, realized returns, and transaction costs.

Finally, we obtain CDS volume data from the DTCC's Trade Information Warehouse (TIW).[34] In particular, we collect gross notional values for the 1000 most active reference

[31] The recovery rate is a composite of those reported by dealers. Ratings are adjusted for seniority of the reference obligation and subcategories are rounded to major rating categories.

[32] In case that more than one restructuring clause is available, we select the clause standardized contracts trade with, i.e., the no restructuring clause for USD denominated contracts and the modified modified restructuring clause for EUR denominated contracts.

[33] Since transaction costs are non-negative, extreme observations are in the right tail of the distribution.

[34] Amongst others, the DTCC provides trade execution and post-trade processing services for OTC CDS

names as well as their weekly transaction activity. This data are only available for part of the sample period and we use data from the week ending on July 9, 2010, to the week ending on February 3, 2012.[35]

### 4.3 Turnover of CDSs and Calibration of $\zeta$

Turnover of assets in fixed supply is typically defined by the ratio of the number of units of the asset that are traded over a given period and the number of units outstanding. In case of CDSs, two problems arise with this definition: First, CDSs are in zero net-supply which means that the number of contracts outstanding changes with the number of contracts traded. Second, CDSs can be written on arbitrary notional amounts. Therefore, we consider the gross notional value traded over a given week instead of the corresponding number of contracts in our definition of a CDS's weekly turnover and we fix the denominator of the ratio at the gross notional value outstanding as of the end of the previous week. That is, we define weekly turnover of a CDS contract referencing entity $i$ by

$$\text{Turnover}_{i,t} = \frac{\text{Gross Notional Transaction Activity of Entity } i \text{ between } t \text{ and } t-1}{\text{Gross Notional Value of Entity } i \text{ as of } t-1}.$$

Note that transaction activity reported by the DTCC includes only transactions that involve a transfer of risk between market participants, i.e., portfolio compressions and assignments to a central clearing counterparty do not contribute to transaction activity. Thus, regulatory attempts to improve transparency and resilience of the CDS market do not artificially inflate turnover of CDSs.

The rationale behind this definition of turnover and its link to $\zeta$ are as follows: Neglecting the impact of counterparty risk, a seller of CDS protection can offset credit risk exposure in multiple equivalent ways. First, the contract can be terminated with the existing counterparty. Second, a new contract with a different counterparty can be entered at the opposite leg. Third, upon approval by the counterparty, contractual obligations can be assigned to a third party. If these three types of transaction activity were the only ones counted by the DTCC, then $\text{Turnover}_{i,t}$ would indeed reflect the likelihood of exiting an existing position over a one-week period. However, DTCC transaction activity also includes new CDS trades that do not offset existing positions and, therefore, $\text{Turnover}_{i,t}$ is an upward biased estimate of actual turnover.[36]

For our empirical analysis we calibrate $\zeta$ as the average weekly turnover of CDS referencing the 555 entities in our sample for which DTCC data are available as well. We find $\widehat{\zeta} = 94.86$ bps and a median weekly turnover of 61.03 bps. For comparison, Dick-Nielsen, Feldhütter, and Lando (2012) report a median quarterly turnover of 4.5% for corporate bonds over a similar sample period, which implies a median weekly turnover of 450.00/13 bps = 34.62 bps.

transactions to all major credit derivatives dealers and more than 2500 buy-side firms. Transactions among DTCC customers are recorded in the TIW and the DTCC (2009) claims that those correspond to more than 95% of global CDS transactions. Weekly data on both current positions in the TIW and transaction activity are publicly available on the DTCC's website `http://www.dtcc.com`.

[35] Weekly DTCC data are reported on Fridays, while we sample returns and transaction costs on Wednesdays. The mismatch is not a concern, because only an average of the data enters the asset pricing model.

[36] Since the DTCC reports gross notional values and transaction activities that aggregate notional amounts over the entire CDS term structure, we implicitly assume that turnover is the same across all maturities.

### 4.4 Portfolio Construction

We conduct our analysis on a set of 40 equally weighted test portfolios rather than at the level of individual CDSs. Portfolios are rebalanced at a quarterly frequency and formed such that they exhibit variation across the credit risk and liquidity dimension.

The portfolio formation proceeds as follows: On month-ends of March, June, September, and December of a given year, we first sort reference names from best to worst credit quality either according to the average issuer credit rating over the previous quarter or according to previous quarter's average five-year EDF (both estimated from daily observations over the previous quarter). In case that we sort on average credit ratings, we group reference names into five credit rating categories: AAA-AA, A, BBB, BB, and B-CCC. In case that we sort on average five-year EDFs, reference names are grouped into five-year EDF quintiles. Subsequently, we sort reference names within a given credit risk group, from most liquid to least liquid, according to their average bid-ask spread over the previous quarter (again estimated from daily observations) and then group them into bid-ask spread quartiles in order to determine portfolio membership.

Since the first quarter of data is used for portfolio formation only, this procedure yields portfolio time series observations from October 11, 2006, to February 1, 2012.[37] During this period, we find two weeks where only a small number of North American reference names have quoted bid-ask spreads.[38] We exclude the corresponding portfolio observations from the analysis, leaving a total of 276 one-week periods during the sample period.

### 4.5 Factor Construction

Since our sample consists of CDSs referencing both North American and European names, we construct factors in such a way that they reflect risks pertaining to both U.S. and European markets.

The market factor is given by the equally weighted excess return on the S&P 500 and the EURO STOXX 50. We compute excess returns on the two indices with respect to one-week OIS rates. The default factor is given by the excess return on the Bank of America Merrill Lynch Global Corporate Index. Excess returns on the index are obtained from Bloomberg and computed with respect to a basket of government bonds.

For the construction of the liquidity factor, we consider an implementable index arbitrage strategy. To illustrate its mechanics, suppose that, at the beginning of a one-week period, index $i$ trades above its theoretical level. The strategy then sells index protection, while simultaneously buying protection on the basket of single-name CDSs that replicates the cash flows of the index contract and vice versa, in case that the index trades below its theoretical level.

As shown in Section 2.2, if held to the index's maturity, this strategy is an arbitrage in the textbook sense. We consider, however, a one-week holding period in which case the

[37] This is due to the fact that portfolio constituents are selected based on data up to and including September 29, 2006, and the actual formation takes place on the following Wednesday, i.e., October 4, 2006. Obviously, the first return is then observed a week later, i.e., October 11, 2006. On any rebalancing date the portfolio formation proceeds equivalently.

[38] Surprisingly, we find some weeks in which virtually no bid and ask quotes are available from the Bloomberg system for North American reference names. In the entire week from December 20, 2007, to December 26, 2007, we identify 28 bid-ask spread observations for eleven North American reference names. A similar problem is observed in the week from May 22, 2008, to May 28, 2008, where a total of 38 observations for 18 different reference names is available. In addition, we find two dates of the sample period on which we cannot infer transaction costs for one of the portfolios and linearly interpolate the four missing values. In order to be sure that this does not introduce a bias in our analysis, we excluded the two dates from the sample and found virtually identical results.

strategy's return is risky and given by

$$\text{sign}\left(B_{i,t-1}\right)\left(r_{i,t}^{e,\text{IDX}} - r_{i,t}^{e,\text{BSK}}\right),$$

where $r_{i,t}^{e,\text{IDX}}$ and $r_{i,t}^{e,\text{BSK}}$ denote one-week excess returns on the five-year index contract and its replicating basket of single-name CDSs, respectively, and $B_{i,t-1}$ is the corresponding index-to-theoretical basis at the beginning of the one-week period.[39] Since returns on the strategy are positive when index-to-theoretical bases narrow, we expect them to be highly (negatively) correlated with innovations in bases.

We apply the strategy to each of the credit indices considered in the construction of the CDS market illiquidity measure and report return descriptive statistics in Panel C of Table 2. Strategy volatilities range from 16.79 to 108.56 bps across indices. As noted by Moskowitz, Ooi, and Pedersen (2012) creating diversified factor portfolios from assets that exhibit considerable cross-sectional variation in volatilities is challenging. Therefore, they scale an assets's return by its conditional volatility before aggregating into a factor portfolio. As estimating conditional volatilities would shorten our sample period, we instead exploit the positive relation between strategy return volatilities and index levels and scale strategy returns by the index levels at the beginning of the respective one-week periods.[40] Specifically, the tradable liquidity factor is constructed as

$$\text{LIQ}_t = \sum_{i=1}^{n_t} w_{i,t-1}\,\text{sign}\left(B_{i,t-1}\right)\left(r_{i,t}^{e,\text{IDX}} - r_{i,t}^{e,\text{BSK}}\right),$$

where $w_{i,t-1} = [1/C_{i,t-1}]/[\sum_{j=1}^{n_t} 1/C_{j,t-1,}]$.

The lower panel of Figure 2 displays the time series evolution of the tradable liquidity factor. Its correlation with innovations to the CDS market illiquidity measure is -0.69.[41] Its annualized mean and standard deviation are 3.26% and 1.13%, respectively, and despite its simple construction the factor's annualized Sharpe ratio, using Lo's (2002) correction for non-independent returns, is 1.85.[42] The annualized Sharpe ratios of the individual index arbitrage strategies are around 1.5 (see third row of Table 2, Panel C). Hence, the high Sharpe ratio of the factor is, in part, due to the moderate correlations between strategy returns, which are reported in Panel D of Table 2.

## 4.6 Results

### Descriptive Statistics

Table 4 displays descriptive statistics for the three factors. Over our sample period, average returns on the market and default factors are negative, but insignificantly different

[39] We compute these returns in the same way as returns on single-name CDS, but using five-year index levels and their theoretical counterparts instead of CDS spreads. Whenever an index roll date, $t_{roll}$, falls within one of the one-week periods the weekly return is obtained by first computing the return on series $S_i$ of index $i$ between $t$ and $t_{roll}$ and then adding to it the return on series $S_i + 1$ over $t_{roll}$ to $t$.

[40] We find a strong positive relation between index levels and strategy volatilities. For instance, the cross-sectional correlation between them is 0.89.

[41] Here we use the residual of an AR(2) specification of the CDS market illiquidity measure in order to compute innovations. The specification is estimated from weekly observations between September 20, 2006, and February 1, 2012.

[42] Note that the Sharpe is inflated because we neither take into account transaction costs nor margin requirements (see Rule 4240 of the Financial Industry Regulatory Authority for margin requirements for CDSs).

from zero.[43] In contrast, the average return on the liquidity factor is positive and significant, with a t-statistic of 4.69 based on Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard error with 24 lags. Correlations among the three factors are of moderate size. The strongest relation prevails between the market and default factors. This reflects the fact that positive stock returns are, in general, accompanied by tightening yield spreads and, therefore, positive excess returns on corporate bonds. It is important to notice that the liquidity factor is only weakly positively correlated with the other two factors.

[Table 4 about here.]

Table 5 displays descriptive statistics for the 40 test portfolios. Panel A provides those for the portfolios formed by first sorting CDS contracts according to credit ratings and then according to bid-ask spreads, and Panel B provides those for the portfolios formed by first sorting CDS contracts according to five-year EDFs and then according to bid-ask spreads.

[Table 5 about here.]

Expected returns, estimated as time-series averages of conditional expected returns, are positive throughout portfolios and strongly significant with t-statistics ranging from 3.70 to 11.09. The former reflects the fact that risk neutral default probabilities in general exceed physical default probabilities. Expected returns increase monotonically with portfolio illiquidity, as captured by the bid-ask spread, and also tend to increase as credit quality, measured by either credit rating or five-year EDF, decreases. For instance, we observe a difference of 4.67% in annual expected returns between a portfolio consisting of the most illiquid low-credit-quality CDSs (B-CCCQ4) and a portfolio consisting of the most liquid high-credit-quality CDSs (AAA-AAQ1). We also observe that average realized returns are not significantly different from zero.[44] In absolute value, t-statistics for the mean range from 0.08 to 1.13. This underscores the importance of using forward-looking information when estimating expected returns.

Average weekly transaction costs, i.e., our estimate of expected weekly transaction costs, are strongly significant with t-statistics ranging from 6.65 to 13.40. For any of the credit risk categories, average transaction costs increase monotonically across liquidity quartiles. Moreover, as credit quality decreases, portfolio level CDS spreads increase monotonically. That is, portfolios exhibit ex-post the properties they were chosen to reflect ex-ante. Finally, turnover at the portfolio level exhibits only little variation around the calibrated value $\widehat{\zeta} = 94.86$ bps.

### Regression Results

First-step regression results are displayed in Panels A and B of Table 6 which report a factor loading's economic magnitude and t-statistic. By economic magnitude we mean the change in a portfolio's weekly return (in bps) in response to a one standard deviation change in the respective factor.

[43] t-statistics for the mean based on Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard errors with 24 lags are -0.39 and -0.21 for the market and default factors, respectively.

[44] Consistent with Bao and Pan (2012), we find that volatility of realized returns on CDSs is strongly related to contract liquidity, as can be seen from the monotone relation between portfolio volatilities and portfolio level bid-ask spreads.

[Table 6 about here.]

Panel A of Table 6 provides results for nested single-factor specifications of regression (2). On its own, each of the factors constitutes a significant explanatory variable of CDS portfolio returns. Market and default factor loadings are statistically significant throughout portfolios and most portfolios also load significantly on the liquidity factor. Note that all portfolios exhibit a positive loading on the liquidity factor indicating that protection sellers systematically realize negative returns when liquidity vanishes from the CDS market and, therefore, may require compensation for bearing this risk.

Panel B of Table 6 displays results for the three-factor model. Loadings on the market and default factors are significant throughout portfolios and almost monotonically increasing along both the liquidity and credit quality dimensions. Loadings on the liquidity factor are significant at the one percent level for 32 out of the 40 portfolios. These loadings also tend to increase along the liquidity and credit quality dimensions. However, especially along the liquidity dimension (as captured by the bid-ask spread) there are exceptions which indicate that portfolios with high bid-ask spreads do not necessarily exhibit larger liquidity risk. Panel C of Table 6 displays adjusted $R^2$s that range from 38% to 67% across portfolios.

The results of estimating alternative specifications of the cross-sectional regression (4) are displayed in Table 7. Factors carry significant prices of risk in one-factor and two-factor models (specifications 1 to 5) and one-factor and two-factor models that in addition account for expected illiquidity (specifications 7 to 11). The significant relation between liquidity risk and expected excess returns also prevails in three-factor models both excluding and including expected illiquidity (specifications 6 and 12, respectively). Here, the insignificance of the market factor is due to a high cross-sectional correlation of market risk and default risk. Moreover, most model specifications cannot be rejected based on a test of the intercept's significance. The intercept in the full model (specification 12) is, however, is significant and negative. This is due to difficulties in pricing high-credit-quality CDSs which, in particular in the pre-crisis period, traded at very low spreads (see also Bongaerts et al. (2011)).

[Table 7 about here.]

**Economic Significance**

To asses the economic importance of expected illiquidity and the factors, we use the full model and decompose the annualized expected excess return on each test portfolio into its four components: The expected illiquidity (defined by $52\widehat{E}[c_{i,t}]\widehat{\zeta}$) and the market, default, and liquidity risk premiums (defined by $52\widehat{\beta}_i^F\lambda_F$, $F \in \{\text{MKT, DEF, LIQ}\}$). Figure 4 displays the resulting decomposition for the 40 test portfolios.

We summarize the information in Figure 4 in two ways. First, we consider the difference in expected excess returns between the two extreme portfolios, B-CCCQ4 and AAA-AAQ1. We use the term *expected return differential* to refer to this difference. Expected illiquidity contributes 0.96% per year to the expected return differential, while liquidity risk contributes 1.49% per year. As such, and in contrast to the results of Bongaerts et al. (2011), liquidity risk is economically more important than expected illiquidity for the pricing of single-name CDSs.[45] Market risk and default risk contribute an annualized 0.21%

[45] Note that Bongaerts et al. (2011) primarily focus on contract-specific liquidity risk as captured by covariation of a contract's transaction cost innovations with a non-traded credit risk factor, while we focus on market-wide liquidity risk captured as covariation of CDS returns with our tradable liquidity factor.

and 2.10%, respectively, to the expected return differential. That is, the contribution of liquidity risk is more than half the contribution of default risk.

[Figure 4 about here.]

As an alternative way to summarize the information in Figure 4, we average the decompositions across test portfolios. In this case, expected illiquidity and liquidity risk contribute 0.29% and 0.43% per year, respectively, to the average expected returns across test portfolios, while the contributions of market risk and default risk are 0.07% and 0.90% per year, respectively. The two measures of economic importance are consistent in that both find that default risk is the most important source of risk, followed by liquidity risk, expected illiquidity, and market risk.

## 4.7 Robustness Checks

In this section, we conduct a number of robustness checks of our benchmark results. First, we examine whether our results are robust to changes in the methodological setup. Second, we examine whether our results hinge on the particular construction of the liquidity factor. Third, we examine whether there are confounding effects due to the fact that the default factor is itself affected by liquidity risk. Finally, we examine whether our results are robust to adding additional risk factors, including liquidity factors from other markets. For each robustness check, the results of the cross-sectional regression are reported in Table 8, while the two measures of the economic importance of expected illiquidity and the factors are reported in Table 9. The two measure typically give similar results so we only comment on the expected return differential.

[Table 8 about here.]

[Table 9 about here.]

### Methodology

**Restriction on intercept** In the benchmark analysis, we find a significantly negative intercept in the full model due to difficulties with pricing high-credit-quality CDS portfolios. Imposing a zero intercept neither affects significance of the factor price of liquidity risk (see specification 1 in Table 8) nor the contribution of liquidity risk to the expected return differential, which reduces slightly to 1.43% annually (see specification 1 in Table 9). It does, however, affect the pricing of market and default risk. Both factor prices of risk are insignificant when removing the intercept and contributions to the expected return differential change considerably. The contribution of market risk increases to 1.15% per year, while that of default risk decreases to 0.87% per year.

**$\zeta$ as a regression coefficient** Instead of calibrating $\zeta$ to CDS volume data, we estimate it as a regression coefficient. This is tantamount to treating expected weekly transaction costs as a portfolio characteristic, in which case the model's cross-sectional relation, given in Equation (3), is inferred by means of the following OLS regression[46]

$$\widehat{E}[r^e_{i,t}] = \lambda_0 + \widehat{E}[c_{i,t}]\zeta + \widehat{\beta}_i^{\mathrm{MKT}}\lambda_{\mathrm{MKT}} + \widehat{\beta}_i^{\mathrm{DEF}}\lambda_{\mathrm{DEF}} + \widehat{\beta}_i^{\mathrm{LIQ}}\lambda_{\mathrm{LIQ}} + u_i. \tag{5}$$

[46] As before, we account for EIV in regression (5) by use of asymptotic GMM standard errors.

Specification 2 in Table 8 shows the results. Adding expected weekly transaction costs as an additional regressor does not change the significance of the factor price of liquidity risk. However, prices of risk of the other two factors become insignificant. The estimated value of $\zeta$ is more than four times larger than the calibrated value used in the benchmark analysis and implies unreasonably large turnover in the CDS market. Specification 2 in Table 9 shows that the contribution of expected illiquidity to the expected return differential increases markedly to 4.07% per year, while liquidity risk contributes about the same amount as in the benchmark analysis, 1.37% per year. Contributions of market and default risk decrease to -0.48% and 0.26%, respectively, per year.

**Alternative Liquidity Factors**

**AR(2) residual of CDS market illiquidity measure** As an alternative to the tradable liquidity factor, we use the residuals of an AR(2) specification for the CDS market illiquidity measure (as mentioned above, the correlation between the two is -0.69). First-step regressions show that a smaller number of portfolios load significantly on this liquidity factor compared to the tradable liquidity factor. However, in the cross-sectional regression, the price of liquidity risk remains statistically significant (see specification 3 in Table 8). Economically, the contribution of liquidity risk to the expected return differential decreases to 0.96%, annualized (see specification 3 in Table 9).

**Alternative construction of tradable liquidity factor** The construction of our tradable liquidity factor is similar to that of Moskowitz et al.'s (2012) time series momentum factor, in that it aggregates signed returns. To account for the considerable cross-sectional variation in volatilities across assets, Moskowitz et al. (2012) scale returns by the assets' conditional volatilities. In contrast, we account for the cross-sectional variation in volatilities by scaling returns by index levels. As an alternative, we construct a tradable liquidity factor by scaling signed returns on the individual arbitrage strategies, $r_{i,t}^{e,\mathrm{IDX}} - r_{i,t}^{e,\mathrm{BSK}}$, by their conditional volatilities. In this case, the liquidity factor is given by

$$\mathrm{LIQ}_t^{\mathrm{MOP}} = \frac{1}{n_t} \sum_{i=1}^{n_t} \mathrm{sign}\left(B_{i,t-1}\right) \frac{40\%}{\sigma_{i,t-1}} \left(r_{i,t}^{e,\mathrm{IDX}} - r_{i,t}^{e,\mathrm{BSK}}\right),$$

where $\sigma_{i,t}^2$ is an estimate of annualized conditional variance of $r_{i,t}^{e,\mathrm{IDX}} - r_{i,t}^{e,\mathrm{BSK}}$ that is obtained from daily returns as in Equation (1) of Moskowitz et al. (2012).[47] The alternative liquidity factor has a correlation of 0.88 with the benchmark liquidity factor indicating that our original weighting scheme effectively mimics the approach of Moskowitz et al. (2012).

First-step regressions produce results similar to those of our benchmark analysis, and in the cross-sectional regression, the price of liquidity risk remains statistically significant (see specification 4 in Table 8). The contribution of expected illiquidity to the expected return differential increases slightly in comparison to our benchmark analysis to 1.01% per year, while that of liquidity risk decreases to 1.02% per year (see specification 4 in Table 9).[48]

[47] The time series of this alternative liquidity factor consists of 252 weekly observations from March 28, 2007, to February 1, 2012. We use the first six-month period to estimate conditional volatility for the computation of the March 28, 2007, observation of the factor.

[48] Due to the fact that we consider expected returns and expected transaction costs measured over the shorter sample period, the contribution of expected illiquidity to the expected return differential changes in this robustness check as well.

**Transaction-cost-based illiquidity factor** Several recent studies (see, e.g., Acharya, Amihud, and Bharath (2012), Bongaerts et al. (2012)) capture liquidity risk as return covariation with respect to innovations in market-wide transaction costs. Consequently, we aggregate each reference name's weekly transaction costs into a market-wide average and then take the AR(2) residual of the resulting illiquidity measure as a factor in the asset pricing model (see specification 5 in Tables 8 and 9). In this case, only one test portfolio exhibits significant exposure to this liquidity factor at the five percent level. Despite this, the cross-sectional regression gives a significant factor price of liquidity risk with the correct sign. Nevertheless, the contribution of liquidity risk to the expected return differential is negative at -0.26%, annualized. This is because the AAA-AAQ1 portfolio is the only portfolio that significantly loads on the transaction-cost-based factor and the loading of the B-CCCQ4 portfolio has the wrong sign.

Obviously, our liquidity factor captures dimensions of liquidity risk distinct from those captured by innovations to aggregate transaction costs. This is also reflected by very low correlations of -0.02 and 0.11 between the transaction-cost-based factor and, respectively, the factor constructed in Section 4.5 and innovations to the CDS market illiquidity measure.

### Alternative Default Factor

So far we have captured default risk as the excess return on a corporate bond index. There is, however, ample evidence that corporate bonds themselves are affected by liquidity risk (see, e.g., Lin et al. (2011), Acharya et al. (2012)). In order to avoid confounding effects, we construct an alternative default factor that is not affected by liquidity. We first aggregate, among reference names in our sample, weekly averages of 5-year EDFs into a market-wide average and then take the AR(2) residual of the resulting default risk measure as a factor in our asset pricing model (see specification 6 in Tables 8 and 9). The EDF-based default factor has a correlation of -0.44 with our benchmark default factor (the correlation is negative since an increase in expected defaults decreases corporate bond returns) and a small number of portfolios do not load on the EDF-based default factor. The factor price of this alternative measure of default risk remains statistically significant as does the factor price of liquidity risk. Relative to our benchmark analysis, the contribution of default risk to the expected return differential decreases to 1.73% per year, while that of market risk increases to 1.21%. The contribution of liquidity risk decreases to 0.99% annually.

### Additional Factors

**Stock market liquidity factors** Both Acharya et al. (2012) and Bongaerts et al. (2012) show that stock market liquidity risk is significantly priced in the cross-section of corporate bond returns. Therefore, we separately add stock market liquidity factors based on the Amihud (2002) illiquidity measure (henceforth Amihud factor) or the Pástor and Stambaugh (2003) liquidity measure (henceforth Pástor and Stambaugh factor) as additional factors in the asset pricing model (see specifications 7 and 8 in Tables 8 and 9).[49] Only

[49] In order to construct stock market liquidity factors we obtain price, return, and volume data for NYSE and AMEX traded ordinary common shares of companies incorporated in the U.S. from the Center of Research in Security Prices' daily stock file. Individual-stock Amihud (2002) illiquidity measures are given as weekly averages of absolute one-day returns per million dollar of daily trading volume. To obtain individual-stock Pástor and Stambaugh (2003) liquidity measures at a weekly frequency, we estimate regression (1) in Pástor and Stambaugh (2003) for each stock with observations within the last 22 trading day window. The construction of market-wide measures proceeds as in the original articles with the exception that we do not scale the market-wide Pástor and Stambaugh (2003) liquidity measure by lagged total dollar value of

three out of the 40 test portfolios exhibit significant exposure to stock market liquidity at the five percent level, using either of the two stock market liquidity factors. Due to liquidity commonality, one intuitively expects returns on CDSs to load positively on stock market liquidity. Some of the loadings on the Amihud factor are indeed positive, however, loadings on the Pástor and Stambaugh factor have a counterintuitive negative sign. Thus, there is no consistent evidence for liquidity spillover effects from the stock market. The factor price of stock market liquidity risk is insignificant in case of the Amihud factor while significant (and negative) in the case of the Pástor and Stambaugh factor. The factor price of CDS market liquidity risk remains significant in both cases. Contributions of stock market liquidity risk to the expected return differential are 0.96% and 0.62% in case of the Amihud and the Pástor and Stambaugh factors, respectively. For comparison, CDS market liquidity risk contributes 1.14% and 1.57% in the two cases.

**Treasury market illiquidity factor** Hu et al. (2012) find that exposure to their Noise measure, capturing Treasury market illiquidity, is priced in returns on assets that are particulary vulnerable to liquidity shocks. Consequently, we add the first difference of the Noise measure as an additional factor in the asset pricing model (see specification 9 in Tables 8 and 9). Only one of the CDS portfolios has a significant loading on this factor at the five percent level. In comparison, all but four CDS portfolios load significantly on our tradable liquidity factor. However, cross-sectional evidence is mixed. In terms of statistical significance, Treasury market liquidity risk is priced, while the factor price of CDS market liquidity risk is statistically insignificant. In terms of economic importance, Treasury market liquidity risk contributes a meager 0.12% per year to the expected return differential, while CDS market liquidity risk has an economically important contribution of 1.01% per year.

**Volatility and jump factors** Finally, we include volatility and jump factors in the asset pricing model. Volatility risk has been shown to be priced in stock and corporate bond returns (see, e.g., Ang, Hodrick, Xing, and Zhang (2006) and Bongaerts et al. (2012) for evidence from stock and corporate bond markets, respectively) and a recent study by Cremers, Halling, and Weinbaum (2012) also finds evidence for priced jump risk in stock returns. We separately include the residual of an AR(2) specification of the VIX index and the return on Cremers et al.'s (2012) MNGN factor-mimicking portfolio as volatility factors, and the return on Cremers et al.'s (2012) MNVN factor-mimicking portfolio as a jump factor in the asset pricing model (see specifications 10, 11, and 12 in Tables 8 and 9). There is no evidence for priced volatility risk; only three out of the 40 test portfolios exhibit significant exposures to the volatility factors at the five percent level, factor prices are insignificant, and contributions to the expected return differential are -0.52% and -0.37%, annualized, for the VIX- and MNVN-based volatility factors, respectively. In comparison, liquidity risk contributes 1.28% and 1.05% annually in the two cases, although its factor price in specification 11 of Table 8 is insignificant. Some of the portfolios load significantly on the jump factor. However, its factor price is insignificant and the contribution to the expected return differential is negligible at -0.05% per year. Liquidity risk contributes 1.11% annually in this case.

In summary, the robustness checks support that liquidity risk is priced in the cross-section

stocks that are included in its construction. The stock market liquidity factors are given as the negative value of the residual of an AR(2) specification of the market-wide Amihud (2002) illiquidity measure and the residual of regression (7) in Pástor and Stambaugh (2003), respectively.

of CDS returns. This is also illustrated in Figure 5, which displays the liquidity risk premium across all specifications. The upper panel displays the contribution of liquidity risk to the expected return differential, which in all specifications is larger than 96 bps, except when using the illiquidity factor based on transaction costs. The lower panel displays the contribution to the average expected return across test portfolios, which in all specifications is larger than 31 bps, except when using the AR(2) residual of the CDS market illiquidity measure and the illiquidity factor based on transaction costs.

[Figure 5 about here.]

# 5 Conclusion

Recent empirical research emphasizes that liquidity effects are important for the pricing of CDSs, but conclusion on whether these effects are due to the level of illiquidity or its variation has not yet been reached. Therefore, we analyze whether liquidity risk, in addition to expected illiquidity, affects expected returns on single-name CDSs.

First, we construct a CDS market illiquidity measure from divergences between published credit index levels and their theoretical counterparts, the so called index-to-theoretical bases. Theoretically, non-zero bases can be realized by trading indices against baskets of single-name CDSs referencing their constituents. These index arbitrage trades keep index-to-theoretical bases close to zero in perfect capital markets. However, we find non-zero and time-varying bases across credit indices referencing the most liquid names of both the investment grade and high-yield universe. The CDS market illiquidity measure aggregates bases across these indices and can be thought of as a summary statistic of the impact of all the different dimensions of illiquidity that are present in the CDS market. Consistent with this, the measure correlates with transaction costs, funding costs, and other commonly used illiquidity proxies.

Then, we construct a tradable liquidity factor from returns on index arbitrage strategies that is highly correlated with innovations to the CDS market illiquidity measure. We investigate whether exposure to this factor is priced in the cross-section of single-name CDS returns and estimate a factor pricing model, which accounts for market risk and default risk in addition to liquidity risk and expected illiquidity. Our results show that liquidity risk is significantly priced in the cross-section of single-name CDS returns and has a larger contribution than expected illiquidity to the difference in expected returns between the most illiquid low-credit-quality CDSs and the most liquid high-credit-quality CDSs.

# Appendices

# A Computation of Theoretical Index Levels

In this Appendix we describe in detail how we infer theoretical credit index levels from single-name CDS spreads on the underlying entities. Our implementation follows the methodology briefly outlined in the Markit Credit Index Primer (2011) and consists of four steps.

First, for each reference name we separately calibrate risk neutral survival probabilities to the quoted term-structure of its single-name CDS spreads. Brigo and Mercurio (2006) argue that this can be done in a close to model independent fashion by imposing the following assumptions: (i) Credit events occur randomly at the first jump times $\tau_i$ of

independent (across constituents $i = 1, \ldots, I$), inhomogeneous Poisson processes with deterministic intensities, (ii) risk neutral intensities are piecewise constant between maturity dates of the single-name CDSs, (iii) interest rates evolve independent of the occurrence of credit events, and (iv) in case a credit event occurs, creditors recover a constant fraction of the reference obligation's par value.

Due to assumption (iii), discount factors can be computed using well-known techniques from the interest rate literature. We first obtain a bootstrapped zero-rate curve from the term-structure of LIBOR rates. Assuming constant instantaneous forward rates between tenor dates, we then construct discount factors for arbitrary horizons using the bootstrapped zero rates. In the following we denote by $D(t, u)$ the time $t$ discount factor applicable to risk free cash flows occurring at time $u \geq t$.

Under assumptions (i)-(iv) the present value of the protection leg of a $T$-maturity single-name CDS on reference name $i$ is given by

$$PV_{1,i}(t, T, R_i) = -\int_t^T (1 - R_i) D(t, u) dS_i(t, u) \tag{A.1}$$

where $S_i(t, u) = \mathbb{Q}(\tau_i > u | \tau_i > t)$ is the risk neutral probability of entity $i$'s survival up to and including time $u$, conditional on not having observed a credit event before time $t$, and $R_i$ denotes the constant recovery rate. The present value of the corresponding premium leg with spread $C_i$ and payment dates $t_0 \leq t < t_1 < \cdots < t_J = T$ is

$$\begin{aligned} PV_{2,i}(t, T, C_i) = \sum_{j=1}^{J} \Bigg( & \alpha C_i (t_j - t_{j-1}) D(t, t_j) S_i(t, t_j) \\ & - \int_{t \vee t_{j-1}}^{t_j} \alpha C_i (u - t_{j-1}) D(t, u) dS_i(t, u) \Bigg) \end{aligned} \tag{A.2}$$

where $\alpha = 365/360$ is a constant factor transforming calendar time measured in years into an ACT/360 daycount convention.[50] Note that the integrals appearing in the above equations can be computed analytically for any sub-period of the integration domain over which both instantaneous forward rates and intensities are constant.

Given the quoted term-structure of par spreads $C_i^{par}(t, T_1), \ldots, C_i^{par}(t, T_K)$ for each of the $I_t$ reference names that, prior to time $t$, have not triggered a credit event and the corresponding recovery rate estimate, $R_i$, survival probabilities can be obtained by bootstrapping over maturities $T_k$, $k = 1, \ldots, K$, such that model implied (clean) par spreads match the quoted ones. That is, one solves

$$0 = PV_{1,i}(t, T_k, R_i) - (PV_{2,i}(t, T_k, C_i^{par}(t, T_k)) - \alpha C_i^{par}(t, T_k)(t - t_0)), \tag{A.3}$$

$k = 1, \ldots, K$, numerically for the survival probability $S_i(t, T_k)$ for any $k$, given the previous $k-1$ survival probabilities.[51] Due to assumption (ii) survival probabilities for intermediate points in time can easily be obtained by interpolation.

[50] The second term of Equation (A.2) is the present value of the accrual on default.

[51] The second term of Equation (A.3) is the spread accrual paid by the protection seller of a standardized CDS contract at inception of trade. Throughout we assume single-name CDS contracts to be standardized apart from their restructuring clauses. That is we assume that (i) on-the-run issues are launched on the 20th of March, June, September, and December, (ii) on-the-run issues launched on the 20th of March (June) [September] expire on the 20th of June (September) [December] of the year following the launch date by the term of the contract, (iii) on-the-run issues launched on the 20th of December expire on the 20th of March of the year following the launch date by the term of the contract plus one, (iv) spread payments occur on the 20th of March, June, September, and December.

In the second step the fitted survival probabilities are used to compute present values—or upfront payments—of the single-name CDSs in the underlying basket of the credit index. These CDSs have the same terms as the credit index, i.e., their maturities equal that of the credit index, $T$, and their spreads equal the index's fixed spread C, which usually differs from the par spreads used to infer survival probabilities.[52] This is tantamount to non-zero present values of the single-name CDSs. Thus, the second step amounts to compute, for each reference name $i$, the present value of a CDS with the same terms as the credit index

$$PV_i^{CDS}(t,T,C) = PV_{1,i}(t,T,R_i) - (PV_{2,i}(t,T,C) - \alpha C(t-t_0)).$$

The third step determines the present value of the underlying basket of the credit index, which is a weighted average of present values computed in the second step. Single-name CDSs in the basket are equally weighted and weights of triggered CDSs are set to zero. This gives the basket's present value

$$PV_{idx}(t,T,C) = \frac{1}{I}\sum_{i=1}^{I_t} PV_i^{CDS}(t,T,C),$$

or equivalently the theoretical upfront charge. Since upfront charges correspond to spread levels, the remaining fourth step requires to convert the theoretical upfront charge into a spread, the theoretical index level. Standardization of CDS markets has led to the convention of using the ISDA's CDS Standard Model to transfer quoted spreads to upfront payments and vice versa.[53] Following this convention the theoretical index level equals the par spread $C^*(t,T)$ of a single-name CDS with the same maturity as the credit index whose upfront payment, when traded at the index's fixed spread, equals the index's theoretical upfront charge, i.e., $C^*(t,T)$ solves

$$PV_{idx}(t,T,C) = PV_{1,idx}(t,T,R_{idx}) - (PV_{2,idx}(t,T,C) - \alpha C(t-t_0)),$$

where $R_{idx}$ is the recovery rate assumption specified in the index's contract terms. Note that $PV_{1,idx}(t,T,R_{idx})$ and $PV_{2,idx}(t,T,C)$ depend on the theoretical level $C^*(t,T)$ through the survival probability $S_{idx}(t,T)$, that is determined by the par spread condition

$$0 = PV_{1,idx}(t,T,R_{idx}) - (PV_{2,idx}(t,T,C^*(t,T)) - \alpha C^*(t,T)(t-t_0)).$$

for the theoretical index level $C^*(t,T)$.

# B Computation of Returns and Transaction Costs

This Appendix explains the construction of returns on CDSs, both realized and expected, and transaction costs.

[52] Note that documentation clauses of the basket's single-name CDSs have to coincide with that of the index as well. Berndt et al. (2007) present a CDS pricing framework that differentiates between restructuring and default events. It, however, fails to account for alternative documentation clauses that consider restructuring as a credit event. Moreover, implementation requires assumptions on the relative frequencies of restructuring and default events and the recovery rate in case of restructuring. Therefore, we do not account for differences in documentation clauses and as such $PV_i^{CDS}(t,T,C)$ always reflects the common documentation clause of the CDSs that are used to infer the survival probabilities and not necessarily that of the index.

[53] A simplified version of the ISDA's CDS Standard Model is used to convert upfront charges into spreads and vice versa. In particular, the model used for conversion assumes a flat spread curve. More detailed information, documentation, and source codes for the ISDA CDS Standard Model are available to the public on `http://www.cdsmodel.com`.

We consider the situation in which an investor sells protection on reference name $i$ with a notional amount $N$ via a $T$-maturity CDS whose date $t$ par spread is denoted by $C_{i,t}$. Over a one-week period, in which default does not occur, the CDS's change in net present value equals[54]

$$\Delta CDS_{i,t} = -N\left(C_{i,t} - C_{i,t-1}\right) PV_{i,2}(t,T,1) + N\frac{7}{360}C_{i,t-1}.$$

$\Delta CDS_{i,t}$ reflects the value of selling CDS protection at time $t-1$ and subsequently covering the exposure by entering into an offsetting transaction at time $t$. It can be shown (see, e.g., Berndt and Obreja (2010)) that the change in net present value relative to the CDS's notional amount approximately equals the excess return on a $T$-maturity par defaultable bond issued by reference name $i$. Thus, the CDS's realized excess return, $r^e_{i,t}$, is[55]

$$r^e_{i,t} = -\left(C_{i,t} - C_{i,t-1}\right) PV_{i,2}(t,T,1) + \frac{7}{360}C_{i,t-1}. \tag{B.1}$$

We use Markit five-year mid spreads and the corresponding recovery rates to construct one-week realized CDS returns. This is done for each reference name whenever spreads are available both at the beginning of the one-week period and its end.[56] Recovery rates, $R_i$, enter Equation (B.1) through the risky present value of a basis point, $PV_{i,2}(t,T,1)$, because risk neutral survival probabilities are inferred such that end-of-period mid spreads and recovery rates satisfy the par spread condition

$$0 = PV_{1,i}(t,T,R_i) - (C_{i,t}PV_{2,i}(t,T,1) - \alpha C_{i,t}(t-t_0)),$$

under the assumption of a constant default intensity.

In case that we take into account transaction costs, protection will be sold at the quoted bid, $C_{i,t-1} - s_{i,1}/2$, and has to be bought at the quoted ask, $C_{i,t} + s_{i,t}/2$, where $C_{i,t}$ and $s_{i,t}$ denote the time $t$ mid spread and the time $t$ bid-ask spread, respectively. Therefore the CDS's change in net present value becomes

$$\begin{aligned}\Delta\widetilde{CDS}_{i,t} = &-N\left(C_{i,t} + \frac{s_{i,t}}{2} - \left(C_{i,t-1} - \frac{s_{i,t-1}}{2}\right)\right) PV_{i,2}(t,T,1)\\ &+ N\frac{7}{360}\left(C_{i,t-1} - \frac{s_{i,t-1}}{2}\right).\end{aligned}$$

Separating parts due to transaction costs from those due to changes in the CDS spread, $\Delta\widetilde{CDS}_{i,t}$ can be written as

$$\Delta\widetilde{CDS}_{i,t} = \Delta CDS_{i,t} - N\left(\frac{1}{2}\left(s_t + s_{t-1}\right) PV_{i,2}(t,T,1) + \frac{7}{360}\frac{s_{t-1}}{2}\right),$$

and excess returns net of transaction costs, $r^e_{i,t} - c_{i,t}$, can be obtained by dividing the expression in the previous display by the notional amount $N$. This yields the following expression for transaction costs, $c_{i,t}$,

$$c_{i,t} = \frac{1}{2}\left(s_t + s_{t-1}\right) PV_{i,2}(t,T,1) + \frac{7}{360}\frac{s_{t-1}}{2}. \tag{B.2}$$

[54] In the event of default by the entity between $t-1$ and $t$, the change in net present value of the protection seller's position equals the negative of loss given default. These cases can be neglected in the portfolio analysis if idiosyncratic jump-to-default risk is not priced; see, e.g., the argument in Bongaerts et al. (2011).

[55] Discount factors and all integrals appearing (either explicitly or implicitly) in the expression of CDS returns, both expected and realized, and proportional transaction costs are evaluated by the same methodologies as in Appendix A.

[56] Recovery rates are set to 40% whenever they are not available.

In order to compute transaction costs, we use Markit five-year mid spreads and the corresponding recovery rates (which determine $PV_{i,2}(t,T,1)$) along with a reference name's weekly average bid-ask spread inferred from Bloomberg data.[57] We use weekly averages instead of end-of-period bid-ask spreads due to a considerable number of missing bid spreads and/or ask spreads. Whenever an entity's end-of-period mid spread is available as well as weekly average bid-ask spreads at the beginning and end of the one-week period, its transaction costs are constructed according to Equation (B.2).

Bongaerts et al. (2011) also show that conditional expected CDS returns can be defined by

$$\begin{aligned}\widehat{E}_t[r^e_{i,t+T}] = \sum_{j=1}^{J} \Bigg( & \alpha C_{i,t}(t_j - t_{j-1}) D(t,t_j) P_i(t,t_j) \\ & - \int_{t \vee t_{j-1}}^{t_j} \alpha C_{i,t}(u - t_{j-1}) D(t,u) dP_i(t,u) \Bigg) + \int_t^T (1 - R_i) D(t,u) dP_i(t,u),\end{aligned} \tag{B.3}$$

where in contrast to expressions (A.1) and (A.2) the time $t$ physical probability of survival up to time $u$, $P_i(t,u) = \mathbb{P}(\tau_i > u | \tau_i > t)$, integrates payoffs rather than the risk neutral probability. Physical survival probabilities are extracted from Moody's KMV one-year and five-year EDFs through

$$\mathbb{P}(\tau_i > 1 | \tau_i > t) = 1 - EDF_{1,t} \qquad \text{and} \qquad \mathbb{P}(\tau_i > 5 | \tau_i > t) = (1 - EDF_{5,t})^5,$$

and intermediate values are obtained by interpolation based on the assumption of piecewise constant instantaneous physical default intensities. Then the entity's conditional expected return for a five-year holding period is inferred from Equation (B.3), whenever in addition to the EDFs, the five-year mid spread is available. Expected returns for any other holding period are identified by assuming that conditional expected CDS returns scale proportionally with time-to-maturity.

We emphasize that conditional expected returns inferred in this way are actually estimates. Their accuracy depends on EDFs being an appropriate measure of conditional default probabilities.[58] As shown in Duffie, Saita, and Wang (2007) there exist alternative specifications of conditional default probabilities that have higher predictive power than EDFs. However, since the increase in predictive power is only marginal and since EDFs are readily available for reference names in our sample, we choose to base our construction of conditional expected returns on EDFs rather than more sophisticated specifications.

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[57] In the above notation, $s_{i,t}$ denotes the weekly average bid-ask spread of entity $i$. We consider only non-negative bid-ask spreads for the computation of weekly averages.

[58] For a discussion concerning the accuracy of EDFs see, e.g., Berndt, Douglas, Duffie, Ferguson, and Schranz (2005) and the references therein.

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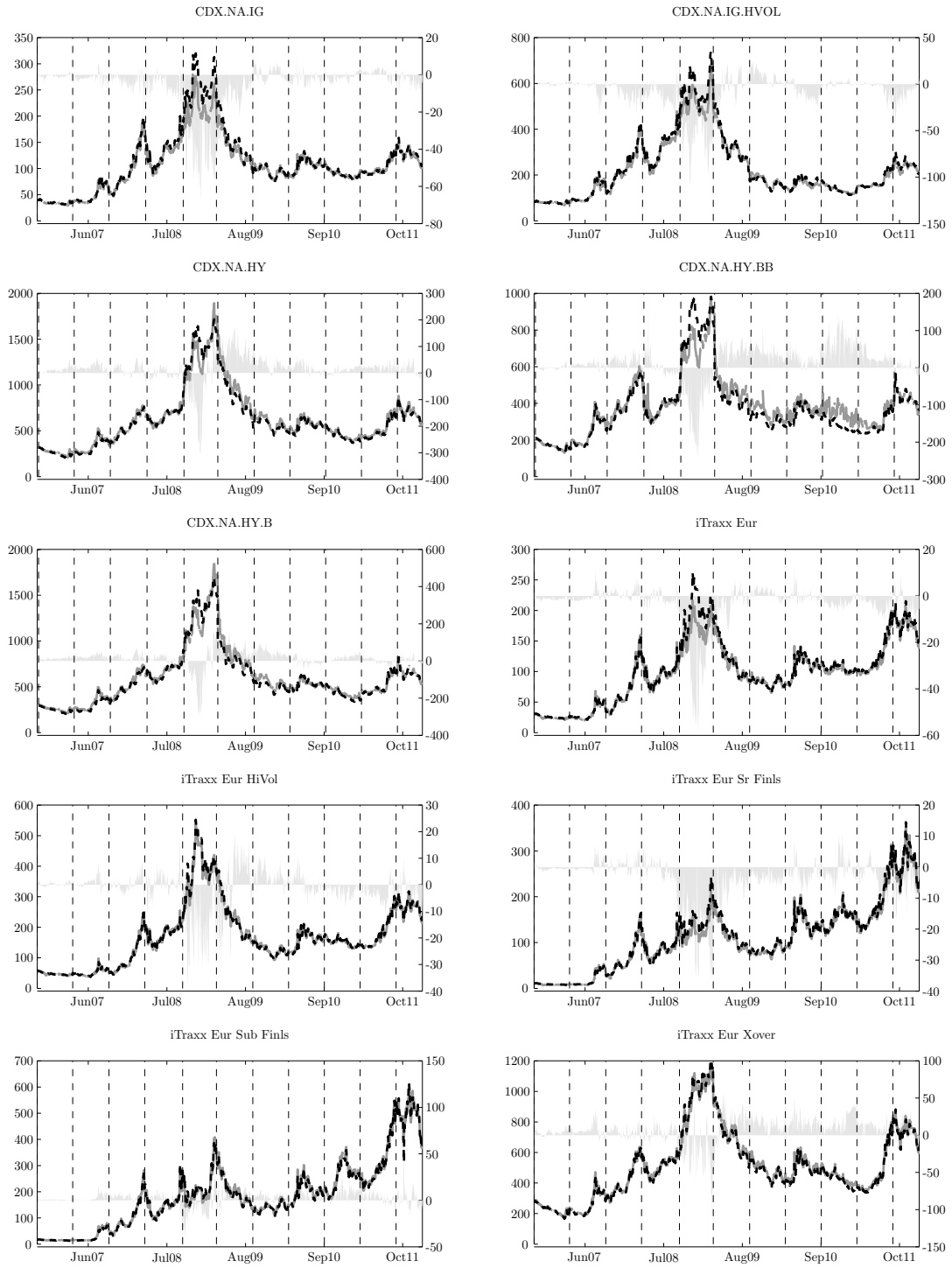


Figure 1: Published Credit Index Levels, Theoretical Index Levels, and Index-to-Theoretical Bases.

The figure displays daily observations of published credit index levels of the five-year continuous on-the-run series (gray lines, left hand scales), theoretical index levels (black dashed lines, left hand scales), and index-to-theoretical bases (light gray shaded areas, right hand scales) from September 20, 2006, to February 1, 2012. Index levels and bases are in basis points and dashed vertical lines correspond to index roll dates.

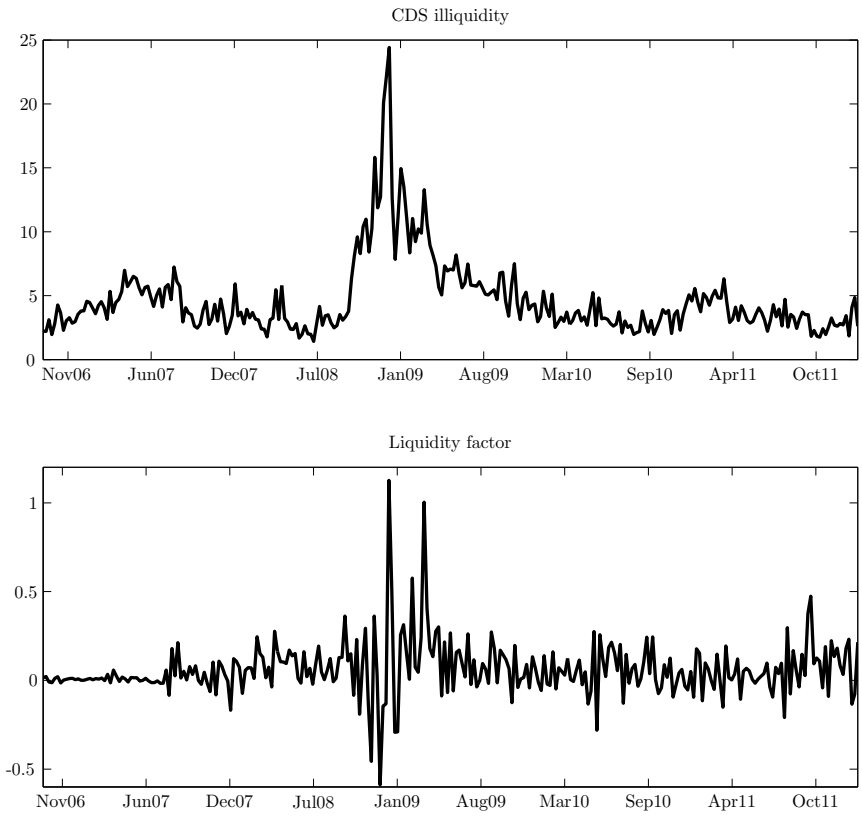


Figure 2: CDS Market Illiquidity Measure and Tradable Liquidity Factor.
The upper panel of the figure displays weekly observations of the CDS market illiquidity measure (in %) between September 20, 2006, and February 1, 2012. The lower panel of the figure displays weekly observations of one-week returns (in %) on the tradable liquidity factor between October 4, 2006, and February 1, 2012.

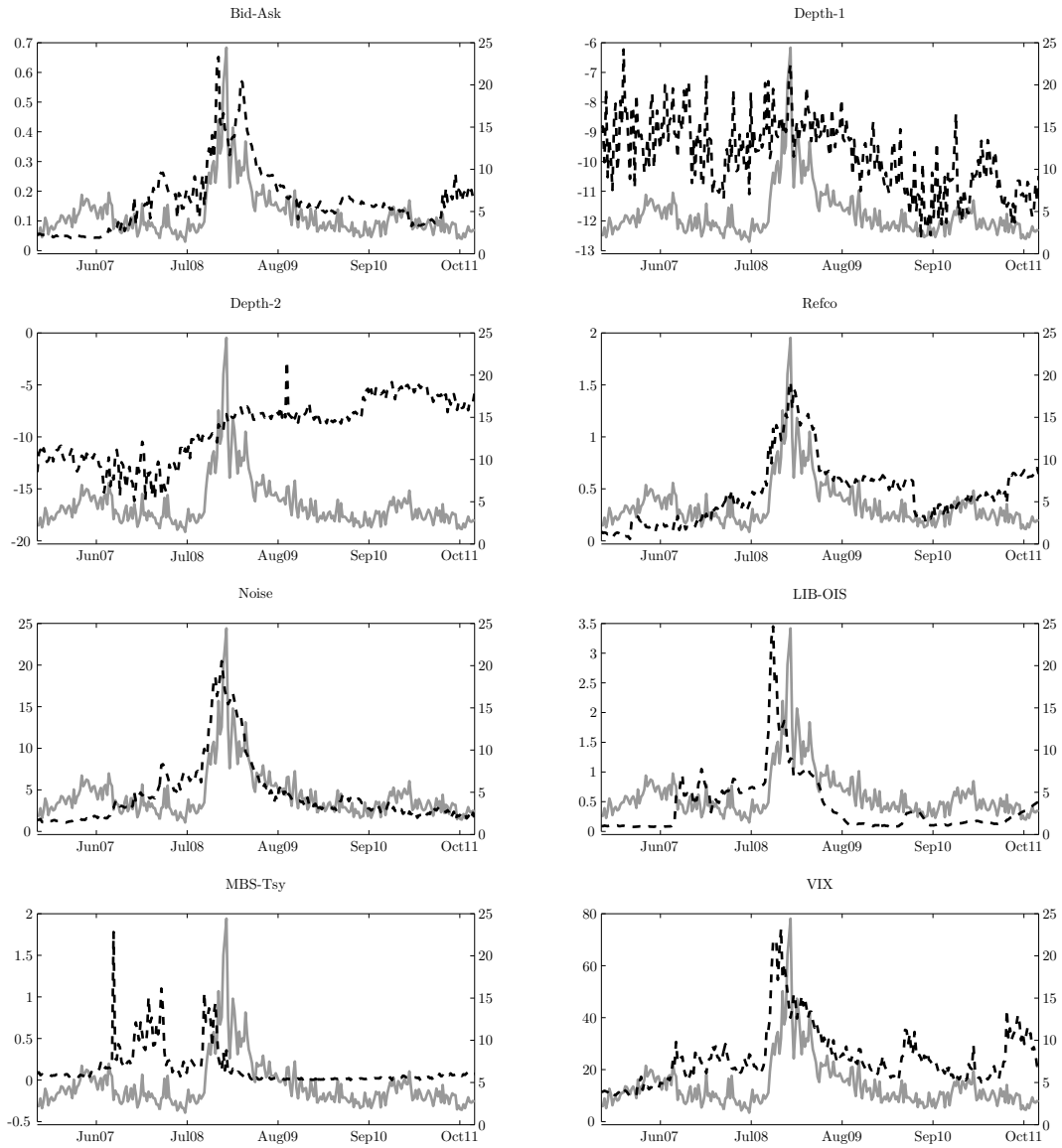


Figure 3: Explanatory Variables vs. CDS Market Illiquidity Measure.
The figure displays weekly observations of the explanatory variables (black dashed lines, left hand scales) and the CDS market illiquidity measure (gray lines, right hand scales) between September 20, 2006, and December 28, 2011. The explanatory variables are: the weighted average (by number of index constituents) mean bid-ask spread of an index constituent's single-name CDS (Bid-Ask), minus the weighted average (by number of index constituents) number of contributors to a composite quote on the five-year continuous on-the-run index (Depth-1), minus the weighted average (by number of index constituents) mean number of contributors to the composite spread quote of an index constituent's five-year contract (Depth-2), the average spread between Resolution Funding Corporation and Treasury constant maturity yields for maturities between three months and ten years (Refco), the Hu, Pan, and Wang (2012) Noise measure (Noise), the spread between three-month USD LIBOR and OIS rates (LIB-OIS), the average spread between Agency MBS and Treasury general collateral repo rates for maturities between one day and three months (MBS-Tsy), and the VIX index (VIX). Bid-Ask, Refco, Noise, LIB-OIS, MBS-Tsy, VIX, and the CDS market illiquidity measure are in %. Depth-1 and Depth-2 are in minus the number of contributors to a composite quote.

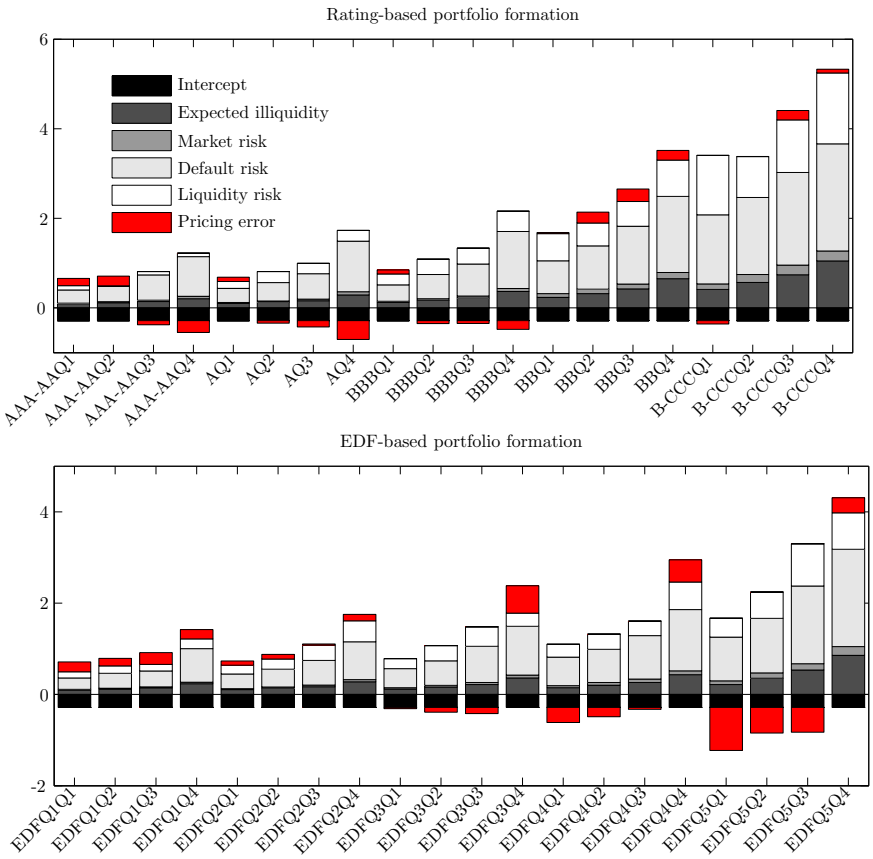


Figure 4: Decomposition of Expected CDS Returns.
The figure displays the decomposition of expected CDS returns (in % p.a.) into factor risk premia at the test portfolio level. Annualized expected CDS returns are decomposed into an intercept term, contributions of, respectively, expected illiquidity and factor risks, and pricing errors as implied by the three-factor specification that accounts for expected illiquidity. The horizontal axis of the respective panels display portfolio identifiers.

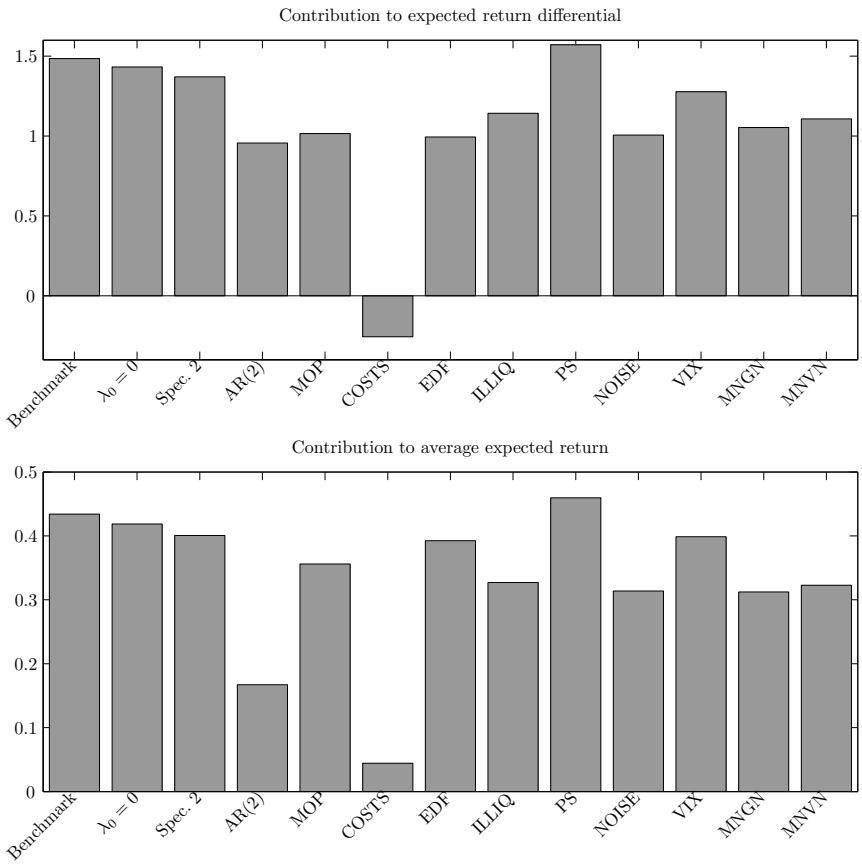


Figure 5: Contribution of Liquidity Risk.
The figure displays the contributions of liquidity risk to expected CDS returns (in % p.a.) in the benchmark specification of the model and in robustness check specifications using alternative measures of economic importance. The upper panel displays the difference in contributions of the B-CCCQ4 and the AAA-AAQ1 portfolios and the lower panel displays the average contribution among the 40 portfolios. The horizontal axis of the respective panels display specification identifiers.

| | CDX North American | | iTraxx Europe | |
|---|---|---|---|---|
| Main index (No. of constituents) | CDX.NA.IG (125) | CDX.NA.HY (100) | iTraxx Eur (125) | iTraxx Eur Xover ($\leq$50) |
| Sub-indices (No. of constituents) | CDX.NA.IG.HVOL (30) | CDX.NA.HY.BB ($\leq$100)<br>CDX.NA.HY.B ($\leq$100) | iTraxx Eur HiVol (30)<br>iTraxx Eur Sr Finls (25)<br>iTraxx Eur Sub Finls (25) | |
| Eligible reference names (ref. names) | Corporate & Financial[a] | Corporate & Financial[a] | Corporate & Financial | Corporate |
| Domicile of eligible ref. names | North America | North America | Europe | Europe |
| Rating of eligible ref. names | Investment grade | High-yield or not rated | Investment grade | High-yield or not rated |
| Index roll dates | March and September $20^{th}$ | March and September $27^{th}$ | March and September $20^{th}$ | March and September $20^{th}$ |
| Inclusion & exclusion (main index) | Eligible ref. names that are not members of the current index series and that rank among the most liquid 20% in terms of market risk activity in the Depository Trust & Clearing Corporation's (DTCC's) Trade Information Warehouse (TIW) over the six-month period preceding an index roll date are to be included in the next index series. Eligible ref. names that are members of the current index series and that rank among the most illiquid 30% in terms of market risk activity in the DTCC's TIW over the six-month period preceding an index roll date are excluded from the new series along with ref. names that are members of the current index series but no longer meet eligibility criteria. | Eligible ref. names that are not members of the current index series and that rank among the most liquid 20% in terms of market risk activity in the DTCC's TIW over the six-month period preceding an index roll date are to be included in the next index series. Eligible ref. names that are members of the current index series and that rank among the most illiquid 30% in terms of market risk activity in the DTCC's TIW over the six-month period preceding an index roll date are excluded from the new series along with ref. names that are members of the current index series but no longer meet eligibility criteria. In addition, most illiquid eligible ref. names are removed from and most liquid ref. names are added to the new series until the weight of industry sectors and the weight of credit rating categories in the index approximately corresponds to that of the most recent series of the Markit iBoxx USD Liquid High Yield Index. | Eligible ref. names have to meet the following additional eligibility criterium: Ref. names have to show weekly transaction activity in the DTCC TIW over the last eight weeks prior to the last Friday of the month preceding an index roll date. Eligible ref. names are ranked within their industry sectors in terms of market risk activity in the DTCC's TIW over the six-month period preceding an index roll date. Then the most liquid ref. names of each industry sector are included in the new series of the index which consists of 30 ref. names from the Autos & Industrials sector, 30 ref. names from the Consumers sector, 20 ref. names from the Energy sector, 20 ref. names from the TMT sector, and 25 ref. names from the Financial sector. | Eligible ref. names have to meet the following additional eligibility criteria: (i) Ref. names have to show weekly transaction activity in the DTCC TIW over the last eight weeks prior to the last Friday of the month preceding an index roll date and (ii) the ref. name's average five-year CDS spread over the last ten London trading days of the month preceding an index roll date has to be at least twice the average spread of the iTraxx Eur Non Finl index over this period. Eligible ref. names are ranked in terms of their market risk activity in the DTCC's TIW over the six-month period preceding an index roll date. Then the 50 most liquid eligible ref. names are included in the new index series. In case that less than 50 eligible ref. names meet the inclusion criteria the number of index constituents will be adjusted to a multiple of five by including non-eligible ref. names that violate eligibility criteria (i) and/or (ii) and that have issued a bond with maturity date comparable to that of a five-year CDS contract whose credit spread satisfies criteria (ii) from above. |
| Inclusion (sub-indices) | The 30 eligible ref. names included in the main index with the widest average CDS spread over the past 90 calendar days, as measured from six days prior to the index roll date, constitute the HVOL sub-index. | Eligible ref. names included in the main index with BB+, BB, or BB- ratings (or Moody's KMV equivalents) comprise the BB sub-index. Eligible ref. names included in the main index with B+, B, or BB- ratings (or Moody's KMV equivalents) constitute the B sub-index. | The 30 eligible ref. names that are included in main index but do no belong to the Financial sector and that exhibit the widest average CDS spread over the last ten London trading days of the month preceding an index roll date constitute the HiVol sub-index. The 25 ref. names from the Financial sector that are included in the main index constitute the Sr Finls index and the Sub Finls index. | |
| Currency of index contract | USD | USD | EUR | EUR |
| Tier of index contract | Senior unsecured debt | Senior unsecured debt | Senior unsecured debt[b] | Senior unsecured debt |
| Documentation clause of index contract | No restructuring | No restructuring | Modified modified restructuring | Modified modified restructuring |
| Maturity of index contract in years | 1, 2, 3, 5, 7, 10 | 3, 5, 7, 10 | 3, 5, 7, 10[c] | 3, 5, 7, 10 |
| Maturity dates of index contract | June and December $20^{th}$ | June and December $20^{th}$ | June and December $20^{th}$ | June and December $20^{th}$ |
| Quotation of index contract | Spread | Price | Spread | Spread |

Table 1: Summary of Index Rules.

[a]Market makers of the index are not eligible for inclusion.

[b]Tier for the Sub Finls sub-index is subordinated or lower Tier2 debt.

[b]Contract maturities of the Sr Finls and Sub Finls sub-indices are 5 and 10 years.

Panel A: Credit Index Levels

| | CDX North American | | | | | iTraxx Europe | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | IG | IG.HVOL | HY | HY.BB | HY.B | Main | HiVol | Sr Finls | Sub Finls | Xover |
| Mean | 106.51 | 221.67 | 631.10 | 382.30 | 596.49 | 97.64 | 167.20 | 108.74 | 186.88 | 514.17 |
| Median | 99.88 | 180.17 | 567.69 | 371.52 | 533.10 | 98.49 | 153.41 | 104.06 | 172.25 | 476.30 |
| Standard Deviation | 49.67 | 125.90 | 312.70 | 150.50 | 293.42 | 48.39 | 99.04 | 72.26 | 130.83 | 217.83 |
| Minimum | 28.88 | 67.38 | 208.52 | 129.37 | 210.79 | 20.09 | 38.69 | 6.81 | 12.43 | 170.75 |
| Maximum | 279.67 | 682.82 | 1893.56 | 972.85 | 1842.83 | 215.92 | 550.00 | 353.00 | 607.80 | 1150.33 |
| N | 1337 | 1341 | 1336 | 1324 | 1325 | 1356 | 1356 | 1355 | 1353 | 1355 |

Panel B: Index-to-Theoretical Bases

| | CDX North American | | | | | iTraxx Europe | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | IG | IG.HVOL | HY | HY.BB | HY.B | Main | HiVol | Sr Finls | Sub Finls | Xover |
| Mean | -6.24 | -9.01 | 17.44 | 15.10 | 17.17 | -3.79 | -1.48 | -3.88 | 2.82 | 7.30 |
| Median | -2.13 | -2.19 | 17.41 | 16.57 | 16.51 | -1.59 | -0.33 | -1.90 | 2.72 | 7.53 |
| Standard Deviation | 12.42 | 18.88 | 50.71 | 47.45 | 51.75 | 9.07 | 7.05 | 6.91 | 8.13 | 16.86 |
| Minimum | -66.91 | -109.84 | -304.65 | -233.37 | -301.86 | -58.64 | -39.02 | -37.02 | -41.02 | -105.65 |
| Maximum | 11.16 | 44.57 | 278.32 | 184.51 | 460.98 | 13.91 | 20.52 | 13.94 | 112.06 | 55.98 |
| Corr. of Abs. Value with Levels | 0.76 | 0.80 | 0.64 | 0.53 | 0.60 | 0.53 | 0.64 | 0.35 | 0.35 | 0.47 |
| N | 1337 | 1341 | 1336 | 1324 | 1325 | 1356 | 1356 | 1355 | 1353 | 1355 |

Panel C: Returns on Index Arbitrage Strategy

| | CDX North American | | | | | iTraxx Europe | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | IG | IG.HVOL | HY | HY.BB | HY.B | Main | HiVol | Sr Finls | Sub Finls | Xover |
| Mean | 4.58 | 7.14 | 15.98 | 14.08 | 19.70 | 3.11 | 4.92 | 3.36 | 11.50 | 13.98 |
| Standard Deviation | 24.03 | 40.14 | 108.56 | 100.96 | 104.07 | 16.79 | 25.24 | 19.02 | 34.98 | 50.79 |
| Annual. Sharpe Ratio | 2.49 | 1.03 | 1.43 | 1.29 | 0.98 | 1.71 | 2.29 | 1.57 | 1.22 | 1.03 |
| Median | 3.38 | 4.16 | 7.65 | 6.60 | 4.37 | 1.02 | 2.41 | 1.30 | 4.88 | 7.71 |
| Skewness | 1.55 | 1.15 | 0.76 | 2.39 | 2.12 | 0.81 | -0.38 | -0.20 | 1.64 | 0.48 |
| Kurtosis | 21.28 | 9.30 | 10.34 | 19.66 | 13.62 | 9.31 | 9.39 | 6.84 | 9.24 | 7.31 |
| $\rho_1$ | -0.14 | -0.07 | -0.04 | 0.09 | 0.08 | -0.00 | -0.28 | -0.16 | 0.14 | 0.01 |
| N | 273 | 272 | 275 | 268 | 268 | 277 | 277 | 277 | 275 | 275 |

Panel D: Pairwise Correlations of Returns on Index Arbitrage Strategy

| | CDX North American | | | | | iTraxx Europe | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | IG | IG.HVOL | HY | HY.BB | HY.B | Main | HiVol | Sr Finls | Sub Finls | Xover |
| IG | 1.00 | 0.47 | 0.09 | 0.17 | 0.05 | 0.44 | 0.15 | 0.13 | 0.09 | 0.09 |
| IG.HVOL | | 1.00 | 0.09 | 0.10 | 0.08 | 0.13 | 0.04 | -0.06 | 0.06 | -0.06 |
| HY | | | 1.00 | 0.25 | 0.48 | 0.27 | 0.16 | -0.09 | 0.06 | 0.05 |
| HY.BB | | | | 1.00 | 0.47 | 0.18 | 0.06 | 0.12 | 0.27 | 0.18 |
| HV.B | | | | | 1.00 | 0.25 | 0.15 | 0.06 | 0.12 | 0.05 |
| Main | | | | | | 1.00 | 0.38 | 0.27 | 0.08 | 0.25 |
| HiVol | | | | | | | 1.00 | 0.06 | 0.03 | 0.10 |
| Sr Finls | | | | | | | | 1.00 | 0.04 | 0.01 |
| Sub Finls | | | | | | | | | 1.00 | 0.19 |
| Xover | | | | | | | | | | 1.00 |

Table 2: Descriptive Statistics.

The table displays descriptive statistics of credit index levels, index-to-theoretical bases, and index arbitrage returns. Panel A provides descriptive statistics of published credit index levels of five-year continuous on-the-run series. Panel B provides descriptive statistics of the corresponding index-to-theoretical bases. Panels C and D provide descriptive statistics of one-week returns on the index arbitrage strategy underlying the construction of the tradable liquidity factor. Descriptive statistics are in basis points and missing observations are neglected in their computation. $\rho_1$ denotes first order autocorrelation and annualization of Sharpe ratios accounts for non-independent returns using Lo's (2002) correction. Time series in Panels A and B consist of the indicated number of daily observations from September 20, 2006, to February 1, 2012. Time series in Panel C and D consist of the indicated number of weekly observations from October 4, 2006, and February 1, 2012.

Panel A:

| | Panel A1: Univariate Specifications | | | | | | | | Panel A2: Multivariate Specifications | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.25 | 2.92 | 0.68 | 0.38 | 0.59 | 0.54 | 0.56 | 0.06 | 3.44 | 3.25 | 3.94 | 3.97 | 3.79 | 3.54 |
| | [0.90] | [2.97] | [1.92] | [1.39] | [2.21] | [2.01] | [1.98] | [0.24] | [2.72] | [2.46] | [2.92] | [2.74] | [2.78] | [2.67] |
| Bid-Ask | 5.20 | | | | | | | | 5.55 | | | | | 1.67 |
| | [3.39] | | | | | | | | [3.61] | | | | | [0.58] |
| Depth-1 | | 0.22 | | | | | | | 0.28 | 0.29 | 0.26 | 0.26 | 0.33 | 0.27 |
| | | [2.77] | | | | | | | [2.96] | [2.85] | [2.73] | [2.54] | [3.24] | [2.62] |
| Depth-2 | | | 0.01 | | | | | | 0.02 | -0.01 | 0.05 | 0.07 | 0.03 | 0.03 |
| | | | [0.46] | | | | | | [0.55] | [-0.34] | [1.37] | [1.80] | [0.87] | [0.72] |
| Refco | | | | 1.59 | | | | | | 1.98 | | | | 0.10 |
| | | | | [3.24] | | | | | | [3.82] | | | | [0.16] |
| Noise | | | | | 0.19 | | | | | | 0.20 | | | 0.17 |
| | | | | | [4.18] | | | | | | [4.37] | | | [1.93] |
| LIB-OIS | | | | | | 0.73 | | | | | | 0.87 | | -0.20 |
| | | | | | | [4.44] | | | | | | [3.98] | | [-0.37] |
| MBS-Tsy | | | | | | | 0.36 | | -0.11 | 0.06 | -0.50 | -0.45 | -0.34 | -0.44 |
| | | | | | | | [0.74] | | [-0.24] | [0.12] | [-1.13] | [-0.81] | [-0.68] | [-0.76] |
| VIX | | | | | | | | 0.04 | | | | | 0.04 | 0.00 |
| | | | | | | | | [3.98] | | | | | [4.22] | [0.19] |
| $\text{CDSILLIQ}_{t-1}$ | 0.76 | 0.84 | 0.87 | 0.76 | 0.70 | 0.82 | 0.87 | 0.80 | 0.70 | 0.69 | 0.64 | 0.76 | 0.73 | 0.64 |
| | [9.72] | [11.43] | [12.51] | [9.61] | [8.92] | [11.86] | [12.65] | [10.71] | [8.52] | [8.11] | [7.57] | [10.06] | [8.87] | [7.58] |
| $\bar{R}^2$ | 0.78 | 0.77 | 0.76 | 0.77 | 0.79 | 0.77 | 0.76 | 0.77 | 0.79 | 0.78 | 0.79 | 0.78 | 0.78 | 0.79 |
| N | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 |

Panel B:

| | Bid-Ask | Depth-1 | Depth-2 | Refco | Noise | LIB-OIS | MBS-Tsy | VIX | $\text{CDSILLIQ}_{t-1}$ | $\text{CDSILLIQ}_t$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Bid-Ask | 1.00 | 0.17 | 0.21 | 0.85 | 0.86 | 0.65 | 0.16 | 0.84 | 0.62 | 0.66 |
| Depth-1 | | 1.00 | -0.38 | 0.13 | 0.33 | 0.31 | 0.17 | 0.09 | 0.40 | 0.42 |
| Depth-2 | | | 1.00 | 0.40 | -0.01 | -0.19 | -0.50 | 0.16 | 0.08 | 0.08 |
| Refco | | | | 1.00 | 0.79 | 0.56 | 0.03 | 0.79 | 0.68 | 0.68 |
| Noise | | | | | 1.00 | 0.79 | 0.32 | 0.81 | 0.72 | 0.75 |
| LIB-OIS | | | | | | 1.00 | 0.57 | 0.77 | 0.45 | 0.49 |
| MBS-Tsy | | | | | | | 1.00 | 0.32 | 0.06 | 0.08 |
| VIX | | | | | | | | 1.00 | 0.56 | 0.58 |
| $\text{CDSILLIQ}_{t-1}$ | | | | | | | | | 1.00 | 0.87 |

Table 3: Time Series Properties of CDS Market Illiquidity.

The table displays results from regressing the CDS market illiquidity measure on proxies for index-specific and Treasury market illiquidity, funding cost measures, and market volatility. Panel A provides results of univariate (Panel A1) and multivariate (Panel A2) regression specifications. Reported are intercepts and slope coefficients, their respective t-statistics in square brackets, adjusted $R^2$'s, and the number of observations. t-statistics are based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors with three lags. Panel B provides pairwise correlations between explanatory variables. Explanatory variables in the regressions are: the weighted average (by number of index constituents) mean bid-ask spread of an index constituent's single-name CDS (Bid-Ask), minus the weighted average (by number of index constituents) number of contributors to a composite quote on the five-year continuous on-the-run index (Depth-1), minus the weighted average (by number of index constituents) mean number of contributors to the composite spread quote of an index constituent's five-year contract (Depth-2), the average spread between Resolution Funding Corporation and Treasury constant maturity yields for maturities between three months and ten years (Refco), the Hu, Pan, and Wang (2012) Noise measure (Noise), the spread between three-month USD LIBOR and OIS rates (LIB-OIS), the average spread between Agency MBS and Treasury general collateral repo rates for maturities between one day and three months (MBS-Tsy), the VIX index (VIX), and the lagged CDS market illiquidity measure $\text{CDSILLIQ}_{t-1}$. Bid-Ask, Refco, Noise, LIB-OIS, MBS-Tsy, VIX, and the CDS market illiquidity measure are in %. Depth-1 and Depth-2 are in minus the number of contributors to a composite quote. Regression are run with time series that consist of the indicated number of weekly observations from September 20, 2006, to December 28, 2011.

| Panel A: | | | |
|---|---|---|---|
| | MKT | DEF | LIQ |
| Mean | -7.71 | -1.40 | 6.33 |
| Standard Deviation | 303.84 | 50.70 | 15.67 |
| Median | 15.99 | 3.80 | 3.63 |
| Skewness | -0.70 | -2.35 | 1.82 |
| Kurtosis | 5.55 | 18.50 | 15.80 |
| $\rho_1$ | -0.06 | 0.50 | 0.08 |

| Panel B: | | | |
|---|---|---|---|
| | MKT | DEF | LIQ |
| MKT | 1.00 | 0.46 | 0.13 |
| LIQ | | 1.00 | 0.15 |
| DEF | | | 1.00 |

Table 4: Descriptive Statistics Factors.
The table displays descriptive statistics for the three factors. Panel A provides descriptive statistics of the three factors and Panel B displays the factor correlation matrix. Descriptive statistics are in basis points and $\rho_1$ denotes first order autocorrelation. Factor time series consist of 276 weekly observations from October 11, 2006, to February 1, 2012.

Panel A:

| | Expected Returns (% p.a.) | | | | Realized Returns (bps per week) | | | | Transaction Costs (%) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bid-Ask Spread | | | | Bid-Ask Spread | | | | Bid-Ask Spread | | | |
| Rating | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| AAA-AA | 0.37 | 0.43 | 0.43 | 0.67 | -1.30 | -0.71 | -0.68 | 0.42 | 0.19 | 0.23 | 0.29 | 0.41 |
| | [6.79] | [7.53] | [6.35] | [6.09] | [-0.97] | [-0.48] | [-0.38] | [0.14] | [11.20] | [10.73] | [10.23] | [7.81] |
| A | 0.40 | 0.47 | 0.57 | 1.02 | -1.28 | -1.13 | -0.49 | 0.80 | 0.21 | 0.26 | 0.33 | 0.59 |
| | [7.75] | [7.12] | [5.80] | [4.36] | [-0.83] | [-0.59] | [-0.17] | [0.13] | [12.57] | [11.39] | [9.50] | [7.44] |
| BBB | 0.56 | 0.74 | 0.99 | 1.68 | -1.36 | -0.99 | 0.80 | 4.99 | 0.24 | 0.34 | 0.44 | 0.75 |
| | [9.60] | [7.16] | [6.43] | [5.32] | [-0.74] | [-0.34] | [0.18] | [0.61] | [12.18] | [9.51] | [8.86] | [7.88] |
| BB | 1.40 | 1.85 | 2.37 | 3.23 | -3.05 | 1.24 | 4.90 | 12.41 | 0.48 | 0.65 | 0.86 | 1.32 |
| | [10.02] | [9.42] | [8.69] | [9.26] | [-0.68] | [0.22] | [0.60] | [1.05] | [9.39] | [8.86] | [8.57] | [9.19] |
| B-CCC | 3.05 | 3.10 | 4.12 | 5.04 | -3.79 | 9.93 | 14.20 | 14.70 | 0.84 | 1.15 | 1.50 | 2.13 |
| | [11.09] | [13.00] | [8.12] | [7.17] | [-0.37] | [0.84] | [0.96] | [0.98] | [6.65] | [7.00] | [7.10] | [9.70] |

| | CDS Spread (% p.a.) | | | | Standard Deviation (bps per week) | | | | Weekly Turnover (in bps) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bid-Ask Spread | | | | Bid-Ask Spread | | | | Bid-Ask Spread | | | |
| Rating | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| AAA-AA | 0.44 | 0.52 | 0.72 | 1.17 | 18.67 | 25.02 | 40.82 | 60.14 | 86.57 | 98.74 | 105.05 | 117.90 |
| A | 0.53 | 0.66 | 0.85 | 1.94 | 22.11 | 28.27 | 36.55 | 66.84 | 83.99 | 86.80 | 87.22 | 103.81 |
| BBB | 0.75 | 1.00 | 1.36 | 2.67 | 28.34 | 36.92 | 47.14 | 73.76 | 82.43 | 87.04 | 96.97 | 101.67 |
| BB | 1.97 | 2.69 | 3.55 | 5.36 | 68.11 | 79.60 | 96.36 | 119.96 | 107.98 | 101.74 | 105.85 | 108.35 |
| B-CCC | 4.59 | 5.72 | 8.00 | 11.70 | 124.68 | 141.48 | 175.99 | 213.41 | 112.17 | 116.64 | 120.79 | 138.66 |

Panel B:

| | Expected Returns (% p.a.) | | | | Realized Returns (bps per week) | | | | Transaction Costs (%) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bid-Ask Spread | | | | Bid-Ask Spread | | | | Bid-Ask Spread | | | |
| 5-year EDF | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| EDFQ1 | 0.43 | 0.51 | 0.63 | 1.14 | -0.80 | -0.30 | -0.16 | 0.69 | 0.20 | 0.24 | 0.29 | 0.47 |
| | [8.76] | [8.38] | [8.47] | [7.36] | [-0.62] | [-0.20] | [-0.09] | [0.17] | [13.35] | [13.40] | [12.96] | [10.58] |
| EDFQ2 | 0.45 | 0.59 | 0.82 | 1.47 | -0.93 | -0.88 | -0.59 | 1.98 | 0.21 | 0.27 | 0.34 | 0.56 |
| | [8.70] | [7.69] | [7.60] | [6.38] | [-0.61] | [-0.45] | [-0.22] | [0.38] | [11.99] | [11.92] | [10.41] | [9.81] |
| EDFQ3 | 0.47 | 0.68 | 1.06 | 2.10 | -2.20 | -1.24 | -0.88 | 4.56 | 0.24 | 0.33 | 0.44 | 0.73 |
| | [6.93] | [6.55] | [6.53] | [7.36] | [-1.13] | [-0.44] | [-0.21] | [0.72] | [10.76] | [9.17] | [9.54] | [10.16] |
| EDFQ4 | 0.48 | 0.83 | 1.28 | 2.67 | -2.69 | 0.35 | 2.08 | 5.05 | 0.30 | 0.41 | 0.53 | 0.88 |
| | [5.14] | [6.13] | [6.47] | [7.17] | [-0.89] | [0.08] | [0.36] | [0.61] | [8.29] | [7.90] | [7.92] | [8.57] |
| EDFQ5 | 0.44 | 1.40 | 2.47 | 4.02 | -0.80 | 4.67 | 7.91 | 13.10 | 0.44 | 0.72 | 1.09 | 1.74 |
| | [3.70] | [7.53] | [7.68] | [8.68] | [-0.17] | [0.59] | [0.74] | [0.93] | [6.68] | [6.71] | [7.08] | [8.90] |

| | CDS Spread (% p.a.) | | | | Standard Deviation (bps per week) | | | | Weekly Turnover (in bps) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bid-Ask Spread | | | | Bid-Ask Spread | | | | Bid-Ask Spread | | | |
| 5-year EDF | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| EDFQ1 | 0.47 | 0.55 | 0.68 | 1.24 | 18.31 | 22.35 | 23.42 | 40.18 | 76.62 | 83.34 | 82.49 | 87.97 |
| EDFQ2 | 0.58 | 0.73 | 0.95 | 1.67 | 24.04 | 28.87 | 36.17 | 53.20 | 82.91 | 87.22 | 92.57 | 98.77 |
| EDFQ3 | 0.72 | 0.95 | 1.32 | 2.42 | 29.57 | 36.38 | 46.84 | 65.39 | 88.92 | 94.48 | 95.48 | 102.16 |
| EDFQ4 | 0.99 | 1.37 | 1.85 | 3.29 | 41.46 | 51.23 | 63.16 | 81.68 | 94.73 | 96.80 | 103.02 | 111.88 |
| EDFQ5 | 1.66 | 3.20 | 4.93 | 8.85 | 68.89 | 94.76 | 116.85 | 158.98 | 102.64 | 108.24 | 113.83 | 120.01 |

Table 5: Descriptive Statistics Test Portfolios.

The table displays descriptive statistics for the 40 test portfolios. Panel A provides descriptive statistics for the portfolios formed by first sorting CDS contracts according to credit ratings and then according to bid-ask spreads. Panel B provides descriptive statistics for the portfolios formed by first sorting CDS contracts according to five-year EDFs and then according to bid-ask spreads. Reported are time series averages of conditional expected one-week excess returns, realized one-week returns, transaction costs of a weekly round-trip, and, in square brackets, their corresponding t-statistics, as well as realized return standard deviation and the time series average of the average five-year CDS spread across portfolio constituents and the average weekly turnover of CDSs referencing portfolio constituents. t-statistics are based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors with 24 lags. Portfolio time series consist of 276 weekly observations from October 11, 2006, to February 1, 2012. Weekly turnover of CDSs is only available for part of the sample period.

Panel A:

| | MKT | | | | DEF | | | | LIQ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bid-Ask Spread | | | | Bid-Ask Spread | | | | Bid-Ask Spread | | | |
| Rating | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| AAA-AA | 9.79 | 14.04 | 20.51 | 34.74 | 11.60 | 14.52 | 22.88 | 37.07 | 4.24 | 3.11 | 5.87 | 8.68 |
| | [12.52] | [6.34] | [7.55] | [7.78] | [10.04] | [11.01] | [8.38] | [7.27] | [3.85] | [1.66] | [2.11] | [1.79] |
| A | 12.42 | 16.36 | 23.37 | 44.82 | 13.48 | 17.76 | 24.61 | 47.83 | 5.88 | 8.65 | 9.69 | 14.21 |
| | [10.13] | [12.34] | [14.08] | [10.94] | [6.28] | [7.63] | [12.59] | [8.92] | [4.26] | [4.75] | [3.93] | [3.06] |
| BBB | 17.29 | 23.22 | 29.92 | 45.04 | 17.06 | 24.13 | 31.33 | 51.69 | 8.63 | 12.03 | 13.65 | 19.40 |
| | [12.31] | [15.02] | [12.03] | [11.90] | [6.47] | [10.74] | [8.33] | [7.13] | [3.72] | [5.20] | [5.66] | [5.11] |
| BB | 45.09 | 54.22 | 63.09 | 80.51 | 39.39 | 48.93 | 60.71 | 78.97 | 21.19 | 20.95 | 23.92 | 32.98 |
| | [6.40] | [11.48] | [14.49] | [9.49] | [4.20] | [4.98] | [7.35] | [6.33] | [2.51] | [2.63] | [3.56] | [3.38] |
| B-CCC | 75.13 | 97.22 | 118.99 | 127.26 | 73.82 | 87.38 | 106.16 | 118.44 | 43.20 | 37.45 | 47.01 | 57.99 |
| | [7.09] | [11.69] | [12.42] | [9.04] | [5.31] | [5.38] | [5.88] | [6.99] | [5.20] | [2.88] | [3.19] | [6.85] |

| | MKT | | | | DEF | | | | LIQ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bid-Ask Spread | | | | Bid-Ask Spread | | | | Bid-Ask Spread | | | |
| 5-year EDF | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| EDFQ1 | 10.20 | 12.05 | 14.12 | 24.33 | 10.83 | 13.59 | 15.00 | 28.97 | 4.96 | 6.00 | 5.94 | 9.90 |
| | [12.17] | [12.92] | [12.60] | [10.57] | [7.30] | [8.72] | [11.56] | [13.26] | [4.19] | [4.40] | [4.15] | [4.23] |
| EDFQ2 | 13.83 | 17.03 | 21.97 | 31.64 | 14.38 | 17.57 | 23.60 | 35.08 | 6.93 | 8.16 | 11.66 | 16.52 |
| | [13.37] | [15.66] | [13.65] | [12.53] | [8.49] | [6.93] | [12.65] | [7.41] | [4.35] | [4.06] | [5.45] | [6.11] |
| EDFQ3 | 18.23 | 22.71 | 30.13 | 42.06 | 18.72 | 23.84 | 33.45 | 45.18 | 8.33 | 11.77 | 15.50 | 14.79 |
| | [13.85] | [12.90] | [10.43] | [16.11] | [7.47] | [11.12] | [9.37] | [7.59] | [3.38] | [5.12] | [5.63] | [3.22] |
| EDFQ4 | 27.46 | 35.43 | 43.29 | 54.19 | 27.93 | 34.17 | 43.08 | 57.89 | 11.50 | 14.00 | 15.26 | 24.07 |
| | [17.04] | [15.79] | [11.66] | [11.82] | [9.04] | [9.61] | [7.76] | [6.68] | [3.40] | [3.99] | [2.64] | [3.86] |
| EDFQ5 | 47.47 | 64.84 | 81.27 | 109.24 | 45.32 | 59.36 | 79.56 | 102.35 | 17.97 | 24.38 | 35.66 | 37.64 |
| | [8.85] | [7.89] | [10.59] | [12.41] | [6.94] | [4.30] | [5.63] | [6.39] | [2.70] | [3.04] | [3.59] | [3.31] |

Panel B:

| | MKT | | | | DEF | | | | LIQ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bid-Ask Spread | | | | Bid-Ask Spread | | | | Bid-Ask Spread | | | |
| Rating | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| AAA-AA | 5.46 | 9.28 | 12.49 | 22.23 | 8.73 | 10.17 | 16.83 | 26.50 | 2.19 | 0.34 | 1.66 | 1.72 |
| | [6.51] | [3.85] | [3.73] | [4.83] | [9.52] | [10.83] | [4.95] | [8.09] | [1.84] | [0.19] | [0.81] | [0.65] |
| A | 7.61 | 9.94 | 14.85 | 28.45 | 9.42 | 12.31 | 16.93 | 33.82 | 3.44 | 5.47 | 5.16 | 5.32 |
| | [7.87] | [8.34] | [9.24] | [7.94] | [5.45] | [6.53] | [8.79] | [7.94] | [2.70] | [2.94] | [2.60] | [2.35] |
| BBB | 11.54 | 14.76 | 19.02 | 26.10 | 10.87 | 16.11 | 21.29 | 38.02 | 5.46 | 7.64 | 7.91 | 10.16 |
| | [10.30] | [9.49] | [6.75] | [8.04] | [5.11] | [7.72] | [6.49] | [5.63] | [3.33] | [3.14] | [3.35] | [3.47] |
| BB | 33.17 | 39.32 | 43.59 | 54.58 | 21.93 | 28.94 | 38.60 | 50.88 | 13.51 | 11.40 | 12.33 | 18.08 |
| | [7.77] | [13.97] | [8.86] | [7.66] | [3.37] | [3.79] | [5.40] | [5.70] | [3.55] | [2.86] | [2.82] | [4.63] |
| B-CCC | 49.90 | 70.72 | 86.93 | 89.54 | 46.12 | 51.45 | 61.81 | 71.48 | 29.63 | 20.37 | 26.23 | 35.38 |
| | [7.14] | [11.84] | [11.73] | [6.74] | [4.60] | [4.17] | [4.82] | [6.92] | [3.25] | [4.09] | [5.15] | [2.68] |

| | MKT | | | | DEF | | | | LIQ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bid-Ask Spread | | | | Bid-Ask Spread | | | | Bid-Ask Spread | | | |
| 5-year EDF | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| EDFQ1 | 6.37 | 7.06 | 8.89 | 13.53 | 7.42 | 9.77 | 10.39 | 21.97 | 2.99 | 3.59 | 3.19 | 4.76 |
| | [7.29] | [8.57] | [8.00] | [7.20] | [5.86] | [7.04] | [8.04] | [11.68] | [2.81] | [3.06] | [2.83] | [3.53] |
| EDFQ2 | 8.80 | 10.95 | 13.49 | 18.82 | 9.63 | 11.73 | 16.21 | 24.78 | 4.30 | 4.94 | 7.41 | 10.26 |
| | [7.43] | [9.78] | [9.37] | [8.58] | [6.82] | [5.69] | [9.79] | [6.39] | [2.77] | [2.30] | [3.00] | [4.15] |
| EDFQ3 | 11.81 | 14.30 | 17.92 | 26.42 | 12.49 | 16.06 | 23.68 | 31.94 | 4.87 | 7.45 | 9.53 | 6.45 |
| | [10.20] | [8.21] | [6.97] | [9.54] | [6.35] | [8.06] | [8.62] | [5.85] | [2.36] | [2.77] | [3.99] | [2.52] |
| EDFQ4 | 18.02 | 24.39 | 29.17 | 33.83 | 18.60 | 21.71 | 28.47 | 40.12 | 6.30 | 7.49 | 7.10 | 13.51 |
| | [9.88] | [10.13] | [7.48] | [11.16] | [6.62] | [7.90] | [6.56] | [5.58] | [2.98] | [3.29] | [2.98] | [4.01] |
| EDFQ5 | 33.01 | 46.59 | 55.00 | 77.38 | 28.59 | 35.78 | 50.87 | 63.73 | 9.29 | 12.83 | 20.70 | 17.80 |
| | [6.80] | [8.06] | [12.02] | [10.65] | [6.67] | [3.36] | [4.56] | [5.40] | [3.04] | [2.97] | [4.84] | [3.41] |

Panel C:

| | Adjusted $R^2$ | | | | | Adjusted $R^2$ | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Bid-Ask Spread | | | | | Bid-Ask Spread | | | |
| Rating | Q1 | Q2 | Q3 | Q4 | 5-year EDF | Q1 | Q2 | Q3 | Q4 |
| AAA-AA | 0.46 | 0.44 | 0.38 | 0.48 | EDFQ1 | 0.47 | 0.47 | 0.54 | 0.62 |
| A | 0.49 | 0.53 | 0.60 | 0.66 | EDFQ2 | 0.50 | 0.51 | 0.58 | 0.57 |
| BBB | 0.53 | 0.60 | 0.60 | 0.61 | EDFQ3 | 0.56 | 0.60 | 0.67 | 0.62 |
| BB | 0.57 | 0.59 | 0.58 | 0.62 | EDFQ4 | 0.63 | 0.65 | 0.65 | 0.67 |
| B-CCC | 0.54 | 0.60 | 0.58 | 0.48 | EDFQ5 | 0.63 | 0.60 | 0.67 | 0.61 |

Table 6: Results Time Series Regressions.

The table displays first-step regression results at the level of individual test portfolios. Panel A provides results for single factor specifications and Panel B provides results for three-factor specifications. Panels A and B report the economic magnitudes of estimated factor loadings and their respective t-statistics, given in square brackets. Economic magnitude of a factor is the change in one-week return (in basis points) in response to a one standard deviation move of the respective factor. t-statistics are based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors with 24 lags. Panel C reports adjusted $R^2$ for the three-factor specifications. Regressions are run with time series that consist of 276 weekly observations from October 11, 2006, to February 1, 2012.

| Spec. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\lambda_0$ | -0.24 | -0.54 | -0.24 | -0.29 | -0.46 | -0.61 | -0.25 | -0.49 | -0.26 | -0.29 | -0.42 | -0.55 |
| | [-1.03] | [-1.83] | [-0.94] | [-1.24] | [-1.65] | [-2.53] | [-1.17] | [-1.88] | [-1.19] | [-1.40] | [-1.66] | [-2.59] |
| $\zeta$ | | | | | | | 94.86 | 94.86 | 94.86 | 94.86 | 94.86 | 94.86 |
| | | | | | | | [—] | [—] | [—] | [—] | [—] | [—] |
| $\lambda_{\text{MKT}}$ | 21.43 | | | 14.04 | | 2.93 | 17.43 | | | 10.15 | | 1.46 |
| | [5.51] | | | [3.88] | | [0.55] | [5.15] | | | [3.10] | | [0.33] |
| $\lambda_{\text{DEF}}$ | | 3.98 | | | 2.93 | 4.14 | | 3.23 | | | 2.17 | 3.26 |
| | | [3.88] | | | [2.58] | [3.76] | | [3.73] | | | [2.13] | [3.36] |
| $\lambda_{\text{LIQ}}$ | | | 2.65 | 1.45 | 1.22 | 1.38 | | | 2.17 | 1.41 | 1.20 | 1.35 |
| | | | [3.44] | [3.46] | [3.10] | [2.58] | | | [3.40] | [3.41] | [3.28] | [2.66] |
| $\bar{R}^2$ | 0.90 | 0.91 | 0.90 | 0.91 | 0.92 | 0.92 | 0.92 | 0.93 | 0.93 | 0.93 | 0.94 | 0.94 |

Table 7: Results Cross-Sectional Regressions.

The table displays results of several specifications of the second-step cross-sectional regressions. Specifications of $\widehat{E}[r^e_{i,t}] - \widehat{E}[c_{i,t}]\widehat{\zeta} = \lambda_0 + \widehat{\beta}_i^{\text{MKT}}\lambda_{\text{MKT}} + \widehat{\beta}_i^{\text{DEF}}\lambda_{\text{DEF}} + \widehat{\beta}_i^{\text{LIQ}}\lambda_{\text{LIQ}} + u_i$ are estimated from expected returns, transaction costs, and factor loadings inferred from time series that consist of 276 weekly observations from October 11, 2006, to February 1, 2012. Reported are factor price of risk estimates (in basis points), the corresponding t-statistics in square brackets, and adjusted $R^2$s. t-statistics are based on asymptotic generalized method of moments standard errors (heteroscedasticity and autocorrelation consistent through the use of Newey and West's (1987) method with 24 lags) that account for error-in-variables problems. In the computation of adjusted $R^2$s, expected CDS returns are treated as the dependent variable and calibrated parameters do not affect the degrees of freedom adjustment.

| Spec. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\lambda_0 = 0$ | | AR(2) | MOP | COSTS | EDF | ILLIQ | PS | NOISE | VIX | MNGN | MNVN |
| $\lambda_0$ | | -0.35 | -0.53 | -0.65 | -0.68 | -0.25 | -0.32 | -0.52 | -0.37 | -0.77 | -0.76 | -0.47 |
| | | [-2.59] | [-3.32] | [-2.93] | [-2.20] | [-1.17] | [-1.34] | [-1.33] | [-1.82] | [-3.32] | [-2.98] | [-1.80] |
| $\zeta$ | 94.86 | 403.78 | 94.86 | 94.86 | 94.86 | 94.86 | 94.86 | 94.86 | 94.86 | 94.86 | 94.86 | 94.86 |
| | [—] | [5.52] | [—] | [—] | [—] | [—] | [—] | [—] | [—] | [—] | [—] | [—] |
| $\lambda_{\text{MKT}}$ | 8.02 | -3.33 | 4.84 | -0.68 | 13.75 | 9.07 | -0.22 | -2.68 | 1.19 | -0.67 | -3.19 | 1.87 |
| | [1.43] | [-0.87] | [0.91] | [-0.13] | [2.02] | [2.16] | [-0.05] | [-0.44] | [0.21] | [-0.12] | [-0.59] | [0.40] |
| $\lambda_{\text{DEF}}$ | 1.35 | 0.40 | 3.54 | 4.20 | 2.61 | | 3.40 | 3.20 | 3.05 | 4.29 | 4.59 | 4.12 |
| | [1.37] | [0.46] | [4.14] | [4.44] | [2.25] | | [3.41] | [2.93] | [3.75] | [4.12] | [4.05] | [3.44] |
| $\lambda_{\text{LIQ}}$ | 1.30 | 1.24 | | | | 1.29 | 1.01 | 1.44 | 0.95 | 1.27 | 0.97 | 1.01 |
| | [3.24] | [2.78] | | | | [3.91] | [2.79] | [2.07] | [1.49] | [2.59] | [1.63] | [2.28] |
| $\lambda_{\text{X}}$ | | | -11.30 | 13.22 | -0.38 | -0.43 | 12.25 | -1.90 | -0.10 | -13.86 | -43.58 | -88.04 |
| | | | [-3.50] | [2.56] | [-3.34] | [-2.23] | [1.33] | [-1.99] | [-4.18] | [-1.48] | [-1.73] | [-1.50] |
| $\bar{R}^2$ | 0.93 | 0.96 | 0.94 | 0.94 | 0.95 | 0.93 | 0.94 | 0.94 | 0.96 | 0.94 | 0.95 | 0.94 |

Table 8: Robustness Cross-Sectional Regressions.

The table displays results of a series of robustness checks. Specifications of $\widehat{E}[r^e_{i,t}] - \widehat{E}[c_{i,t}]\widehat{\zeta} = \lambda_0 + \widehat{\beta}_i^{\text{MKT}}\lambda_{\text{MKT}} + \widehat{\beta}_i^{\text{DEF}}\lambda_{\text{DEF}} + \widehat{\beta}_i^{\text{LIQ}}\lambda_{\text{LIQ}} + \widehat{\beta}_i^{\text{X}}\lambda_{\text{X}} + u_i$ are estimated except in case of specification 2 the estimated model is $\widehat{E}[r^e_{i,t}] = \lambda_0 + \widehat{E}[c_{i,t}]\zeta + \widehat{\beta}_i^{\text{MKT}}\lambda_{\text{MKT}} + \widehat{\beta}_i^{\text{DEF}}\lambda_{\text{DEF}} + \widehat{\beta}_i^{\text{LIQ}}\lambda_{\text{LIQ}} + u_i$. Below the specification number it is indicated whether any of the model parameters is restricted or whether an additional factor (X) is included in the model. In case of an additional factor abbreviations are as follows: AR(2) is a CDS illiquidity factor given by the AR(2) residual of the CDS market illiquidity measure. MOP is a CDS liquidity factor whose construction mirrors that of Moskowitz, Ooi, and Pedersen's (2012) time series momentum factor. COSTS is a CDS illiquidity factor given by the AR(2) residual of the time series of average weekly transaction costs of CDS contracts in our sample. EDF is a default risk factor given by the AR(2) residual of the time series of weekly average Moody's KMV 5-year Expected Default frequencies among reference names in our sample. ILLIQ and PS are a stock market liquidity factors, respectively, based on the Amihud (2002) illiquidity measure and the Pástor and Stambaugh (2003) liquidity measure. NOISE is a market-wide illiquidity factor given by the first difference of the weekly time series of the Hu, Pan, and Wang (2012) Noise measure. VIX is a volatility risk factor given by the AR(2) residual of the VIX index. MNGN and MNVN are the volatility and jump risk factors of Cremers, Halling, and Weinbaum (2012). Specifications are estimated from expected returns, transaction costs, and factor loadings inferred from time series that consist of 276 weekly observations from October 11, 2006, to February 1, 2012, unless the additional factor is not available. This is the case for MOP, NOISE, MNGN, and MNVN. The time series of MOP consists of 252 weekly observations from March 28, 2007, to February 1, 2012. The time series of NOISE consists of 273 weekly observations from October 11, 2006, to December 28, 2011. MNGN, and MNVN time series consist of 275 weekly observations from October 11, 2006, to February 1, 2012, due to a missing observation on March 11, 2009. Reported are factor price of risk estimates (in basis points), the corresponding t-statistics in square brackets, and adjusted $R^2$s. t-statistics are based on asymptotic generalized method of moments standard errors (heteroscedasticity and autocorrelation consistent through the use of Newey and West's (1987) method with 24 lags) that account for error-in-variables problems. In the computation of adjusted $R^2$s, expected CDS returns are treated as the dependent variable and calibrated parameters do not affect the degrees of freedom adjustment.

| Spec. | 0<br>Benchmark | 1<br>$\lambda_0 = 0$ | 2 | 3<br>AR(2) | 4<br>MOP | 5<br>COSTS | 6<br>EDF | 7<br>ILLIQ | 8<br>PS | 9<br>NOISE | 10<br>VIX | 11<br>MNGN | 12<br>MNVN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Expected illiquidity | 0.96 | 0.96 | 4.07 | 0.96 | 1.01 | 0.96 | 0.96 | 0.96 | 0.96 | 0.95 | 0.96 | 0.95 | 0.95 |
| | [0.29] | [0.29] | [1.24] | [0.29] | [0.31] | [0.29] | [0.29] | [0.29] | [0.29] | [0.29] | [0.29] | [0.29] | [0.29] |
| Market risk | 0.21 | 1.15 | -0.48 | 0.72 | -0.10 | 2.02 | 1.21 | -0.03 | -0.38 | 0.17 | -0.12 | -0.46 | 0.27 |
| | [0.07] | [0.39] | [-0.16] | [0.24] | [-0.03] | [0.68] | [0.52] | [-0.01] | [-0.13] | [0.06] | [-0.03] | [-0.15] | [0.09] |
| Default risk | 2.10 | 0.87 | 0.26 | 2.26 | 2.87 | 1.83 | 1.73 | 2.05 | 2.12 | 1.96 | 2.91 | 3.05 | 2.69 |
| | [0.90] | [0.37] | [0.11] | [0.99] | [1.20] | [0.75] | [0.34] | [0.93] | [0.90] | [0.82] | [1.20] | [1.27] | [1.19] |
| Liquidity risk | 1.49 | 1.43 | 1.37 | 0.96 | 1.02 | -0.26 | 0.99 | 1.14 | 1.57 | 1.01 | 1.28 | 1.05 | 1.11 |
| | [0.43] | [0.42] | [0.40] | [0.17] | [0.36] | [0.04] | [0.39] | [0.33] | [0.46] | [0.31] | [0.40] | [0.31] | [0.32] |
| Additional risk factor | | | | | | | | 0.96 | 0.62 | 0.12 | -0.52 | -0.37 | -0.05 |
| | | | | | | | | [0.04] | [0.16] | [0.11] | [-0.04] | [0.08] | [-0.25] |

Table 9: Economic Importance of Risk Sources.

The table displays the economic importance of expected illiquidity and risk factors (generically referred to as risk sources) in the benchmark specification and in specifications used for the robustness checks. To arrive at economic importance measures, annualized expected CDS portfolio returns are decomposed into contributions of the separate sources of risk. For each source of risk, two alternative economic importance measures are reported: The difference in contributions of the B-CCCQ4 and the AAA-AAQ1 portfolios (reported in the same row as the source of risk) and the average contribution among the 40 test portfolios (reported in square brackets in the first row below the source of risk). Specification identifiers are given in the second row of the table.