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. An aggregation of bases 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 view, 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

Keywords: CDS, Credit Indices, Expected Illiquidity, Liquidity Risk

Contains Internet Appendix

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

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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 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.

Net protection buyers use the CDS market to hedge existing credit risk exposure, while net protection sellers, typically the marginal liquidity providers, use the market for speculative motives. When market liquidity deteriorates, CDS spreads tend to widen and protection sellers experience mark-to-market losses that, in particular, lead to reduced liquidity provision of net protection sellers. If protection sellers are wealth constrained losses may eventually result in contract liquidations, which are particulary costly because of the reduced liquidity. Therefore, protection sellers may require a premium for bearing the risk associated with covariation between CDS returns and market-wide liquidity, which is the notion of liquidity risk on which our analysis focuses.[1]

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 that replicates the cash flows of the index. 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 that reference the most liquid North American and European names of both the investment grade and high yield universes and therefore cover a substantial part of the overall CDS market.

The rationale behind the construction of our 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. Thus, our measure captures illiquidity not only in terms of the transaction costs and margin requirements of these trades but also, in a broader sense, in terms of capital constraints and other limits to arbitrage. 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.

[1] This 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 stock market and by Lin, Wang, and Wu (2011) and Bongaerts, de Jong, and Driessen (2012) in the corporate bond market.

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

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 29%. Consistent with interpreting our aggregate measure as capturing illiquidity in broad terms, we show that it correlates with other liquidity measures, capital supply measures, and measures of overall market conditions.

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 risk and default risk in addition to liquidity risk and expected illiquidity.[3] In the model liquidity risk arises due to return covariation with respect to a market-wide liquidity factor and expected illiquidity reflects the expected transaction cost.

The market-wide liquidity factor is the return on a diversified portfolio of credit index relative value trades. These are based on a simple strategy that holds both the credit index and its replicating basket so as to profit from a contracting index-to-theoretical basis. Consequently, the liquidity factor is tradable and highly correlated with innovations to the CDS market illiquidity measure.

Expected transaction cost are factorized in two terms: The expected cost conditional on a transaction and the likelihood with which a transaction occurs. We capture the former by the average cost of a weekly round-trip, while the latter is calibrated to average weekly turnover across CDSs. We compute turnover at the reference entity level from notional values of transactions among customers of the Depository Trust & Clearing Corporation (DTCC), a major settlement service provider for transactions of OTC derivatives.

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 excess returns. Average realized excess returns on CDSs are very noisy estimates of expected excess returns because of the the short sample period and the peso problem that arises in the return computation of securities subject to default risk. This peso problem is due the rare occurrence of defaults and the extreme returns associated with them. For these reasons, we follow Bongaerts, de Jong, and Driessen (2011, henceforth BDD) in obtaining forward-looking estimates of conditional expected excess returns by using Moody's KMV Expected Default Frequencies (EDFs) to calculate expected default losses. Across all portfolios, unconditional expected excess returns are positive from a protection seller's perspective, 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. The CDS portfolios have significant loadings on the market, default, and liquidity factors, which together explain between 39% and 77% of the time-series variation in CDS portfolio returns. Sellers of CDS protection tend to realize negative returns, when the stock market drops, default risk increases, and CDS market illiquidity increases. In the second step, we

[3] 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.

estimate factor prices of risk from a cross-sectional regression of expected excess returns net of expected transaction costs on first-step factor loadings. We find that liquidity risk is both a statistically significant and economically important 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, 1.89% is due to liquidity risk, while 0.95% of this difference is due to expected illiquidity and another 1.88% is due to market and default risk. Alternatively, considering the average expected excess returns across test portfolios, 0.55% is due to liquidity risk, while 0.29% of the average is due to expected illiquidity and another 0.57% is due to market and default risk. 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. Concerning the latter, we find some evidence that exposure to Treasury and stock market liquidity is priced in the cross-section of CDS returns in addition to exposure to CDS market liquidity, while this does not appear to be the case for corporate bond market liquidity.

The analysis of liquidity effects in the cross-section of single-name CDS returns is related to that by BDD. 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, BDD 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.

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 (2013), and Pasquariello (2011) in how we construct the CDS market illiquidity measure. Both Fontaine and Garcia (2012) and Hu et al. (2013) consider the U.S. Treasury market and derive illiquidity measures, respectively, based 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. (2013) 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 in 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 trade with lower costs and higher liquidity than most single-name CDSs or cash bonds.[4] 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.[5]

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.[6] 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 $1/4 \times 0.0060 \times 10,000,000 = 15,000$ USD.[7] 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 $1/125 \times (1 - 0.9151) \times 10,000,000 + 1/125 \times (1 - 0.94) \times 10,000,000 = 11,592$ USD.[8] Due to the credit events, the spread payment on September 20, 2008, is reduced to $1/4 \times 123/125 \times 0.0060 \times 10,000,000 = 14,760$ 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 $1/125 \times (1 - 0.57) \times 10,000,000 = 34,400$ USD payout and reduces subsequent spread payments to $1/4 \times 122/125 \times 0.0060 \times 10,000,000 =$

[4] For the three-month period from June 20, 2011, to September 19, 2011, market activity reports published by the DTCC show that the average daily notional amount of trades is 28.8 million USD, on average, across single-name CDSs referencing corporate names that belong to the 1000 most actively traded single-name CDSs. 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 4 trades per day for the average single-name CDS contract.

[5] 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.

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

[7] In practice the actual number of days during the quarter is determined by ACT/360 day-count convention.

[8] 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.

$14,640$ USD. Second, the Chapter 11 filing of CIT Group on November 1, 2009, triggers a $1/125 \times (1-0.68125) \times 10,000,000 = 25,500$ USD payout and reduces successive spread payments to $1/4 \times 121/125 \times 0.0060 \times 10,000,000 = 14,520$ 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, 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 3 in the Internet Appendix briefly summarizes index rules and provides additional information concerning the major indices of the CDX North American and iTraxx Europe families.

2.2 Index Arbitrage

In this section we present the replication argument on which index arbitrage is based.

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.[9] 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

[9] 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.

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.

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 day-count 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.[10]

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 and theoretical 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.[11] 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-

[10] 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.

[11] 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 contract, they prefer to continue trading the version including the defaulted name.

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.

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 B rated entities of the CDX.NA.HY comprise 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 1. 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 1 about here.]

Figure 1 displays the time series of on-the-run index levels (thin black line in each panel) for the main indices of the CDX North American and iTraxx Europe families. Figures for the sub-indices can be found in the Internet Appendix. 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 (thick gray 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 -61.12 and -58.55 bps, respectively. These are extreme moves compared to the standard deviations of these bases which are 11.58 and 9.05 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 -451.93 and -106.15 bps, respectively, at the height of the crisis.

The negative sign of 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.[12] 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 1. 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 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 last row of Table 1, Panel B, and varies between 0.34 (for iTraxx Eur Sub Finls) and 0.74 (for CDX.NA.IG). 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 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.[13] The CDS market illiquidity measure peaks at 28.84% at the end of December 2008, i.e., during the market turmoil that followed the collapse of Lehman Brothers. As can be seen from Figure 2, the CDS market illiquidity measure is strongly persistent, which is confirmed by its 0.95 first-order autocorrelation at the daily frequency.

[Figure 2 about here.]

[12] 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, 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.

[13] 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.

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, capital supply measures, and measures capturing overall market conditions. The other illiquidity measures considered in this section can be divided in two categories: Measures that capture CDS market illiquidity and measures that capture bond market illiquidity. Exact definitions of all measures are provided in Appendix A and plots of their time series dynamics can be found in the Internet Appendix.

3.1 CDS Market Illiquidity Measures

CDS market illiquidity is measured in three ways. First, it is measured by average bid-ask spreads of single-name CDSs (Bid-Ask). 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, CDS market illiquidity is measured by the average absolute spread change per quote contributed across single-name CDSs (ILLIQ-1). To the extent that volume can be proxied by the number of contributors, this measure captures price impact of trade much alike the Amihud (2002) illiquidity measure. Third, CDS market illiquidity is measured by the average price impact of trade across credit index contracts (ILLIQ-2). In particular, we construct this measure in the same way as our CDS market illiquidity measure but using the absolute spread change per quote contributed instead of the absolute value of the percentage index-to-theoretical basis. Naturally, we expect higher CDS market illiquidity, the higher the price impact of trade for both CDSs and credit index contracts.

3.2 Bond Market Illiquidity Measures

To capture bond market illiquidity, we use two proxies for Treasury market illiquidity and a corporate bond market illiquidity measure. The first Treasury market illiquidity measure is the yield spread between Resolution Funding Corporation and U.S. Treasury bonds (RefCorp). 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 is the Hu, Pan, and Wang (2013) Noise measure (Noise). It captures deviations of U.S. Treasury yields from the respective points on a fitted smooth yield curve. Hu et al. (2013) argue that deviations from fair values are wider, whenever risk capital is scarcer. In such circumstances, we also expect less activity by index arbitrage traders and a wider CDS market illiquidity measure. Finally, we use Dick-Nielsen, Feldhütter, and Lando's (2012) λ as a corporate bond illiquidity measure (λ). This measure captures the common component of several bond-specific liquidity measures. In theory, CDS spreads and bond yields are linked by a no-arbitrage relation. We, therefore, expect liquidity in the two markets to be correlated.

3.3 Capital Supply 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. We use the three-month LIBOR-OIS spread (LIB-OIS) and the spread between three-month Agency MBS and Treasury general collateral repo rates (Repo) to, respectively, capture the costs associated with unsecured and secured financing. The three-month LIBOR-OIS spread is a commonly used measure of risk in (unsecured) interbank markets (see, e.g., Filipović and Trolle (2013)), while the 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. Another important determinant may be the amount of capital that hedge funds direct towards index arbitrage. This amount is likely to be correlated with the overall net asset value managed by hedge funds, which is proxied by the level of the Hedge Fund Research Global Index (HFRX). This index represents the overall hedge fund universe both in terms of strategies and geographical locations.

3.4 Market Conditions

Market conditions are captured by three measures. The first measure is the yield spread between Baa- and Aaa-rated bonds (Default). As shown by He and Milbradt (2013), increased default risk lowers secondary market corporate bond illiquidity, which further increases default risk through lower primary market valuations and the associated rollover losses. Due to this positive feedback loop, we expect a positive relation between the default spread and the CDS market illiquidity measure. The second measure is the CBOE VIX index (VIX), which is an option implied estimate of S&P 500 volatility that has become generally known as the investors' "fear gauge." 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. The third measure is the average CDS-bond basis across U.S. investment grade bonds (CDS-Bond). As mentioned above, CDS spreads and bond yields are, in theory, linked by a no-arbitrage relation. In practice, this relation is less than perfect and gives rise to the CDS-bond basis. Similar to the index-to-theoretical basis, the size of the CDS-bond basis can be viewed as capturing illiquidity in broad terms and, therefore, we expect the CDS market illiquidity measure and the CDS-bond basis to be correlated.

3.5 Results

For each group of explanatory variables, we separately run both univariate and multivariate ordinary least squares (OLS) regressions of monthly changes in the CDS market illiquidity measure on monthly changes in the explanatory variables.[14] The regression are run using data up to December 30, 2011, because the Noise measure is available up to this date only. For those measures that are available on a daily frequency, we obtain the monthly time series by averaging daily observations within each month. Regression results are exhibited in Panels A to D of Table 2 and pairwise correlations of monthly changes in the explanatory variables are reported in Table 3.

[Table 2 about here.]

[Table 3 about here.]

Considering the other CDS market illiquidity measures first (Panel A of Table 2), we find a significant relation of our illiquidity measure with respect to average bid-ask spreads

[14] We run regression in first-differences in order to avoid spurious results due to persistence of the dependent and explanatory variables. Unit root tests are available upon request.

and price impact of credit index trades. The relation with the other price impact measure is less strong, as can be seen from its insignificance and the lower value of the adjusted R^2. Collectively, the CDS market illiquidity measures can explain a quarter of the time series variation of our measure.

Second, consider the relation of our CDS market illiquidity measure with measures of bond market illiquidity (Panel B of Table 2). Both Treasury bond market illiquidity measures are strongly significant in univariate regressions, but only the Noise measure remains significant in the multivariate regression. In contrast, the corporate bond market illiquidity measure appears to be unrelated to our CDS market illiquidity measure. Overall, bond market liquidity measures can explain about 40% of the time series variation of the CDS market illiquidity measure.

Next, consider capital supply measures in Panel C of Table 2. The unsecured funding cost differential is strongly significant, while the secured one is insignificant. This indicates that index arbitrage traders primarily fund their trades in unsecured interbank markets, which is consistent with the fact that CDSs cannot be used as collateral in repo transactions. Moreover, changes in hedge fund net asset values are significantly related to changes in the CDS market illiquidity measure and can explain 17% of its time series variation. The estimated slope coefficient suggests that for each additional index point of capital managed by hedge funds, the CDS market illiquidity measure decreases by three basis points. This suggests that in the CDS market, liquidity provision by hedge funds constitutes an important source of overall liquidity.

Finally, consider the measures of overall market conditions (Panel D of Table 2). On its own, each of the three measures is significant and can explain between 12% and 28% of the time series variation of the CDS market illiquidity measure. As can be seen from its significance in the multivariate regression, the relation with respect to the CDS-Bond basis is strongest. Thus, the existence of non-zero index-to-theoretical bases can be partly attributed to slow-moving capital. This is because one of the main implications of slow-moving capital is that seeming arbitrage opportunities persist across different markets at the same time.

As can be seen from Table 3, a fair amount of explanatory variables are strongly correlated. Thus, a regression including all twelve variables will be subject to multicollinearity. Indeed, unreported results show that most variables become insignificant in this regression and some regression coefficients exhibit the wrong sign. Collectively, all explanatory variables together can explain 55% of the time series variation of the CDS market illiquidity measure. This leaves a substantial part of unexplained time series variation and we test in the next section whether this variation is priced in the cross-section of CDSs returns.

4 Asset Pricing Implications

This section investigates whether liquidity risk is priced in the cross-section of single-name CDS returns. 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 β_i in the regression

$$r^e_{i,t} = \alpha_i + \beta_i^{\text{MKT}}\,\text{MKT}_t + \beta_i^{\text{DEF}}\,\text{DEF}_t + \beta_i^{\text{LIQ}}\,\text{LIQ}_t + \epsilon_{i,t}, \tag{1}$$

where MKT_t, DEF_t, and LIQ_t denote the market, default, and liquidity factors, respectively. MKT_t is the excess return on a stock market index and DEF_t is the excess return from selling credit index protection. 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 BDD, who, in the context of their equilibrium asset pricing model, find evidence for priced market and default 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), a CDS can be replicated by portfolio of par floating rate notes and it has become standard practice (see, e.g., Berndt and Obreja (2010), BDD, Bao and Pan (2013)) 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 cost, conditional on a trade occurring, times the likelihood of trading. Specifically, expected excess returns are given by

$$E[r^e_{i,t}] = E[c_{i,t}]\zeta + \beta_i^{\text{MKT}}\lambda_{\text{MKT}} + \beta_i^{\text{DEF}}\lambda_{\text{DEF}} + \beta_i^{\text{LIQ}}\lambda_{\text{LIQ}}, \tag{2}$$

where λs denote factor prices of risk, $c_{i,t}$ denotes weekly round-trip transaction costs per dollar of notional amount of a contract referencing entity i, and ζ is denotes the unconditional likelihood of exiting a CDS contract after one week.[15] For our empirical analysis, we calibrate ζ 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 OLS estimates, $\widehat{\beta}_i$, of the slope coefficients in regression (1). In the second step, we estimate factor prices of risk via OLS from a cross-sectional regression of expected CDS returns net of expected transaction cost on first-step factor loadings, i.e.,

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

where $\widehat{\zeta}$ is the calibrated value of ζ 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.

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,

[15] 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 cost 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 ζ can indeed be interpreted as the reciprocal of the expected holding period.

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 BDD, 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 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 (3) 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 the sample size.

Due to estimation error in first-step factor loadings, standard errors of coefficient estimates in regression (3) have to be adjusted for errors-in-variables (EIV). We account for EIV by use of asymptotic generalized method of moments standard errors (see pp. 240–243 in Cochrane (2001)). In addition, we use standard errors that, besides taking into account EIV, also account for potential model misspecification. That is, we allow for the possibility that, even in population, there is no combination of ζ and λs such that Equation (2) is satisfied. Kan, Robotti, and Shanken (2013) argue that in such cases it makes sense to consider population parameters that minimize population pricing errors according to some objective function. This objective function can be chosen such that factor price estimates under potential model misspecification coincide with the ones assuming a correctly specified model, i.e., the OLS estimates in regression (3).[16] As shown in Kan et al. (2013), inference under correctly specified and potentially misspecified models can differ substantially, in particular for factors that exhibit only low correlation with realized returns. Internet Appendix E describes the standard error computation in more detail.

4.2 Data and Construction of Portfolios and Factors

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.[17] Spreads are obtained for CDS contracts written on senior unsecured debt and denominated in either EUR or USD.[18] 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

[16]Because ζ is calibrated to average turnover it is not a population parameter in our case. But even if it were a population parameter potential misspecification could be taken into account.

[17]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.

[18]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.

in the Markit database. Thus, our sample consists of North American and European reference names with data coverage by each of the three providers. Credit events in our sample are identified from settlement auctions of CDSs and we collect credit event data from the corresponding settlement protocols and auction results.[19]

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. Furthermore, we delete all erroneous 'D' ratings from the ratings data.

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.[20] 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 141,296 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).[21] In particular, we collect gross notional values for the 1000 most active reference 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.[22]

Turnover of CDSs and Calibration of ζ

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

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

[19] Creditex and Markit administrate credit event auctions and publish auction results on `www.creditfixings.com`. Settlement protocols are published by the ISDA.

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

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

[22] 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.

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 ζ 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.[23]

For our empirical analysis we calibrate ζ 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 et al. (2012) report a median quarterly turnover of 4.50% for corporate bonds over a similar sample period, which implies a median weekly turnover of 450/13 bps = 34.62 bps.

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 dimensions.

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.[24] During this period, we find two weeks where only a small number of North American reference names have quoted bid-ask spreads.[25] We exclude the corresponding portfolio observations

[23] 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.

[24] 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.

[25] 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

from the analysis, leaving a total of 276 one-week periods during the sample period.

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. Similarly, the default factor is constructed as the average excess return from selling protection on the CDX.NA.IG and iTraxx Eur.[26] All excess returns are computed with respect to one-week OIS rates.

For the construction of the liquidity factor, we consider an implementable trading 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. However, we consider a one-week holding period in which case the strategy's return is risky and given by

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

where $r_{i,t}^{\mathrm{IDX}}$ and $r_{i,t}^{\mathrm{BSK}}$ denote one-week 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.[27] Since returns on the strategy are positive when index-to-theoretical bases narrow, we expect them to be highly (negatively) correlated with innovations to 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 A of Table 4. Strategy volatilities range from 16.36 to 95.41 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 returns 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.[28] Specifically, the tradable liquidity factor is constructed as

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

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.

[26] In particular, for each index we consider returns on that version of the on-the-run series that has the largest number of contributing dealers.

[27] We compute these returns from the upfront charge on a credit index contract and its replicating basket of single-name CDSs; for details see Appendix B. Whenever an index roll date, t_{roll}, falls within a one-week period, the weekly return is obtained by first computing the return on series S_i of index i between $t-1$ and t_{roll} and then adding to it the return on series $S_i + 1$ over t_{roll} to t.

[28] We find a strong positive relation between index levels and strategy volatilities. For instance, their cross-sectional correlation is 0.80.

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

[Table 4 about here.]

Figure 3 displays the time series evolution of the tradable liquidity factor. Its correlation with innovations to the CDS market illiquidity measure is -0.69.[29] Its annualized mean and standard deviation are 2.99% and 1.03%, respectively, and despite its simple construction the factor's annualized Sharpe ratio, using Lo's (2002) correction for non-independent returns, is 2.34.[30] The annualized Sharpe ratios of the individual trading strategies are 1.65 on average (see Table 4, Panel A). Hence, the high Sharpe ratio of the factor is, in part, due to the moderate correlations between strategy returns, which are reported in Panel B of Table 4.

[Figure 3 about here.]

4.3 Results

Descriptive Statistics

Table 5 displays descriptive statistics for the three factors. Over our sample period, average returns on the market and default factors are negative, but not significantly different from zero.[31] In contrast, the average return on the liquidity factor is positive and significant, with a t-statistic of 5.44 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 CDS spreads and, therefore, positive returns from selling credit index protection.

[Table 5 about here.]

Table 6 displays descriptive statistics for the portfolios formed by first sorting CDS contracts according to credit ratings and then according to bid-ask spreads. Those for the portfolios formed by first sorting CDS contracts according to five-year EDFs and then according to bid-ask spreads are provided in Table 4 in the Internet Appendix.

[Table 6 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 around 4.00 to around 13.00. 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

[29] 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.

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

[31] 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 -1.06 for the market and default factors, respectively.

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.[32] In absolute value, t-statistics for the mean range from about 0.10 to about 1.10. 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 around 7.00 to around 13.00. 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 Table 7, which reports a factor loading's economic magnitude and t-statistic. By economic magnitude we mean the change in a portfolio's weekly realized return (in bps) in response to a one standard deviation change in the respective factor.

[Table 7 about here.]

Loadings on the default factor are significant throughout portfolios and almost monotonically increasing along both the liquidity and credit quality dimensions. A similar monotone relation prevails among loadings on the market factor although more than half of them are insignificant and some of them have a counterintuitive negative sign. Loadings on the liquidity factor are significant at the five percent level for 32 out of the 40 portfolios.[33] 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. 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. Unreported adjusted R^2s of the regressions range from 39% to 77% across portfolios.

The results of estimating alternative specifications of the cross-sectional regression (3) are displayed in Table 8. In the row that begins with the corresponding symbol, we report factor price of risk estimates. Underneath each estimate we report regular t-statistics in parenthesis and robust t-statistics in square brackets. Regular t-statistics account for EIV and robust t-statistics in addition account for potential model misspecification. The last two rows of each column contain cross-sectional R^2s and their 95% confidence intervals.[34]

[Table 8 about here.]

[32] Consistent with Bao and Pan (2013), 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.

[33] Unreported results for nested single-factor specifications of regression (1) show that, on its own, each of the three factors constitutes a significant explanatory variable of CDS portfolio returns.

[34] Standard error computation for cross-sectional R^2s proceeds along the lines of Kan et al. (2013). Details are deferred to Internet Appendix E.

Factors carry significant prices of risk in one-factor and two-factor models (specifications 1 to 3) and one-factor and two-factor models that in addition account for expected illiquidity (specifications 5 to 7). The significant relation between liquidity risk and expected excess returns also prevails in three-factor models both excluding and including expected illiquidity (specifications 4 and 8, respectively). Inference under potential model misspecification is, in general, similar to the one under correctly specified models. Only in specifications 7 and 8 does inference change upon taking into account misspecification. Here, insignificance of factor prices is not due largely higher standard errors but a sharp decrease of point estimates upon taking into account the expected illiquidity.

As it is usually the case in regressions without an intercept, the cross-sectional R^2s are quite high. Moreover, their confidence intervals are fairly tight, which is in sharp contrast to Lewellen, Nagel, and Shanken (2010) who report wide confidence intervals of cross-sectional R^2s in tests of a number of popular asset pricing models. However, in the tests expected returns are estimated using average realized returns. Thus, the tight confidence intervals we observe might be due to the very precise expected return estimates we are employing in our asset pricing tests.

Recently, Kan et al. (2013) pointed out an important issue concerning factor prices of risk in multi-factor models. Traditionally, a factor is said to be priced if its factor price of risk estimate is significantly different from zero. Kan et al. (2013) show that a factor which is not priced in this sense can significantly improve the model's overall explanatory power. Moreover, they show that a factor without significant incremental explanatory power has an insignificant coefficient in a regression of expected returns on return covariances with factors, or, equivalently, in a regression on one-factor model loadings. They, therefore, argue to consider these coefficients in order to determine the relevant factors in a multi-factor model. We run such regressions and report the results in Table 5 in the Internet Appendix. The results show that under correctly specified models the liquidity factor has an incremental contribution to the model's overall explanatory power. Under potential model misspecification results differ only in case of the three-factor models (specifications 4 and 8) where none of the factors has incremental explanatory power over the other two.

Economic Importance

To assess the economic importance of expected illiquidity and the factors, we use specification 8 and decompose the annualized expected excess return on each test portfolio into four components: The expected illiquidity (defined by $52\widehat{E}[c_{i,t}]\widehat{\zeta}$) and the market, default, and liquidity risk premia (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 0.95% per year to the expected return differential, while liquidity risk contributes 1.89% per year. As such, and in contrast to the results of BDD, liquidity risk is economically more important than expected illiquidity for the pricing of single-name CDSs. Together market risk and default risk contribute an annualized 1.88% to the expected return differential.[35] That is, the contribution of liquidity risk is similar to what market and default risk contribute together.

[35] We compare the contribution of liquidity risk to the sum of contributions of market and default risk because it is difficult to disentangle their contributions precisely. This is due to co-movement of the market and default factors and their strongly correlated factor loadings.

[Figure 4 about here.]

As an alternative way to summarize the information in Figure 4, we average the components across test portfolios. In this case, expected illiquidity and liquidity risk contribute 0.29% and 0.55% per year, respectively, to the average expected return across test portfolios, while the contribution of market and default risk is 0.57% per year. Thus, the two measures of economic importance are qualitatively consistent.

Comparison to Bongaerts, de Jong, and Driessen (2011)

Our results differ from those of BDD in that we find a statistical significant and economically important role of liquidity risk, whereas they find no liquidity risk premium. We argue that this is due to the very different notions of liquidity risk that have been subject of the two studies.

BDD focus on a rather non-standard notion of liquidity risk that is implied by their equilibrium asset pricing model. In their model liquidity risk arises due to transaction costs that may increase when systematic default risk increases. This impairs hedge quality of CDSs and reduces protection buyers' demand, which, in equilibrium, leads to lower expected returns for protection sellers. In contrast, we focus on liquidity risk that arises from widening CDS spreads when aggregate liquidity deteriorates. Realizing negative returns, wealth constrained protection sellers may be forced to terminate their positions exactly when aggregate liquidity is low and, therefore, require a premium for bearing this risk.

When we estimate our factor pricing model and employ the notion of liquidity risk used by BDD, we find negligible contributions of liquidity risk to the expected return differential (0.09% per year) and average expected returns (0.16% per year).[36] Contributions of this form of liquidity risk decrease even further, when we estimate a model that allows our notion of liquidity risk to affect expected returns as well. Thus, the dissent regarding priced liquidity risk is indeed due to the very different notions of liquidity risk considered in our and BDD's analysis.

4.4 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 prevail when using alternative liquidity factors. Third, we examine whether there are confounding effects due to the fact that the default factor may itself be affected by liquidity risk. Finally, we examine whether our results are robust to the inclusion of additional risk factors, e.g., liquidity factors from other markets. For each robustness check, the results of the cross-sectional regression are reported in Table 9, while the two measures of economic importance of expected illiquidity and the factors are reported in Table 10. The two measures typically give similar results so we only comment on the expected return differential. The construction of some of the additional factors is detailed in Appendix C.

[Table 9 about here.]

[Table 10 about here.]

[36] Results are available upon request.

Methodology

Intercept in the cross-sectional regression In accordance with theoretical predictions, the cross-sectional regression's intercept is not significantly different from zero (see specification 1 in Table 9). Since the estimated intercept is negative, contributions of factors to the expected return differential may be inflated. This is indeed the case for liquidity risk, whose contribution to the expected return differential increases slightly to 2.04% per year. In contrast, contributions of market and default risk are unaffected by the inclusion of an intercept. In fact, their joint contribution decreases marginally to an annualized 1.77%.

ζ as a regression coefficient Instead of calibrating ζ to CDS volume data, we estimate it as a regression coefficient. This is tantamount to treating expected transaction cost as a portfolio characteristic, in which case the model's cross-sectional relation, given in Equation (2), is inferred by means of the following OLS regression

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

Specification 2 in Table 9 shows the results. Adding expected transaction costs as an additional regressor does not impair significance of the factor price of liquidity risk under correct model specification. However, prices of risk of the other two factors become insignificant. The estimated value of ζ is about four times the calibrated value used in the benchmark analysis and implies unreasonably large turnover in the CDS market. Specification 2 in Table 10 shows that the contribution of expected illiquidity to the expected return differential increases markedly to 3.76% per year, while liquidity risk contributes 1.36% per year. The contributions of market and default risk approximately offset each other.

As an additional methodological robustness check we estimate the asset pricing model by weighted least squares. The results of this robustness check are almost identical to the ones reported in Section 4.3 and can be found in Internet Appendix F.

Alternative Liquidity Factors

AR(2) residual of CDS market illiquidity measure As an alternative to the tradable liquidity factor, we use the residual of an AR(2) specification of the CDS market illiquidity measure. At the five percent level, 35 out of 40 portfolios load significantly on this illiquidity factor in first-step regressions. Also the price of liquidity risk is statistically significant in the second-step cross-sectional regression (see specification 3 in Table 9). Economically, the contribution of liquidity risk to the expected return differential decreases to 1.65%, annualized (see specification 3 in Table 10).

Transaction-cost-based illiquidity factor Several recent studies (see, e.g., Acharya, Amihud, and Bharath (2013), Bongaerts et al. (2012)) capture liquidity risk as return covariation with respect to innovations to market-wide transaction costs. We aggregate reference names' Winsorized 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 4 in Tables 9 and 10). In first-step regressions only about half of the test portfolios exhibit significant exposure to this liquidity factor. Nevertheless, the cross-sectional regression gives a significant factor price of liquidity risk and the contribution of liquidity risk to the expected return differential is 1.24% per year.

We also show that our results do not hinge on the particular construction of the tradable liquidity factor. In particular, we construct a tradable liquidity factor along the lines of Moskowitz et al. (2012) and find very similar results (see Internet Appendix F for details).

Alternative Default Factor

So far we have captured default risk by excess returns from selling credit index protection. Since we cannot rule out that credit indices are affected by liquidity risk as well and in order to avoid confounding effects, we construct an EDF-based default factor that should not be affected by liquidity (see specification 5 in Tables 9 and 10). A small number of portfolios do not load on the EDF-based default factor and its factor price is statistically significant under correct model specification. Relative to our benchmark analysis, the contribution of market and default risk to the expected return differential increases to 2.69% per year. The contribution of liquidity risk decreases to 1.08% per year.

In Internet Appendix F we show that our main results continue to hold when we consider a default factor that is given by the excess return on a portfolio of corporate bonds.

Additional Factors

Treasury market illiquidity factor Hu et al. (2013) 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 residual of an AR(2) specification of the Noise measure as an additional factor to the asset pricing model (see specification 6 in Tables 9 and 10). Only twelve of the CDS portfolios have a significant loading on this factor at the five percent level. In comparison, all but nine CDS portfolios load significantly on our tradable liquidity factor. In terms of statistical significance, both Treasury market liquidity risk and CDS market liquidity risk are priced under correct model specification. In terms of economic importance, Treasury market liquidity risk contributes 0.64% per year to the expected return differential, while CDS market liquidity risk contributes about twice as much, 1.29% per year.

Corporate bond market liquidity factor There is ample evidence for priced liquidity risk in the cross-section of corporate bond returns (see, e.g., Lin et al. (2011), Acharya et al. (2013)). Due to the no-arbitrage relation between CDS spreads and corporate bond yields, corporate bond market liquidity risk may also be priced in CDS returns. Thus, we investigate whether the presence of a corporate bond market liquidity factor affects the pricing of CDS market liquidity risk (see specification 7 in Tables 9 and 10). The corporate bond market liquidity factor we use in this robustness check is based on an aggregate of Amihud (2002) illiquidity measures and it is highly correlated with innovations to Dick-Nielsen et al.'s (2012) λ. Although about a quarter of the CDS portfolios loads significantly on the corporate bond market liquidity factor, its factor price is insignificant. With an annualized 1.86% contribution to the expected return differential, pricing of CDS market liquidity risk is largely unaffected by the presence of the corporate bond market liquidity factor.

Stock market liquidity factor Both Acharya et al. (2013) and Bongaerts et al. (2012) show that stock market liquidity risk is priced in the cross-section of corporate bond returns. Therefore, we add a stock market liquidity factor based on the Amihud (2002) illiquidity measure as an additional factor to the asset pricing model (see specification 8 in Tables 9 and 10). Due to liquidity commonality, one intuitively expects returns on CDSs to load positively on stock market liquidity, which is indeed the case. All loadings on the stock market liquidity factor are positive and most of them are significant at the five percent level. Under a correctly specified model, the factor prices of stock market and CDS market liquidity risk are significant, while both factor prices are insignificant under potential model misspecification. The contribution of stock market liquidity risk to the expected return differential, 1.52% per year, is about the same as that of CDS market liquidity risk, 1.48% per year.

In case that the Pástor and Stambaugh (2003) liquidity measure is used to construct the stock market liquidity factor, we find similar but less strong results in first-step regressions and a counterintuitive negative factor price of risk (see Internet Appendix F).

Balance sheet constraints of financial intermediaries The limits to arbitrage literature predicts an impact of financial intermediaries' risk bearing capacity on asset prices. Adrian, Etula, and Muir (2013) capture such effects by a stochastic discount factor that depends on the leverage of broker-dealers and show that their model prices portfolios of stocks and bonds remarkably well. Given the institutional nature of the CDS market, this market is presumably better suited for investigating the effects of financial intermediaries' balance sheet constraints on asset prices. As mentioned in the introduction, our factor measures liquidity in broad terms and may also capture lack of capital of financial intermediaries. We, therefore, check whether Adrian et al.'s (2013) leverage factor mimicking portfolio drives out our liquidity factor when added to the model. Only a few test portfolios load significantly on this factor. Loadings on the leverage factor mimicking portfolio and its factor price of risk estimate are counterintuitively negative.[37] As can be seen from specification 9 of Tables 9 and 10, the liquidity factor remains statistically significant and economic important even in the presence of the leverage factor mimicking portfolio. That is, in line with its interpretation as a broad liquidity measure, our factor seems to capture more than just balance sheet constraints of financial intermediaries.

Volatility factor Finally, we include a volatility factor 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). We, therefore, include the residual of an AR(2) specification of the VIX index (see specification 10 in Tables 9 and 10) as a volatility factor in the asset pricing model. There is some evidence for priced volatility risk. Although only five test portfolios exhibit significant exposure to the volatility factor at the five percent level, its factor prices is strongly significant under correctly specified models. In line with theoretical arguments and prior empirical work, we find a negative volatility risk contribution of -0.95% per year to the expected return differential. The contribution of liquidity risk is literally unchanged by the inclusion of the volatility factor.

Internet Appendix F shows that this result also holds for an alternative index-option-return-based volatility factor and that similar results are obtained for an index-option-return-based jump factor.

In summary, the robustness checks support priced liquidity risk in the cross-section of CDS returns. This is also illustrated in Figure 5, which displays the liquidity risk pre-

[37] We have confirmed that this is a multivariate regression effect. In a one-factor model all test portfolios exhibit significantly positive loadings on the leverage mimicking factor and, in line with theoretical predictions, its factor price of risk is positive.

mium across all robustness checks. The upper panel displays the contribution of liquidity risk to the expected return differential, which in all specifications is larger than 1.08%. The lower panel displays the contribution to the average expected return across test portfolios, which in all specifications is larger than 0.35%.

[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 index-to-theoretical bases, i.e., divergences between published credit index levels and their theoretical counterparts. Theoretically, non-zero bases can be realized by trading indices against baskets of single-name CDSs referencing their constituents. These relative value 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 universes. 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. Consistently, the measure correlates with other liquidity measures, capital supply measures, and measures of overall market conditions.

Then, we construct a tradable liquidity factor that is highly correlated with innovations to the CDS market illiquidity measure from returns on credit index relative value trades. 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 Time Series Properties: Explanatory Variables

A.1 CDS Market Illiquidity Measures

Bid-Ask Bid and ask quotes for EUR or USD denominated senior five-year CDS contracts come from Bloomberg. Contract specific bid-ask spreads are monthly averages over daily bid-ask spreads, which are calculated whenever more than five non-negative daily spread observations are available within the month. For each month, Bid-Ask is the average of contract specific bid-ask spreads.

ILLIQ-1 CDS data for non-government sector companies domiciled in Europe and North America come from Markit. For European reference names, spreads are for EUR denominated senior five-year CDS contracts with modified modified restructuring clause. For North American reference names, spreads are for USD denominated senior five-year CDS contracts with either modified restructuring or no modified restructuring documentation clauses. This is because prior to the implementation of the ISDA's CDS 'Big Bang' Protocol on April 8, 2009, almost all single-name CDSs on North-American investment grade names traded with modified restructuring, while single-name CDSs on North-American high yield names traded with no restructuring. As part of the changes in trading conventions, due to the implementation of the protocol, CDSs referencing North American names started trading with standardized contract specifications under which no restructuring is the applicable documentation clause. Thus, for a given month, spreads for North American reference names are for the documentation clause with the larger number of observations. In case of equal numbers of observations, the spreads are for the no restructuring clause.

For each reference name, the ILLIQ-1 measure is the monthly average of absolute daily spread changes divided by the number of contributors, $Depth_{i,t}$, to the spread quotation on day t. That is,

$$ILLIQ_{i,m} = \frac{1}{N_{i,m}} \sum_{t=1}^{N_{i,m}} \frac{|C_{i,t} - C_{i,t-1}|}{Depth_{i,t}},$$

where for reference name i, $N_{i,m}$ is the number of spread changes in month m that are no further apart than four calendar days and $C_{i,t}$ is the respective CDS spread. For each month, ILLIQ-1 is the average $ILLIQ_{i,m}$ measure over reference names with $N_{i,m} > 5$.

ILLIQ-2 Data for the construction of ILLIQ-2 are those described in Section 2.3. For each day, ILLIQ-2 is the weighted average (by number of index constituents) of the absolute change in the index level from the previous date with available data divided by the number of contributors, $Depth_i(t, 5Y)$, across the five-year on-the-run credit indices considered in the construction of the CDS market illiquidity measure, i.e.,

$$ILLIQ_t = \sum_{i=1}^{n_t} w_{i,t} \frac{|C_i(t, 5Y) - C_i(t-1, 5Y)|}{Depth_i(t, 5Y)},$$

where $C_i(t, 5Y)$, n_t, and $w_{i,t}$ are defined as in Section 2.4. For each month, ILLIQ-2 is the average value of $ILLIQ_t$ over the month.

A.2 Bond Market Illiquidity Measures

RefCorp Resolution Funding Corporation and U.S. Treasury constant maturity yields come from Bloomberg's fair value yield curves. The RefCorp measure is the monthly average of daily yield spreads at the ten-year maturity.

Noise Noise measure data come from Jun Pan's website `http://www.mit.edu/~junpan/`. Noise is the monthly average of daily observations.

λ The monthly time series of Dick-Nielsen et al.'s (2012) λ corporate bond illiquidity measure comes from Peter Feldhütter's website `http://feldhutter.com/`.

A.3 Capital Supply Measures

LIB-OIS USD LIBOR and OIS data come from Bloomberg. LIB-OIS is the monthly average of daily spread observations between three-month LIBOR and OIS rates.

Repo Repo rates come from Bloomberg. Repo is the monthly average of daily spread observations between three-month Agency MBS and Treasury general collateral repo rates.

HFRX The monthly time series of the Hedge Fund Research Global Index comes from Bloomberg.

A.4 Market Conditions

Default Moody's yields on seasoned AAA- and BAA-rated bonds across all industries come from the website of the Board of Governors of the Federal Reserve System `http://www.federalreserve.gov/`. Default is the monthly average of daily yield spreads between BAA- and AAA-rated bonds.

VIX VIX Index data come from Bloomberg. VIX is the monthly average of daily index levels.

CDS-Bond The time-series of the CDS-bond basis across U.S. investment grade bonds comes from J.P. Morgan. CDS-Bond is the monthly average of daily observations of the CDS-bond basis.

B Computation of Returns and Transaction Costs

This Appendix describes the computation of expected and realized returns on a CDS trading at par, the computation of transaction costs, and the computation of realized returns on a credit index. Further details of the implementation are deferred to the Internet Appendix.

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

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

where $PVBP_{i,t}(T)$, defined in Equation (D.2) in the Internet Appendix, is the T-maturity present value of a basis point on the t-th observation date of the time series. $\Delta CDS_{i,t}$ 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

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

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.[38] Recovery rates, R_i, enter Equation (B.1) through the present value of a basis point, $PVBP_{i,t}(T)$, because risk neutral survival probabilities are inferred such that end-of-period mid spreads and recovery rates satisfy the par spread condition, Equation (D.3) in the Internet Appendix, under the assumption of a constant default intensity.

In the event of default by reference name i between $t-1$ and t, the change in the CDS's net present value equals the negative of loss given default, i.e., $\Delta CDS_{i,t} = -N\left(1 - R_i\right)$, and, therefore, the CDS's excess return is $r^e_{i,t} = -\left(1 - R_i\right)$. For each reference name that triggered a credit event, we compute the realized return over the one-week period that contains the credit event date, using the recovery rate determined in the credit event auction. In case of failure to pay and Restructuring credit events, we resume realized return

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

computation from the first week following the credit event auction onwards and delete all intermediate data. Our sample includes a total of 22 credit events among 21 different reference names and losses per dollar of notional range from 23.38% for the Governor and Company of the Bank of Ireland to 98.75% for Landsbanki.[39]

In case that we take into account transaction costs, protection will be sold at the quoted bid, $C_{i,t-1} - s_{i,t-1}/2$, 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

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

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

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

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, $c_{i,t}$,

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

In order to compute transaction costs, we use Markit five-year mid spreads and the corresponding recovery rates (which determine $PVBP_{i,t}(T)$) along with a reference name's weekly average bid-ask spread inferred from Bloomberg data.[40] 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).

BDD also show that conditional expected CDS returns can be defined by

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

where in contrast to expressions (D.1) and (D.2) in the Internet Appendix 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 survival probability. Physical survival probabilities are extracted from Moody's KMV one-year and five-year EDFs through

$$\mathbb{P}(\tau_i > 1 | \tau_i > t) = 1 - EDF1Y_{i,t} \qquad \text{and} \qquad \mathbb{P}(\tau_i > 5 | \tau_i > t) = (1 - EDF5Y_{i,t})^5,$$

[39] Two restructuring credit events occurred in respect of Irish Life & Permanent in 2011.

[40] 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.

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.[41] 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.

Finally, we consider the situation in which an investor sells T-maturity protection with a notional amount of N on credit index i. The index trades with fixed spread C and date t upfront charge, $UF_{i,t}(T,C)$, per dollar of notional amount. In the same spirit as in the above computation of the realized (excess) return on a CDS that trades at par, we take the index contract's change in net present value relative to its notional amount as its return, i.e.,

$$r_{i,t}^{\mathrm{IDX}} = -\left(UF_{i,t}(T,C) - UF_{i,t-1}(T,C)\right) + \frac{7}{360}\frac{I_t}{I}C - \frac{1}{I}\left(L_{i,t} - L_{i,t-1}\right), \tag{B.4}$$

where $L_{i,t}$ is the cumulative loss due to credit events among index constituents on the t-th observation date.[42] The minus sign in front of the first expression on the right hand side is due to the convention that $UF_{i,t}(T,C)$ is the index contract's net present value from a protection buyer's perspective. As mentioned in Section 2.3, Markit reports spread and price quotations for credit index contracts. By convention, the date t price, $P_{i,t}(T,C)$, of a T-maturity index i that trades with fixed spread C is given by $P_{i,t}(T,C) = 1 - UF_{i,t}(T,C)$. Thus, $r_{i,t}^{\mathrm{IDX}}$ can be readily computed from Markit credit index data. In order to compute the return on the replicating basket, $r_{i,t}^{\mathrm{BSK}}$, we replace $UF_{i,t}$ and $UF_{i,t-1}$ in the previous display by the respective values inferred from Markit's theoretical price quotations.

C Robustness Checks: Factor Constructions

C.1 Alternative Default Factor

EDF We first aggregate, among reference names in our sample, weekly averages of Winsorized 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. The EDF-based default factor has a correlation of -0.39 with our benchmark default factor (the correlation is negative since an increase in expected defaults decreases credit index returns).

C.2 Additional Factors

BLIQ We use transaction data from the Financial Industry Regulatory Authority's Trade Reporting and Compliance Engine to construct the corporate bond market liq-

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

[42] As in case of CDS returns, losses cumulated in $L_{i,t}$ are given as 1 minus the recovery value determined in a credit event auction.

uidity factor. In particular, we obtain transaction data for plain vanilla fixed rate bullet bonds issued by U.S. corporations. The data are filtered for erroneous transactions using Dick-Nielsen's (2009) methodology and, as in Dick-Nielsen et al. (2012), transactions with par volume below $100,000 are discarded. Bond-specific Amihud (2002) illiquidity measures are obtained each day by averaging absolute returns of consecutive transactions per million dollar of par volume traded. These are converted to a weekly frequency by taking the within-week median of daily measures. Each week the market-wide measure is obtained as the weighted average (by amount issued) of bond-specific measures. The corporate bond market liquidity factor is then obtained as the negative value of the residual of an AR(2) specification of the market-wide illiquidity measure. When converting bond-specific Amihud (2002) illiquidity measures to a monthly rather than a weekly frequency, the resulting corporate bond illiquidity measure has a correlation of 0.93 in levels and 0.79 in first differences with Dick-Nielsen et al.'s (2012) λ.

SLIQ In order to construct the stock market liquidity factor 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 and each week the market-wide measure is obtained as the cross-sectional mean of Winsorized individual-stock measures. The stock market liquidity factor is given as the negative value of the residual of an AR(2) specification of the market-wide illiquidity measure.

LMP The leverage factor mimicking portfolio is a tradable stock portfolio that is maximally correlated with Adrian et al.'s (2013) non-tradable leverage factor (the seasonally adjusted log change in the leverage ratio of an aggregate broker-dealer balance sheet). The mimicking portfolio is composed of Fama and French (1993) portfolios (two-way sort on size and book-to-market into six portfolios) and the momentum factor. Thus, we infer the leverage factor mimicking portfolio as the weighted average of one-week excess returns on the components, using the weights provided in Adrian et al. (2013). For the computation of the components' one-week excess returns, we use daily returns from Kenneth French's data library, which we compound to a weekly frequency after subtracting risk free rates. Risk free rates for the excess return computation come from Kenneth French's data library as well.

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Figure 1: 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 on-the-run series (thin black lines, left hand scales), theoretical index levels (thick gray 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.

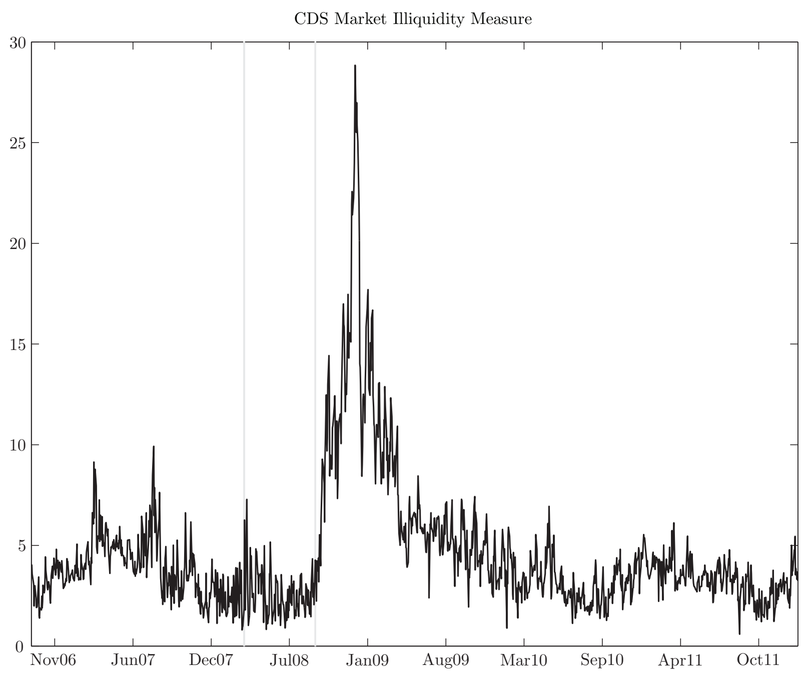

Figure 2: CDS Market Illiquidity Measure.
The figure displays the CDS market illiquidity measure (in %). The time series consists of 1381 daily observations from September 20, 2006, to February 1, 2012. Gray vertical lines correspond to (from left to right) the Bear Stearns near bankruptcy on March 17, 2008, and the default of Lehman Brothers on September 15, 2008.

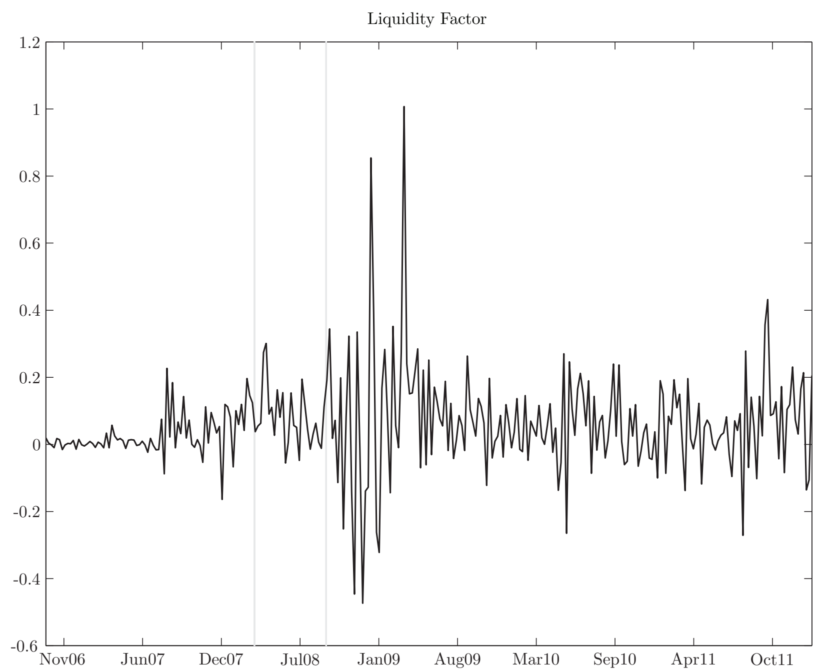

Figure 3: Liquidity Factor.
The figure displays one-week returns (in %) on the tradable liquidity factor. The time series consists of 279 weekly observations from October 4, 2006, to February 1, 2012. Gray vertical lines correspond to (from left to right) the Bear Stearns near bankruptcy on March 17, 2008, and the default of Lehman Brothers on September 15, 2008.

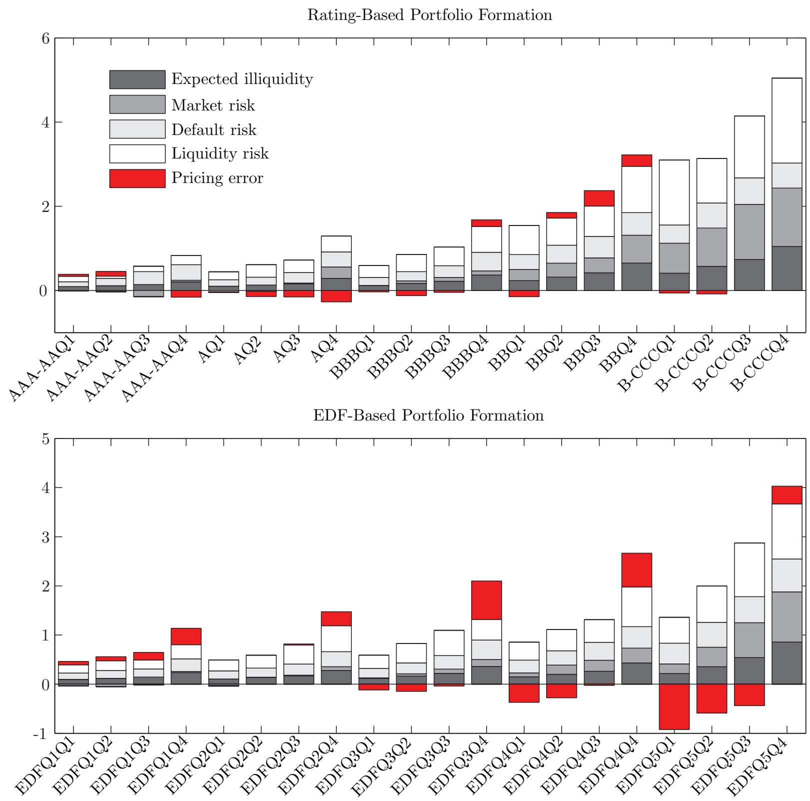

Figure 4: Decomposition of Expected CDS Returns.
The figure displays the decomposition of expected CDS returns (in % p.a.) into factor risk premia at the test portfolio level. Annualized expected CDS returns are decomposed into an intercept term, contributions of, respectively, expected illiquidity and 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.

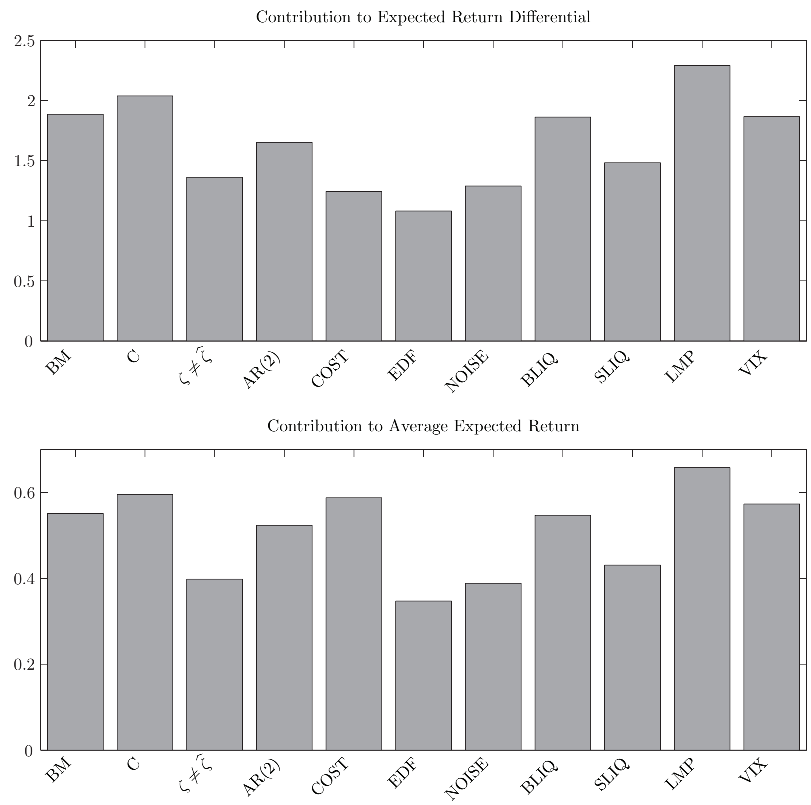

Figure 5: Contribution of Liquidity Risk.
The figure displays the contributions of liquidity risk to expected CDS returns (in % p.a.) in the benchmark specification of the model and in robustness check specifications using alternative measures of economic importance. The upper panel displays the difference 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.

Panel A: Credit Index Levels

	CDX North American				
	IG	IG.HVOL	HY	HY.BB	HY.B
Mean	106.48	221.62	630.94	382.25	596.33
Standard Deviation	49.66	125.87	312.64	150.45	293.36
Minimum	28.88	67.38	208.52	129.37	210.79
Maximum	279.67	682.82	1893.56	972.85	1842.83
N	1338	1342	1337	1325	1326

	iTraxx Europe				
	Main	HiVol	Sr Finls	Sub Finls	Xover
Mean	97.60	167.11	108.69	186.70	514.04
Standard Deviation	48.39	99.05	72.26	130.75	217.81
Minimum	20.09	38.69	6.81	12.43	170.75
Maximum	215.92	550.00	353.00	607.80	1150.33
N	1357	1357	1356	1356	1356

Panel B: Index-to-Theoretical Bases

	CDX North American				
	IG	IG.HVOL	HY	HY.BB	HY.B
Mean	-4.85	-6.00	2.40	14.13	0.42
Standard Deviation	11.58	16.98	68.31	49.94	67.17
Minimum	-61.12	-99.52	-451.93	-246.58	-406.75
Maximum	12.17	29.47	172.45	188.92	396.90
Corr. Abs. Value and Level	0.74	0.72	0.64	0.55	0.68

	iTraxx Europe				
	Main	HiVol	Sr Finls	Sub Finls	Xover
Mean	-3.76	-1.42	-3.84	2.34	3.61
Standard Deviation	9.05	7.03	6.88	7.48	16.48
Minimum	-58.55	-39.01	-36.99	-41.87	-106.15
Maximum	13.93	20.53	10.64	33.50	49.89
Corr. Abs. Value and Level	0.53	0.64	0.35	0.34	0.53

Table 1: Descriptive Statistics.
The table displays descriptive statistics of credit index levels and index-to-theoretical bases. 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. Descriptive statistics are in basis points and missing observations are neglected in their computation. Time series in Panels A and B consist of the indicated number, N in Panel A, of daily observations from September 20, 2006, to February 1, 2012.

Panel A: CDS Market Illiquidity Measures

Intercept	-0.06	0.00	-0.01	-0.07
	[-0.35]	[0.01]	[-0.06]	[-0.41]
ΔBid-Ask	0.31			0.32
	[2.70]			[2.34]
ΔILLIQ-1		0.24		-0.30
		[0.78]		[-1.52]
ΔILLIQ-2			1.42	0.95
			[2.71]	[2.24]
$\bar{R}^2$	0.23	0.02	0.08	0.25

Panel B: Bond Market Illiquidity Measures

Intercept	-0.05	-0.01	-0.00	-0.02
	[-0.40]	[-0.06]	[-0.00]	[-0.20]
ΔRefCorp	7.86			2.48
	[3.16]			[1.58]
ΔNoise		0.80		0.68
		[5.30]		[3.85]
$\Delta\lambda$			0.18	-0.07
			[0.84]	[-0.40]
$\bar{R}^2$	0.25	0.41	-0.01	0.41

Panel C: Capital Supply Measures

Intercept	-0.01	0.00	-0.05	-0.05
	[-0.03]	[0.01]	[-0.27]	[-0.27]
ΔLIB-OIS	1.71			1.08
	[2.22]			[1.74]
ΔRepo		2.65		-0.79
		[1.34]		[-0.40]
ΔHFRX			-0.03	-0.02
			[-2.36]	[-1.84]
$\bar{R}^2$	0.09	0.05	0.17	0.16

Panel D: Market Conditions

Intercept	-0.02	-0.02	-0.01	-0.02
	[-0.14]	[-0.09]	[-0.05]	[-0.14]
ΔDefault	4.19			2.23
	[2.16]			[0.78]
ΔVIX		0.10		0.02
		[2.17]		[0.42]
ΔCDS-Bond			-3.50	-1.70
			[-2.95]	[-1.92]
$\bar{R}^2$	0.28	0.12	0.27	0.29

Table 2: Time Series Properties of CDS Market Illiquidity.
The table displays results from regressing monthly changes in the CDS market illiquidity measure on monthly changes in the average bid-ask spread of single-name CDSs (Bid-Ask), the average absolute spread change per quote contributed across single-name CDSs (ILLIQ-1), the weighted average (by number of index constituents) of absolute spread changes per number of quote contributors across five-year on-the-run credit indices (ILLIQ-2), the spread between ten-year Resolution Funding Corporation and Treasury constant maturity yields (RefCorp), the Hu, Pan, and Wang (2013) Noise measure (Noise), Dick-Nielsen, Feldhütter, and Lando's (2012) λ corporate bond illiquidity measure, the spread between three-month LIBOR and OIS rates (LIB-OIS), the spread between three-month Agency MBS and Treasury general collateral repo rates (Repo), the level of the Hedge Fund Research Global Index (HFRX), the yield spread between Baa- and Aaa-rated bonds (Default), the VIX index (VIX), and the average CDS-bond basis across U.S. investment grade bonds (CDS-Bond). Reported are intercepts and slope coefficients, their respective t-statistics in square brackets, and adjusted R^2s. t-statistics are based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors with three lags. Bid-Ask, ILLIQ-1, ILLIQ-2, and Noise are in basis points. RefCorp, LIB-OIS, Repo, Default, VIX, CDS-Bond, and the CDS market illiquidity measure are in %. λ and HFRX are in index points. Regression are run with time series that consist of 63 monthly observations from October 2006 to December 2011.

	ΔILLIQ-1	ΔILLIQ-2	ΔRefCorp	ΔNoise	$\Delta\lambda$	ΔLIB-OIS	ΔRepo	ΔHFRX	ΔDefault	ΔVIX	ΔCDS-Bond
ΔBid-Ask	0.54	0.44	0.50	0.72	0.15	0.27	0.38	-0.59	0.77	0.58	-0.64
ΔILLIQ-1		0.56	0.31	0.30	0.38	0.25	0.12	-0.43	0.39	0.44	-0.46
ΔILLIQ-2			0.23	0.23	0.68	0.41	0.34	-0.56	0.28	0.69	-0.29
ΔRefCorp				0.65	0.13	0.10	0.13	-0.53	0.52	0.45	-0.38
ΔNoise					0.14	0.31	0.50	-0.57	0.65	0.54	-0.64
$\Delta\lambda$						0.48	0.33	-0.57	0.17	0.53	-0.18
ΔLIB-OIS							0.75	-0.49	0.44	0.62	-0.56
ΔRepo								-0.51	0.41	0.68	-0.46
ΔHFRX									-0.59	-0.75	0.53
ΔDefault										0.52	-0.80
ΔVIX											-0.49

Table 3: Correlations Explanatory Variables.

The table displays the correlation of monthly changes in the explanatory variables of the time series properties regressions. The explanatory variables are: The average bid-ask spread of single-name CDSs (Bid-Ask), the average absolute spread change per quote contributed across single-name CDSs (ILLIQ-1), the weighted average (by number of index constituents) of absolute spread changes per number of quote contributors across five-year on-the-run credit indices (ILLIQ-2), the spread between ten-year Resolution Funding Corporation and Treasury constant maturity yields (RefCorp), the Hu, Pan, and Wang (2013) Noise measure (Noise), Dick-Nielsen, Feldhütter, and Lando's (2012) λ corporate bond illiquidity measure, the spread between three-month LIBOR and OIS rates (LIB-OIS), the spread between three-month Agency MBS and Treasury general collateral repo rates (Repo), the level of the Hedge Fund Research Global Index (HFRX), the yield spread between Baa- and Aaa-rated bonds (Default), the VIX index (VIX), and the average CDS-bond basis across U.S. investment grade bonds (CDS-Bond). Bid-Ask, ILLIQ-1, ILLIQ-2, and Noise are in basis points. RefCorp, LIB-OIS, Repo, Default, VIX, and CDS-Bond are in %. λ and HFRX are in index points. The time series consist of 63 monthly observations from October 2006 to December 2011.

Panel A: Return Descriptive Statistics

	CDX North American				
	IG	IG.HVOL	HY	HY.BB	HY.B
Mean	4.66	8.54	13.06	11.51	13.56
Standard Deviation	21.71	36.03	73.32	95.41	71.90
Sharpe Ratio	2.44	1.34	1.54	1.55	1.94
Skewness	0.68	1.11	0.24	1.56	1.42
Kurtosis	13.54	9.10	5.96	14.54	7.95
ρ_1	-0.12	0.01	-0.06	-0.05	0.02
N	273	272	264	267	265

	iTraxx Europe				
	Main	HiVol	Sr Finls	Sub Finls	Xover
Mean	2.89	4.58	3.16	10.26	12.41
Standard Deviation	16.36	24.42	18.25	33.32	44.85
Sharpe Ratio	1.59	2.12	1.61	1.24	1.16
Skewness	0.83	-0.36	-0.29	1.64	0.69
Kurtosis	9.38	10.40	6.95	8.91	6.10
ρ_1	-0.01	-0.28	-0.17	0.14	0.04
N	277	277	277	277	275

Panel B: Pairwise Correlations

	CDX North American				
	IG	IG.HVOL	HY	HY.BB	HY.B
IG		0.39	0.17	0.13	0.14
IG.HVOL			0.08	0.04	0.08
HY				0.45	0.60
HY.BB					0.49

	iTraxx Europe				
	Main	HiVol	Sr Finls	Sub Finls	Xover
Main		0.39	0.27	0.08	0.28
HiVol			0.05	0.02	0.11
Sr Finls				0.01	0.00
Sub Finls					0.19

Table 4: Return Descriptive Statistics.
The table displays descriptive statistics of of one-week returns on the trading strategy underlying the construction of the tradable liquidity factor. Mean and standard deviation are in basis points per week, the Sharpe ratio is annualized using Lo's (2002) correction for non-independent returns, and ρ_1 denotes first-order autocorrelation. Missing observations are neglected in the computation of descriptive statistics. Time series consist of the indicated number, N in Panel A, of weekly observations from October 4, 2006, to February 1, 2012.

Panel A: Descriptive Statistics			
	MKT	DEF	LIQ
Mean	-7.71	-3.07	5.80
Standard Deviation	303.84	42.28	14.23
Skewness	-0.70	-0.42	1.46
Kurtosis	5.55	4.84	13.73
ρ_1	-0.06	-0.11	0.05

Panel B: Correlations			
	MKT	DEF	LIQ
MKT	1.00	0.72	0.13
LIQ		1.00	0.07
DEF			1.00

Table 5: 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 ρ_1 denotes first-order autocorrelation. Factor time series consist of 276 weekly observations from October 11, 2006, to February 1, 2012.

	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	0.40	0.19	0.23	0.29	0.41
	[6.79]	[7.53]	[6.35]	[6.09]	[-0.97]	[-0.48]	[-0.39]	[0.13]	[11.20]	[10.73]	[10.23]	[7.81]
A	0.40	0.47	0.57	1.02	-1.28	-1.12	-0.52	0.74	0.21	0.26	0.33	0.59
	[7.75]	[7.10]	[5.80]	[4.37]	[-0.83]	[-0.58]	[-0.18]	[0.12]	[12.57]	[11.40]	[9.46]	[7.44]
BBB	0.56	0.74	0.99	1.68	-1.36	-1.00	0.79	4.90	0.24	0.34	0.44	0.75
	[9.60]	[7.16]	[6.43]	[5.33]	[-0.74]	[-0.34]	[0.18]	[0.60]	[12.18]	[9.51]	[8.86]	[7.88]
BB	1.40	1.85	2.37	3.22	-3.06	1.22	4.86	11.98	0.48	0.65	0.86	1.33
	[10.02]	[9.42]	[8.71]	[9.31]	[-0.68]	[0.21]	[0.59]	[1.00]	[9.39]	[8.86]	[8.63]	[9.10]
B–CCC	3.04	3.05	4.14	5.04	-3.89	8.33	12.76	17.13	0.84	1.16	1.49	2.12
	[11.13]	[13.35]	[8.34]	[6.64]	[-0.38]	[0.72]	[0.89]	[1.10]	[6.65]	[6.94]	[7.15]	[9.78]

	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	18.68	25.02	40.85	60.21	86.57	98.74	105.05	117.90
A	0.53	0.66	0.85	1.97	22.12	28.27	36.59	66.89	83.99	86.80	87.22	103.81
BBB	0.75	1.00	1.36	2.77	28.35	36.92	47.15	73.84	82.43	87.04	96.97	101.67
BB	1.97	2.69	3.56	5.96	68.12	79.64	96.23	120.31	107.98	101.74	105.85	108.35
B–CCC	4.71	5.88	9.07	18.61	124.82	142.17	174.64	220.77	112.17	116.64	122.28	136.77

Table 6: Descriptive Statistics Rating-Based Portfolio Formation.
The table displays descriptive statistics for the 20 test portfolios formed by first sorting CDS contracts according to credit ratings 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: Rating-Based Portfolio Formation

	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	-0.51	-1.31	-6.73	1.83	13.81	21.19	37.45	45.01	3.04	1.16	2.93	5.05
	[-0.56]	[-0.68]	[-2.20]	[0.41]	[16.98]	[10.42]	[7.13]	[9.86]	[1.63]	[0.54]	[0.99]	[1.26]
A	-1.56	-0.91	0.84	12.42	18.68	22.82	30.19	43.63	4.43	6.88	6.84	8.71
	[-1.06]	[-0.46]	[0.36]	[2.54]	[8.25]	[10.38]	[11.43]	[7.78]	[2.12]	[2.30]	[1.98]	[1.59]
BBB	0.05	2.73	4.17	4.48	22.83	26.85	34.06	54.05	6.67	9.46	10.22	14.18
	[0.03]	[1.03]	[1.08]	[0.72]	[10.23]	[13.18]	[8.31]	[7.44]	[2.88]	[2.40]	[2.20]	[1.95]
BB	12.14	15.13	16.30	30.33	43.04	51.81	62.21	65.30	16.04	15.01	16.66	25.49
	[2.35]	[3.17]	[2.28]	[4.27]	[7.74]	[7.78]	[6.49]	[6.89]	[4.67]	[3.16]	[2.34]	[3.21]
B–CCC	32.69	41.76	60.20	63.67	52.70	72.46	76.55	72.33	35.86	24.53	34.18	46.81
	[4.85]	[5.46]	[7.09]	[5.32]	[4.04]	[6.48]	[6.77]	[3.88]	[3.00]	[2.90]	[3.91]	[2.22]

Panel B: EDF-Based Portfolio Formation

	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	-1.58	-2.44	-0.72	1.12	15.72	19.38	19.91	31.14	3.87	4.59	4.24	6.72
	[-1.46]	[-1.49]	[-0.64]	[0.33]	[10.83]	[9.06]	[15.98]	[11.96]	[2.39]	[2.19]	[2.02]	[1.95]
EDFQ2	-1.31	0.26	0.50	3.57	20.18	22.54	27.69	37.35	5.14	6.05	8.99	12.22
	[-0.78]	[0.16]	[0.16]	[0.75]	[8.94]	[10.79]	[13.07]	[8.28]	[2.15]	[1.99]	[2.29]	[2.39]
EDFQ3	0.51	2.13	4.05	6.48	23.31	27.13	33.72	48.28	6.23	9.12	11.91	9.70
	[0.28]	[0.71]	[1.56]	[1.25]	[11.08]	[12.91]	[12.36]	[9.27]	[2.20]	[2.19]	[2.40]	[1.90]
EDFQ4	3.71	8.60	10.26	13.77	31.59	35.45	44.60	53.30	8.46	10.01	10.64	18.76
	[1.33]	[1.95]	[2.81]	[2.28]	[10.60]	[9.79]	[8.98]	[7.48]	[2.54]	[2.34]	[2.97]	[2.94]
EDFQ5	8.99	18.14	32.72	46.98	51.35	62.04	64.44	81.46	12.28	17.18	25.32	26.04
	[3.48]	[3.92]	[4.99]	[5.69]	[11.43]	[7.41]	[7.42]	[8.25]	[2.44]	[2.56]	[3.40]	[2.20]

Table 7: Results Time Series Regressions.
The table displays first-step regression results at the level of individual test portfolios. 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. 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
ζ					94.86	94.86	94.86	94.86
					(—)	(—)	(—)	(—)
					[—]	[—]	[—]	[—]
λ_{MKT}		11.99		16.25		8.48		12.71
		(4.27)		(2.85)		(3.33)		(2.46)
		[2.68]		[1.81]		[2.10]		[1.62]
λ_{DEF}			0.92	1.01			0.59	0.67
			(2.56)	(3.65)			(1.79)	(2.53)
			[1.71]	[2.22]			[1.25]	[1.66]
λ_{LIQ}	2.29	1.44	1.83	1.29	1.84	1.33	1.63	1.18
	(3.67)	(3.28)	(4.40)	(2.92)	(3.63)	(3.15)	(4.20)	(2.83)
	[3.70]	[2.02]	[3.24]	[1.67]	[3.66]	[2.00]	[3.05]	[1.70]
R^2	0.96	0.96	0.96	0.97	0.97	0.97	0.97	0.97
	[0.94,0.98]	[0.95,0.98]	[0.95,0.98]	[0.95,0.98]	[0.96,0.99]	[0.96,0.98]	[0.96,0.98]	[0.96,0.99]

Table 8: Results Cross-Sectional Regressions.
The table displays results of several specifications of the second-step cross-sectional regression. Specifications of $\widehat{E}[r^e_{i,t}]-\widehat{E}[c_{i,t}]\widehat{\zeta} = \widehat{\beta}_i^{\text{MKT}}\lambda_{\text{MKT}}+\widehat{\beta}_i^{\text{DEF}}\lambda_{\text{DEF}}+\widehat{\beta}_i^{\text{LIQ}}\lambda_{\text{LIQ}}+u_i$ 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), t-statistics based on asymptotic generalized method of moments standard errors that account for error-in-variables problems (in parenthesis), t-statistics based on Kan, Robotti, and Shanken's (2013) asymptotic standard errors that that account for error-in-variables problems and potential model misspecification (in square brackets), cross-sectional R^2s, and their 95% confidence intervals. Standard errors are heteroscedasticity and autocorrelation consistent through the use of Newey and West's (1987) method with 24 lags. In the computation of cross-sectional R^2s, expected CDS returns are treated as the dependent variable.

Spec.	1	2	3	4	5	6	7	8	9	10
	C	$\zeta \neq \widehat{\zeta}$	AR(2)	COST	EDF	NOISE	BLIQ	SLIQ	LMP	VIX
ζ	94.86	374.61	94.86	94.86	94.86	94.86	94.86	94.86	94.86	94.86
	(—)	(5.12)	(—)	(—)	(—)	(—)	(—)	(—)	(—)	(—)
	[—]	[4.37]	[—]	[—]	[—]	[—]	[—]	[—]	[—]	[—]
λ_{MKT}	10.57	2.27	14.69	17.42	7.47	8.96	13.04	5.79	11.77	13.53
	(2.02)	(0.45)	(3.31)	(2.29)	(1.89)	(1.33)	(2.75)	(1.47)	(2.10)	(2.91)
	[0.88]	[0.35]	[2.81]	[2.25]	[1.71]	[1.15]	[1.79]	[0.83]	[1.44]	[1.89]
λ_{DEF}	0.84	-0.34	0.64	0.23		0.50	0.68	0.63	0.23	0.63
	(2.26)	(-0.79)	(2.74)	(0.81)		(1.56)	(2.33)	(2.33)	(0.74)	(2.63)
	[1.95]	[-0.65]	[2.17]	[0.60]		[1.22]	[1.73]	[1.75]	[0.39]	[1.58]
λ_{LIQ}	1.27	0.85			1.18	0.84	1.19	0.92	1.43	1.24
	(3.49)	(2.46)			(3.81)	(1.97)	(2.95)	(2.99)	(3.14)	(2.81)
	[1.58]	[1.31]			[1.47]	[1.94]	[1.72]	[1.28]	[1.91]	[1.92]
λ_{X}	-0.19		-12.89	-0.34	-0.37	-0.10	-0.41	16.21	-0.97	-18.08
	(-0.91)		(-3.39)	(-2.88)	(-1.90)	(-3.18)	(-0.10)	(2.03)	(-0.24)	(-3.16)
	[-0.38]		[-2.33]	[-2.23]	[-1.57]	[-1.62]	[-0.07]	[1.19]	[-0.14]	[-1.61]
R^2	0.94	0.98	0.97	0.98	0.97	0.98	0.97	0.98	0.97	0.98
	[0.90,0.97]	[0.97,0.99]	[0.96,0.99]	[0.97,0.99]	[0.96,0.98]	[0.97,0.99]	[0.96,0.99]	[0.96,0.99]	[0.96,0.99]	[0.96,0.99]

Table 9: Robustness Cross-Sectional Regressions.
The table displays results of a series of robustness checks. Specifications of $\widehat{E}[r^e_{i,t}] - \widehat{E}[c_{i,t}]\widehat{\zeta} = \widehat{\beta}_i^{\text{MKT}}\lambda_{\text{MKT}} + \widehat{\beta}_i^{\text{DEF}}\lambda_{\text{DEF}} + \widehat{\beta}_i^{\text{LIQ}}\lambda_{\text{LIQ}} + \widehat{\beta}_i^{\text{X}}\lambda_{\text{X}} + u_i$ (specification 1 and 3–10) and $\widehat{E}[r^e_{i,t}] = \widehat{E}[c_{i,t}]\zeta + \widehat{\beta}_i^{\text{MKT}}\lambda_{\text{MKT}} + \widehat{\beta}_i^{\text{DEF}}\lambda_{\text{DEF}} + \widehat{\beta}_i^{\text{LIQ}}\lambda_{\text{LIQ}} + u_i$ (specification 2) 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 an additional factor is available only for part of the sample period). Specification identifiers are given in the second row of the table. Reported are factor price of risk estimates (in basis points), t-statistics based on asymptotic generalized method of moments standard errors that account for error-in-variables problems (in parenthesis), t-statistics based on Kan, Robotti, and Shanken's (2013) asymptotic standard errors that that account for error-in-variables problems and potential model misspecification (in square brackets), cross-sectional R^2s, and their 95 percent confidence intervals. Standard errors are heteroscedasticity and autocorrelation consistent through the use of Newey and West's (1987) method with 24 lags. In the computation of cross-sectional R^2s, expected CDS returns are treated as the dependent variable.

Spec.	0	1	2	3	4	5	6	7	8	9	10
	BM	C	$\zeta \neq \widehat{\zeta}$	AR(2)	COST	EDF	NOISE	BLIQ	SLIQ	LMP	VIX
Expected illiquidity	0.95	0.95	3.76	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
	[0.29]	[0.29]	[1.15]	[0.29]	[0.29]	[0.29]	[0.29]	[0.29]	[0.29]	[0.29]	[0.29]
Market and default risk	1.88	1.77	0.00	2.11	2.34	2.69	1.35	1.94	1.09	1.41	2.61
	[0.57]	[0.62]	[-0.13]	[0.61]	[0.53]	[0.81]	[0.42]	[0.59]	[0.42]	[0.44]	[0.61]
Liquidity risk	1.89	2.04	1.36	1.65	1.24	1.08	1.29	1.86	1.48	2.29	1.87
	[0.55]	[0.60]	[0.40]	[0.52]	[0.59]	[0.35]	[0.39]	[0.55]	[0.43]	[0.66]	[0.57]
Additional risk factor							0.64	-0.06	1.52	-0.01	-0.95
							[0.30]	[-0.01]	[0.27]	[0.02]	[-0.06]

Table 10: 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.

Internet Appendix to "Liquidity Risk in Credit Default Swap Markets"

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Content

Appendix D presents implementation details regarding the computation of expected returns, realized returns, and transactions costs. Appendix E illustrates the computation of standard errors of factor price of risk estimates and cross-sectional R^2s under potential model misspecification. Appendix F presents the results of additional robustness checks. Appendix G contains additional figures and tables.

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D Implementation Details

The computation of expected and realized returns on a CDS trading at par and the computation of transaction costs is based on a standard CDS pricing model.

It is assumed that: (i) Credit events occur randomly and independently across reference names at the first jump times τ_i of a homogeneous Poisson processes with constant intensities, (ii) interest rates evolve independent of the occurrence of credit events, and (iii) in case a credit event occurs, creditors recover a constant fraction of the reference obligation's par value.

Due to assumption (ii), 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)-(iii) the present value of the protection leg of a T-maturity single-name CDS on reference name i is given by

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

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

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

where $\alpha = 365/360$ is a constant factor transforming calendar time measured in years into an ACT/360 day-count convention and $PVBP_i(t,T)$ denotes the present value of a basis point.[1] Note that the integrals appearing in the above equations can be computed analytically for any sub-period of the integration domain over which instantaneous forward rates are constant.

Given the quoted T-year par spread $C_i(t,T)$ for reference name i and the corresponding recovery rate estimate, R_i, survival probabilities can be calibrated such that model implied (clean) par spreads match the quoted ones. That is, one solves

$$0 = PV_{1,i}(t,T,R_i) - (C_i(t,T) \cdot PVBP_{i,t}(T) - \alpha C_i(t,T)(t - t_0)), \tag{D.3}$$

numerically for the survival probability $S_i(t,T)$.[2] Due to assumption (i), survival probabilities for intermediate points in time can easily be obtained by interpolation.

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

[2] The last term of Equation (D.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)

E Standard Error Computation

Standard Errors of Factor Price of Risk Estimates

We will illustrate standard error computation for a general K-dimensional vector of factors, f_t, and the most general case that we consider in the paper, namely, the case of a cross-sectional regression with intercept and expected transaction cost as a characteristic. In this case, the counterparts of Equations (1) and (2) in vector notation are

$$r_t = \alpha + \beta f_t + \epsilon_t \tag{E.1}$$

and

$$\mu_\xi = 1_N \lambda_0 + \mu_c \zeta + \beta \lambda = X\gamma \tag{E.2}$$

where $r_t = [r^e_{1,t},\ \ldots,\ r^e_{N,t}]'$ denotes the N-dimensional vector of realized excess returns, α denotes the N-dimensional vector of regression intercepts, β denotes the $N \times K$ matrix of factor loadings, $\epsilon_t = [\epsilon_{1,t},\ \ldots,\ \epsilon_{N,t}]'$ denotes the N-dimensional vector of mean zero error terms, μ_ξ denotes the mean of the N-dimensional vector of conditional expected excess returns, $\xi_t = [\xi_{1,t},\ \ldots,\ \xi_{N,t}]'$ with $\xi_{i,t} = E_t[r^e_{i,t+1}]$, μ_c denotes the mean of the N-dimensional vector of transaction costs, $c_t = [c_{1,t},\ \ldots,\ c_{N,t}]'$, X and γ are defined by $X = [1_N,\ \mu_c,\ \beta]$ and $\gamma = [\lambda_0,\ \zeta,\ \lambda']'$, and 1_N denotes an N-dimensional vector of ones. Note that in contrast to the standard two-pass cross-sectional regression method, there is a distinction between expected excess returns, μ_ξ, and the mean of realized excess returns, μ_r.

Moreover, we define $Y_t = [f_t',\ r_t']'$ and denote its mean and covariance matrix by $\mu = [\mu_f',\ \mu_r']'$ and V, respectively. In what follows, we will use the following convenient partition of V,

$$V = \begin{bmatrix} V_f & V_{rf}' \\ V_{rf} & V_r \end{bmatrix},$$

which gives rise to $\beta = V_{rf} V_f^{-1}$. As in Kan, Robotti, and Shanken (2013), we will assume finite fourth moments, stationarity, and ergodicity of the time series $[Y_t',\ \xi_t',\ c_t']'$.

Under a potentially misspecified model, there is no γ such that Equation (E.2) is satisfied and γ is chosen to minimize the sum of squared population pricing errors, $e = \mu_\xi - X\gamma$, i.e.,

$$\gamma = \underset{\delta}{\operatorname{argmin}} (\mu_\xi - X\delta)'(\mu_\xi - X\delta) = (X'X)^{-1}X'\mu_\xi.$$

From this expression an estimate of γ can be obtained by replacing population moments with their sample counterparts, i.e.,

$$\widehat{\gamma} = (\widehat{X}'\widehat{X})^{-1}\widehat{X}'\widehat{\mu}_\xi,$$

where $\widehat{X} = [1_N,\ \widehat{\mu}_c,\ \widehat{\beta}]$, $\widehat{\mu}_\xi$ and $\widehat{\mu}_c$ are given by

$$\widehat{\mu}_\xi = \frac{1}{T}\sum_{t=1}^{T} \xi_t \quad \text{and} \quad \widehat{\mu}_c = \frac{1}{T}\sum_{t=1}^{T} c_t,$$

[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.

respectively, and $\widehat{\beta}$ is given by $\widehat{\beta} = \widehat{V}_{rf}\widehat{V}_f^{-1}$, with

$$\widehat{V} = \begin{bmatrix} \widehat{V}_f & \widehat{V}_{rf}' \\ \widehat{V}_{rf} & \widehat{V}_r \end{bmatrix} = \frac{1}{T}\sum_{t=1}^{T}(Y_t - \widehat{\mu})(Y_t - \widehat{\mu})', \quad \text{where} \quad \widehat{\mu} = \frac{1}{T}\sum_{t=1}^{T} Y_t.$$

It is well known that $\widehat{\theta} = [\widehat{\mu}',\ \widehat{\mu}_\xi',\ \widehat{\mu}_c',\ \text{vec}(\widehat{V})']'$ is the method of moments estimator of $\theta = [\mu',\ \mu_\xi',\ \mu_c',\ \text{vec}(V)']'$. Under the above assumptions,[3]

$$\sqrt{T}(\widehat{\theta} - \theta) \xrightarrow[T\to\infty]{d} N(0, S_0)$$

where $S_0 = \sum_{j=-\infty}^{\infty} E[\psi_t \psi_{t+j}']$ and ψ_t is the moment function,

$$\psi_t = [(Y_t - \mu)',\ (\xi_t - \mu_\xi)', (c_t - \mu_c)',\ \text{vec}((Y_t - \mu)(Y_t - \mu)' - V)']'.$$

Since γ is a smooth function of θ, an application of the delta method shows

$$\sqrt{T}(\widehat{\gamma} - \gamma) \xrightarrow[T\to\infty]{d} N(0, (\partial\gamma/\partial\theta')S_0(\partial\gamma/\partial\theta')').$$

Using the expression for S_0 from above, the asymptotic variance of $\widehat{\gamma}$, $(\partial\gamma/\partial\theta')S_0(\partial\gamma/\partial\theta')'$, becomes $\sum_{j=-\infty}^{\infty} E[h_t h_{t+j}']$, with $h_t = (\partial\gamma/\partial\theta')\psi_t$.

Before proceeding further, let us fix the following notation: $H = (X'X)^{-1}$ and $A = HX'$. Also note that with e defined as above, γ satisfies the first-order conditions

$$X'e = 0_{K+2} \quad \Leftrightarrow \quad 1_N'e = 0, \quad \mu_c'e = 0, \quad \text{and} \quad \beta'e = 0_K,$$

where here and in what follows 0_m denotes an m-dimensional vector of zeros.

In order to find an explicit expression for h_t it remains to compute $\partial\gamma/\partial\theta'$. Using the above partition of θ,

$$\frac{\partial\gamma}{\partial\theta'} = \left[\frac{\partial\gamma}{\partial\mu'},\ \frac{\partial\gamma}{\partial\mu_\xi'},\ \frac{\partial\gamma}{\partial\mu_c'},\ \frac{\partial\gamma}{\partial\,\text{vec}(V)'}\right] = \left[0_{(K+2)\times(K+N)},\ A,\ \frac{\partial\gamma}{\partial\mu_c'},\ \frac{\partial\gamma}{\partial\,\text{vec}(V)'}\right],$$

where $0_{m\times n}$ denotes an $m \times n$ matrix of zeros. For the remaining expressions, we get

$$\frac{\partial\gamma}{\partial\mu_c'} = \{(H \otimes e') - (\gamma' \otimes A)\}\frac{\partial\,\text{vec}(X)}{\partial\mu_c'}, \tag{E.3}$$

$$\frac{\partial\gamma}{\partial\,\text{vec}(V)'} = \{(H \otimes e') - (\gamma' \otimes A)\}\frac{\partial\,\text{vec}(X)}{\partial\,\text{vec}(V)'}. \tag{E.4}$$

Note that $\text{vec}(X) = [1_N',\ \mu_c',\ \text{vec}(\beta)']'$. Thus,

$$\frac{\partial\,\text{vec}(X)}{\partial\mu_c'} = [0_{N\times N},\ I_N,\ 0_{N\times N\cdot K}]' = ([0,\ 1,\ 0_K']' \otimes I_N),$$

$$\frac{\partial\,\text{vec}(X)}{\partial\,\text{vec}(V)'} = \left[0_{(N+K)^2\times 2\cdot N},\ \left(\frac{\partial\,\text{vec}(\beta)}{\partial\,\text{vec}(V)'}\right)'\right]' = ([[0_{K\times 2}, V_f^{-1}]',\ 0_{(K+2)\times N}] \otimes [-\beta,\ I_N]),$$

[3] As noted by Kan et al. (2013), S_0 is a singular matrix. This is due to the fact that $\widehat{V}$ is symmetric, i.e., it contains linearly dependent elements. One could alternatively consider the parameter vector $\tilde{\theta} = [\mu',\ \mu_\xi',\ \mu_c',\ \text{vech}(V)']'$, in which case the covariance matrix of the limiting normal distribution would be non-singular.

where we used $(\partial\,\mathrm{vec}(\beta)/\partial\,\mathrm{vec}(V)') = ([V_f^{-1},\ 0_{K\times N}] \otimes [-\beta,\ I_N])$ and I_N denotes an N-dimensional identity matrix. Substituting these expressions into Equations (E.3) and (E.4) and using the first-order conditions yields

$$\begin{aligned}\frac{\partial\gamma}{\partial\mu_c'} &= (H([0,\ 1,\ 0_K']') \otimes e') - \zeta A,\\ \frac{\partial\gamma}{\partial\,\mathrm{vec}(V)'} &= ([H([0_{K\times 2}, V_f^{-1}]'),\ 0_{(K+2)\times N}] \otimes [0_K',\ e']) - ([\lambda' V_f^{-1}, 0_N'] \otimes [-A\beta, A]).\end{aligned}$$

Again making use of the first-order conditions, h_t can now be explicitly expressed as

$$\begin{aligned}h_t = \frac{\partial\gamma}{\partial\theta'}\psi_t =& A(\xi_t - \mu_\xi) + H[0,\ e'c_t,\ 0_K']' - \zeta A(c_t - \mu_c)\\ &+ H[0_2', e'(r_t - \mu_r)(f_t - \mu_f)'V_f^{-1}]'\\ &- A(r_t - \mu_r)(f_t - \mu_f)'V_f^{-1}\lambda + A\beta(f_t - \mu_f)(f_t - \mu_f)'V_f^{-1}\lambda\\ =&(\gamma_t - \gamma) - \zeta A(c_t - \mu_c) - \{A(r_t - \mu_r) - [0_2', (f_t - \mu_f)']'\}w_t + Hz_t \end{aligned} \tag{E.5}$$

where $\gamma_t = A\xi_t$, $z_t = [0,\ e'c_t,\ u_t(f_t - \mu_f)'V_f^{-1}]'$, $u_t = e'(r_t - \mu_r)$, and $w_t = (f_t - \mu_f)'V_f^{-1}\lambda$.

Applying the Newey and West (1987) method, a heteroskedasticity and autocorrelation consistent estimator for the asymptotic variance of $\widehat{\gamma}$ is given by

$$\frac{1}{T}\sum_{t=1}^{T}\widehat{h}_t\widehat{h}_t' + \frac{1}{T}\sum_{l=1}^{m}\sum_{t=l+1}^{T}(1 - \frac{l}{m+1})(\widehat{h}_t\widehat{h}_{t-l}' + \widehat{h}_{t-l}\widehat{h}_t')$$

where

$$\widehat{h}_t = (\widehat{\gamma}_t - \widehat{\gamma}) - \widehat{\zeta}\widehat{A}(c_t - \widehat{\mu}_c) - \{\widehat{A}(r_t - \widehat{\mu}_r) - [0_2', (f_t - \widehat{\mu}_f)']'\}\widehat{w}_t + \widehat{H}\widehat{z}_t,$$

and $\widehat{H} = (\widehat{X}'\widehat{X})^{-1}$, $\widehat{A} = \widehat{H}\widehat{X}'$, $\widehat{e} = \widehat{\mu}_\xi - \widehat{X}\widehat{\gamma}$, $\widehat{\gamma}_t = \widehat{A}\xi_t$, $\widehat{z}_t = [0,\ \widehat{e}'c_t,\ \widehat{u}_t(f_t - \widehat{\mu}_f)'\widehat{V}_f^{-1}]'$, $\widehat{u}_t = \widehat{e}'(r_t - \widehat{\mu}_r)$, and $\widehat{w}_t = (f_t - \widehat{\mu}_f)'\widehat{V}_f^{-1}\widehat{\lambda}$. The finite sample approximation of the variance of $\widehat{\gamma}$ is obtained as $1/T$ times the estimate of the asymptotic variance.

Based on Equation (E.5) it is straightforward to break down asymptotic variation of $\widehat{\gamma}$ into three components. The first one, $\gamma_t - \gamma$, is variation of $\widehat{\gamma}$ in case that the model is correctly specified and estimated using population values, i.e., there is no error associated with the estimation of the characteristic, μ_c, and factor loadings, β. It should be noted that this is the only source of variation, which is taken into account by the Fama and MacBeth (1973) method. The second source of variation are errors-in-variables (EIV). The second term of Equation (E.5) captures variation associated with the estimation of the characteristic, μ_c, and the third term of Equation (E.5) captures variation associated with the estimation of factor loadings. Variation from the first two sources is, e.g., accounted for by generalized-method-of-moments-based inference.[4] The third source of variation is due to potential model misspecification and captured by Hz_t. Note that this term vanishes when the model is correctly specified, i.e., $e = \mu_\xi - X\gamma = 0_N$. Thus, setting $e = 0_N$ gives the asymptotic variance of $\widehat{\gamma}$ in a generalized method of moments estimation of $\widehat{\beta}$, $\widehat{\mu}_c$, and $\widehat{\gamma}$. As mentioned above, this asymptotic variance takes into account EIV but neglects potential model misspecification.

[4] As in Cochrane (2001), the estimation of $\widehat{\beta}$, $\widehat{\mu}_c$, and $\widehat{\gamma}$ can be formulated as a generalized method of moments (GMM) estimation. It can be shown that in this GMM estimation the asymptotic variance of $\widehat{\gamma}$ has a representation $\sum_{j=-\infty}^{\infty} E[\tilde{h}_t\tilde{h}_{t+j}']$, where $\tilde{h}_t = (\gamma_t - \gamma) - \zeta A(c_t - \mu_c) - \{A(r_t - \mu_r) - [0_2', (f_t - \mu_f)']'\}w_t$.

In case that the intercept is restricted to zero, $\gamma = [\zeta,\ \lambda']'$, $X = [\mu_c,\ \beta]$ and h_t is given by

$$h_t = (\gamma_t - \gamma) - \zeta A(c_t - \mu_c) - \{A(r_t - \mu_r) - [0, (f_t - \mu_f)']'\}w_t + Hz_t$$

where $z_t = [e'c_t,\ u_t(f_t - \mu_f)'V_f^{-1}]'$, and A, H, γ_t, u_t, and w_t are defined as above. In case that ζ is calibrated to some fixed value $\widehat{\zeta}$, $\gamma = [\lambda_0,\ \lambda']'$, $X = [1_N,\ \beta]$, $e = \mu_\xi - \widehat{\zeta}\mu_c - X\gamma$, and h_t is given by

$$h_t = (\gamma_t - \gamma) - \widehat{\zeta}A(c_t - \mu_c) - \{A(r_t - \mu_r) - [0, (f_t - \mu_f)']'\}w_t + Hz_t,$$

where $z_t = [0,\ u_t(f_t - \mu_f)'V_f^{-1}]'$, and A, H, γ_t, u_t, and w_t are defined as above. If both the intercept is restricted to zero and ζ is calibrated to some fixed value $\widehat{\zeta}$, then $\gamma = \lambda$, $X = \beta$, $e = \mu_\xi - \widehat{\zeta}\mu_c - \beta\lambda$, and h_t becomes

$$h_t = (\gamma_t - \gamma) - \widehat{\zeta}A(c_t - \mu_c) - \{A(r_t - \mu_r) - (f_t - \mu_f)\}w_t + Hz_t$$

where $z_t = V_f^{-1}(f_t - \mu_f)u_t$, and A, H, γ_t, u_t, and w_t are defined as above.

Standard Errors of the Cross-Sectional R^2

The standard error computation for the cross-sectional R^2 is based on the same principle as that for the factor price of risk estimates. Again, we derive standard errors for the most general case that we consider in the paper and we discuss less general cases at the end of this section.

Let ρ^2 denote the population value of the R^2, i.e.,

$$\rho^2 = 1 - \frac{Q}{Q_0} = 1 - \frac{e'e}{e_0'e_0},$$

where $e_0 = (I_N - (1/N)1_N 1_N')\mu_\xi$ are population deviations of expected excess returns from their cross-sectional average. Replacing population values in the previous display by their sample estimates, obviously, gives the R^2.

Assume that $0 < \rho^2 < 1$, i.e., the model is neither correctly specified nor is it misspecified and unable to explain any cross-sectional variation in expected returns. As in the previous section, ρ^2 is a smooth function of θ and an application of the delta method yields

$$\sqrt{T}(R^2 - \rho^2) \xrightarrow[T\to\infty]{d} N(0, (\partial\rho^2/\partial\theta')S_0(\partial\rho^2/\partial\theta')') \tag{E.6}$$

where S_0 is defined as in the previous section, $(\partial\rho^2/\partial\theta')S_0(\partial\rho^2/\partial\theta')' = \sum_{j=-\infty}^{\infty} E[\eta_t\eta_{t+j}]$, and $\eta_t = (\partial\rho^2/\partial\theta')\psi_t$. Thus, it remains to compute $\partial\rho^2/\partial\theta'$ in order to obtain an explicit expression for η_t.

$$\frac{\partial\rho^2}{\partial\theta'} = \left[\frac{\partial\rho^2}{\partial\mu'},\ \frac{\partial\rho^2}{\partial\mu_\xi'},\ \frac{\partial\rho^2}{\partial\mu_c'},\ \frac{\partial\rho^2}{\partial\operatorname{vec}(V)'}\right] = \left[0_{1\times(K+N)},\ \frac{\partial\rho^2}{\partial\mu_\xi'},\ \frac{\partial\rho^2}{\partial\mu_c'},\ \frac{\partial\rho^2}{\partial\operatorname{vec}(V)'}\right]$$

with

$$\frac{\partial\rho^2}{\partial\mu_\xi'} = \frac{2}{Q_0}\{(1-\rho^2)e_0' - e'\}, \tag{E.7}$$

$$\frac{\partial\rho^2}{\partial\mu_c'} = \frac{2}{Q_0}(\gamma'\otimes e')\frac{\partial\operatorname{vec}(X)}{\partial\mu_c'} = \frac{2\zeta}{Q_0}e', \tag{E.8}$$

$$\frac{\partial\rho^2}{\partial\operatorname{vec}(V)'} = \frac{2}{Q_0}(\gamma'\otimes e')\frac{\partial\operatorname{vec}(X)}{\partial\operatorname{vec}(V)'} = \frac{2}{Q_0}([\lambda'V_f^{-1},\ 0_N']\otimes[0_K',\ e']), \tag{E.9}$$

where, in order to arrive at expressions (E.7), (E.8), and (E.9), we made use of $1_N' e_0 = 0$ and the first-order conditions, and we replaced $\partial \operatorname{vec}(X)/\partial \mu_c'$ and $\partial \operatorname{vec}(X)/\partial \operatorname{vec}(V)'$ by the expressions derived in the previous section. Then,

$$\eta_t = \frac{\partial \rho^2}{\partial \theta'} \psi_t = \frac{2}{Q_0} \big\{ (1-\rho^2) e_0' (\xi_t - \mu_\xi) - e'(\xi_t - \mu_\xi) + \zeta e' c_t + u_t w_t \big\}, \tag{E.10}$$

where, as before, $u_t = e'(r_t - \mu_r)$ and $w_t = (f_t - \mu_f)' V_f^{-1} \lambda$. As in the previous section, the Newey and West (1987) method applied to η_t's sample analog, $\widehat{\eta}_t$, gives a consistent estimate of the asymptotic variance of the R^2.

Note that $\eta_t = 0_N$ both under correct model specification (i.e., $e = 0_N$ and, therefore, $\rho^2 = 1$) and in case of a misspecified model that does not have any explanatory power (i.e., $\zeta = 0$ and $\lambda = 0_K$ and, therefore, $\rho^2 = 0$). Thus, in both cases the statistic in Equation (E.6) has a degenerate limiting distribution. It can, however, be shown that in these two cases the statistic $T(R^2 - \rho^2)$ has a non-degenerate limiting distribution (see Kan et al. (2013)).

In case that ζ is calibrated to some fixed value $\widehat{\zeta}$, its value in Equation (E.10) has to be replaced by $\widehat{\zeta}$ when computing standard errors. In case that the intercept is restricted to zero, then ρ^2 is redefined so as to be in accordance with the R^2 of a regression without intercept. That is, the denominator of ρ^2 becomes $Q_0 = \mu_\xi' \mu_\xi$. The corresponding expressions of η_t for the standard error computation are obtained by replacing e_0 in Equation (E.10) with μ_ξ.

F Additional Robustness Checks

Tables 1 and 2, respectively, display cross-sectional regression results and economic importance for some additional robustness checks.

[Table 1 about here.]

[Table 2 about here.]

Methodology

As an additional methodological robustness check we estimate the cross-sectional regression (3) by weighted least squares (WLS), i.e., using a diagonal weighting matrix whose inverse corresponds to a matrix that has the sample variances of first-step regression residuals along its diagonal. We use the WLS estimator because it is typically more robust than the generalized least squares estimator based on an estimated residual covariance matrix and because, in light of the apparent heteroscedasticity of returns on the CDS portfolios, it is likely to be more efficient than the OLS estimator.[5]

Specification 11 in Table 1 reports the results of a WLS estimation of the asset pricing model. WLS point estimates do not differ by large amounts from their OLS counterparts and, indeed, happen to be more efficient. For instance, standard errors of the factor prices of market risk, default risk, and liquidity risk under potential model misspecification decrease from 7.85, 0.40, and 0.69 bps to 6.78, 0.40, and 0.54 bps, respectively. However, these efficiency gains are insufficient to affect inference under potential model misspecification. Because OLS and WLS factor prices of risk are similar, WLS implied contributions to the expected return differential resemble those of the benchmark specification. As can

[5] Heteroscedasticity among first-step regression residuals is even more severe.

be seen from specification 11 in Table 2, the WLS implied contribution of market and default risk to the expected return differential is 1.70% per year, while that of liquidity risk is an annualized 1.61%.

Alternative Liquidity Factors

The construction of our tradable liquidity factor is similar to that of Moskowitz, Ooi, and Pedersen'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 their conditional volatilities. In contrast, we account for the cross-sectional variation in volatilities by scaling credit index returns by past index levels. As an alternative, we construct a tradable liquidity factor from signed returns on the individual arbitrage strategies, $r_{i,t}^{\mathrm{IDX}} - r_{i,t}^{\mathrm{BSK}}$, that are scaled by their conditional volatilities. In this case, the liquidity factor is given by

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

where $\sigma_{i,t}^2$ is an estimate of annualized conditional variance of $r_{i,t}^{\mathrm{IDX}} - r_{i,t}^{\mathrm{BSK}}$, which is obtained from daily returns as in Equation (1) of Moskowitz et al. (2012). Because we use the first six-month period to estimate the conditional volatility for the computation of the alternative liquidity factor's first observation, its time series consists of 252 weekly observations from March 28, 2007, to February 1, 2012. The alternative liquidity factor has a correlation of 0.87 with the benchmark liquidity factor indicating that our index-level-based weighting scheme effectively mimics the approach of Moskowitz et al. (2012).

Despite a large number of test portfolios that do not exhibit significant exposure to the alternative liquidity factor in first-step regressions, the factor price of liquidity risk in the second-step cross-sectional regression is statistically significant (see specification 12 in Table 1). In comparison to our benchmark specification, the contribution of expected illiquidity to the expected return differential increases slightly to 1.01% per year, while that of liquidity risk decreases to 1.21% per year (see specification 12 in Table 2).[6]

Alternative Default Factor

Results of a robustness check with an alternative default factor are reported as specification 13 in Tables 1 and 2. This default factor is given by the excess return on the Bank of America Merrill Lynch Global Corporate Index. Excess returns on this corporate bond index are obtained from Bloomberg and computed with respect to a basket of government bonds. The correlation between the alternative default factor and the benchmark default factor is 0.56.

First-step factor loadings (unreported) and the factor price of default risk (in Table 1) are strongly statistical significant for the alternative default factor. The contribution of market and default risk to the expected return differential in Table 2 is essentially the same as in our benchmark specification, while that of liquidity risk decreases slightly to 1.65% per year.

[6] 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.

Additional Factors

Stock market liquidity factor As an alternative to the stock market liquidity factor based on the Amihud (2002) illiquidity measure, we construct a factor based on the Pástor and Stambaugh (2003) liquidity measure. The data used for the construction of the factor are described in Appendix C. 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 the market-wide liquidity measure proceeds as in Pástor and Stambaugh (2003) with the exception that we do not scale the market-wide liquidity measure by the lagged dollar value of the stocks included in its construction. Having constructed the market-wide measure, we run regression (7) in Pástor and Stambaugh (2003) and obtain the liquidity factor as this regression's residual.

Only a few test portfolios have a significant loading with respect to this stock-market liquidity factor at the five percent level. The estimated factor price of risk is significant under correct model specification but counterintuitively negative (see specification 14 in Tables 1). Consequently, the contribution of stock market liquidity risk to the expected return differential in Table 2 is negative at -0.13% per year. In comparison, CDS market liquidity risk contributes 2.12% per annum.

Volatility and jump factors As mentioned in the paper, volatility risk has been shown to be priced in stock and corporate bond returns and a recent study by Cremers, Halling, and Weinbaum (2013) also finds evidence for priced jump risk in stock returns. We, therefore, check whether such effects exist for CDSs as well and if taking them into account has an impact on liquidity risk effects. In particular, we separately include returns on Cremers et al.'s (2013) MNGN and MNVN index option portfolios as volatility and jump factors in the asset pricing model (see specifications 15 and 16 in Tables 1 and 2). Only a few test portfolios exhibit significant exposure to the volatility factor and despite the significant factor price of risk estimate under correct model specification, there is no contribution of volatility risk to the expected return differential. Some of the portfolios load significantly on the jump factor and in line with Cremers et al. (2013) we find a significantly negative factor price of risk under correct model specification. Nevertheless, the contribution of jump risk to the expected return differential is counterintuitively positive at 0.69% per year.

G Additional Figures and Tables

Figure 1 displays index-to-theoretical bases and published and theoretical on-the-run index levels for the sub-indices of the CDX North American and iTraxx Europe families.

[Figure 1 about here.]

Figure 2 depicts monthly time series of the explanatory variables of the time series properties regressions against the monthly time series of the CDS market illiquidity measure.

[Figure 2 about here.]

Table 3 summarizes index rules for the main indices of the CDX North American and iTraxx Europe credit index families.

[Table 3 about here.]

Table 4 displays descriptive statistics for the portfolios formed by first sorting CDS contracts according to five-year EDFs and then according to bid-ask spreads.

[Table 4 about here.]

Table 5 displays results for cross-sectional regressions of expected returns on one-factor model loadings.

[Table 5 about here.]

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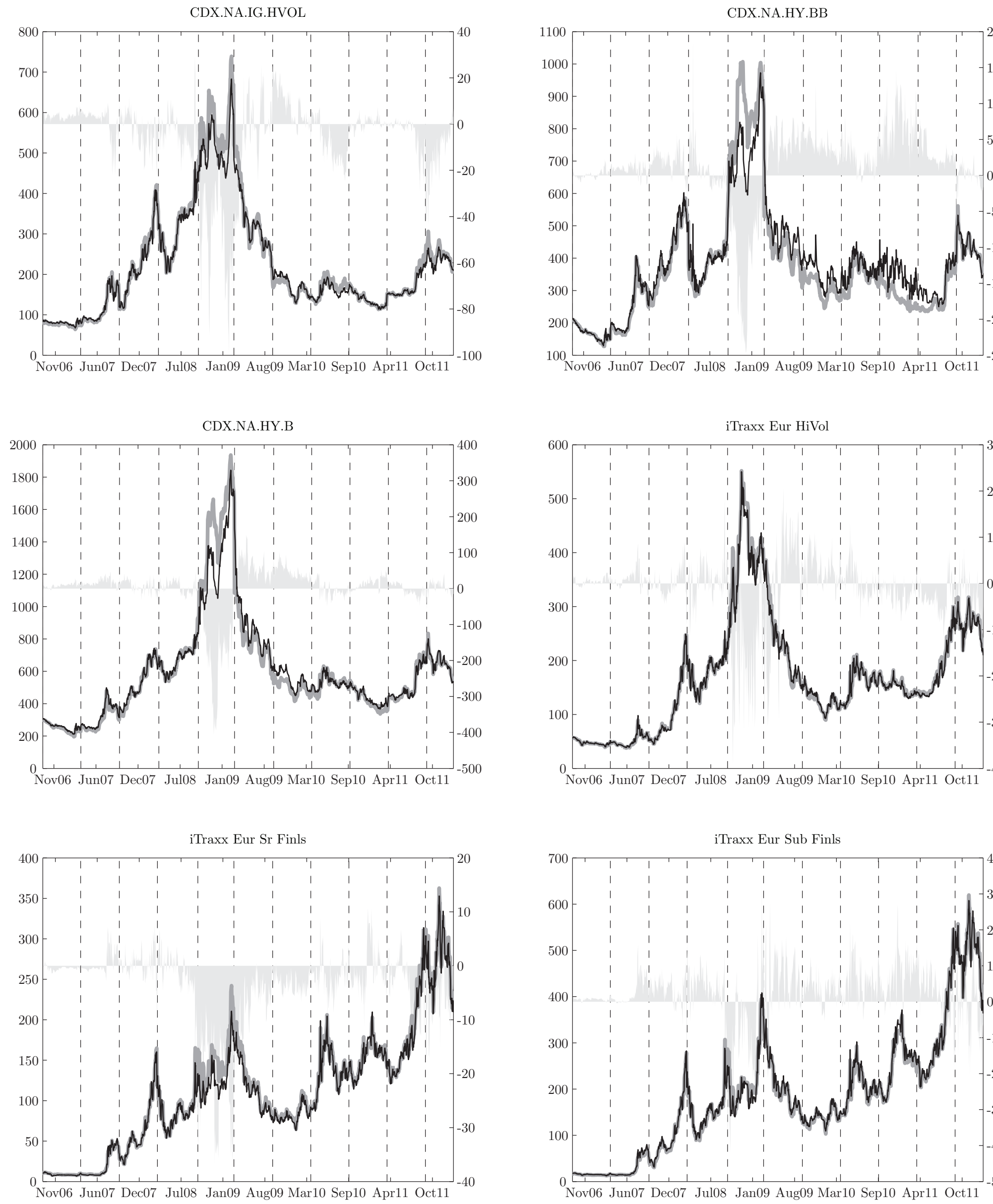

Figure 1: Credit Index Levels, Theoretical Index Levels, and Index-to-Theoretical Bases. The figure displays daily observations of published credit index levels of the five-year on-the-run series (thin black lines, left hand scales), theoretical index levels (thick gray lines, left hand scales), and 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.

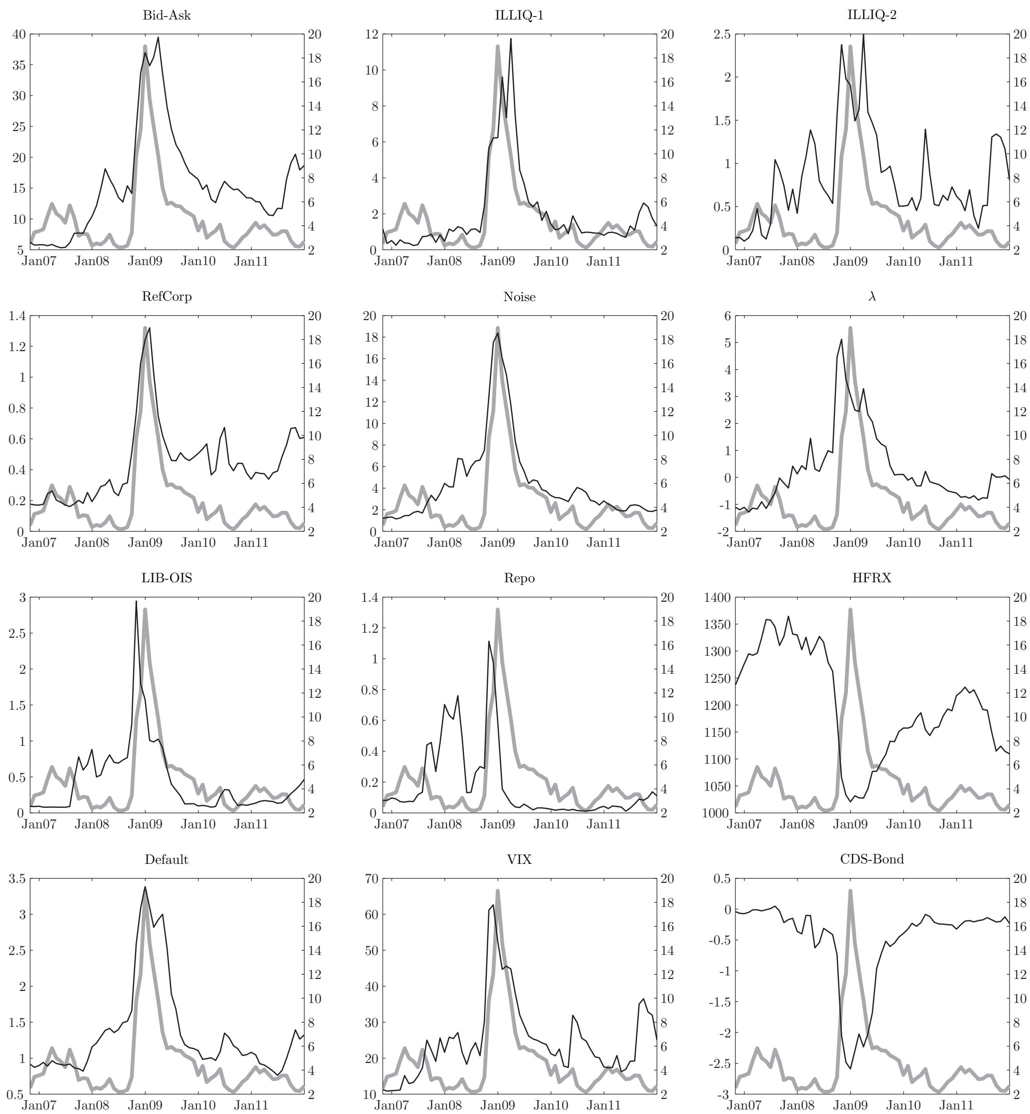

Figure 2: Explanatory Variables vs. CDS Market Illiquidity Measure.
The figure displays monthly observations of the explanatory variables in the time series properties regressions (thin black lines, left hand scales) and the CDS market illiquidity measure (thick gray lines, right hand scales). The explanatory variables are: The average bid-ask spread of single-name CDSs (Bid-Ask), the average absolute spread change per quote contributed across single-name CDSs (ILLIQ-1), the weighted average (by number of index constituents) of absolute spread changes per number of quote contributors across five-year on-the-run credit indices (ILLIQ-2), the spread between ten-year Resolution Funding Corporation and Treasury constant maturity yields (RefCorp), the Hu, Pan, and Wang (2013) Noise measure (Noise), Dick-Nielsen, Feldhütter, and Lando's (2012) λ corporate bond illiquidity measure, the spread between three-month LIBOR and OIS rates (LIB-OIS), the spread between three-month Agency MBS and Treasury general collateral repo rates (Repo), the level of the Hedge Fund Research Global Index (HFRX), the yield spread between Baa- and Aaa-rated bonds (Default), the VIX index (VIX), and the average CDS-bond basis across U.S. investment grade bonds (CDS-Bond). Bid-Ask, ILLIQ-1, ILLIQ-2, and Noise are in basis points. RefCorp, LIB-OIS, Repo, Default, VIX, CDS-Bond, and the CDS market illiquidity measure are in %. λ and HFRX are in index points. The time series consist of 63 monthly observations from October 2006 to December 2011.

Spec.	11	12	13	14	15	16
	WLS	MOP	BDEF	SLIQ2	MNGN	MNVN
ζ	94.86	94.86	94.86	94.86	94.86	94.86
	(—)	(—)	(—)	(—)	(—)	(—)
	[—]	[—]	[—]	[—]	[—]	[—]
λ_{MKT}	10.27	15.23	5.64	11.28	11.07	11.84
	(2.15)	(2.62)	(1.05)	(1.61)	(2.44)	(2.59)
	[1.52]	[2.05]	[0.62]	[0.89]	[1.61]	[1.56]
λ_{DEF}	0.79	0.98		0.79	0.79	0.94
	(3.51)	(5.47)		(2.67)	(2.59)	(4.61)
	[1.95]	[3.22]		[3.01]	[1.70]	[2.74]
λ_{LIQ}	1.01		1.30	1.32	0.95	0.81
	(3.27)		(2.97)	(2.86)	(1.92)	(3.09)
	[1.86]		[1.93]	[1.46]	[1.31]	[1.49]
λ_{X}		15.93	1.75	-1.24	-36.04	-89.60
		(3.84)	(1.91)	(-2.11)	(-1.78)	(-1.95)
		[2.11]	[1.28]	[-0.55]	[-1.19]	[-1.14]
R^2	0.94	0.97	0.97	0.97	0.98	0.98
	[0.92,0.97]	[0.95,0.99]	[0.96,0.98]	[0.96,0.99]	[0.96,0.99]	[0.96,0.99]

Table 1: Robustness Cross-Sectional Regressions.
The table displays results of a series of robustness checks. Specifications of $\widehat{E}[r^e_{i,t}] - \widehat{E}[c_{i,t}]\widehat{\zeta} = \widehat{\beta}_i^{\mathrm{MKT}}\lambda_{\mathrm{MKT}} + \widehat{\beta}_i^{\mathrm{DEF}}\lambda_{\mathrm{DEF}} + \widehat{\beta}_i^{\mathrm{LIQ}}\lambda_{\mathrm{LIQ}} + \widehat{\beta}_i^{\mathrm{X}}\lambda_{\mathrm{X}} + u_i$ 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 (unless an additional factor is available only for part of the sample period). Specification identifiers are given in the second row of the table. Reported are factor price of risk estimates (in basis points), t-statistics based on asymptotic generalized method of moments standard errors that account for error-in-variables problems (in parenthesis), t-statistics based on Kan, Robotti, and Shanken's (2013) asymptotic standard errors that that account for error-in-variables problems and potential model misspecification (in square brackets), cross-sectional R^2s, and their 95% confidence intervals. Standard errors are heteroscedasticity and autocorrelation consistent through the use of Newey and West's (1987) method with 24 lags. In the computation of cross-sectional R^2s, expected CDS returns are treated as the dependent variable.

Spec.	0	11	12	13	14	15	16
	BM	WLS	MOP	BDEF	SLIQ2	MNGN	MNVN
Expected illiquidity	0.95	0.95	1.01	0.95	0.95	0.95	0.95
	[0.29]	[0.29]	[0.31]	[0.29]	[0.29]	[0.29]	[0.29]
Market and default risk	1.88	1.70	2.40	1.93	1.81	1.79	1.93
	[0.57]	[0.59]	[0.78]	[0.75]	[0.61]	[0.60]	[0.69]
Liquidity risk	1.89	1.61	1.21	1.65	2.12	1.52	1.28
	[0.55]	[0.47]	[0.41]	[0.42]	[0.62]	[0.45]	[0.38]
Additional risk factor					-0.13	-0.00	0.69
					[-0.10]	[0.08]	[0.06]

Table 2: 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.

	CDX North American		iTraxx Europe	
Main index (No. of constituents)	CDX.NA.IG (125)	CDX.NA.HY (100)	iTraxx Eur (125)	iTraxx Eur Xover (≤50)
Sub-indices (No. of constituents)	CDX.NA.IG.HVOL (30)	CDX.NA.HY.BB (≤100) CDX.NA.HY.B (≤100)	iTraxx Eur HiVol (30) iTraxx Eur Sr Finls (25) 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 3: 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.

	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]	[-0.63]	[-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	-0.86	-0.49	1.84	0.21	0.27	0.34	0.56
	[8.70]	[7.68]	[7.62]	[6.38]	[-0.61]	[-0.43]	[-0.18]	[0.35]	[11.99]	[11.90]	[10.37]	[9.81]
EDFQ3	0.47	0.68	1.05	2.10	-2.19	-1.25	-0.94	4.62	0.24	0.33	0.44	0.73
	[6.94]	[6.55]	[6.59]	[7.38]	[-1.13]	[-0.44]	[-0.23]	[0.73]	[10.74]	[9.18]	[9.54]	[10.17]
EDFQ4	0.48	0.83	1.28	2.67	-2.69	0.37	2.11	4.93	0.30	0.41	0.53	0.88
	[5.14]	[6.13]	[6.48]	[7.19]	[-0.89]	[0.09]	[0.36]	[0.60]	[8.29]	[7.90]	[7.92]	[8.58]
EDFQ5	0.44	1.41	2.43	4.03	-0.84	4.43	7.92	11.47	0.44	0.72	1.09	1.74
	[3.68]	[7.50]	[7.93]	[8.39]	[-0.17]	[0.57]	[0.74]	[0.80]	[6.68]	[6.74]	[7.03]	[8.98]

	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	1.27	18.32	22.35	23.42	40.19	76.62	83.34	82.49	87.97
EDFQ2	0.58	0.73	0.95	1.70	24.04	28.99	35.78	53.66	82.91	86.72	92.51	99.14
EDFQ3	0.72	0.95	1.32	2.44	29.43	36.43	46.51	65.67	88.98	94.75	95.58	101.93
EDFQ4	0.99	1.37	1.86	3.30	41.47	51.09	63.61	82.05	94.73	96.63	103.49	112.27
EDFQ5	1.66	3.24	5.14	11.70	68.81	94.74	117.30	159.53	102.43	108.38	113.62	121.58

Table 4: Descriptive Statistics EDF-Based Portfolio Formation.
The table displays descriptive statistics for the 20 test 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.

Spec.	1	2	3	4	5	6	7	8
ζ					94.86	94.86	94.86	94.86
					(—)	(—)	(—)	(—)
					[—]	[—]	[—]	[—]
γ_{MKT}		8.14		18.60		4.89		15.26
		(1.20)		(1.44)		(0.77)		(1.31)
		[1.06]		[1.00]		[0.65]		[0.93]
γ_{DEF}			0.53	-1.10			0.24	-1.09
			(0.67)	(-0.88)			(0.34)	(-0.95)
			[0.62]	[-0.68]			[0.30]	[-0.76]
γ_{LIQ}	2.29	1.39	1.82	1.20	1.84	1.30	1.62	1.11
	(3.67)	(3.13)	(4.31)	(2.75)	(3.63)	(2.97)	(4.10)	(2.66)
	[3.70]	[1.87]	[3.15]	[1.49]	[3.66]	[1.87]	[2.97]	[1.54]
R^2	0.96	0.96	0.96	0.97	0.97	0.97	0.97	0.97

Table 5: Results Cross-Sectional Regressions on One-Factor Model Loadings.
The table displays results of several specifications of the second-step cross-sectional regression. Specifications are of the form $\widehat{E}[r^e_{i,t}] - \widehat{E}[c_{i,t}]\widehat{\zeta} = \widehat{b}_i^{\mathrm{MKT}}\gamma_{\mathrm{MKT}} + \widehat{b}_i^{\mathrm{DEF}}\gamma_{\mathrm{DEF}} + \widehat{b}_i^{\mathrm{LIQ}}\gamma_{\mathrm{LIQ}} + u_i$, where $\widehat{b}_i^F$ denotes the estimate of the slope coefficient in the time series regression $r^e_{i,t} = \alpha_i + b_i^F F_t + \epsilon_{i,t}$, $F \in \{\mathrm{MKT}, \mathrm{DEF}, \mathrm{LIQ}\}$. 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. Reported are coefficient estimates (in basis points), t-statistics based on asymptotic generalized method of moments standard errors that account for error-in-variables problems (in parenthesis), t-statistics based on Kan, Robotti, and Shanken's (2013) asymptotic standard errors that that account for error-in-variables problems and potential model misspecification (in square brackets), and cross-sectional R^2s. Standard errors are heteroscedasticity and autocorrelation consistent through the use of Newey and West's (1987) method with 24 lags. In the computation of cross-sectional R^2s, expected CDS returns are treated as the dependent variable.