Market-Wide Liquidity in Credit Default Swap Spreads

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Abstract

This paper analyzes the importance of market-wide illiquidity of CDS market on changes of CDS spreads of credit quality portfolios for five alternative maturities. We document that aggregate liquidity is a pricing factor in CDS spreads. Illiquidity CDS betas across credit quality portfolios and maturities are positive and statistically significant. Low credit rating CDS spreads tend to be highly sensitive to aggregate illiquidity shocks relative to high credit quality CDS spreads. Using a two- factor intensity model we also document a significant illiquidity risk premium embedded in the CDS term structure, especially for high-yield portfolios.

JEL classification: G01, G11, G15, G32

Keywords: Market-wide illiquidity; credit default swaps; flight to liquidity; intensity models; risk premium

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1 Introduction

It is generally accepted that credit default swap (CDS, hereafter) spreads can be decomposed into the expected loss, a default risk premium, a liquidity risk premium related to the impact of trades on the spread and the adverse selection effect associated with the asymmetric information between the CDS sellers and buyers, and the correlation-induced components.[1] However, initial papers on CDS spreads have considered the spreads as a pure measure of creditworthiness of a company. The existence of a potentially important liquidity component is originally suggested by the evidence reported by Blanco, Brennan, and Marsh (2005), and Berndt, Duglas, Duffie, Ferguson, and Schranz (2008). Indeed, Blanco et al. (2005) report average CDS spreads larger than the underlying corporate bond yield spreads for most of the entities on their sample, and Berndt et al. (2008) find that, on average, a significant component of the spreads cannot be explained by default risk measured by the Moody's KMV's expected default frequencies.

These papers motivate a relatively large literature about the importance of the liquidity component on the CDS spreads.[2] The empirical evidence clearly supports the presence of a liquidity component of CDS spreads independently of credit quality, maturity and type of underlying. This is the case despite the large variety of econometric methodologies and theoretical models employed in the estimation. For example, Chen et al. (2005), Chen et al. (2010), and Buhler and Trapp (2009) employ the intensity framework for pricing CDS spreads proposed by Duffie and Singleton (2003) and Pan and Singleton (2008), where liquidity enters the picture as a further spread, or intensity, over and above the risk neutral arrival rate of a credit event component. On the other hand, Bongaerts et al. (2011) propose an equilibrium derivative pricing model with liquidity effects in which the zero net-supply feature of the derivative market generates very different liquidity effects than the liquidity pricing model of Acharya and Pedersen (2005). They find that only compensation for expected liquidity is significant with higher expected liquidity being associated with higher expected returns for the protection sellers. As pointed out by Brigo et al. (2010) this finding is contrary to Chen et al. (2005), and Chen et al. (2010) that found protection buyers to obtain the liquidity premium. In any case, not only these theoretically-based papers, but also other empirical-based literature mentioned above concludes that CDS spreads cannot be assumed to be pure measures of credit risk. CDS liquidity seems to be significantly

[1] See Buhler and Trapp (2009), Jarrow (2011), and Bongaerts, Jong, and Driessen (2011), among others.

[2] See Chen, Cheng, and Wu (2005), Tang and Yan (2008), Chen, Fabozzi, and Sverdlove (2010), Buhler and Trapp (2009), Brigo, Predescu, and Capponi (2010), Pires, Perreira, and Martins (2010), Bongaerts et al. (2011), and Coro, Dufour, and Varotto (2012).

priced in CDS spreads.

However, most papers analyze the importance of liquidity at the individual level.[3] This is surprising given the available evidence from the corporate and sovereign bond markets. Xing, Zhang, and Zhou (2007) document a strong commonality in individual bond liquidity changes after controlling for both bond specific determinants, such as price and volatility, and macroeconomic state variables. They find that the covariance of a bond's liquidity with respect to market liquidity shocks is a significant risk factor in determining the yield spreads. More recently, Acharya, Amihud, and Bharath (2010) report that during stress periods, liquidity risk is a significant factor in affecting corporate bond prices, especially of low-rated bonds, and Panyanukul (2009) finds that liquidity risk is a priced factor in explaining sovereign bond returns. As in the previous paper, this is especially the case during the period 2007 to 2009. This research suggests a strong conditional component of market-wide liquidity effects in both corporate and sovereign bond markets.

This paper contributes to the literature by analyzing market-wide liquidity in the CDS market. We study thoroughly the impact of illiquidity on CDS spreads on an aggregate level. Our analysis is developed in two parts. We first show that, for a given maturity and credit rating, there is a strong commonality in the liquidity of CDS contracts. Then, we show that market-wide illiquidity is a powerful determinant of CDS spreads. There is a consistently positive and significant relation between CDS spreads and market-wide illiquidity changes across all maturities and credit qualities even after extracting potentially confounding credit risk expousure in the bid-ask spreads. Finally, there is a monotonic relationship between sensitivity to market-wide changes of liquidity and credit ratings, being this sensitivity stronger for high yield underlyings. Aggregate illiquidity risk seems to be an equally important factor as the credit risk in the CDS market. This conclusion is also supported by a significant flight-to-liquidity given the time-varying nature of liquidity risk embedded in CDS spreads. This is particularly important at the shortest maturities proceeding from the underlying CDS market and at all horizons proceeding from the US equity market. Crisis episodes also reflect strong flight-to-credit quality.

Secondly, we analyze the time-series behavior of default and illiquidity components of CDS spreads. We employ a multi-factor affine intensity model in the spirit of Duffie, Pedersen, and Singleton (2003) or Pan and Singleton (2008) to model the arrival of credit (λ_t^Q) and illiquidity (γ_t^Q) events. We assume a lognormal,

[3] An important exception is the paper by Coro et al. (2012) who employ European CDS data from GFI Group and Bloomberg that covers the period from January 1, 2006 to July 31, 2009.

mean-reversion structure for the instantaneous risk-neutral arrival rate of λ_t^Q and γ_t^Q processes. From the information content of the CDS term structure for each individual firm, we employ the most traded maturity to infer the time-series properties of λ_t^Q. This lead us to define illiquidity as the additional compensation of trading with CDS maturities other than the most liquid one. In this way, we hypothesize a *relative* illiquidity process. Our results exhibit a correlation between default and illiquidity processes of around 34% (45%) in highest (lowest) rating portfolio. Additionally, the maximum likelihood (ML) model estimates reveal that not only a positive default but also illiquidity risk premium is being priced in the market.[4] More precisely, although similar arrival rates of illiquidity shocks are expected under the actual measure, risk-neutral illiquid environment is much more strained. The risk-neutral γ_t^Q estimates indicate that the arrival of illiquid events is more expected as portfolio's creditworthiness deteriorates. Finally, the market price of illiquidity risk systematically exhibits a higher level and volatility than default risk component.

The remainder of the paper is organized as follows. Section 2 describes the data employed in the analysis and the methodology for constructing CDS portfolios. Section 3 presents the relation between CDS spread changes and market-wide variables for portfolios sorted by maturity and credit quality. The flight-to-liquidity and flight-to-quality analysis are performed in Section 4. Section 5 presents the intensity two-factor model and its main results. Lastly, Section 6 concludes with summary and final remarks.

2 Data, credit-quality-sorted portfolios, and aggregate variables

We obtain data on CDS spreads from Markit Group Ltd., a leading data provider that creates composite CDS spreads. We consider corporate (non-sovereign) CDS names incorporated in North America, which are or have been part of the CDX North America index. We further restrict our sample to CDS contracts, which are (i) denominated in US dollars (ii) are written on senior unsecured debt of companies, and (iii) incorporate the modified restructuring clause as a credit event. These are the typical terms that a CDS contract trades on in North America. In our analysis, we consider the time period from January 2004 to April 2011. Additionally, for each CDS name we use the spreads with 1, 3, 5, 7, and 10 year maturities. Finally, our analysis deals

[4]We focus on the distress risk premium which accounts for the compensation to investors due to changes in the default or illiquidity environment (see Duffee (1999), Pan and Singleton (2008) or Longstaff, Pan, Pedersen, and Singleton (2011), among others). The compensation required for the bond price changes at the event of default (Jarrow, Lando, and Yu (2005), Driessen (2005) or Berndt et al. (2008)) is called default event premium and it is not studied here.

with monthly CDS spreads. In particular, we construct monthly CDS spreads for a given name and maturity by taking the last non-missing daily CDS spread for each month. The above criteria leave us with an overall sample of 284 CDS names, which amount to 21,623 issuer-month observations.

Table 1 provides the distribution of CDS names in our sample by sector and rating group. The reported rating is the resulting average of Moody's and S&P ratings that are adjusted to the seniority of the instrument and are rounded not to include the plus and minus levels. Markit uses 10-sector ICB classification and adds one additional category for Government. Those sectors are Financial, Oil & Gas, Basic Materials, Industrial, Consumer Goods, Consumer Services, Health Care, Telecommunications, Utilities, Technology and Government. Nearly 52% of the CDS contracts in our database are written on the debt of investment grade companies, whereas the share of CDS contracts written on the debt of high-yield companies is 48%. There are four industries represented individually by more than 10% of the total number of contracts. These are CDS contracts written on the debt of companies from the Consumer Services, Financial, Consumer Goods, and Industrial sectors. These four sectors cover around 65% of our sample.

Figure 1 display the time series of aggregate monthly CDS spreads by maturity. These series are calculated by taking the cross-sectional average of individual CDS spreads for each month and maturity. We observe that CDS spreads of all maturities are relatively stable before mid 2007. Afterwards, there is a sharp increase in CDS spreads up to the beginning of 2009. The dramatic increase of mid 2007 is associated with the burst of the housing bubble in the US around August 2007, and the associated losses on subprime mortgage asset backed securities, collateralized debt obligation bonds, and CDS on the asset backed holdings. When these financial securities lost value due to the housing market crash, financial institutions using these products did not have enough capital to respond to the enormous losses realized. Specifically, the upward sloping trend of CDS spread time series is followed by a series of credit events, such as the collapse of Lehman Brothers, the bailout of AIG group and the federal takeover of Fannie Mae and Freddie Mac in September 2008.[5] The slope of the term structure of CDS spreads is mostly positive, so that the spreads of short maturity horizons tend to be lower than the spreads of longer horizons. However, Figure 1 also shows that from mid 2008 till mid 2009 the CDS spreads with short-term maturity are higher than CDS spreads with long-term maturity. The inversion of the slope of the term structure during stress periods has also been documented by Pan and

[5]See Jarrow (2011) for an overall discussion on the CDS market and the website of Federal Reserve of St. Louis for a detailed timeline of the credit events associated with the subprime financial crisis (http://timeline.stlouisfed.org/index.cfm?p=timeline).

Singleton (2008) for some emerging countries during periods of financial or political crisis. It is important to point out that the inversion of the slope is perfectly monotonic.[6]

2.1 Credit-quality-sorted portfolios of CDS spreads

To assess the impact of market-wide illiquidity on CDS spreads, we construct credit-quality-sorted portfolios. In all subsequent sections we perform our regression analysis based on the CDS spreads of these credit-quality-sorted portfolios.

For a given maturity (1, 3, 5, 7, and 10 year horizons), we classify all CDS spreads according to the credit rating of the underlying asset. To have enough observations in each portfolio, we form 4 credit-quality-sorted portfolios of CDS spreads: AAA to A-, BBB+ to BBB-, BB+ to BB-, and B+ to D. We equally weight CDS spreads in each portfolio. To construct these four portfolios, first we obtain data on corporate credit ratings of the CDS names in our database. More specifically, we download this data from Thomson Reuters 3000 Xtra. Then, for each CDS name we can have data on credit rating assigned by S&P, Fitch or Moody's. In addition, we have detailed data on credit ratings for different categories of a debt of a particular company, such as long-term issuer rating, short-term issuer rating, issuer outlook, rating on debt in local currency, etc. When constructing our portfolios, we employ only the long-term issuer rating assigned by S&P, Fitch and Moody's. We have therefore to obtain a monthly time series of composite credit ratings for each CDS using three agencies. In order to construct this series, we take the previously assigned credit rating by a particular agency and apply it to all months up to the next month the agency issues a new rating. For instance, the long-term issuer rating assigned by S&P to Cox Communications Inc. was BBB for August 2008, and BBB- in December 2008. Hence, we take the BBB to be the issuer credit rating assigned by S&P for all four months from August 2008 to November 2008. We construct the composite rating measure by taking the average of at most three ratings on long-term issuers assigned by the three credit rating agencies to a CDS name for a given month. To calculate the average rating of a CDS name, we transform the long-term issuer ratings from the letter scale to numerical, by taking the letter rating designation of S&P as a common base (AAA = 1, AA+

[6]Schneider, Sogner, and Veza (2009) point out that the one-year CDS spread exhibits time-varying behavior higher-maturity spreads do not share. They presume that investment funds primarily use the 1 year CDS spreads to express their views on the creditworthiness of CDS names. Hence, they argue the economic driver behind the unique pattern in 1 year spreads is a supply-and-demand premium induced by such large traders. It should be pointed out however that the pattern shown in Figure 1 is the complete and monotonic inversion of the slope of the term structure. This implies that this phenomenon is not uniquely related to the shortest maturity CDS spreads.

= 2, . . . , D = 22). As Moody's uses a different scale than S&P and Fitch, beforehand we translate the rating tier of Moody's to the scale equivalent to S&P's by equating the categories as Aaa = AAA, Baa1 = BBB+, etc. Finally, we obtain the composite rating assigned to a CDS name for a given month by transforming the averaged numerical rating (rounded to the nearest integer) to the letter scale used by S&P. This procedure leaves us with 4 equally-weighted portfolios of CDS spreads for a given maturity.[7]

Table 2 reports the summary statistics of these portfolios. Portfolio CDS spreads increase on average as the portfolio maturity increases. This holds for all CDS portfolios. This is consistent with a (average) positive slope of the term structure of CDS spreads. Simultaneously, holding the maturity constant, the portfolio CDS spreads increase as the credit quality of the corresponding CDS portfolio deteriorates. The same observations hold for the median of portfolio CDS spreads. On the other hand, the standard deviation of portfolio CDS spreads grows as the maturity of the corresponding CDS portfolio decreases. In other words, for a given credit-quality-sorted portfolio of CDS, spreads with short-term maturity are more volatile than CDS spreads with long-term maturity. And, for a given maturity, the volatility of the spreads increases with the deterioration of credit quality.

Figure 2 plots the time series of portfolio CDS spreads with 5 year maturity for alternative credit ratings. The dynamics of the spreads across different rating categories reinforce our previous observation that the portfolio CDS spreads are higher as the credit quality of the corresponding portfolio declines. Looking at the cross-section, it is also noticeable how spreads increase non-linearly as credit rating deteriorates. We also observe that the portfolio CDS spreads increase substantially after the start of the financial crisis of August 2007, and this is especially true for lowest rating portfolio.

2.2 *Aggregate illiquidity measures*

To control for the illiquidity of the CDS market we construct an aggregate measure based on the absolute bid-ask spreads of CDS names. We estimate the aggregate bid-ask spread measure of illiquidity for the CDS market by taking the cross-sectional average of absolute bid-ask spreads of CDS names per month.[8] We use absolute (rather than relative) bid-ask spreads as they are already a proportional measure and, therefore, they

[7]Before calculating the portfolio CDS spreads, 1 and 99 percentiles of CDS spreads are removed from the cross-sectional distribution of CDS spreads for each month and maturity.

[8]We remove 1 and 99 percentiles of CDS bid-ask spreads from their respective distribution for each month and maturity.

do not need to be scaled by the average of CDS bid and ask quotes.[9] As in the case of CDS spreads, we construct the monthly absolute bid-ask spread of a CDS name by taking the last non-missing daily absolute bid-ask spread for each month. Additionally, we obtain the aggregate bid-ask spread measures of illiquidity for maturities of one, three, five, seven, and ten years. Data on CDS bid-ask spreads are taken from CMA Datastream and are available from January 1, 2004 till September 30, 2010.[10]

To control for the illiquidity of other markets, in particular of the US stock market, and the potential spillovers from the stock market to the CDS market, we employ the aggregate illiquidity measure suggested by Amihud (2002). We calculate the individual Amihud ratio for each stock trading in the US market as,[11]

$$ILLIQ_t^i = \frac{1}{D_t^i} \sum_{d=1}^{D_t^i} \frac{|R_{td}^i|}{V_{td}^i}, \tag{1}$$

where D_t^i is the number of days for which data is available for stock i in month t, R_{td}^i is the return on stock i on day d in month t, and V_{td}^i is the trading volume (in US dollars) for stock i on day d in month t. We obtain the aggregate Amihud ratio for the US stock market by taking the cross-sectional average of individual Amihud ratios for each month.[12] Finally, we estimate the aggregate measure of illiquidity (*ILS*) for the US stock market by taking the AR(2) residuals of the regression of the aggregate ratio on its first two lags as suggested by Acharya and Pedersen (2005).

2.3 Other aggregate (control) variables

In addition to aggregate illiquidity measures, we consider series of additional aggregate potential determinants of CDS spreads. Corporate CDS spreads might include a premium for bearing risk associated with the state of the economy. To the extent that macroeconomic conditions affect the risk preferences of participants in the CDS market, we would expect to find economic and statistically significant relationships between CDS spreads and aggregate variables. To capture the state of the economy or, even more importantly, to predict

[9] See (Bongaerts et al., 2011, p.221) and Pires et al. (2010) for a formal argument.

[10] To calculate the aggregate bid-ask spread measure of illiquidity for the CDS market we use the bid and ask quotes from CMA database for the companies that coincide with those in Markit database. Then we compare the difference in monthly CDS spreads between these two sources using the measure of mean absolute error (MAE). The mean (median) of MAE for the average of bid and ask quotes from CMA database and CDS spreads from Markit database across 262 companies are 37 (14), 25 (7), 19 (3), 21 (5), and 25 (8) basis points for maturities of 1, 3, 5, 7, and 10 years, respectively.

[11] We use data from CRSP and only data on stock returns and trading volume from the NYSE.

[12] Before calculating the aggregate Amihud ratio for the equity market, we remove the stock returns that fall outside of the 1st and 99th percentile of the cross-sectional distribution of stock returns per trading volume ($R_{t,d}^i/V_{t,d}^i$) for each day.

future real activity, we should employ state variables with proved predicting capacity of future output growth.

The term spread, measured as the difference between the interest rates on long and short maturity government debt maturities, is probably the most common financial leading indicator of real activity. Among many others, Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Stock and Watson (2003), and Ang, Piazzesi, and Wei (2006) show the significant predictive content of the spread for production growth, including its capacity to forecast a recession indicator in probit regressions. Additionally, there is a growing body of literature exploring the transmission of credit conditions into the real economy. Among recent papers, Mueller (2009) and Gilchrist, Yankov, and Zakrajsek (2009) show the forecasting power of the term structure of credit spreads for future output growth. These authors argue that there is a pure credit component orthogonal to macroeconomic conditions that accounts for a large part of the predicting capacity of credit spreads. We approximate the slope of the US term structure of interest rates by the difference between 10 year constant maturity Treasury bond yields and the 3 month constant maturity Treasury bill yields (TERM).

To capture the credit conditions, we use the difference between corporate bond index yields of Bank of America Merrill Lynch (BofA ML) and treasury bond yields. More specifically, we calculate default spreads for the rating groups of AAA to A-, BBB+ to BBB-, BB+ to BB-, and B+ to D and maturities of 1, 3, 5, 7, and 10 years. For instance, to calculate the default spread of AAA to A- rated bonds with 10 year maturity (DEF AAAtoA10y), we take the difference between corporate bond index yields of AAA to A- rated bonds and 10 year constant maturity treasury bond yields. In further analysis we also use default spreads by maturity. To calculate default spread $DEF(M)y$ for M year maturity we take the difference between corporate and Treasury bond yields with M year maturity, respectively. Finally, we calculate the difference between corporate bond index yields for investment grade and high yield bonds (DEF) to capture credit conditions within IG and HY markets. We download the data on corporate bond yields of BofA ML from the website of Federal Reserve Bank of St. Louis.

There has been considerable recent attention to financial uncertainty as a predictor of real activity. An increasingly popular measure of the risk premium potentially embedded in financial uncertainty is given by the variance risk premium (VRP) as discussed by Bollerslev, Tauchen, and Zhou (2009), Longstaff et al. (2011) and Zhou (2010). It is well known that the difference between the realized volatility during a particular month and the risk neutral counterpart represented by VIX gives the (annualized) monthly volatility risk premium proxy. The realized variance is estimated as the (annualized) squared daily returns for a given month of the S&P500 index. The variance risk premium is reported to be negative on average.[13] It may be noted that the difference between the realized variance and (the square of) VIX can be understood as the payoff of a variance swap contract. The average negative payoff of the contract suggests that investors are willing to accept negative returns for purchasing realized variance. Equivalently, investors who are sellers of variance and are providing insurance to the market, require substantial positive returns. This may be rational since the correlation between volatility shocks and market returns is known to be strongly negative and investors want protection against stock market crashes.

Finally, the aggregate risk preferences of market participants are proxied by the time-varying relative risk aversion (*RA*) measure under habit preferences based on the consumption surplus ratio of Campbell and Cochrane (1999). It is estimated as,

$$RA_t = \frac{\gamma}{S_t}, \tag{2}$$

where S_t is the surplus consumption ratio given by $S_t = (C_t - X_t)/C_t$, C_t is the monthly seasonally adjusted real per capita consumption expenditures on nondurable goods and services, X_t is the level of habit approximated by an autoregressive process consistent with a low volatile enough interest rate, and γ is the inverse of the elasticity of intertemporal substitution.[14]

2.4 *Descriptive statistics of aggregate variables*

Table 3 provides the summary statistics of the aggregate illiquidity measures and the macroeconomic control variables. In Panels A and B we further break down the summary statistics of the aggregate illiquidity measure for the CDS market (given by the aggregate absolute bid-ask spread) and the default spread by portfolio rating and maturity. From Panel A we observe that, for a given credit rating, the shorter maturities are always

[13] See Carr and Wu (2009)

[14] We obtain nominal consumption expenditures on nondurable goods and services from the Table 2.8.5 of the National Institute of Pension Administrators (NIPA). Population data are from NIPA's Table 2.6 and the price deflator is computed using prices from NIPA's Table 2.8.4 with the year 2000 as its basis. All this information is used to construct monthly seasonally adjusted real per capita consumption expenditures on nondurable goods and services. The autoregressive parameter of the habit process is estimated using the price-dividend ratio obtained from the original series on Robert Shiller's website. The actual procedure to estimate the surplus consumption ratio follows the methodology described by Campbell and Cochrane (1999) with $\gamma = 2$.

more illiquid than longer maturities. This is especially the case for the shortest maturity portfolios which are relatively highly illiquid contracts. The 5 year CDS contracts are the most liquid with the only exception of the high yield portfolios in which the 5, 7, and 10 year maturities have approximately the same illiquidity level. Therefore, the (average) slope of the term structure of bid-ask illiquidity for CDS spreads presents an asymmetric U-shaped pattern. At the same time, the standard deviation of portfolio illiquidity decreases almost everywhere as maturity increases. On the other hand, for a given maturity, portfolio illiquidity increases as the credit quality of the portfolio drops. This holds for portfolio CDS spreads for all maturities in terms of both mean and median, and it also holds for the standard deviation of illiquidity. Moreover, holding maturity constant, the increase in portfolio illiquidity is considerable when moving from the investment grade to the high-yield category of CDS portfolios. For instance, the average of the most liquid 5 year bid-ask spread of AAA/A- and BBB+/BBB- portfolios are around 6 and 7 basis points, whereas the average 5 year bid-ask spread of BB+/B- and B+/D are around 17 and 43 basis points respectively.

Figure 3 depicts the time series of aggregate bid-ask spreads by maturity. We observe that the lower the maturity, the higher the illiquidity of the CDS contracts. This is particularly the case during stress periods, with the known exception of the 5 year contract which is overall the most liquid contract. As expected, the illiquidity of the CDS market increases substantially after the start of the financial crisis and it reaches its peak at the end of 2008 around the collapse of Lehman Brothers.

Panel B of Table 3 shows that the default spread increases as credit quality decreases, but decreases as maturity increases. We recall that the default spreads for a given rating group with different maturities are calculated by taking the difference between the corporate bond index yield for that given rating group and Treasury bond yields at different maturities. Hence, the decreasing effect of maturity is due to the way default spreads are defined.

Panel C of Table 3 also reports descriptive statistics for aggregate illiquidity for alternative horizons without distinguishing across credit quality both for bid-ask spreads and default spreads, market-wide illiquidity of the stock market, time-varying risk aversion, the variance risk premium, the slope of the term structure and default risk between HY and IG markets, respectively. As before, aggregate illiquidity measured by the absolute bid-ask spread shows that short-term maturity contracts are highly illiquid, the average variance risk premium is negative, and the slope and default state variables are, as expected, positive on average during our sample period. Figure 4 depicts the time series of aggregate Amihud ratio and aggregate Amihud illiquidity, the AR(2) residuals, for the US stock market. The series reveals a substantial increase in the aggregate illiquidity of stock markets when Lehman Borthers went bankrupt. Figure 5 displays the aggregate time-varying risk aversion under habit preferences. Risk aversion tends to increase during stress periods but, of course, it is striking the enormous increase of risk aversion during the current economic and financial crisis. It reaches unknown levels of risk aversion which should strongly impact discount rates and financial prices. Figure 6 represents the annualized volatility risk premium. As expected, the volatility under the risk neutral measure tends to be higher than the volatility under the objective probability measure except in periods of great distress in which realized volatility is extremely high.

Table 4 displays the correlation matrix among the aggregate illiquidity and other control variables for the whole sample period from January 2004 to September 2010. Though not present in the table, we observe that there is a high level of correlation among bid-ask spreads of CDS contracts for different maturities. More specifically, all the pairwise correlation coefficients between any two series of bid-ask spreads with different maturities are higher than 90%. This already suggests that there might be a high commonality in bid-ask spreads of different maturities.

The aggregate illiquidity measure for the US equity market has a relatively high (above 0.50 and less than 0.65) correlation with the aggregate illiquidity measures of CDS spreads. We also observe moderate and positive correlation coefficients between the aggregate illiquidity variable of the CDS market and both, the variance risk premium and changes in default risk. In particular, as the credit quality of CDS portfolio decreases, the correlation between changes in bid-ask spreads and changes in default risk increases across all maturities with the exception of BBB portfolios. This suggests that aggregate CDS bid-ask spreads might also include a default component in addition to liquidity. It is interesting to note the negative correlation between the variance risk premium and aggregate risk aversion. When risk aversion increases, the expected variance under the risk neutral measure becomes higher relative to realized variance generating a negative association between these two variables.

3 Effects of market-wide illiquidity on CDS spreads

3.1 Illiquidity commonality

As already mentioned before, the high correlation levels between aggregate CDS bid-ask spreads for different maturities suggest that there is a high level of liquidity commonality among aggregate bid-ask spreads of CDS contracts of different maturities. To examine the degree of commonality of CDS illiquidity spreads in terms of the overall aggregate bid-ask spreads, we run the following ordinary least squares (OLS) autocorrelation-robust standard error regressions:

$$\Delta CDS_{pt} = a + b\Delta ILBAS_t + \varepsilon_t, \tag{3}$$

where ΔCDS_{pt} is the change of the bid-ask spread of credit-quality-sorted portfolio p at month t with either 1, 3, 5, 7, and 10 year maturity, and $\Delta ILBAS_t$ is the maturity independent aggregate bid-ask spread of the CDS market. Before constructing the aggregate measure of bid-ask spread illiquidity of the market, individual bid-ask spreads of a CDS name are averaged across maturity. Table 5 contains the empirical results. It shows that there is a strong commonality across all portfolios and maturities.[15] Most of the slope coefficients are positive and statistically significant. However, it is striking the strong illiquidity commonality, both in terms of regression coefficients and R-squared statistics, for high-yield underlings with ratings from BB+ to D. More importantly, this is especially the case for the higher default risk portfolio with ratings from B+ to D. Aggregate illiquidity seems to have an enormous impact on the CDS market segment of the lowest credit-quality-sorted portfolios.

3.2 Market-wide illiquidity and CDS spreads

We next investigate the relationship between changes in CDS spreads and market-wide illiquidity. For a given maturity, and for each portfolio p of a particular credit quality, we run the following OLS autocorrelation-

[15] A similar result is found by Mayordomo, Peña, and Moreno (2012) who report evidence of liquidity commonality in individual CDS spreads across different countries.

robust standard error regressions:

$$\begin{aligned}\Delta CDS_{pt} &= \beta_{p0} + \beta_{pilbas} resILBASy_t + \beta_{pils} ILS_t \\ &+ \beta_{pra} RA_t + \beta_{pvrp} VRP_t + \beta_{pterm} \Delta TERM_t + \beta_{pdef} \Delta DEF_{pt} + e_{pt},\end{aligned} \tag{4}$$

where ΔCDS_{pt} is the change of the monthly CDS spread of portfolio p for a given maturity, $resILBASy_t$ is the residual that we obtain when regressing changes in aggregate (equally weighted) absolute bid-ask spread for a given maturity on changes in default spread for the same maturity, and the other variables have previously been defined. We consider the residual measure of bid-ask spreads as an aggregate measure of illiquidity for the CDS market because, as already pointed out, the aggregate CDS bid-ask spreads might include a credit risk component in addition to liquidity. To illustrate this point, consider a CDS contract with party B (protection buyer) buying protection from party S (protection seller) on the credit risk of a reference entity X. At least three situations might arise that will induce either of the parties to suffer losses. First, if the reference entity X underlying the CDS contract defaults, protection seller S might suffer a big unexpected loss and be driven into default. In this scenario the protection buyer B might not receive the protection payment from protection seller. Second, protection buyer B can also suffer losses even if the reference entity X does not default but the protection seller S does. If the latter happens, the protection buyer can terminate the existing contact with the protection seller, and try to buy credit protection on the same underlying from another counterparty. However, if the credit quality of the reference entity has decreases considerably, then the new default premium will be higher. This will expose the protection buyer to a mark-to-market movements in the default premium. Third, protection seller S can suffer losses if protection buyer B fails to pay the premium for whatever reason. In this scenario the protection seller S can terminate the existing contract and try to sell protection on the same credit to another counterparty. This time the protection seller will be exposed to mark-to-market risk. To sum up, in a world with higher credit risk the bid-ask spread can widen not because of the risk of underlying CDS name X defaulting, but because of the risk of protection buyer or seller defaulting. Hence, CDS bid-ask spreads can be capturing credit risk in addition to illiquidity.

Table 6 contains the regression results for the time period from 01/2004 to 09/2010 where each panel corresponds to a given horizon of 1-, 3-, 5-, 7-, and 10- year maturities. The key result of this section is the positive relationship between changes in portfolio CDS spreads and changes in the aggregate bid-ask spread measure of illiquidity of the CDS market. The regression coefficients, which we interpret as illiquidity CDS betas, are estimated with precision across credit ratings and maturities. More specifically, for many specifications of portfolio CDS maturity and rating groups, the illiquidity betas are positive and statistically significant for standard confidence levels. Moreover, as one would expect, the magnitude of the coefficients tends to be larger for high yield underlings. Therefore, low credit rating CDS spreads tend to be highly sensitive to aggregate illiquidity shocks relative to high credit quality CDS spreads. This is a robust and economically important result. It suggests that changes of CDS spreads are not only determined by changes in the credit quality of the underlying corporate bond. In other words, CDS spreads do not only reflect expected default and the associated default risk premium, but also expected market-wide illiquidity and the related illiquidity risk premium. A consequence of this result is that, at least for corporate CDS contracts, the well known one-factor intensity model for pricing CDS spreads of Pan and Singleton (2008) is likely to be badly specified.

The aggregate measure of Amihud illiquidity of the US equity market tends to be a significant factor mainly for AAA to A- and B+ to D rated CDS portfolios. The regression coefficients are positive for AAA to A- rated CDS portfolio and negative for the B+ to D portfolio, and are estimated with precision. Therefore, possible spillovers effects of market-wide illiquidity equity shocks seem to be relevant especially for the highest and lowest rated underlings, respectively. However the negative sign of the coefficients of B+ to D credit portfolio is puzzling.

The uncertainty embedded in financial assets, and proxied by the volatility risk premium, is mainly related to AAA to A- CDS portfolios. The regression coefficients of these CDS portfolios are negatively and significantly related to VRP. Hence, it seems that equity volatility shocks only impact CDS spreads of highly rated underlings. It is interesting to note the negative relationship between VRP and CDS spreads. It should be recalled that the VRP is estimated as the difference between the ex-post realized volatility and VIX. This is just the payoff of the future contract on realized variance. This means that when realized volatility is not as high as expected, traders on the CDS market interpret the lower observed volatility as good news for the economy, and CDS spreads become lower.

Time-varying risk aversion under habit preferences does not seem to be a consistently price factor in the CDS spread market. Most of the coefficients are insignificant or estimated with very low precision.

In general, inverted zero-coupon curves tend to anticipate recessions, while upward-sloping curves tend to forecast expansions. This suggests that increases in TERM should be negatively related to changes in CDS spreads. This state variable does not seem to be a consistently important factor in the CDS market. The regression coefficients tend to be negative but they are estimated with very low precision. The only exception is the behavior of BBB+ to BBB- credit quality portfolios which show a relatively precise coefficients, and AAA to A- credit portfolios especially at short horizons. It may be that this segment is dominated by an industry particularly sensitive to interest rate risks.

Finally, changes in default spread DEF_{pt} for different credit ratings p and maturities t are one of the key factors that consistently explain changes in CDS spreads. DEF_{pt} reflects aggregate default risk and, therefore, we expect a positive sign for the regression coefficients. This is systematically the case. Moreover, the low the credit quality of portfolios, the stronger the positive relationship between default risk and CDS spreads with the exception AAA to A- CDS portfolios. Nearly for all credit portfolios regression coefficients for default spread become lower the longer the maturity of the CDS contract.

Overall, our selected market-wide variables explain a high percentage of the variability of CDS portfolios except for BBB+ to BBB- rated CDS portfolio. On average, the R-squared statistics for all portfolios except for BBB+ to BBB- is approximately 0.67 for the sample period across all five maturities, and 0.36 for BBB+ to BBB- CDS portfolio. Overall, the model fits the best the lowest rated CDS portfolio.[16]

To conclude, market-wide illiquidity in the CDS market and default risk are the aggregate variables that are systematically related to changes in CDS spreads. Additionally, financial uncertainty represented by the volatility risk premium, is consistently associated with the AAA to A- CDS portfolio.

4 Flight-to-liquidity, flight-to-quality and CDS spreads

The result of the previous section show that, especially in distress macroeconomic scenarios, a negative market-wide illiquidity shock in the CDS market raises the sensitivity of CDS spreads to those shocks. This effect is stronger in junk underlings than in high quality corporate bonds. We next investigate whether these findings suggest a flight-to-liquidity and/or flight-to-quality phenomena in CDS markets.

[16]Alternative specifications with either levels or changes of RA and VRP, and with or without RA or TERM do not seem to affect the overall conclusions.

Flight-to-liquidity phenomenon suggests that investors substitute less liquid corporate bonds for highly liquid bonds. This relatively higher demand for investment grade bonds during negative aggregate illiquidty shocks may simultaneously increase the demand for CDSs of investment grade bonds relative to the demand for junk CDS spreads. This phenomenon should consequently raise the CDS spread associated to those high quality bonds relative to low quality bonds. Therefore, an adverse illiquidity shock should result in a more negative difference between high yield and investment grade CDS spreads.

We study how the difference between the CDS spread of the B+ to D and the spread of the AAA to A- portfolio is explained by default and illiquidity market-wide risks in expansion and in moments of financial distress. Hence, we first form an additional CDS portfolio as the difference of the spreads between our two extreme portfolios. Secondly, we perform OLS autocorrelation-robust standard error regressions of the form,

$$\begin{aligned}
\Delta CDS_{pt}^{LH} &= \beta_{p0} + \beta_{pilbas} resILBASy_t + \beta_{pils} ILS_t \\
&+ \beta_{pra} RA_t + \beta_{pvrp} VRP_t + \beta_{pterm} \Delta TERM_t + \beta_{pdef} \Delta DEF_t \\
&+ \beta_{pdilbas} resILBASy_t \times D_t + \beta_{pdils} ILS_t \times D_t \\
&+ \beta_{pdra} RA_t \times D_t + \beta_{pdvrp} VRP_t \times D_t + \beta_{pdterm} \Delta TERM_t \times D_t + \beta_{pddef} \Delta DEF_t \times D_t + e_{pt}, \quad (5)
\end{aligned}$$

where ΔCDS_{pt}^{LH} is now the difference between the CDS spreads of the junk portfolio given by the B+ to D ratings (L) and the CDS portfolio spreads associated with the AAA to A- underlings (H), and D is a dummy variable taking the value of 1 during the financial crisis (after June 2007) and 0 otherwise. Recall that DEF is the difference between corporate index yields for HY and IG bonds. For each maturity, we run these regressions with and without the illiquidity aggregate variables, both from the CDS and equity markets, to check the differences between the cross-product terms of the illiquidity variables and the recession dummy. If the sign of the regression coefficient associated with the cross-product is negative and significant, once we include market-wide illiquidity, we may conclude that that there is flight-to-liquidity during stress times in the CDS market. We then pursue the same procedure to analyze the potential flight-to-quality in this market. We first run regression (5) omitting the default variable, and then we add it to check the sign and significance of the cross-product coefficient.

Table 7 contains the results regarding flight-to-liquidity. Each column corresponds to a given maturity where we report the results first without liquidity variables and then adding these variables and the cross-product terms. Market-wide illiquidity in the CDS market presents positive and significant results for shortest maturity. Additionally, there is a significant and negative coefficient of the cross-product term $resILBAS_{1y} \times D_t$ which suggests a short-term flight to liquidity in this market. As for the US stock market, ILS presents positive and significant results nearly for all maturities. However the regression coefficients for maturities over 3 years are estimated with low precision. Nevertheless, the coefficient of cross-product term $ILS \times D_t$ is always negative and statistically significant for all maturities, which suggests a flight-to-liquidity from the equity market at all horizons. Overall, the flight-to-liquidity finding is exclusively a short-term phenomenon that proceeds from the underlying CDS market, but there is a strong evidence of flight-to-liquidity in the CDS market from the equity market.

Table 8 shows the same results where we now omit the default risk variables rather than the illiquidity variables. Default risk seems to be an important factor that can explain changes in the differential CDS spreads. Nearly all regression coefficients of DEF and $\Delta DEF \times D_t$ are estimated with high precision. Moreover, the coefficient of $\Delta DEF \times D_t$ is positive and statistically significant, which suggest flight-to-quality in CDS market. Moreover, this result holds nearly for all maturities. It is also important to point out the very large increase experimented by the explanatory power of the model when we include the measure of default spread. The R-squared statistics increase two- to three-fold when we add default spread into the regressions. Overall, we find a strong evidence of flight-to-credit quality in the CDS market during the stress sub-period.

5 Default and illiquidity risk premia under the two-factor model

Default swap spreads contain a premium for compensating against the risk of changes in the credit environment. Using a sample of sovereign default swaps, Pan and Singleton (2008) and Longstaff et al. (2011) empirically show that this risk premium is related to some macroeconomic and financial variables. Since our previous results indicate that aggregate illiquidity matters when pricing CDS portfolios, an interesting question is to examine whether CDS investors *also* require a premium for bearing the aggregate illiquidity in the market, particularly during distressed circumstances. This section presents an affine model which provides some estimates of default and illiquidity premium embedded in CDS spreads.

5.1 The model

Pan and Singleton (2008) propose an intensity model à la Duffie and Singleton (1997) and Lando (1998) to analyze the risk-neutral arrival rate of default events using the information content in the term structure of sovereign CDS spreads. Within this framework, the credit event is triggered by the first jump of a Poisson process driven by a stochastic intensity. Their modeling framework allows to decompose CDS spreads in both risk premium and default components. Following the Pan and Singleton technique, Longstaff et al. (2011) conclude that compensation for changes in the default environment accounts for around one-third of the spread for a sovereign CDS sample.

We hypothesize that CDS investors consider not only default risk but also illiquidity when pricing CDS contracts. Since CDS are traded in OTC markets, no reliable information about its volume or transaction data is available to us. The most liquid CDS contracts are assumed to be the ones with 5 year maturity. We then assume that investors care about the *relative* illiquidity risk of trading in CDS contracts with maturities other than 5 year. Thus, we consider that maturities different from 5 year embed an illiquidity risk premium that compensate investors for being off-the-liquid contract. This assumption is also consistent with Pan and Singleton (2008), who suggest that 1 year and perhaps 10 year contracts include an idiosyncratic liquidity component due to the short/long-term nature of these instruments. Not surprisingly, these authors point out the different behavior of 1 year contracts with regard to the ones other maturities, maybe because of supply/demand effects. Accordingly, we extract this relative illiquidity component from the 1 year CDS premium.

Our modeling proposal considers two independent state-variables for capturing the credit and (relative) illiquidity factors driving CDS spreads. Under the risk-neutral measure Q the intensity of the Poisson process is driven by two independent factors that follow a log Ornstein-Uhlenbeck (log-OU) process,

$$\begin{bmatrix} d\ln\lambda_t^Q \\ d\ln\gamma_t^Q \end{bmatrix} = \begin{bmatrix} \kappa_{11}^Q & 0 \\ 0 & \kappa_{22}^Q \end{bmatrix} \begin{bmatrix} \theta_1^Q - \ln\lambda_t^Q \\ \theta_2^Q - \ln\gamma_t^Q \end{bmatrix} dt \times \begin{bmatrix} \sigma_1^Q & 0 \\ 0 & \sigma_2^Q \end{bmatrix} \begin{bmatrix} dW_{1t}^Q \\ dW_{2t}^Q \end{bmatrix}, \tag{6}$$

where λ_t^Q is the default process and γ_t^Q is the relative illiquidity of CDS spreads with respect to the 5 year maturity ones. Parameters κ_{11}^Q, κ_{22}^Q stand for the mean-reversion speed; θ_1^Q and θ_2^Q are the long-run means and σ_1^Q, σ_2^Q are the volatility of the process, respectively.

The log-OU specification of intensity (6) ensures the positiveness of default process, and it has been previously employed by Pan and Singleton (2008) and Longstaff et al. (2011). Berndt et al. (2008) also suggest the log-OU process for crisis periods against alternatives like OU or Cox, Ingersoll and Ross (CIR).[17] With regard to illiquidity, it has been previously modeled by Longstaff, Mithal, and Neis (2005) using a standard Brownian motion with constant variance. Chen et al. (2005) employ an OU model to capture the liquidity component in CDS spreads. Both studies analyze the pre-crisis period. To the best of our knowledge, there is no previous formulation of relative illiquidity in continuous-time within the context of CDS pricing.

We assume a change of measure where the Brownian motion under Q satisfies $dW_t^Q = \Lambda_t dt + dW_t^P$,

$$\Lambda_t = \begin{bmatrix} \delta_{01} \\ \delta_{02} \end{bmatrix} + \begin{bmatrix} \delta_{11} & 0 \\ 0 & \delta_{22} \end{bmatrix} \begin{bmatrix} \ln \lambda_t^Q \\ \ln \gamma_t^Q \end{bmatrix}, \tag{7}$$

where dW_t^Q, dW_t^P is a two-dimensional vector of independent Brownian motions and Λ_t is the price of risk. This price of risk is assumed to be an affine function of state variables $\ln \lambda_t^Q$ and $\ln \gamma_t^Q$, respectively. From expressions (6) and (7), the process under P results

$$\begin{bmatrix} d\ln \lambda_t^Q \\ d\ln \gamma_t^Q \end{bmatrix} = \begin{bmatrix} \kappa_{11}^P & 0 \\ 0 & \kappa_{22}^P \end{bmatrix} \begin{bmatrix} \theta_1^P - \ln \lambda_t^Q \\ \theta_2^P - \ln \gamma_t^Q \end{bmatrix} dt \times \begin{bmatrix} \sigma_1^Q & 0 \\ 0 & \sigma_2^Q \end{bmatrix} \begin{bmatrix} dW_{1t}^P \\ dW_{2t}^P \end{bmatrix}, \tag{8}$$

where $\kappa_{ii}^P \theta_i^P = \kappa_{ii}^Q \theta_{ii}^Q + \delta_{0i}\sigma_i^Q$ and $\kappa_{ii}^Q = \kappa_{ii}^P + \delta_{ii}\sigma_i^Q$, $i = 1,2$.

Under this formulation, the CDS spreads are computed as

$$CDS_t^Q(M) = \frac{4L^{\mathbb{Q}} \int_t^{t+M} D(t,u) E_t^{\mathbb{Q}} \left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u (\lambda_s^{\mathbb{Q}} + \gamma_s^Q)\, ds} \right] du}{\sum_{i=1}^{4M} D(t, t+j/4) E_t^{\mathbb{Q}} \left[e^{-\int_t^{t+.25i} (\lambda_s^{\mathbb{Q}} + \gamma_s^Q)\, ds} \right]} \quad , \tag{9}$$

where M is the maturity of the CDS, L^Q is the risk-neutral loss given default (LGD) and $D(\cdot)$ is the risk-free discount rate. To get some intuition of expression (9), we take a look at its constituents. On the one hand, the nominator captures the expected payments of the protection seller in case of default: the expected

[17]For example, the Feller condition in CIR processes limits the long-term mean of the intensity to the square-root of its long-term variance. This requirement is frequently violated in our sample due to the extreme movements of default swap spreads during the crisis period.

losses (assumed to be constant) times the default probability. On the other hand, the denominator reflects the discounted value of a constant, risky annuity of USD 1 paid quarterly until maturity or default, whichever comes first. At the moment of inception, the premium on this risky annuity (the CDS spread) paid by the protection buyer must equal the discounted payments faced by the protection seller. As commonly assumed in the literature, we impose that L^Q equals to real expected losses L^P and its fixed to 60%. Additionally, the risk-free term structure is taken as given.

5.2 *Estimation procedure and results*

We estimate the parameters of our intensity model for the four portfolios under study (AAA+ to A-, BBB+ to BBB-, BB+ to BB- and B+ to D) by maximum likelihood (ML). We closely follow Pan and Singleton (2008), summarizing here the main steps of their methodology. For the sake of notation, we denote λ^Q and γ^Q by λ and γ, respectively. We assume that 1- and 5 year CDS contracts are perfectly priced. Additionally, we also assume that the 5 year contracts *just* account for default risk and 1 year CDS spreads accounts for both default and illiquidity risk. Former assumptions lead us to conjecture an illiquidity path from 1 year CDS.

We proceed as follows. First, given a set of κ^Q, θ^Q and σ^Q parameters, we extract a time series of the λ process by inversion of the pricing function of the 5 year CDS using a non-linear technique. Conditional on the λ path, we repeat this procedure on the 1 year contract to obtain a path for γ. Both λ and γ processes are employed subsequently for pricing the remaining default swaps. Second, differences between sample and theoretical 3, 7 and 10 year CDS contracts are priced with normally distributed errors ε_{3y}, ε_{7y} and ε_{10y} with zero mean and standard deviations $\sigma(3)$, $\sigma(7)$ and $\sigma(10)$, respectively. Third, we employ the bootstrapped USD Libor-Swap curve as risk-free rates to discount future payoffs. We use the 3, 6, 9 and 12-month USD Libor that is published by the British Bankers' Association and the 2, 3, 4, 5, 7 and 10 year USD interest rate swaps from the Federal Reserve Statistical Release H.15. Fourth, expectations of log-OU process are not given in closed form, so they are computed using the Crank-Nicholson scheme. Finally, we maximize the likelihood function

$$\begin{aligned} f^P(\Theta,\lambda,\gamma) &= f^P(\varepsilon_{3y}|\Theta,\lambda,\gamma) \times f^P(\varepsilon_{7y}|\Theta,\lambda,\gamma) \times f^P(\varepsilon_{10y}|\Theta,\lambda,\gamma) \\ &\times f^P_{AR}(\ln\lambda|\Theta) \times \left|\partial CDS^Q(\lambda|\Theta)/\partial\lambda\right|^{-1} \\ &\times f^P_{AR}(\ln\gamma|\Theta,\lambda) \times \left|\partial CDS^Q(\gamma|\Theta,\lambda)/\partial\gamma\right|^{-1}, \end{aligned} \quad (10)$$

where the parameter vector $\Theta = (\kappa^Q_{ii}, \kappa^Q_{ii}\theta^Q_i, \sigma^Q_i, \kappa^P_{ii}, \kappa^P_{ii}\theta^P_i, \sigma(3), \sigma(7), \sigma(10))$, $i = 1,2$ and $f^P(\cdot)$ is the density function of the Normal distribution, $f^P_{AR}(\cdot)$ is the Gaussian density of an AR(1) process and Δt is equal to 1/12.

The ML estimates of the two-factor model are displayed on Table 9. Some interesting conclusions arise. Concerning to the default processes, the mean-reversion rate (κ^Q_{11}) under Q measure is almost constant across portfolios. Since the mean-arrival rate of credit events under Q (implied by the product $\kappa^Q_{11}\theta^Q_1$) increases as credit quality deteriorates, the model indicates that the arrival of a credit event is much more likely in low quality portfolios. On another front, mean reversion rates ($\kappa^P_{11} > \kappa^Q_{11}$) are consistently higher under P than Q measure. Additionally, the arrival of credit events $\kappa^Q_{11}\theta^Q_1 > \kappa^P_{11}\theta^P_1$ is much more intense in the risk-neutral than actual world. These facts suggest a systematic departure of risk-neutral to real intensities that diverges as time goes by. In other words, risk-neutral environment worsens through time (the arrival of credit events increases) with respect to the actual intensity. This fact is also corroborated by the negative signs of $\delta_{01} = (-1.58, -2.53, -2.80, -1.01)$ and $\delta_{11} = (-0.28, -0.50, -0.73, -0.38)$. These observations are consistent with a systematic default risk premium being priced in the market, as pointed out by Pan and Singleton (2008). Surprisingly enough, the default volatility σ^Q decreases as portfolio quality deteriorates.

With regard to the illiquidity process, the ML parameters in Table 9 show that relative illiquidity increases dramatically as portfolio rating deteriorates. This conclusion is consistent with the OLS regression results in Section 3. First, the risk-neutral environment worsens dramatically: as creditworthiness decreases, mean-reversion rate (κ^Q_{22}) decreases and long-run mean ($\kappa^Q_{22}\theta^Q_2$) increases. Within the context of our model, this is understood as a huge increase of illiquidity events that is expected from the market. Second, illiquidity risk premia are positive, as inferred from $\delta_{02} = (-6.26, -3.02, -12.35, -8.12)$ and $\delta_{22} = (-0.84, -0.42, -1.44, -0.97)$. Third, the arrival of credit events $\kappa^Q_{22}\theta^Q_2 > \kappa^P_{22}\theta^P_2$ is much more intense in the risk-neutral than actual world: such a size disparity in mean-reversion and long-run parameters under the actual measure indicates that, although rare arrival rates of illiquid events are expected, the risk-neutral scenario is significantly stressed. To put it another way, CDS investors seem to demand a higher risk premium for trading an illiquid contract with respect to the 5 year benchmark. Lastly, the volatility of illiquidity process almost double for low-rating portfolios.

Concerning to the performance of the model, it decreases as creditworthiness deteriorates. This fact is reflected in the standard deviations of the pricing errors, which tend to increase for lower credit quality portfolios. In this way, the model likelihood also decreases, probably due to the (highly) non-linear behavior of non-investment grade CDS spreads, specially in the lowest quality portfolio.

Finally, Figure 7 depicts the averaged pricing error of default swap contracts. In general, our model seems to be successful in capturing the dynamics of the CDS term structure. On average, our model differs around a 10.7%, 1.9% and 5.2% with respect to 3, 7 and 10 year sample CDS spreads.

5.3 How does the illiquidity evolve?

In order to understand the evolution of illiquidity through time, Figure 8 exhibits the default and illiquidity processes for the portfolios under study. To better interpret our results, we also depict three major economic events during the crisis: first, the BNP withdrawal of three funds in August 9, 2007, considered as the starting point of the financial crisis. Second, the Lehman Brothers bankruptcy in September 15, 2008. Finally, we also include the financial regulatory reform of Dood-Frank Act in December 11, 2009.

Figure 8 shows that default problems started around August 2007, peaking when Lehman filed Chapter 11 in September 2008. Default intensities keep their level stable around December 2009. As expected, default intensity level increases as creditworthiness diminishes.

Relative illiquidity process is important during the first part of 2004, maybe reflecting the liquidity premia associated to a relative small market during its early stage (Blanco et al., 2005). Again, illiquidity triggers during August 2007. According to Figure 8, illiquidity and default processes are intimately related during the crisis period 2007-2010. This relationship is stronger for extreme portfolios: correlation coefficients of AAA+ to A- (B+ to D) portfolios are 34.05% (44.90%). Not surprisingly, illiquidity is much more intense in these two portfolios, specially during stressed periods.

5.4 Risk premia

Under our modeling framework, the risk premium stands for the compensation due to changes in the default conditions (market volatility, monetary policy, etc.) instead of rewarding the default itself. The former is called *distress* premium and it has been previously analyzed by Pan and Singleton (2008) and Longstaff et al. (2011), among others. As mentioned previously, the latter is called default-event premium and it is out of the scope of this paper. Jarrow et al. (2005) presents an unifying framework of both distress and default event premia within the intensity modeling.

Can we quantify the size of this risk premium? To solve this question, Longstaff et al. (2011) notice that equation (6) collapses to (8) when the risk-premium is equal to zero (no compensation for changes in the default and illiquidity environment). Then, if CDS investors are not rewarded for bearing the uncertainty due to changes in the risk and/or liquidity environment, the difference between CDS spreads (CDS^Q) computed under risk-neutral Q and the *pseudo*-spreads,

$$CDS_t^P(M) = \frac{4L^{\mathbb{Q}} \int_t^{t+M} D(t,u) E_t^{\mathbb{P}} \left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u \lambda_s^{\mathbb{Q}} ds} \right] E_t^{\mathbb{P}} \left[e^{-\int_t^u \gamma_s^{\mathbb{Q}} ds} du \right]}{\sum_{i=1}^{4M} D(t,t+j/4) E_t^{\mathbb{P}} \left[e^{-\int_t^u \lambda_s^{\mathbb{Q}} ds} \right] E_t^{\mathbb{P}} \left[e^{-\int_t^u \gamma_s^{\mathbb{Q}} ds} du \right]} \quad , \tag{11}$$

is zero. Otherwise, divergences between CDS^Q and CDS^P are capturing the risk premium embedded in CDS spreads for compensating changes in the risk factor conditions.

Figure 9 shows the total risk premium for the four portfolios under analysis. The total compensation is positive after August 2007, and it increases as credit quality deteriorates. The Lehman default seemed to conclude in a systemic event that spread across portfolios, resulting in a wide-increase of the risk premium of all portfolios. Finally, negative risk premia is registered during the pre-crisis period for high yield portfolios, specially in shorter maturities.

Moving a step forward, we apply the arguments in Longstaff et al. (2011) for computing the contribution of default (RP_{def}) and illiquidity (RP_{illiq}) risk premium components of the CDS spread,

$$RP_{def} = CDS^Q - CDS^P_{def} \tag{12}$$

$$RP_{liq} = CDS^Q - CDS^P_{liq}, \tag{13}$$

where

$$CDS^{P}_{def,t}(M) = \frac{4L^{\mathbb{Q}} \int_t^{t+M} D(t,u) E_t^{\mathbb{P}} \left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u \lambda_s^{\mathbb{Q}} ds} \right] E_t^{\mathbb{Q}} \left[e^{-\int_t^u \gamma_s^{\mathbb{Q}} ds} du \right]}{\sum_{i=1}^{4M} D(t,t+j/4) E_t^{\mathbb{P}} \left[e^{-\int_t^u \lambda_s^{\mathbb{Q}} ds} \right] E_t^{\mathbb{Q}} \left[e^{-\int_t^u \gamma_s^{\mathbb{Q}} ds} du \right]} \tag{14}$$

and

$$CDS^{P}_{illiq,t}(M) = \frac{4L^{\mathbb{Q}} \int_t^{t+M} D(t,u) E_t^{\mathbb{Q}} \left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u \lambda_s^{\mathbb{Q}} ds} \right] E_t^{\mathbb{P}} \left[e^{-\int_t^u \gamma_s^{\mathbb{Q}} ds} du \right]}{\sum_{i=1}^{4M} D(t,t+j/4) E_t^{\mathbb{Q}} \left[e^{-\int_t^u \lambda_s^{\mathbb{Q}} ds} \right] E_t^{\mathbb{P}} \left[e^{-\int_t^u \gamma_s^{\mathbb{Q}} ds} du \right]}. \tag{15}$$

Figure 10 displays the compensation for default risk. As expected, default compensation increases as i) credit quality worsens and ii) the maturity of the contract enlarges. Moreover, the distance between 1 to 5 year default premia widens in high yield portfolios. It is paradigmatic the results in portfolio B+ to D, where default seem not to be priced in the 1 year default swap.

Figure 11 exhibits the compensation due to illiquidity risk. Since 5 year CDS does not contains any liquidity premium by assumption, we just display the 1 year CDS contract. Results are surprising. Illiquidity premium is positive in portfolios AAA+ to A- and B+ to D. The remaining portfolios show more fluctuations than previously referred. Finally, compensation for 1 year CDS in the high yield portfolio is extremely positive, indicating that short-term CDS are employed as liquidity hedging instruments instead of default ones.

5.5 *The price of risk*

Expression (7) provides a functional form for the price of risk within our model. From direct substitution of the estimated parameters in Table 9, Figure 12 depicts the time evolution of the estimated prices of risk. Illiquidity exhibits systematically a higher price of risk than the default component. This result is consistent across portfolios. Additionally, the fluctuations in the price of illiquidity risk are much higher than default, especially for high yield portfolios. Finally, credit events tend to be related to extreme reductions (even negative) of illiquidity price of risk.

6 Conclusions

The recent financial crisis has raised some concerns about the liquidity of CDS contracts. At this point, it is generally accepted that CDS spreads cannot be understood as a pure measure of creditworthiness of a company. CDS spreads can be explained by factors related not only to the credit risk of a company, but also to liquidity related components. Although there are several papers analyzing the relationship between CDS spreads and illiquidity proxies, there is no work focusing on the effects of aggregate illiquidity from the CDS market on CDS spreads.

This article documents a strong commonality in the illiquidity of CDS portfolios. This result suggests that measures of market-wide illiquidity may explain changes in CDS spreads. Indeed, this turns out to be the case. There is a positive and significant relationship between changes in CDS spreads and changes in aggregate bid-ask spread for a given maturity of the CDS contract. Even after extracting potentially confounding credit risk expousure in the bid-ask spreads, illiquidity CDS betas across credit quality portfolios and maturities are positive and statistically significant. Moreover, as one would expect, the magnitude of the coefficients tends to be larger for high yield underlings. Therefore, low credit rating CDS spreads tend to be highly sensitive to aggregate illiquidity shocks relative to high credit quality CDS spreads. There is also evidence of flight-to-liquidity during stress periods from the underlying CDS market, at least at short horizons, and strong evidence of flight-to-liquidity from equity markets and flight-to-quality nearly for all maturities.

Using the information content on the 1 year CDS contract, a two-factor intensity model has lead us to extract the risk-neutral arrival of default (λ^Q) and relative illiquidity (γ^Q) processes embedded in the term structure of sorted CDS portfolios. Our results show a correlation between default and illiquidity processes, specially in the case of lower quality portfolio. The ML model estimates plot an extremely stressed risk-neutral illiquidity scenario where the arrival of illiquidity shocks is much more persistent than under actual measure. Within this context, a systematic risk premium associated to the arrival of illiquid events is being priced. The size of this premium increases as portfolio's creditworthiness deteriorates. Moreover, the market price of illiquidity risk systematically exhibits a higher level and volatility than default risk component.

In conclusion, our empirical evidence suggests that changes of CDS spreads are not only determined by changes in the credit quality of the underlying corporate bond. In other words, CDS spreads do not only reflect expected default and the associated default risk premium, but also expected market-wide illiquidity and the related illiquidity risk premium. These results are reinforced by our continuous-time modeling framework. To sum up, our results address a high and economically relevant illiquidity risk premium being priced in the CDS market that has not been previously reported in the financial literature.

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Table 1: CDS names by Sector and Rating

	AA	A	BBB	BB	B	CCC	Total
Basic Materials		1	7	6	2		16
Consumer Goods		1	13	12	1	6	42
Consumer Services	1	6	29	14	2	2	72
Financials	3	11	9	8	4	8	43
Health Care	1	6	2	3	2		14
Industrials	1	5	16	6	4		32
Oil & Gas		4	6	8	1		19
Technology		6	5	3	4		18
Telecommunications		7	2	4		1	14
Utilities		1	5	3	3	2	14
Total	6	48	94	67	5	19	284

This table shows the distribution of CDS names in our database by rating and ICB Industry category. The rating is the average of the Moody's and S&P ratings that are adjusted to the seniority of the instrument and are rounded not to include the plus and minus levels.

Table 2: Portfolio CDS Spreads

	AAA to A-			BBB+ to BBB-			BB+ to BB-			B+ to D		
	mean	med	sd	mean	med	sd	mean	med	sd	mean	med	sd
1y	51.52	20.99	75.55	64.41	39.79	72.29	185.91	120.71	202.24	526.80	293.18	688.73
3y	59.61	36.91	67.28	84.45	60.79	69.05	249.60	189.71	175.46	642.15	445.50	597.18
5y	69.53	47.75	62.77	104.25	80.22	63.59	297.62	240.15	159.56	696.43	519.11	522.80
7y	73.61	56.10	56.59	111.91	92.00	56.23	308.67	255.50	141.38	690.32	545.11	463.65
10y	78.94	64.14	51.25	120.68	104.87	49.80	318.76	284.56	128.64	680.67	558.40	405.81

This table reports summary statistics (in basis points) for equally-weighted CDS spreads of credit-quality-sorted portfolios with different maturities. The frequency of portfolio CDS spreads is monthly. The sample period spans from January 2004 to April 2011.

Table 3: Liquidity Proxies and Macro Variables

Panel A: Portfolio Bid-Ask Spreads

	AAA to A-			BBB+ to BBB-			BB+ to BB-			B+ to D		
	mean	med	sd	mean	med	sd	mean	med	sd	mean	med	sd
1y	11.36	7.01	9.65	13.97	10.39	9.60	32.09	20.91	30.62	80.38	43.52	99.50
3y	8.43	6.18	5.27	10.48	8.37	4.89	23.33	18.85	16.49	55.42	31.66	68.77
5y	6.17	5.24	3.68	7.28	6.30	3.38	17.13	14.27	12.71	43.19	26.48	60.54
7y	7.07	5.91	3.19	8.74	7.78	2.77	18.66	16.06	11.65	43.17	26.50	61.18
10y	7.13	5.98	2.86	8.93	8.19	2.39	18.34	16.63	10.59	42.12	27.27	57.52

Panel B: Default Spreads

	AAA to A-			BBB+ to BBB-			BB+ to BB-			B+ to D		
	mean	med	sd	mean	med	sd	mean	med	sd	mean	med	sd
1y	2.43	2.46	1.60	3.57	3.43	2.23	6.78	6.03	3.96	9.09	8.01	5.39
3y	2.02	1.61	1.33	3.16	2.60	1.96	6.37	5.29	3.73	8.68	7.29	5.18
5y	1.55	1.23	1.14	2.69	1.99	1.75	5.89	4.56	3.54	8.21	6.47	5.01
7y	1.20	0.78	1.07	2.34	1.81	1.64	5.55	4.22	3.42	7.86	5.96	4.91
10y	0.88	0.70	1.02	2.01	1.32	1.54	5.22	3.81	3.31	7.54	5.56	4.80

Panel C: Aggregate Iliquidity Proxies and Macro Variables

	mean	sd	min	5%	med	95%	max	Obs.
ILBAS1y	30.20	33.32	7.86	8.63	14.83	106.41	184.66	81
ILBAS3y	20.85	19.81	6.94	8.14	12.07	54.21	143.56	81
ILBAS5y	15.27	16.08	4.83	5.88	9.18	39.62	121.12	81
ILBAS7y	16.32	15.42	6.54	7.57	10.68	36.19	120.43	81
ILBAS10y	16.07	14.21	6.93	7.69	11.04	32.77	113.23	81
ILS	-0.03	0.46	-1.92	-0.46	-0.04	0.49	2.52	84
RA	51.13	38.11	23.74	24.26	28.58	130.24	139.00	84
VRP	-3.69	4.54	-12.65	-11.20	-3.60	3.41	16.65	88
TERM	1.82	1.37	-0.61	-0.32	2.14	3.52	3.78	88
DEF1y	1.99	1.94	0.22	0.32	1.29	7.25	7.81	88
DEF3y	2.01	1.54	0.64	0.69	1.46	5.82	6.87	88
DEF5y	2.15	1.53	0.82	0.87	1.53	6.07	6.78	88
DEF7y	2.14	1.44	0.93	0.99	1.77	5.83	6.82	88
DEF10y	2.09	1.15	1.08	1.16	1.60	5.01	5.83	88
DEF HYIG	4.01	2.38	1.50	1.89	3.13	10.55	13.13	88

This table reports the summary statistics for our illiquidity measures and macroeconomic variables. Panel A and B provide the summary statistics for bid-ask spread measure of illiquidity of the CDS market and default spread in terms of maturity and credit quality, respectively. Credit-quality-sorted bid-ask spreads are calculated in the same way as the portfolio CDS spreads, whereas default spreads are calculated by taking the difference between corporate bond index yields for different rating groups and Treasury bond yields for different maturities. Panel C provides the summary statistics for the aggregate measures and macroeconomic variables without taking into account the credit quality dimension. ILS is the aggregate measures of illiquidity for US stock market. RA is the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP is the variance risk premium, $TERM$ is the term spread of interest rate curve. $DEF(M)y$ is the default spread with M year maturity, and DEF is the difference between corporate bond index yields of HY and IG bonds, respectively. The frequency of all measures is monthly. The data for most of the measures are from January 2004 to April 2011, except for bid-ask spreads and bond market illiquidity, which end in December 2009 and September 2010, respectively.

Table 4: Correlation Matrix of Liquidity Proxies and Macro Variables

Panel A: 1 year maturity

	Δ ILBAS1y	ILS	RA	VRP	Δ TERM	Δ DEF AAAtoA1y	Δ DEF BBB1y	Δ DEF BB1y	Δ DEF BtoD1y
Δ ILBAS1y	1.000								
ILS	0.641	1.000							
RA	-0.083	-0.067	1.000						
VRP	0.494	0.567	-0.415	1.000					
Δ TERM	0.158	0.158	-0.023	0.044	1.000				
Δ DEF AAAtoA1y	0.363	0.575	-0.174	0.388	0.693	1.000			
Δ DEF BBB1y	0.330	0.707	-0.175	0.571	0.414	0.832	1.000		
Δ DEF BB1y	0.617	0.802	-0.150	0.584	0.201	0.730	0.840	1.000	
Δ DEF BtoD1y	0.773	0.795	-0.134	0.616	0.173	0.647	0.736	0.938	1.000

Panel B: 3 year maturity

	Δ ILBAS3y	ILS	RA	VRP	Δ TERM	Δ DEF AAAtoA3y	Δ DEF BBB3y	Δ DEF BB3y	Δ DEF BtoD3y
Δ ILBAS3y	1.000								
ILS	0.525	1.000							
RA	-0.052	-0.067	1.000						
VRP	0.412	0.567	-0.415	1.000					
Δ TERM	0.159	0.158	-0.023	0.044	1.000				
Δ DEF AAAtoA3y	0.400	0.692	-0.153	0.402	0.371	1.000			
Δ DEF BBB3y	0.289	0.766	-0.154	0.564	0.169	0.844	1.000		
Δ DEF BB3y	0.569	0.801	-0.135	0.562	0.085	0.836	0.887	1.000	
Δ DEF BtoD3y	0.701	0.797	-0.126	0.602	0.100	0.759	0.792	0.940	1.000

Panel C: 5 year maturity

	Δ ILBAS5y	ILS	RA	VRP	Δ TERM	Δ DEF AAAtoA5y	Δ DEF BBB5y	Δ DEF BB5y	Δ DEF BtoD5y
Δ ILBAS5y	1.000								
ILS	0.514	1.000							
RA	-0.047	-0.067	1.000						
VRP	0.367	0.567	-0.415	1.000					
Δ TERM	0.212	0.158	-0.023	0.044	1.000				
Δ DEF AAAtoA5y	0.490	0.724	-0.166	0.455	0.222	1.000			
Δ DEF BBB5y	0.327	0.778	-0.160	0.600	0.052	0.828	1.000		
Δ DEF BB5y	0.595	0.800	-0.136	0.572	0.031	0.857	0.890	1.000	
Δ DEF BtoD5y	0.701	0.791	-0.126	0.606	0.065	0.806	0.810	0.943	1.000

Panel D: 7 year maturity

	Δ ILBAS7y	ILS	RA	VRP	Δ TERM	Δ DEF AAAtoA7y	Δ DEF BBB7y	Δ DEF BB7y	Δ DEF BtoD7y
Δ ILBAS7y	1.000								
ILS	0.515	1.000							
RA	-0.036	-0.067	1.000						
VRP	0.363	0.567	-0.415	1.000					
Δ TERM	0.211	0.158	-0.023	0.044	1.000				
Δ DEF AAAtoA7y	0.485	0.642	-0.191	0.537	0.062	1.000			
Δ DEF BBB7y	0.296	0.721	-0.174	0.654	-0.057	0.817	1.000		
Δ DEF BB7y	0.571	0.775	-0.142	0.594	-0.016	0.858	0.888	1.000	
Δ DEF BtoD7y	0.693	0.777	-0.129	0.621	0.036	0.796	0.799	0.940	1.000

Panel E: 10 year maturity

	Δ ILBAS10y	ILS	RA	VRP	Δ TERM	Δ DEF AAAtoA10y	Δ DEF BBB10y	Δ DEF BB10y	Δ DEF BtoD10y
Δ ILBAS10y	1.000								
ILS	0.503	1.000							
RA	-0.031	-0.067	1.000						
VRP	0.348	0.567	-0.415	1.000					
Δ TERM	0.217	0.158	-0.023	0.044	1.000				
Δ DEF AAAtoA10y	0.418	0.656	-0.218	0.479	0.061	1.000			
Δ DEF BBB10y	0.237	0.726	-0.189	0.615	-0.062	0.807	1.000		
Δ DEF BB10y	0.548	0.782	-0.149	0.581	-0.018	0.843	0.875	1.000	
Δ DEF BtoD10y	0.678	0.781	-0.133	0.613	0.035	0.778	0.783	0.939	1.000

This table reports the correlation matrix among aggregate illiquidity variables with different maturities and maco finance variables. The correlation matrix at each maturity is based on the months for which the data on all variables overlap.

Table 5: Portfolio Bid-ask spread versus Aggregate bid-ask spread illiquidity

	Year 1 Dependent Variable: $\Delta\, CDS_{pt}$			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.02	0.03	-0.07	-0.44
	(0.05)	(0.09)	(-0.08)	(-0.29)
Δ ILBAS	0.18^{***}	0.10	1.22^{***}	4.90^{***}
	(3.21)	(1.60)	(9.50)	(55.55)
N	80	80	80	80
adj. R^2	0.289	0.141	0.849	0.941

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Year 3 Dependent Variable: $\Delta\, CDS_{pt}$			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.04	0.06	0.00	-0.56
	(0.19)	(0.32)	(0.01)	(-0.51)
Δ ILBAS	0.08^{**}	0.07^{**}	0.82^{***}	4.56^{***}
	(2.31)	(2.14)	(12.53)	(23.48)
N	80	80	80	80
adj. R^2	0.169	0.210	0.897	0.972

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Year 5 Dependent Variable: $\Delta\, CDS_{pt}$			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.01	0.01	-0.13	-0.70
	(0.06)	(0.07)	(-0.37)	(-0.54)
Δ ILBAS	0.05^{*}	0.04^{**}	0.74^{***}	4.07^{***}
	(1.75)	(2.04)	(14.15)	(20.99)
N	80	80	80	80
adj. R^2	0.116	0.156	0.872	0.963

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Year 7 Dependent Variable: $\Delta\, CDS_{pt}$			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.05	0.05	0.00	-0.49
	(0.33)	(0.43)	(0.00)	(-0.33)
Δ ILBAS	0.04	0.05^{**}	0.74^{***}	4.04^{***}
	(1.64)	(2.33)	(15.86)	(18.42)
N	80	80	80	80
adj. R^2	0.098	0.156	0.909	0.963

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Year 10 Dependent Variable: $\Delta\, CDS_{pt}$			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.06	0.08	0.01	-0.53
	(0.44)	(0.61)	(0.05)	(-0.36)
Δ ILBAS	0.04	0.04^{**}	0.71^{***}	3.79^{***}
	(1.57)	(2.27)	(16.85)	(17.20)
N	80	80	80	80
adj. R^2	0.077	0.109	0.909	0.960

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table reports monthly regressions with changes in 1, 3, 5, 7, 10 year portfolio bid-ask spread (equally weighted) as a dependent variable (constructed in the same way as credit quality sorted CDS spreads). t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity. N denotes the number of observations used in the regression analysis. Adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS$ denotes changes in aggregate CDS bid-ask spread (aggregated by maturity). "Maturity-independent" bid-ask spread series for each CDS name are constructed by averaging monthly bid-ask spreads over all maturities. ILBAS is constructed by averaging the cross sectional "maturity-independent" bid-ask spreads for each month. The time period is from January 2004 to September 2010.

Table 6: Portfolio CDS Spreads, Aggregate CDS Bid-ask spread and Stock Illiquidity

This table reports monthly regressions with changes in portfolio CDS spread (equally weighted) with different maturities as a dependent variable. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. Adj. R^2 denotes the adjusted R^2 statistics. $resILBAS(M)y$ denotes residuals that we obtain when regressing changes in aggregate CDS bid-ask spread with M year maturity on changes of Default spread with M year maturity. ILS is the aggregate measures of illiquidity for US stock market. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread, and $\Delta DEF(P)(M)y$ denotes changes in default spreads for credit portfolio P with M year maturity.

Panel A: Maturity 1 year

	01/2004 to 09/2010			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	-4.43	2.38	1.66	-20.19
	(-1.36)	(0.94)	(0.24)	(-0.88)
resILBAS1y	0.57^{***}	0.63^{***}	1.67^{***}	4.65^{***}
	(4.55)	(2.99)	(2.67)	(4.15)
ILS	18.54^{**}	-6.59	-48.66	-304.32^{**}
	(2.03)	(-0.40)	(-1.24)	(-2.60)
RA	-0.09	-0.05	0.12	-0.21
	(-1.40)	(-0.95)	(0.99)	(-0.63)
VRP	-2.56^{**}	0.19	3.16	-4.60
	(-2.14)	(0.25)	(1.29)	(-0.51)
Δ TERM	-54.19^{**}	-23.63^{***}	-26.65^{*}	-19.96
	(-2.11)	(-3.72)	(-1.92)	(-0.44)
Δ DEF AAAtoA1y	86.81^{**}			
	(2.64)			
Δ DEF BBB1y		24.46		
		(1.65)		
Δ DEF BB1y			57.36^{***}	
			(3.51)	
Δ DEF BtoD1y				206.75^{***}
				(3.61)
N	80	80	80	80
adj. R^2	0.511	0.295	0.636	0.751

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Maturity 3 year

	01/2004 to 09/2010			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.35	1.43	−1.44	−13.41
	(−0.73)	(0.57)	(−0.29)	(−0.78)
resILBAS3y	0.38***	0.58**	1.86***	2.31**
	(3.85)	(2.52)	(5.70)	(2.08)
ILS	18.82***	−2.76	−28.29	−261.07**
	(3.89)	(−0.19)	(−0.94)	(−2.64)
RA	−0.08	−0.04	0.00	−0.19
	(−1.32)	(−0.77)	(0.05)	(−0.81)
VRP	−1.62*	−0.06	0.13	−3.51
	(−1.82)	(−0.07)	(0.09)	(−0.60)
Δ TERM	−15.95**	−17.60**	−12.74	33.73
	(−2.00)	(−2.17)	(−0.74)	(0.80)
Δ DEF AAAtoA3y	53.47***			
	(5.32)			
Δ DEF BBB3y		28.43**		
		(2.13)		
Δ DEF BB3y			57.49***	
			(4.19)	
Δ DEF BtoD3y				177.24***
				(4.18)
N	80	80	80	80
adj. R^2	0.611	0.351	0.724	0.778

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Maturity 5 year

	01/2004 to 09/2010			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	-2.48	0.06	0.05	-21.19
	(-1.23)	(0.02)	(0.01)	(-1.24)
resILBAS5y	0.25^{**}	0.65^{***}	1.56^{***}	0.88
	(2.48)	(2.84)	(4.91)	(0.62)
ILS	16.44^{***}	-1.54	-3.38	-256.34^{***}
	(3.00)	(-0.11)	(-0.12)	(-2.67)
RA	-0.06	-0.03	0.02	-0.31^{*}
	(-1.32)	(-0.73)	(0.22)	(-1.76)
VRP	-1.68^{**}	-0.46	0.20	-8.08
	(-2.15)	(-0.57)	(0.11)	(-1.34)
Δ TERM	-10.00^{*}	-16.49^{**}	-9.00	45.54
	(-1.77)	(-2.01)	(-0.46)	(0.95)
Δ DEF AAAtoA5y	60.24^{***}			
	(4.45)			
Δ DEF BBB5y		31.81^{**}		
		(2.17)		
Δ DEF BB5y			43.08^{**}	
			(2.46)	
Δ DEF BtoD5y				177.42^{***}
				(4.04)
N	80	80	80	80
adj. R^2	0.697	0.387	0.586	0.774

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel D: Maturity 7 year

	01/2004 to 09/2010			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	-2.84	-0.76	-1.00	-25.10
	(-1.39)	(-0.30)	(-0.16)	(-1.53)
resILBAS7y	0.16^{*}	0.55^{***}	1.48^{***}	1.61
	(1.89)	(3.15)	(4.38)	(1.41)
ILS	24.13^{***}	4.49	0.67	-211.65^{**}
	(3.81)	(0.46)	(0.02)	(-2.29)
RA	-0.08^{*}	-0.04	-0.00	-0.36^{**}
	(-1.73)	(-0.97)	(-0.05)	(-2.13)
VRP	-2.15^{***}	-0.94	-0.47	-10.43^{*}
	(-2.92)	(-1.03)	(-0.25)	(-1.69)
Δ TERM	-3.09	-13.49^{*}	-10.97	55.77
	(-0.67)	(-1.70)	(-0.60)	(1.08)
Δ DEF AAAtoA7y	50.18^{***}			
	(4.11)			
Δ DEF BBB7y		30.93^{**}		
		(2.30)		
Δ DEF BB7y			41.27^{**}	
			(2.27)	
Δ DEF BtoD7y				164.61^{***}
				(4.04)
N	80	80	80	80
adj. R^2	0.668	0.375	0.535	0.750

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel E: Maturity 10 year

	01/2004 to 09/2010			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−2.75	−0.97	−3.05	−19.72
	(−1.33)	(−0.39)	(−0.59)	(−1.37)
resILBAS10y	0.29***	0.67***	0.51	2.72***
	(3.46)	(3.41)	(1.37)	(3.17)
ILS	21.18***	3.62	−16.63	−172.45**
	(3.88)	(0.41)	(−0.59)	(−2.08)
RA	−0.05	−0.03	0.05	−0.22
	(−1.06)	(−0.58)	(0.69)	(−1.42)
VRP	−1.69**	−0.76	−0.19	−7.33
	(−2.60)	(−0.96)	(−0.11)	(−1.47)
Δ TERM	−3.97	−15.80**	−15.95	50.04
	(−0.84)	(−2.05)	(−0.92)	(1.05)
Δ DEF AAAtoA10y	46.22***			
	(4.07)			
Δ DEF BBB10y		27.70***		
		(2.65)		
Δ DEF BB10y			45.66***	
			(3.50)	
Δ DEF BtoD10y				138.76***
				(3.86)
N	80	80	80	80
adj. R^2	0.681	0.392	0.546	0.773

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Flight-to-Liquidity: Extreme Portfolio CDS Spreads, CDS Bid-Ask Illiquidity and Amihud Stock Illiquidity

This table reports monthly regressions with changes in extreme-portfolio CDS spread with different maturities as a dependent variable (with and without aggregate illiquidity variables). Extreme-portfolio CDS spreads are calculated as the difference between CDS spreads of AAA to A- and B to D CDS portfolios. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. Adj. R^2 denotes the adjusted R^2 statistics. $resILBAS(M)y$ denotes residuals that we obtain when regressing changes in aggregate CDS bid-ask spread with M year maturity on changes of Default spread with M year maturity. ILS is the aggregate measures of illiquidity for US stock market. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread. ΔDEF denotes changes in default spreads, calculated as the difference between corporate index yields of HY and IG bonds, repectively. D_t is a recession dummy equal to 0 before June 2007 and 1 afterwards.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	−37.95	−47.78	−15.71	−34.51	−12.80	−37.23	−22.19	−35.79	−33.87	−27.46
	(−0.70)	(−0.64)	(−0.34)	(−0.59)	(−0.27)	(−0.66)	(−0.51)	(−0.68)	(−0.95)	(−0.60)
RA	1.96	2.41	1.44	2.15	1.40	2.31	1.97	2.41	2.55*	2.20
	(0.92)	(0.83)	(0.79)	(0.94)	(0.75)	(1.04)	(1.15)	(1.17)	(1.79)	(1.21)
RA×D_t	−2.06	−2.17	−1.86	−2.13	−2.11	−2.46	−2.60	−2.62	−2.85**	−2.34
	(−0.96)	(−0.89)	(−1.00)	(−1.08)	(−1.18)	(−1.30)	(−1.59)	(−1.51)	(−2.05)	(−1.49)
VRP	4.65**	3.05*	6.66***	5.71**	5.92***	4.97**	7.58***	5.89**	8.81***	7.25***
	(2.11)	(1.68)	(2.95)	(2.45)	(2.96)	(2.42)	(2.96)	(2.45)	(3.28)	(2.81)
VRP×D_t	−11.80	−4.54	−15.76	−9.55	−20.45	−13.43	−22.74*	−15.31	−20.29*	−13.64
	(−0.66)	(−0.35)	(−1.16)	(−1.03)	(−1.52)	(−1.38)	(−1.75)	(−1.63)	(−1.83)	(−1.66)
Δ TERM	37.56*	92.14***	46.20*	23.99	44.85***	39.63**	51.39***	48.03***	23.54	17.31
	(1.92)	(3.76)	(1.96)	(0.95)	(2.70)	(2.24)	(3.60)	(3.69)	(0.84)	(0.55)
Δ TERM×D_t	84.36	97.53	42.59	124.28	19.83	82.46	10.43	53.82	68.39	73.67
	(0.51)	(0.87)	(0.35)	(1.28)	(0.19)	(0.84)	(0.10)	(0.61)	(0.71)	(0.89)
Δ DEF	129.97***	85.76***	126.98***	103.12***	126.66***	112.16***	111.50***	93.96***	125.51***	102.19***
	(5.97)	(5.46)	(6.55)	(6.09)	(8.28)	(7.64)	(7.92)	(6.31)	(7.02)	(5.47)
Δ DEF×D_t	154.80*	254.87**	113.16*	207.93**	108.53	198.76*	116.47*	203.25**	70.43	126.55
	(1.92)	(2.06)	(1.70)	(2.04)	(1.62)	(1.93)	(1.81)	(2.17)	(1.24)	(1.49)
ILS		48.95**		75.30***		42.86*		71.61*		67.86*
		(2.32)		(3.27)		(1.91)		(1.88)		(1.95)
ILS×D_t		−350.45***		−317.85***		−278.06***		−291.90***		−235.84**
		(−2.83)		(−3.08)		(−2.80)		(−2.89)		(−2.56)
resILBAS1y		14.53***								
		(3.81)								
resILBAS1y×D_t		−8.38**								
		(−2.12)								
resILBAS3y				−6.14						
				(−1.30)						
resILBAS3y×D_t				9.69*						
				(1.98)						
resILBAS5y						−0.01				
						(−0.00)				
resILBAS5y×D_t						2.57				
						(0.40)				
resILBAS7y								4.91		
								(0.99)		
resILBAS7y×D_t								−1.60		
								(−0.31)		
resILBAS10y										1.91
										(0.33)
resILBAS10y×D_t										2.74
										(0.47)
N	80	80	80	80	80	80	80	80	80	80
adj. R^2	0.470	0.637	0.512	0.643	0.506	0.624	0.501	0.632	0.497	0.630

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Flight-to-Quality: Extreme Portfolio CDS Spreads, CDS Bid-ask Spread Illiquidity and Amihud Stock Illiquidity

This table reports monthly regressions with changes in extreme-portfolio CDS spread with different maturities as a dependent variable (with and without default spread). Extreme-portfolio CDS spreads are calculated as the difference between CDS spreads of AAA to A- and B to D CDS portfolios. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. Adj. R^2 denotes the adjusted R^2 statistics. $resILBAS(M)y$ denotes residuals that we obtain when regressing changes in aggregate CDS bid-ask spread with M year maturity on changes of Default spread with M year maturity. ILS is the aggregate measures of illiquidity for US stock market. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread. ΔDEF denotes changes in default spreads, calculated as the difference between corporate index yields of HY and IG bonds, repectively. D_t is a recession dummy equal to 0 before June 2007 and 1 afterwards.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	86.92	−47.78	95.58	−34.51	100.92*	−37.23	98.45*	−35.79	74.60*	−27.46
	(1.21)	(−0.64)	(1.54)	(−0.59)	(1.84)	(−0.66)	(1.81)	(−0.68)	(1.67)	(−0.60)
RA	−2.82	2.41	−3.01	2.15	−3.22	2.31	−2.87	2.41	−1.92	2.20
	(−1.00)	(0.83)	(−1.24)	(0.94)	(−1.48)	(1.04)	(−1.34)	(1.17)	(−1.09)	(1.21)
RA×D_t	2.30	−2.17	2.24	−2.13	2.24	−2.46	1.86	−2.62	1.20	−2.34
	(0.99)	(−0.89)	(1.13)	(−1.08)	(1.28)	(−1.30)	(1.11)	(−1.51)	(0.86)	(−1.49)
VRP	3.33	3.05*	6.26**	5.71**	5.31*	4.97**	6.43**	5.89**	7.34**	7.25***
	(1.65)	(1.68)	(2.40)	(2.45)	(1.80)	(2.42)	(2.18)	(2.45)	(2.34)	(2.81)
VRP×D_t	9.02	−4.54	2.19	−9.55	−0.85	−13.43	−2.77	−15.31	−3.34	−13.64
	(0.84)	(−0.35)	(0.26)	(−1.03)	(−0.11)	(−1.38)	(−0.37)	(−1.63)	(−0.54)	(−1.66)
Δ TERM	117.49***	92.14***	−4.82	23.99	9.30	39.63**	18.81	48.03***	−11.56	17.31
	(4.57)	(3.76)	(−0.13)	(0.95)	(0.37)	(2.24)	(1.24)	(3.69)	(−0.29)	(0.55)
Δ TERM×D_t	−95.45	97.53	−16.19	124.28	−82.26	82.46	−103.22	53.82	−44.52	73.67
	(−0.77)	(0.87)	(−0.15)	(1.28)	(−0.98)	(0.84)	(−1.31)	(0.61)	(−0.59)	(0.89)
Δ DEF		85.76***		103.12***		112.16***		93.96***		102.19***
		(5.46)		(6.09)		(7.64)		(6.31)		(5.47)
Δ DEF×D_t		254.87**		207.93**		198.76*		203.25**		126.55
		(2.06)		(2.04)		(1.93)		(2.17)		(1.49)
ILS	84.08***	48.95**	140.66***	75.30***	113.33***	42.86*	134.45***	71.61*	129.64***	67.86*
	(3.15)	(2.32)	(5.17)	(3.27)	(3.06)	(1.91)	(3.78)	(1.88)	(3.78)	(1.95)
ILS×D_t	−65.12	−350.45***	−72.65	−317.85***	−40.14	−278.06***	−53.92	−291.90***	−80.63	−235.84**
	(−0.67)	(−2.83)	(−0.88)	(−3.08)	(−0.51)	(−2.80)	(−0.68)	(−2.89)	(−1.12)	(−2.56)
resILBAS1y	24.65***	14.53***								
	(6.04)	(3.81)								
resILBAS1y×D_t	−14.83***	−8.38**								
	(−3.24)	(−2.12)								
resILBAS3y			−6.29	−6.14						
			(−1.11)	(−1.30)						
resILBAS3y×D_t			13.91**	9.69*						
			(2.35)	(1.98)						
resILBAS5y					3.92	−0.01				
					(0.48)	(−0.00)				
resILBAS5y×D_t					4.21	2.57				
					(0.49)	(0.40)				
resILBAS7y							−5.56	4.91		
							(−0.90)	(0.99)		
resILBAS7y×D_t							13.34**	−1.60		
							(2.04)	(−0.31)		
resILBAS10y									6.82	1.91
									(0.78)	(0.33)
resILBAS10y×D_t									1.67	2.74
									(0.19)	(0.47)
N	80	80	80	80	80	80	80	80	80	80
adj. R^2	0.370	0.637	0.282	0.643	0.219	0.624	0.199	0.632	0.314	0.630

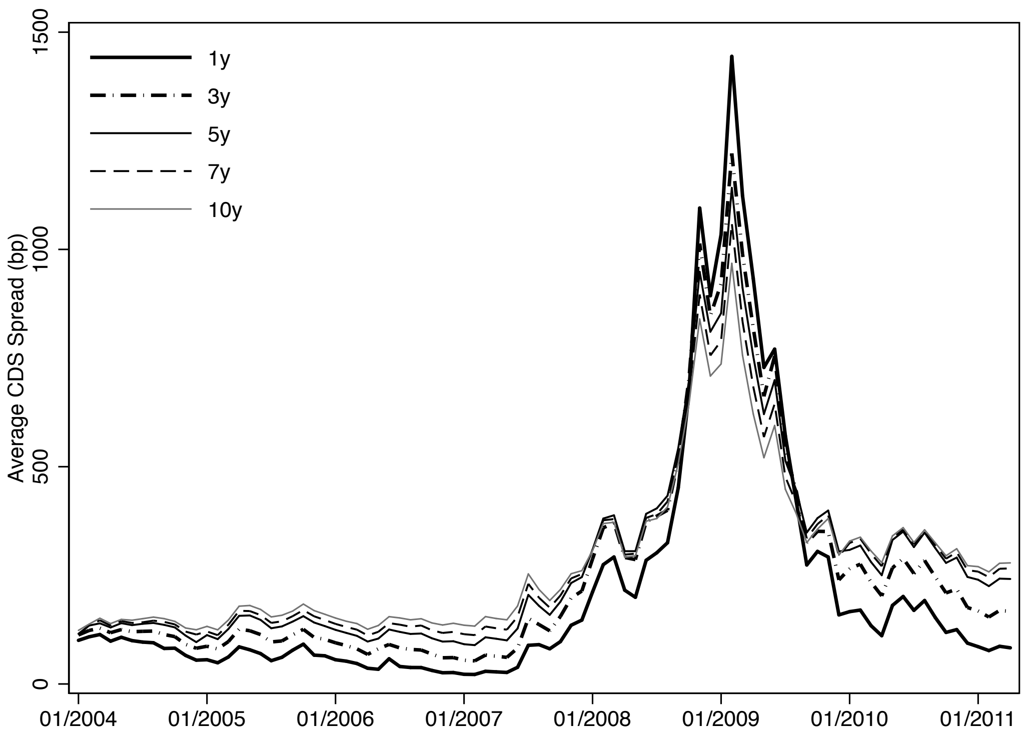
t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: ML Parameters

	Portfolios			
Parameters	AAA+ to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
κ_{11}^{Q}	0.3703	0.3698	0.3715	0.3700
	(0.0006)	(0.0005)	(0.0047)	(0.0037)
$\kappa_{11}^{Q}\theta_{1}^{Q}$	-2.4098	-2.2789	-1.5320	-1.0700
	(0.0282)	(0.0042)	(0.0074)	(0.0013)
σ_{1}^{Q}	1.7011	1.7395	1.3035	0.8785
	(0.0199)	(0.0031)	(0.0153)	(0.0123)
κ_{11}^{P}	0.8394	1.2402	1.3268	0.7022
	(0.5897)	(0.7052)	(0.7288)	(0.5378)
$\kappa_{11}^{P}\theta_{1}^{P}$	-5.0957	-6.6817	-5.1782	-1.9600
	(3.3129)	(3.6653)	(2.9124)	(1.7007)
κ_{22}^{Q}	0.6784	0.4397	-0.9413	-1.1600
	(0.0278)	(0.0124)	(0.0721)	(0.1750)
$\kappa_{22}^{Q}\theta_{2}^{Q}$	-9.2447	-6.0143	-1.7579	3.3710
	(0.3505)	(0.1567)	(0.2766)	(1.1738)
σ_{2}^{Q}	3.8546	3.3526	6.8171	6.4433
	(0.0457)	(0.0218)	(0.1678)	(0.2629)
κ_{22}^{P}	3.9206	1.8592	8.8742	5.0888
	(0.6093)	(0.7735)	(1.3127)	(1.2685)
$\kappa_{22}^{P}\theta_{2}^{P}$	-33.3743	-16.1310	-85.9151	-48.9558
	(5.6862)	(7.3795)	(16.0942)	(11.9478)
$\sigma(3)$	0.0014	0.0017	0.0037	0.0098
	(0.0002)	(0.0002)	(0.0002)	(0.0016)
$\sigma(7)$	0.0010	0.0011	0.0026	0.0178
	(0.0001)	(0.0001)	(0.0003)	(0.0060)
$\sigma(10)$	0.0013	0.0017	0.0028	0.0224
	(0.0002)	(0.0003)	(0.0003)	(0.0067)
LogLk	2449.7981	2318.6371	1869.0923	1306.0300
Obs.	88	88	88	88

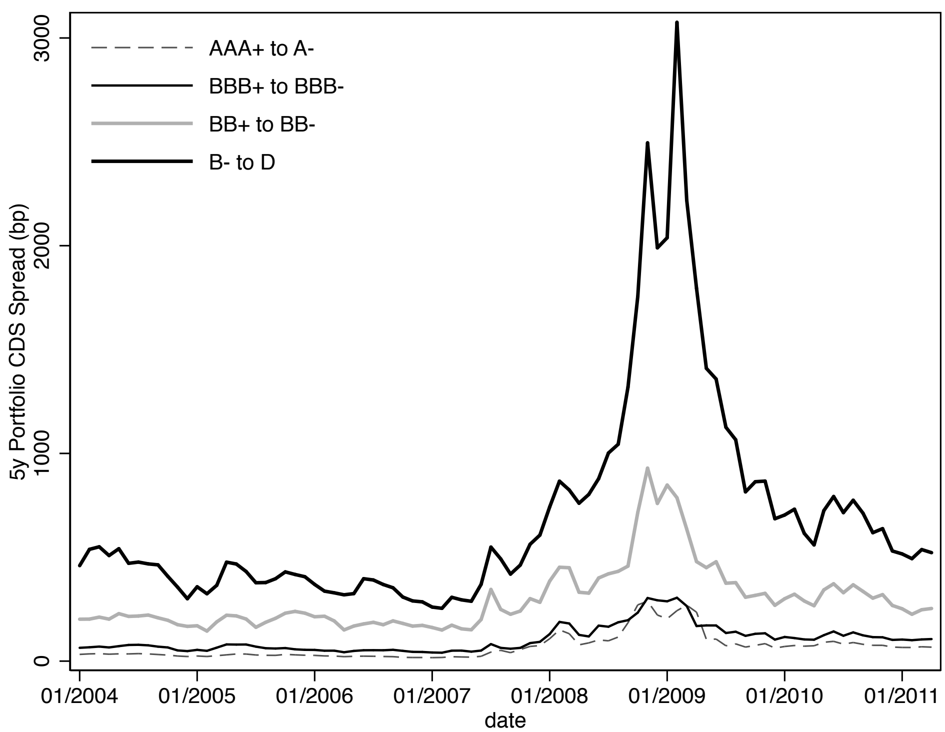
This Table provides the maximum likelihood estimates for the two-factor version of Pan and Singleton (2008) model. Standard errors are in parenthesis. κ_{ii}^{Q}, θ_{i}^{Q} and σ_{i}^{Q}, with $i = 1, 2$, denote the mean reversion, long run mean and instantaneous volatility of default intensity processes λ^{Q} and γ^{Q} under the Q probability measure, respectively. Analogously, κ_{ii}^{P} and θ_{i}^{P} are the mean reversion rate and long run mean under the objective measure P. $\sigma(M)$ is the deviation of CDS spread misspricing for maturities 3-, 7- and 10-years. Data frequency is monthly and it comprises from January 2004 to April 2011.

Figure 1: Time series of sample mean CDS spreads



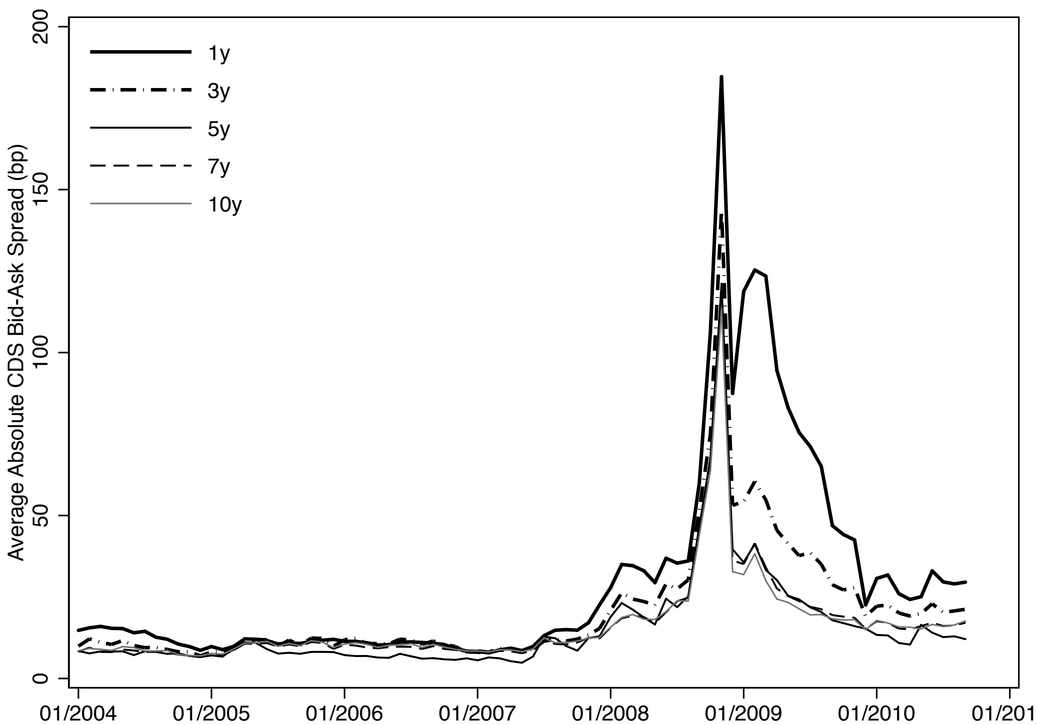
This graphs plots the monthly time series of CDS spreads by maturity. The time series of monthly CDS spreads for each maturity is constructed by taking the cross-sectional average of CDS spreads for each month and maturity. The time period of our sample spans from January 2004 to April 2011.

Figure 2: Time series of CDS spreads of credit quality sorted portfolios (equally weighted)



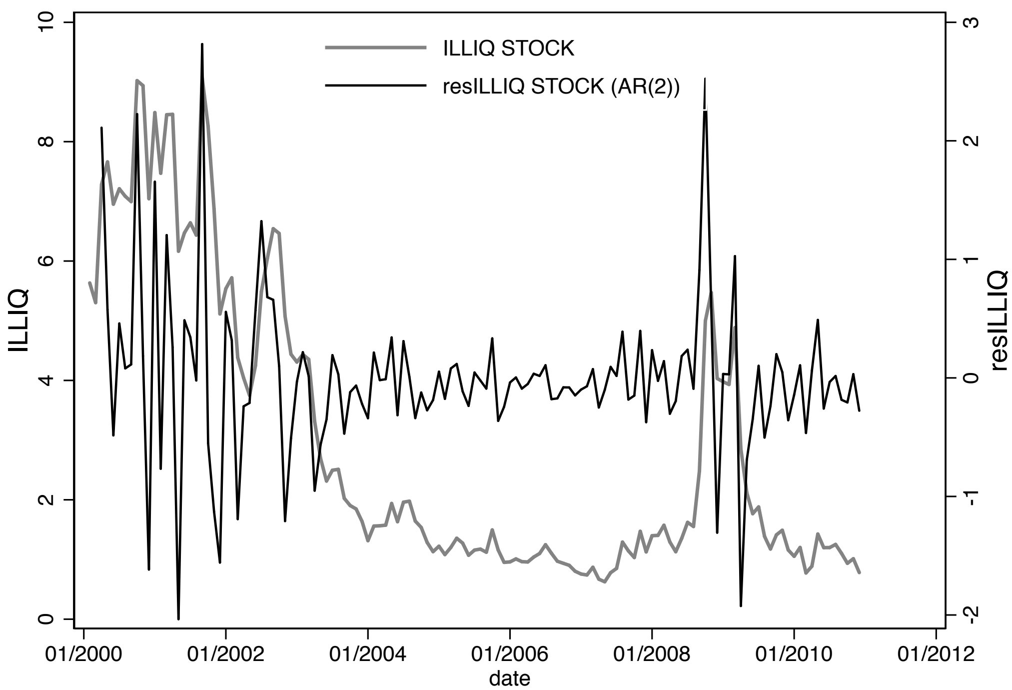
This graphs depicts the time series of CDS spreads of credit quality sorted portfolios. The time period of our sample spans from January 2004 to April 2011.

Figure 3: Time series of aggregate absolute CDS bid-ask spread



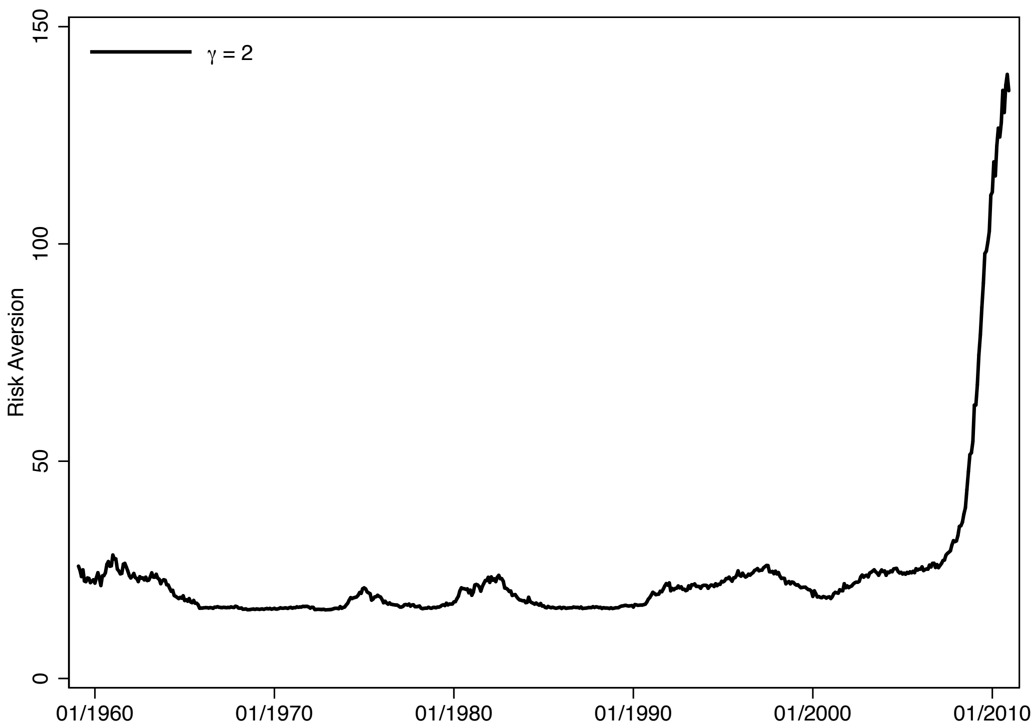
This graphs depicts the time series of aggregate Bid-ask spreads by maturity. The time series of aggregate Bid-ask spreads are obtained by taking the cross-sectional average of individual bid-ask spreads of CDS names in our database for each month and maturity. The time period of our sample spans from January 2004 to September 2010.

Figure 4: Time series of aggregate Amihud ratio and illiquidity



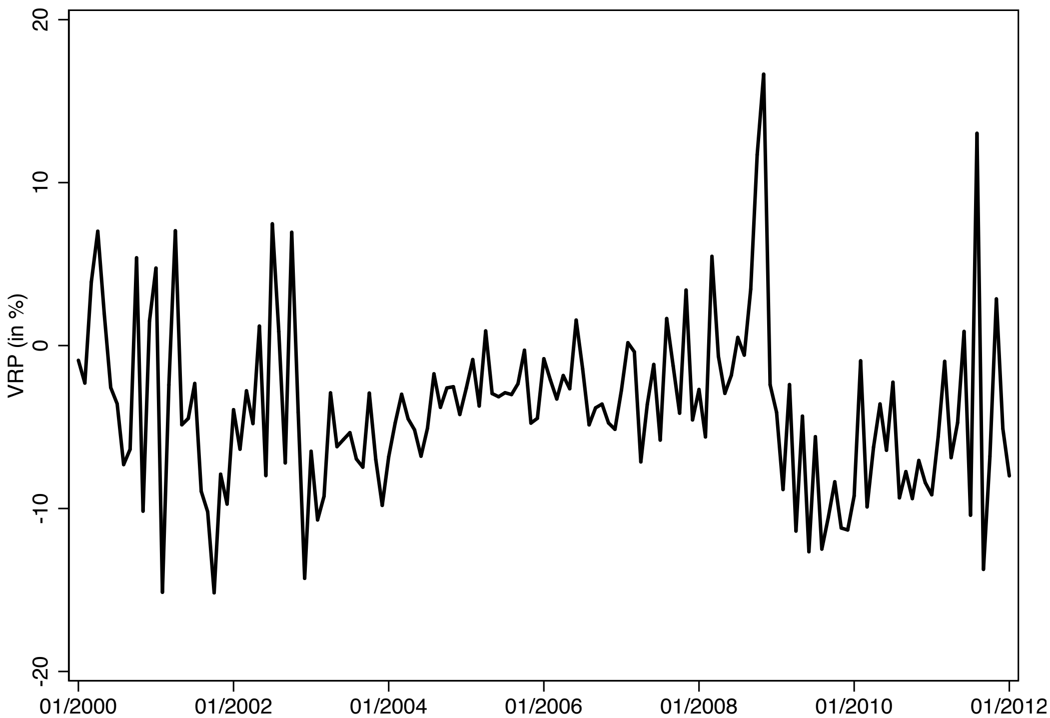
This graphs depicts the time series of the aggregate ratio of Amihud and aggregate measure of illiquidity of Amihud (AR(2) residual of aggregate Amihud ratio). The time period is from January 2000 to December 2011.

Figure 5: Time series of Risk Aversion



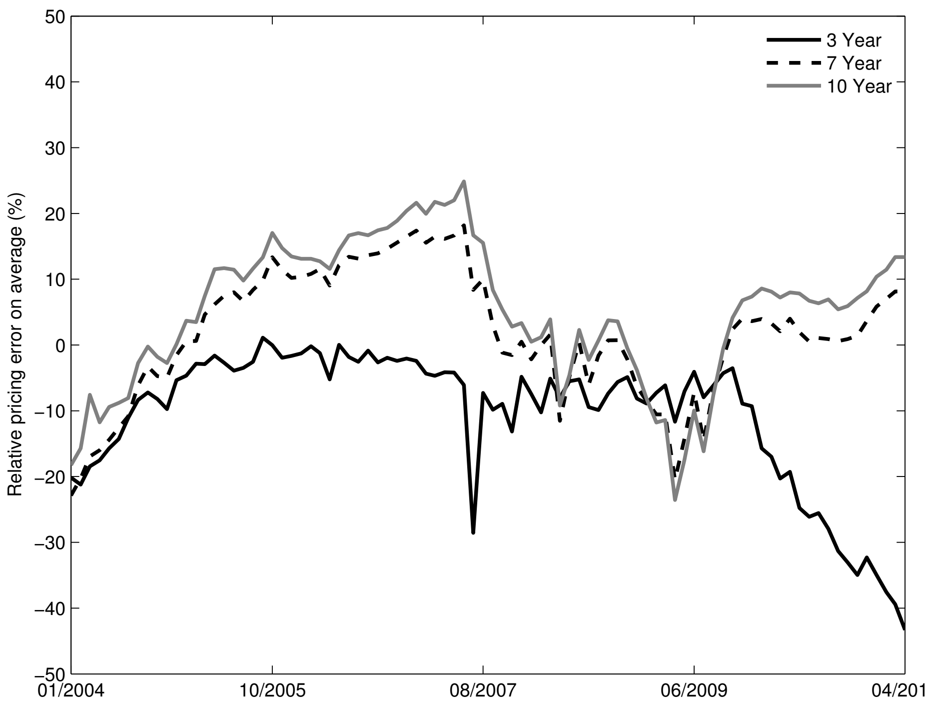
This graphs plots the time series of the time-varying risk aversion under habit preferences based on the consumption surplus ratio. The time period spans from February 1959 to December 2010.

Figure 6: Time series of Variance Risk Premium



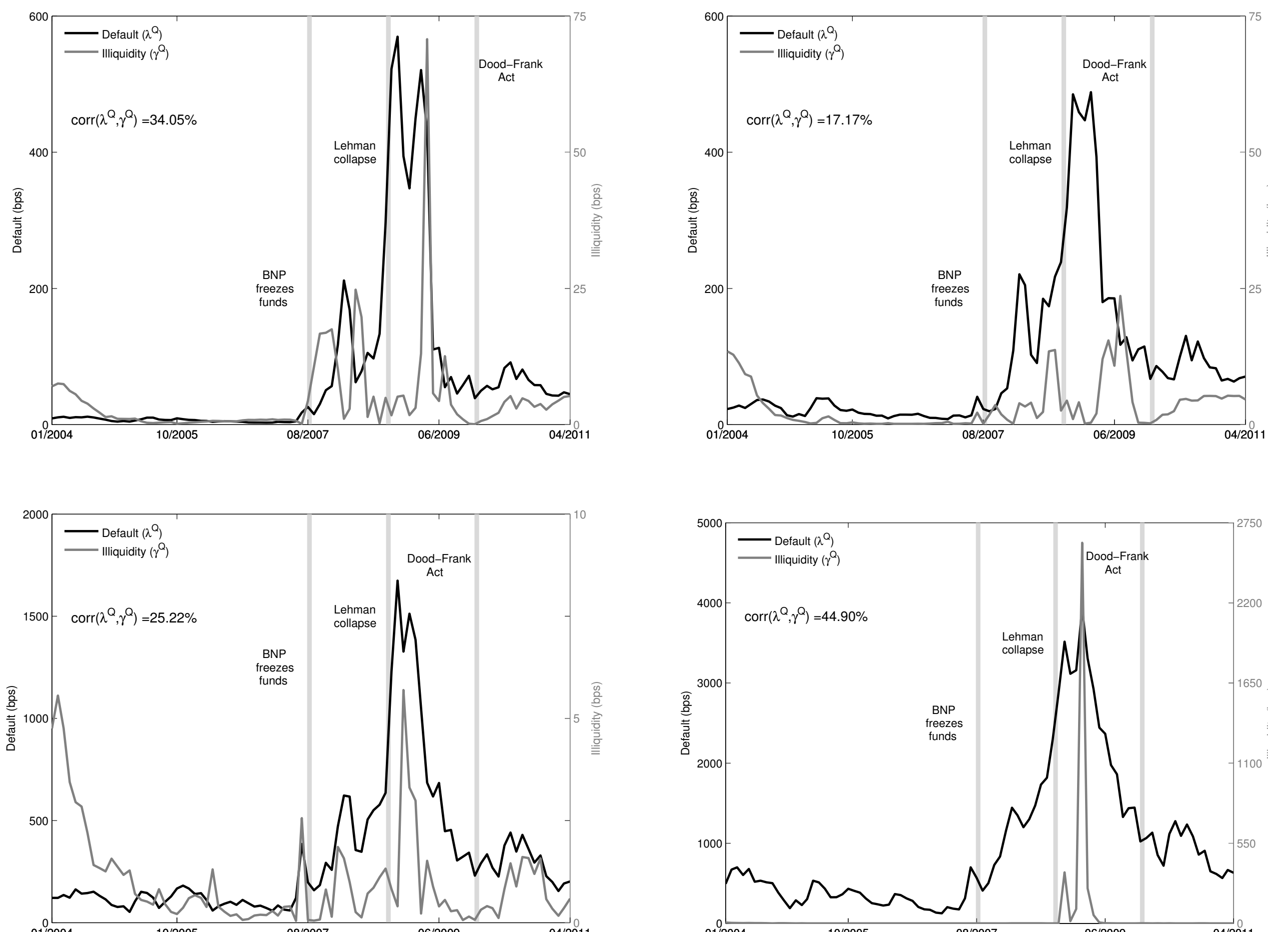
This graphs depicts the time series of variance risk premium (VRP). We calculate the VRP by taking the difference between the monthly and realized volatility of the returns of the S&P 500 index (annualized volatility) and the end-of-month value of the VIX index for the corresponding month. The time series spans from January 2000 to January 2012.

Figure 7: Relative pricing errors



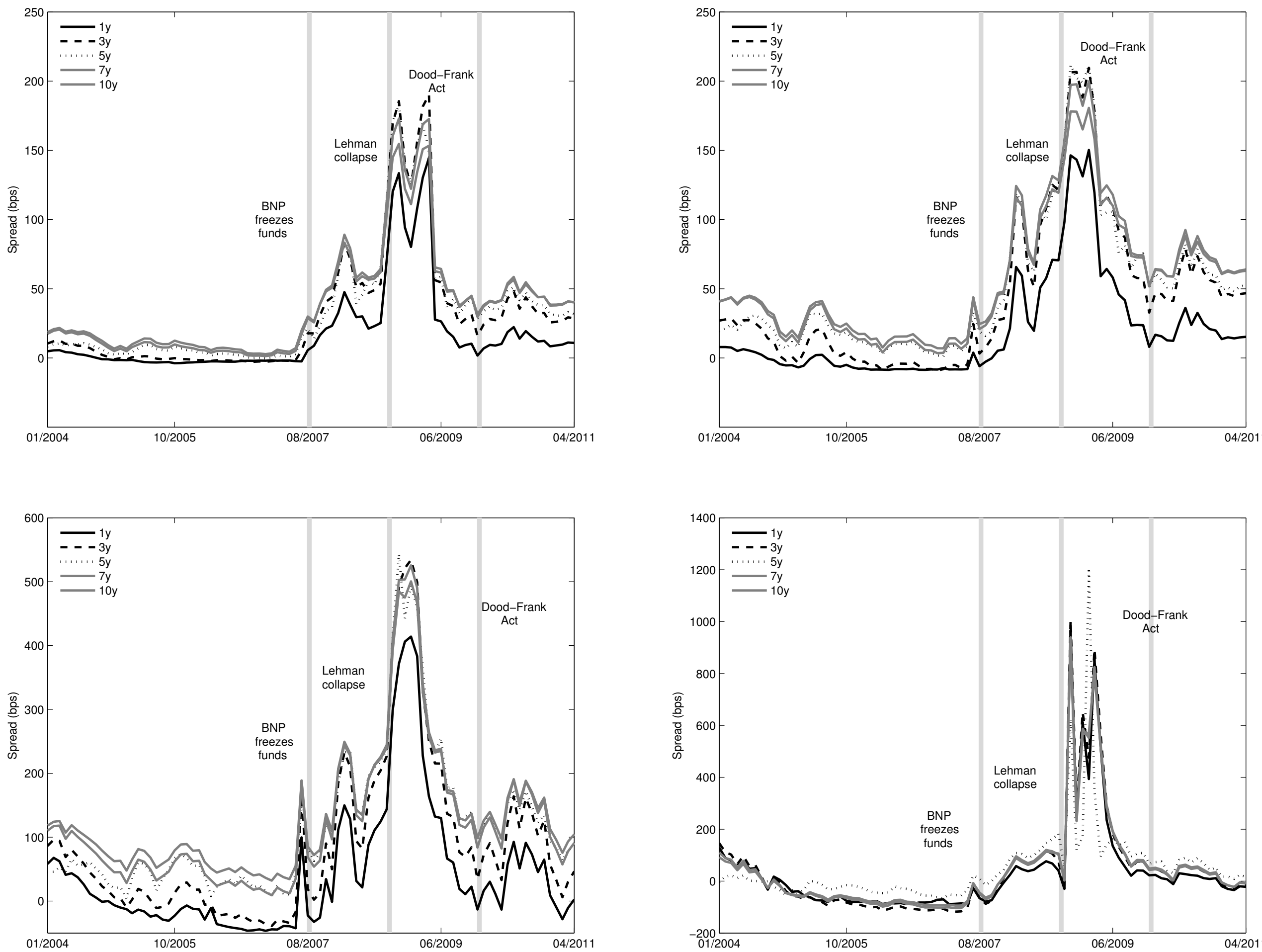
Relative pricing errors (in percentage) for 1, 3, 7, and 10 year CDS spreads, respectively. Relative pricing errors are computed as $(CDS_{sample} - CDS^{Q})/CDS_{sample}$. Data sample is monthly and it covers from January 2004 to April 2011.

Figure 8: Default and illiquidity processes



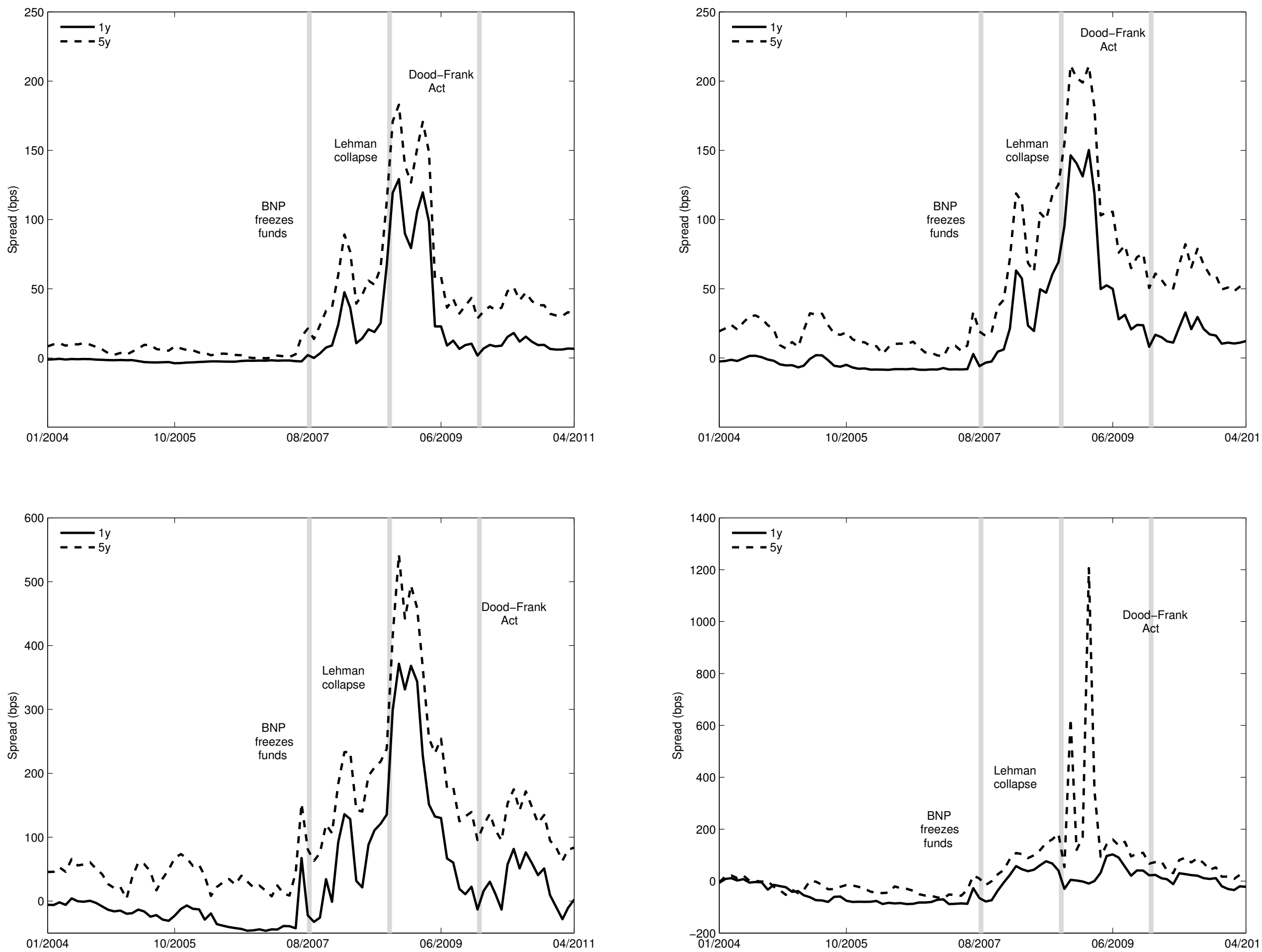
Default (left) and Illiquidity (right axis) processes for aggregate CDS spread portfolios. Portfolio AAA+ to A- is upper left. Portfolio BBB+ to BBB- is upper right. Portfolio BB+ to BB- is below left. Portfolio B+ to D is below right. Data sample is monthly and it covers from January 2004 to April 2011.

Figure 9: Risk premium



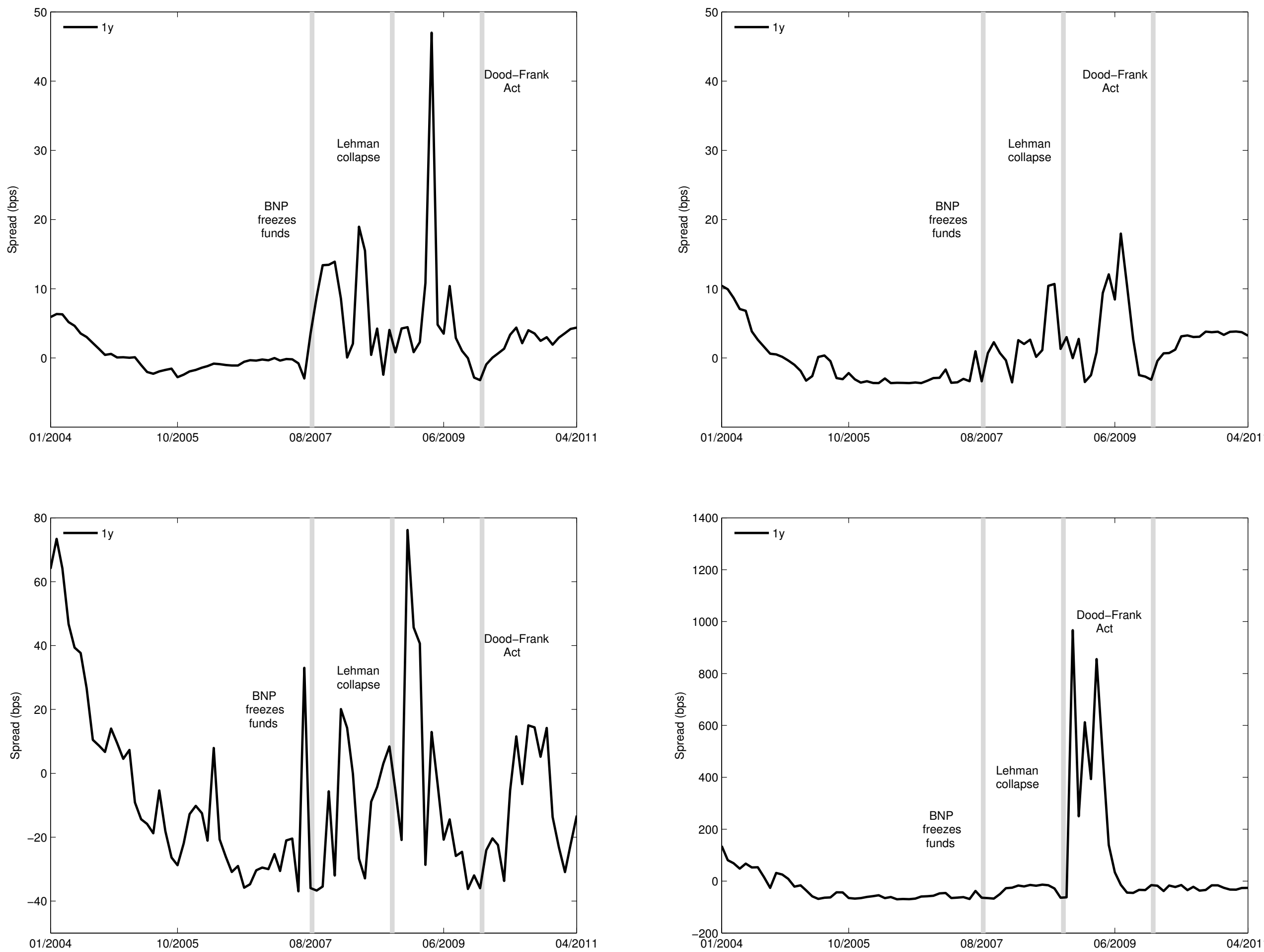
Total risk premium for aggregate CDS spread portfolios. Risk premium is computed as the difference $CDS^Q - CDS^P$ and it comprises the compensations due to both default and illiquidity risk. Portfolio AAA+ to A- is upper left. Portfolio BBB+ to BBB- is upper right. Portfolio BB+ to BB- is below left. Portfolio B+ to D is below right. Data sample is monthly and it covers from January 2004 to April 2011.

Figure 10: Default risk premium



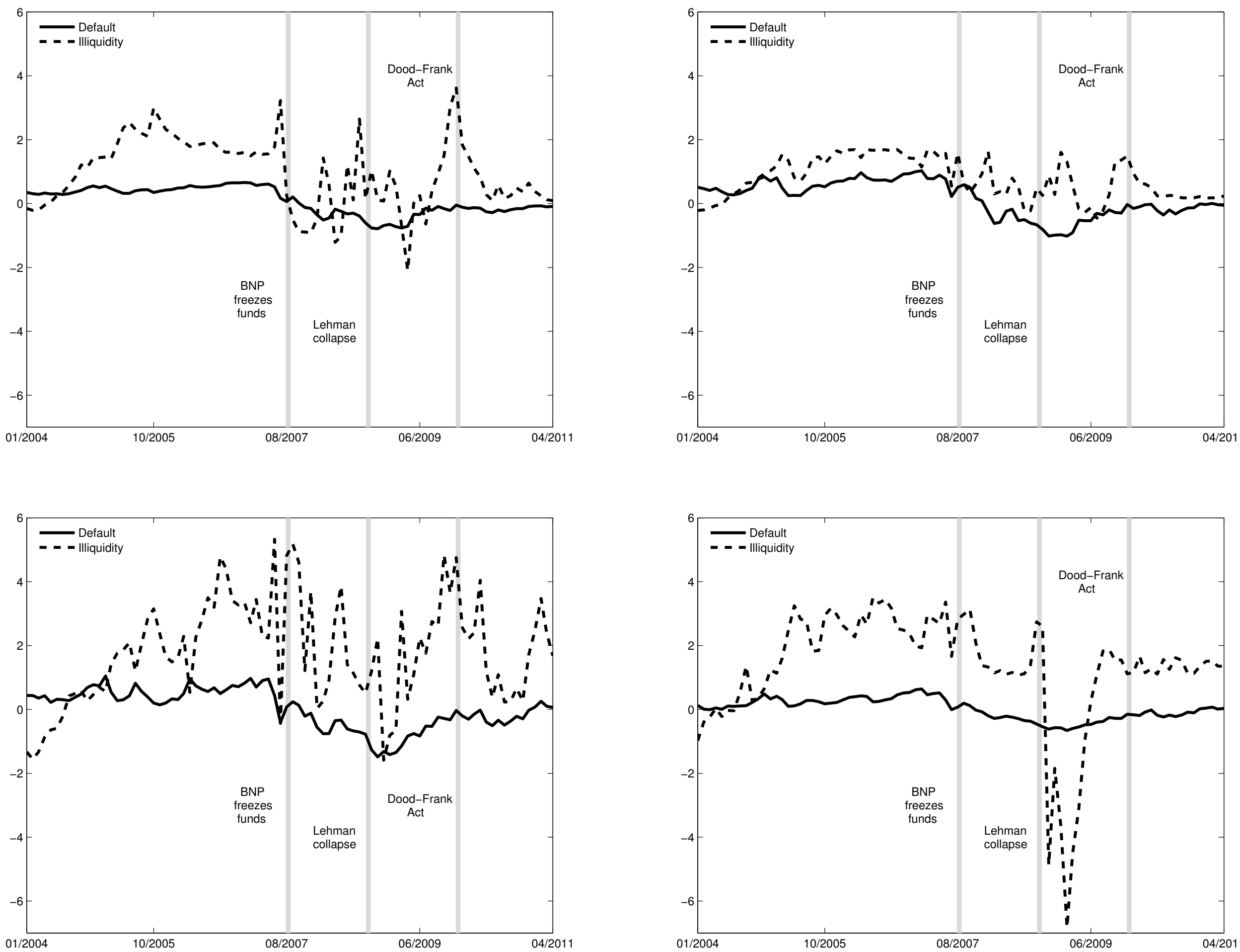
Default risk premium for aggregate CDS spread portfolios. It is computed as the difference between CDS^{Q} and CDS^{P}_{def}. Portfolio AAA+ to A- is upper left. Portfolio BBB+ to BBB- is upper right. Portfolio BB+ to BB- is below left. Portfolio B+ to D is below right. Data sample is monthly and it covers from January 2004 to April 2011.

Figure 11: (Relative) illiquidity risk premium



Relative illiquidity risk premium for aggregate CDS spread portfolios. It is computed as the difference between CDS^{Q} and CDS^{P}_{illiq}. Portfolio AAA+ to A- is upper left. Portfolio BBB+ to BBB- is upper right. Portfolio BB+ to BB- is below left. Portfolio B+ to D is below right. Data sample is monthly and it covers from January 2004 to April 2011.

Figure 12: Price of risk



Price of risk for default (solid) and illiquidity (dashed line) processes for aggregate CDS spread portfolios. Portfolio AAA+ to A- is upper left. Portfolio BBB+ to BBB- is upper right. Portfolio BB+ to BB- is below left. Portfolio B+ to D is below right. Data sample is monthly and it covers from January 2004 to April 2011.