The time varying properties of credit and liquidity components of CDS spreads

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Abstract

This paper investigates the role of credit and liquidity factors in explaining corporate CDS price changes during normal and crisis periods. We find that liquidity risk is more important than credit risk regardless of market conditions. Moreover, in the period prior to the recent "Great Recession" credit risk plays no role in explaining CDS price changes. The dominance of liquidity effects casts serious doubts on the relevance of CDS price changes as an indicator of default risk dynamics. Our results show how multiple liquidity factors including firm specific and aggregate liquidity proxies as well as an asymmetric information measure are critical determinants of CDS price variations. In particular, the impact of informed traders on the CDS price increases when markets are characterised by higher uncertainty, which supports concerns of insider trading during the crisis.

Keywords: CDS, Liquidity, Credit Risk, Financial Crisis, Informed trading, Trade impact.
JEL Classification: G01, G11, G15, G32.

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1. Introduction

Early work on credit default swaps (CDSs) often assumes that the CDS price is driven only by the credit risk of the reference entity (e.g. Longstaff, Mithal and Neis, 2005; Blanco, Brennan, and Marsh, 2005). However, the 2007-2009 financial crisis has dramatically highlighted the effect of illiquidity on asset prices. Chen, Cheng, and Wu (2005), are among the first to address the interplay between credit and liquidity risk in the CDS market. Tang and Yan (2007) use panel regressions to show that a set of liquidity factors helps explain CDS spreads. They also employ the liquidity adjusted CAPM of Acharya and Pedersen (2005) and estimate a liquidity premium similar to that observed in the Treasury and corporate bond markets. Bongaerts, de Jong and Driessen (2011) provide a general equilibrium pricing model for CDS contracts that extends the liquidity adjusted CAPM of Acharya and Pedersen (2005). They find that illiquidity can push CDS prices upwards, evidence that credit protection sellers command a liquidity premium. Other relevant works are Bhuler, and Trapp (2008) and Chen, Lesmond and Wei (2007) who develop closed-form pricing equations for CDSs that incorporate credit and liquidity risk components. Our study contributes to the existing literature by providing answers to the following questions:

- How does the impact of credit and liquidity risk on CDS prices vary during tranquil and turbulent periods? If the role of the two risks in explaining CDS price dynamics changes over time, then interpreting the CDS spread as an indicator of default risk, which is common in the industry, may not be meaningful. For example, if liquidity effects increase substantially during a crisis then a corresponding rise in the CDS prices may not necessarily reflect higher default risk.
- Does the presence of informed traders have a significant impact on price formation in the CDS market? If so, how did informed trading impact on CDS prices in the course of the 2007-2009 financial crisis? This is particularly relevant given the criticism that CDSs have attracted in the light of anecdotal evidence of insider trading (see Acharya and Johnson, 2007) and widespread concerns about the destabilising effect of speculation in the CDS market, which was a prominent factor in the demise of Lehman Brothers and AIG (Tang and Yan, 2010).
- To what extent are CDS prices influenced by industry-wide liquidity and firm-specific liquidity? For example, during the recent crisis illiquidity appeared to be widespread across the whole banking sector. This raises the question of the importance of commonality of liquidity effects on CDS spreads, and its implication for CDS pricing.

Our analysis is three-pronged. First, we study the presence and relevance of asymmetric information in the CDS market. Acharya and Johnson (2007) consider this issue but, surprisingly, conclude that the degree of asymmetric information, which they proxy with the number of a firm's bank relationships, does not appear to influence CDS prices. They suggest "using intraday data on actual transactions in the CDS market" to derive a more accurate proxy of information asymmetries. We follow their suggestion and reach opposite conclusions. With intraday data, we estimate asymmetric information through the *persistent price impact* of order flow on CDS prices. This is a measure of the magnitude of informed trading which is based on the analysis of Hasbrouck (1991) in the stock market.[1] Our results show that order flow has a significant, positive and time-varying impact on CDS prices, which is consistent with the implications of theoretical asymmetric information models. To our knowledge, ours is the first empirical work that investigates the influence of informed trading on CDS prices using a microstructure approach. Tang and Yan (2007) use the "probability of informed trading" or PIN developed by Easley et al. (1997) to look at the sensitivity of liquidity variables to changes in the level of asymmetric information in the CDS market. However, they do not attempt to measure the direct contribution of informed trading to CDS price variations.

In the second part of our study we provide an investigation of the determinants of CDS price changes. While controlling for credit risk, we look at whether CDS prices are related to *firm-specific* and *industry-wide* illiquidity variables. Several authors have investigated firm-specific illiquidity effects in CDS prices (Acharya, and Johnson, 2007; Tang and Yan, 2007; Pires et al. 2010). However, an analysis of industry-wide illiquidity in the CDS market is new to this study. The motivation for considering industry-wide liquidity stems from the work of Chordia et al. (2000) and Hasbrouck and Seppi (2001) who find common liquidity effects in the equity market. We use two industry-wide liquidity proxies: the average *bid-ask spread* and an *asymmetric information* measure. In addition to the widely used bid-ask spread we consider the latter liquidity proxy, estimated as the average permanent price impact of CDS trades in a given industry, as we aim to test the original intuition in Chordia et al. (2000) who suggest that asymmetric information may exhibit commonality across firms in the same industry. Our results show that there is a significant liquidity effect on CDS prices and a large portion of the CDS variability is explained by both firm-specific and industry-wide liquidity variables. Interestingly, it appears that

[1]Several authors have looked at the price impact of informed traders in the stock market including Kyle (1985) Glosten and Harris (1988), Hasbrouck (1991), Brennan and Subrahmanyam (1996), Easley (1997), Dufour and Engle (2000).

asymmetric information at the industry level plays an important role in the CDS price formation during crisis periods.

Finally, we look at how liquidity and credit effects vary in tranquil and turbulent markets. We find that, before the "Great Recession", credit effects on CDS price changes are unimportant, which confirms the empirical observation of artificially low credit spreads during the credit boom preceding the crisis (Acharya et al., 2009). The credit risk factor, however, becomes highly statistically significant during the crisis. Strikingly, the explanatory power of the liquidity measures is greater than that of the credit measures in both tranquil and crisis periods.

The paper is organised as follows. In Section 2 we describe the data. In Section 3 we present our methodology to estimate (i) the permanent trade impact induced by information asymmetries in the CDS market and (ii) the determinants of CDS price changes. In Section 4 we describe our findings and Section 5 concludes the paper.

2. Data

Our dataset combines data from two sources, GFI Group and Bloomberg. The former provides intraday prices on credit default swaps as well as descriptive information on individual CDS contracts. The latter is used to retrieve market capitalization and balance sheet information for the companies on which the CDS contracts are written, the so-called "reference entities." This company specific information is then used to derive a time-varying measure of default risk for each reference entity. The combined dataset covers the period from January 1, 2006 to July 31, 2009. The reference entities are European companies. The CDS price data consists of time stamped best bid and offer quotations and transaction prices. Unfortunately, no information is provided on the volume of the transactions, the identity of buyers and sellers, and the depth of the market. The representativeness of this dataset is guaranteed by the primary role of the GFI Group in the credit derivative market (Tang and Yan, 2010). The GFI Group supplies a hybrid trading system that combines voice and electronic trading. Both types of trades are recorded in the GFI database. For our empirical analysis we keep only CDS data which satisfy the following conditions: the maturity of the CDS contract is 5 years; the restructuring clause is modified-modified[2] (standard for the European market); the underlying debt is senior unsecured; the quoted

[2]For a complete description see ISDA 2003 definitions.

bid-ask spread is greater than 0; and transactions are executed during days when bid and offer quotations are recorded.[3] In addition, we select only reference entities for which we are able to source market capitalization and short-term and long-term liabilities over the whole sample period. Finally, we consider only those industry sectors well represented throughout the observation period, namely, financials, consumer goods, consumer services and telecommunications.

In Table 1 we report summary statistics of trades and quotes for our sample, which includes a total of 135 reference entities. The Table indicates that the sectors with highest and lowest trading activity and quote revisions are telecommunications and financials respectively. Note that the number of bid quotes and the number of offer quotes may differ because market makers are allowed to post one-side quote revisions.

3. The model

In this section we present the econometric framework for our empirical analysis and we derive a series of testable assumptions.

3.1 Evidence of informed trading in the CDS market

We conduct our investigation of informed trading in the CDS market by employing a model inspired by the work of Hasbrouck (1991). The rationale behind Hasbrouck's model is that, in a market with informed traders, order flow conveys information and has a permanent impact on prices. To minimize the losses that may derive from trading with better informed traders, liquidity providers tend to raise their quotes after buyer-initiated trades and lower them after seller-initiated trades. The magnitude of the quote revision is then positively related to the likelihood of informed trading. Further, as theoretically formalised in Easley and O'Hara (1987) and empirically substantiated by Hasbrouck (1991), the trade impact may also depend on the size of the bid-ask spread at the time of the trade. In particular, the wider the spread the larger the trade impact. With these considerations in mind we capture the price impact of informed trading in the CDS market with the following model:

[3] This condition is necessary in order to estimate the asymmetric information measure based on trade impact that we employ in this study.

$$r_{it} = \alpha + \lambda_0 Q_{i,t} + \lambda_1 Q_{i,t-1} + \lambda_2 Q_{i,t-2} + \eta\ Q_{i,t} S_t + u_t \qquad (1)$$

where i is the reference entity, t is the trade time, r_{it} is the difference between the mid-quotes prevailing at t+60 seconds and at t, respectively. As a result, r_{it} is positive when the midpoint is revised upwards and negative when it is revised downwards. Q_t denotes the "sign" of the trade at time t, that is, whether the trade was initiated by a buyer or a seller. Unfortunately, our dataset does not contain information about the initiator of the trade. Hence, the sign of the trade is inferred using the algorithm suggested by Hasbrouck (1991) where Q_t takes the value +1 if the trade price is above the prevailing quote midpoint; -1 if the trade price is below the prevailing quote midpoint and 0 if the trade price is equal to the quote midpoint. Accordingly, trades are classified as buyer-initiated, seller-initiated or undetermined, respectively. The lagged signed trade variables Q_{t-1}, Q_{t-2} are introduced to control for potential delayed effects of trades on mid-quotes. Finally, S_t is the prevailing bid-ask spread before the trade at time t. Regression (1) is estimated with a standard "within transformation" whereby all terms in the panel are expressed as differences from the respective firm level means. As the demeaned model will have a zero intercept we recover the regression constant by adding to all the terms in (1) the respective panel means, as suggested by Cameron and Trivedi (2005).[4] We also derive t-statistics adjusted for clustering at the firm level.

The focal point of the analysis is the persistent component of the trade impact which we define as $\lambda = \lambda_0 + \lambda_1 + \lambda_2$. A positive and statistically significant estimate of λ would reveal that liquidity suppliers tend to revise strategically their quotations conditionally on the order flow. This would confirm that, as for equity and bond markets, the CDS market is characterized by the presence of informed traders, and market makers use order flow to revise their estimates of CDS prices. On the contrary, a non-significant estimate of λ would reveal that trading activity is not relevant to CDS price formation. Hasbrouck (1991) suggests using impulse response functions to capture the informational (persistent) impact of a trade on prices. He indicates that this measure could be approximated by the sum of the trade coefficients in his return equation. Our use of λ to measure informed trading is consistent with his approach because our λ, by construction, only includes persistent effects. This is achieved by estimating λ using model (1) with mid-quote adjustments r_{it} defined over an extended period of 60 seconds which we assume to be long enough to eliminate temporary micro-structure effects.

[4] See , Cameron and Trivedi (2005) p. 697-706.

3.2. Determinants of CDS price changes

The second step of our analysis is to provide a new perspective on the determinants of CDS price changes. As mentioned in the introduction we are the first to look at commonality in liquidity effects in the CDS market at the industry level, and to explore the impact of informed trading on CDS prices with a microstructure model. In addition, our work contributes to the debate about whether the bid-ask spread is an important liquidity variable in explaining CDS price variations. Our results support this conclusion and are in line with the findings of Pires et al. (2010) and Bongaerts et al. (2011), while they disagree with those of Tang and Yan (2007) and Acharya and Johnson (2007). Finally, our study provides the first valuable insights into the credit and liquidity determinants of CDS price changes in the European market as previous studies have mainly focused on the US market.

In the following, first we provide a summary list of the credit and liquidity proxies we employ and then we describe each proxy variable in detail, justify its use and develop testable hypotheses:

- Credit variable: distance to default;
- Firm-specific liquidity variables: time-weighted absolute bid-ask spread, demand pressure, trading intensity and quote imbalance;
- Industry-wide liquidity variables: industry average bid-ask spread and industry average trade impact.

The analysis of the determinants of CDS price changes is performed with the above explanatory variables sampled on a monthly basis. The *distance to default* (DTD) is calculated as in Vassolou and Xing (2004). We source data on equity prices and book values of short term and long term liabilities from Bloomberg. The distance to default is first computed for every week of the sample and then averaged over each calendar month. Similarly to Acharya and Johnson (2007) and Chen et al. (2005), we employ an up-to-date measure of credit risk instead of using credit ratings which tend not to vary in a timely manner (Altman and Rijken, 2004 and 2005). As the distance to default increases with the reference entity's credit quality, the following hypothesis is expected to hold.

Hypothesis 1*: Changes in CDS prices are negatively related to changes in the distance to default (DTD).*

The *bid-ask spread* has been extensively used in the literature to measure the liquidity of equity, debt and OTC derivative markets. The spread captures the cost of executing small size trades (for order book markets) or normal size trades (for quote driven markets). It is considered a good approximation of the costs incurred by liquidity providers such as order processing costs, adverse selection costs, inventory costs,[5] and is affected by the level of competition among market makers. While the relative values of the bid-ask spread is commonly used in the equity market, in the context of the CDS market, it is still an open debate whether relative or absolute bid-ask spread should be used. In our opinion, Pires et al. (2010) convincingly show that the bid-ask spread of CDS prices is already a proportional measure and does not need to be divided by the CDS price. They then show that there is a positive and significant relationship between CDS prices and absolute bid-ask spreads.[6] This result is in line with the findings reported by Bongaerts et al. (2011). Conversely, Acharya and Johnson (2007) and Tang and Yan (2007) use relative bid-ask spread and reach different conclusions. Acharya and Johnson (2007) do not detect any influence of the bid-ask spread on CDS prices, whereas Tang and Yan (2007) find only a weak relationship.

The positive effect of the bid-ask spread on the CDS price is consistent with the assumption that liquidity providers are typically protection sellers who demand a premium when facing illiquidity. Evidence of a liquidity premium demanded by CDS sellers is also found in Tang and Yan (2007). Bongaerts et al. (2011) provide an alternative explanation and argue that, when short selling is taken into account "illiquid assets can trade at higher prices than liquid assets".

To capture the relationship between illiquidity and CDS prices we proxy illiquidity with the daily time-weighted average bid-ask spread (TBAS). Each bid-ask spread observed within a trading day is weighted by the number of seconds it remains available. Next, we take simple monthly averages of the daily average spreads.[7] The bid-ask spread is a broad illiquidity measure as it reflects inventory costs, processing costs and asymmetric information. Later we will introduce a firm specific trading intensity measure (TI) to isolate the impact of asymmetric information as a source of illiquidity. By using TBAS and TI in isolation and jointly in our

[5]See Amihud and Mendelson (1980), Ho and Stoll (1981), Copeland and Galai (1983), Easley and O'Hara (1987), Glosten and Milgrom (1985).

[6] Similarly, when studying liquidity effects in the corporate bond market, Chen, Lesmond, and Wei (2007) find that there is a positive relationship between the yield spread and bid-ask spread.

[7] Instead of the quoted bid-ask spread we could have computed the effective bid-ask spread. However, this measure would have led to several missing observations due to the often low level of trading activity in our sample.

regression analysis we seek to capture the influence on CDS prices of illiquidity stemming from asymmetric information on one side and the remaining factors (inventory costs and processing costs) on the other, and their relative importance. Similarly, we further introduce proxies to detect commonality in liquidity (industry average bid-ask spread, IBAS, and industry average asymmetric information, ASY) with the aim of disentangling and comparing firm specific and systematic illiquidity effects on CDS price changes. As for TBAS, we test the following hypothesis:

Hypothesis 2: C*hanges in CDS prices are positively related to changes in the time-weighted absolute bid-ask spread (TBAS).*

Bollen and Whaley (2004) study the effect of demand pressure on the implied volatility for index and individual stock options. Garleanu, Pedersen and Potherman (2009) provide a theoretical model that shows how option prices are affected by the corresponding demand level. It is reasonable to expect that *demand pressure* could be a significant factor in explaining price changes in the credit derivative market as well. The obvious justification for this assumption is that liquidity suppliers (protections sellers) are not willing to sell an unlimited amount of a particular CDS contract at the current price. Following Bollen et al.'s (2004) work, we define demand pressure (DP) for each company and for each month as the difference between the number of buyer-initiated trades and the number of seller-initiated trades. If a firm has no trades over a particular month then the demand pressure is set to zero. Assuming that liquidity suppliers demand a liquidity premium as a response to an excessive demand of credit protection, the following hypothesis is expected to hold:

Hypothesis 3: *Changes in CDS prices are positively related to changes in the demand pressure (DP).*

A natural candidate to measure the effects of asymmetric information on CDS prices at the firm level would be the λ, that is, the permanent trade impact discussed in Section 3.1. However, λ cannot be derived reliably over time for a number of companies in our sample due to thin trading. So, we will use λ as an industry aggregate measure of asymmetric information, as explained later in this Section. At the firm level instead, we employ an alternative asymmetric information proxy, the *trading intensity* (TI). For each company and each month in the sample period, TI is calculated

as the average number of daily trades in that month. Chordia et al. (2000) argue that the number of trades is a good indicator of asymmetric information in the market. They suggest that this could be the case because informed traders try to conceal their trading by splitting large orders into smaller ones hence increasing the number of executions. A theoretical justification for using a proxy of trading intensity as a determinant of equity prices is offered by Easley and O'Hara (1992) and corroborating empirical evidence is provided by Dufour and Engle (2000) who show that the price impact of equity trades is larger when trading intensity is greater. Their intuition is that uninformed traders are expected to trade independently of the existence of information and hence should exhibit a uniform trading presence in the market over time whereas informed traders access the market only when they possess valuable information. As a result, liquidity providers revise their quotations by a greater magnitude when trading intensity is higher as they believe they are more likely to face informed traders.[8] In the context of the CDS market, protection sellers may charge a higher liquidity premium (higher offering price) when trading activity increases because this implies higher adverse selection costs. Given these considerations, the following hypothesis is expected to hold:

Hypothesis 4: *Changes in CDS prices are positively related to changes in trading intensity (TI).*

An imbalance between bid and ask quotes for a particular firm may reveal a momentum effect whereby when a dealer posts a more aggressive bid or ask quote other dealers compete to revise quotes in the same direction and outdo the first revision. This phenomenon is supported by conversations we held with a senior CDS trader that employs the GFI platform. We capture momentum with the quote imbalance (QI), which is defined as the difference between the number of bid quote updates and the number of ask quote updates for a single name over a given month. This is similar to the "net buying interest" employed by Tang and Yan (2010). A predominance of buy quote revisions may indicate greater competition to buy CDSs which would push CSD prices up. Conversely, a predominance of sell quote revisions would indicate decreasing prices.

[8] The existing literature offers a couple of additional approaches for measuring the level of information asymmetry in the market. Easley, Kiefer, O'Hara, and Paperman (1996) devise an econometric model which uses the number of buy and sell trades to estimate the probability of informed trading (PIN). Easley, Hvidkjaer and O'Hara (2002) show that PIN is particularly important in explaining the dynamic of the equity returns and that assets with larger returns have higher PIN. In our case, however, the implementation of this measure is not feasible because often firms have very thin trading. An alternative approach is proposed by Acharya and Johnson (2007) who suggest measuring information asymmetries by calculating the number of banking relationships that each company has over the time. However, they find no influence of information asymmetries on CDS price levels.

Hypothesis 5: *Changes in CDS prices are positively related to the quote imbalance (QI).*

While TBAS and TI are firm specific measures of liquidity, it may be reasonable to explore the presence of a systematic liquidity component. In the stock market, Chordia et al. (2000) and Hasbrouck and Seppi (2001) find evidence of commonality in liquidity. Following their lead, we investigate whether changes in firm-specific liquidity measures (e.g. TBAS) remain significant after introducing industry-wide liquidity proxies. Our monthly aggregate liquidity measure for a given industry sector is the average of the monthly time weighted bid-ask spread across all the firms in that sector (IBAS). In addition, we measure the specific impact of asymmetric information with an industry-wide (persistent) trade impact indicator based on the λs estimated with model (1). For this purpose, we cluster observations by industry and execute daily rolling regressions based on a time window of 30 days. Finally, ASY is calculated as the monthly average of the daily λs estimated over the sample period. Our testable hypothesis is as follows.

Hypothesis 6: *Changes in CDS prices are positively related to changes in industry wide information asymmetries (ASY) and industry wide bid-ask spread (IBAS).*

To test the above hypotheses we run a panel regression of changes in CDS prices on changes of the credit and liquidity proxies we have introduced. The dependent variable of the regression is the change in the monthly average of daily CDS mid-quotes. The daily mid-quote of any given CDS contract is the weighted average of all the intra-day mid quotes where the weights are the number of seconds each quotation remains outstanding divided by the total length of the trading day in seconds. Then, we estimate the following model,

$$\Delta CDS_{it} = \alpha + \beta_1 \Delta DTD_{it} + \beta_2 \Delta TBAS_{it} + \beta_3 DP_{it} + \beta_4 \Delta TI_{it} + \beta_5 QI_{it} + \beta_6 \Delta ASY_{st} + \beta_7 \Delta IBAS_{st} + u_{it} \quad (2)$$

where $i = 1,...,N$ indexes the firms, $t = 1,\ldots,T$ denotes time in months and s a specific industry sector. Regression (2) is estimated with a standard "within transformation" where all the terms in the panel are expressed as differences from the respective firm level means. As the demeaned model will have a zero intercept we recover the regression constant by adding the respective panel means to all the terms in (2). We adjust regression coefficients' standard errors and t-statistics for clustering at the firm level. Although other studies (e.g. Acharya and Johnson, 2007; Tang and

Yan, 2007) estimate the relationship between the level of CDS prices and the level of explanatory variables, we employ first differences as we find that CDS prices and our credit and liquidity proxies, with the exception of the demand pressure and quote imbalance, are non-stationary over the crisis period.

3.3. Credit and liquidity contribution to CDS prices

To determine the relative importance of credit and liquidity effects in explaining changes in CDS prices we compute credit and liquidity "proportions" based on Beber et al. (2008). These show the percentage contribution of credit and liquidity effects, as measured with model (2), to variations in expected CDS prices. The indicators will enable us to investigate how credit and liquidity effects evolve over time and, especially, how they change because of the recent financial crisis. We define credit and liquidity proportions as follows,[9]

$$\text{Credit proportion}_{it} = \frac{|\text{credit contribution}_{it}|}{|\text{credit contribution}_{it}| + |\text{liquidity contribution}_{it}|}$$

$$\text{Liquidity proportion}_{it} = \frac{|\text{liquidity contribution}_{it}|}{|\text{credit contribution}_{it}| + |\text{liquidity contribution}_{it}|}$$

where credit and liquidity contributions are calculated as,

$$\text{Credit contribution}_{it} = \hat{\beta}_1 \Delta DTD_{it}$$

$$\text{Liquidity contribution}_{it} = \hat{\beta}_2 \Delta TBAS_{it} + \hat{\beta}_3 DP_{it} + \hat{\beta}_4 \Delta TI_{it} + \hat{\beta}_5 QI_{it} + \hat{\beta}_6 \Delta ASY_{st} + \hat{\beta}_7 \Delta IBAS_{st}$$

4. Results

We first report the results of the trade impact of order flow in the CDS market, estimated with regression (1). The findings are shown in Table 2 for the entire sample and two sub-periods: the

[9] We compute credit proportions by the taking the absolute value of credit contributions at a specific point in time, rather than time-series averages as in Beber et al. (2008). We do so to prevent time series variations to cancel each other out. This, which is not an issue in Beber et al. (2008) as they look at CDS price levels, is more of a concern in our analysis as we focus on CDS price changes and the contributions of our covariates to those changes.

pre-2007-2009 financial crisis and the crisis periods. We identify the beginning of the financial crisis with the bankruptcy of *New Century Financial* (the second largest US subprime lender) on April 22, 2007 which is one of the first precursors of the subprime debacle. In the Table, model *a* refers to regression (1), while model *b* is an expanded version that includes interactions of the explanatory variables with dummies. The dummies capture firm-specific characteristics that are normally related to the quality of the information available on a given firm, namely, its credit rating and market capitalization. The credit quality dummy, IG, takes the value 1 when the firm has an investment grade rating. For market capitalization we employ two dummies, L and S, which take value 1 when the firms fall in the large firm and small firm sub-samples respectively. These sub-samples correspond to the first and third terciles of the sample distribution stratified by the firms' market capitalization.

As a measure of persistent trading effects on the CDS price we use λ, that is, the sum of the coefficients of the variable *Signed Trade* and its lags. We find λ to be positive for model *a* and model *b*, over the whole sample as well as the pre-crisis and crisis sub-samples. This is a strong indication of the presence of informed trading regardless of market conditions. An *F*-test on λ reveals that it is statistically significant at the 0.1% level in all cases. The value of λ indicates by how much, on average, the CDS midpoint adjusts upward (downward) after a purchase (sale), while taking into account delayed effects of past trades. As one would expect, the λ during the crisis (0.727 for model *b*) is markedly higher than the λ in the pre-crisis period (0.430). This shows that price corrections following a trade are stronger in crisis periods as the extent of the information asymmetry between liquidity providers and informed traders widens.

Higher uncertainty about the price of the CDS in periods of market turmoil is also reflected in larger bid-ask spreads. We recognise that a larger spread will necessarily imply a greater trade impact. Indeed, the interaction between the signed trade variable Q_t and the bid ask spread is positive and statistically significant in the crisis period. From a study of the equity market, Hasbrouck (1991) finds that companies with larger market capitalisation and higher credit rating tend to have a lower persistent price impact of order flow. Hasbrouck concludes that blue chip stocks have lower information asymmetry due to the larger quantity of information available in the market for those firms. In agreement with these findings, we observe that CDS trades on large companies tend to have a lower price impact. But this correction is statistically significant only in the pre-crisis period. This suggests that the greater availability of information does not help in a

crisis, either because the quality of public information deteriorates or because the inside information problem becomes more acute. Interestingly, during the crisis it is credit quality rather than firm size that affects the magnitude of trade impact. The negative and statistically significant sign of the investment grade variable (interacted with the sign trade variable) indicates that, in the crisis period, dealers revise quotes more aggressively for sub-investment grade companies. The finding implies that asymmetric information is more severe in the case of low credit quality firms when the market is characterised by higher uncertainty.

Summary statistics and pair-wise correlations for the dependent variable and covariates in regression (2) are given in Table 3. All variables are calculated on a monthly basis. In panel A we show summary statistics of the variables in levels. We can see that although there seems to be a balance between buyer initiated trades and seller initiated trades (the median value of the demand pressure, DP, is 0), quote revisions are more frequent on the bid side (quote imbalance, QI, has a median of 7). This may imply that dealers need to compete more to buy credit protection, which may be the result of hedging pressure to cover for the positions they have taken when providing liquidity as protection sellers. Surprisingly, we observe that sometimes the distance to default is negative as evidenced by the minimum value of the DTD variable. We have explored the issue and found that this happens exclusively for the financial institutions in our sample. The distance to default is defined as the difference between the expected log value of a reference entity's assets and the default trigger, represented by reference entity's log liabilities.[10] Financial institutions were amongst the worst hit by the financial crisis, so much so that their expected (log) asset values, in some cases, fell below the default trigger.[11]

The correlations between changes in the CDS price and the credit and liquidity variables over the whole sample, and the pre-crisis and crisis sub-samples, are reported in the second column of panel B. These correlations broadly confirm all the hypotheses introduced in the previous section. When we look at the whole sample, ΔCDS is negatively correlated with the credit variable ΔDTD (-0.17) while it is positively correlated with all the liquidity variables. Among the latter, the highest correlation is with firm specific bid-ask spread ΔTBAS (0.51). Interestingly, the third column of Panel B shows that the credit variable is negatively correlated with firm specific and industry bid-ask spread (TBAS and IBAS) as well as the industry asymmetric information proxy

[10] Following Vassolou and Xing (2004) which is in turn based on the KMV default model (see, for example, Crosbie, 2003), we define the default trigger as the log value of short term liabilities plus 50% of long term liabilities.

[11] This happens because expected asset values are driven by the trend observed in the firm's stock prices which, for many financial institutions, fell sharply during the crisis.

(ASY), which suggests that an increase in a firm's creditworthiness (higher DTD) coincides with an increase in liquidity (lower TBAS, IBAS and ASY).[12] We look at a case study to illustrate this further. In Figure 1 we plot the time-series levels of a selection of the variables in equation (2) for *Telecom Italia*, the leading telecommunication company in Italy. We can see that DTD falls notably around January 2008 which is accompanied by a concurrent rise in the CDS price and the firm-specific and industry-wide bid-ask spreads. However, prior to January 2008, the relationship between the variables appears to be weak. This suggests that when the financial crisis became more acute, following the debacle of Northern Rock in the third quarter of 2007, correlations between the changes in CDS price, distance to default, firm specific and industry wide bid-ask spread intensified. This is evidenced in the second column of Table 3 Panel B where correlation coefficients for the above variables become larger, in absolute value, when we move from the pre-crisis to the crisis period. Indeed, Figure 2, which shows the market average CDS price and bid-ask spread over the sample period, indicates that the case of Telecom Italia is representative of a wider market trend.

In Table 4 we report the estimation results for equation (2) where we regress CDS price changes on credit and liquidity variables. The full model in column *h* shows that all explanatory variables have the expected sign. Also, all the regressors, except for demand pressure DP and trade intensity (TI), are highly statistically significant. The negative coefficient of the credit variable ΔDTD confirms that higher default risk is associated with an increase in CDS prices, as one would expect. On the other hand, CDS price changes are also positively related to illiquidity. Specifically, the positive coefficient of ΔTBAS (2.267) is consistent with the findings of Pires et al. (2010).[13] However, differently from Pires et al. (2010), we do not ascribe this effect to information asymmetries alone, but to the interplay among transaction costs, liquidity providers' competition as well as information asymmetries. The price impact of information asymmetries has been widely investigated in the equity market but less so in the CDS market. Easley, Hvidkjaer and O'Hara (2002) find that the probability of informed trading (PIN) is a relevant factor in explaining cross-sectional equity returns. On the other hand, Acharya and Johnson (2007) use bank relationships as a proxy for informed trading and find it does not influence CDS prices. These authors suggest employing intraday data and microstructure models to shed light on the

[12] Odders-White and Ready (2005) similarly find that credit quality and liquidity are positively related in the equity market. Specifically, they observe that illiquidity stemming from asymmetric information is stronger when credit quality declines.

[13] Pires et al. (2010) propose a quantile regression to analyse the determinants of the CDS spread. However, while they focus on levels, we consider first differences as we detect non-stationarity in our variables during the crisis period.

price impact of informed trading in the CDS market. As indicated by the microstructure analysis conducted with regression (1) and reported in Table 2, indeed asymmetric information measured with λ, the trade impact of the order flow, has a positive and statistically significant influence on CDS prices. Unfortunately, thin trading does not allow us to estimate a firm level variable based on the trade impact for a sufficiently large number of firms to be used in regression (2). However, we are able to build a λ-based asymmetric information proxy at the industry level. In Table 4 we show that the industry aggregate asymmetric information variable, ΔASY, plays a significant role in explaining CDS price dynamics. Interestingly, firm specific asymmetric information which we proxy with the trading intensity variable TI,[14] although significant and with the correct sign when regressed without other liquidity variables, becomes not significant in the general model. We find that TI becomes insignificant when we include in the regression the quote imbalance, QI. This suggests that an imbalance between bid and ask quotes may also be an indicator of trading activity. More importantly, the positive and significant coefficients of ΔIBASs as well as ΔASY show the strong linkages between *aggregate* market liquidity and CDS prices. This confirms the findings of Tang and Yan (2007) who also detect commonality in liquidity in the CDS market.

The fact that the demand pressure is not statistically significant is puzzling. The failure to detect demand pressure effects on CDS prices could depend on the fact that DP is approximated using the difference between the number of buy and the number of sell trades and not actual order flows. This would be a noisy estimator of demand pressure if there is a great deal of variation in the size of buy and sell trades.

An analysis of the goodness of fit of regression (2) when one liquidity variable is added in turn to the credit variable (models from *a* to *g* in Table 4) suggests that the firm-specific and industry-wide bid-ask spreads have the greatest explanatory power (+24.3% and +17.6% adjusted R-squared respectively), followed by the asymmetric information variable ASY (+2.4%). This confirms the prominence of the aggregate liquidity measures and the importance of taking their effect into account when pricing CDS contracts. On the other hand, the explanatory power of the credit variable appears to be low in our sample as the adjusted R-squared when ΔDTD is used alone is a only 2.7%. This suggests that the common practice of interpreting changes in CDS prices as mainly driven by changes in default risk may be misleading and could generate substantial errors in the assessment of the credit risk of individual assets especially in periods of

[14] Trading intensity can be estimated more easily than the trade impact on a daily basis as it does not require the estimation of a regression.

high market uncertainty. Indeed, when we repeated the analysis on the pre-crisis and crisis sub-samples (reported in Table 5) our conclusions are broadly confirmed. The explanatory power of ΔDTD is only marginally higher during the crisis, and still substantially lower than that of the liquidity proxies based on firm-specific and industry-wide bid-ask spreads.

The results for the pre-crisis and crisis analysis reported in Table 5 are striking. Before the crisis (Panel A, model *h*), the credit variable ΔDTD and information asymmetry proxy ΔASY are not statistically significant. During the crisis (Panel B, model *h*), they turn strongly significant as for the whole sample estimation. So, the results for the whole sample appear to be mainly driven by the crisis period. It is not surprising that the credit variable is not significant before the crisis as CDS spreads and credit spreads in the bond market were "artificially" low in that period.[15] Credit effects become significant during the crisis as default risk rises. Similarly, adverse selection costs due to asymmetric information become more of a concern for dealers during the crisis when default losses are more likely to materialise. This conclusion is confirmed by the positive and significant relationship between CDS price changes and ΔASY during the crisis. The finding is consistent with the well-known adverse selection problem in insurance markets. Indeed, with regard to CDS trading, Acharya and Johnson (2007) state that "[t]he threat of informed purchase of [default] insurance leads to a lemon's problem in which insurance premia are set too high and the quantity of insurance written in equilibrium is too low".

Interestingly, the coefficient of the bid-ask spread ΔTBAS falls relative to the pre-crisis period, whereas the coefficient of ΔIBAS rises significantly. These findings suggest that the importance of firm-specific liquidity becomes less prominent during turbulent periods, and that changes in CDS prices are more related to variations in industry-wide liquidity. As for the momentum effect, it appears to be present throughout the sample. Its proxy, the quote imbalance (QI), is significant before and during the crisis, though it has a slightly larger effect in the latter part of the observation period.

To illustrate the relative importance of credit and liquidity effects on expected CDS price changes we have computed credit and liquidity proportions, as detailed in Section 3.3. Figure 3

[15] Acharya et al. (2009), p. 12-13, report that "There is almost universal agreement that the fundamental cause of the crisis was the combination of a credit boom and a housing bubble … [T]here was just a fundamental mispricing in capital markets – risk premiums were too low and long term volatility reflected a false belief that future short term volatility would stay at its current low levels. This mispricing necessarily implied low credit spreads and inflated prices of risky assets."

reports the findings. As the credit risk variable is not significant before the crisis, the liquidity proportion accounts for 100% of the explained CDS price volatility. During the crisis, on the other hand, the credit proportion rises to 35% of the total but is still dominated by liquidity effects. As it can be noted from Figures 1 and 2, the crisis was characterised by periods of acute market stress and phases of relative calmness where CDS prices and bid-ask spreads fell considerably from their peaks. Additionally, there is no general consensus on the starting date of the crisis. To assess the robustness of our findings with respect to our definition of the crisis period we consider alternative approaches for separating phases of turmoil and relative calm. In particular, we split the sample in periods with high and low market uncertainty where the uncertainty is measured using three variables: the CDS price level, CDS price volatility and CDS bid-ask spread. High/low uncertainty sub-samples are built by grouping firm-level observations according to whether a chosen indicator is above or below its time-series median. The results are shown in Table 6. Our previous conclusions are broadly confirmed. However, there are some differences. As during the crisis, default risk and asymmetric information effects are always stronger and highly significant in the high uncertainty period. Also, firm specific and systematic liquidity, as measured by company level and aggregate bid-ask spreads, are significant in both sub-samples as before. But, their relative change in importance when market uncertainty changes, is now not as clear cut as in the earlier pre-crisis and crisis analysis. The coefficient of the quote imbalance variable increases with uncertainty, as it does when we move into the crisis period. But it is not significant with low uncertainty while it was significant before the crisis. To summarise the relative strength of credit and liquidity effects we report credit and liquidity proportions for the different definitions of high and low uncertainty samples. As shown in Figure 4, liquidity effects are always stronger, which supports our previous conclusions. Moreover, for all three uncertainty indicators, the findings for high uncertainty are similar to those for the crisis period. Also, with low uncertainty, two out of the three uncertainty measures indicate a nil contribution of credit effects to changes in CDS prices as we saw in the pre-crisis period.

5. Conclusion

In this paper, we explore the credit and liquidity determinants of CDS prices and investigate how their role changed as a result of the 2007-2009 “Great Recession,” by many indicators the worst period of market turmoil since the Great Depression. In general, we observe that liquidity effects dominate CDS price variations. Although our credit risk proxy is very significant during

the crisis, it has a lower explanatory power than liquidity proxies, a confirmation of the commonly held view that the severity of the crisis was primarily due to liquidity factors. This suggests that CDS price changes may not be accurate indicators of changes in default risk, even in periods of high uncertainty, contrary to accepted wisdom in the industry. Interestingly, liquidity effects are the only ones that preserve a statistically significant explanatory power in the pre-crisis period. This provides evidence to the perception that default risk was commonly under-priced during the pre-crisis credit bubble. In addition, we find that informed trading has a more prominent impact on CDS prices during the crisis, which indirectly supports concerns that insider information may play a role in CDS price formation (Acharya and Johnson, 2007). In this context, our paper is one of the first to use intraday data to measure the level of asymmetric information in the CDS market. We observe that the order flow has a significant impact on CDS prices and its extent varies depending on the time period, the firms' characteristics and the size of the bid-ask spread. In particular, the trade impact increases after the onset of the financial crisis for CDS contracts with higher bid-ask spread and it decreases for high credit quality firms. Before the crisis, on the other hand, the size of the firm appears to affect the price impact, with larger firms attracting a lower impact. This is in line with the view that public information is more readily available for larger firms. However, during the crisis this informational advantage seems to vanish. We conjecture that the result may be due to the lower quality of public information during a crisis or the greater severity of the asymmetric information problem. Our results highlight the importance of systematic liquidity, especially in the Great Recession period. The finding, which corroborates similar evidence in the stock market (Hasbrouck and Seppi, 2001) suggests that illiquidity, particularly when resulting from asymmetric information among market participants, has a high potential for contagion. This lends support to the great emphasis placed by regulators and governments on tackling market illiquidity, for example, by increasing transparency in the CDS market, via central clearing arrangements, and through the standardisation of CDS contracts. An interesting avenue of future research would be the assessment of whether these new measures introduced since the onset of the crisis can indeed achieve their intended outcome.

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Table 1
Summary Statistics

This table shows summary statistics for our credit default swap dataset. For the purpose of our study we focus on European companies with CDS contracts of 5-years maturity, unsecured underlying debt, from January 1, 2006 to July 31, 2009. In total we analyse 135 firms. The "Trade" column indicates the number of executed trades for which quotes are available on the same day; Bid and Offer denotes the number of bid and offer price updates in the sample period.

Industry Sector	No. of firms	No. of Trades	No. of Bids	No. of Offers
Consumer Goods	32	5,956	7,495	7,512
Consumer Services	29	7,316	9,382	9,416
Financials	41	2,560	3,384	3,377
Telecommunications	33	8,881	10,902	10,901
Total	135	24,713	31,163	31,206

Table 2
Regression results on trade impact

This table shows estimates of trade impact based on microstructure model (1) for the whole sample, the pre-crisis period and the crisis period. The sample period is January 1, 2006 to July 31, 2009.The pre-crisis period goes from January 1, 2006 to April 21, 2007. The crisis periods is from April 22, 2007 to July 31, 2009. The dependent variable is the difference, for reference entity *i*, between the mid quote 60 seconds after the trade that takes place at time *t* and the mid quote at time *t*. The explanatory variables are Q_t (*Signed Trade*) is the direction of the trade at *t* and takes the value +1 if the trade is buyer-initiated, -1 if it is seller-initiated and 0 if it is not classifiable. The model is extended to include the interaction term $Q_{i,t}S_{t-1}$ (*Signed BAS*) which is the product between the direction of trade and the bid ask spread before time t. The above variables are also interacted with the following variables: (a) dummy variables L and S which take value 1 when the firms fall in the large and small capitalization sub-samples respectively. Small, and large capitalization sub-samples correspond to the first and third terciles of the sample distribution stratified by the firm's market capitalization; and (b) a dummy variable IG which takes the value 1 when the firm has an investment grade rating. The panel estimation is carried out by using firm-level fixed-effects and panel-robust standard errors (clustering at the firm level) to control for autocorrelation and heteroskedasticity. *,** and *** denote significance at 5%,1% and 0.1%, levels respectively.t-statistics are given in parenthesis.

Regressors	Whole sample		Pre-crisis		In-crisis	
	Model (a)	Model (b)	Model (a)	Model (b)	Model (a)	Model (b)
Constant	0.079***	0.086***	0.039***	0.043***	0.113***	0.119***
	(18.007)	(18.010)	(9.344)	(11.594)	(16.543)	(15.595)
Signed Trade	0.429***	0.623***	0.387***	0.461***	0.521***	0.855***
	(8.953)	(8.000)	(8.346)	(6.902)	(7.882)	(6.545)
Signed Trade(lag1)	-0.082***	-0.080***	-0.027*	-0.027**	-0.097***	-0.096***
	(-5.182)	(-5.073)	(-2.552)	(-2.763)	(-4.001)	(-3.869)
Signed Trade(lag2)	-0.029	-0.029	-0.003	-0.004	-0.034	-0.032
	(-1.795)	(-1.758)	(-0.321)	(-0.353)	(-1.219)	(-1.146)
Signed BAS	0.051***	0.030***	0.01	0.003	0.056***	0.034**
	(6.361)	(3.365)	(1.342)	(0.288)	(7.137)	(3.277)
S*Signed Trade		-0.034		-0.032		0.107
		(-0.286)		(-0.335)		(0.510)
S*Signed BAS		0.036*		0.03		0.021
		(2.460)		(1.430)		(1.288)
L*Signed Trade		-0.125		-0.241**		-0.09
		(-0.886)		(-2.865)		(-0.521)
L*Signed BAS		-0.006		0.074		-0.022
		(-0.209)		(1.598)		(-0.712)
IG*Signed Trade		-0.167		-0.061		-0.369*
		(-1.757)		(-0.802)		(-2.329)
IG*Signed BAS		0.011		0.003		0.021
		(0.805)		(0.254)		(1.390)
Observations	24713	24713	11054	11054	13659	13659
Adjusted R^2	0.112	0.119	0.126	0.133	0.119	0.125

Table 3
Summary statistics and pair-wise correlation of credit and liquidity variables

The Table shows summary statistics for CDS prices and credit and liquidity determinants. All variables are computed on a monthly basis. CDS is the midquote price; DTD is the distance to default; TBAS is the time-weighted absolute bid-ask spread; ASY is an industry-wide asymmetric information index; TI is the number of executed trades; DP is the demand pressure; IBAS is the cross sectional bid-ask spread for the industry sectors considered in our sample (that is financials, consumer goods, telecommunications and consumer services) and QI is the quote imbalance. The sample period is January 1, 2006 to July 31, 2009.The pre-crisis period goes from January 1, 2006 to April 21, 2007. The crisis period is from April 22, 2007 to July 31, 2009.

Panel A: Summary statistics

	CDS	DTD	TBAS	TI	DP	ASY	IBAS	QI
Mean	118.51	6.39	9.21	8.45	-0.68	0.58	11.52	10.04
Median	68.45	5.71	4.3	3	0	0.49	6.54	7
St. Dev.	137.17	4.75	15.97	14.83	3.93	0.98	9.51	15.04
Min	2.75	-1.82	0	0	-50	-3.16	2.44	-123
Max	1000	26.68	250	260	32	3.48	35.85	133
N	3746	3746	3746	3746	3746	3746	3746	3746

Panel B: Cross-sectional time series pair-wise correlations

	ΔCDS	ΔDTD	ΔTBAS	ΔTI	DP	ΔASY	ΔIBAS
			Whole sample				
ΔDTD	-0.17						
ΔTBAS	0.51	-0.09					
ΔTI	0.02	-0.01	-0.02				
DP	0.02	0	0.01	0.01			
ΔASY	0.16	-0.04	0.04	-0.01	0		
ΔIBAS	0.45	-0.25	0.31	0.06	0.01	0	
QI	0.12	-0.05	0.05	0.14	-0.01	0.02	0.14
			Pre-crisis				
ΔDTD	-0.05						
ΔTBAS	0.39	-0.01					
ΔTI	0.08	-0.01	-0.07				
DP	-0.07	-0.01	-0.01	0.03			
ΔASY	0.07	-0.06	0.08	0.06	0		
ΔIBAS	0.19	-0.16	0.23	0.06	-0.05	0.15	
QI	0.16	-0.02	0.02	0.22	-0.09	0.11	0.22
			In-crisis				
ΔDTD	-0.2						
ΔTBAS	0.51	-0.11					
ΔTI	0.03	-0.03	-0.02				
DP	0.02	0.01	0.01	0			
ΔASY	0.16	-0.04	0.04	-0.02	0		
ΔIBAS	0.45	-0.3	0.3	0.1	0.01	0	
QI	0.13	-0.07	0.06	0.1	0.04	0.01	0.16

Table 4
Credit and liquidity determinants of CDS price changes

The dependent variable of the panel regressions shown in this table is the change in the midquote price. The explanatory variables are the change in the distance to default (ΔDTD),the change in the time-weighted absolute bid-ask spread (ΔTBAS), the change in the industrial information asymmetries index (ΔASY), the change in the number of executed trades (ΔTI), the buying pressure (DP), the change in the industry-wide bid-ask spread (ΔIBAS) and the quote imbalance (QI). Dependent variable and explanatory variables are sampled on a monthly basis. The sample period is January 1, 2006 to July 31, 2009. The panel estimation is carried out by using firm-level fixed-effects and panel-robust standard errors (clustering at the firm level) to control for autocorrelation and heteroskedasticity. *,** and *** denote significance at 5%,1% and 0.1%, levels respectively. t-statistics are given in parenthesis.

Regressors	Models							
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Constant	1.975***	1.310***	2.054***	1.997***	2.403***	0.308	-1.346***	-0.731**
	(14.037)	(9.771)	(13.54)	(14.006)	(16.581)	(1.382)	(-3.151)	(-2.218)
ΔDTD	-7.644***	-5.577***	-7.643***	-7.625***	-7.613***	-2.722***	-7.337***	-2.105***
	(-6.695)	(-5.935)	(-6.708)	(-6.648)	(-6.447)	(-3.678)	(-6.639)	(-3.290)
ΔTBAS		2.805***						2.267***
		(7.486)						(6.355)
DP			0.116					0.067
			(1.245)					(0.885)
ΔTI				0.074***				0.018
				(4.086)				(0.930)
ΔASY					8.726***			8.110***
					(6.981)			(7.152)
ΔIBAS						6.183***		4.391***
						(11.054)		(8.655)
QI							0.335***	0.143***
							(8.400)	(4.493)
Observations	3920	3920	3920	3920	3746	3920	3920	3746
Adjusted R^2	0.027	0.27	0.026	0.027	0.051	0.203	0.04	0.38

Table 5
Credit and liquidity determinants of credit spreads before and during the 2007-2009 financial crisis

The table exhibits the estimation results of regression (2) before and after the crisis. The dependent variable is the change in the midquote price. The explanatory variables are the change in the distance to default (ΔDTD),the change in the time-weighted absolute bid-ask spread (ΔTBAS), the change in the number of executed trades (ΔTI), the demand pressure (DP), the change in the industrial information asymmetries index (ΔASY), the change in the industry-wide bid-ask spread (ΔIBAS) and the quote imbalance (QI). Dependent variable and explanatory variables are sampled on a monthly basis. The pre-crisis period goes from January 1, 2006 to April 21, 2007. The crisis periods is from April 22, 2007 to July 31, 2009. The panel estimation is carried out by using firm-level fixed-effects and panel-robust standard errors (clustering at the firm level) to control for autocorrelation and heteroskedasticity. *,** and *** denote significance at 5%,1% and 0.1%, levels respectively. t-statistics are given in parenthesis.

Panel A: Pre-crisis period

Regressors	Models							
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Constant	-1.248***	-1.124***	-1.401***	-1.288***	-1.205***	-0.876***	-3.106***	-2.652***
	(-89.222)	(-33.216)	(-10.626)	(-56.039)	(-57.429)	(-10.813)	(-10.468)	(-6.863)
ΔDTD	-0.437	-0.432	-0.433	-0.426	-0.393	-0.088	-0.322	-0.229
	(-0.780)	(-0.869)	(-0.778)	(-0.759)	(-0.716)	(-0.175)	(-0.616)	(-0.501)
ΔTBAS		3.367***						3.220***
		(3.294)						(3.114)
DP			-0.135					-0.126
			(-1.150)					(-1.314)
ΔTI				0.042*				0.036*
				(1.960)				(1.881)
ΔASY					4.698*			0.196
					(1.927)			(0.109)
ΔIBAS						5.236***		1.471**
						(4.417)		(2.005)
QI							0.170***	0.133***
							(6.193)	(4.951)
Observations	1030	1030	1030	1030	1030	1030	1030	1030
Adjusted R^2	0.001	0.154	0.004	0.006	0.004	0.039	0.041	0.196

Table 5 - continued

Panel B: Crisis period

Regressors	Models							
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Constant	2.866***	2.090***	3.018***	2.949***	3.174***	0.797**	-0.737	-0.325
	(11.446)	(9.919)	(10.966)	(11.465)	(13.333)	(2.255)	(-1.378)	(-0.742)
ΔDTD	-11.906***	-8.635***	-11.920***	-11.864***	-11.529***	-4.255***	-11.415***	-3.262***
	(-7.893)	(-6.723)	(-7.950)	(-7.841)	(-7.851)	(-3.967)	(-7.749)	(-3.698)
ΔTBAS		2.765***						2.262***
		(7.403)						(6.333)
DP			0.321*					0.177
			(1.729)					(1.376)
ΔTI				0.123***				0.027
				(2.886)				(0.777)
ΔASY					8.635***			8.147***
					(6.903)			(7.159)
ΔIBAS						6.046***		4.276***
						(10.965)		(8.518)
QI							0.382***	0.157***
							(8.310)	(4.080)
Observations	2716	2716	2716	2716	2716	2716	2716	2716
Adjusted R^2	0.039	0.281	0.04	0.04	0.063	0.207	0.054	0.383

Table 6
Credit and liquidity determinants of credit spreads in periods of high and low risk

The table exhibits the estimation results of regression (2) on low/high risk sub-samples created with various firm-specific risk indicators (bid-ask spread, CDS price and CDS price volatility). The high/low risk sub-samples are built by grouping firm-level observations according to whether a chosen indicator is above or below its time-series median. The dependent variable is the change in the midquote price. The explanatory variables are the change in the distance to default (ΔDTD),the change in the time-weighted absolute bid-ask spread (ΔTBAS), the change in the number of executed trades (ΔTI), the demand pressure (DP), the change in the industrial information asymmetries index (ΔASY), the change in the industry-wide bid-ask spread (ΔIBAS) and the quote imbalance (QI). Dependent variable and explanatory variables are sampled on a monthly basis. The sample period is from January 1, 2006 to to July 31, 2009. The panel estimation is carried out by using firm-level fixed-effects and panel-robust standard errors (clustering at the firm level) to control for autocorrelation and heteroskedasticity. *,** and *** denote significance at 5%,1% and 0.1%, levels respectively. t-statistics are given in parenthesis.

	Bid-ask spread		**Price volatility**		**CDS price**	
Regressors	Low	High	Low	High	Low	High
Constant	-0.409	-1.183**	-1.518***	-0.886	-1.254***	-0.245
	(-1.346)	(-2.012)	(-4.062)	(-1.566)	(-5.029)	(-0.437)
ΔDTD	0.111	-7.350***	-0.994**	-3.952***	-0.434	-6.089***
	(0.270)	(-4.317)	(-2.225)	(-3.226)	(-1.328)	(-3.310)
ΔTBAS	2.351***	2.253***	1.305**	2.420***	2.237***	2.243***
	(8.842)	(5.601)	(2.467)	(5.243)	(5.964)	(5.734)
ΔTI	0.03	0.076	0.029	-0.001	0.051***	0.008
	(1.501)	(1.106)	(1.433)	(-0.039)	(2.676)	(0.170)
DP	-0.008	0.087	-0.021	0.012	0.029	-0.012
	(-0.158)	(0.394)	(-0.451)	(0.092)	(0.500)	(-0.060)
ΔASY	-3.024	8.590***	2.681	9.487***	0.369	8.834***
	(-1.489)	(7.292)	(1.522)	(7.026)	(0.139)	(7.354)
ΔIBAS	5.030***	3.909***	2.881**	4.326***	4.376***	4.012***
	(10.603)	(7.703)	(2.554)	(7.898)	(5.506)	(7.943)
QI	0.022	0.247***	0.044	0.199***	0.026	0.242***
	(0.875)	(4.535)	(1.563)	(4.293)	(1.098)	(4.984)
Observations	1872	1874	1824	1922	1868	1878
Adjusted R^2	0.444	0.379	0.155	0.402	0.338	0.382

Figure 1. Time-series determinants of CDS prices. The case of Telecom Italia.
TBAS is the time-weighted bid-ask spread for Telecom Italia CDS, DTD is the distance to default, IBAS is the industry average bid-ask spread and CDS is the CDS price in basis points.

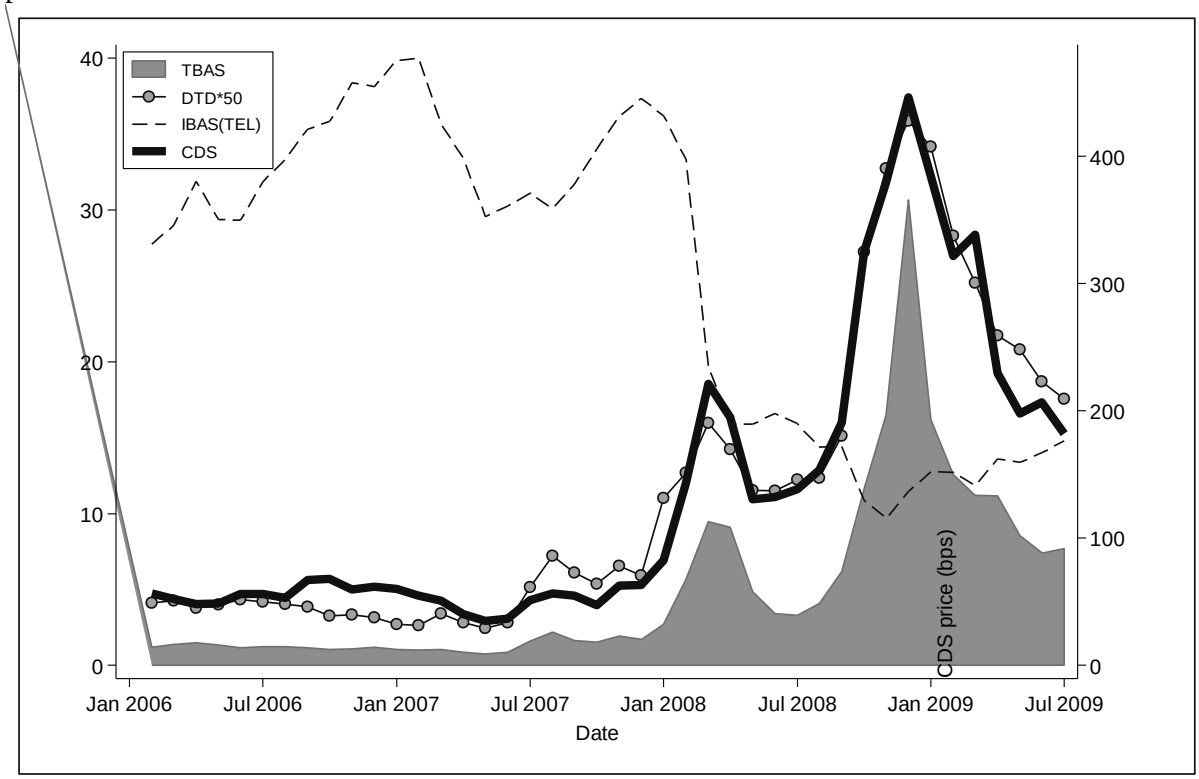

Figure 2. Market average bid-ask spread and CDS price

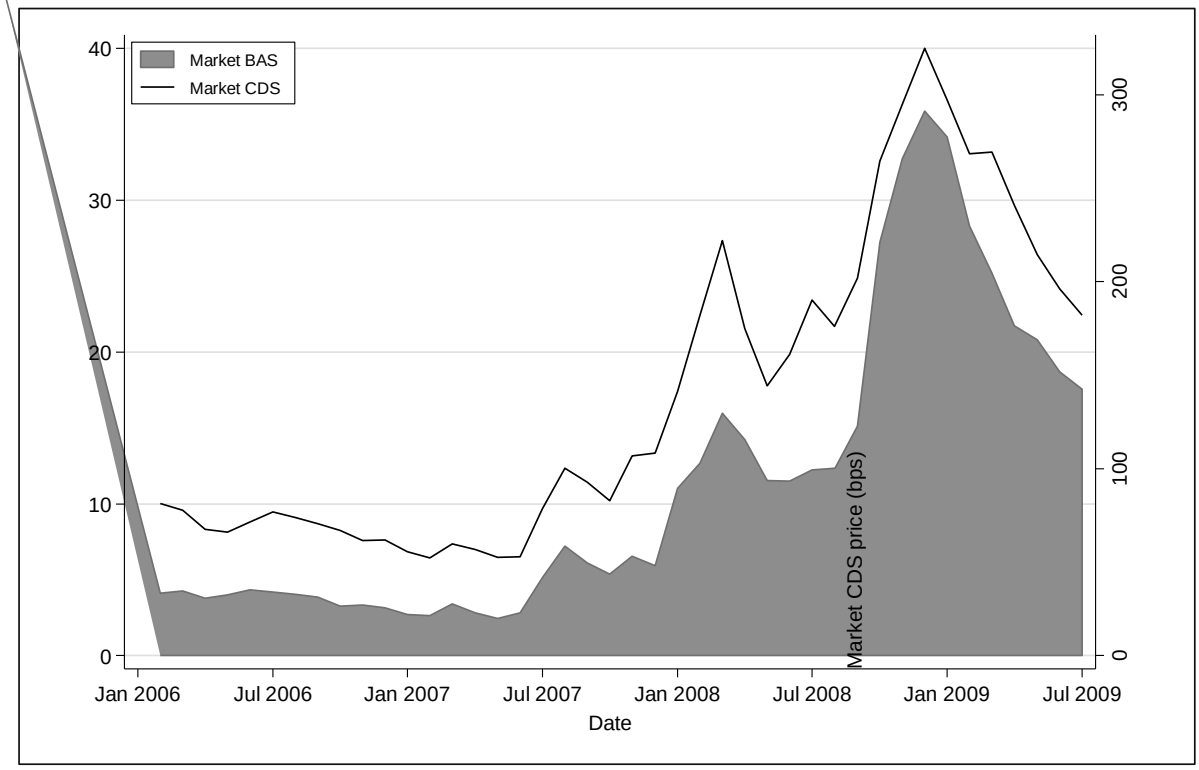

Figure 3. Credit and liquidity proportions in the pre-crisis and crisis periods.

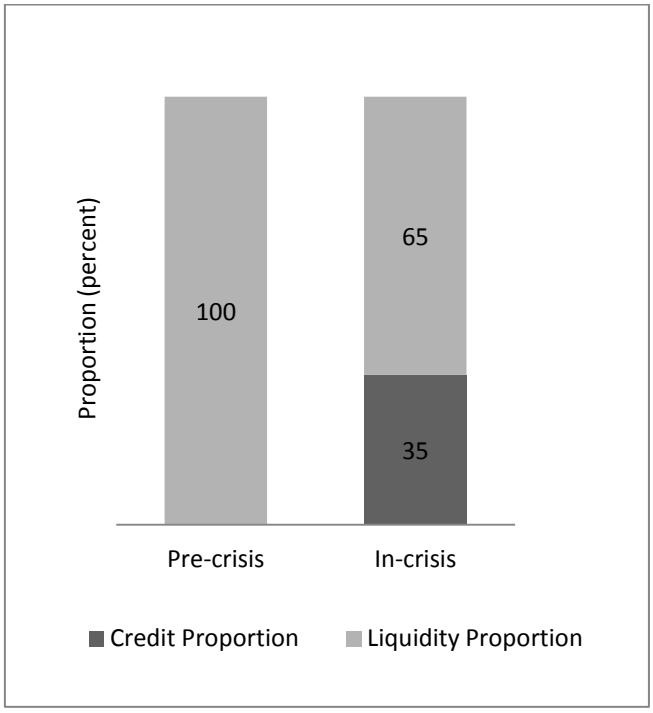
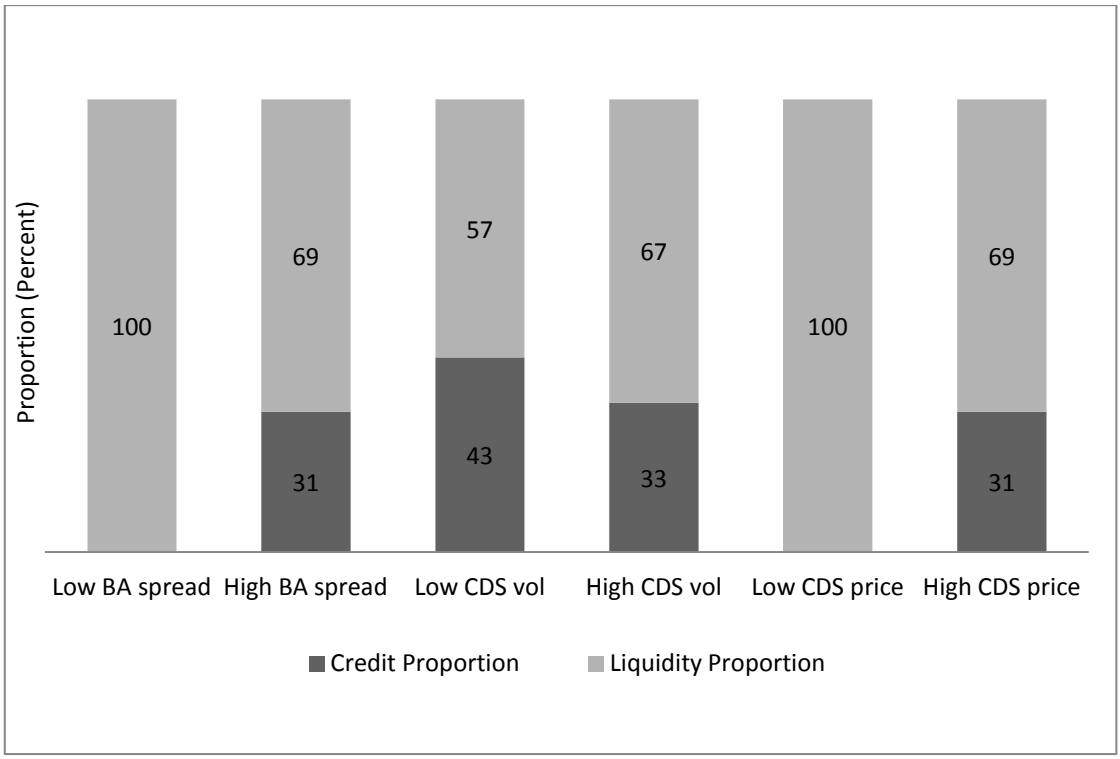
Figure 4. Credit and liquidity proportions in periods of high and low market uncertainty as measured by bid ask spread, CDS price and price volatility.