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Demand–supply imbalances in the credit default swap market: empirical evidence

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This paper empirically examines demand–supply imbalances in the credit default swap (CDS) market and provides evidence of its effect on the CDS spread dynamics. Analysis is conducted on a large and homogenous data set of the 92 non-financial European companies with the most quoted Euro-denominated CDS contracts during the 2002–2008 period. Main findings indicate that short-term CDS price movements, not related to fundamentals, are positively affected by demand–supply imbalances when protection buyers outstrip protection sellers. Results illustrate that CDS spreads reflect not only the price of credit protection, but also a liquidity premium for the anticipated cost of unwinding the position of protection sellers, especially during stress periods.

Keywords: credit default swaps; demand–supply imbalance; liquidity premium

JEL Classifications: G01; G12

1. Introduction

A widely accepted finding in the empirical literature on corporate bonds is that corporate bond yield spreads are substantially affected by non-default components such as taxes, illiquidity, and market microstructure effects (Elton et al. 2001; Longstaff, Mithal, and Neis 2005; Ericsson and Renault 2006; Chen, Lesmond, and Wei 2007). In contrast, prices of credit default swap (CDS) contracts have often been labeled as a 'near-ideal' measure of default risk in view of the fact that a CDS is theoretically designed to serve as an effective financial instrument for hedging and trading credit risk. A single-name CDS represents a type of bilateral insurance contract that provides protection against default by a particular reference entity (company or sovereign). As such, the premium that the protection buyer pays to the seller – the CDS spread – is directly linked to the credit quality of the reference entity and is expected to provide a 'pure' measure of the credit risk premium.

This argument has been used in several studies and CDS spreads emerged as a preferred market benchmark for credit risk when analyzing the bond market or when testing the performance of structural credit risk models (Blanco, Brennan, and Marsh 2005; Longstaff, Mithal, and Neis 2005; Saita 2006; Ericsson, Reneby, and Wang 2007; Han and Zhou 2008; Nashikkar, Subrahmanyam, and Mahanti 2011). A few recent studies, however, demonstrate that CDS spreads do in fact contain non-default components. Tang and Yan (2007) explicitly consider different facets of liquidity and find that its effect on the CDS premium is significant. Bongaerts, de Jong, and Driessen (2011) propose a theoretical asset pricing model that allows for liquidity effects and find evidence of a liquidity premium earned by the protection seller. Bühler and Trapp (2010)

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decompose CDS spreads using a reduced-form model and find, on average, a positive liquidity premium. Finally, recent episodes of financial turmoil suggest that CDS spreads are not free of non-default components and that liquidity should eventually be one of the most important non-default drivers of CDS spreads.

Liquidity is an obscure concept and no consensus yet exists on what precisely is and how it can be measured. In general, liquidity could be defined as the ability of market participants to trade large quantities of an asset rapidly, without affecting the asset's price. Amihud, Mendelson, and Pedersen (2005) suggest several sources of illiquidity that might have an effect on asset prices: exogenous transaction costs, information asymmetry, search costs, demand pressure and inventory risk. Acharya, Schaefer, and Zhang (2007) draw on the term 'market liquidity' to refer to both liquidity and liquidity risk, associating liquidity with transaction costs and liquidity risk with unpredictable changes in transaction costs. In addition to market liquidity, traders are concerned with 'funding liquidity' which refers to the availability of funds and the ability to unwind or settle positions as they come due (i.e. the easiness with which funds could be raised if necessary). Brunnermeier and Pedersen (2009) provide a theoretical framework that links market liquidity and funding liquidity showing that, under certain conditions, their inter-linkage may lead to a mutual reinforcement and liquidity spirals.

While liquidity has been broadly analyzed in the equity and bond markets, there is still not much concluding evidence on all the features and effects it has in the CDS market. The analysis of liquidity issues in the CDS market is not straightforward: CDSs are contracts traded in a concentrated, interconnected and opaque over-the-counter market, in which the participants are mainly insiders. Liquidity in the CDS market is usually proxied by the bid–ask spread (Meng and Gwilym 2008; Chen, Fabozzi, and Sverdlove 2010; Bongaerts, de Jong, and Driessen 2011). Other considered measures include volatility-to-volume, number of outstanding contracts, trades to quotes and quote updating frequency (Chen, Cheng, and Wu 2005; Tang and Yan 2007).[1]

One additional, intuitive, but formally unexplored aspect of the CDS market liquidity is the demand–supply imbalance. The effect of demand–supply imbalances on liquidity and prices has been previously studied in the stock and bond markets, however. Chordia and Subrahmanyam (2004) study the daily time-series relation between order imbalances and individual stock returns, showing that excess buy orders drive prices up, whereas excess sell orders drive prices down. Chordia, Roll, and Subrahmanyam (2002) show that these microstructure effects are not restricted to the firm level and provide evidence that market-wide order imbalances have a significant impact on stock returns at the aggregate market level. Greenwood and Vayanos (forthcoming), using time-series data as well, empirically show that the supply of government debt positively affects bond yields and expected returns.

In the context of the CDS market the imbalance between the demand for and supply of credit protection is of particular importance. Unlike stocks and bonds, CDS contracts are in zero-net supply; hence, they exist only if at least some investors demand credit protection and at least some investors are willing to sell credit protection. In positive-net supply markets – as the stock and bond markets – a trade means the transfer of the ownership right upon some existing assets. Once the trade has been completed the seller is no longer concerned about the liquidity of the asset sold; only the buyer is concerned. In contrast, in a CDS contract both the seller and the buyer will continue to be concerned about the liquidity after the transaction has been completed. Nevertheless, buyers and sellers do not tend to emerge at the same pace in the CDS market and, as reported by Fitch, Inc. (2004), protection buyers often exceed protection sellers. This intuitively implies that in periods when sellers are comparatively scarce, sellers are likely to demand a liquidity premium as a compensation for the anticipated costs of unwinding their position. The effect of this asymmetry will be the deviation of the mid bid–ask quote from the pure credit risk premium. To be more precise, the higher liquidity premium required by protection sellers will push the mid bid–ask spread above the pure credit risk premium. As a corollary to the previous argument – and this is of particular relevance for the present study – the traditional use of the bid–ask spread as a measure of market liquidity may be limited in the presence of strong demand–supply imbalances. Put it simple, the liquidity premium could change even if the size of the bid–ask spread remains unchanged – i.e. the pure credit risk premium could just get closer to the bid or to the ask quote. Bühler and Trapp (2007, 2010) have already shown that transaction costs in the CDS market are asymmetric and not equally divided between the buyer and the seller.

This paper contributes to the existing literature on liquidity in the CDS market by investigating the effects of demand–supply imbalances. The analysis is conducted on a large and homogenous data set of the 92 non-financial European companies with the most quoted Euro-denominated CDS contracts during the 2002–2008 period. The main findings of the paper could be summarized as follows. First, demand–supply imbalances significantly influence the CDS spread dynamics: CDS changes not related to fundamentals are positively related to an increase in the number of bids as regards offers, and vice versa. This result indicates that CDS spreads reflect not only a pure credit risk premium, but also a liquidity premium as a compensation for the anticipated costs of unwinding the position of protection sellers. Second, this aspect of the CDS market liquidity is not fully captured by the bid–ask spread; that is, the effect of the demand–supply imbalance on CDS spreads remains even after controlling for the bid–ask spread. This confirms the intuition that changes in the supply of, or demand for, credit protection influence the deviation of the pure credit risk premium from the mid-market quote. Third, the economic effect of demand–supply imbalances on the CDS spread dynamics is magnified during turbulent times when sellers of protection become unwilling to bear more risk. Fourth, market-wide demand–supply imbalances have a stronger effect on CDS spreads than firm-specific demand–supply imbalances, which supports the funding liquidity argument of Brunnermeier and Pedersen (2009). Finally, the effect of demand pressure is greater for speculative grade issuers, measured in absolute terms and relative to the bid–ask spread.

The remaining of the paper is organized as follows. Section 2 describes the set of hypothesis. Section 3 introduces the database. Section 4 describes the methodology applied for deriving CDS changes not related to fundamentals. Section 5 proposes different demand–supply imbalance measures. Section 6 presents the main empirical results. Section 7 concludes.

2. Hypothesis development

The analysis of the impact that demand–supply imbalances might have in the CDS market is formally structured around four testable hypotheses as described below.

Hypothesis 1. Demand–supply imbalances are priced in the CDS market.

Hypothesis 1 reflects the main research question of the paper and follows directly from the discussion provided in the introduction.

Hypothesis 2. The impact of demand–supply imbalances is magnified in crisis times.

The imbalance between the demand for and supply of credit protection is time varying in nature. In good times, when capital is abundant, investors are willing to take on credit risk. In bad times, when capital is scarce, funding conditions worsen and traders are willing to assume smaller inventory positions. Brunnermeier and Pedersen (2009) show that funding liquidity is an important driver of market liquidity and that in bad times, small changes in underlying funding conditions can lead to sharp reductions in liquidity. As CDS contract transfers credit risk from the buyer to the seller, potential claims against sellers and their risk of hitting funding constraints increase sharply during periods of financial stress. Sellers of protection, anticipating the difficulty of unwinding their position under such conditions, are likely to move the mid CDS quote up, setting the pure credit risk premium closer to the bid quote. Thus, the likely effect is the higher sensitivity of CDS spreads to increasing demand pressure during stress times.

Hypothesis 3. The impact of market-wide demand–supply imbalances is stronger relative to firm-specific demand–supply imbalances.

The CDS market is characterized with liquidity commonalities. Pu (2009) finds a strong common liquidity factor, extracted from various individual liquidity measures, that impacts the portion of changes in CDS spreads unexplained by default factors. Mayordomo, Peña, and Rodríguez-Moreno (2012) show that liquidity commonalities in the CDS market vary over time, being stronger in periods when global, counterparty, and funding liquidity risks increase. It could be argued that liquidity commonality in the CDS market is due to co-movements in supply of credit protection: the risk of hitting funding constraints common to all market participants implies the shortage of liquidity on the aggregate market level (Brunnermeier and Pedersen 2009). In this setting, the interconnectedness of market players and the high level of concentration in the CDS market are expected to further magnify co-movements in supply and, consequently, to magnify the price impact of aggregate demand–supply imbalances on firm-specific CDS spreads.

Hypothesis 4. The effect of demand pressure is higher for high-yield firms.

Naturally, it is expected that liquidity premia increases with credit risk. The rationale behind this view is as follows. On the one hand, the bond market is in general less liquid than the CDS market, and liquidity typically further deteriorates for entities with lower credit rating. The CDS market serves as an alternative to avoid the loss from selling the low liquid bonds and, thus, it is expected that demand for credit protection increases for sub-investment grade underlyings. On the other hand, the supply of credit protection is reduced precisely for the sub-investment grade sector given that, as reported by Mengle (2007), institutional investors (pension funds, hedge funds, and mutual funds), which are limited to investment grade exposures, turn out to be net protection sellers in the CDS market. Overall, we would expect the effect of demand (supply) pressure to be positively (negatively) related to the credit risk: higher for sub-investment grade firms and lower for investment grade firms. The current empirical evidence is mixed and depends on whether liquidity is measured in absolute or relative terms. Pu (2009) reports lower level of liquidity in the CDS market for the sub-investment grade firms. Bühler and Trapp (2007), however, report that liquidity premia, when measured relative to the pure credit risk premia, is smaller for the sub-investment grade sector. The reasoning behind this finding, as stipulated by these authors, is that investors trading sub-investment grade CDS contracts seek to take on credit risk and use CDS contracts as substitutes to low liquid bonds, whereas investors trading investment grade CDS contracts seek to buy credit protection.

3. Data Set

Data on CDS spreads are provided by GFI, an inter-dealer broker in credit derivatives.[2] The GFI data comprise information on intra-day quotes and trades, the reference entity, seniority of the reference issue and maturity.[3] The initial data set contains 1,641,326 intra-day quote and trade entries expressed in basis points for 643 European reference entities (including sovereigns, financial and non-financial companies, publicly and not publicly traded companies). The data refer to actual executable and executed market prices where dealers commit capital. As such, the data reflect market sentiment rather than indications. The time period spans from January 2002 to December 2008.[4] The number of available quote and trade entries is not evenly distributed across time but is increasing gradually till 2007 reflecting the steady development of the CDS market activity during the time period considered.

In this study I consider only the most liquid Euro-denominated five-year maturity contracts (87% of the sample) and contracts drawn on senior unsecured debt (88% of the sample). Given that further analysis requires data on market capitalization, sovereigns and companies that are not publicly traded (18.4% of the sample) are not taken into account, whereas companies in the banking and finance sector are excluded due to their different capital structure (27.4% of the sample). Companies from the GFI database are manually matched (by company name and industry) with the Datastream database, and several companies are further excluded due to the lack of data.

With the purpose of isolating the short-lived demand–supply imbalance effects, the data are further limited to the set of the quote and trade data for the most frequently traded Euro-denominated CDS contracts: all the companies with no trades in any of the considered years, and companies with quotes and trades available for less than 5% of the trading days in any of the considered years, are excluded. Consequently, the final sample comprises a representative data set of 622,488 intra-day bid and ask quotes and trade entries for 92 non-financial European companies with sufficiently regular quote updating frequency. The average European company in the sample has market capitalization of 16 billion Euros, leverage of 0.51, and historical equity volatility of 37%. In comparison to the initial sample, the final sample comprises around 40% of all initially available quote and trade entries, and around 65% of the quote and trade entries of all non-financial publicly traded companies pertaining to the European region. Moreover, the final set of quotes and trades follows the pattern of the distribution of initially available quotes and trades over different years. Another important characteristic of this final set of companies is that the homogeneity of the sample is ensured for the entire 2002–2008 period so that the possibility of obtaining spurious results due to changes in the sample composition over time is avoided. It is important to note that for the rest of the sample the data are rather sparse. By way of example, there are as much as 104 entities with no trades and 151 entities with less than 20 quotes during the overall sample period.

Table 1 provides the main characteristics of the final data set of quote and trade entries. In total, there are data on 578,727 quotes (NQ) and 43,761 transactions (NT). Therefore, out of all entries, transactions are represented with only 7%. Out of the available quotes, 384,277 (66.4%) are two-sided quotes (NTSQ), 121,959 (21.1%) are net bid quotes (NNBQ), and 72,491 (12.5%) are net ask quotes (NNAQ).[5] In general, there are more bid quotes (protection buyers) than ask quotes (protection sellers), which is already an indication that the CDS market is likely to be subject to structural imbalances. The division by yearly time segments further confirms the finding that the CDS market seems to be a net bidder market in which sellers are liquidity providers and that the CDS market activity is increasing over time. For the homogenous sample that is considered, the maximum of 633 quotes and 44 transactions per day is recorded in 2007.

Table 1. Quote and trade entries.

	NNBQ		NNAQ		NTSQ		NQ		NT	
Period	Total	Per day	Total	Per day	Total	Per day	Total	Per day	Total	Per day
2002	6268	24	5649	22	13,203	51	25,120	96	3573	14
2003	4749	18	3716	14	16,201	62	24,666	95	2816	11
2004	8411	32	3253	12	28,098	107	39,762	152	4310	16
2005	15,107	58	8208	32	28,440	109	51,755	199	4523	17
2006	24,591	95	13,213	51	77,385	298	115,189	443	9007	35
2007	31,024	119	18,137	69	116,038	445	165,199	633	11,432	44
2008	31,809	121	20,315	78	104,912	400	157,036	599	8100	31
All	121,959	67	72,491	40	384,277	213	578,727	320	43,761	24

Notes: This table reports the number of quote and trade entries for the overall sample and across different yearly periods. NNBQ refers to the number of net bid quotes, NNAQ to the number of net ask quotes, NTSQ to the number of two-sided quotes, NQ to the total number of quotes, and NT to the number of transactions.

Given that the data set contains only intra-day bid and ask quotes, daily CDS spread observations are constructed on the end-of-day basis in the following manner: if on a given day both bid and ask quotes are present, the CDS spread refers to the midpoint of the last bid and last ask quote; if on a given day only bid (ask) quotes are present, the CDS spread refers to the midpoint of the last bid (ask) on a given day and the most recently available ask (bid) quote entry. In this way, there is a total of 86,864 available daily observations for the selected reference entities or 944 per company, on average. This means that for an average company in the sample, a new quote is available approximately every second trading day. Even so, there are substantial differences between companies, with a minimum of 12% and a maximum of 97% of the trading days with quotes availability. The missing data are filled in assuming the last observable CDS spread (i.e. the most recent quote), following the reasoning that if there is no new bid or ask quote, there is no new information leaked in the market for that specific company.

4. Fundamentals and CDS spreads

In order to investigate the effect of demand–supply imbalances in the CDS market, it is necessary to relate it to the part of the CDS premium that is not driven by fundamentals. Theoretically, variables perceived by structural models (market value of the firm's assets, volatility, leverage, and risk-free rate) should be the main determinants of credit spreads. In most empirical studies, these variables are taken separately in a linear manner to account for changes in credit risk (Collins-Dufresne, Goldstein, and Martin 2001; Aunon-Nerin et al. 2002; Blanco, Brennan, and Marsh 2005; Abid and Naifar 2006; Avramov, Jostova, and Philipov 2007; Ericsson, Reneby, and Wang 2007; Tang and Yan 2007; Greatrex 2009). In contrast to this approach, I consider just one variable to account for the fundamentals: the theoretical credit spread implied from the stock market (ICS). The advantages of this approach are twofold. First, theoretical credit spreads in a single measure account for the key variables that are suggested by economic theory to be the main determinants of credit risk, simultaneously respecting their highly nonlinear functional relationship. Second, theoretical ICSs can be directly confronted and contrasted to CDS spreads as both measures represent alternative proxies for the same latent variable – the 'pure' credit spread. To be precise, the theoretical credit spread is determined on the basis of the modified version of the structural model of Leland and Toft (1996) suggested by Forte (2011) as a function of the firm's asset value and other variables necessary to specify the model (risk-free rate, volatility, default barrier and recovery rate). The risk-free rate and recovery rate are treated as observables. The proxy chosen for the risk-free rate in the structural model is the swap rate. The model considers 1–10 year swap rates implicitly taking into account the term structure of interest rates. The recovery rate is set to 40%, in line with the studies of Covitz and Han (2004), Altman et al. (2005), and the industry practice.[6] The unobservable set of variables (firm's asset value, volatility, and default barrier) are estimated using the Forte (2011) iterative algorithm procedure. The method considers the equity pricing equation $S_t = g(V_t|\sigma, \beta)$ as a function of the firm's asset value (V_t), conditional on the firm's asset volatility (σ), and conditional on the default-to-debt ratio (β) which determines the default barrier. The firm's asset value and volatility are estimated from readily available stock market data (and a small subset of balance sheet and income statement items), and the default barrier is calibrated from CDS premia as the value that minimizes the divergence between ICSs and observed CDS spreads.[7] The solution to this minimization problem requires the simultaneous calibration of (V_t, σ) for any guess of β by means of the following algorithm:

(1) proposing an initial value for σ, σ_0;
(2) estimating the V_t series using the information on the stock market capitalization S_t, so that equity pricing equation holds for all t;
(3) estimating a new volatility σ_1 from the obtained V_t series;
(4) ending the process if $\sigma_1 = \sigma_0$. Otherwise, σ_1 is proposed at step 1.

The resulting values for (V_t, σ, β) are used to estimate the time series of stock market ICSs as the premium from issuing, at par value, a hypothetical bond with the same maturity as the corresponding CDS contract – five years in our case. A detailed description of the method is given in Appendix 1.

At this point, it is important to note that, as long as the default parameter remains constant, its value will affect only the general level of the ICS series, but not its short- or long-term dynamics (Forte and Peña 2009). As a result, the analysis conducted in this study is not materially affected by the choice of the default barrier estimation method which is, for the purpose of robustness, confirmed by replicating the analysis for an alternative default barrier specification.

Summary statistics for CDS spreads and ICSs on a cross-sectional basis are provided in Panel A of Table 2. On average, ICSs underestimate observable CDS spreads by 7.6 bp. For the entire sample, the mean CDS spread is 103.3 bp, whereas the mean ICS is 95.7 bp. More formal measures of pricing discrepancy: the average basis – avb, the average percentage basis – avb(%), the average absolute basis – avab, the average absolute percentage basis – avab(%), and the root-mean-squared error – RMSE, are presented in Panel B of Table 2. As expected, pricing errors are larger in times of credit market turbulence and lower in tranquil times, with the fit being the best between 2004 and 2006 and the worst in 2008. In terms of their explanatory power, the obtained ICS are able to explain, on average, around 66.3% of the daily cross-sectional variations in CDS spread levels.

In addition to firm-specific credit spreads, there is a possibility to consider CDS and ICS market indices. For that purpose I construct a CDS market index (CDS_m) and its direct counterpart – an ICS market index (ICS_m), as an equally weighted portfolio of all companies in the sample (i.e. the market-wide portfolio). In this way, the constructed historical synthetic time series of CDS_m and ICS_m indices have an important desirable property: they are homogeneous across time.[8] Figure 1 illustrates constructed CDS_m and ICS_m global market indices for the European region.

Table 2. Summary statistics for CDS spreads and ICS estimates.

Panel A

	CDS			ICS		
Period	Mean	Median	s.d.	Mean	Median	s.d.
2002	153.56	93.38	162.17	115.18	74.61	136.17
2003	131.33	70.94	151.11	171.91	108.34	182.88
2004	84.95	45.27	113.21	102.86	58.23	138.10
2005	71.92	40.31	98.14	82.46	43.13	120.82
2006	57.73	36.89	68.76	45.63	22.54	63.03
2007	55.84	36.16	61.77	42.84	31.97	44.77
2008	173.10	119.78	151.69	109.73	84.52	82.68
All	103.31	69.46	93.81	95.71	56.38	101.64

Panel B

	avb	avb (%)	avab	avab (%)	RMSE
Period	Mean	Mean	Mean	Mean	Mean
2002	−38.39	−0.27	69.50	0.51	79.83
2003	40.58	0.50	44.09	0.48	53.27
2004	17.91	0.31	30.93	0.44	35.60
2005	10.55	0.17	32.35	0.54	35.67
2006	−12.10	−0.19	35.57	0.67	37.58
2007	−28.12	−0.51	38.76	0.77	42.84
2008	−46.49	−0.44	95.46	0.67	109.73
All	−7.59	−0.06	48.91	0.58	67.75

Notes: Panel A reports main cross-sectional descriptive statistics for CDS spreads and model implied credit spreads (ICS) for the overall sample and across different yearly periods. Panel B provides mean values of the standard measures of credit spread differentials between ICS and CDS spread series: avb, the average basis; avb(%), the average percentage basis; avab, the average absolute basis; avab(%), the average absolute percentage basis, and RMSE, the root-mean-squared error. Measures of pricing discrepancy are reported for the overall sample and across different yearly periods.

5. Imbalance measures

In order to illustrate the effect of demand (supply) pressure on CDS prices and to ensure the robustness of the findings, I construct various proxies for the demand–supply imbalance directly from intra-day transaction data as a function of the number of bid and the number of ask quotes. A detailed description follows.

BAQ imbalance is defined as the difference of the relative proportion of the number of bid (NBQ) and the number of ask quotes (NAQ) in the total number of quotes (NQ):

$$\mathrm{BAQ} = \frac{\mathrm{NBQ} - \mathrm{NAQ}}{\mathrm{NQ}}.$$

Given that the data set consists of one-way and two-way quotes, both are considered for calculating the BAQ measure. The aim of this imbalance measure is to capture the direction of the imbalance, not only the general imbalance between bid quotes and ask quotes. Chordia and Subrahmanyam (2004) use the number of buyer-initiated minus seller-initiated trades scaled by

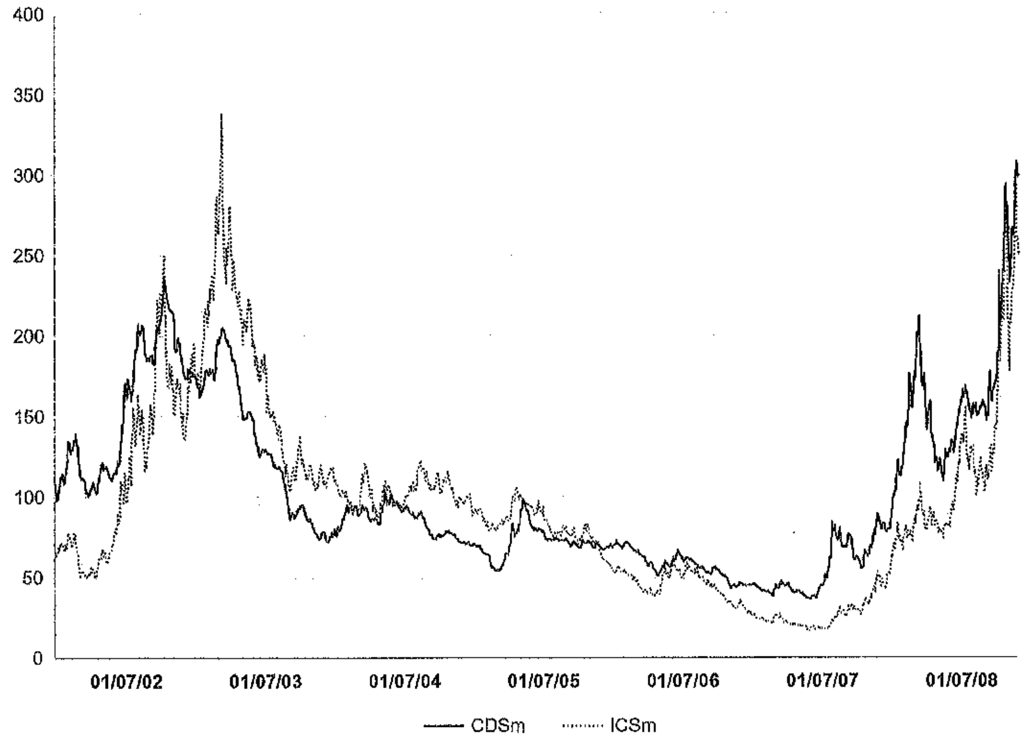

Figure 1. illustrates CDS (CDS_m) and ICS (ICS_m) market indices for the European region. Indices are constructed as an equally weighted portfolio of all the companies in the sample.

the total number of trades, as measure of imbalance for the stock market. Acharya, Schaefer, and Zhang (2007) use a similar measure of imbalance for the bond market, but constructed in terms of volume. Meng and Gwilym (2008) consider the absolute value of one minus the ratio of the number of offers (NAQ) to the number of bids (NBQ) on a given trading day as one of the explanatory variables of the bid–ask spread in the CDS market. While this measure proxies for the general demand–supply imbalance, it does not reveal its direction and, therefore, does not represent a reasonable candidate for the effect that is analyzed in this study.

Offerer imbalance is defined as the ratio between the number of net ask quotes (NNAQ) and the total number of quotes (NQ):

$$\text{Offerer} = \frac{\text{NNAQ}}{\text{NQ}}.$$

Acharya, Schaefer, and Zhang (2007) construct a similar measure for the bond market as the ratio of the net quantity of the offer quote providers on a particular day to the total number of quote providers. As the GFI data set comprises no information on the actual number of quote providers, I proxy supply pressure with the proportion of the number of net ask quotes.

Bidder imbalance is constructed to complement the Offerer measure and to proxy for demand pressure. The Bidder measure is defined as the ratio of the number of net bid quotes (NNBQ) to the total number of quotes (NQ):

$$\text{Bidder} = \frac{\text{NNBQ}}{\text{NQ}}.$$

NBA imbalance is defined as the ratio between the number of bid quotes (NBQ) and the number of ask quotes (NAQ):

$$\text{NBA} = \frac{\text{NBQ}}{\text{NAQ}}.$$

IMB is defined as the overall demand–supply imbalance measure. Given that the proposed imbalance variables (BAQ, Offerer, Bidder, and NBA) are measuring the same underlying construct – how far away is supply of from demand for credit protection – they are correlated with one another. In order to consider just one summary variable as a measure of the quantity of protection demanded relative to the quantity of protection supplied, a principal component analysis is conducted. The IMB is defined as the first principal component that accounts for most of the variance in the observed demand–supply variables. To be exact, the variance proportion explained by the first principal component amounts to as much as 71%.

As control variables I consider the bid–ask spread (BA) and the trades-to-quotes (T2Q) ratio. The bid–ask spread proxies for transaction costs in the market and is calculated as the difference between the last available ask and bid quote on a given day using exclusively two-sided quotes. The trades-to-quotes ratio proxies for matching intensity in the CDS market (Tang and Yan 2007) and is calculated as the number of trades (NT) to the number of quotes (NQ).

As regards the effect on the CDS spreads, the BAQ, Bidder, and NBA imbalance measures, as measures of demand pressure, are expected to have a positive impact. That is, at times when sellers are scarce, buyers are likely to be willing to bid higher prices, and sellers are likely to ask a liquidity premium for taking on credit risk in the situation when it becomes more difficult to unwind the taken position. The Offerer measure, as a measure of supply pressure, in contrast, is expected to have negative impact on CDS spreads. Namely, at good times, when investors are willing to sell credit protection, they are likely to ask lower prices. Taken as a whole, the farther away supply is from demand, the higher the overall imbalance measure (IMB) and the lower the liquidity. As regards control variables, the bid–ask spread is expected to be positively related to CDS spreads, as higher bid–ask spread should signal higher illiquidity. The trades-to-quotes ratio and CDS spreads are likely to be negatively related, as higher matching intensity should signal improved liquidity.

Although there is a possibility to draw on the total number of quotes and trades or the absolute difference between the number of bid and ask quotes on a given day, I refrain from this approach for the following reason: a higher level of quotes and trades, as a measure of total market activity, could imply higher demand for credit protection, but could also be an indication of the CDS market steady development and maturation reflected through the steady increase in the number of players in the market. In that sense, for the effect that is going to be analyzed, demand–supply imbalance measures constructed in relative terms seem more appropriate as they have a more meaningful and direct interpretation.

Firm-specific imbalance measures are considered only if both – bid and ask quotes – are available on the same day. On a cross-sectional basis, preliminary evidence suggests that the number of bids overpasses the number of offers for the majority of the trading days. To be precise, on 86% of the trading days the aggregate demand for credit protection surpasses the aggregate supply. On a firm-specific daily level, the balanced demand–supply is present in 27.7% of the cases; for as much as 50% of the pooled sample the demand surpasses the supply, whereas the opposite occurs in 22.3% of the cases.

6. Empirical results

6.1 *Methodology*

The empirical methodology applied in this paper is based on extracting the part of the CDS spreads not explained by fundamentals, and relating this non-default component to different demand–supply imbalance measures. Given that the primary interest of the paper is on the time variation in the non-default component, there are two additional issues that need to be discussed further: should analysis be conducted on levels or changes, and the time frequency at which the demand–supply imbalance effect is going to be analyzed. CDS spreads have unit roots. Running the augmented Dickey–Fuller test (ADF) for the presence of unit roots shows that firm-specific CDS spreads for 85 out of the 92 companies (92.4%) are non-stationary at the 95% confidence level. Almost the same findings are obtained for firm-specific ICS time series: for 83 out of the 92 companies (90.2%) ICS are non-stationary at the 95% confidence level. On the contrary, the null hypothesis of non-stationarity for the first differences of CDS spread (and ICS) series is rejected for all companies in the sample. The unit root analysis is also conducted for CDS_m and ICS_m indices. Analogous to firm-specific CDS and ICS time series, CDS_m and ICS_m indices are $I(1)$ processes in levels and $I(0)$ processes in differences. Given that CDS spreads are mostly $I(1)$ processes, running a time-series regression directly on CDS spread levels would give a high R^2, but these regressions are potentially spurious. One of the immediate responses to the non-stationarity of CDS spread series is to consider changes in CDS spreads instead of levels, which is the approach adopted in this paper and discussed further.

Another important issue refers to the chosen time frequency. By way of example, if changes in CDS_m are regressed only on contemporaneous changes in ICS_m, the R^2 sharply rises from 16% for daily frequency, to 45% for weekly, and to 50% for monthly frequency. Although lowering the time frequency at which the data are analyzed has the effect of raising the R^2 statistics, analysis of short-lived liquidity effects asks for higher time frequencies. The majority of the studies on CDS spread determinants use lower time frequencies, however. For example, Tang and Yan (2007) and Greatrex (2009) use monthly data. This choice of the time frequency is brought by insufficient number of observations on daily basis at the firm-specific level, and possible increased noise in the daily data. For the specific sample of CDSs used in this paper, bid and ask quotes – and consequently imbalance measures – are available on average every second trading day on a firm-specific level.[9] One possibility to bypass these issues is to construct market indices by averaging on a cross-sectional basis. This has the effect of minimizing the noise in the data while allowing for observations on a daily level. The other possibility is to use weekly data on a firm-specific level as in Blanco, Brennan, and Marsh (2005) and Ericsson, Jacobs, and Oviedo (2009). For the aim of robustness, both approaches are adopted in this paper and will be discussed further.

In the vein of Acharya and Johnson (2007), the first step consists of isolating the component of CDS spread changes that is specific solely to the credit market, and that is not attributable to changes in fundamentals (i.e. CDS innovations). Specifically, CDS innovations are obtained as the residuals from regressing changes in CDS spreads on contemporaneous and lagged changes in fundamentals (ICS), and on lagged changes in CDS spreads. As such, the residuals of the specified regression could be seen as stock market independent CDS shocks. For the market level and constructed CDS_m and ICS_m indices, the analysis is conducted on a daily basis with a lag length of five days, assuming that this is a reasonable time to allow for all information processing and transmission, while controlling for the issues of autocorrelation. The model is described in

the following equation:[10]

$$\Delta\text{CDS}_{\text{m},t} = \alpha_\text{m} + \sum_{k=0}^{5} \beta_{\text{m},t-k}\Delta\text{ICS}_{\text{m},t-k} + \sum_{k=1}^{5} \gamma_{\text{m},t-k}\Delta\text{CDS}_{\text{m},t-k} + e_{\text{m},t}. \tag{1a}$$

Results from regression (1a), conducted using CDS_m and ICS_m market indices, are presented in Table 3, Panel A. For the overall period, 2002–2008, the adjusted R^2 amounts to 36%.[11] In order to better capture the time-series variation in CDS spreads, fundamentals, and imbalance factors, while allowing for the eventual presence of structural breaks, the overall period considered is further divided into three sub-periods: year 2002 (Period 1), 2003 to mid-2007 (Period 2), and mid-2007 till the end of 2008 (Period 3). In the first sub-period (Period 1), the CDS market is not only in the development stage, but is also characterized by credit market turbulence and high levels of CDS spreads. Starting from the late 2001, the CDS market faced massive bankruptcies and other credit events such as the ones of Enron (December 2001), WorldCom (July 2002), Xerox (December 2002), and Conseco (August 2002). Global corporate default rates peaked in the second half of 2002 and substantially declined in the periods that followed (Standard & Poor's, 2006). The second sub-period (Period 2) is characterized by increased contract standardization, growing CDS market activity measured by the number of quotes and trades per day, and declining CDS spreads until mid-2007. The third sub-period (Period 3) is the period of the recent financial crisis and is of particular interest. In fact, the last sub-period includes significant events for the CDS market such as the money market 'freeze' (August 2007), the collapse of Bear Stearns (March 2008), and the collapse of Lehman Brothers (September 2008).

Such a classification allows for comparing empirical findings between normal (Period 2) and stress (Period 1 and Period 3) regimes. As regards regression (1a) the adjusted R^2 turns out to be substantially higher during periods of credit market turbulence (34% and 44% for Period 1 and Period 3, respectively) and lower during a quiet period (29% for Period 2). This result is in line with the common finding in the literature that the strength of the co-movement between the equity and CDS markets increases with credit risk (Norden and Weber 2009).

For the firm-specific level, the analysis is conducted by running time-series regressions on a weekly basis to obtain firm-specific weekly residuals. For that purpose I consider a model in which changes in CDS spreads are regressed on contemporaneous and one lag changes in ICSs, and one lag changes in CDS spreads:

$$\Delta\text{CDS}_{i,t} = \alpha_i + \sum_{k=0}^{1} \beta_{i,t-k}\Delta\text{ICS}_{i,t-k} + \gamma_{i,t-1}\Delta\text{CDS}_{i,t-1} + e_{i,t}. \tag{1b}$$

Table 3, Panel B, presents the summary of the firm-specific regressions described in Equation (1b). As to the overall period, the mean adjusted R^2 amounts to 21%. In line with the previous findings, the mean explanatory power is higher during the crisis periods (27% and 25% for Period 1 and Period 3, respectively) and lower during the tranquil period (16% for Period 2). On a firm-by-firm basis, this relation holds for 53 out of 92 companies (58% of the sample). The explanatory power of the model is significantly altered by the CDS quote and/or trade availability and, as expected, is higher for names with more active CDS contracts. The correlation between the firm-specific adjusted R^2 and the firm-specific number of days with available quote and trade entries is 0.36 and is statistically significant at the 1% level.

Table 3. Regressions of CDS spreads on fundamentals.

Variable	Coefficient	Period 1	Period 2	Period 3	All
Panel A					
$\Delta ICS_{m,t-k,k=0,\dots,5}$	$\Sigma\beta_{m,t-k}$	0.36***	0.21***	0.73***	0.43***
		(4.05)	*(5.02)*	*(5.91)*	*(6.61)*
$\Delta CDS_{m,t-k,k=1,\dots,5}$	$\Sigma\gamma_{m,t-k}$	0.47***	0.47***	0.29**	0.40***
		(4.32)	*(7.00)*	*(2.34)*	*(5.46)*
Adj R^2		0.34	0.29	0.44	0.36
No. of observations		245	1125	369	1739
Panel B					
$\Delta ICS_{i,t-k,k=0,1}$	$\Sigma\beta_{i,t-k}$	0.45**	0.19**	0.54**	0.35***
		(2.47)	*(2.32)*	*(2.18)*	*(2.91)*
$\Delta CDS_{i,t-1}$	$\gamma_{i,t-1}$	0.22*	0.22***	0.25**	0.26***
		(1.83)	*(3.20)*	*(2.06)*	*(3.05)*
Adj R^2		0.27	0.16	0.25	0.21
No. of firms		92	92	92	92

Notes: This table depicts results from regressing changes in CDS spreads on contemporaneous and lagged changes in fundamentals (ICS) and lagged changes in CDS spreads for the overall sample period and three distinctive sub-periods: 2002 (Period 1), 2003 to mid-2007 (Period 2), and mid-2007 to 2008 (Period 3). Panel A presents the results from the time-series regression: $\Delta CDS_{m,t} = \alpha_m + \sum_{k=0}^{5} \beta_{m,t-k}\Delta ICS_{m,t-k} + \sum_{k=1}^{5} \gamma_{m,t-k}\Delta CDS_{m,t-k} + e_{m,t}$, conducted for the market level (i.e. for CDS_m and ICS_m market indices) using daily frequency. T-statistics are given in parentheses. Standard errors are calculated as Newey–West HAC Standard Errors. Panel B presents the mean regression results from 92 firm-specific time-series regressions: $\Delta CDS_{i,t} = \alpha_i + \sum_{k=0}^{1} \beta_{i,t-k}\Delta ICS_{i,t-k} + \gamma_{i,t-1}\Delta CDS_{i,t-1} + e_{i,t}$, conducted using weekly frequency.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

6.2 *Impact of demand–supply imbalances on CDS innovations*

In the second step, extracted daily CDS innovations at the market level and weekly CDS innovations at the firm-specific level are related to constructed imbalance measures (BAQ, Bidder, Offerer, NBA, and IMB) and control variables (bid–ask spread and trades-to-quotes ratio) within the multivariate regression framework of the following form:

$$CDS_{inov_t} = \alpha_0 + \delta_{imb}Imb_t + \delta_{ba}BA_t + \delta_{t2q}T2Q_t + \varepsilon_t. \quad (2)$$

The regression results based on the daily market CDS innovations are reported in Table 4, Panel A. As expected, demand pressure has a positive effect on CDS innovations (BAQ, Bidder, and NBA are statistically significant with positive sign). Supply pressure, on the other hand, has a negative effect on CDS innovations (Offerer measure is statistically significant with negative sign).[12] For the overall sample period, the demand–supply imbalance has little explanatory power (1–2%).[13] In terms of economic significance, a one standard deviation shock in demand pressure, measured by the overall imbalance factor (IMB), is equivalent to a 0.3 bp increase in the CDS innovations. Control variables are not found to be statistically significant.

Panel B of Table 4 depicts the results from multivariate time-series regressions of firm-specific weekly CDS innovations on different imbalance and control variables. Given that the data set now turns into a pooled time-series and cross-section unbalanced panel in which both firm and time

Table 4. Regressions of CDS innovations on imbalance measures.

Variable	BAQ		Offerer		Bidder		NBA		IMB	
Panel A: Market level										
$Imb_{m,t}$	2.83***	2.94***	−2.18***	−2.29**	2.75***	2.78***	1.51***	1.56***	0.20***	0.20***
	(5.08)	*(4.09)*	*(−3.11)*	*(−2.51)*	*(5.15)*	*(5.11)*	*(5.52)*	*(4.96)*	*(5.54)*	*(4.93)*
$BA_{m,t}$		0.01		0.01		0.00		0.00		0.01
		(0.49)		*(0.34)*		*(0.10)*		*(0.26)*		*(0.44)*
$T2Q_{m,t}$		−0.67		−0.59		−1.26		−0.53		−0.61
		(−0.48)		*(−0.42)*		*(−0.96)*		*(−0.38)*		*(−0.45)*
Adj R^2	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02
Panel B: Firm level										
$Imb_{i,t}$	2.64***	2.82***	−4.53***	−5.35***	6.51***	6.29***	1.63***	1.68***	0.67***	0.66***
	(4.29)	*(5.33)*	*(−3.40)*	*(−3.81)*	*(6.00)*	*(6.40)*	*(5.51)*	*(5.99)*	*(7.06)*	*(7.02)*
$BA_{i,t}$		0.11**		0.12**		0.11**		0.11**		0.11**
		(2.18)		*(2.24)*		*(2.16)*		*(2.14)*		*(2.19)*
$T2Q_{i,t}$		−0.51		0.81*		0.91**		−0.01		0.47
		(−0.69)		*(1.93)*		*(2.12)*		*(−0.01)*		*(1.10)*
Adj R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02

Notes: This table reports results obtained from regressing market-wide daily CDS innovations (Panel A) and firm-specific weekly CDS innovations (Panel B) on different imbalance measures (BAQ, Offerer, Bidder, NBA, and IMB), and control variables (BA and T2Q). Imbalance and control measures at the market level are calculated as cross-sectional averages at each time point. Panel A presents the results from estimating the following model: $CDS_{inov_{m,t}} = \alpha_0 + \delta_{imb}Imb_{m,t} + \delta_{ba}BA_{m,t} + \delta_{t2q}T2Q_{m,t} + \varepsilon_{m,t}$, with and without control variables. Number of observations is 1739. Standard errors are calculated as Newey–West HAC Standard Errors. T-statistics are given in parentheses. Panel B presents the results from estimating the following model: $CDS_{inov_{i,t}} = \alpha_0 + \delta_{imb}Imb_{i,t} + \delta_{ba}BA_{i,t} + \delta_{t2q}T2Q_{i,t} + \varepsilon_{i,t}$, with and without control variables. Number of observations is 25,268. Standard errors are clustered by time and firm dummies are included to control for the firm effect. T-statistics are given in parentheses.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

effects are present, standard errors must be corrected for the possible dependence in residuals. Following Petersen (2009) the firm effect is controlled for in a parametric form by including firm dummies, whereas the time effect is eliminated using clustered by time period standard errors.[14] To avoid the eventual effect of outliers, firm-specific weekly observations are included only if both bid and ask quotes are available.

Results at the firm-specific level confirm that all considered demand–supply imbalance measures are significant and with the expected sign: higher demand (supply) pressure is associated with higher (lower) CDS innovations. These results confirm that Hypothesis 1 holds at the market level and at the firm-specific level. As regards the control variables, the bid–ask spread now turns to be significantly positively related with CDS innovations. The trades-to-quotes ratio, when significant, is found to have a positive sign, although we would naturally expect a negative sign in all of the cases. One possible explanation could be the result of Acharya and Johnson (2007) who find evidence of informed trading in the most actively traded contracts suggesting, as in Tang and Yan (2007), that the risk of adverse selection is priced in the CDS market. In fact, if the baseline regression (2) is augmented with the interaction term between demand–supply imbalance and trading interest (measured by the number of quotes and trades), the interaction term turns out significant showing that trading interest magnifies the effect of demand–supply imbalances on CDS innovations. As the number of posted quotes and trades signals the arrival of new information to the market, this might suggest that informed trading comes from buyers of credit protection and that sellers are those that face adverse selection problems.

6.3 *Impact of demand–supply imbalances on CDS innovations in crisis vs. tranquil periods*

In order to investigate whether the demand pressure effect increases during the periods of financial crisis, I consider the supplementary model with a dummy variable interaction term Crisis (or $\text{Crisis}_{\text{sub}}$) of the following form:

$$\text{CDS}_{\text{inov}_t} = \alpha_0 + \alpha_1\text{Crisis} + (\delta_{\text{imb}} + \delta_{\text{imb,Crisis}}\text{Crisis})\text{Imb}_t + \text{Controls}_t + \varepsilon_t, \tag{3}$$

where $\text{Controls}_t = (\delta_{\text{ba}} + \delta_{\text{ba,Crisis}}\text{Crisis})\text{BA}_t + (\delta_{\text{t2q}} + \delta_{\text{t2q,Crisis}}\text{Crisis})\text{T2Q}_t$ and the interaction dummy variable Crisis takes the value 1 for the observations belonging to year 2002 or the sub-prime crisis period (mid-2003 to 2007), and the value 0 otherwise. Alternatively, an interaction dummy variable $\text{Crisis}_{\text{sub}}$ that takes the value 1 only for the sub-prime crisis period and 0 otherwise is considered.

The coefficients and corresponding t-statistics for crisis and non-crisis periods are depicted in Table 5. The overall picture differs substantially across considered sub-periods: the explanatory power and the slope of the imbalance coefficients considerably increases during crisis periods, especially during the sub-prime crisis.[15] To be specific, during the recent financial turmoil (Period 3) considered liquidity factors are able to explain up to 17% of the variations in daily CDS innovations on the aggregate market level (Table 5, Panel A). These findings are consistent with Acharya, Schaefer, and Zhang (2007). In the 'clinical study of Ford and GM downgrade', these authors corroborate that the measures of liquidity have little explanatory power in the quiet non-downgrade period (R^2 of the order of 1–3%), but substantial explanatory power during the stress downgrade period. Although imbalance measures are also significant and with the expected signs during the non-crisis period, the absolute value of the coefficients substantially rises in the period of the sub-prime crisis, suggesting a drastic increase in their economic significance. Specifically, in crisis times, a one standard deviation shock in the market-wide demand pressure, measured by the overall imbalance factor (IMB), is equivalent to a 1.5 bp increase in market-wide CDS

innovations. To put these numbers into perspective, Bühler and Trapp (2010) report an average overall liquidity premium of 1.94 bp for their sample of Euro-denominated CDS contracts between June 2001 and June 2007.

Results at the firm-specific level (Table 5, Panel B) are consistent with previous findings at the aggregate market level. Specifically, the explanatory power for the non-crisis period is around 1%, and for crisis periods it ranges between 3% and 7%. In terms of economic significance, at the firm-specific level, a one standard deviation shock in demand pressure is equivalent to a 0.5 bp increase in the CDS innovations during the tranquil periods, and a 2.2 bp increase in CDS innovations during the crisis periods, on average.

This empirical evidence is consistent with the theoretical framework of Brunnermeier and Pedersen (2009) and the argument of funding constraints of sellers in the CDS market (Hypothesis 2). As sellers are those who provide market liquidity in the CDS market, their ability to do so depends on their availability of funding. In non-crisis periods when capital is abundant, the sensitivity of the CDS innovations to demand–supply imbalances is low. In the crisis periods, however, when capital is scarce, funding conditions worsen, as does the risk of hitting the funding constraints. Under such conditions the sensitivity of the CDS innovations to demand pressure becomes significantly higher.

6.4 *Impact of market-wide demand–supply imbalances on firm-specific CDS innovations*

Another interesting issue to consider is to what extent firm-specific CDS innovations are influenced by the aggregate, market demand–supply imbalance. To investigate this question, I regress firm-specific CDS innovations not only on firm-specific imbalance measures (Imb_i), but also on aggregate market imbalance measures (Imb_{m}). The model takes the following form:

$$\text{CDS}_{\text{inov}_{i,t}} = \alpha_0 + \delta_{\text{i}}\text{Imb}_{i,t} + \delta_{\text{m}}\text{Imb}_{m,t} + \delta_{\text{ba}}\text{BA}_{i,t} + \delta_{\text{t2q}}\text{T2Q}_{i,t} + \varepsilon_{i,t}. \tag{4a}$$

$$\text{CDS}_{\text{inov}\,i,t} = \alpha_0 + \alpha_1\text{Crisis} + (\delta_{\text{i}} + \delta_{\text{i,Crisis}})\text{Imb}_{i,t} + (\delta_{\text{m}} + \delta_{\text{m,Crisis}})\text{Imb}_{m,t} + \text{Controls}_{i,t} + \varepsilon_{i,t}. \tag{4b}$$

The results from regressions (4a) and (4a), shown in Table 6, reveal that firm-specific CDS innovations are largely affected by the aggregate market imbalance. In particular, although the CDS innovations are affected by both firm-specific and aggregate market demand pressure, the economic effect is much more pronounced for the market-level variables. In normal regimes a one standard deviation increase in firm-specific demand pressure, measured by the overall imbalance factor (IMB), has the effect of a 0.3 bp increase in CDS innovations; however, the effect of a one standard deviation increase in aggregate market demand pressure is of 0.7 bp. The economic effect considerably amplifies during crisis periods: a one standard deviation shock in the firm-specific demand pressure is equivalent to a 1.5 bp increase in firm-specific CDS innovations, while a one standard deviation shock in the market-wide demand pressure increases firm-specific CDS innovations by almost 3 bp. These results indicate that market-wide liquidity has a stronger effect on CDS innovations than firm-specific liquidity does, which confirms Hypothesis 3 and the presence of liquidity commonalities in the CDS market. The effect of the firm-specific demand–supply imbalance is still present after accounting for the market-wide demand–supply imbalance. One possible explanation for this finding could be the presence of traders with private information on the underlying bond. Sellers faced with adverse selection problem will then charge a liquidity premium.

Table 5. Regressions of CDS innovations on imbalance measures: *Crisis vs. tranquil periods.*

Variable	BAQ		Offerer		Bidder		NBA		IMB	
Panel A: Crisis vs. Non-crisis periods – Market level										
Imb$_{m,t}$	1.20***	0.77**	−0.39	0.14	0.97***	0.94***	0.61***	0.57***	0.08***	0.06***
	(3.66)	*(2.07)*	*(−0.69)*	*(0.25)*	*(3.42)*	*(3.07)*	*(4.17)*	*(3.38)*	*(4.09)*	*(2.74)*
*Crisis**Imb$_{m,t}$	5.73**		−7.54**		14.60***		3.88***		0.48***	
	(2.50)		*(−2.20)*		*(4.17)*		*(3.87)*		*(3.35)*	
Crisis$_{sub}$*Imb$_{m,t}$		20.95***		−34.37***		27.77***		9.03***		1.35***
		(6.41)		*(−5.98)*		*(6.40)*		*(6.92)*		*(6.94)*
Adj R^2	0.03	0.11	0.02	0.08	0.05	0.09	0.05	0.10	0.05	0.11
Adj R^2 − *Crisis*	0.04	0.16	0.02	0.12	0.06	0.13	0.05	0.16	0.05	0.17
Adj R^2 − *Non − Crisis*	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Panel B: Crisis vs. Non-crisis periods – Firm level										
Imb$_{i,t}$	1.49***	2.22***	−1.26	−2.33**	2.58***	4.21***	0.79***	1.20***	0.30***	0.43***
	(3.59)	*(4.32)*	*(−1.47)*	*(−2.31)*	*(3.29)*	*(4.50)*	*(3.66)*	*(4.72)*	*(4.15)*	*(4.84)*
Crisis Imb$_{i,t}$	4.06***		−11.18***		10.53***		2.64***		0.91***	
	(2.93)		*(−3.77)*		*(4.28)*		*(3.90)*		*(4.42)*	
Crisis$_{sub}$ *Imb$_{i,t}$		1.90**		−11.49**		9.05***		1.71**		0.92***
		(2.50)		*(−2.55)*		*(2.92)*		*(2.14)*		*(3.03)*
Adj R^2	0.02	0.03	0.02	0.03	0.02	0.03	0.02	0.03	0.02	0.03
Adj R^2–*Crisis*	0.03	0.06	0.03	0.06	0.03	0.07	0.03	0.06	0.03	0.07
Adj R^2–*Non-Crisis*	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Notes: This table reports results obtained from estimating the model with a dummy variable interaction term Crisis or Crisis$_{sub}$, where Crisis is a dummy variable that takes the value 1 for the observations belonging to year 2002 and sub-prime period (mid-2003 to 2007). Crisis$_{sub}$ is a dummy variable that takes the value 1 only for the sub-prime crisis period and 0 otherwise. Panel A presents the results at the market level from estimating the following model: $CDS_{inov_{m,t}} = \alpha_0 + \alpha_1 Crisis + (\delta_{imb} + \delta_{imb,Crisis} Crisis) Imb_{m,t} + Controls_{m,t} + \varepsilon_{m,t}$ with and without control variables. Number of observations is 1739. Standard errors are calculated as Newey–West HAC Standard Errors. *T*-statistics are given in parentheses. Panel B presents the results at the firm-specific level from estimating the following model: $CDS_{inov_{i,t}} = \alpha_0 + \alpha_1 Crisis + (\delta_{imb} + \delta_{imb,Crisis} Crisis) Imb_{i,t} + Controls_{i,t} + \varepsilon_{i,t}$, with and without control variables. Number of observations is 25,268. Standard errors are clustered by time and firm dummies are included to control for the firm effect. *T*-statistics are given in parentheses. Coefficients for control variables are not reported to save space.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

Table 6. Regressions of weekly CDS innovations on firm and market imbalance measures.

Variable	BAQ		Offerer		Bidder		NBA		IMB	
Panel A: Whole sample										
Imb$_{i,t}$	1.83***	1.91***	−4.83***	−4.81***	4.52***	4.43***	0.98***	1.00***	0.45***	0.44***
	(3.72)	*(3.65)*	*(−4.41)*	*(−4.42)*	*(4.83)*	*(4.94)*	*(3.83)*	*(3.83)*	*(5.54)*	*(5.30)*
Imb$_{m,t}$	11.20***	12.51***	−4.03	−2.74	8.99***	8.59***	8.41***	8.64***	0.83***	0.87***
	(3.80)	*(3.86)*	*(−0.32)*	*(−1.39)*	*(2.91)*	*(2.94)*	*(4.23)*	*(4.29)*	*(4.26)*	*(4.47)*
BA$_{i,t}$		0.12**		0.12**		0.11**		0.11**		0.12**
		(2.27)		*(2.24)*		*(2.15)*		*(2.19)*		*(2.22)*
T2Q$_{i,t}$		−0.45		0.83*		0.83**		−0.01		0.29
		(−0.79)		*(1.95)*		*(2.02)*		*(−0.02)*		*(0.80)*
Adj R^2	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.02

(*Continued*)

Table 6. Continued.

Variable	BAQ		Offerer		Bidder		NBA		IMB	
Panel B: Crisis vs. Non-crisis periods										
$Imb_{i,t}$	0.89**	1.61***	−0.79	−2.95***	1.46**	3.28***	0.37*	0.75***	0.16**	0.30***
	(2.06)	*(3.55)*	*(−0.85)*	*(−2.64)*	*(2.34)*	*(3.95)*	*(1.96)*	*(3.24)*	*(2.47)*	*(3.85)*
$Crisis*Imb_{i,t}$	3.04**		−8.87***		7.78***		2.02***		0.68***	
	(2.49)		*(−3.75)*		*(3.67)*		*(3.19)*		*(3.65)*	
$Crisis_{sub}*Imb_{i,t}$		1.05		−7.75**		4.76*		1.12		0.65***
		(1.35)		*(−2.53)*		*(1.95)*		*(1.47)*		*(2.68)*
$Imb_{m,t}$	7.17***	7.56***	−1.95	−2.74	3.75***	3.58***	4.46***	5.09***	0.45***	0.51***
	(4.09)	*(3.42)*	*(−1.09)*	*(−1.13)*	*(3.39)*	*(2.63)*	*(4.70)*	*(4.03)*	*(4.31)*	*(3.85)*
$Crisis*Imb_{m,t}$	27.99***		−20.98**		72.04***		20.09***		2.48***	
	(2.86)		*(−2.10)*		*(3.01)*		*(2.96)*		*(3.19)*	
$Crisis_{sub}*Imb_{m,t}$		30.83*		−58.51		89.71***		18.40*		2.35**
		(1.89)		*(−1.60)*		*(3.11)*		*(1.89)*		*(2.12)*
Adj R^2	0.03	0.04	0.02	0.03	0.03	0.04	0.04	0.04	0.04	0.04
Adj R^2–*Crisis*	0.04	0.07	0.03	0.07	0.04	0.08	0.04	0.07	0.04	0.08
Adj R^2–*Non-Crisis*	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.01

Notes: This table shows the coefficients and corresponding t-statistics from regressing firm-specific CDS innovations on different firm-specific (Imb_i) and market-wide (Imb_m) imbalance measures (BAQ, Offerer, Bidder, NBA, and IMB). Panel A presents the results from estimating the following model: $CDS_{inov_{i,t}} = \alpha_0 + \delta_i Imb_{i,t} + \delta_m Imb_{m,t} + \delta_{ba} BA_{i,t} + \delta_{t2q} T2Q_{i,t} + \varepsilon_{i,t}$, with and without control variables. Panel B presents the results from estimating the model with a dummy variable interaction term Crisis or $Crisis_{sub}$ of the following form: $CDS_{inov_{i,t}} = \alpha_0 + \alpha_1 Crisis + (\delta_i + \delta_{i,Crisis}) Imb_{i,t} + (\delta_m + \delta_{m,Crisis}) Imb_{m,t} + Controls_{i,t} + \varepsilon_{i,t}$, where Crisis is a dummy variable that takes the value 1 for the observations belonging to year 2002 and sub-prime period (mid-2003 to 2007). $Crisis_{sub}$ variable is a dummy variable that takes the value 1 only for the sub-prime crisis period and 0 otherwise. Coefficients for control variables in Panel B are not reported to save space. Number of observations is 25,268. Standard errors are clustered by time and firm dummies are included to control for the firm effect. T-statistics are given in parentheses.

*Significance at the 10% level.

**Significance at the 5% level.

***ignificance at the 1% level.

Table 7. Regressions of weekly CDS innovations on firm and market imbalance measures.

Variable	BAQ		Offerer		Bidder		NBA		IMB	
$Imb_{i,t}$		1.91***		−4.85***		4.47***		1.02***		0.44***
		(3.90)		*(−4.18)*		*(4.89)*		*(3.78)*		*(5.25)*
$Imb_{m,t}$		14.31***		0.57		7.52**		9.90***		0.94***
		(3.74)		*(0.11)*		*(2.49)*		*(3.89)*		*(3.98)*
$SImb_{m,t}$	6.20**	−3.21	−17.18*	−14.69	10.93	3.66	4.27**	−2.21	0.50**	−0.15
	(2.28)	*(−0.91)*	*(−1.85)*	*(−1.51)*	*(1.46)*	*(0.48)*	*(2.24)*	*(−0.92)*	*(2.15)*	*(−0.56)*
$BA_{i,t}$	0.11**	0.12**	0.11**	0.12**	0.11**	0.11**	0.11**	0.11**	0.11**	0.12**
	(2.18)	*(2.28)*	*(2.20)*	*(2.21)*	*(2.20)*	*(2.16)*	*(2.22)*	*(2.19)*	*(2.20)*	*(2.22)*
$T2Q_{i,t}$	0.68	−0.42	0.82*	0.82*	0.85*	0.87*	0.71	0.00	0.72	0.31
	(1.55)	*(−0.64)*	*(1.77)*	*(1.76)*	*(1.77)*	*(1.80)*	*(1.60)*	*(0.01)*	*(1.61)*	*(0.70)*
Adj R^2	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.02

Notes: This table shows the coefficients and corresponding t-statistics from regressing firm-specific CDS innovations on different firm-specific (Imb_i) and market-wide (Imb_m) imbalance measures (BAQ, Offerer, Bidder, NBA, and IMB), market-wide shocks to demand (supply) pressure ($SIMb_m$), and control variables (BA and T2Q) in a model of the following form: $CDS_{inov_{i,t}} = \alpha_0 + \delta_i Imb_{i,t} + \delta_m imb_{m,t} + \delta_{sm} SImb_{m,t} + \delta_{ba} BA_{i,t} + \delta_{t2q} T2Q_{i,t} + \varepsilon_{i,t}$. Imbalance and control measures at the market level are calculated as cross-sectional averages at each time point. Shocks to demand (supply) pressure are constructed from residuals of an AR(1) regression model of the variation in demand–supply imbalance. Number of observations is 24,632. Standard errors are clustered by time and firm dummies are included to control for the firm effect. T-statistics are given in parentheses.

*Significance at the 10% level.

**Significance at the 5% level.

***Significance at the 1% level.

Given the evidence of a strong effect of market-wide demand–supply imbalances, I examine further if firm-specific CDS innovations are affected by shocks to aggregate balance between demand and supply of credit protection. Common liquidity shocks are defined as innovations in market-wide demand–supply variables. Given that lagged demand–supply imbalances affect CDS innovations for up to five days, liquidity risk factor for weekly data is constructed from residuals of an AR(1) regression model of the variation in demand–supply imbalance measures. Results from regressing firm-specific CDS innovations on the firm-specific and market-wide demand–supply imbalance, as well as on the market-wide shocks to demand (supply) pressure, are presented in Table 7. Reported results suggest that unexpected contemporaneous demand (supply) shocks have a positive (negative) impact on contemporaneous firm-specific CDS innovations. However, if both market-wide demand–supply imbalance and shocks to demand (supply) pressure are entered in the same specification, the effect of unexpected changes in demand or supply pressure disappears. This is in line with Bongaerts, de Jong, and Driessen (2011) who find that most of the liquidity effect in the CDS market comes from the expected liquidity component.

6.5 *Impact of demand–supply imbalances on CDS innovations for investment vs. sub-investment grade issuers*

Another issue to explore is the eventual difference of the demand pressure effect, conditional on the rating of the underlying reference entity. In order to analyze this issue the following model with interaction effects is estimated:

$$CDS_{inov_{i,t}} = \alpha_0 + \alpha_1 Junk + (\delta_i + \delta_{i,Junk}) Imb_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, \qquad (5)$$

where $\text{Controls}_t = (\delta_{ba} + \delta_{ba,Junk}\text{Junk})\text{BA}_t + (\delta_{t2q} + \delta_{t2q,Junk}\text{Junk})\text{T2Q}_t$, and the interaction dummy variable Junk takes the value 1 if the underlying reference entity at time t has a speculative grade status (BB+ and lower) and 0 if it has an investment grade status (BBB− and higher). In total, the majority of observations refer to investment grade issuers (89%). Results from estimating Equation (5) are illustrated in Table 8. Essentially, the main findings from regressing CDS innovations on imbalance factors in terms of sign and significance of the coefficients remain the same across the two different rating classes. Moreover, there seems to be no substantial difference, in terms of explanatory power, between investment grade and speculative grade sub-samples. In absolute and relative terms, the economic effect is grater for the speculative grade sub-sample. A one standard deviation shock in demand pressure has the effect of a 4.2 bp increase in CDS innovations (13.6% of the average bid–ask spread) for the non-investment grade, and of 0.8 bp (8.8% of the average bid–ask spread) for the investment grade sub-sample. This finding supports Hypothesis 4.

6.6 *Robustness checks*

To ensure the robustness of the presented findings several additional analyses are conducted.[16] First consideration is given to the way the parameters of the structural model, and consequently ICSs, are estimated. In order to ensure the robustness of the results I consider the possibility of estimating the default barrier parameter using the smooth-pasting condition value. In this way, all unknown parameters of the model (volatility, default barrier, and firm's asset value) are estimated exclusively from the stock market and a small set of balance sheet and income statement items. Second, in order to show that results of the paper are not affected by the specific measure of default and/or methodology used, the analysis is replicated using the distance-to-default as a measure of default risk. Distance-to-default is calculated as described in Crosbie and Bohn (2003). The results obtained using either new ICSs or the distance-to-default measure are virtually the same as those reported in the paper, confirming that neither the default barrier specification nor the method applied alter the dynamics of CDS innovations.

Third, I consider the model described in Equation (6), in which changes in CDS spreads are regressed on contemporaneous and lagged changes in fundamentals (ICSs), lagged changes in CDS spreads, and contemporaneous and lagged changes in different imbalance measures (Imb):

$$\Delta \text{CDS}_t = \alpha + \sum_{k=0}^{l} \beta_{t-k}\Delta \text{ICS}_{t-k} + \sum_{k=1}^{l} \gamma_{t-k}\Delta \text{CDS}_{t-k} + \sum_{k=0}^{l} \delta_{\text{imb},t-k}\Delta \text{Imb}_{t-k}$$
$$+ \sum_{k=0}^{l} \delta_{\text{ba},t-k}\Delta \text{BA}_{t-k} + \sum_{k=0}^{l} \delta_{\text{t2q},t-k}\Delta \text{T2Q}_{t-k} + e_t, \tag{6}$$

where lag length, l, is set to 5 for daily frequency and market level, and to 1 for weekly frequency and firm-specific level. The estimation results are presented in Table 9. Panel A depicts results for the aggregate market level and Panel B results for the firm-specific level. The signs of the significant coefficients are consistent with previous findings. Namely, an increase in the demand pressure proxied by positive changes in BAQ, Bidder, and NBA measures is positively related to changes in CDS spreads. In contrast, an increased supply pressure, proxied by positive changes in the Offerer measure, is negatively related to changes in CDS spreads. The hypothesis that the sum of the imbalance coefficients equals zero is strongly rejected at the 1% level in all of the cases.

Table 8. Regressions of non-investment grade vs. investment grade observations.

Variable	BAQ		Offerer		Bidder		NBA		IMB	
$\text{Imb}_{i,t}$	1.77***	1.81***	−3.84***	−5.03***	4.51***	4.28***	1.28***	1.14***	0.49***	0.49***
	(3.63)	*(3.91)*	*(−3.96)*	*(−6.65)*	*(5.16)*	*(5.80)*	*(5.42)*	*(4.97)*	*(6.26)*	*(6.24)*
Junk *$\text{Imb}_{i,t}$	12.14***	12.38***	−11.40	−10.36	18.18***	19.10***	3.51**	5.03***	2.10***	2.15***
	(3.43)	*(3.55)*	*(−1.44)*	*(−1.49)*	*(3.28)*	*(3.33)*	*(2.12)*	*(2.82)*	*(3.34)*	*(3.38)*
$\text{BA}_{i,t}$		0.22**		0.22***		0.22**		0.22**		0.22**
		(2.19)		*(3.32)*		*(2.19)*		*(2.18)*		*(2.20)*
Junk *$\text{BA}_{i,t}$		−0.22*		−0.22**		−0.23*		−0.22*		−0.22*
		(−1.92)		*(−2.03)*		*(−1.96)*		*(−1.94)*		*(−1.95)*
$\text{T2Q}_{i,t}$		0.09		1.08**		1.15**		0.43		0.78**
		(0.12)		*(2.01)*		*(2.10)*		*(0.67)*		*(1.50)*
Junk* $\text{T2Q}_{i,t}$		−2.03		−2.15		−1.37		−1.70		−1.81
		(−0.80)		*(−1.19)*		*(−0.76)*		*(−0.91)*		*(−1.00)*
Adj R^2	0.01	0.03	0.01	0.03	0.01	0.03	0.01	0.03	0.01	0.03
Adj R^2–*Junk*	0.01	0.02	0.00	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Adj R^2–*Investment*	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05

Notes: This table shows coefficients and corresponding t-statistics from estimating the following model: $\text{CDS}_{\text{inov}_{i,t}} = \alpha_0 + \alpha_1\text{Junk} + (\delta_i + \delta_{i,\text{Junk}})\text{Imb}_{i,t} + \text{Controls}_{i,t} + \varepsilon_{i,t}$, with and without control variables, where Junk is an interaction dummy variable that takes the value 1 if the underlying reference entity at time t has the speculative grade status (BB+ and lower) and 0 if the underlying reference entity at time t has the investment grade status (BBB− and higher). Number of observations is 25,268. Standard errors are clustered by time and firm dummies are included to control for the firm effect. T-statistics are given in parentheses.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

Table 9. Regression results.

Variable	Coefficient	BAQ		Offerer		Bidder		NBA		IMB	
Panel A: Market level											
$\Delta ICS_{m,t-k,k=0,\ldots,5}$	$\Sigma\beta_{m,t-k}$	0.42***	0.41***	0.43***	0.42***	0.41***	0.40***	0.43***	0.41***	0.41***	0.40***
		(6.43)	*(6.48)*	*(6.58)*	*(6.62)*	*(6.44)*	*(6.50)*	*(6.38)*	*(6.35)*	*(6.38)*	*(6.42)*
$\Delta CDS_{m,t-k,k=1,\ldots,5}$	$\Sigma\gamma_{m,t-k}$	0.42***	0.40***	0.41***	0.39***	0.42***	0.40***	0.41***	0.39***	0.42***	0.40***
		(5.77)	*(5.41)*	*(5.61)*	*(5.25)*	*(5.73)*	*(5.39)*	*(5.46)*	*(5.16)*	*(5.84)*	*(5.47)*
$\Delta Imb_{m,t-k,k=0,\ldots,5}$	$\Sigma\delta_{imb,m,t-k}$	15.76***	14.02***	−20.48***	−18.46***	22.45***	20.20***	3.23***	3.08***	1.12***	1.00***
		(3.76)	*(3.42)*	*(−3.32)*	*(−3.13)*	*(3.59)*	*(3.36)*	*(3.71)*	*(3.57)*	*(3.98)*	*(3.66)*
$\Delta BA_{m,t-k,k=0,\ldots,5}$	$\Sigma\delta_{ba,m,t-k}$		0.24		0.25		0.24		0.25		0.22
			(0.80)		*(0.86)*		*(0.81)*		*(0.83)*		*(0.77)*
$\Delta T2Q_{m,t-k,k=0,\ldots,5}$	$\Sigma\delta_{t2q,m,t-k}$		−4.28		−3.50		−5.46		−2.99		−3.95
			(−0.73)		*(−0.62)*		*(−1.00)*		*(−0.40)*		*(−0.68)*
Adj R^2		0.37	0.41	0.37	0.40	0.38	0.41	0.38	0.42	0.38	0.41
Panel B: Firm level											
$\Delta ICS_{i,t-k,k=0,1}$	$\Sigma\beta_{i,t-k}$	0.48***	0.47***	0.48***	0.47***	0.47***	0.47***	0.46***	0.47***	0.47***	0.47***
		(8.53)	*(8.15)*	*(8.55)*	*(8.17)*	*(8.52)*	*(8.15)*	*(8.63)*	*(8.15)*	*(8.49)*	*(8.12)*
$\Delta CDS_{i,t-1}$	γ_{t-1}	0.21***	0.16***	0.21***	0.16***	0.21***	0.16***	0.19***	0.16***	0.21***	0.16***
		(3.30)	*(2.81)*	*(3.31)*	*(2.82)*	*(3.31)*	*(2.83)*	*(3.17)*	*(2.82)*	*(3.29)*	*(2.81)*
$\Delta Imb_{i,t-k,k=0,1}$	$\Sigma\delta_{imb,i,t-k}$	2.27***	2.20***	−9.49***	−10.14***	8.84***	7.95***	1.91***	1.67***	0.81***	0.74***
		(2.77)	*(2.72)*	*(−5.17)*	*(−5.53)*	*(5.97)*	*(5.40)*	*(4.04)*	*(2.92)*	*(5.58)*	*(4.98)*
$\Delta BA_{i,t-k,k=0,1}$	$\Sigma\delta_{ba,i,t-k}$		0.71***		0.72***		0.71***		0.71***		0.71***
			(3.62)		*(3.65)*		*(3.62)*		*(3.61)*		*(3.61)*
$\Delta T2Q_{i,t-k,k=0,1}$	$\Sigma\delta_{t2q,i,t-k}$		0.60		1.73**		1.95***		0.93		1.38*
			(0.62)		*(2.42)*		*(2.62)*		*(1.06)*		*(1.88)*
Adj R^2		0.21	0.30	0.21	0.30	0.21	0.30	0.20	0.30	0.21	0.30

Notes: This table reports results obtained from estimating the model of the following form: $\Delta CDS_t = \alpha + \sum_{k=0}^{l}\beta_{t-k}\Delta ICS_{t-k} + \sum_{k=1}^{l}\gamma_{t-k}\Delta CDS_{t-k} + \sum_{k=0}^{l}\delta_{imb,t-k}\Delta Imb_{t-k} + \sum_{k=0}^{l}\delta_{ba,t-k}\Delta BA_{t-k} + \sum_{k=0}^{l}\delta_{t2q,t-k}\Delta T2Q_{t-k} + e_t$ where lag length, l, is set to 5 for daily frequency and market level (Panel A), and to 1 for weekly frequency and firm-specific level (Panel B). Imb refers to different imbalance measures (BAQ, Offerer, Bidder, NBA and IMB). For daily frequency and market-level standard errors are calculated as Newey–West HAC Standard Errors. For weekly frequency and firm-specific level standard errors are clustered by time and firm dummies are included to control for the firm effect. T-statistics are given in parentheses.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

The other valid approach would be to consider deviations from the long-run equilibrium relationship between CDS and ICS series. If we depart from the idea that CDS spreads and ICSs price credit risk equally in the long run, then we can apply the cointegration approach and explore the transitory movements in CDS spreads. Given that the CDS spread series are integrated of order 1, innovations in CDS spreads contain at least one permanent component which should be directly associated with permanent changes in fundamentals. If there exists a linear combination of CDS spreads and ICSs that is stationary, then there exists a time-varying long-run equilibrium relationship between employed variables. Furthermore, if changes in ICSs are only the reflection of permanent changes in fundamentals, transitory changes in CDS spreads (CDS innovations) would correspond to changes in cointegrating residuals.

The presence of cointegration is tested on the basis of the econometric methodology developed by Johansen and Juselius (1990) and Johansen (1996). If variables are cointegrated, then they allow the vector error correction model representation, defined shortly as:

$$\Delta Y_t = \mu_0 + \alpha\beta' Y_{t-1} + \sum_{i=1}^{\infty}\Gamma_i \Delta Y_{t-i} + \varepsilon_t. \tag{7}$$

where Y_t is a 2×1 vector of $I(1)$ time series ($Y_t' = [CDS_t; ICS_t]$), $\Delta = 1 - L$ is the lag operator, Π and Γ_i are $p \times p$ matrices of coefficients, and μ_0 is a vector of constants. The specification that is estimated allows for a separate drift in VAR and a non-zero mean for the cointegrating equation. I find significant cointegrating relationships for 51 companies (55% of the sample) at the 5% significance level, and for 56 companies (61% of the sample) at the 10% significance level. A significant cointegration relationship for the majority of the examined companies further implies that structural models are able to price credit risk in the long run.

For the sub-sample of companies with a significant cointegrating relationship at the 10% level, CDS innovations streaming from the cointegrating residuals are first aggregated to weekly levels and then related to different imbalance measures. In this way I deal only with short-run movements in firm-specific CDS spreads that are not explained by firm-specific fundamentals. The regression framework is summarized in Equation (8). It contains contemporaneous and one-period lagged imbalance measures, as well as one-period lagged dependent variable as cointegrating residuals seem to be quite persistent:

$$\begin{aligned} CDS_{inov_{i,t}} = {} & \alpha + \sum_{k=0}^{1}\delta_{imb,k}Imb_{i,t-k} + \sum_{k=0}^{1}\delta_{ba,k}BA_{i,t-k} + \sum_{k=0}^{1}\delta_{t2q,k}T2Q_{i,t-k} \\ & + \eta_{t-1}CDS_{inov_{i,t-1}} + \varepsilon_{i,t}. \end{aligned} \tag{8}$$

Results for the overall sample period with and without control variables are depicted in Table 10. The reported slopes and t-statistics (in parentheses) are computed using firm dummies and clustering by time. Results are consistent with previous findings and indicate that imbalance measures significantly influence short-run CDS transitory movements in the expected direction.

As an additional robustness check, I consider the possibility that demand–supply imbalance might be correlated with credit risk. Precisely for that reason the analysis in this paper does not consider changes in CDS spreads directly but CDS innovations that back out the effect of contemporaneous and lagged fundamentals. It could be argued, however, that ICS do not account for the credit risk completely, and that the problem of endogeneity between CDS innovations and demand–supply imbalance might be an issue. To be specific, the ICS as a measure of default is constructed using the information from the stock market. Given the possibility that the speed with

Table 10. Regression results – cointegration approach.

Variable	Coefficient	BAQ		Offerer		Bidder		NBA		IMB	
$\mathrm{Imb}_{i,t-k,k=0,1}$	$\Sigma\delta_{\mathrm{imb}_{i,t-k}}$	5.60***	5.36***	−5.09*	−4.79*	10.64***	9.68***	3.88***	3.68***	1.22***	1.14***
		(3.03)	*(3.06)*	*(−1.92)*	*(−1.94)*	*(3.57)*	*(3.73)*	*(3.92)*	*(3.98)*	*(4.39)*	*(4.61)*
$\mathrm{BA}_{i,t-k,\ k=0,1}$	$\Sigma\delta_{\mathrm{ba},i,t-k}$		0.51**		0.52**		0.51**		0.51**		0.51**
			(2.56)		*(2.58)*		*(2.56)*		*(2.55)*		*(2.56)*
$\mathrm{T2Q}_{i,t-k,k=0,1}$	$\Sigma\delta_{t2q,i,t-k}$		0.62		0.91		1.02		0.65		0.70
			(0.58)		*(0.83)*		*(0.91)*		*(0.61)*		*(0.66)*
$\mathrm{CDS}_{\mathrm{inov}_{i,t-1}}$	γ_{t-1}	0.11*	0.10	0.11*	0.10	0.11*	0.10	0.11**	0.10	0.11*	0.10
		(1.85)	*(1.47)*	*(1.89)*	*(1.50)*	*(1.86)*	*(1.49)*	*(2.01)*	*(1.47)*	*(1.85)*	*(1.48)*
Adj R^2		0.02	0.05	0.01	0.05	0.02	0.05	0.02	0.05	0.02	0.05

Notes: This table reports the results obtained from estimating the following model: $\mathrm{CDS}_{\mathrm{inov}_{i,t}} = \alpha + \sum_{k=0}^{1} \delta_{\mathrm{imb},k}\mathrm{Imb}_{i,t-k} + \sum_{k=0}^{1} \delta_{\mathrm{ba},k}\mathrm{BA}_{i,t-k} + \sum_{k=0}^{1} \delta_{t2q,k}\mathrm{T2Q}_{i,t-k} + \eta_{t-1}\mathrm{CDS}_{\mathrm{inov}_{i,t-1}} + \varepsilon_{i,t}$ in which CDS innovations are obtained as changes in cointegrating residuals. Regressions are estimated using weekly frequency. Number of observations is 16,955. The reported slopes and t-statistics (in parentheses) are computed using firm dummies and clustering by time.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

which the stock and the CDS market incorporate information as regards credit risk is different, the estimation of CDS innovations as the non-default portion of the CDS changes might be affected. To address the concern of endogeneity I first apply the most common approach: CDS innovations are regressed on the lagged imbalance measures. Results are completely consistent with previous findings. Second, to ensure that results reported in the paper are not affected by information asymmetries between the stock and the CDS market as regards credit risk, I estimate the time-varying Gonzalo and Granger (1995) and Hasbrouck (1995) measures of information shares using the methodology described in Forte and Lovreta (forthcoming). Adding these additional explanatory variables in the baseline regression framework does not affect the results reported in this paper. Finally, I regress CDS innovations on several commonly used aggregate risk measures that are not explicitly captured by the structural model: changes in the aggregate rating, return on the EURO STOXX 50, and changes in the VSTOXX index. Aggregate credit rating is obtained by averaging credit ratings across reference entities using the numerical scale of Odders-White and Ready (2006). Return on the EURO STOXX 50 is used as a proxy for changes in the overall business climate (Collins-Dufresne, Goldstein, and Martin 2001). The VSTOXX is the implied volatility derived from EURO STOXX 50 Index Options and is used as a proxy for changes in investors risk aversion (Pan and Singleton 2008). Results show that CDS innovations are not explained with these aggregate risk factors.

Finally, in order to ensure the robustness of the results to the way in which daily CDS spread observations are constructed, all the analyses conducted in this study are repeated for several alternative ways of constructing daily CDS spread observations. The first alternative is as follows: if on a given day both bid and ask quotes are present, then the CDS spread refers to the midpoint of the average bid and average ask quotes; if only bid (ask) quotes are available on a particular day, then the ask (bid) is computed assuming that the relative bid–ask spread is equal to the one on the previous most recent day. The second possibility refers to using only two-sided quotes when calculating CDS spread observations. The third possibility consists of using only realized transaction entries as reference CDS spread observations. Main findings of the study are not materially affected by these different CDS specifications.

7. Conclusions

The recent financial crisis has put doubt on considering CDS spreads as a 'pure' measure of credit risk by revealing their clear sensitivity to liquidity shocks. To shed light upon this issue, I empirically examine the effect of demand–supply imbalances on changes in CDS spreads that cannot be attributed to fundamentals. Theoretical determinants of credit risk are jointly accounted for by means of theoretical stock market implied credit spreads derived on the basis of a structural credit risk model. Data set consists of a large and homogenous sample of 92 non-financial European companies with the most actively traded CDS contracts during 2002–2008 period.

Results indicate that short-term CDS price movements, not related to fundamentals, are affected by demand–supply imbalance. An increase in the demand pressure, captured by various imbalance measures, has a positive effect on CDS prices, especially during the recent financial turmoil. This indicates that CDS spreads reflect not only the price of credit protection, but also a premium charged by protection sellers in situations when it becomes more difficult to offset the taken position. Results also suggest that the market-wide demand pressure has a stronger effect on CDS innovations than the firm-specific one. The demand–supply imbalance effect on CDS spreads remains even after controlling for the transaction costs measured by the bid–ask spread, suggesting that demand–supply imbalance should be undoubtedly considered as an important liquidity factor in the context of the CDS market.

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Notes

1. Tang and Yan (2007) consider also the number of quotes, the probability of informed trading, and the order imbalance as auxiliary measures of liquidity environment, and use them to separate segments of the CDS market with distinctive liquidity features.
2. The GFI CDS database has been previously used by Hull, Predescu, and White (2004), Predescu (2005), Saita (2006), and Nashikkar, Subrahmanyam, and Mahanti (2011), among others.
3. The data are previously corrected for errors using both experienced data analysts and statistical cleansing algorithms by GFI.
4. On the initiative of the International Swaps & Derivatives Association (ISDA), the 'Big-Bang' protocol with new CDS convention – the Standard North American Contract – was launched in April 2009. For the European region the standardization began from June 2009. Therefore, these events do not affect the data in the sample considered.
5. Two-sided quotes are joint observations of bid and ask quotes at the same point of time.
6. The analysis is verified for different specifications of the recovery rate.
7. The subset of balance sheet and income statement items used in the estimation include short-term liabilities (STL) and long-term liabilities (LTL), interest expenses (IE), and cash dividends. Data on these items are downloaded from Datastream.
8. Although there is also the possibility to refer to the iTraxx index here, I refrain from such approach for several reasons. First, the iTraxx index is available on a regularly basis only from mid-2004, what would imply a considerable reduction in the sample period. Second, constituencies of the iTraxx index have been changing over time, resulting in the loss of homogeneity.
9. Firm-specific imbalance measures are calculated only in the case when both – bid and ask quotes – are present on a given trading day.
10. In the original study Acharya and Johnson (2007) extract CDS innovations on the basis of nonlinearly related equity returns, used as a reflection of fundamentals. Instead, I use theoretical credit spreads – ICS.
11. Most of the explanatory power can be attributed to contemporaneous and lagged changes in ICSs. This is demonstrated by estimating reduced models in which either (a) lagged changes in CDS spreads or (b) contemporaneous and lagged changes in ICSs are omitted.
12. The analysis is also conducted for the absolute demand/supply imbalance as described in Meng and Gwilym (2008). The sign of this imbalance measure is not stable suggesting that what matters for CDS pricing is whether the imbalance comes from demand or supply side, not the general imbalance. Given that in the CDS market demand for credit protection more frequently surpasses the supply, in general the impact of the absolute imbalance is found to be positive.
13. The aim of the paper is to see if there is any significant relationship between demand (supply) pressure and CDS innovations. Despite the low R^2 we can still obtain valuable information and draw important conclusions about how changes in demand pressure are associated with changes in CDS innovations.
14. Standard errors clustered by time are higher than White standard errors and somewhat higher than standard errors clustered by firm.
15. CDS innovations are estimated separately for the three considered sub-periods to allow for eventual structural shifts in the CDS–ICS dynamics.
16. For the sake of brevity most of the results in this section are omitted. Unreported results are available upon request.

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Appendix 1

The model

The market value of total assets at any time t, V_t, is assumed to evolve according to the continuous diffusion process:

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dz, \tag{A1}$$

where μ is the expected rate of return on the asset value, δ is the fraction of the asset value paid out to investors, σ is the asset return volatility, and z is a standard Brownian motion. Default occurs whenever V_t reaches a specific critical point V_b, defined as a fraction β of the nominal value of total debt P:

$$V_b = \beta P. \tag{A2}$$

With Forte (2011) modification of the original Leland and Toft (1996) model, the value of an individual bond d_n, with maturity τ_n, principal p_n, and constant coupon flow c_n is given by

$$d_n(V_t, \tau_n) = \frac{c_n}{r} + e^{-r\tau_n}\left[p_n - \frac{c_n}{r}\right][1 - F_t(\tau_n)] + \left[(1-\alpha)\beta p_n - \frac{c_n}{r}\right]G_t(\tau_n), \tag{A3}$$

for $n = \{1, \ldots, N\}$, where r is the risk-free rate, α represents bankruptcy costs, and

$$F_t(\tau_n) = \Phi[h_{1t}(\tau_n)] + \left(\frac{V_t}{V_b}\right)^{-2a}\Phi[h_{2t}(\tau_n)],$$

$$G_t(\tau_n) = \left(\frac{V_t}{V_b}\right)^{-a+z}\Phi[q_{1t}(\tau_n)] + \left(\frac{V_t}{V_b}\right)^{-a-z}\Phi[q_{2t}(\tau_n)];$$

where

$$q_{1t} = \frac{-b_t - z\sigma^2\tau_n}{\sigma\sqrt{\tau_n}}; \qquad q_{2t} = \frac{-b_t + z\sigma^2\tau_n}{\sigma\sqrt{\tau_n}};$$

$$h_{1t} = \frac{-b_t - a\sigma^2\tau_n}{\sigma\sqrt{\tau_n}}; \qquad h_{2t} = \frac{-b_t + a\sigma^2\tau_n}{\sigma\sqrt{\tau_n}};$$

$$a = \frac{r - \delta - \sigma^2/2}{\sigma^2}; \qquad b_t = \ln\left(\frac{V_t}{V_b}\right); \qquad z = \frac{\sqrt{(a\sigma^2)^2 + 2r\sigma^2}}{\sigma^2}.$$

The total debt value is then represented by the sum of all outstanding bonds:

$$D(V_t) = \sum_{n=1}^{N} d_n(V_t, \tau_n). \tag{A4}$$

In order to resemble the true debt structure as much as possible, it is assumed that at each instant t the company has 10 bonds – 1 with a maturity of 1 year and principal equal to STL and 9 with maturity ranging from 2 to 10 years, each with principal equal to 1/9 of LTL. The coupon of each bond is determined as the fraction of average IE proportional to the weight of the principal of each individual bond p_n, over the total principal value of debt P. The total principal is defined as the sum of the *STL* and *LTL*.

Finally, the equity value is expressed as

$$S_t = g(V_t) = V_t - D(V_t \mid \alpha = 0), \tag{A5}$$

where $D(V_t|\alpha = 0)$ is the market value of total debt when bankruptcy costs equal zero.

The theoretical credit spread at time t is determined as the premium from issuing at par value a hypothetical bond with the same maturity as the corresponding CDS contract – in this case, five years. This bond is assumed to pay a coupon $c_t(5,p)$, so that the following equation holds:

$$d(V_t, 5 \mid p) = p. \tag{A6a}$$

Accordingly, the bond yield is

$$y_t^E(5) = \frac{c_t(5,p)}{p} \tag{A6b}$$

and consequently the theoretical credit spread is determined as the difference between the yield of this hypothetical bond and the corresponding risk-free rate:

$$ICS_t = y_t^E(5) - r_t. \tag{A6c}$$

Estimation procedure

For an assumed initial arbitrary value of β, constant volatility σ and the series of total firm assets value V_t are simultaneously estimated on the basis of the following algorithm:

(1) proposing an initial value for σ, σ_0;
(2) estimating V_t series using the information on the stock market capitalization S_t, so that Equation (A5) holds for all t;
(3) estimating new volatility σ_1 from the obtained V_t series;
(4) end of the process if $\sigma_1 = \sigma_0$. Otherwise, σ_1 is proposed at step 1.

The process is repeated until convergence is achieved.

As a result, different ICS series can be estimated on the basis of Equation (A5), depending on the value imposed for the default point indicator, β. The default point is determined such that the divergence between credit spread series, measured by the RMSE, is minimized:

$$\beta \equiv \underset{\beta}{\operatorname{argmin}}(\text{RMSE}), \tag{A7}$$

where

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\text{ICS}_t - \text{CDS}_t)^2}. \tag{A8}$$

Appendix 2

List of variables

NAQ	Number of ask quotes
NNAQ	Net number of ask quotes
NBQ	Number of bid quotes
NNBQ	Net number of bid quotes
NQ	Number of quotes
NT	Number of transactions
BAQ	Relative proportion of bid and ask quotes in the total number of quotes
Offerer	Ratio between the number of net ask quotes and the total number of quotes
Bidder	Ratio between the number of net bid quotes and the total number of quotes
NBA	Ratio between the number of bid quotes and the number of ask quotes
IMB	Overall imbalance measure
BA	Bid–ask spread
T2Q	Trades-to-quotes ratio