Transparency Regime Initiatives and Liquidity in the CDS Market [1]

Andras Fulop
ESSEC Business School [2]

Laurence Lescourret
ESSEC Business School [3]

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[2]ESSEC Business School, Avenue Bernard Hirsch, 95021 Cergy-Pontoise, France. *E-mail address*: `fulop@essec.edu`

[3]ESSEC Business School, Avenue Bernard Hirsch, 95021 Cergy-Pontoise, France. *E-mail address*:`lescourret@essec.edu`. Phone: +33 134 43 33 62. Fax: +33 134 43 32 12.

Abstract

This paper investigates liquidity changes in the corporate CDS market around two events that increased transparency in the midst of the financial crisis: the regular dissemination of post-trade data by DTCC starting November 2008, and the implementation of the Small Bang in June 2009. We build an econometric model based on intra-daily bid and ask quotes to measure liquidity and volatility in thinly traded CDS. We find that, after DTCCs release, the market-wide deterioration in CDS liquidity becomes less important for banks and major dealers, consistent with information revelation on counterparty risk. The Small Bang also improved liquidity, particularly for more illiquid CDS.

Keywords: Credit Default Swap, Liquidity, Transparency, Small Bang, Counterparty Risk

JEL Classification code: C51, G14, G18

"*Congress could require that dealers in over-the-counter credit-default swaps publicly report both their trades and the value of those trades. This would make the market more transparent, and make it easier for everyone engaged in credit-default swaps to assess their value.*" Ch. Cox, chairman of the United States Securities and Exchange Commission, "Swapping Secrecy for Transparency," October 18, 2008, The New York Times.

1 Introduction

Choosing the right degree of market transparency is one of the most difficult tasks faced by regulators and self-regulated organizations such as trading exchanges. Market transparency refers to the information available to participants about market conditions.[1] Transparency should facilitate price formation and ease best execution services. In practice one can observe a broad spectrum of transparency regimes which vary with market structures and operating systems. Historically, over-the-counter (OTC) markets such as those of Credit Default Swaps (CDS) are opaque with few detailed data available about prices, trading volumes, or collateral posted.[2]

The lack of transparency is suspected to be a key driver of the 2008 financial crisis. U.S. insurer American International Group (AIG) sold CDS on $440 billion of debt including $57.8 billion in paper related to subprime mortgages. When the subprime mortgage crisis erupted, AIG needed a $85 billion bailout. The opacity of the CDS market made it impossible for market participants and for regulators to understand the consequences for the financial system of letting AIG default.[3] Similarly, Lehman Brothers had been one of the major dealers active on the corporate CDS market prior to default on September 15, 2008. Due to the opacity of the market, there was wild speculation about the systemic

[1] A distinction is made between "pre-trade" transparency (information available to market participante *ex ante*, i.e., before trading) and "post-trade" transparency (information disseminated regarding transactions).

[2] A CDS contract transfers the credit risk of a reference entity's instrument from a buyer of a credit protection to the seller. The seller is compensated for taking the credit risk by periodic (e.g., quarterly) premium payments. In case a credit event (say, the default of a corporate bond) occurs the seller pays the buyer an amount reflecting the market value loss of the credit instruments.

[3] Opacity and the absence of margins requirement if the broker-dealer had a good enough credit-rating were the reasons why AIG sold so many CDS. When it was downgraded, it could not meet a $30 billion liquidity call which had the potential to cause AIG to fail, which would had potentially inflicted losses to its other counterparties, among which were cities, states, retirement funds, ..., and other significant financial institutions, which could also have failed, etc.

risk posed Lehman's default on the market in general and on the CDS positions written on Lehman in particular.[4] Such events put the spotlight on the functioning of the CDS market.

This paper analyzes the impact on liquidity in the corporate CDS market of the transparency initiatives undertook in the aftermath of AIG bailout and the Lehman collapse. At that time, the market faced a period of slow-down due to the lack of transparency on open CDS positions. In an attempt to improve the market's viability and restore investors' confidence, substantial changes in the CDS market started to be made at the end of 2008 and in 2009. First, on November 4, 2008, the Depository Trust & Clearing Corporation (hereafter DTCC), which supports the post-trade processing of OTC derivatives contracts, began publishing weekly aggregate post-trade data on notional amounts of CDS trades by reference entity, index and maturity from its Trade Information Warehouse (DTCC-TIW).[5] Releasing such level of data granularity was unexpected, new and a real improvement in terms of market transparency compared to a total absence of public trading data. However, to our knowledge, no academic study predicts or tests why and how the release of aggregate post-trade data should have an impact on liquidity.[6] Second, in 2009, CDS trading changed considerably with the implementation of the Big Bang (in the U.S.) and the Small Bang (in Europe) protocols and new trading conventions initiated by the International Swaps and Derivatives Association (ISDA). The goal of these changes was to enhance the standardization of CDS contracts in order to make the market more transparent and easier to understand in terms of price comparison across CDS contracts. The changes also meant to facilitate inventory management in case an unwinding of positions is necessary. Transparency in our paper thus refers to a broader notion than just making data public, as we also consider product standardization as a key driver of higher transparency.

To investigate the changes in CDS liquidity caused by the dissemination by DTCC of

[4] Ultimately, such speculation proved to be overblown and the auction settled with a net payout of 5.2 billion USD.

[5] DTCC-TIW, the U.S. trade repository that houses 98% of all CDS contracts, made available the outstanding gross and net notional values of CDS traded contracts registered in its warehouse aggregated by reference entity (See its website www.dtcc.com/derivserv).

[6] In May 2014, some U.S. equity platforms characterized by a similar opacity (termed as "dark pools") have also started to release weekly aggregate weekly trading volume and number of trades by security on the request of the Financial Industry Regulatory Authority (FINRA). FINRA then reports on its website on a delayed basis. Interestingly, FINRA has chosen the same level of data granularity for opaque equity markets than DTCC's data release.

aggregate post-trade data and the implementation of the Small Bang, we need an accurate estimate of CDS liquidity and CDS volatility reflecting intra-daily price formation in this market. The CDS market is very thin compared to equity market. A very active corporate CDS may trade twenty times a day; most trade hardly once per day. The standard measures of liquidity used to analyze equity market are therefore too noisy for our purposes. We develop a state-space model of bid and ask quotes based on Hasbrouck (1999) that takes into account the low quoting activity of the CDS market and provides clean estimates of transaction costs and volatility. Recent papers (e.g., Hendershott and Menkveld, 2014; Koopman et al, 2007) underline the benefit of state-space models compared to other approaches such as the generalized method of moments (GMM) estimation when dealing with inactively traded securities. Our model of intradaily price formation links the observed best ask and bid prices to an unobserved efficient CDS price. The bid or ask quoted prices are rounded transformations of the implicit efficient CDS premium and of stochastic transaction costs. Transaction costs are made up of two components: the relative (half-) bid-ask spread, and a measure reflecting heterogeneity of dealers' idiosyncratic inventory costs, which we call "quote dispersion". We include data errors that deal endogenously with outliers that cannot be dropped ex ante due to "jump-to-default" large price changes characterizing CDS premia. Filtering and estimation in the resulting non-linear state-space system is solved using simulation-based methods. We then use our estimates of transaction costs, quote dispersion, and of volatility of the implicit efficient CDS price to analyze the impact on liquidity of transparency regime changes.

Our data come from CreditMatch, the trading platform from leading broker GFI Group Inc. (GFI). The dataset contains time-stamped information on intraday trade and firm quotes for corporate CDS, but does not include information on volume (quoted depth or trade size). We estimate the state-space model for the 172 most active European CDS based on intra-daily prices from 2006 to 2009.[7] The average model-based bid-ask spread is about 12%. There is however large cross-sectional variation. For most liquid CDS, the bid-ask spread is 0.5%, while it is 69% for the less liquid CDS.

To assess the validity of our estimates, we analyze the main determinants of illiquidity in the CDS market. We find that the relationship between relative bid-ask spread, CDS volatility, and other explanatory variables like quote dispersion and credit risk (proxied by

[7]Unfortunately, we cannot use U.S. CDS contracts in our estimation due to a lack of observations.

the default probability) is more in line with the predictions of the existing literature when we use our model-based estimates as opposed to some of the more standard measures such as the quoted bid-ask spread. In particular, we document a significant positive relation between illiquidity and CDS volatility, and between illiquidity and quote dispersion.

To investigate liquidity changes around transparency initiatives, we conduct two event-studies using the first day of post-trade data dissemination by DTCC and the first day of trading with new trading conventions for CDS Small Bang. We use the econometric model to produce estimates of illiquidity, CDS volatility and quote dispersion around the event dates, using a two-month pre-event and post-event estimation period. We then analyze changes in liquidity in a regression framework that allows to control for changes in CDS volatility, quote dispersion and credit risk.

Our results show that, following the post-trade transparency initiative by DTCC, liquidity deteriorates significantly less for CDS contracts whose reference entity is a bank, or a major dealer of the CDS market. This result indicates DTCC release alleviates concerns related to counterparty risk, and leads to lessen asymmetric information and to an improvement in liquidity in these CDS contracts compared to other reference entities. Relative to the pre-event average bid-ask spread, CDS bid-ask spread on banks and major dealers increase by 16 percentage points difference compared to 43 percentage points difference for the other reference entities. Regarding the implementation of the Small Bang, we find that liquidity has significantly improved after the introduction of the new trading conventions and the new standardized definitions of CDS contracts. We observe a decrease in average relative half-bid-ask spread of 7 percentage points difference. The decrease is stronger for CDS which used to be more illiquid before the implementation of the Small Bang. We test the robustness of our concmusion by instrumenting a dummy variable corresponding to the highest tertile of illiquidity. We then use a two-stage selection model and find results corroborating that more illiquid contracts benefitted more from the Small Bang.

Our paper contributes to the effort to understand the impact of implementing transparency in opaque markets. Market transparency is a way to enforce competition. The pre-financial crisis CDS market is a totally opaque and under-regulated dealers market. A very small number of dealers held more than 80% of the notional outstanding value of CDS and had an effective oligopoly in the intermediation of CDS contracts (Duffie, 2013). The relative opaqueness is well-known to make possible extraction of significant rents (see, for instance, Foucault et al, 2013). Maintaining such high profits will be harder once market transparency will be implemented as illustrated by past experiences in some OTC markets. In July 2002, the U.S. corporate bond market has undergone a reform to increase transparency. The National Association for Securities Dealers (NASD, now FINRA) started to require that bond dealers report all transactions in publicly issued corporate bonds in its TRACE system (Trade Reporting and Compliance Engine) in order to publicly and freely disseminate this information.[8] Empirical evidence (Bessembinder et al, 2006 ; Edwards et al, 2007 ; Goldstein et al, 2007) show that transaction costs decreased following the implementation of TRACE.

Increasing post-trade transparency exposes however market participants with large inventory to predatory pricing (Brunnermeier and Pedersen, 2005; Cujean and Praz, 2013), or front-running from large investors. Empirically, Bessembinder and Maxwell (2008) find that large investors face now smaller transaction costs in the bond market but more difficulties to find dealers willing to take a large trade and carry inventory. Asquith et al (2013) find that TRACE leads to a significant reduction in trading activity in particular for large issue size bonds (up to 41.3%). The literature also reports conflicting findings on transparency following the implementation of post-trade transparency on January 31, 2005 on the municipal bond market (see Schultz, 2012 vs. Chalmers et al, 2013). Recently, Loon and Zhong (2014a) find that, for *voluntarily* cleared U.S. corporate CDS, daily post-trade data dissemination by CCPs improves liquidity and trading activity. Results are more contrasted for CDS subject to *mandatory* central clearing (like index CDS contracts). Loon and Zhong (2014b) find that liquidity increases for centrally cleared index CDS, IOSCO (2014) obtains more ambiguous results on trading activity. Central clearing and simultaneous real-time reporting might have confounding impacts because of the impact of counterparty risk. Our paper focuses only on transparency changes and complement these papers by examining the impact of the first transparency initiatives in the non-cleared corporate CDS market taken in the aftermath of the AIG bailout and the Lehman collapse.

The paper is organized as follows. Section 2 describes and discusses the challenge of

[8]The implementation was gradual: from very large bonds in 2002 to all bonds in 2005 and from 75 minutes delay in 2002 to a 15-minute delay to report in 2005.

implementing transparency in the corporate CDS market. Section 3 develops a state-space model for estimating daily liquidity and CDS volatility. Section 4 analyzes changes in liquidity around transparency regime initiatives undertaken in the CDS market in 2008 and 2009.

2 Transparency in the CDS market

2.1 The CDS market

From a peak of $58 trillion before the financial crisis, gross notional amounts of outstanding CDS have declined to $21 trillion at the end of 2013 (Bank of International Settlements). Corporate single-name CDS account for approximately 28% of total gross notional amount.[9]

The market of corporate CDS is organized as a decentralized dealer market, like most instruments traded over the counter. Trading is conducted in bilateral non-anonymous communication over the phone. The market is exclusively limited to large investors that must be ‘Eligible Contract Participants” (e.g., banks, insurance companies, or investment funds). The CDS trading network is two-tiered, since it consists of an inner core of major dealers called the “G14” during our time period and a periphery of end-users and dealer clients. The group is composed of the largest global derivatives dealers: Bank of America Merrill Lynch, Barclays, BNP Paribas, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Royal Bank of Scotland, Societe Generale, UBS, and Wells Fargo.[10]

Trades between dealers (inter-dealer trading) account for approximately half of the outstanding gross notional of CDS contracts. Dealers trade directly and non-anonymously with each other or they trade using an interdealer broker. Interdealer brokers are usually hybrid, voice and electronic. Dealers thus might call a broker over the phone to trade or use the trading platform of the broker to enter anonymously limit orders and wait for them to be hit (e.g., like the platform CreditMatch operationalized by the broker GFI).

[9] Other important market segments are single-name sovereign CDS (14%), and index CDS and tranched CDS (46%). Source: DTCC-TIW, June 2014.

[10] Nomura Holdings joined the group in September 2011 and Credit Agricole in the first quarter of 2012. The group has thus been renamed “G16”. See Peltonen et al (2013) for a detailed analysis of the network in the CDS market.

Participants in the CDS market have access to prices (dealer quotes) only after indication of interest or request for quotes. Participants have information on some screen prices. However, usually prices on screen are only indicative and most dealers will not stand behind their pre-trade indicated prices. End-users (like commercial banks) have a very limited access to pre-trade information. Dealers use interdealer brokers that display, through electronic platforms, best prices and, sometimes, pending limit orders in the book. Through interdealer electronic platforms, dealers might also see trades reported one hour after they occurred (like in GFI's CreditMatch).

2.2 Hypotheses

2.2.1 DTCC's transparency initiative

In the midst of the financial crisis, DTCC announced on October 31, 2008 that it will begin to publish aggregate post-trade data from its Trade Information Warehouse (TIW) starting on November 4, 2008. Before the release of DTTC data, it was complex for regulators and investors to assess the size of the CDS market, due its structural opacity. After the bailout of AIG and the Lehman collapse, the fear of contagion and systemic risk created by banks' positions in this highly concentrated and interconnected market was large. Figure 2 depicts search query data from *Google Trends* over the period from 1 May 2008 to 30 June 2009. We report search volume on the term "Credit Default Swap" with an obvious semantic connection with regulators and investors concern after the Lehman bankruptcy.[11] A surge of query volume is observed in the week following the Lehman failure, and then drops to previous level, in particular after DTCC release. This figure is consistent with the view that the post-trade disclosure by DTTC was intended to stop unfounded speculation on the size of the CDS market (with estimates ranging from $35 trillion to $55 trillion before the publication) and threat of systemic risk.

We posit that the release by DTCC-TIW of aggregated post-trade amounts has alleviated information asymmetry about contagion and counterparty risk of protection sellers, helping to mitigate the illiquidity problem arising during the post-Lehman turmoil. CDS trading on banks and on major CDS dealers is heavily influenced by counterparty risk

[11] Google query volumes proxy for investor concern, and are found to precedes drops in financial markets (see, for instance, Preis et al. 2013).

(see Arora et al, 2012). First, market participants worry about "wrong-way risk". Du et al (2015) show that some market participants manage counterparty risk by trading less with sellers of protection whose credit risk is highly correlated with the credit risk of the reference entity to avoid wrong-way risk.[12] Second, net notional amount of CDS written on banks, and in particular on G14 dealers in the CDS market, are a relevant proxy for counterparty risk in the CDS market. Gündüz (2015) finds that CDS buyers mitigate counterparty risk on sellers by purchasing protection on these sellers.[13] Third, Shachar (2012) shows that liquidity deteriorates in the CDS market when counterparty risk heats up. DTCC post-trade data made the size of the CDS market public, a size that contrasted with fears that CDS volumes have surged to represent several times the amount of debt they insure, and that protection sellers possibly will be unable to make payments in case of defaults triggering the contracts. Trading CDS correlated with the "disclosed" default of dealers should thus be easier after DTCC data release, and liquidity should improve in these CDS, and also in the more correlated reference entities, i.e., banks.

2.2.2 The initiative of the ISDA

The pre-financial crisis CDS market is a totally opaque and under-regulated dealers market. At their 2009 Pittsburgh summit, the leaders of the G20 agreed on regulatory initiatives to make the CDS market more transparent. By translating the G20 commitment into regulatory action, the Dodd-Frank Wall Street Reform and Consumer Protection Act ("Dodd-Frank Act") and the European Market Infrastructure Regulation (EMIR) require central clearing for more standardised CDS, mandatory reporting, collateralisation, and higher capital requirements for non-centrally cleared CDS.[14]

The first step for central clearing has been to implement a greater standardization for CDS. In 2009, the ISDA decided to implement substantial changes with the implementation of the Big Bang and Small Bang protocols (meant to solve challenges around

[12]Consider a hedge fund that might be reluctant to trade or expect a discount to buy a CDS on HSBC from Barclays, due to the correlation of default between HSBC and Barclays. However Barclays being more informed (and in our case more sanguine) about counterparty risk might not accept to trade at the conditions of the buyer.

[13]Arora et al. (2012) show that the CDS price of banks cannot be used as proxy for counterparty risk since its effect on CDS price is economically of negligible magnitude.

[14]The Dodd-Frank Act took effect on October 12, 2012. EMIR went into force on August 16, 2012.

restructuring events through the auction process).[15,16] In the meantime, new CDS trading conventions have been introduced in order to increase transparency. Standard European CDS must trade with fixed coupons (25, 100, 500 and 1000), facilitating thus the comparison of prices (ex ante or ex post) across maturities as well as greatly simplifying the netting of offsetting CDS positions (within or outside a potential clearing house).[17]

However, as Markit points out, existing CDS in 2009 that did not conform to new standards could become even more illiquid, which could then lead to deteriorate the liquidity of newly issued CDS and of the market as a whole. Haas and Reynolds (2015) report that equity liquidity deteriorated after the Big Bang, suggesting that the event might not have been beneficial for CDS liquidity of U.S reference entities. The impact of the Small Bang on the liquidity of European corporate CDS is therefore an empirical question. Our second event-study investigates changes in liquidity around the implementation of the Small Bang.

3 Data and methodological issues

3.1 The sample

The data are from GFI, a major CDS inter-dealer broker. GFI is usually ranked No. 1 in CDS trading by Risk magazine. GFI claims it represents 60% of the inter-dealer brokerage activity.

GFI is a hybrid voice-electronic execution platform for CDSs dedicated only to dealers. The GFI electronic platform, CreditMatch, is an electronic platform connected to voice brokers, in which dealers may submit, revise or cancel orders. It has a minimum trade size of $1 million. Only GFI brokers (and not dealers) can see the identity of limit order

[15] The Small Bang applies to CDS contracts that include a modified restructuring credit event (like in Europe), while the Big Bang applies to CDS with the old restructuring credit event (like in the U.S.). Neither the Big Bang nor Small Bang applied to Municipal CDS, Loan CDS, or CDS on ABS.

[16] Until recently, CDS contracts were exempt from supervision by both the U.S. Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) since CDS are neither futures nor securities. From legal standpoint, CDS were governed by the International Swaps and Derivatives Association (ISDA) master agreement framework. Note that the implementation of the Dodd-Frank Act in 2012 implies that corporate CDS, which are security-based, are now regulated by the Securities Exchange Commission (SEC).

[17] Most trades gravitate around 100 and 500 coupons. Corporate investment grade reference entities trade with a 100 coupon and high yield reference entities with a 500 coupon. European sovereigns are quoted with a 25 or 100 coupon.

traders, and the depth of the market. They also have information on transactions (size, price, direction, and identity) for the current and last trading days. In contrast, clients of the platform — bank dealers — can only observe anonymous limit orders, and the last trade occurred in the platform (price, volume, and direction, but not the identity except when counterpart of the trade). As in a standard limit order book, dealers may be providers of liquidity when they post pending orders. They may also consume liquidity when they hit a quote. A strength of GFI data is that best quotes are time-stamped and not consensus or indicative prices unlike other existing datasets (CMA DataVision, Markit).[18]

The dataset we use in this paper runs from March 31, 2006 through December 31, 2009. It contains intradaily time-stamped trades and best quotes on 5-year CDS contracts on senior reference issues. Note that GFI-CreditMatch does not report the depth of best limit orders nor the size of transactions.[19] Note also that there is no reporting requirements for CDS trades in CreditMatch. CDS trades might be executed electronically (through CreditMatch) or by voice (through a physical broker). Some brokers report trades at the end of the business day in CreditMatch. Time-stamps of trades might therefore not reflect the time at which the trade actually occurred. Moreover only 20% of trades in our dataset are close enough from a pair of bid-ask quotes to correctly sign a trade using the Lee and Ready algorithm. For these reasons, we conservatively choose to focus on illiquidity measures based only on bid or/and ask quotes.[20]

We restrict our sample to CDS with reference entities having at least 25 quarterly observations for our panel analysis and at least 50 observations for pre-/post-event periods in event studies. This criterion removes most U.S. firms from the sample, so we focus on European CDS. Finally we retain CDS that have complete firm-level probability of default data coming from the Risk Management Institute (RMI) at National University of Singapore.[21] The final sample contains 172 European CDS.

[18]As pointed by Mayordomo et al (2010), there might exist large difference between consensus prices from main providers and GFI prices. One of the reason might be that consensus prices originate from back office which does not have the front office's market view.

[19]Chen et al. (2011) document an average trade size of $5 million for trades in the corporate single-name CDS market.

[20]Therefore, we cannot estimate any measure of effective spreads from our GFI data. Biswas et al (2015) use the effective bid-ask spread for measuring CDS illiquidity using DTCC-TIW regulatory data, which consists of more detailed data than public data and might provide more accurate time-stamps for trades.

[21]In July 2009 , RMI launched the non-profit Credit Research Initiative (CRI) to promote independent

3.2 Liquidity in the CDS market

Dealers, and in particular the G14, are the primary source of liquidity in the CDS market as they facilitate the vast proportion of trades. For instance, they participate in 98% of all traded volume in U.K. single name CDS (Benos et al, 2013). Because of this very specific market organization, the number of quote providers (or dealers) is often used as a proxy for CDS liquidity (see, e.g., Qiu and Yu, 2011). While the number of providers provides a good proxy for the size of the market, its use as a measure of liquidity is questionable. First, the selection of the number of quote providers results from a non-transparent process. Second this measure might be sticky or inaccurate since it may happen that "one dealer might occasionally miss a data to Markit" (Qiu and Yu, 2011).[22]

Another possible measure of CDS market liquidity is bid-ask spread (see, e.g., Tang and Yan, 2013 or Mara, 2014).[23] Bid-ask spreads are based on intra-daily price formation and should thus more accurately pin down daily liquidity. Credit market is however much more illiquid than equity market and standard measures of liquidity like the quoted bid-ask spread or price volatility must be used cautiously because of the noise that the measures may contain, especially when using indicative quoted prices. In order to try to overcome this concern, we use a state-space model in order to get model-based estimates of daily transaction costs and CDS volatility (see section below) and compare them to easy-to-compute measures like quoted bid-ask spreads and adjusted-Roll volatility (detailed below).

transparent research in the credit risk arena. The foundation of the CRI is a database of over 60,000 listed firms in 46 countries across the Asian-Pacific, North American, Western European and Latin American regions. The proprietary database that underlies this output includes extensive panel data on firm stock price, financial statement data, and events of default from 1990 to the present categorized by default class. The RMI probabilities of default (PDs) are similar to Expected Default Frequencies (EDF) by Moodys KMV. The crucial difference is that the RMI default forecasts condition on a richer information set adding financial ratios to the distance to default as predictors. Further the RMI system uses a completely transparent methodology described in RMI staff article, 2015.

[22] Markit is a financial information and services firm.

[23] Other measures of CDS liquidity exist: Oehmke and Zawadowski (2013) use daily positions published by DTCC-TIW from 2010, while Shachar (2012) and Gündüz et al. (2013) use order flow imbalances to investigate price impact.

3.3 A dynamic model of quoted prices in an illiquid limit order book

This section proposes a measure of illiquidity based on a state-space model suited to the thin trading observed in the CDS market. Based on Hasbrouck (1999), the model simply links each single best quote to an unobserved efficient price, and cast the resulting estimation task as a missing-data problem.[24] In addition to denoising bid-ask spreads, our econometric model provides us with clean estimates of the volatility of the efficient CDS spread and quote dispersion, quantities that we will use as important controls later in our cross-sectional regressions.

3.3.1 State-space model

We consider a model conditional on the update of the best bid and best ask prices of the CDS premium. Let $\tau_i, i = 0, ..., T$ denote the joint arrivals of these data points. Let $\mathcal{D}_i$ denote the information set up to τ_i. We either have a best bid or a best ask observation at τ_i denoted by B_{τ_i}, or A_{τ_i} respectively, or we may have both. We then link all observed best ask and bid prices to an unobservable efficient log CDS price, M_{τ_i}.

The unobserved efficient CDS price model. The logarithm of the unobserved efficient CDS premium evolves as:

$$m_{\tau_i} = m_{\tau_{i-1}} + \exp(\frac{\sigma^2}{2})\sqrt{\Delta\tau_i}u_i \quad (1)$$

where $m_{\tau_i} = log(M_{\tau_i})$, $\Delta\tau_i = \tau_i - \tau_{i-1}$, σ^2 is the log fundamental variance (termed hereafter as the CDS volatility), and u_i is a standard normal random variable.[25]

The transaction cost model. To develop an economic intuition behind the model, suppose that dealers, who submit orders in the trading platform, are exposed to several costs and risks (like information leakage risk and adverse selection risk). The mean compensation for liquidity provision on the buy (bid) or on the sell (ask) side is denoted

[24] The implicit efficient price is the standard estimate of the full-information price based on all available public information (proxied by the observed order flow).

[25] We have also estimated a version of the model where the efficient price innovation is allowed to have fat-tails, a prevalent feature of CDS data. Results are similar to those reported in the paper.

κ_{τ_i} and writes:

$$ln(\kappa_{\tau_i}) = \mu + m_{\tau_i} \tag{2}$$

We incorporate the level of the efficient premium in our model to get rid of the artificial level effect, in accordance with the literature related to CDS spreads (e.g., Acharya and Johnson, 2007).

We also assume the existence of a dealer-specific independent private value for the asset. In particular, dealers may vary by their private needs to hedge and by their level of impatience, risk aversion or capital requirements. They may thus value the speed of execution of their orders differently. To account for this heterogeneity in private costs, we suppose that best quotes can differ from the average with normal errors in a proportional sense, that is, the volatility of the private value is proportional to the level of the CDS premium:

$$c_i \sim N(0, \exp(\sigma_c^2) \times \exp(2m_{\tau_i})) \tag{3}$$

In summary, the best quotes are made of a mean cost of liquidity supply, κ, and an idiosyncratic cost reflecting heterogeneity of private values across dealers, c. We call $exp(\mu)$ the model-based average (half-) bid-ask spread and $exp(\sigma_c^2)$ the quote dispersion.[26] In our model, quote dispersion reflects inventory risks faced by CDS dealers (investors' search costs cannot be captured in inter-dealer trading mechanisms). Inventory risks in this highly concentrated market are a key driver of CDS pricing (Shachar, 2012; Siriwardane, 2015) and should also play an important role in explaining CDS liquidity.

Last, we also have to deal with outliers. We allow for data errors with some probability p. Later, in the implementation of the model, we set $p = 1\%$, which can be interpreted as if 1% of our data is disposed of. This yields terms of

$$\varepsilon_i^A \sim q_i^A N(0, \sigma_\varepsilon^2) \tag{4}$$

$$\varepsilon_i^B \sim q_i^B N(0, \sigma_\varepsilon^2) \tag{5}$$

where q_i^A and q_i^B are Bernoulli's with probability p.

[26] The term quote dispersion is chosen in reference to the price dispersion measure of Jankowitsch et al (2010) developed to capture investors' search costs and dealers' inventory costs in the bond market.

Finally, the bid and ask prices set in the limit order book are given by:

$$a_{\tau_i} = M_{\tau_i} + \kappa_{\tau_i} + c_i + \varepsilon_i^A \quad (6)$$

$$b_{\tau_i} = M_{\tau_i} - \kappa_{\tau_i} - c_i + \varepsilon_i^B \quad (7)$$

Then, if the tick size is K, the discrete bid and ask prices are given by

$$A_{\tau_i} = Ceiling(a_{\tau_i}, K) \quad (8)$$

$$B_{\tau_i} = Floor(b_{\tau_i}, K) \quad (9)$$

where the floor and ceiling functions round down and up respectively to the next multiple of the tick size K.

3.3.2 Filtering and estimation

Our econometric model decomposes the innovations of the observed noisy bid and ask quotes into innovations of the unobserved CDS premium, average transaction costs, idiosyncratic costs, and observation noise (data errors and price discreteness). By estimating the fixed parameters of the model, we can estimate the two main outputs of our model which are the level of the mean relative (half-) bid-ask spread ($exp(\mu)$), the CDS volatility ($exp(\sigma^2)$), and the quote dispersion ($exp(\sigma_c^2)$).

Filtering. The first task is to filter the unobserved dynamic states given the observed data. Our econometric model can be cast in state-space form, where the transition equation is defined by the movement of the efficient premia in (1) while the observation equations are in (2)-(9). Note that data errors in (4) and (5) make the measurement equations (8) and (9) non-gaussian. Further nonlinearity is present in the measurement equations both because the log efficient premia enters equations (6) and (7) after an exponential transformation ($M_{\tau_i} = e^{m_{\tau_i}}$) and because of the discretization in (8) and (9). Since our system is both non-gaussian and non-linear, Kalman Filtering cannot be applied. We can still derive a theoretical recursion to sequentially update the state of the system using Bayes' rule. To implement the recursion numerically, we resort to a sequential importance sampling (see Fulop and Lescourret, 2009, for more details).

Monte Carlo EM algorithm. We now address the issue of computing the maximum likelihood (ML) estimates for the model parameters. The log-likelihood function which can be generated from the particle filtering algorithm described in the preceding section is inherently irregular with respect to the parameters.[27] Usual gradient-based optimization is thus precluded. We adopt an indirect approach to the ML estimation via the EM algorithm of Dempster et al. (1977), which involves two steps, Expectation and Maximization (hence its name).[28] Note that the E-step of our model is complex and computed using the particle filter. We are thus using a version of the Monte Carlo EM (MCEM) algorithm. Casting optimization as an EM algorithm problem effectively circumvents the irregularity induced by the particle filter.[29]

Finally, it is worth noticing that, in our model, asymptotic standard error for the maximum likelihood estimate cannot be computed using the negative Hessian matrix nor using the inner product of the individual scores.[30] We thus apply the alternative estimator proposed by Duan and Fulop (2010), which uses the smoothed individual scores to compute the asymptotic error.

3.3.3 Summary statistics and model-based estimates

Table 1 shows the summary statistics of the main variables. The average firm in our sample has a CDS premium of 94 basis points (calculated as midpoint based on bid and ask quotes). The quoting and trading activities vary across corporate CDS. On average, we observe roughly 6 daily bid and ask quotes, and less than 1 trade per day. The average difference between two consecutive trades is 22 days, hiding a trading and quoting activity which is event-driven. Trades might thus cluster over one day, or even one week, while there may not have any trading activity during entire weeks. Figure 1 represents the daily activity of two CDS contracts. Deutsche Bank is actively quoted and traded (above the

[27]The irregularity arises from the resampling step required for any particle filter.

[28]The EM algorithm is an alternative way of obtaining the ML estimates for incomplete data models, where incomplete data refers to the situation in which the model contains some random variables without corresponding observations. The first step consists of writing down the complete-data log-likelihood function. Since it is not observable, one needs to compute its expected value by conditioning on the observed data in conjunction with some assumed parameter values. This completes the expectation step. Secondly, in the maximization step, one finds the new parameter values that maximize the expected complete-data log-likelihood function. The updated parameter values are then used to repeat the E- and M-step until convergence to the ML estimates.

[29]Fulop and Lescourret (2009) describe the complete data likelihood and the MCEM algorithm.

[30]None is directly computable because the individual observed log-likelihood function is highly irregular due to using the particle filter.

median in our sample) while Unibail is less actively quoted and traded (below the median). In particular, we observe that the activity of Unibail is strongly clustered, illustrating the complex task of estimating liquidity on these illiquid instruments. Quotes imbalance reveals more bid quotes than offer quotes on average, which is consistent with the buying pressure observed in this market (see, for instance, Tang and Yan, 2013, using also GFI data). The average quarterly amount of public bond issues for firms in our sample is \$1,067 Mio with a high of \$184,208 Mio. Notably, there are firms without quaterly public bond issues in our sample.

Table 2 presents ML estimates averaged across the 172 European CDS contracts and across the period. The average relative (half-) bid-ask spread, the CDS volatility and the dealers' inventory costs heterogeneity (quote dispersion) are reported. The model-based relative bid-ask spread is approximately 12% on average. Figure 3 shows the averaged estimates quarter by quarter during our sample period. The top graph of Figure 3 plots the bid-ask spread and the CDS volatility. Illiquidity peaks after the Lehman collapse until the Small Bang initiation, while CDS volatility peaks during the first quarter 2008. The bottom graph relates our quote dispersion measure to the noise measure developed by Hu et al (2010).[31] It shows that our quote dispersion measure is sensitive to the funding liquidity shocks captured by the noise measure. In particular, both measures peak after the Lehman default (which corresponds also to the quarter of DTCC release).

3.4 Determinants of illiquidity

To check the consistency and properties of our model-based estimates, we perform a regression analysis of the determinants of illiquidity, based on Bollen et al (2004). Specifically, we run a regression on the model-based and the quoted bid-ask spread several market microstructure determinants of liquidity. Order-processing costs are measured as the inverse of the square root of the daily number of CDS trades ($1/\sqrt{nb\_trade\_d}$) (Bollen et al, 2004). Inventory-holding costs are proxied by the CDS volatility estimated in our econometric model, and the quote dispersion. Adverse-selection costs are proxied by the CDS volatility. We control for credit risk by adding the probability of default linearly and non-linearly (quadratic term). Qiu and Yu (2012) document an inverse-U shaped between trading activity and credit risk. We control for industry fixed effect and quarter

[31] Noise measure data are available on the authors' website.

fixed effects. The analysis uses all the quarterly observations for the 172 CDS in our sample, for a total of 1,809 observations.

Table 3 reports least-squares estimates of the regression model. Panel A use relative bid-ask spread, CDS volatility and quote dispersion estimates from our state-space model while Panel B reports relative quoted bid-ask spread and Roll-adjusted volatility estimated from data without the use of our model. Note that quote dispersion is based on the model and cannot be estimated directly from data. There are several interesting patterns to observe. First, one can see that the explanatory power of the same regression specification is significantly higher (R^2 is equal to 0.59 vs. 0.31) when using the model-based estimates, presumably due to the denoising effect of our state-space framework and to the use of the quote dispersion measure. Second, in accord with the usual microstructure literature, the coefficient of the CDS volatility is positive, significant and stable across all specifications both in Panel A and Panel B, corroborating the importance of controlling for it. Last, the quote dispersion measure is positively and statistically significantly related to CDS illiquidity. A shock of one standard deviation in quote dispersion implies a change of 28% in average bid-ask spread, corroborating the importance of controlling for heterogeneity in dealers' idiosyncratic inventory costs.

It is important to note that we use relative bid-ask spread, which has been extensively used in the literature to measure illiquidity (in equity, bond or derivatives markets). A practical question that arises on the CDS market is whether one uses absolute or relative bid-ask spreads as a measure of illiquidity. In our paper, we follow Acharya and Johnson (2007) and Tang and Yan (2007) and use relative bid-ask spreads to control for the general positive relationship between the level of the CDS premia and the bid-ask spreads. To check for any remaining level effects of CDS premia on bid-ask spreads, we estimate a flexible piecewise regression of the relative bid-ask spread on the CDS premia using the pooled quarterly panel described above. Figure 4 presents graphically the estimation results where we allow for two changes in the slope coefficient of relative bid-ask spread at 25 and 50 basis points respectively.[32] Essentially a nonzero-slope signals residual level effects. Figure 4 shows statistically significant nonlinearity. It also suggests that such effect is concentrated to less risky CDS (CDS premium below 25 bp) corresponding less than 10% of CDS in our sample. Given that our following event studies scarcely include

[32]Tabulated results from the piecewise regressions are available upon request.

such names, we feel comfortable with using the relative bid-ask spread as the dependent variable.

4 Changes in CDS liquidity around transparency initiatives

4.1 Post-trade aggregated data published by DTCC

Since November 4, 2008 (the "Event" date) and continuing weekly, DTCC has published on its website the outstanding gross and net notional values CDS contracts registered in the Warehouse for the top 1,000 underlying single-name reference entities.[33] The analysis examines the CDS market liquidity during a two-month period prior to the Event date (1 September 2008 to 30 October 2008) and the two-month period beginning after the Event date (5 November 2008 to 31 December 2008). We run an event-study regression controlling for variables affecting liquidity (see previous results in Table 3).

$$\begin{aligned} Illiq_{i,t} = \alpha + \beta_1 \times D\_AfterEvent_i + \beta_2 \times D\_DTCCGroup_i \\ + \beta_3 \times D\_AfterEvent_i \times D\_DTCCGroup_i + \gamma \times \mathbf{W_{i,t}} + \varepsilon_{i,t} \end{aligned} \quad (10)$$

where $Illiq_i$ is the model-based bid-ask spread described by Eq. (1), (8) and (9), $D\_AfterEvent$ is a dummy that take 1 if the period is after the Event date, $D\_DTCCGroup$ is a dummy that takes 1 if the reference entity belongs to a certain Group that will be defined below. The matrix $\mathbf{W_i}$ controls for characteristics affecting CDS liquidity, namely: the CDS volatility and quote dispersion estimated from our model (the main variables of interest in Table 3), the probability of default (1-year) and its quadratic term to take into account nonlinear effects of credit risk. Finally, we include industry fixed effects.

Table 4 presents the results of the estimation. The dependent variable is the model-based relative bid-ask spread. We report three specifications according to the dummy of the DTCC group ($D\_DTCCGroup$) used. The first dummy refers to the group of banks (33 reference entities in our sample) for which DTCC has disclosed post-trade data. The

[33] Gross notional amounts correspond to the cumulative total of past transactions while net notional outstanding amounts represent the maximum amount of funds that could theoretically be transferred from sellers of protection to buyers (assuming a zero recovery rate).

second dummy refers to the group of European dealers belonging to the G14 (subset of the first group), representing the core dealers of the CDS network (Barclays, BNP Paribas, Credit Suisse, Deutsche Bank, HSBC, RBS, Societe Generale, UBS). The third dummy refers to the group of banks excluding the G14 European dealers (25 reference entities).

In Table 4 column 1, we regress model-based relative bid-ask spread on the interaction term between the dummy After-event and the dummy Banks. This regression shows that liquidity deteriorates after the release of aggregate post-trade data by DTCC (the dummy d_after is negative), but statistically significantly less for the group of banks compared to other reference entities: the interaction term between the dummy After-event and the the dummy of banks is positive and statistically significant at the 1% level. When we investigate the effect on G14 European dealers, reported in column 2, we find similar results. Liquidity is significantly less worse for reference entities related to the G14 European dealers compared to other reference entities after the Event date. However, it is not this subset group that drives results in column 1. As shown in column 3, we obtain very similar results for the group of banks excluding the G14 European dealers: the interaction term between the dummy post-event and the group of banks excluding the G14 is also statistically significantly positive (at the 1% level).

In the midst of the financial crisis, liquidity in the CDS corporate market severely decreased. CDS bid-ask spreads enlarge by 2.3 % after November 4, 2008 which corresponds to an increase of a magnitude of 43.1 percentage points difference from the pre-event average illiquidity level. In comparison, the bid-ask spreads of CDS on banks or on G14 dealers increase much less: 0.9% or 16.9 percentage points difference relative to the pre-event average bid-ask spread. We can thus deduce that the publication of DTCC was beneficial for the liquidity of CDS on banks and G14 dealers, from which the crisis started. The interpretation of our results is that aggregated post-trade data disclosed by DTCC revealed information on counterparty risk mitigating asymmetric information problems.

4.2 Impact of the Small Bang

The hypothesis tested below is that the Small Bang has improved contracts' fungibility and trading transparency, which in turn has increased liquidity. The new quoting conventions for CDS Small Bang saw their first day of trading on June 22, 2009. Contract changes were implemented in advance of July 31, 2009 - the commitment date made by dealers to the European Commission to trade under these new protocols. We investigate the effect of these new protocols on liquidity around the implementation date of the Small Bang. Our pre-event period, lasting two months, stops just before the first day of trading (June 22, 2009). The post-event period, also lasting two months, begins the day after the committed deadline (July 31, 2009) to take into account the possible gradual nature of the process.

We run the following regression to study the impact of the event.

$$Illiq_{i,t} = \alpha + \beta \times D\_PostEvent_i + \gamma \times \mathbf{W_{i,t}} + \varepsilon_{i,t} \tag{11}$$

where the dummy variable $D\_PostEvent_i$ takes 1 if the period is after the implementation of the Small Bang, and the remaining control variables are as detailed in the previous section.

Table 5 presents OLS estimates of the regression model. Column (1) presents the results of the model using the RMI 1-year probability of default (PD), while Column (2) uses the RMI 5-year PD. The most important result of Table 5 is that the impact of the Small Bang on illiquidity is negative and statistically significant at the 5% level, indicating that liquidity of corporate single-name contracts has improved with efforts on standardization. In terms of economic impact, relative bid-ask spreads have decreased by 0.5%, or about 7.4 percentage points difference from the pre-Small Bang level of illiquidity.

We also investigate the relation between the pre-event level of liquidity of the CDS contracts and liquidity improvement from the standardization. We run the following regression:

$$\Delta Illiq_{i,t} = \alpha + \beta Illiq_{i,t-1} + \gamma \times \mathbf{\Delta W_{i,t}} + \epsilon_{i,t} \tag{12}$$

where the dependent variable is the illiquidity change around the Small Bang, $Illiq_{i,t-1}$ is the illiquidity level before the Small Bang, and the remaining control variables are as detailed in the previous section and taken in first differences. We use two specifications for measuring the illiquidity level pre-Small Bang. The first one is the model-based relative bid-ask spread described above. The second specification uses dummy variables obtained from a tertile split of the pre-event model-based bid-ask spread to isolate which reference entities benefitted most from the Small Bang.

Column 1 in Table 6 shows that the level of bid-ask spread before the Small Bang is negative and significant at 1% level (t-statistic -3.49). The result indicates that more illiquid contracts have become more liquid with standardization. Column 2 confirms this result: the dummy for the highest tertile ($d\_[66, 100]$) is also negative and statistically significant at 1% level (t-statistic -3.23), while the dummy for the second tertile is weaker but still significant at 5% (t-statistic -2.26). The impact of the Small Bang has thus benefited more illiquid CDS, which is interesting from a regulatory point of view.

One possible criticism of this analysis is that our result might be due to the serial correlation present in bid-ask spreads. Although we think that our use of tertile dummy variables alleviates this concern somewhat, we go one step further. Keeping only the dummy variable corresponding to the highest tertile of bid-ask spreads, we instrument it and use a two-stage selection model to test the robustness of our conclusions. The estimation involves two equations. The first equation is:

$$Pr(d\_[66, 100]_{i,t} = 1) = \lambda(\alpha w_{i,t} + \beta \times \mathbf{\Delta W_{i,t}} + \epsilon_{i,t})$$

where $\lambda(.)$ is a logit function and w is our instrument. Our identification strategy uses the amount of bonds issued during the first quarter of 2009 as an instruments for CDS illiquidity, as suggested by Oehmke and Zawadowski (2015).[34] The rationale for this instrument is that a high volume of bond issuance makes it more likely that institutional investors use the CDS market to hedge and manage the risk of their bond portfolio. Note also that the time period the instrument refers to (January to March 2009) does not overlap with the time interval during which the illiquidity change around the Small Bang is calculated (April-May to August-September 2009). This makes us confident that the instrument respects both the inclusion and the exclusion restrictions. The second stage equation is:

$$\Delta Illiq_{i,t} = \gamma \hat{d}\_[66, 100]_{i,t} + \gamma \times \mathbf{\Delta W_{i,t}} + e_{i,t}$$

[34] As far as we know, there is no European corporate bond trading data available (except for the case of the Italian bond market, because only Italy has extended pre-trade and post-trade transparency requirements to bonds). Therefore, we cannot compute any bond liquidity measures or bond fragmentation measures for the European bond market related to our reference entities. Note that the Review of the Markets in Financial Instruments Directive (MiFID) in Europe could dramatically change the level of post-trade (and even pre-trade) transparency by changing how bond market makers would be obliged to report to regulators and to the market.

Table 7 presents results. The instrumented illiquidity dummy variable is negative and significant at the 1% level, corroborating that more illiquid CDS benefitted more from the Small Bang. In terms of economic impact, the decrease in relative bid-ask spreads is 1.61% for more illiquid contracts, which is similar with results obtained in Table 6 (1.4% decrease for CDSs belonging to the highest tertile of pre-event illiquidity).

4.3 Placebo tests

We also test for the robustness of our results by running placebo tests using only data from April 2006 to December 2006, to avoid undue influence from the subprime crisis (August 2007-August 2008). Given that our sample size is smaller in 2006, we only require to have 25 observations before and after the event in order to have enough reference entities in the cross-section.

First we consider that a placebo DTCC event has occurred on October 31, 2006. We estimate the model described by Eq. (1), (8) and (9) using a two-month period before and after the placebo treatment. No particular shock has hit the group of DTCC banks and G14 dealers on this specific day. We thus re-estimate Equation (10) and expect the estimate "$d\_PlaceboAfter \times d\_DTCCGroup$" be statistically non-significant. Results are provided in Table 8 Panel A. The placebo event is not statistically significant across all groups. The placebo event has no effect as expected.

Table 8 Panel B reports the results of the placebo test for the Small Bang. We use the following placebo periods to estimate our model and run the event-study regression described in Eq (11): two months before June 2, 2006 and two months after July 31, 2006. This alternative test fails to find evidence of a difference in illiquidity, the placebo treatment having no statistically significant effect.

5 Conclusion

In early November 2008, DTCC contributed to increased transparency in the opaque CDS market by posting aggregate post-trade data on its Web site. The data gave the industry a first comprehensive look at the numbers of contracts traded in the CDS market, the total gross and net notional amounts. A few months later, the ISDA intervened to standardize

CDS contracts – the so-called Big Bang in the U.S. and Small Bang in Europe – in order to encourage transparency across CDS contracts. Our paper investigates changes in liquidity around these transparency regimes initiatives. Liquidity is one of the necessary conditions of a well-functioning market, and a prerequisite for a switch to any automatised trading platforms as recommended by the G20.

We find new evidence that aggregated post-trade data publication by DTCC made liquidity better for reference entities related to banks and CDS major dealers, consistent with information revelation about contagion and counterparty risk in the CDS market. Second, we find that liquidity improves across all CDS contracts, and especially for CDS which used to be more illiquid pre-Small Bang. We thus show that the first transparency regimes initiatives had a small but significant positive impact in terms of liquidity, despite the expected small effects of these light regulatory changes. We thus expect that the drastic regulatory changes implemented by EMIR in Europe or the Dodd-Frank Act in the U.S. will have stronger positive impact on liquidity for contracts eligible to real-time post-trade transparency. Our new results will hopefully contribute to the current debate on transparency in the CDS market.

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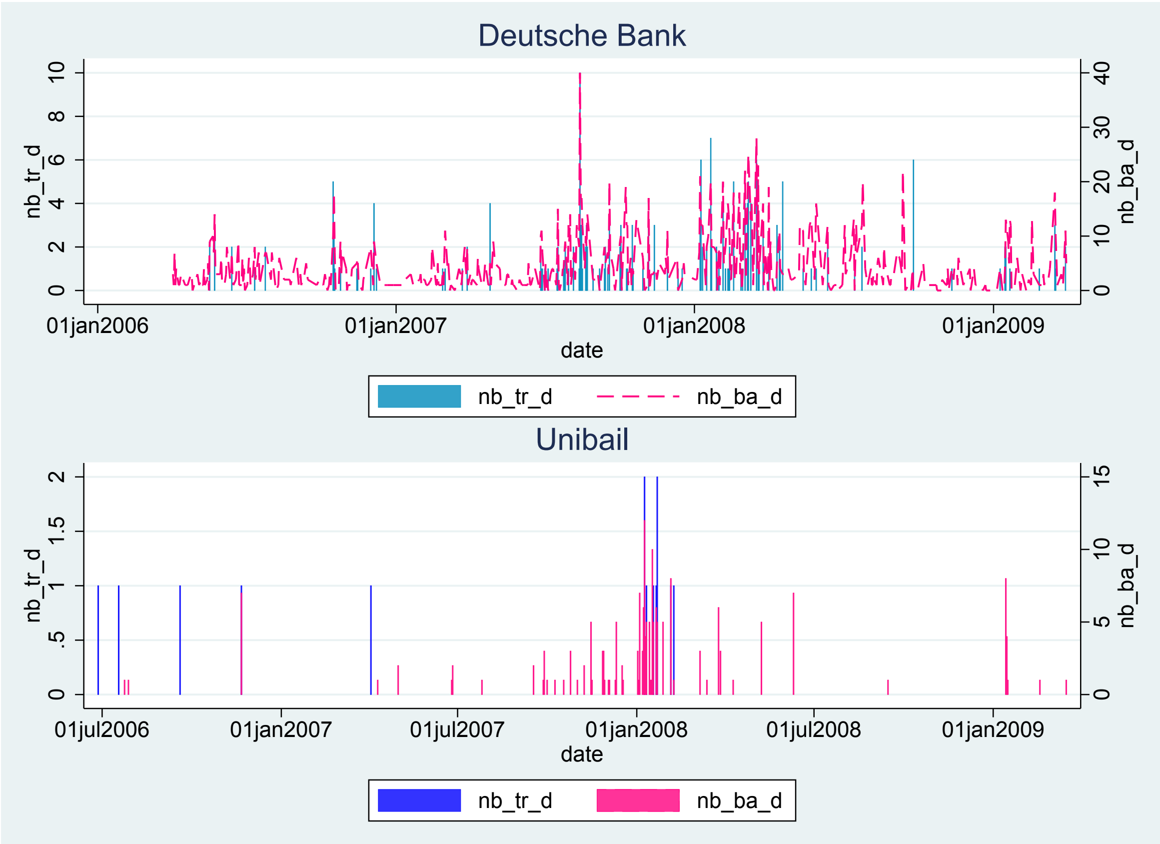

Figure 1: Number of daily trades and quotes for Deutsche Bank and Unibail

Figure 1 represents the daily trading and quoting activity (number of trades, *nb_tr_d*, and number of quotes, *nb_ba_d*) of Deutsche Bank and Unibail 5-year CDS. Deutsche Bank is a reference entity which trading and quoting activity in the 5-year CDS market is above the median of our sample, while Unibail has a trading and quoting activity below the median.

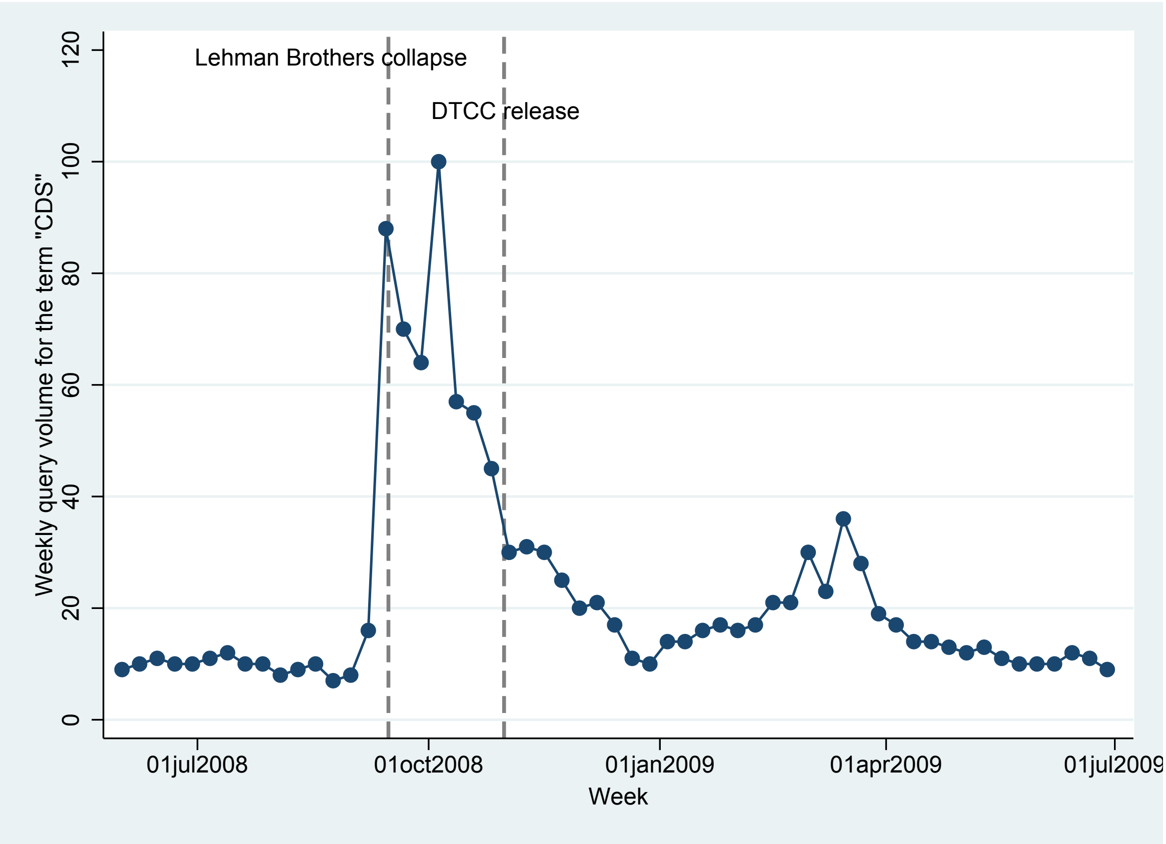

Figure 2: Search query volume for the term "Credit Default Swap" from *Google Trends*

Figure 2 represents the weekly query volume for the term "Credit Default Swap" from *Google Trends* during the period from May, 2008 to July, 2009. *Google Trends* is a publicly available service provided by the search engine *Google*. Data are retrieved from the *Google Trends* website (http://www.google.com/trends).

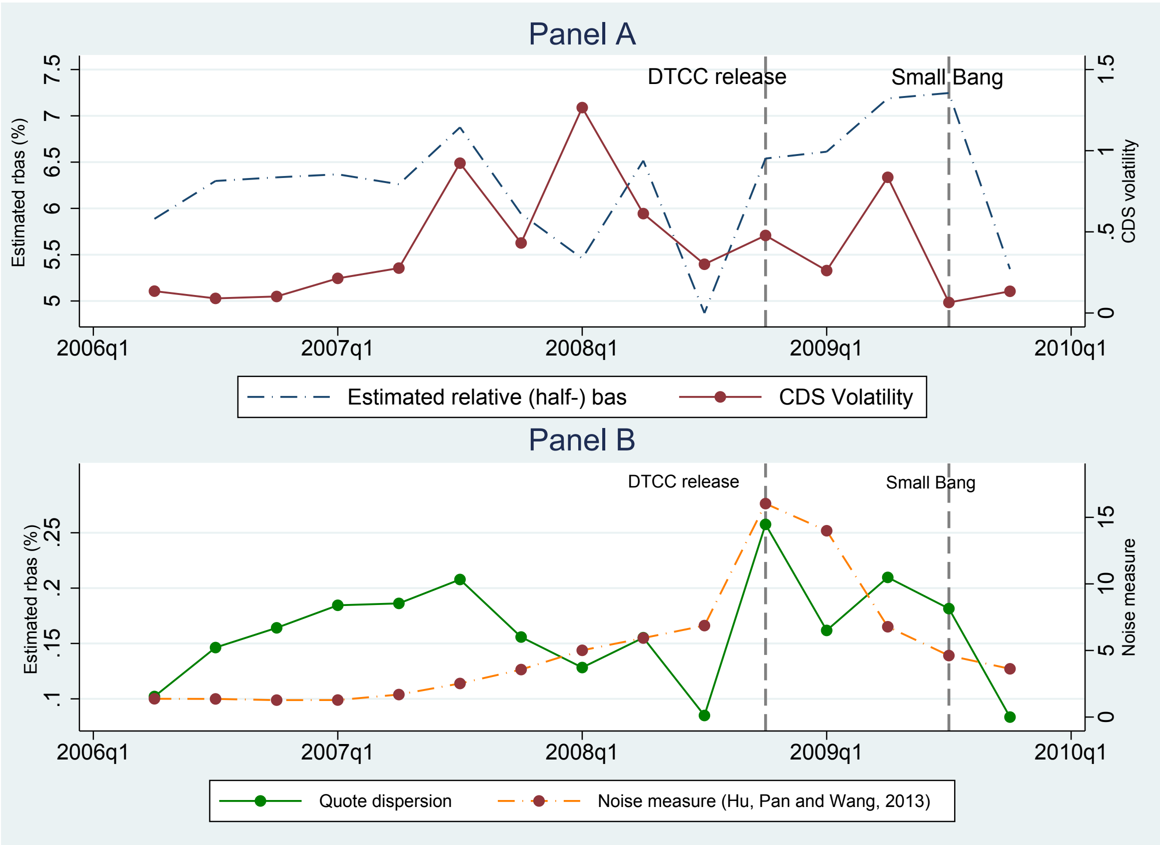

Figure 3: Overview of the quarterly estimates during the period from April 1, 2006 to December 31, 2009

The top graph (Panel A) plots the model-based relative (half-) bid-ask spread and the CDS volatility, estimated every quarter during our sample period and averaged across the 172 European CDS in sample. The bottom graph (Panel B) does the same with the model-based quote dispersion and a measure of funding liquidity (the noise measure of Hu, Pan and Wang, 2013).

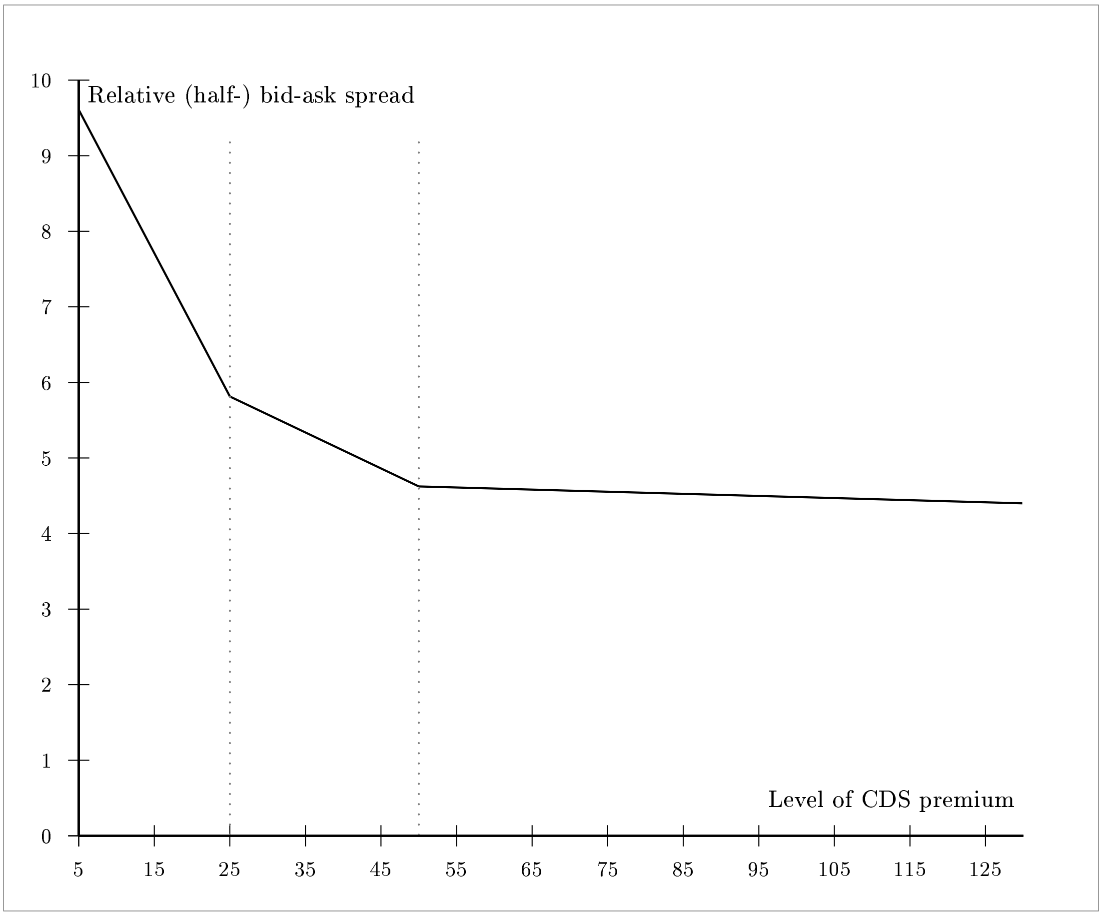

Figure 4: Relationship between the relative bid-ask spread and CDS price

Figure 4 plots the relationship between the model-based relative (half-) bid-ask (b/a) spread and the level of the CDS premium implied by a piecewise linear regression of the relative b/a spread on CDS price and other CDS characteristics (credit risk, quote dispersion, CDS volatility) for 172 European CDS from April 1, 2006 to December 31, 2009. The following variables are used to estimate piecewise linear regressions:

$$Mdpt\_0to25 = \begin{cases} Mdpt \text{ if } Mdpt < 25 \\ 25 \text{ if } Mdpt \geq 25 \end{cases}$$

$$Mdpt\_25to50 = \begin{cases} 0 \text{ if } Mdpt < 25 \\ Mdpt - 25 \text{ if } 25 \leq Mdpt < 50 \\ 25 \text{ if } Mdpt \geq 50 \end{cases}$$

$$Mdpt\_50Over = \begin{cases} 0 \text{ if } Mdpt < 50 \\ Mdpt - 50 \text{ if } Mdpt \geq 50 \end{cases}$$

where $Mdpt$ is the CDS price midpoint (see caption of Table 1).

Table 1

Summary statistics

This table presents summary statistics for the CDS data used in this study. We use data from GFI, one of the main inter-dealer CDS broker, from which we retrieve time-stamped (down to the second) information on bid quotes, ask quotes, and transaction prices during the period from March 31, 2006 to December 31, 2009, i.e., 18 quarters, for 172 European CDS contracts. We use a sample of 5-year CDS. These contracts have been selected on the highest number of data points (number of quotes). These data are complemented by data from SDC and RMI-CRI.
The CDS price midpoint (CDS premium mdpt) is computed as (ask + bid)/2, calculated when we observe a pair of quotes, averaged each quarter over the sample period and reported in basis point. Daily number of trades is the number of trades divided by the number of days during which at least one trade occurs during the quarter. Difference between two consecutive trades is the average number of days between two consecutive transactions. Total # Trades is the number of trades during the quarter. Total # Bid-ask spread is the total number of observations of pair of bid and ask quotes during the quarter. Daily average number of bid (resp. ask) quotes - Daily # Best Bid (resp. Ask) - is the total number of bid (ask) quotes divided by the number days during which at least one bid (ask) quotes is registered. The quoted half-bid-ask spread is the average difference between the best ask and the best bid divided by 2, when both quoted prices are observed for the same time-stamp. The relative quoted (half-) spread is the average (half-) bid-ask spread divided by the midpoint for the same time-stamp. Quote imbalance is the average daily number of bid quotes minus the daily number of ask quotes over the number of bid and ask quotes. Adjusted-Roll volatility is computed as the variance of midpoint changes adjusted by the autocovariance of two consecutives midpoint changes as follows:

$$\text{Adjusted-Roll volatility} = Var(\Delta mdp_t) + 2Cov(\Delta mdp_t, \Delta mdp_{t-1}) \tag{13}$$

where $mdp = log$(CDS premium mdpt). The RMI-1 year and RMI-5 year probability of default (PD) are extracted from the database from RMI - Credit Research Institute and are reported in %.

Variables	N	Mean	Median	Std. Dev.	Min	Max
CDS Premium Mdpt (bp)	1809	93	60	101	4	895
# Daily Trades	1809	0.37	0.23	0.47	0.02	5.67
Difference between 2 consecutives trades (Days)	1793	22	9	41	0	500
Total # Trades / Quarter	1809	18	9	29	1	363
Total # Bid-ask spread / Quarter	1809	228	154	232	14	1972
# Daily Best Bid	1809	6.5	5	4	1.4	34.2
# Daily Best Ask	1809	6	4.5	3.8	1.2	34
Quoted (half-) bid-ask spread (bp)	1809	6.5	4	7.19	0.70	86
Relative quoted (half-) bid-ask spread (%)	1809	3.76	3.39	1.81	0.93	23.28
Quote imbalance (%)	1809	8.5	7.30	9.50	-39.80	72.95
Adjusted-Roll Volatility (%)	1797	0.80	0.55	0.97	0.002	24.15
RMI 1-year PD (%)	1809	0.19	0.10	0.28	0.001	4.85
RMI 5-year PD (%)	1809	1.23	1.00	0.92	0.08	10.77
Total Bonds Issued / Quarter ($000,000)	1809	1067	0	5165	0	184,208

Table 2

Estimation results for the transaction cost econometric model

This table presents the average Maximum Likelihood (ML) estimates of the state-space model based on bid and ask quotes of 172 5-year European CDS contracts, on a quarterly basis, from March 31, 2006 through December 31, 2009. It contains the average ML estimates for the mean (half-) bid-ask spread ($exp(\mu)$),the CDS volatility ($exp(\sigma^2)$), and the quote dispersion ($exp(\sigma_c^2)$) across all 172 CDS.

Variables	N	Mean	Median	Std. Dev.	Min	Max
Relative bid-ask spread (%) - estimates	1809	5.97	5.36	2.89	0,00	34.30
CDS volatility (%) - estimates	1809	0.38	0.25	0.39	0.0004	3.76
Quote dispersion (%) - estimates	1809	0.15	0.10	0.22	0.007	3.84

Table 3

Determinants of CDS liquidity

This table reports least-squares estimates of the relation between the CDS liquidity of a corporate reference entity and variables that determine liquidity. Panel A presents the results when the left-hand side variable is the average relative (half-) bid-ask spread ($exp(\mu)$) estimated using the model described by Eq. (1), (6) and (7) and when the CDS volatility ($exp(\sigma^2)$) and quote dispersion ($exp(\sigma_c^2)$), which are right-hand side variable are also estimated using the model described by Eq. (1), (6) and (7). Panel B presents results when the left-hand side variable is the observed relative quoted bid-ask spread. Adjusted-Roll volatility a right-hand side variable- is computed using the Roll model (see for more details the caption of Summary Statistics). Order-Processing Costs are computed as the inverse of the square root of the daily number of trades ($1/\sqrt{nb\_trades\_d}$). All other right-hand side variables are described in the caption of the Summary Statistics. All specifications contain industry dummies. T-statistics are calculated using robust standard errors clustered by reference entity. The symbols ***, **, * denote significance levels of 1%, 5% and 10%, respectively, for the two-tailed hypothesis test that the coefficient equals zero.

Panel A

Dependent variable:	Estimated Bid-Ask Spread (%)	
	(1)	(2)
CDS Volatility	0.435 **	0.414 **
	(2.17)	(2.10)
Quote Dispersion	7.368 ***	7.382 ***
	(4.50)	(4.51)
Order-Processing Costs	0.904 ***	0.903 ***
	(14.19)	(14.11)
Quote imbalances	-0.007	-0.007
	(-0.85)	(-0.86)
RMI 1-year PD	-0.492	
	(-1.12)	
(RMI 1-year PD)^2	0.001	
	(0.09)	
RMI 5-year PD		-0.131
		(-0.88)
(RMI 5-year PD)^2		0.000
		(0.16)
Intercept	2.869 ***	2.943 ***
	(11.17)	(10.56)
Industry FEs	Yes	Yes
N	1809	1809
R-squared	0.59	0.59

Panel B		
Dependent variable:	Relative Quoted (Half-) Bid-Ask Spread	
	(1)	(2)
Adjusted-Roll Volatility	0.396 ***	0.390 ***
	(2.92)	(2.93)
Order-Processing Costs	0.673 ***	0.674 ***
	(15.53)	(15.44)
Quote imbalances	-0.013 *	-0.013 *
	(-1.80)	(-1.81)
RMI 1-year PD	-0.824 **	
	(-2.31)	
(RMI 1-year PD)^2	0.010	
	(1.17)	
RMI 5-year PD		-0.270 *
		(-1.77)
(RMI 5-year PD)^2		0.002
		(0.87)
Intercept	2.361 ***	2.512 ***
	(12.16)	(11.61)
Industry FEs	Yes	Yes
N	1797	1797
R-squared	0.31	0.30

Table 4

CDS liquidity around the DTCC's publication of aggregated post-trade data on October 31, 2008

This table presents least-squares estimates of the relation between the liquidity of 5-year CDS of single-name corporate entities and a dummy variable representing the time period (2 months) before or after the event date, which is the DTCC's publication of aggregated post-trade data. The left-hand side variable is a measure of liquidity (bid-ask spread) estimated using the model described by Eq. (1), (6) and (7). The right-hand side variables are defined as follows. The variable d_after is an indicator variable that takes 1 if an observation belongs to the 2-month period after the event, and zero otherwise. The variable d_banks (d_G14) is an indicator variable that takes the value 1 if the reference entity belongs to the group of banks (resp. G14). The variable d_bankswoG14 is an indicator variable that takes the value 1 if the reference entity belongs to the group of banks excluding G14 dealers. The variables of interest are the interaction terms between d_after and d_banks, d_G14 and d_bankswoG14, respectively. CDS volatility is the estimated volatility of the efficient CDS price described by Eq. (1), (6) and (7). Quote Dispersion is a measure of quote heterogeneity described by Eq. (3). The probability of default of the reference entity (12 month) is the RMI-1 year probability of default computed by RMI - Credit Research Institute. All specifications contain industry dummies. T-statistics are calculated using robust clustered standard errors. The symbols ***, **, * denote significance levels of 1%, 5% and 10%, respectively, for the two-tailed hypothesis test that the coefficient equals zero.

Dependent variable:	Estimated Bid-Ask Spread (%)		
	(1)	(2)	(3)
d_banks	0.004		
	(1.09)		
d_G14		0.007 *	0.005
		(1.72)	(1.16)
d_banksw/oG14			0.003
			(0.68)
d_after	0.023 ***	0.022 ***	0.023 ***
	(5.35)	(5.30)	(5.31)
d_after X banks	-0.014 ***		
	(-3.74)		
d_after X G14		-0.013 ***	-0.015 ***
		(-3.54)	(-3.59)
d_after X d_banksw/oG14			-0.012 **
			(-2.88)
CDS volatility	0.661 *	0.797 **	0.666 *
	(1.97)	(2.38)	(1.96)
Quote dispersion	5.698 *	5.686 *	5.699 *
	(1.94)	(1.92)	(1.93)
RMI 1-year PD	-1.044 **	-1.110 **	-1.056 **
	(-2.39)	(-2.49)	(-2.31)
(RMI 1-year PD)^2	0.120 *	0.129 **	0.123 **
	(1.94)	(2.13)	(1.99)
Intercept	0.039 ***	0.040 ***	0.039 ***
	(35.83)	(35.78)	(35.59)
Industry FEs	Yes	Yes	Yes
N	200	200	200
R-squared	0.51	0.51	0.51

Table 5

CDS liquidity around the Small Bang

This table presents least-squares estimates of the relation between the illiquidity of 5-year CDS of single-name corporate entities and a dummy variable representing the time period (2 months) before or after the event date. The event date is the implementation date of the Small Bang, 31 July 2008. The left-hand side variable is relative bid-ask spread estimated using the model described by Eq. (1), (6) and (7). The right-hand side variables are defined as follows. The variable d_afterSmallBang is an indicator variable that takes 1 if an observation belongs to the 2-month period after the event, and zero otherwise. The other variables are described in the caption of Table 4. All specifications contain industry dummies. T-statistics are calculated using robust clustered standard errors. The symbols ***, **, * denote significance levels of 1%, 5% and 10%, respectively, for the two-tailed hypothesis test that the coefficient equals zero.

Dependent variable:	Estimated Bid-Ask Spread (%)			
	(1)		(2)	
d_afterSmallBang	-0.005	**	-0.004	**
	(-2.35)		(-2.26)	
CDS Volatility	0.029		-0.005	
	(0.21)		(-0.04)	
Quote Dispersion	15.305	***	15.404	***
	(7.23)		(7.20)	
RMI 1-year PD	-3.180			
	(-1.58)			
(RMI 1-year PD)^2	2.382			
	(1.49)			
RMI 5-year PD			-1.520	**
			(-2.27)	
(RMI 5-year PD)^2			0.289	**
			(2.34)	
Intercept	0.066	***	0.055	***
	(5.72)		(6.77)	
Industry FEs	Yes		Yes	
N	192		192	
R-squared	0.68		0.68	

Table 6

Did Small Bang help improve liquidity of more illiquid CDS?

This table presents least-squares estimates of the relation between the illiquidity change of 5-year CDS of single-name corporate entities around the Small Bang and the level of illiquidity of these CDS before the Small Bang. The left-hand side variable is a measure of first difference in liquidity (relative bid-ask spread) estimated using the model described by Eq. (1), (6) and (7). The right-hand side variables are defined as follows. The variable lag_ba spread is the level of transaction costs estimated by the model over the 2-month period before the Small Bang. The variable d_$[33, 66]$ (resp. d_$[66, 100]$) takes 1 if the level of lagged transaction costs (measured by lag_ba spread) belongs to (resp. is above) the second tercile of the distribution of lagged transaction costs. All other right-hand side variables are described in the caption of Table 4. We take the first differences of these control variables. All specifications contain industry dummies. T-statistics are calculated using robust clustered standard errors. The symbols ***, **, * denote significance levels of 1%, 5% and 10%, respectively, for the two-tailed hypothesis test that the coefficient equals zero.

Dependent variable:	Δ Estimated Bid-Ask Spread (%)	
	(1)	(2)
lag_b/a spread (%)	-0.213 ***	
	(-3.49)	
d_[33,66]		-0.007 **
		(-2.26)
d_[66,100]		-0.014 ***
		(-3.23)
Δ CDS Volatility	-0.557 ***	-0.524 ***
	(-5.19)	(-7.12)
Δ Quote Dispersion	3.923 ***	4.400 ***
	(2.92)	(3.04)
Δ RMI 1-year PD	-1.542	-1.724 *
	(-1.65)	(-1.74)
Δ (RMI 1-year PD)^2	0.237 *	0.264 *
	(1.82)	(1.93)
Intercept	0.009 **	0.001
	(2.25)	(0.37)
Industry FEs	Yes	Yes
N	96	96
R-squared	0.54	0.51

Table 7

Robustness: Two-stage selection model

This table presents two-stage estimates of the relation between the illiquidity change of 5-year CDS of single-name corporate entities around the Small Bang and the instrumented dummy for very illiquid CDS before the Small Bang. In the first-stage equation regression, the left-hand side variable is the latent variable d_[66,100] which takes 1 if the level of lagged transaction costs is above the second tercile of the distribution of these lagged transaction costs (see caption of Table 6 for more details regarding variables). The instrument is the total amount of bond issued in euro. This variable, computed from SDC, is measured at the quarter ending at least 3 months before the event, i.e. quarter one 2009. In the second-stage, the left-hand side variable is a measure of first difference in liquidity (relative bid-ask spread, μ) estimated using the model described by Eq. (1), (6) and (7). The right-hand side variables are defined in caption of Table 6. Estimated rhô is the estimated correlation between first and second stage error terms. All specifications contain industry dummies. T-statistics are calculated using robust clustered standard errors. The symbols ***, **, * denote significance levels of 1%, 5% and 10%, respectively, for the two-tailed hypothesis test that the coefficient equals zero.

Dependent variable:	Δ Estimated Bid-Ask Spread (%)	
Second stage results		
d_[66,100]	-0.0161	***
[instrumented]	[0.0057]	
Δ CDS Volatility	-0.5094	***
	[0.0524]	
Δ Quote Dispersion	4.6712	***
	[1.366]	
Δ RMI 1-year PD	-3.1533	
	[1.944]	
Δ (RMI 1-year PD)^2	2.1967	*
	[1.3049]	
Intercept	0.0092	
	[0.0026]	***
Industry FEs	Yes	
Estimated rhô	0.3902	*
	[0.2246]	
Chi-square test (rhô=0)	3.02	*
N	96	
First stage results		
Total # bond issues ($)	-0.2322	***
	[0.0894]	

Table 8

Robustness: Placebo tests

This table presents least-squares estimates of the relation between the liquidity of 5-year CDS of single-name corporate entities and a dummy variable representing the time period (2 months) before or after a fake event date. The left-hand side variable is a measure of liquidity (bid-ask spread) estimated using the model described by Eq. (1), (6) and (7). The left-hand side variable d_PlaceboAfter is an indicator variable that takes 1 if an observation belongs to the 2-month period after the fake event, and zero otherwise. In panel A, the placebo regression tests the robustness of changes in illiquidity around the DTCCs publication. We consider a placebo DTCC event has occurred on October 31, 2006. Panel B reports results for the placebo regression for the Small Bang. A placebo Small Bang is supposed to have occurred between June 2, 2006 and July 31, 2006. All other right-hand side variables are described in the caption of Table 4. All specifications contain industry dummies. T-statistics are calculated using robust clustered standard errors. The symbols ***, **, * denote significance levels of 1%, 5% and 10%, respectively, for the two-tailed hypothesis test that the coefficient equals zero.

Panel A				
Dependent variable:	Estimated Bid-Ask Spread (%)			
	(1)		(2)	
d_banks	0.047	***		
	(4.57)			
d_G14			-0.019	***
			(-2.70)	
d_afterPlacebo	-0.000	*	-0.000	
	(-1.81)		(-1.38)	
d_afterPlacebo X banks	-0.001			
	(-0.54)			
d_afterPlacebo X G14			0.000	
			(1.46)	
CDS volatility	-0.697	**	-0.718	**
	(-2.08)		(-2.19)	
Quote dispersion	8.966	***	9.199	***
	(2.83)		(2.83)	
RMI 1-year PD	-17.272	**	-15.298	**
	(-2.61)		(-2.34)	
(RMI 1-year PD)^2	19.992	*	20.068	*
	(1.83)		(1.84)	
Intercept	0.034	***	0.033	***
	(6.20)		(6.19)	
Industry FEs	Yes		Yes	
N	154		154	
R-squared	0.36		0.35	

Panel B		
Dependent variable:	Estimated Bid-Ask Spread (%)	
	(1)	(2)
d_afterPlaceboSmallBang	-0.001	-0.001
	(-0.40)	(-0.54)
CDS Volatility	-0.599 ***	-0.595 ***
	(-3.99)	(-3.99)
Quote Dispersion	31.452 ***	31.866 ***
	(7.19)	(7.29)
RMI 5-year PD	-0.549	
	(-0.63)	
(RMI 5-year PD)^2	0.017	
	(0.05)	
RMI 1-year PD		-0.300
		(-0.07)
(RMI 1-year PD)^2		-7.783
		(-0.73)
Intercept	0.032 ***	0.028 ***
	(5.87)	(7.63)
Industry FEs	Yes	Yes
N	156	156
R-squared	0.74	0.74