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ORIGINAL RESEARCH

Explaining co-movements between equity and CDS bid-ask spreads

Miriam Marra[1]

Abstract In this paper I show that the co-movements between bid-ask spreads of equities and credit default swaps vary over time and increase over crisis periods. The co-movements are strongly related to systematic risk factors and to the theoretical debt-to-equity hedge ratio. I document that hedging and asymmetric information, besides higher funding costs and market volatility risk, are driving factors of the commonality and are significantly priced in CDS bid-ask spreads.

Keywords Credit default swap · Bid-ask spread co-movement · Funding costs · Systematic risk · Hedging · Capital structure arbitrage

JEL Classification G1 · G12 · G14 · G19

1 Introduction

Liquidity and its impact on asset prices have become a major focus in the academic literature. While most studies focus on the liquidity characteristics of a specific security market (e.g. stocks, bonds, options, credit default swaps) and examine the liquidity commonality of securities within each market, there are still gaps in the literature on the characteristics of cross-market liquidity. In particular, to the best of my knowledge, there is no study that examines the channels of liquidity commonality across equity and credit default swaps.[1]

[1] Some existing papers study instead the CDS-bond liquidity commonality (see Pu 2009) and the equity-equity options liquidity commonality (see Cao and Wei 2010).

A previous version of this paper has been circulated with the title: *Co-movements in Equity and CDS Illiquidity*.

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This paper is a first step towards filling this gap. I study the liquidity of these two markets and the drivers of the co-movements between credit default swap (CDS) and equity bid-ask spreads. As outlined by structural models, equity and CDS markets have strong inter-linkages[2] which increase in bad times when firms' leverage and credit risk widen. In addition, the increasing use of CDSs over the past decade has made arbitrage and hedging across equity and debt markets easier. Studying the joint liquidity dynamics of CDSs and equities has key implications for cross-market trading and is important to understand whether higher integration across these markets may lead to higher liquidity risk for investors. Thus, the contribution of my paper is to show the existence of liquidity risk due to the time-varying co-movements across equity and CDS market liquidity costs and explain the sources of this co-movements.

A few researchers have attempted to detect the existence of illiquidity co-movements across equity and CDS markets (Tang and Yan 2006; Jacoby et al. 2009), but have not provided any explanation of this phenomenon. To explain the equity-CDS illiquidity co-movements I instead examine two important drivers which are at the centre of the debate on the financial crisis of 2007–2009: (i) funding risk and fire-sales effects across asset markets; and (ii) negative information spillovers and trading across correlated markets.

The existing theoretical literature explains that systematic risk factors, such as common negative shocks to traders' income, higher costs of funding, and wider market volatility, can increase the commonality in illiquidity across different security markets (Schleifer and Vishny 1997; Kyle and Xiong 2001; Xiong 2001; Gromb and Vayanos 2002, 2010; Brunnermeier and Pedersen 2009). In a crisis period, financial constraints and extreme volatility risk may give rise to the forced withdrawal of liquidity in several markets simultaneously, often accompanied by fire-sales of assets. Comerton-Forde et al. (2010), Hameed et al. (2010), and Ben-David et al. (2012), amongst others, provide empirical evidence for this theory in equity markets. However, no study has tested yet this mechanism (which I call 'funding channel') for the co-movements between equity and CDS bid-ask spreads, as my paper instead does.

While a 'funding channel' of illiquidity co-movements can exist between markets with or without correlated fundamentals, across two correlated markets higher hedging and arbitrage trading may induce even stronger commonality. Illiquidity may spread across correlated markets via dealers' hedging activity and via transmission of asymmetric information risk. CDS dealers (mostly sophisticated banks) can hedge their unbalanced CDS positions in the equity market, particularly in presence of higher credit risk. They recover the hedging cost (given by the delta-hedging ratio times the equity bid-ask spread) by increasing the CDS bid-ask spread. As the models by Biais and Hillon (1994) and Huh et al. (2015) explain, larger hedging activity in the derivative market may convey a signal of higher information risk to the dealers in the underlying (equity) market. Equity dealers protect themselves from this risk by increasing bid-ask spreads in the equity market. This increase may widen further the cost of hedging for CDS dealers and the CDS bid-ask spreads, thereby reinforcing the co-movements ('hedging channel').

A model by Foucault et al. (2014) also points out that arbitrageurs' informed trading activity may cause dealers in two correlated markets to increase bid-ask spreads. When capital structure arbitrageurs observe a significant mispricing between CDS and equity (particularly after a negative shock to the firm, which tends to be impounded first into CDS prices), they may decide to trade across the two markets to profit from it. This will cause a

[2] The seminal paper by Merton (1974) explains that equity and credit are claims written on the underlying firm's assets, so they are fundamentally related.

reaction from less informed equity and CDS dealers who will increase both equity and CDS bid-ask spreads. The commonality then augments ('arbitrage channel').

Thus, the CDS and equity markets provide a useful laboratory where to test the relative significance and impact of the 'funding channel' and the 'hedging–arbitrage channel'. I analyze a sample of U.S. firms over the period April 2003–December 2009 and I observe that the co-movement between their equity and CDS bid-ask spreads changes over time: it is much higher in 2003 than during the period 2004–2006 and then it rises again during the crisis period of 2007–2009. In panel analysis I detect a significant positive effect of systematic factors, such as higher funding constraints and market volatility, on the equity-CDS bid-ask spread commonality. This result confirms the existence of a 'funding channel'. However, I also show that the hedge ratio (estimated from the Merton's model) is another important determinant of the increase in bid-ask spread commonality. The debt-to-equity hedge ratio measures the sensitivity of debt (or credit) claims to changes in the value of equity. When this sensitivity increases, the liquidity costs in the two markets are linked more strongly. To confirm the existence of a 'hedging–arbitrage channel' I use instrumental-variable panel regressions. I instrument the hedge ratio using proxies for risk-aversion, asymmetric information, CDS demand pressure, and CDS-equity mispricing (indicative of hedging and arbitrage trading interest). Finally, in order to provide more evidence on the mechanisms and effects of the two channels (the 'funding channel' and the 'hedging–arbitrage channel'), I also analyze the determinants of CDS bid-ask spreads. After controlling for the significant effects of higher market volatility and crisis-periods effects, I confirm that hedging costs, asymmetric information risk and mispricings across CDS and equity markets significantly explain the increase in CDS bid-ask spreads.

The paper is organized as follows. Section 2 describes the data employed and presents some statistical evidence on the existence of equity-CDS bid-ask spreads co-movements. Section 3 explains the funding and hedging–arbitrage channels. Sections 4 and 5 test the channels by examining respectively the effects of systematic risk factors and debt-to-equity hedge ratio on the commonality in illiquidity, and the determinants of CDS bid-ask spreads. Section 6 concludes.

2 Detecting co-movements between equity and CDS bid-ask spreads

In this section I first report some basic facts about equity and CDS markets, then I describe the data sample used, and finally I analyse the co-movements between equity and CDS bid-ask spreads.

2.1 CDS and equity markets microstructure

In normal times, equity and CDSs are liquid markets. In particular, the CDS market is much more liquid than the underlying corporate bond market. Thus, it is the market to which investors are more likely to turn when they want to take long or short credit positions for a relatively short time.[3] While the mix of participants in the equity market is heterogeneous, the CDS market is mainly a trading venue for hedging and speculative activity of institutional investors. For example, banks hedge their large portfolios of loans in the CDS market and hedge funds and private equity firms use CDSs for a variety of

[3] In September 2009 the corporate CDS market has nearly outsized the bond market, reaching USD 9.7 trillion versus USD 10.0 trillion for their long-term debt securities (BIS, Quarterly Review, March 2010).

trading strategies (popularly known as capital structure arbitrage) that attempt to arbitrage across equity and credit markets.[4]

The microstructure of CDS and equity markets is different. The CDS market is a bilateral dealership over-the-counter market, with no centralized quote disclosure mechanism and with a less than fully competitive network of (private) dealers, usually controlled by a group of major banks.[5] In the CDS market many banks act as dealers by posting bid and ask quotes for CDS protection. Apart from their role as dealers, banks also use CDSs for managing the risk connected to their own loan exposure (and they are net buyers of CDS protection).[6] Therefore, some of the dealers in the CDS market potentially have access to companies' private credit information. The role of the dealers in the equity market is much less ambiguous, as they are liquidity-providers with no particular information advantage on the stocks for which they provide a market. Moreover, stocks are exchange-traded and all dealers can access centralized and transparent quote-disclosure mechanisms.

Despite their differences, in both CDS and equity markets the fundamental role of the dealers is to provide liquidity in their respective assets. The dealer buys a security on her own account (at the bid price) or sells a security from her own account (at the ask price). The bid-ask spread is the cost of a round-trip transaction and also represents the compensation earned by the dealer for providing liquidity. Dealers try to make a profit by maximizing the spreads they earn, given the volumes traded and the costs they have to bear.

2.2 Data description

I employ data on U.S. companies which remain stable components of the Dow Jones 5-years CDX North America Investment Grade Index (CDX.NA.IG) throughout the whole sample period in order to ensure continuous series of CDS quotes.[7] I use 5-year CDS contracts because trading liquidity and data availability is highest in this maturity. The CDX.NA.IG index is composed of 125 firms; however, 45 firms remain after excluding financial firms[8] and companies recording missing values in the CDS series for more than 20 consecutive days over the period 2003–2009. The firms in my sample are investment-grade firms that did not suffer from major distress and restructuring events over the period considered. These companies are publicly traded, have large market capitalization and are typically followed by a large number of analysts. Their stocks and CDSs are typically more

[4] Hedge funds constitute a major force in the CDS market. Between 2004 and 2006 they doubled their market share and with 30% of volume traded on both sides of the market, they became the second largest group of participants in the CDS market, after banks (British Bankers Association 2006).

[5] According to a survey by Fitch Ratings (2009) conducted amongst 26 banks which play a major role in the CDS market, the five largest banks are responsible for 88% of notional amount bought and sold.

[6] Banks' trading activity constitutes 33 and 36% respectively of total sold and purchased volume of CDSs. Banks' loan portfolio activity represents instead 7% of total sold volume of CDS, and 18% of total bought volume. On the sell side of the CDS market, insurance companies are also particularly active and provide around 18% of total CDS supply (British Bankers Association 2006).

[7] Being able to use continuous and reliable bid and ask quotes to estimate the illiquidity co-movements, instead of inferring them or interpolating discontinuous series (particularly during the crisis period), is important to minimize measurement errors in the key variable of the analysis.

[8] I exclude the financial and insurance companies, after observing that during the crisis these firms (e.g. American International Group) have been target of direct/indirect Government intervention which likely had a one-off impact also on the trading costs of their securities (and set the firms apart for a different kind of analysis).

liquid than the stocks and CDSs of small and distressed firms. This sample selection ensures more conservative results in terms of detecting substantial equity and CDS illiquidity and commonality across their bid-ask spreads.

For each firm I select the corresponding stock and the 5-years on-the-run credit default swap. I collect daily quotes (bid and ask prices) and daily close trading data (price and volume) for firms' stocks from The Center for Research in Security Prices (CRSP) Daily Stock dataset. The sample period goes from April 2003 to December 2009. The CRSP stock dataset includes all transactions and quotes from NYSE, AMEX, and NASDAQ. I use daily CDS data from Bloomberg, which in turn sources its CDS data from the Credit Market Analysis (CMA) database.[9] Mayordomo et al. (2014) show that the CMA database leads in CDS price discovery, when compared to other five major CDS data providers (GFI, Fenics, Reuters, Markit and JP Morgan). After filtering the data,[10] I obtain a daily equity dataset of 75,825 observations and a daily CDS dataset of 72,739 observations.

Prior literature has examined liquidity using different proxies for trading costs, trading frequency or trading impact on prices (see for example Kluger and Stephan 1997) and for different markets (Spiegel 2008). I have information on CDS quotes from CMA, but I do not have transaction prices and traded volumes for CDS contracts over the period 2003–2009. So I am left with one possible measure of liquidity: the CDS bid-ask spread. I want to ascertain that the bid-ask spread is an informative measure of liquidity for equity in order to use bid-ask spreads as consistent and significant measures of liquidity costs for both CDS and equity markets. Since for equity I have information on daily prices, volumes and quotes from CRSP,[11] I construct a number of liquidity proxies at weekly frequency (Amihud measure, Roll measure, effective spread, bid-ask spread, run length and inverse turnover index) and then perform Principal Component Analysis (PCA) across all of them. I observe that the pattern of the average equity bid-ask spread over time is consistent with other measures of transaction costs and price impact of trades. However, the PCA reveals that the bid-ask spread has the highest loading in the First Principal Component, amongst all other illiquidity measures.[12]

Since equity bid and ask prices are quoted in dollar terms, while CDS bid and ask prices are quoted in basis points, for CDS bid-ask spread I use the difference between quoted bid and ask prices (as in Bongaerts et al. 2011, Völz and Wedow 2011, Coro et al. 2013; Pires et al. 2015), while for equity bid-ask spread I use the ratio between quoted bid-ask spread and mid-quote price. In the existing literature, the CDS bid-ask spread has been measured by the difference between ask and bid quotes (absolute bid-ask spread, as in Coro et al. 2013, and Pires et al. 2015), or by this difference normalized by the mid-quote point (percentage bid-ask spread, as for example in Hilscher et al. 2015). I favour the former measurement: Pires et al. (2015) provide a convincing numerical argument and show that since the CDS bid-ask spread is already a proportional measure there is no need to divide it by the mid-quote (as it is done instead for the equity bid-ask spread). This choice is particularly appropriate to perform a correct comparison between CDS and equity bid-ask

[9] At the time of my data collection, CMA data could be freely downloaded from Bloomberg. Currently, a licence is needed to download the CMA data.

[10] For each firm I delete all observations which exhibit for equity and CDS at least one of the following conditions: null bid or ask price; negative bid-ask spread (Ask price–Bid price < 0). Equity and CDS bid-ask spreads and returns are winsorized at the 0.5% lowest and highest values.

[11] I do not have intra-daily quotes and prices from TAQ.

[12] The results of this analysis are unreported for brevity, but they are available upon request.

spreads. Using my sample of data from April 2003 to December 2009, I find that the average CDS absolute bid-ask spread is equal to 6 bps; it is therefore lower than the average equity percentage bid-ask of 9 bps. The medians are however both very close to 5 bps. The standard deviations of the bid-ask spreads are equal to 14 bps for equity and 3 bps for CDS.[13]

2.3 Statistical analysis of co-movements

Given the different distributional properties of the two variables, Figs. 1, 2, and 3 plot the normalized bid-ask spreads to facilitate the comparison of their time-trends over the whole sample and in two sub-samples, before and during the financial crisis (i.e. July 2003–December 2006 and January 2007–December 2009).[14] I observe that equity and CDS bid-ask spreads are closely related: both are downward trending over the pre-crisis period, jump upwards during the crisis period and decline towards the end of the sample.

Pearson's, Kendall's Tau and Spearman's Rho measures of correlation between equity and CDS bid-ask spreads are calculated for each firm over each quarter (with no overlapping observations). The three estimated correlations are used as alternative measures of commonality in illiquidity. Pearson's correlation (ψ) measures the degree of linear association between equity and CDS bid-ask spreads. Rank correlation coefficients, such as Spearman's rank correlation (ρ) and Kendall's rank correlation (τ), measure how well the relationship between the two variables can be described using a monotonic function, without requiring the function to be linear.[15] The cross-sectional value-weighted averages are 56% for Pearson, 31% for Spearman's Rho, and 20% for Kendall's Tau. Table 1 shows instead the distributions of these measures of correlation (averaged over different time samples) across all 45 firms. Despite the dispersion of values being quite wide, the estimated measures remain on average largely positive over the whole sample period (from 15 to 42%), as well as over the sub-samples of 2003 (from 38 to 57%) and of 2007–2009 (from 13 to 27%). Correlation distributions present nearly zero average values only in the middle of the sample (2004–2006). In all subperiods, the correlation measures are statistically significant at the 1% significance level.

To summarize this preliminary statistical analysis, I find evidence of co-movements between equity and CDS bid-ask spreads of 45 firms using different measures of association. However, the co-movement varies over time and becomes prominent only over periods of higher credit risk and market turbulence, such as in 2003 and in 2007–2009. Outside these periods, little or no co-movement is observable.

[13] Hilscher et al. (2015) compare CDS and equity percentage bid-ask spreads over a sample that goes from 2001 to 2007. They find that the average percentage bid-ask spreads are higher for CDSs than for equity. If I used the percentage measure for CDS liquidity costs, I would reach the same conclusions of Hilscher et al. (2015): the percentage bid-ask spread for CDSs over the period 2003–2007 results equal to 10.48 bps on average (median 9.8 bps), so it is higher that the equity market average bid-ask of 7.40 bps (median 4.3 bps), while the absolute CDS bid-ask spread is on average only 5.13 bps (median 5 bps). By favouring the measurement of CDS liquidity costs as absolute bid-ask spreads for the reasons exposed above and by including the period 2007–2009, I find that liquidity costs appear lower for CDS contracts than for equity on average.

[14] For the empirical analysis in the remainder of the paper I use instead actual bid-ask spreads (not normalized).

[15] In my study the Fisher z-transformation (inverse hyperbolic function) is applied to all sample correlation coefficients r (where $r = (\psi, \tau, \rho)$): $z = 0.5ln(\frac{1+r}{1-r})$.

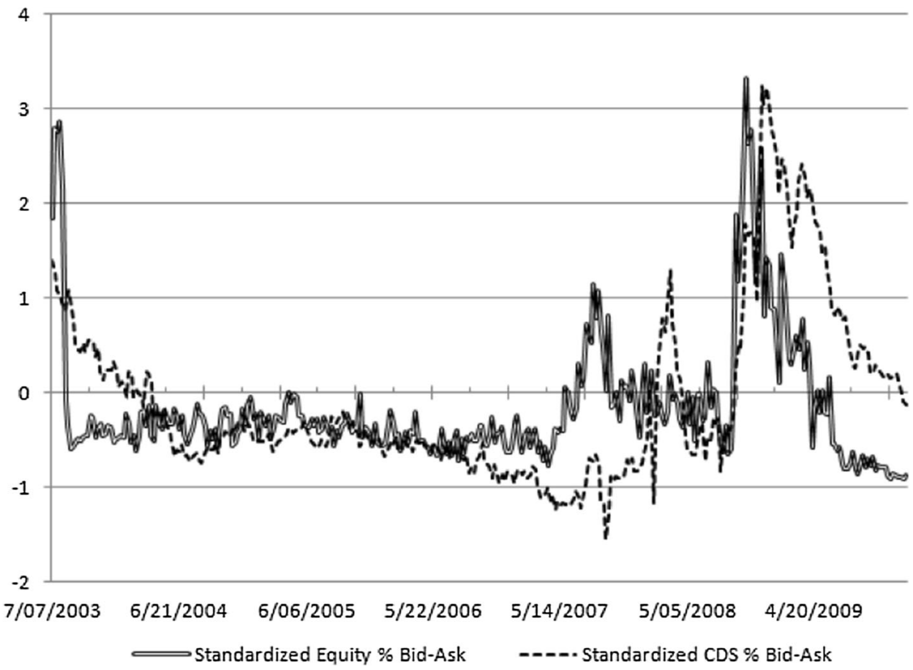


Fig. 1 Cross-sectional value-weighted average of normalized CDS and equity bid-ask spreads—All sample *(Weekly: July 2003–December 2009, Cross-Section of 45 Firms)*

3 What may determine co-movements in equity and CDS bid-ask spreads?

Statistical analysis has detected the existence of time-varying co-movements between equity and CDS bid-ask spreads. The next step of the study is to investigate the sources of the commonality. Some existing theoretical literature suggests two (not mutually exclusive) explanations: a 'funding channel' and a 'hedging–arbitrage channel'. In this section I explain the intuition behind these channels of CDS-equity bid-ask spread co-movements.

3.1 The funding channel (or supply channel)

Equity and CDS bid-ask spreads can surge contemporaneously because of an independent response of equity and CDS dealers to market-wide frictions. Previous literature has pointed out that the ability of dealers to supply liquidity in equity and CDS markets depends on the cost of funding, on the level of market volatility, and on the level of systematic risk (see, amongst others, Brunnermeier and Pedersen 2009). An increase in these factors in fact causes larger uncertainty and inventory risk for dealers, and wider dealership costs. In a crisis period these costs can be so high to force a withdrawal of liquidity supply in both equity and CDS markets and an increase in their liquidity costs. I define this channel of co-movements between equity and CDS bid-ask spreads as the 'funding channel'.

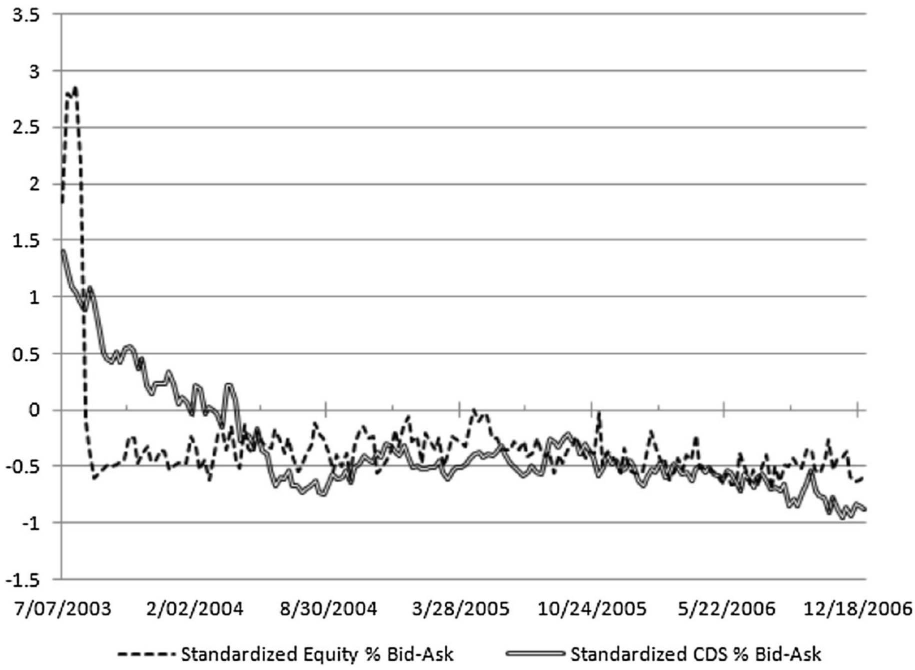


Fig. 2 Cross-sectional value-weighted average of normalized CDS and equity bid-ask spreads—pre-crisis sample *(Weekly: July 2003–December 2006, Cross-Section of 45 Firms)*

3.2 The Hedging–Arbitrage channel (or demand channel)

Let us consider the three groups of agents examined in most market microstructure models: (i) risk-averse dealers; (ii) uninformed risk-averse noise traders; and (iii) well-informed risk-neutral arbitrageurs. As explained in Sect. 2.1, in the CDS market the dealers can be informed or uninformed agents, while noise traders are uninformed agents mostly demanding CDS protection.[16] In the equity market both dealers and noise traders are uninformed agents. Noise traders enter into trades mainly for liquidity reasons. Arbitrageurs acquire and analyse public and private information (at a cost) to discover the 'fair' value of the assets, the 'correct' hedge ratio between the two markets, and how they vary over time. In this way, they can immediately recognize when prices in the equity and CDS markets are inconsistent and trade in order to profit from the mispricing.

Now let us analyse what may happen when the credit risk of a firm and its debt-to-equity hedge ratio increase and how this may affect the CDS-equity bid-ask spread commonality. I begin by considering the CDS dealers and their hedging needs and then turn to examining the interaction between the dealers in the CDS and equity markets, and the interaction between arbitrageurs and dealers.

The risk-averse (RA) CDS dealer who supplies CDS liquidity to noise-traders (e.g. bond investors) and arbitrageurs can hedge her short CDS unbalanced position (say X) by

[16] For example, bond market investors with passive hedging demand can be considered noise traders in the CDS market who want to hedge their credit risk exposures. CDS dealers are net sellers of CDSs to noise traders.

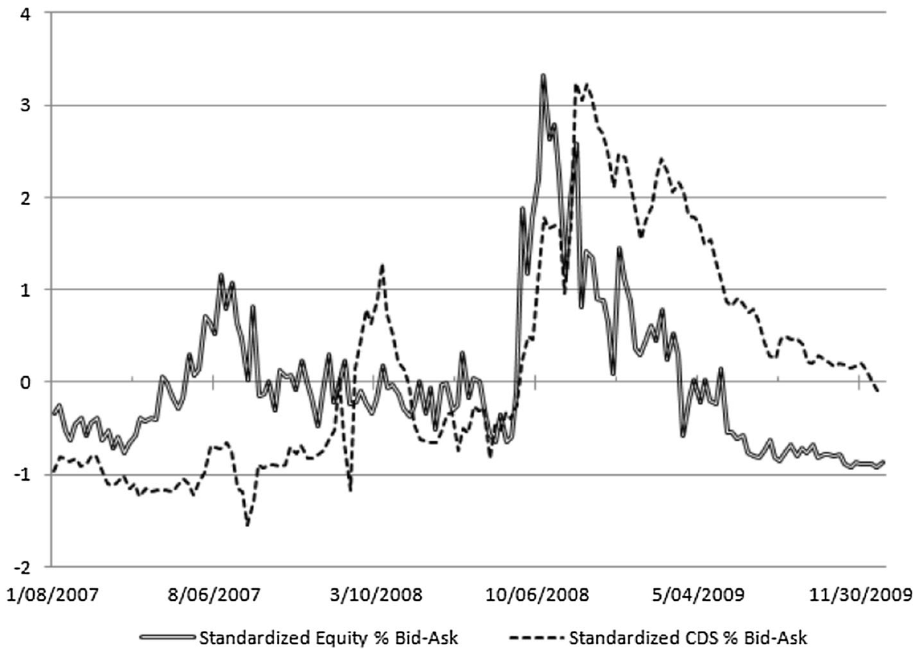


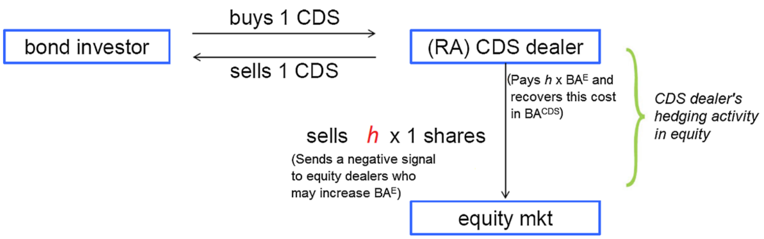
Fig. 3 Cross-sectional value-weighted average of normalized CDS and equity bid-ask spreads—Crisis sample *(Weekly: January 2007–December 2009, Cross-Section of 45 Firms)*

Table 1 Distributions of Pearson, Kendall and Spearman Correlations between equity and CDS bid-ask spreads (45 Firms; Time-Average Correlations are measured in decimals)

	Mean	Median	Std. Dev.	Inter-quartile range
All sample				
Pearson	0.4151	0.4170	0.1675	0.2247
Kendall	0.1469	0.1431	0.1004	0.1459
Spearman	0.2188	0.2128	0.1444	0.2071
Year 2003				
Pearson	0.5677	0.5867	0.1883	0.2618
Kendall	0.3830	0.3997	0.1121	0.1328
Spearman	0.5512	0.5782	0.1575	0.1792
Years 2004–2006				
Pearson	0.0144	0.0095	0.1528	0.1412
Kendall	0.0064	−0.0042	0.0931	0.1009
Spearman	0.0083	−0.0079	0.1374	0.1497
Years 2007–2009				
Pearson	0.2724	0.2780	0.1710	0.1372
Kendall	0.1300	0.1322	0.1134	0.1103
Spearman	0.1945	0.1960	0.1642	0.1578

shorting the corresponding equity (for an amount equal to hX).[17] The implicit cost of the hedging is the bid-ask spread of equity multiplied by the hedge ratio ($h \times E^{BA}$).[18] This hedging cost is recovered by the CDS dealer from the bid-ask spread she sets in the CDS market (CDS^{BA}). When the size of the hedge ratio h increases (this should also be large enough to have a recognizable effect) and the CDS dealer faces an increasing demand for CDS protection from noise-'CDS buyers', the cost of hedging surges and becomes a more important component of the CDS bid-ask spread, creating a stronger linkage between the liquidity costs in the CDS market and the liquidity costs in the equity market.

As explained also by Huh et al. (2015) model, when derivative dealers hedge their unbalanced positions in the equity market in presence of asymmetric information, they involuntarily convey a signal to equity dealers about the higher information risk. Some dealers-banks have an informational advantage over equity dealers. As a consequence, equity bid-ask spreads widen and further increase CDS bid-ask spreads. This hedging channel can help to explain not only the effect of the hedge ratio on the bid-ask spread commonality, but also the existence of illiquidity spillovers running from CDS to equity (signal effect) which I report in Appendix 2. The hedging channel mechanism is depicted in the graph below:



Furthermore, past literature has assessed that firm-specific bad news tends to be incorporated first in the CDS market and then in the equity market ahead of possible credit events, when the hedge ratio is particularly high (see, for example, Acharya and Johnson 2007; Qiu and Yu 2012; refer also to my detailed analysis of lead-lag relationships between CDS and equity market in Appendix 2). Xiang et al. (2015) test the economic significance of CDS price discovery on a similar sample to mine (non-financial investment-grade US firms from 2005 to 2009) and document non-trivial economic profits from trading stocks according to the credit risk price signal of the CDS market. The asymmetric information can generate a temporary mispricing between CDS and equity for a specific firm and it can fuel arbitrage trading across the two markets (so-called capital structure arbitrage).[19] For

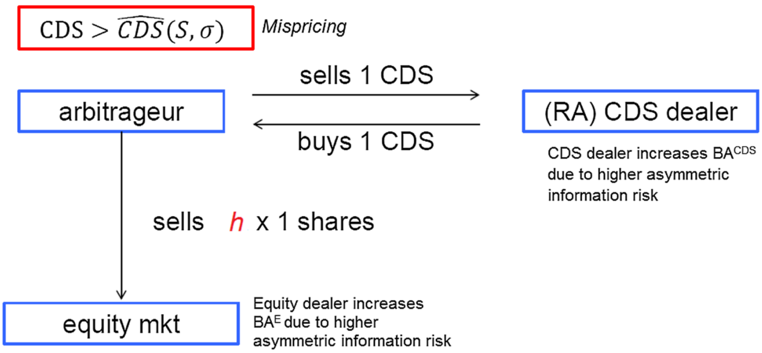
[17] The bigger is h, the more difficult is to hedge a CDS position, as this requires an increasing position in equity. However, when h increases, the incentive to hedge CDS position in the equity increases as well.

[18] Once the dealer closes her CDS position, she also closes her equity position and pays the bid-ask spread to the equity dealer as cost of the round-trip transaction.

[19] In recent years capital structure arbitrage (CSA) has become increasingly popular, particularly among hedge funds, as a result of the development of the credit default swap market that has allowed market participants to take short positions in credit risk more easily (Currie and Morris 2002). Yu (2006) and Duarte et al. (2007) analyse CSA trades involving credit default swaps (CDS) and equity and find that the strategy appears to offer attractive Sharpe ratios of around 0.8. In a more recent study, Ju et al. (2015) show that CSA can be a profitable strategy, especially when based on a relatively short holding period and on investment-grade obligors: they find a monthly median return of 6.45% for simulated 30-day strategies. The LIPPER TASS Asset Flow Report for hedge funds in the second quarter of 2008 disclaims a per-annum average compounded growth of 17% for funds invested in capital structure arbitrage strategies over the period January 1994–June 2008.

example, if well-informed arbitrageurs (e.g., hedge funds) believe that the market CDS premium for a specific firm is too high with respect to the CDS premium implied by the firm's equity price S and volatility σ ($\widehat{CDS}(S, \sigma)$), they take a short position (Z) in the CDS and a short position (hZ) in the corresponding equity.[20] The size of their cross-market positions is equal or proportional to the debt-to-equity hedge ratio estimated from a sophisticated structural model.[21] A higher hedge ratio, coupled with a substantial mispricing, therefore commands a larger correlated liquidity demand from informed arbitrageurs across the two markets, to which uninformed CDS and equity dealers react by increasing CDS and equity bid-ask spreads (see Foucault et al. 2014). Thus, if the CDS-equity arbitrage is possible and convenient (i.e. the CDS mispricing and h are significantly above 0), then bid-ask spreads should increase in both markets due to a surge in asymmetric information (Glosten and Milgrom 1985; Kyle 1985; Amihud and Mendelson 1986; Easley and O'Hara 1987; Admati and Pfleiderer 1988).[22]

This arbitrage channel represents another potential source of CDS-equity bid-ask spread commonality. Its mechanism is depicted in the graph below:



To sum up, when a firm's credit condition worsens and its debt-to-equity hedge ratio increases, higher commonality between CDS and equity bid-ask spreads can arise because of:

20 After a negative shock, the CDS premium may either over-react to the arrival of the new information or incorporate it correctly before the equity price. The cross-market arbitrage trading narrows the mispricing between CDS and equity and allows the capital structure arbitrageurs to profit from the trading regardless of whether the CDS premium will then decrease (after the initial over-reaction) to match the correct level of the equity price, or the equity price will decrease to match the new correct level of the CDS premium.

21 Yu (2006) reports that: "From what traders describe in media accounts, the equity hedge is often 'static', staying unchanged through the duration of the strategy. Moreover, traders often modify the model-based hedge ratio according to their own opinion of the particular type of convergence that is likely to occur". For example "the trader may decide to underhedge" or "he may overhedge".

22 In principle, if a CDS dealer could hedge all the risk related to her CDS position in the equity market, no cost of informed trading in the CDS market would arise. Nevertheless, when the hedge ratio is high, hedging activity can be very costly and dealers are more likely to apply a form of partial, rather than perfect, hedging (see Froot and Stein 1998). Therefore, they can remain exposed to the risk of losses due to informed trading. The information risk is not borne instead by superiorly-informed CDS dealers, who may decide not to increase CDS bid-ask spreads when this risk is higher. Thus, on aggregate, I should observe an average increase in CDS bid-ask spreads in response to larger information risk, but the effect should be less pronounced than in the equity market. Consistently, average equity bid-ask spread appears higher and more volatile than average CDS bid-ask spread during turbulent times (see Fig. 1). Moreover, it should be noticed that when the firm's credit risk is very high, the superiorly-informed CDS dealers may decide to withdraw from the market: thus, the CDS dealers who remain available to supply CDS contracts to noise traders could be mainly uniformed agents.

(1) Larger hedging costs for CDS dealers who need to rebalance their positions in the equity market: CDS dealers react by increasing the CDS bid-ask spreads;
(2) Negative signal of higher asymmetric information risk conveyed by CDS dealers to equity dealers via their hedging activity: equity dealers react by increasing equity bid-ask spreads;
(3) Larger demand for liquidity across CDS and equity markets from better-informed capital-structure arbitrageurs (when a CDS-equity mispricing arises): uninformed CDS and equity dealers react by setting higher bid-ask spreads in both equity and credit markets.

Next, I perform two tests on the existence of the ‘funding channel’ and ‘hedging–arbitrage channel’:

(A) A test on the effects of systematic factors and debt-to-equity hedge ratio on equity-CDS bid-ask spreads co-movements;
(B) A test on the effects of funding costs, hedging costs, CDS mispricing, and asymmetric information costs on CDS bid-ask spreads.

Sections 4 and 5 illustrate the tests’ methodologies and results.

4 Test (A): effects of systematic factors and hedge ratio on bid-ask spread co-movements

In this test the bid-ask spread commonality variable $Comm_{i,t}^{BA}$ is represented by Kendall’s Tau measure of correlation (Fisher-transformed) between daily equity and CDS bid-ask spreads of firm i constructed over each quarter t from April 2003 to December 2009.[23]

I first identify ‘funding channel’ variables that affect dealers’ ability to provide liquidity:

- Systematic risk factors (Fama-French market, size, and book-to-market factors):
  Higher exposure of a firm to market, size, and book-to-market risk factors (*MktRf*, *SMB*, and *HML*) may cause higher inventory costs for dealers operating in both the CDS and equity market of the specific firm, which then translate in higher bid-ask spreads.
- Cost of external funds (proxied by the spread between the 3-month LIBOR rate and the 3-month T-Bill yield, *TED*):[24]
  Dealers in different markets open and maintain their positions by borrowing external funds (the cost of funding also represents an opportunity-cost). Therefore, the higher funding cost can generate unwinding of positions across multiple markets, fire-sales, and large illiquidity discounts on assets. Additionally, the higher risk of assets’ devaluation can cause further pressure on dealership costs.

[23] Kapadia and Pu (2012) use Kendall’s Tau to measure the co-movement between CDS and equity returns and the level of integration between the markets. They stress three advantages of using this measure: first, Kendall’s Tau does not need any parametric setup; second, it is not impacted by non-linearities; third, being intuitively related to the variables’ co-movement, it is not affected by interpretation-ambiguity, unlike other measures, such as the coefficient of determination. A more positive Kendall’s Tau corresponds to equity-CDS markets being more integrated in their liquidity costs.

[24] In the financial crisis literature, the TED spread is often used as measure of short-term liquidity in the credit market and credit risk in the interbank lending market (see also Chiang et al. 2015, who study the TED spread effect on the dynamics of stock-bond correlations).

– Market volatility (proxied by the S&P500 option implied volatility index, *VIX*): Higher volatility can increase inventory costs and cause dealers to impose larger bid-ask spreads across all markets where they provide liquidity.

Furthermore, I analyse the effects of the 'hedging–arbitrage channel' on the bid-ask spread commonality $Comm_{i,t}^{BA}$ using a hedge ratio proxy. $H_{i,t}^{SS}$ is the estimated debt-to-equity hedge ratio for firm i in quarter t. Appendix 1 describes the two methodologies followed (from Vassalou and Xing 2004, and Schaefer and Strebulaev 2008) to estimate the debt-to-equity hedge ratio using the Merton (1974) model.[25] The two methodologies are called respectively VX and SS for brevity. For the main analysis I employ the hedge ratio obtained from the SS methodology. Afterwards, I check also the effect of the hedge ratio obtained from the VX methodology in order to provide more robustness to the results.

To investigate the relative effects of the two channels on illiquidity commonality I perform the following panel least squares regression:

$$\begin{aligned} Comm_{i,t}^{BA} = \alpha_i + \beta_1 MktRf_t + \beta_2 SMB_t + \beta_3 HML_t + \delta_1 TED_t + \delta_2 VIX_t + \\ + \theta H_{i,t}^{SS} + \epsilon_{i,t} \end{aligned} \tag{1}$$

where i is the firm index and t is the time (quarter) index. α_i represents firm-fixed effects. I estimate White firms-clustered standard errors (Petersen 2007).

If the 'funding channel' drives $Comm_{i,t}^{BA}$ higher, then the estimated coefficients $\beta_1, \beta_2, \beta_3, \delta_1$, and δ_2 will appear positive and statistically significant. If the 'hedging–arbitrage channel' explains $Comm_{i,t}^{BA}$, then the estimated θ coefficient will be positive and statistically significant, after controlling for firms' (unobservable) fixed effects.

I indicate as Specification I the panel regression for Eq. (1) without the VIX Index; and as Specification II the panel regression which includes the VIX index on the right-hand side of the Equation. This differentiation aims to disentangle the potential effect of TED-VIX collinearity on the estimation results. In all model specifications I include firms' fixed effects.[26] In further Specifications (III and IV) I also control for time effects. In Specification III, I augment the right-hand side of Eq. (1) by interacting the hedge ratio variable $H_{i,t}^{SS}$ with $Qtr_{2003:2}, \ldots, Qtr_{2009:3}$, which represent dummies for each quarter of each year in the sample. In Specification IV, I control for time-fixed effects: I drop all regressors which vary only over the time-dimension (the three Fama- French factors, TED and VIX) and replace them with the time-dummies and a control variable which proxies firms' exposures to systematic risk $SysRisk_{i,t}$. This variable is obtained for each firm as a Fisher

[25] In addition to equity data from CRSP and CDS premia from Bloomberg, I employ firms' accounting information from COMPUSTAT. Two main reasons support the use of the Merton (1974) model to estimate the sensitivity of debt to equity (hedge ratio). First, sophisticated investors rely on structural models to perform arbitrage trading across equity and credit markets. Capital-structure arbitrageurs—mainly hedge funds – use in fact modified implementations of Merton's model (the most popular proprietary models are Moody's KMV and RiskMetrics' CreditGrades). Second, the empirical literature has found that the simple Merton model can be correctly used to predict firms' hedge ratios (Schaefer and Strebulaev, 2008).

[26] I cannot control for time-fixed effects in the Specifications I and II as some regressors change only over the time-dimension (*MktRf*, *SMB*, *HML*, *TED*, *VIX*). However, Specification III and IV include time-fixed effects. Furthermore, in order to report only robust results and mitigate eventual concerns on unit-roots in the key-variables, the panel regression are performed on a sub-sample of 18 companies which display stationarity in both the commonality and the hedge ratio series. The tests of unit roots are run using Augmented Dickey–Fuller equations with number of lags set by Schwartz information criterion and at 5% significance level. In unreported analysis, I observe that the results of the regression hold unchanged when all 45 firms are included in the panel.

z-transformation of the R^2s from the regressions of the firm's daily excess returns on the three Fama-French factors over each quarter. Specifications III and IV represent two robustness checks on the effect of the hedge ratio on the commonality variable, since the time dummies can capture the effects of extreme events (e.g., 2007–2008 subprime crisis).

Finally, I repeat the estimation of Specifications I and II of Eq. (1) by replacing the hedge ratio H^{SS} with its component orthogonal to general market default risk and volatility ($H^{SS,ORT}$). This check should alleviate the concern that the hedge ratio's influence on the equity-CDS bid-ask spread commonality simply picks up the increase in default risk and volatility at the market level, particularly over the crisis period. A change in economic conditions can in fact influence default risk and hedge ratios of many firms. To isolate this orthogonal component I regress the hedge ratio on: (i) the difference between Moody's AAA Corporate Bond Index yield and the 20-year government bond yield (market default risk factor *DEF*); and (ii) the *VIX* index. I then use the residuals from this regression ($H^{SS,ORT}$) as an explanatory variable in Eq. (1).

4.1 Analysis of the variables and results of test (A)

Tables 2 and 3 respectively report the pair-wise correlation and the (Granger) causality matrices for the relevant variables. The hedge ratio is highly correlated with bid-ask spread commonality and return commonality.[27] The bid-ask spread commonality and the hedge ratio are also closely related to the market default risk, the VIX index, the TED spread, and the SMB systematic risk-factor (see Table 2). The pair-wise causality matrix in Table 3 suggests that the hedge ratio Granger-causes all commonality variables. However, market default risk and VIX index Granger-cause both the commonality variables and the hedge ratio. This justifies a control for the orthogonalised hedge ratio ($H^{SS,ORT}$). The causality relationship between bid-ask spread commonality and return commonality remains instead ambiguous and their correlation is only about -7%. Thus, the return commonality proxy is not included in right-hand side of Eq. (1).

The hedge ratio represents a first approximation to the arbitrage relationship between equity and CDS; in fact, it is obtained as the elasticity of the CDS (or underlying debt) value to the equity value of the firm (see Appendix 1). Figure 4 illustrates the time-series plot of the value-weighted average of the hedge ratio across all firms. It shows that the average debt-to-equity elasticity (hedge ratio) H and sensitivity h gradually decrease from 2003 over the following years; they then rise again from the second semester of 2007 and decrease towards the end of 2009. Figure 5 displays a similar pattern for both the average hedge ratio estimated with SS methodology and with VX methodology (April 2003–November 2008). Noticeably, Fig. 6 reveals a very close relationship between the average hedge ratio and CDS-equity bid-ask spread commonality over time.

The panel analysis in Table 4 (Panel A) reveals positive and significant effects of the TED spread, VIX index, and systematic risk factors on the bid-ask spread commonality, but also a positive influence of the hedge ratio, after controlling for firms' unobservable

[27] I construct the following commonality variables: $\psi_{i,t}^{BA}$, $\tau_{i,t}^{BA}$, and $\rho_{i,t}^{BA}$, respectively the Fisher's z-Transformation of Pearson Correlation, Kendall's Tau Rank Correlation, and Spearman's Rho Rank Correlation between equity and CDS bid-ask spreads of firm i estimated over each quarter t; and $\psi_{i,t}^{RET}$, $\tau_{i,t}^{RET}$, and $\rho_{i,t}^{RET}$ the same correlation measures between equity and CDS returns. For more details on the correlation measures see Sect. 2.3.

Table 2 Correlation matrix between bid-ask spread commonality, return commonality, TED, VIX, market default risk, and Fama-French risk factors

	BA Comm (K)	BA Comm (S)	Ret.Comm (K)	Ret.Comm (S)	Hedge Ratio	TED	VIX	Default	MktRf	HML
BA Comm (S)	0.995381									
t-Statistic	*361.1159*									
p value	<0.00001									
Ret.Comm (K)	−0.068303									
t-Statistic	*−2.384421*									
p value	*0.0173*									
Ret.Comm (S)		−0.072636	0.996432							
t-Statistic		*−2.536464*	*411.1636*							
p value		*0.0113*	<0.00001							
Hedge Ratio	0.258303	0.251053	−0.254563	−0.256957						
t-Statistic	*9.312236*	*9.033028*	*−9.167993*	*−9.26028*						
p value	<0.00001	<0.00001	<0.00001	<0.00001						
TED	0.109773	0.110083	−0.100302	−0.09801	0.215783					
t-Statistic	*3.846441*	*3.857447*	*−3.511029*	*−3.429677*	*7.696638*					
p value	*0.0001*	*0.0001*	*0.0005*	*0.0006*	<0.00001					
VIX	0.188536	0.187813	−0.22052	−0.222179	0.551195	0.744990				
t-Statistic	*6.686281*	*6.659684*	*−7.874163*	*−7.93645*	*23.00773*	*38.89642*				
p value	<0.00001	<0.00001	<0.00001	<0.00001	<0.00001	<0.00001				
Default	0.177576	0.173902	−0.249649	−0.2503	0.521315	0.786631	0.950148			
t-Statistic	*6.284526*	*6.15039*	*−8.979128*	*−9.004082*	*21.27631*	*44.37234*	*106.1322*			
p value	<0.00001	<0.00001	<0.00001	<0.00001	<0.00001	<0.00001	<0.00001			
MktRf	0.053059	0.050337	−0.033195	−0.036412	0.041955	−0.712126	−0.450048	−0.452300		
t-Statistic	*1.850539*	*1.755368*	*−1.156763*	*−1.269005*	*1.462509*	*−35.32794*	*−17.55239*	*−17.66270*		
p value	*0.0645*	*0.0794*	*0.2476*	*0.2047*	*0.1439*	<0.00001	<0.00001	<0.00001		
HML	0.037804	0.027749	0.040904	0.040836	−0.085198	−0.336986	−0.414908	−0.334351	0.312539	
t-Statistic	*1.317575*	*0.966805*	*1.425807*	*1.423413*	*−2.978123*	*−12.46571*	*−15.88202*	*−12.35593*	*11.45919*	

Table 2 continued

	BA Comm (K)	BA Comm (S)	Ret.Comm (K)	Ret.Comm (S)	Hedge Ratio	TED	VIX	Default	MktRf	HML
p value	*0.1879*	*0.3338*	*0.1542*	*0.1549*	*0.0030*	<0.00001	<0.00001	<0.00001	<0.00001	
SMB	0.156487	0.153082	−0.041619	−0.046224	0.202025	−0.212835	−0.055779	−0.024626	0.411131	0.286635
t-Statistic	*5.518136*	*5.395145*	*−1.450759*	*−1.611635*	*7.184298*	*−7.586482*	*−1.945709*	*−0.857929*	*15.70788*	*10.42018*
p value	<0.00001	<0.00001	*0.1471*	*0.1073*	<0.00001	<0.00001	*0.0519*	*0.3911*	<0.00001	<0.00001

Time Sample: 2003Q2–2009Q4; Number of cross-section: 45 Firms; Number of Total Quarterly Observations: 1215; Comm (K) = Fisher transformation of Kendall Tau Measure of Association; Comm (S) = Fisher transformation of Spearman Measure of Association

Table 3 Pair-wise Granger causality test matrix between bid-ask spread commonality, return commonality, TED, VIX and market default risk

X	Hedge Ratio	BA Comm (K)	BA Comm (S)	Ret.Comm (K)	Ret.Comm (S)	VIX	Default
Y							
Hedge ratio	–	0.59798	0.49305	5.84912	5.67158	22.0451	57.8109
	–	*0.55010*	*0.61090*	*0.00300*	*0.00350*	<0.00001	<0.00001
BA Comm (K)	26.3359	–	–	4.2486	–	29.6549	28.3934
	<0.00001	–	–	*0.01451*	–	<0.00001	<0.00001
BA Comm (S)	24.8627	–	–	–	3.89849	27.1447	26.2406
	<0.00001	–	–	–	*0.02051*	<0.00001	<0.00001
Ret.Comm (K)	45.5806	3.82037	–	–	–	52.9075	59.2915
	<0.00001	*0.02220*	–	–	–	<0.00001	<0.00001
Ret.Comm (S)	46.8871	–	3.18702	–	–	54.6119	60.9786
	<0.00001	–	*0.04170*	–	–	<0.00001	<0.00001
VIX	3.08414	4.78519	4.14365	9.96393	9.52758	–	163.2780
	0.04620	*0.00850*	*0.01610*	*0.00005*	*0.00008*	–	<0.00001
Default	9.85346	2.0633	1.57617	5.81489	5.42138	123.675	–
	0.00006	*0.12750*	*0.20720*	*0.00310*	*0.00450*	<0.00001	–

Null Hypothesis: X does NOT Granger cause Y; The F-statistics are reported in this Table together with their p values (in italic); The Granger causality tests include 2 lags; Time Sample: 2003Q2–2009Q4; Number of Cross-sections: 45 Firms; Number of Total Quarterly Observations: 1215; Comm (K) = Fisher transformation of Kendall Tau Measure of Association; Comm (S) = Fisher transformation of Spearman Measure of Association

fixed effects.[28] The positive effect of the hedge ratio on the bid-ask spread commonality survives when I replace the hedge ratio with its component orthogonal to market default risk and market volatility ($H^{SS,ORT}$). I also evaluate the separate economic impact of the hedge ratio versus the impact of market frictions and systematic risk factors. In Table 4 (Panel B) I notice that the aggregate economic significance of all systematic factors is about 0.60 (in terms of standard deviations impact) and the economic significance of the hedge ratio is around 0.16.[29]

In Table 5 I control more directly for time-effects. This check is needed since the period analyzed includes the crisis event. I notice that when the hedge ratio is interacted with time-quarter dummies (Panel A), its positive effect on the bid-ask spread commonality variable is strong and significant only during the first two quarters of 2003, the first three quarters of 2007, the third quarter of 2008 and the second quarter of 2009. The effect of the hedge ratio instead decreases and even turns negative but insignificant during the third quarter of 2005. Furthermore, the panel analysis results reported in Table 5 (Panel B), where the bid-ask spread commonality is regressed on the hedge ratio, the firm's exposure

[28] In addition, the selection of investment-grade firms in the sample ensures a more conservative result on the impact of the hedge ratio on illiquidity commonality.

[29] The economic significance is obtained by multiplying the estimated beta coefficient by the ratio of the standard deviation of the explanatory variable to the standard deviation of the dependent variable. The reason why the economic significance is reported in Table 4 is to provide a clear comparative assessment of the impact of all regressors, accounting for their different measurement scales and distributional properties.

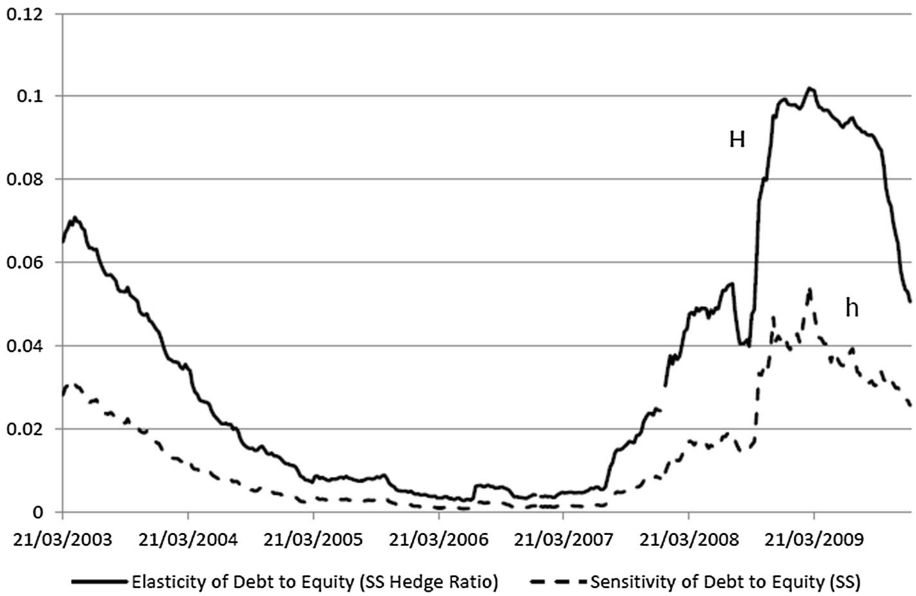


Fig. 4 Cross-sectional value-weighted average of debt-to-equity sensitivity *h* and hedge ratio *H* (Merton model calibration–SS methodology) *(Measured in decimals, Weekly: March 2003–December 2009, Cross-Section of 45 firms)*

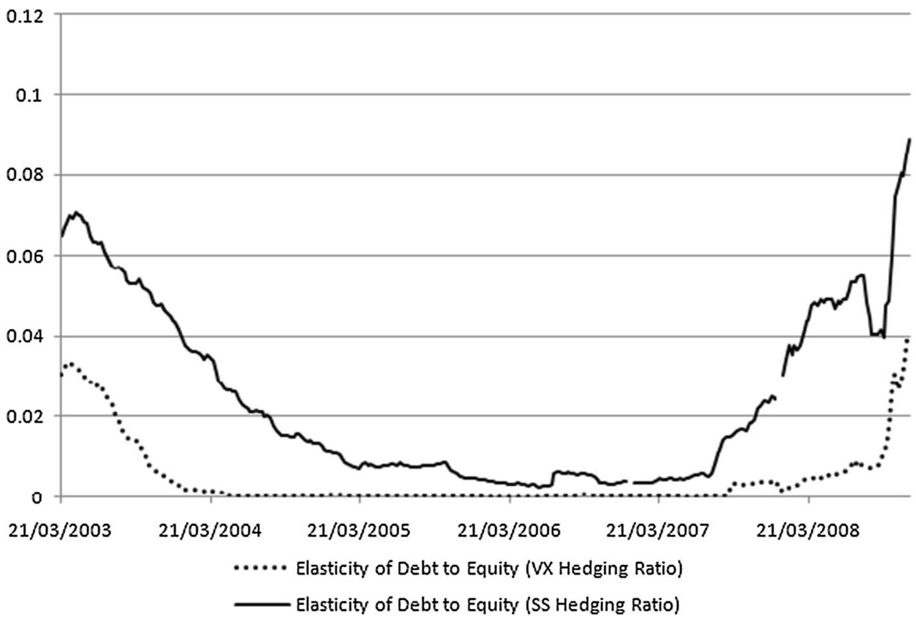


Fig. 5 Cross-sectional value-weighted average of debt-to-equity hedge ratio *H* (Merton model calibration—SS vs. VX methodology) *(Measured in decimals, Weekly: March 2003–November 2008, Cross-Section of 45 firms)*

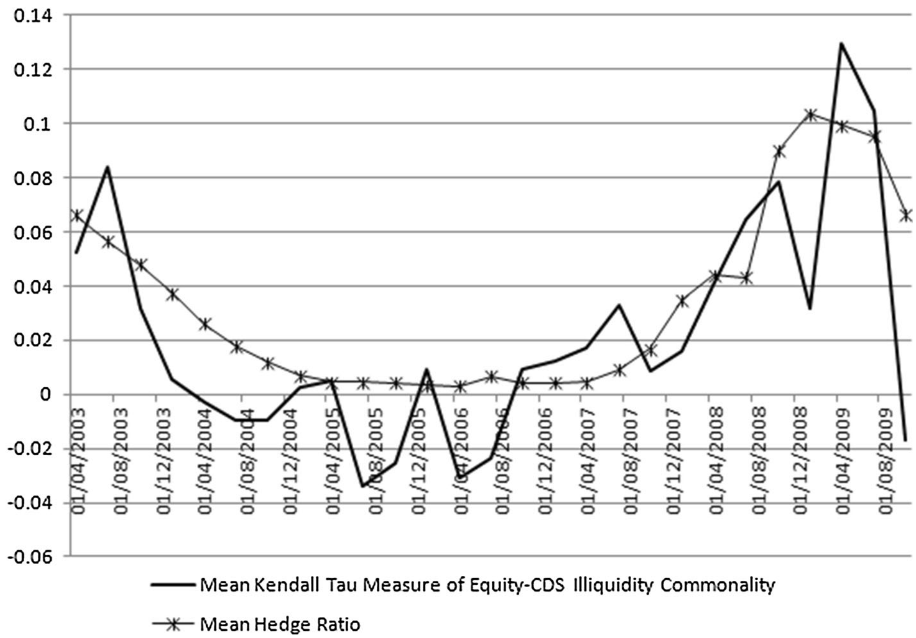


Fig. 6 Cross-sectional value-weighted averages of CDS-equity Illiquidity correlation (Kendall measure) and debt-to-equity hedge ratio (Merton model calibration—SS methodology) *(Measured in decimals, Quarterly: April 2003–December 2009, Cross-Section of 45 firms)*

to systematic risk and the time dummies, confirm that the positive and significant effects of hedge ratio and systematic risk is not wiped out after controlling for time fixed effects.

4.2 Robustness checks on the hedge ratio as proxy for hedging–arbitrage trading

A possible concern may come from the fact that the hedge ratio—both measures implied from the Merton structural model—relates to the firm's volatility and leverage which capture the firm's individual risks. These risks are also underlying factors for the illiquidity commonality between equity and CDS. If the hedge ratio is just a proxy of the firm-specific risks, the conclusion that hedging and arbitrage trading are determinants of the illiquidity co-movement may be in doubt. In order to address this concern and check whether the hedge ratio carries information on the hedging–arbitrage activity, I instrument this variable and carry out a Haussman-Wu test and a Two-Stage Least Squares estimation of Eq. (1) Specification I. As instruments I select variables that proxy the 'sources' of hedging activity of CDS dealers (namely, higher risk aversion, higher CDS demand pressure, and higher asymmetric information), and the 'sources' of cross-market arbitrage trading (namely, higher asymmetric information and larger CDS-equity mispricing). The risk aversion is proxied by the *VIX* index. In absence of CDS transaction data, the CDS demand pressure is proxied by the increase in total bonds' traded volume ($\Delta BondV$). If there is an increase in the volume of traded bonds for a specific firm, it is more likely that there would also be an increase in the demand for CDS protection from bondholders (and therefore higher CDS demand pressure). To obtain this measure, I select for each firm the transacted volumes for all its traded bonds from the TRACE database; I then sum the bonds' volumes

Table 4 Test of determinants of commonality between equity and CDS bid-ask spreads

	Panel A										
	Regression of Equity-CDS Bid-Ask Spread Commonality on Exogenous Risk Factors and Hedge Ratio										
	Spec.	Int.	MktRf	Smb	Hml	TED	VIX	H^{SS}	$H^{SS,ORT}$	$Adj.R^2$	*LR TestFirms FE*
Dep. Var. Kendall Corr. (CDS-Equity Bid-Ask)	I	-0.0435***	16.3739**	23.0302**	10.4497	5.8369***		0.5434***		8.40%	0.9582
		−3.69	*2.49*	*2.25*	*1.51*	*3.76*		*3.27*			*0.50*
	I	−0.0436***	16.2548**	22.8609**	10.5402*	5.8073***		0.5565***		8.53%	No FE
		−3.05	*2.51*	*2.36*	*1.95*	*3.12*		*4.37*			
	II	−0.0453**	16.4088**	22.9595**	10.7479	5.6216***	0.0172	0.5195**		8.21%	0.9572
		−2.57	*2.47*	*2.22*	*1.49*	*2.59*	*0.13*	*2.05*			*0.51*
	II	−0.0445**	16.2556**	22.8045**	10.6950*	5.7003**	0.0082	0.5468***		8.34%	No FE
		−2.49	*2.51*	*2.33*	*1.75*	*2.36*	*0.08*	*2.87*			
	I	−0.0375***	17.4499***	25.6136**	6.7355	8.0275***			0.5953***	7.79%	0.9501
		−3.03	*2.88*	*2.52*	*1.22*	*4.02*			*3.08*		*0.51*
	I	−0.0374**	17.3971***	25.5531***	6.7359	8.0407***			0.6034***	7.96%	No FE
		−2.57	*2.78*	*2.62*	*1.24*	*4.28*			*3.62*		
	II	−0.0542***	16.4333***	22.9797**	10.7235	5.5677**	0.1481**		0.5104**	8.17%	0.9574
		−4.13	*2.60*	*2.27*	*1.74*	*2.14*	*2.00*		*2.31*		*0.51*
	II	−0.0538***	16.2654**	22.8097**	10.6638*	5.6515**	0.1458**		0.5400***	8.31%	No FE
		−3.25	*2.51*	*2.33*	*1.75*	*2.34*	*2.03*		*2.84*		

Table 4 continued

	Panel B									
	Economic Significance of Regressors									
	Spec.	MktRf	Smb	Hml	TED	VIX	H^{SS}	$H^{SS,ORT}$	$Adj.R^2$	*LR TestFirms FE*
Dep. Var. Kendall Corr. (CDS-Equity Bid-Ask)	I	0.1674**	0.1049**	0.0728*	0.2413***		0.1619***		8.53%	No FE
		2.51	*2.36*	*1.95*	*3.12*		*4.37*			
	II	0.1674**	0.1046**	0.0738*	0.2368**	0.0068	0.1591***		8.34%	No FE
		2.51	*2.33*	*1.75*	*2.36*	*0.08*	*2.87*			
	I	0.1791***	0.1172***	0.0465	0.3341***			0.1548***	7.96%	No FE
		2.78	*2.62*	*1.24*	*4.28*			*3.62*		
	II	0.1675**	0.1046**	0.0736*	0.2348**	0.1204**		0.1385***	8.31%	No FE
		2.51	*2.33*	*1.75*	*2.34*	*2.03*		*2.84*		

The panel regressions are estimated with least squares; Panel dataset includes 18 non-financial companies and 27 quarters (from 2003:2 to 2009:4); Specification I is the panel regression for Eq. (1) without the VIX Index; Specification II is the panel regression which instead also includes the VIX index on the right-hand side of Eq. (1)—this differentiation aims to disentangle the potential effect of TED-VIX collinearity on the estimation results; Estimated standard errors are robust to firm clustering; t-statistics are reported in italic; Each equation is estimated first including firm fixed effects and then without firm fixed effects (the latter estimation is indicated in the column 'LR Test Firm FE' as 'No FE' = No FE included); Only for the former estimation the likelihood ratio (LR) test of fixed effects (FE) redundancy is performed: the test uses the pooled regression with no fixed effects as baseline for comparison, the LR test F-statistics and *p* values (in italic) are reported in the column 'LR Test Firm FE'; Coefficients are marked respectively with $*$, $**$, and $***$ when regressors are significant at the 10, 5, and 1% S.L.; All variables are measured in decimals; Economic significance (Panel B) is obtained by multiplying the estimated beta coefficient by the ratio of the standard deviation of the relative explanatory variable to the standard deviation of the dependent variable.

Table 5 Test of determinants of commonality between equity and CDS bid-ask spreads—Robustness check including time effects: panel regressions with time-interaction variables (Panel A-Specification III) or time dummies (Panel B-Specification IV)

Panel A—Specification III

FE	H^{SS}	$H^{SS} \times Qrt_{2003:2}$	$H^{SS} \times Qrt_{2003:3}$	$H^{SS} \times Qrt_{2005:3}$	$H^{SS} \times Qrt_{2007:1}$	$H^{SS} \times Qrt_{2007:3}$	$H^{SS} \times Qrt_{2008:3}$	$H^{SS} \times Qrt_{2009:2}$	$Adj.R^2$
Dep. Var. Kendall Correl. (CDS-Eq.BA)									
Firm	−0.8482	2.1646*	1.4379*	−4.5545**	16.3920***	5.3435**	2.6917	1.8995**	6.66%
	−0.93	*1.88*	*1.70*	*−2.28*	*4.36*	*2.57*	*1.47*	*2.07*	
No	−0.8861	2.2752*	1.5041*	−6.2181***	9.4564*	5.0820***	2.7864*	1.9810**	6.77%
	−0.94	*1.94*	*1.79*	*−3.53*	*1.83*	*3.69*	*1.76*	*2.11*	

Panel B—Specification IV

FE	Int.	H^{SS}	*SysRisk*	$Adj.R^2$	*LR Test* **FE**
Dep. Var. Kendall Correl. (CDS-Eq.BA)					
No	−0.0099*	0.8441***	0.0065	5.28%	No
	−1.91	*6.20*	*1.59*		
Time	−0.0069	0.6211***	0.0087**	16.29%	3.4279
	−1.12	*3.09*	*2.38*		<0.00001
Time	−0.0041	0.5770**	0.0064	16.39%	2.4831
& Firm	*−0.61*	*2.57*	*1.08*		<0.00001
Time	0.0015	0.5186**		15.44%	2.4195
& Firm	*0.31*	*2.35*			<0.00001

The panel regressions are estimated with least squares; Panel dataset includes 18 non-financial companies and 27 quarters (from 2003:2 to 2009:4). In Specification III, I augment the right-hand side of Eq. (1) by interacting the hedge ratio variable $H^{SS}_{i,t}$ with $Qtr_{2003:2}, \ldots, Qtr_{2009:3}$, which represent dummies for each quarter of each year in the sample; in Specification IV I drop all regressors in Eq. (1) which vary only over the time-dimension (the three Fama- French factors, TED and VIX) and replace them with the time-dummies and a control variable which proxies firms' exposures to systematic risk $SysRisk_{i,t}$. This variable is obtained for each firm as a Fisher z-transformation of the R^2s from the regressions of the firm's daily excess returns on the three Fama-French factors over each quarter. Estimated standard errors are robust to firm clustering; t-statistics are reported in italic; The FE column indicates which fixed effects are included in the panel regression ('No' = No fixed effects included); Likelihood ratio (LR) tests of fixed effects (FE) redundancy use the panel regressions with no fixed effects as baseline for comparison: the LR test F-statistics and p values (in italic) are reported in the column 'LR Test FE'; No = No FE included; Coefficients are marked respectively with $*, **$, and $***$ when regressors are significant at the 10, 5, and 1% S.L.; All variables are measured in decimals; For Specification III only the hedge ratio and the statistically significant interaction variables (hedge ratio × time-quarter dummies) are reported in the Table (Panel A) for brevity, however *Hml* and *VIX* are also significant respectively at the 5 and 10% S.L.

and take the first differences. The asymmetric information (*AsymInfo*) is proxied by the dispersion of analysts' forecasts. If there is wide analysts' disagreement on the future perspectives of a well-known large U.S. firm, this means that less public information is available and the risk of asymmetric information is higher. I construct the dispersion of analysts' forecasts on firm's earnings per share over a forecasting period of three months as the ratio between the standard deviation of earnings forecasts for each firm across all analysts and the relative median. I use analysts' forecasts of earnings per share taken from the Institutional Brokers Estimate System (I/B/E/S) database.[30] Finally, the CDS-equity mispricings (*Log CDS Mispricing*) are obtained as residuals from a structural model. For this purpose, I use an implicit structural model that includes the usual controls for firms' leverage ratio, asset volatility and for short spot interest rate (Merton 1974), but also controls for firms' (equity) illiquidity, size and market-wide default risk.

To evaluate the goodness of the instruments, I perform the usual checks. First, the instruments should present low and statistically insignificant correlation with the errors of the panel Eq. (1) Specification I. So I check heuristically whether the residuals from the original panel regression Eq. (1) Specification I are correlated with the four proposed instruments. The correlation between the residuals and the analysts' forecasts dispersion variable is about -3% and it is not statistically significant. The correlation between the residuals and log CDS mispricing is about -14% but statistically significant at the 5% level, while the correlation between the residuals and the change in bonds' traded volume is about -5% and statistically insignificant. The correlation between the residuals and VIX is 0.3% and not statistically significant. The unconditional correlations of the instruments with the residuals are low and insignificant, with the exception of log CDS mispricing which is therefore excluded from the instrument list. I perform a further check on the conditional correlations: I regress the residuals on the three remaining instruments and find that none of them represents a significant explanatory variable. The F-statistics of this regression also rejects their joint significance. Second, the instruments should be significantly correlated with the hedge ratio. I check the correlations between the hedge ratio and *AsymInfo*, $\Delta BondV$, and *VIX*. These are respectively 15, 7, and 55% and are all statistically different from 0 at the 1% significance level. So the asymmetric information proxy, the VIX index, and the change in bonds' traded volume are used as instruments in this robustness analysis.

In Table 6 (Panel A) I present the results of the Hausmann–Wu test. For this test, I run an auxiliary panel regression which includes the hedge ratio as the dependent variable and the three instrumental variables as regressors. The fitted values $\widehat{H}$ from this regression are then used as additional regressor in the panel Equation (1) Specification I. If the hedge ratio H captures already the drivers of the hedging–arbitrage trading, then $\widehat{H}$ should not appear significant in the regression. Given my choice of instruments, I find that the coefficient of the fitted variable $\widehat{H}$ appears in fact insignificant.[31] Using the same instrumental variables, I also perform a 2-Stage Least Squares estimation (with and without fixed effects) of

[30] This database contains individual analyst's forecasts organized by forecast date and last date when the forecast was revised and confirmed as accurate. Following Buraschi et al. (2014), and Diether et al. (2002), I use only stock-split unadjusted data. As an initial step, I match analysts' forecast data with the equity and CDS data in my sample. I extend each forecast date to its revision date: if, for example, a forecast is made in January 2007 and it is last confirmed in March 2007, I use this forecast for January, February, and March 2007. If more than one forecast per month is recorded for the same analyst, I use the forecast which was confirmed most recently.

[31] The same result is achieved also when using each instrument separately. The test loses power when applied to small samples. Since there may be a small sample bias, I need to be cautious when interpreting the results of the test. For this reason, I also perform a 2-Stages Least Squares estimation.

Table 6 Test of determinants of commonality between equity and CDS bid-ask spreads—Robustness check on hedge ratio as proxy for Hedging–Arbitrage Trading

	Panel A									
	Hausmann–Wu test									
	Spec.	Int.	MktRf	Smb	Hml	TED	H^{SS}	H^{SS}*Fitted*	*Adj.*R^2	*Firms FE*
Dep. Var. Kendall correlation (CDS-Equity Bid-Ask)	I	−0.0485***	18.4016***	11.2315	13.9285**	6.3699***	0.4538*	0.0864	7.09%	No
		−3.40	*2.78*	*0.97*	*2.38*	*3.11*	*1.87*	*0.18*		
	I	−0.0479***	18.1460***	11.5873	13.0597**	6.8498***	0.5391**	−0.1895	7.15 %	Yes
		−3.90	*2.64*	*0.98*	*2.17*	*3.14*	*1.96*	*−0.34*		

	Panel B								
	2-Stages least squares estimation of the model								
	Spec.	Int.	MktRf	Smb	Hml	TED	H^{SS}	*Adj.*R^2	*Firms FE*
Dep. Var. Kendall correlation (CDS-Equity Bid-Ask)	I	−0.0485***	18.1209***	11.0671	13.8245**	6.4709***	0.5082***	7.30%	No
		−3.38	*2.69*	*0.95*	*2.40*	*3.45*	*2.67*		
	I	−0.0479***	18.4797***	11.7498	13.4410**	6.5492***	0.4484**	7.35%	Yes
		−3.97	*2.64*	*1.00*	*2.30*	*3.43*	*2.15*		

The panel regressions for the Hausmann–Wu Test (Panel A) are estimated with least squares; The variable $\boldsymbol{H^{SS}}$***Fitted*** corresponds to the fitted values from a regression of the hedge ratio H^{SS} on proxies for risk-aversion, asymmetric information and CDS demand pressure (resp., VIX Index, analysts' forecasts dispersion, and changes in bonds' traded volume). These three variables are used as instruments in the 2SLS estimation (Panel B). Panel dataset includes 18 non-financial companies and 27 quarters (from 2003:2 to 2009:4); Estimated standard errors are robust to firm clustering; t-statistics are reported in italic; Firms' Fixed Effects: No = No FE included; Yes = FE included; Coefficients are marked respectively with $*, **$, and $***$ when regressors are significant at the 10, 5, and 1% S.L.; All variables are measured in decimals.

Eq. (1) Specification I. The results are reported in Table 6 (Panel B) and confirm the significance of the hedge ratio's coefficient, the robustness of analysis and its interpretation.

As a final robustness check I repeat the analysis (Specifications I and II) using:

(1) As alternative dependent variables (measures of commonality) the Spearman rank measure of association and the Pearson correlation between equity and CDS bid-ask spreads;
(2) As an alternative measure of the hedge ratio, the one estimated with the Vassalou and Xing (2004) methodology.[32] Details on this methodology are provided in Appendix 1.

A comparison between the results of the three alternative regressions in Panel A of Table 7 shows that using Spearman's instead of Kendall's correlation does not change the results, while using the Pearson correlation as the dependent variable in the regression leads to the hedge ratio and the size factor being the only significant variables. Also, the economic impact of the hedge ratio (unreported) remains in a range between 0.13 and 0.16 standard deviations.

When I replace the hedge ratio estimated using the Schaefer and Strebulaev (SS) methodology with the one estimated using the Vassalou-Xing (2004) methodology, I find that the latter is also significant in the panel regressions (Table 7, Panel B) and has very similar economic significance to the SS hedge ratio (0.15–0.17 standard deviations). However, the R-squared halves with respect to the case when I use the SS hedge ratio, so the Vassalou-Xing measure of the hedge ratio appears less useful than the SS measure.

To sum up the results in this section, the equity-CDS bid-ask spread commonality increases with higher funding costs, higher market volatility and systematic risk. The debt-to-equity hedge ratio is also found strongly significant, both statistically and economically, and survives several robustness checks. The hedge ratio appears to capture well the effects of hedging and arbitrage trading on the equity-CDS bid-ask spread commonality. There is evidence of both a 'funding channel' and a 'hedging–arbitrage channel'.

5 Test (B) on the determinants of CDS bid-ask spreads

The hedging–arbitrage channel of equity-CDS illiquidity commonality offers some testable hypotheses on the determinants of CDS bid-ask spreads. In this section I test these hypotheses to provide further evidence on the mechanisms behind this channel.

The CDS bid-ask spreads should depend on:

– The cost of hedging in the equity market.
  This cost should become more significant when the hedge ratio is substantial and when the CDS dealer faces an increasing demand for CDS protection from 'noise-traders' (e.g. bondholders).
– The amount of informed trading across equity and credit markets.
  Asymmetric information should affect the CDS bid-ask spread via an increase in CDS dealers' hedging activity and/or via informed arbitrage trading across the markets (when a CDS-equity mispricing arises).

[32] When I use the hedge ratio from the VX Methodology instead of the SS hedge ratio I consider a restricted time sample running from April 2003 to October 2008.

Table 7 Test of determinants of commonality between equity and CDS bid-ask spreads—further robustness checks

	Panel A									
	Panel regressions: comparison between three alternative dependent variables									
	Specification		Int.	MktRf	Smb	Hml	TED	VIX	H^{SS}	$Adj.R^2$
Dep. Var Kendall correlation	II	*Coeff*	−0.0445**	16.2556**	22.8045**	10.6950*	5.7003**	0.0082	0.5468***	8.34%
		t-stat	*−2.49*	*2.51*	*2.33*	*1.75*	*2.36*	*0.08*	*2.87*	
Dep. Var. Spearman correlation	II	*Coeff*	−0.0659***	23.5711**	33.5391**	14.1709	8.0997***	0.0239	0.7888**	8.37%
		t-stat	*−2.63*	*2.48*	*2.23*	*1.39*	*2.63*	*0.13*	*2.37*	
Dep. Var. Pearson correlation	II	*Coeff*	−0.0154	8.0886	39.5789***	−6.3317	4.7113	−0.1281	0.5321**	3.61%
		t-stat	*−1.17*	*1.02*	*2.89*	*−0.94*	*1.58*	*−1.15*	*2.29*	
	Panel B									
	Panel regression—alternative hedge ratio (Vassalou and Xing 2004)									
	Specification		Int.	MktRf	Smb	Hml	TED	VIX	H^{VX}	$Adj.R^2$
Dep. Var. Kendall correlation	I	*Coeff*	0.0090	−5.7458	14.9055	−9.0884	1.5265		1.2799**	4.73%
		t-stat	*1.00*	*−1.05*	*1.52*	*−1.42*	*1.29*		*2.39*	
	II	*Coeff*	−0.0093	−3.8054	11.6913	−6.6383	−0.5774	0.1705	1.0813*	4.97%
		t-stat	*−0.86*	*−0.71*	*1.12*	*−1.08*	*−0.26*	*1.45*	*1.84*	

The panel regressions are estimated with least squares; Panel regression includes 18 non-financial companies and 27 quarters (from 2003:2 to 2009:4) when Hedge SS is used; Panel regression includes 30 non-financial companies and 23 quarters (from 2003:2 to 2008:4) when Hedge VX is used; Estimated standard errors are robust to firm clustering; t-statistics are reported in italic; No fixed effects are included; Coefficients are marked respectively with $*$, $**$, and $***$ when regressors are significant at the 10, 5, and 1% S.L.; All variables are measured in decimals

– The level of market volatility and funding cost.
  CDS dealers need to hold some capital to finance their activities and set the bid-ask spreads in the CDS markets in order to recover the cost of the funding needed. Higher market volatility augments the cost of keeping unbalanced positions and the risk of a freeze in funding availability.

In panel analysis, I regress CDS bid-ask spreads on: (i) hedging costs, represented by the equity bid-ask spread times the delta-hedging factor ($BA^{E} \times h^{SS}$); (ii) the proxy for asymmetric information (*AsymInfo*); (iii) the proxy for CDS mispricing (*Log CDS Mispricing*); and (iv) the VIX index. These variables have been explained in paragraph 4.2.

Additionally, I want to examine whether the hedging-cost effect on CDS bid-ask spreads is caused primarily by an increase in the hedging activity of CDS dealers because of: (i) higher asymmetric information; or (ii) higher liquidity demand. Therefore, I interact the hedging-cost proxy ($BA^{E} \times h^{SS}$) respectively with the analysts' forecasts dispersion (*AsymInfo*) and with the proxy of the amount of CDS liquidity demand (the weekly changes in total bonds' traded volume: $\Delta BondV$).

Finally, I test for the impact of capital structure arbitrageurs' trading activity. When mispricing arises in the CDS market, they perform informed trading across the equity and credit markets. To investigate the effect of this cross-market arbitrage, I include as explanatory variable the proxy for CDS mispricings (*Log CDS Mispricing*). I also interact this variable with the hedging cost to understand whether the presence of these superiorly informed traders can enhance CDS dealers' activity (and so the effect of the hedging cost on the CDS bid-ask spreads).

I estimate the following panel regression (including firm-fixed effects α_i):

$$\begin{aligned} BA^{CDS}_{i,t} = {} & \alpha_i + \beta_0 (BA^{E}_{i,t} \times h^{SS}_{i,t}) + \beta_1 (BA^{E}_{i,t} \times h^{SS}_{i,t}) \times AsymInfo_{it-1} \\ & + \beta_2 (BA^{E}_{i,t} \times h^{SS}_{i,t}) \times LogCDSMispr_{it-1} \\ & + \beta_3 (BA^{E}_{i,t} \times h^{SS}_{i,t}) \times \Delta BondV_{it} \\ & + \gamma AsymInfo_{it-1} + \delta LogCDSMispricing_{it-1} + \zeta VIX_t + \epsilon_{i,t} \end{aligned} \tag{2}$$

I perform the test at the weekly frequency. The following elements represent desirable properties of the test of Eq. (2) when compared to the previous test performed on the bid-ask spread commonality variable—Equation (1): (i) the test is executed on CDS bid-ask spreads directly, therefore it does not need to rely on estimated measures of correlation; (ii) the frequency of the analysis increases from quarterly to weekly; and (iii) the test employs data for all 45 companies in the sample after assessing the stationarity of the relevant variables.

5.1 Results of test (B)

In the panel regression analysis at the weekly frequency for CDS bid-ask spreads (Table 8) market volatility (VIX) is found positively significant. After controlling for all cost-components, the economic impact of VIX is always in a range between 0.23 and 0.25 SD (depending on the regression specification, when using the whole sample of data or the crisis sub-sample). In addition, the hedging-cost component enters significantly in all estimated equations, also when I include a control for (time and firms) fixed effects or the VIX index. A 1 standard deviation (SD) change in hedging costs generates an increase of around 0.4 SD in the CDS bid-ask spread. The hedging cost component alone can explain about one third of the variation in the CDS bid-ask spreads. When I add other control

Table 8 Test of CDS bid-ask spread determinants: effects of hedging costs, information risk, CDS mispricing, and market volatility on CDS bid-ask spreads

Dependent variable: CDS bid-ask spread (BA_{it}^{CDS})

	Int.	$h_{it}^{SS} \times BA_{it}^{E}$	$(h_{it}^{SS} \times BA_{it}^{E}) \times (\Delta Bond\,Volume_{it})$	$(h_{it}^{SS} \times BA_{it}^{E}) \times (Asym\,Info_{it-1})$	$(h_{it}^{SS} \times BA_{it}^{E}) \times (Log\,CDS\,Mispricing_{it-1})$	$Asym\,Info_{it-1}$	$Log\,CDS\,Mispricing_{it-1}$	VIX	FE	$Adj.R^2$
Coeff	0.052***	4.330***							*Firms*	32.98%
t-stat	*62.92*	*4.61*								
Econ. Sign.		0.41								
Coeff	0.054***	2.321***							*Firms*	
t-stat	*79.87*	*3.03*							*+ Time*	*49.15%*
Econ. Sign.		0.22								
Coeff	0.039***	2.756***	0.006	0.163***				0.0007***	*Firms*	41.70%
t-stat	*12.34*	*3.39*	*1.43*	*2.65*				*4.32*		
Econ. Sign.		0.26	0.01	0.01				0.23		
Coeff	0.039***	2.564***	0.004	0.240***		0.0005*	0.022***	0.0008***	*Firms*	50.18%
t-stat	*15.61*	*3.32*	*0.72*	*3.35*		*1.73*	*5.82*	*5.34*		
Econ. Sign.		0.24	0.01	0.17		0.08	0.32	0.24		
Coeff	0.039***	2.089***	0.010	−0.051	5.126***	0.0004*	0.014***	0.0008***	*Firms*	59.62%
t-stat	*17.10*	*2.81*	*1.58*	*−0.69*	*7.39*	*1.92*	*5.82*	*5.58*		
Econ. Sign.		0.20	0.02	−0.03	0.29	0.07	0.22	0.25		
Coeff	0.054***	1.365**	0.009	−0.033	5.140***	0.0003**	0.018***		*Firms*	71.67%
t-stat	*17.10*	*2.14*	*1.57*	*−0.56*	*8.21*	*1.99*	*5.80*		*+ Time*	
Econ. Sign.		0.13	0.02	−0.02	0.29	0.06	0.28			

The panel regressions are estimated with least squares; Panel dataset includes 45 non-financial companies and 300 weeks (Sep 2003 to Dec 2009); Estimated standard errors are robust to firm clustering; t-statistics are reported in italic; Economic significance is obtained by multiplying the estimated beta coefficient by the ratio of the standard deviation of the relative explanatory variable to the standard deviation of the dependent variable; FE = Fixed Effects included; Coefficients are marked respectively with $*$, $**$, and $***$ when regressors are significant at the 10, 5, and 1% S.L.

variables (particularly time-fixed effects), the impact of the hedging costs on the CDS bid-ask spread remains still significant, but it is halved.

In principle, the effect of hedging costs on CDS bid-ask spreads should be larger when the CDS demand from noise bondholders is higher. However, I find that the hedging cost interacted with the change in the amount of traded bond volumes has at most a weakly significant positive coefficient (with less than 10% significance level). In terms of economic impact, the interaction term adds on average only 0.09 SD to the impact of the hedging factor.[33,34] I find instead that the hedging activity of CDS dealers becomes a more significant cost-component of the CDS bid-ask spread when it is triggered by higher asymmetric information and speculative demand, rather than by higher uninformed liquidity demand in the CDS and bond markets. In fact, the hedging cost interacted with the analysts' forecast dispersion is positively significant at the 1% significance level. On average a 1 SD increase in the interaction variable has an additional impact of 0.17 SD on the hedging factor.[35] When I interact the hedging cost with the lagged positive CDS mispricing, I observe also a significant effect (at 1% significance level). On average, a 1 SD increase in this interaction variable has an additional impact of 0.11 on the hedging factor.[36] When both the CDS mispricing and the asymmetric information proxy are interacted with the hedging cost variable, the latter becomes insignificant.

Table 8 also shows that the CDS mispricing variable alone is found highly significant (with 1% significance level and 0.32 SD economic impact). Interestingly, when the CDS mispricing is included in the panel regression together with the proxy for asymmetric information, the latter appears only weakly insignificant (at 10% significance level). These results seem to suggest that: (1) the asymmetric information risk is connected to some form of speculative trading across markets; (2) potential speculative demand can also affect directly the CDS bid-ask spreads, outside the hedging channel. CDS dealers do not know with certainty the timing and size of capital structure arbitrageurs' trading and cannot completely protect themselves by hedging in the equity market. Some unhedged information risk remains and increases dealership costs further.

To conclude, the CDS bid-ask spread is significantly influenced by the cost of dealers' hedging activity in the equity market. This activity consolidates the linkage between the liquidity of the CDS market and the liquidity of the equity market. Higher asymmetric information and higher speculative demand increase the effect of CDS dealers' hedging activity on the CDS bid-ask spread, more significantly than higher uninformed liquidity-demand. The explanatory power of analysts' disagreement and CDS mispricing (proxy for arbitrage interest) suggests that CDS dealers may not be able to perfectly hedge against the risk of informed speculative activity.[37] Time-fixed effects and higher market volatility are also found highly significant in explaining an increase in CDS dealership costs and bid-ask

[33] This number is calculated by multiplying the economic significance of the interaction term 0.01 by the average positive change in total bond volumes transacted.

[34] I also repeat the analysis using as proxy for increased CDS demand the lagged value of CDS returns (as in Qiu and Yu 2012), but I still find insignificant results.

[35] This number is calculated by multiplying the economic significance of the interaction term 0.11 by the average value of the lagged dispersion variable.

[36] This number is calculated by multiplying the economic significance of the interaction term 0.29 by the average value of the lagged positive CDS mispricing variable.

[37] Given the unavailability of high-frequency transaction data for the CDS market over the period 2003–2009, I have used panel analysis at the weekly frequency. The relatively low frequency of the analysis should bias the results towards under-detecting the incidence of cross-market hedging and arbitrage activity on CDS bid-ask spreads, since the relative trading takes place at higher frequency. Nevertheless, the data

spreads and capture the crisis effect. The most complete specifications of the panel regression in Eq. (2) exhibit impressive adjusted R^2s between 50 and 72%. The adjusted R^2s drop to 40–55% when fixed effects are removed, but they are still large. In separate panel analysis, I also find a strong effect of CDS bid-ask spreads and VIX on equity bid-ask spreads, but I observe that the equity bid-ask spreads are not significantly influenced by CDS mispricings and asymmetric information. The information risk signal is instead conveyed to the equity dealers by the CDS dealers via their hedging activity. In fact, when I include the past value of the CDS dealers' hedging costs in the panel equation (I use past values to avoid endogeneity issues), I find that this variable is highly significant to explain an increase in equity bid-ask spreads. However, the adjusted R^2 of this regression is lower than the one obtained from the regressions of CDS bid-ask spreads.[38]

6 Conclusions

In this paper I examine the channels of the co-movements in illiquidity of equity and CDS markets. The correlation between equity and CDS bid-ask spreads is time-varying, but increases during periods of crisis.

Building on previous theoretical literature, I document that higher funding costs, market volatility and systematic risk can determine stronger illiquidity linkages between equity and CDS markets. When traders are forced to withdraw their positions due to lack of funding or to higher market risk, liquidity decreases in both markets and liquidity costs rise. This analysis appears of critical importance since the financial crisis of 2007–2009 was characterized by a market-illiquidity contagion episode which was exacerbated by traders' lack of financial resources.

Further, I show that the illiquidity co-movements in equity and CDS markets can be also explained by a hedging–arbitrage trading channel. Risk-averse CDS dealers (mainly banks) can hedge their CDS exposures in the equity market and then recover the hedging costs (given by the hedge ratio times the equity bid-ask spread) through the CDS bid-ask spreads. When the firm's hedge ratio increases, the hedging cost paid by CDS dealers becomes a larger component of the CDS bid-ask spread. When the hedging increases because of larger risk of informed trading, CDS dealers also convey a negative signal to equity dealers. As a consequence, equity dealers protect themselves by setting higher equity bid-ask spreads (and this has a further effect on CDS bid-ask spreads). In addition, temporary CDS-equity mispricings (due to asymmetric information across the markets) can fuel informed CDS-equity arbitrage trading. After a firm-specific shock, uninformed equity and CDS dealers protect themselves from the higher likelihood of informed trades of sophisticated arbitrageurs by increasing the bid-ask spreads on equity and CDS. As a consequence, the correlation between equity and CDS illiquidity increases further.

The paper offers some inputs for the future development of a consistent theory of illiquidity commonality across correlated assets based on their arbitrage-hedging linkages and information flows. While this paper is focused on the study of CDS-equity illiquidity linkages, further research should be devoted to a more extensive identification of the

Footnote 37 continued
and test I have employed in this paper suggest that hedging-costs and arbitrage activity are significant determinants of the CDS bid-ask spreads.

[38] These results are unreported for brevity, but are available upon request.

sources and nature of information flows across correlated markets and to their effects on prices and bid-ask spreads.

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Appendix 1

Estimation of the debt-to-equity hedge ratio from the Merton's model (1974)

The Merton model (1974) assumes that the total value of a firm's asset A follow a log-normal diffusion process with constant growth rate μ^A and constant volatility σ^A:

$$dA_t = \mu^A A_t dt + \sigma^A A_t dW_t \tag{3}$$

where dW_t is a variable following a Wiener process.

The firms' liabilities consist of risky debt B (with face value D and maturity T) and equity E. The firm's leverage L is defined as the ratio between the present value of debt promised payment D and the total value of the assets A. Thus, it is equal to: $L = \frac{De^{-rT}}{A}$, where r is the continuously compounded risk-free interest rate in the market.

Under the assumptions of the Black and Scholes (1973) model[39], the Merton (1974) model prices equity and risky debt of a firm as contingent claims written on the firm's

[39] The Assumptions behind Black-Scholes model (1973) and Merton model (1974) are the following:

- Market are competitive and efficient: agents are price-takers and trading has no affect on prices;
- There are no transaction costs;
- Agents trade continuously;
- Agents have unlimited access to short-selling and assets are indivisible;
- There are no bankruptcy costs in case of firm's default;
- There are no corporate taxes or tax advantages from issuing debt;
- Agents can borrow and lend at the same continuously compounded risk-free rate r;
- The firm has issued only two kinds of claims: non-dividend paying equity and debt. Debt is a pure zero-coupon bond that pays at maturity T an amount D.

assets. The equity E_0 of the firm is priced as a call option on the assets of the firm with strike price equal to the face value of debt D.

$$E_0 = C^{BS}(A_0, \sigma^A, D, r, T) = A_0 N(d_1) - De^{-rT} N(d_2) \tag{4}$$

where N(.) is the cumulative function for the standard Normal distribution,

$$d_1 = \frac{ln(\frac{A}{De^{-rT}})}{\sigma^A \sqrt{T}} + \frac{\sigma^A \sqrt{T}}{2} = \frac{-ln(L)}{\sigma^A \sqrt{T}} + \frac{\sigma^A \sqrt{T}}{2}$$

and $d_2 = d_1 - \sigma^A \sqrt{T}$.

The sensitivity (first derivative) of equity to firm's total assets value is determined by the call option delta: $N(d_1) = \Delta_C$.

The risky debt B_0 of the firm is instead evaluated as a short put position on the firm's asset (with strike equal to the promised debt payment D) and a long position on a riskless bond:

$$B_0 = PV(D) - P^{BS}(A_0, \sigma^A, D, r, T) = De^{-rT} - (De^{-rT} N(-d_2) - A_0 N(-d_1)) \tag{5}$$

The sensitivity (first derivative) of risky debt to assets' value which is given by the delta of the put option: $N(-d_1) = \Delta_P$.

The sensitivity of debt to equity is then given by:

$$\frac{\partial B}{\partial E} = \frac{\frac{\partial B}{\partial A}}{\frac{\partial E}{\partial A}} = \frac{N(-d_1)}{N(d_1)} = \frac{1}{\Delta_c} - 1 = h \tag{6}$$

Therefore it depends on the delta of a European call option written on the firm's assets with exercise price equal to the face value of debt. The debt-to-equity elasticity (hedge ratio) is obtained as:

$$H = \left(\frac{\partial B}{\partial E}\right)\left(\frac{E}{B}\right) = h\left(\frac{1}{L} - 1\right) \tag{7}$$

Two common methodologies to estimate H are the one of Vassalou and Xing (2004)—henceforth VX Methodologyand the one implemented by Schaefer and Strebulaev (2008)—henceforth SS Methodology.

The VX methodology requires the knowledge of the outstanding debt of the firm, the equity value, and the equity volatility[40] in order to estimate the value and volatility of the firm's assets from a system of two non-linear equations. Since the equity is a function of assets' value (4), it is possible to apply Ito's Lemma to determine the instantaneous volatility of equity σ^E from total assets' volatility σ^A (Jones et al. 1984):

$$\sigma^E = \frac{\sigma^A A_0 N(d_1)}{E_0}. \tag{8}$$

Equations (4) and (8) represent a system of two equations in two unknowns (A_0 and σ^A). Therefore I can determine the unknowns by solving the non-linear equations. In practice, I

[40] Typically, equity volatility is estimated from historical annualized volatility of equity daily log returns; the firm's equity value is obtained as a product of the firm's equity price and the number of its outstanding shares (i.e. the firm's market capitalization); and the outstanding amount of debt can be obtained as the book value of the firm's current debt plus half of its long-term debt value.

adopt a recursive procedure (the so-called KMV method; see also Crosbie and Bohn 2003, and Bharath and Shumway 2004) that involves inverting the Black-Scholes formula.[41]

The SS Methodology estimates asset volatility in a "more direct, model-free approach that is based only on observables" and "recognizes that debt bears some asset risk and that equity and debt covary" (Schaefer and Strebulaev 2008). The methodology requires an estimation of the asset volatility for each firm i at time t as square root of:

$$\sigma_{i,t}^{A\,2} = (1 - L_{i,t})\sigma_{i,t}^{E\,2} + L_{i,t}\sigma_{i,t}^{D\,2} + 2(1 - L_{i,t})L_{i,t}\sigma_{i,t}^{ED} \tag{9}$$

$\sigma_{i,t}^{D}$ is the time t unconditional volatility of firm i debt-estimated as the historical annualized volatility of debt log returns; $\sigma_{i,t}^{E}$ is the time t unconditional volatility of firm i equity-estimated as the historical annualized volatility of equity log returns; $\sigma_{i,t}^{ED}$ is the time t covariance between firm i debt and equity-estimated as the historical annualized covariance between equity and debt returns; and $L_{i,t}$ is the leverage ratio of firm i at time t. Once A and σ^A are estimated, then it is possible to estimate also $N(d_1)$ and the debt-to-equity hedge ratio H implied by the Merton (1974) model.[42]

Appendix 2

Analysis of lead/lag relationship between CDS and equity returns and between their bid-ask spreads

In Appendix 2, I perform some analysis on the lead/lag relationship between CDSs and equities.[43] First, after ascertaining that equity and CDS bid-ask spreads are stationary by using the Augmented Dickey-Fueller tests, I perform pair-wise Granger causality tests at the individual firm level for daily CDS and equity bid-ask spreads over the period running from April 2003 to December 2009 for the 45 firms in my sample. Table 9 shows the results of the Granger causality tests: the causality runs from CDS to equity for 24 firms and in both directions for 17 firms (but for 12 of these firms the evidence of casuality running from CDS to equity is much stronger than the other way round).[44]

Second, I perform regressions of each individual CDS (equity) bid-ask spread on the firm's asset volatility and CDS (equity) market average bid-ask spread (the average excludes the individual firm). The regressions reveal that for all firms equity and CDS bid-

[41] Crosbie and Bohn (2003) explain that the model linking equity and asset volatility, described by the system of Equations (4) and (8), holds only instantaneously. In practice the market leverage moves around in a substantial way and the system does not provide reasonable results. Instead of using the instantaneous relationships given by Equations (4) and (8), I follow Crosbie and Bohn (2003) and produce the hedge ratio using a more complex iterative procedure to solve for the asset volatility. Crosbie and Bohn (2003) describe it as a procedure that "uses an initial guess of the volatility to determine the asset value and to de-lever the equity returns. The volatility of the resulting asset returns is used as the input to the next iteration of the procedure that in turn determines a new set of asset values and hence a new series of asset returns. The procedure continues in this manner until it converges. This usually takes no more than a handful of iterations if a reasonable starting point is used".

[42] For this purpose, I set $T = 5$ (maturity of the CDS contracts) and r equal to the 1-month T-Bill yield.

[43] The analysis also repeats some of the steps of the paper by Hilscher et al. (2015), using however a time-sample which includes also the crisis period (2007–2009).

[44] The reported results are obtained from Granger-causality tests including only two lags of the variables. Increasing the number of lags appear to strengthen the result in favour of illiquidity spillovers running form CDS to equity.

Table 9 Pair-wise Granger tests of causality for equity and CDS bid-ask spreads

Ticker	Obs.	Equity BA does not Granger cause CDS BA		CDS BA does not Granger cause equity BA		Causality direction
		F-Stat	*p* value	F-Stat	*p* value	
HON	1477	9.65655	0.00007	72.0589	0.00000	Both directions†
DD	1319	0.02757	0.97280	16.4846	0.00000	CDS to Equity
GR	1470	12.9241	0.00000	94.7041	0.00000	Both directions†
IBM	1402	1.31877	0.26780	0.91107	0.40230	No causality
COP	1293	12.8915	0.00000	13.0634	0.00000	Both directions
KR	1411	16.3281	0.00000	59.1789	0.00000	Both directions†
GIS	1378	0.93471	0.39290	12.8862	0.00000	CDS to Equity
CAT	1426	5.26131	0.00530	8.04736	0.00030	Both directions
DE	1461	1.88282	0.15250	24.2157	0.00000	CDS to Equity
BA	1408	3.63554	0.02660	70.3464	0.00000	CDS to Equity
DOW	1477	0.69962	0.49690	29.8767	0.00000	CDS to Equity
LMT	1357	2.85577	0.05790	22.3741	0.00000	CDS to Equity
MOT	1496	6.59504	0.00140	53.2859	0.00000	Both directions†
FE	1449	0.52073	0.59420	18.9554	0.00000	CDS to Equity
PGN	1438	0.45748	0.63300	3.77172	0.02320	No causality
HAL	1239	6.84928	0.00110	11.58	0.00001	Both directions
AA	1324	2.07183	0.12640	14.6745	0.00000	CDS to Equity
NOC	1502	0.40535	0.66680	16.7724	0.00000	CDS to Equity
RTN	1457	4.93599	0.00730	31.055	0.00000	Both directions†
CPB	1357	1.0173	0.36180	22.762	0.00000	CDS to Equity
DIS	1489	1.55099	0.21240	44.4972	0.00000	CDS to Equity
HPQ	1411	4.72621	0.00900	32.8771	0.00000	Both directions†
DUK	1438	11.4569	0.00001	49.0586	0.00000	Both directions†
ARW	1466	9.53989	0.00008	63.6657	0.00000	Both directions†
OMC	1433	7.58392	0.00050	32.8313	0.00000	Both directions†
CSC	1440	6.06369	0.00240	3.05712	0.04730	Equity to CDS
MCD	1475	3.1774	0.04200	46.7617	0.00000	CDS to Equity
TGT	1273	0.18758	0.82900	14.2473	0.00000	CDS to Equity
BNI	1315	2.29332	0.10130	28.3297	0.00000	CDS to Equity
WMT	1320	12.7869	0.00000	9.35591	0.00009	Both directions
CAG	1400	10.2588	0.00004	46.5928	0.00000	Both directions
JWN	1412	0.55032	0.57690	5.15584	0.00590	CDS to Equity
NSC	1311	2.39611	0.09150	7.51527	0.00060	CDS to Equity
NWL	944	1.82804	0.16130	11.5742	0.00001	CDS to Equity
D	1465	2.38068	0.09280	28.4344	0.00000	CDS to Equity
APC	1397	1.49916	0.22370	7.01297	0.00090	CDS to Equity
CCL	1551	3.98564	0.01880	6.79041	0.00120	CDS to Equity
SWY	1464	8.22348	0.00030	57.5242	0.00000	Both directions†
TWX	1478	1.89036	0.15140	34.1322	0.00000	CDS to Equity
EMN	1470	9.18974	0.00010	54.5439	0.00000	Both directions†
VLO	1434	2.17625	0.11380	16.0766	0.00000	CDS to Equity

Table 9 continued

Ticker	Obs.	Equity BA does not Granger cause CDS BA		CDS BA does not Granger cause equity BA		Causality direction
		F-Stat	p value	F-Stat	p value	
MAR	1492	0.49772	0.60800	19.4288	0.00000	CDS to Equity
SRE	1433	7.80696	0.00040	17.1864	0.00000	Both directions
DVN	1333	0.58351	0.55810	1.06841	0.34390	No causality
KFT	1478	2.93716	0.05330	44.7342	0.00000	CDS to equity

(Test at 1% S.L.; 2 Lags included, Daily frequency; † indicates that evidence is stronger for causality running from CDS to Equity than the other way round as the difference between the relative F-stats is >20)

ask spreads are affected by average market illiquidity; however, while for 22 firms out of 45 (half the sample) the CDS bid-ask spread is also strongly positively affected by the firm's asset volatility, for 80% of the sample this variable has no significant positive effect on the equity bid-ask spread (see Table 10).[45] In (unreported) regression analysis on CDS and equity prices, I also find a significant effect of asset volatility on the CDS premium for a larger number of firms than on the equity price, after controlling for aggregate market effects.[46] These results suggest an asymmetric response of the two markets to firm-specific asset volatility shocks: they have a larger impact on CDS liquidity and CDS price than on equity. These results reflect the CDS' nature as a deep out-the-money put option written on the firm's assets with larger exposure to volatility risk. More importantly, they suggest that a negative firm-specific shock (increasing the firm's asset volatility) can be a source of information and illiquidity spillovers from CDS to equity, rather than of simultaneous independent illiquidity increases in both CDS and equity.

Third, I use panel regressions to check the explanatory power of lagged CDS (equity) returns for equity (CDS) returns at the daily frequency. Results are reported in Table 11. When the whole sample (2003–2009) is considered, current and first lag of CDS returns, but not second lag, are significant to explain equity returns, after controlling for lagged equity returns. Their significance is—however—not very high. The economic and statistical significance of the CDS returns increases when negative news prevail in the market (i.e. when I observe positive CDS returns), and even more when the negatives news arrive during the financial crisis period (2007–2009). Current equity returns, as well as their first and second lags, are almost always statistically significant to explain current CDS returns. However, their economic significance decreases during days of bad news (with negative equity returns) and during the financial crisis.

Fourth, I perform analysis of predictive nature by estimating VAR systems. In Table 12 I observe that when the whole sample is considered, current and lagged CDS returns are insignificant to predict next day's equity returns, while current and lagged equity returns are strongly significant to predict next day's CDS returns. When I restrict the sample and include only positive CDS returns (negative information), CDS returns appear significant to predict next day's equity returns. When I restrict the sample to include only positive

[45] This evidence does not change substantially between more volatile and calmer periods. Moreover, no significant cross-sectional differences among firms (by sector, industry, and size) are found in the results of this analysis.

[46] Also this evidence does not change substantially between more volatile and calmer periods and no significant cross-sectional differences among firms (by sector, industry, size) are found in the results.

Table 10 Regressions of CDS and equity bid-ask spreads on asset volatility and average market Illiquidity

Ticker	Dep. Var. equity bid-ask spread				Dep. Var. CDS bid-ask spread			
	Equity market Ill.		Asset vol		CDS market Ill.		Asset vol	
	Coeff	*p* value	Coeff	*p* value	Coeff	*p* value	Coeff	*p* value
HON	0.9127***	0.0001	−0.0026	0.9017	0.9334***	0.0000	−0.0407***	0.0000
DD	0.7095***	0.0000	0.0185	0.1747	0.9179***	0.0000	0.0382***	0.0000
GR	1.2947***	0.0000	0.0415*	0.0883	0.6977***	0.0000	0.0021	0.5217
IBM	0.7442***	0.0000	0.0239	0.1849	0.7956***	0.0000	−0.0406***	0.0000
COP	0.9451***	0.0081	0.0108	0.6225	0.6203***	0.0000	−0.0036	0.1384
KR	0.7274***	0.0079	−0.1506***	0.0023	0.7314***	0.0000	−0.0002	0.9743
GIS	1.1031***	0.0000	−0.0066	0.8730	0.4410***	0.0000	0.0347***	0.0000
CAT	0.9141***	0.0000	0.0627**	0.0290	1.7590***	0.0000	0.0653***	0.0000
DE	0.8704***	0.0000	0.0298*	0.0988	1.1517***	0.0000	0.0478***	0.0000
BA	0.6745***	0.0000	0.0363***	0.0030	1.3947***	0.0000	0.0706***	0.0000
DOW	0.8822***	0.0000	0.0817***	0.0001	2.9490***	0.0000	0.0994***	0.0000
LMT	2.0731***	0.0003	0.0720	0.1482	0.8362***	0.0000	−0.0756***	0.0000
MOT	1.7936***	0.0000	0.3197***	0.0000	2.7295***	0.0000	0.1173***	0.0000
FE	2.1069***	0.0030	−0.0580**	0.0492	0.7234***	0.0000	0.0308***	0.0000
PGN	0.9714***	0.0000	0.0393	0.3044	0.6667***	0.0000	−0.0956***	0.0000
HAL	1.1143***	0.0016	0.0501	0.1443	0.4850***	0.0000	−0.0115***	0.0008
AA	0.8955***	0.0000	0.0867***	0.0000	5.2807***	0.0000	0.2015***	0.0000
NOC	1.1949***	0.0000	0.0559	0.2146	0.8489***	0.0000	0.0646***	0.0000
RTN	0.9591***	0.0098	−0.0471	0.1600	0.7163***	0.0000	−0.0700***	0.0000
CPB	1.2514***	0.0001	0.0439	0.3552	0.1627***	0.0041	0.0561***	0.0000
DIS	0.6358***	0.0000	0.0209	0.3212	0.9670***	0.0000	0.0077	0.1224
HPQ	0.5683***	0.0000	−0.0296	0.2380	0.9634***	0.0000	−0.0505***	0.0000
DUK	1.1297***	0.0001	0.0781***	0.0014	0.1846***	0.0023	0.0038	0.3758
ARW	0.7554***	0.0006	0.0541	0.2016	2.0952***	0.0000	−0.0200***	0.0003
OMC	0.5606***	0.0001	−0.0095	0.7880	2.3112***	0.0000	−0.0200**	0.0362
CSC	1.7570***	0.0061	−0.0412	0.4200	0.5096***	0.0000	−0.0035	0.3270
MCD	0.2519***	0.0012	0.0067	0.8520	0.3642***	0.0000	0.0272	0.1076
TGT	0.2794*	0.0768	−0.0091	0.5817	1.2647***	0.0000	0.0165***	0.0029
BNI	0.4397**	0.0484	−0.0882***	0.0054	0.7158***	0.0000	−0.0622***	0.0000
WMT	0.2768***	0.0017	−0.0564**	0.0278	0.7477***	0.0000	−0.0521***	0.0000
CAG	0.5374***	0.0000	0.0046	0.9268	0.3484***	0.0000	0.0206***	0.0009
JWN	1.1609***	0.0002	0.0517*	0.0598	2.9263***	0.0000	0.1400***	0.0000
NWL	1.0236***	0.0033	0.1358***	0.0000	0.9752***	0.0000	0.0674***	0.0000
NSC	1.0680***	0.0001	−0.0489	0.1250	0.7198***	0.0000	−0.0552***	0.0000
D	1.9557***	0.0058	0.0215	0.6875	0.4879***	0.0000	−0.0477***	0.0000
APC	0.9337***	0.0001	0.0521***	0.0083	1.3697***	0.0000	0.0535***	0.0000
CCL	1.9054***	0.0000	−0.0072	0.6473	3.0202***	0.0000	−0.0054	0.2321
SWY	0.6973***	0.0000	−0.0129	0.7992	0.7673***	0.0000	0.0206***	0.0003
TWX	1.3812***	0.0000	0.0471	0.3028	1.2639***	0.0000	0.0363***	0.0000
EMN	1.0327***	0.0002	0.0526	0.1295	1.3878***	0.0000	−0.0431***	0.0000
VLO	0.7816***	0.0002	0.0773***	0.0001	0.5905***	0.0000	0.1769***	0.0000

Table 10 continued

Ticker	Dep. Var. equity bid-ask spread				Dep. Var. CDS bid-ask spread			
	Equity market Ill.		Asset vol		CDS market Ill.		Asset vol	
	Coeff	*p* value	Coeff	*p* value	Coeff	*p* value	Coeff	*p* value
MAR	1.2102***	0.0000	0.0746***	0.0016	2.4101***	0.0000	0.1775***	0.0000
SRE	0.8180***	0.0004	−0.0198	0.5074	0.4755***	0.0000	−0.0001	0.9908
DVN	0.9887***	0.0015	−0.0126	0.5586	0.2252***	0.0019	0.0118**	0.0124
KFT	0.4462***	0.0017	0.0247	0.2493	0.6190***	0.0000	0.1007***	0.0000

45 Industrial Firms; Weekly frequency; April 2003–December 2009; Asset volatility is estimated as in Schaefer and Strebulaev (2008); CDS Market Illiquidity = Value-weighted average of CDS bid-ask spreads across the 44 remaining firms; Equity Market Illiquidity = Value-weighted average of Equity bid-ask spreads across the 44 remaining firms; Coefficients are marked respectively with $*, **$, and $***$ when regressors are significant at the 10, 5, and 1% S.L.; Newey-West S.E. are estimated using GMM

Table 11 Panel regressions of CDS (equity) returns on current and lagged equity (CDS) returns

Response of equity returns to (current and lagged) CDS returns—all sample			
Lags	0	1	2
Coeff.	−0.0354***	−0.0050**	−0.0020
t-stat	*−6.14*	*−2.31*	*−0.92*
Econ. Significance	−0.0741	−0.0105	−0.0043
Observations	64,202		
Response of equity returns only to positive (current and lagged) CDS returns—all sample			
Lags	0	1	2
Coeff.	−0.0674***	−0.0240**	−0.0180
t-stat	*−5.26*	*−2.22*	*−1.53*
Econ. significance	−0.0984	−0.0341	−0.0258
Observations	6,680		
Response of equity returns only to positive (current and lagged) CDS returns—crisis sample			
Lags	0	1	2
Coeff.	−0.0987***	−0.0349**	−0.0294**
t-stat	*−5.99*	*−2.36*	*−1.99*
Econ. significance	−0.2840	−0.0432	−0.0373
Observations	3,004		
Response of CDS returns to (current and lagged) equity returns—all sample			
Lags	0	1	2
Coeff.	−0.1509***	−0.2317***	−0.1814***
t-stat	*−14.34*	*−17.86*	*−11.47*
Econ. significance	−0.0721	−0.1118	−0.1238
Observations	64,202		
Response of CDS returns only to negative (current and lagged) equity returns—all sample			
Lags	0	1	2
Coeff.	−0.1302***	−0.1785***	−0.1481***
t-stat	*−2.86*	*−4.82*	*−4.21*
Econ. significance	−0.0452	−0.0626	−0.0490

Table 11 continued

Observations	6,680		
Response of CDS returns only to negative (current and lagged) equity returns—crisis sample			
Lags	0	1	2
Coeff.	−0.1424***	−0.2187***	−0.1306***
t-stat	*−2.76*	*−4.37*	*−3.07*
Econ. significance	−0.0556	−0.0861	−0.0480
Observations	3,004		

45 Industrial firms; Daily frequency; All sample: April 2003–December 2009 (number of observations: 64,202); Crisis Sample: January 2007–December 2009; The panel regressions are estimated with least squares and include also a control for two AR terms; Estimated standard errors are robust to firm clustering; t-statistics are reported in italic; Coefficients are marked respectively with $*$, $**$, and $***$ when regressors are significant at the 10, 5, and 1% S.L.; Economic significance is obtained by multiplying the estimated beta coefficient by the ratio of the standard deviation of the relative explanatory variable to the standard deviation of the dependent variable; Firms' fixed effects included

Table 12 VAR predictability tests on equity and CDS returns at the daily frequency

		CDS ret (t + 1)	Equity ret (t + 1)	CDS ret (t + 1)	Equity ret (t + 1)	CDS ret (t + 1)	Equity ret (t + 1)
All sample							
CDS ret	Lag						
	t	−0.0569***	−0.0001	−0.0827***	−0.0021	−0.0950***	−0.0017
		[−15.51]	*[−0.08]*	*[−21.05]*	*[−1.11]*	*[−23.83]*	*[−0.90]*
	t − 1			0.0560***	−0.0040**	0.0538***	0.0008
				[14.84]	*[−2.20]*	*[13.45]*	*[0.43]*
	t − 2					0.0334***	0.0018
						[8.69]	*[0.96]*
Equity ret	t	−0.2200***	−0.0220***	−0.2276***	−0.0265***	−0.2219***	−0.0371***
		[−27.93]	*[−5.72]*	*[−28.17]*	*[−6.76]*	*[−26.82]*	*[−9.33]*
	t − 1			−0.1778***	−0.0236***	−0.1803***	−0.0241***
				[−21.74]	*[−5.95]*	*[−21.59]*	*[−5.99]*
	t − 2					−0.0815***	0.0034
						[−9.70]	*[0.85]*
Sub-sample of positive CDS returns							
CDS ret	Lag						
	t	−0.0464***	−0.0111***	−0.0637***	−0.0101***	−0.0761***	−0.0066**
		[−7.05]	*[−3.44]*	*[−9.02]*	*[−2.95]*	*[−10.67]*	*[−1.96]*
	t − 1			0.0703***	−0.0066**	0.0598***	0.0045*
				[12.51]	*[−2.43]*	*[10.12]*	*[1.79]*
	t − 2					0.0258***	0.0039
						[4.43]	*[1.41]*

Table 12 continued

All sample

		CDS ret (t + 1)	Equity ret (t + 1)	CDS ret (t + 1)	Equity ret (t + 1)	CDS ret (t + 1)	Equity ret (t + 1)
Equity Ret	t	−0.2529***	−0.0369***	−0.2668***	−0.0449***	−0.2492***	−0.0578***
		[−21.58]	*[−6.43]*	*[−22.01]*	*[−7.68]*	*[−20.03]*	*[−9.79]*
	t − 1			−0.1772***	−0.0173***	−0.1899***	−0.0157***
				[−14.28]	*[−2.90]*	*[−15.03]*	*[−2.62]*
	t − 2					−0.0563***	−0.0053
						[−4.34]	*[−0.85]*
Crisis sub-sample of positive CDS returns							
CDS Ret	Lag						
	t	0.0202**	−0.0191***	0.0069	−0.0227***	−0.0132	−0.0205***
		[2.10]	*[−3.41]*	*[0.60]*	*[−3.28]*	*[−1.12]*	*[−2.93]*
	t − 1			0.0963***	−0.0132**	0.0922***	0.0101*
				[10.81]	*[−2.46]*	*[9.35]*	*[1.73]*
	t − 2					0.0095	0.0031
						[1.06]	*[0.58]*
Equity Ret	t	−0.2631***	−0.0608***	−0.2867***	−0.0808***	−0.2687***	−0.1035***
		[−17.57]	*[−6.98]*	*[−17.97]*	*[−8.44]*	*[−16.16]*	*[−10.55]*
	t − 1			−0.1537***	−0.0130	−0.1780***	−0.0097
				[−9.36]	*[−1.32]*	*[−10.48]*	*[−0.97]*
	t − 2					−0.0067	−0.0023
						[−0.38]	*[−0.22]*

45 Industrial Firms; Daily frequency; All Sample: April 2003–December 2009; Crisis Sample: January 2007–December 2009; 3 Lag are included; t-statistics are reported in italics within squared brackets; Coefficients are marked respectively with $*, **$, and $***$ when regressors are significant at the 10, 5, and 1% S.L.

Table 13 Panel regressions of CDS (equity) bid-ask spread on current and lagged equity (CDS) equity bid-ask spreads

Panel A: Response of equity BAs to CDS BAs when CDS BAs increase

Lags	0	1	2
Coeff	1.3183***	0.0795	0.8670*
t-Stat	*3.81*	*0.11*	*1.73*
Econ. sign.	0.4075	0.0228	0.2353

Panel B: Response of CDS BAs to equity BAs when equity BAs increase

Lags	0	1	2
Coeff	0.0004	0.0008	0.0060
t-Stat	*0.78*	*0.82*	*0.37*

Table 13 continued

Panel B: Response of CDS BAs to equity BAs when equity BAs increase			
Lags	0	1	2
Econ. sign.	0.0021	0.0021	0.0091

45 industrial firms; Daily frequency; Sample: April 2003–December 2009; Number of Observations: 7463 for regression in Panel A; 10,751 for regression in Panel B; The panel regressions are estimated with least squares and include also a control for two AR terms; Estimated standard errors are robust to firm clustering; t-statistics are reported in italics; Coefficients are marked respectively with $*, **$, and $***$ when regressors are significant at the 10, 5 and 1% S.L.; The economic significance is obtained by multiplying the estimated beta coefficient by the ratio of the standard deviation of the relative explanatory variable to the standard deviation of the dependent variable; Firms' fixed effects are included

Table 14 VAR Predictability Tests on Equity and CDS Bid-Ask Spreads at the Daily Frequency

		All Sample		Sub-sample with CDS BAs increase		Sub-sample of Crisis Period with CDS BAs increase	
CDS BA	Lag	CDS BA(t+1)	Equity BA(t+1)	CDS BA(t+1)	Equity BA(t+1)	CDS BA(t+1)	Equity BA(t+1)
	t	0.3918***	0.0778	0.3024***	0.3614***	0.5097***	0.5591***
		[93.97]	*[1.30]*	*[46.37]*	*[3.80]*	*[43.53]*	*[3.16]*
	t − 1	0.1718***	−0.1652***	0.2431***	−0.9302***	0.1224***	−0.9326***
		[39.29]	*[−2.63]*	*[32.59]*	*[−8.56]*	*[10.10]*	*[−5.08]*
	t − 2	0.1263***	0.1093*	0.0727***	0.2853***	0.0729***	0.6864***
		[28.68]	*[1.73]*	*[11.74]*	*[3.16]*	*[6.15]*	*[3.84]*
	t − 3	0.0846***	0.0865	0.1738***	0.2430**	0.1250***	−0.3038
		[19.28]	*[1.38]*	*[24.98]*	*[2.40]*	*[10.34]*	*[−1.67]*
	t − 4	0.1392***	0.0335	0.1312***	−0.1023	0.1278***	−0.0252
		[29.73]	*[0.50]*	*[18.98]*	*[−1.02]*	*[10.58]*	*[−0.14]*
	t − 5	0.0632***	0.1499**	0.0760***	0.3499***	0.0490***	0.1031
		[14.51]	*[2.40]*	*[12.01]*	*[3.80]*	*[4.63]*	*[0.65]*
Equity BA	t	−0.0002	0.1099***	0.0005	0.0881***	0.0004	0.0792***
		[−0.85]	*[26.49]*	*[1.05]*	*[13.33]*	*[0.49]*	*[6.78]*
	t − 1	0.0004	0.1128***	0.0007	0.0969***	0.0021**	0.0668***
		[1.25]	*[27.00]*	*[1.46]*	*[14.58]*	*[2.55]*	*[5.35]*
	t − 2	0.0003	0.1053***	−0.0006	0.1085***	0.0003	0.1280***
		[1.11]	*[25.36]*	*[−1.43]*	*[16.39]*	*[0.41]*	*[10.81]*
	t − 3	−0.00001	0.1131***	0.0011**	0.1120***	0.0026***	0.0972***
		[−0.02]	*[27.34]*	*[2.34]*	*[16.88]*	*[3.06]*	*[7.58]*
	t − 4	0.0004	0.1107***	−0.0002	0.1132***	−0.0007	0.0605***
		[1.54]	*[26.94]*	*[−0.43]*	*[17.03]*	*[−0.86]*	*[4.99]*
	t − 5	0.0002	0.1071***	−0.0005	0.1321***	−0.0016**	0.1379***
		[0.70]	*[26.01]*	*[−1.03]*	*[20.20]*	*[−2.05]*	*[11.41]*

45 industrial firms; Daily frequency; 5 Lags included; All Sample: April 2003–December 2009 (Number of observations: 57,188); Crisis Sample: January 2007–December 2009; T-statistics are reported in italics within squared brackets; Coefficients are marked respectively with $*, **$, and $***$ when regressors are significant at the 10, 5, and 1% S.L.

CDS returns during the financial crisis period, CDS returns appears even more significant to predict next day's equity returns, while only current equity returns (but not their lags) remain significant to predict next day's CDS returns.

Next, since my attention in this paper is mainly focused on CDS and equity bid-ask spreads, I present more results on the lead/lag relationships between these two variables. In panel analysis I regress equity (CDS) bid-ask spreads on contemporaneous and lagged CDS (equity) bid-ask spreads, controlling also for lagged equity (CDS) bid-ask spreads. The regressions are performed only on a sub-sample of observations for which CDS (equity) bid-ask spreads increase from one day to the next one. The results are reported in Table 13. I notice that while contemporaneous and lagged CDS bid-ask spreads affect equity bid-ask spreads, neither the contemporaneous nor the lagged equity bid-ask spreads can explain CDS bid-ask spreads. The significance of the CDS bid-ask spreads is also economically substantial. These results are consistent with the results of the Granger causality tests in Table 9 and the results of the regressions in Table 10. However, rather than including all the observations, the sample is now restricted: I only look at negative spillovers which cause an increase in the liquidity costs of the two markets.

Finally, I estimate VAR systems for CDS and equity bid-ask spreads. By including 5 lags (this is a conservative approach that takes into account the high level of autocorrelation in the bid-ask spread series), in Table 14 I observe that CDS bid-ask spreads (lags 1 and 5) can predict next day's equity bid-ask, whereas equity bid-ask spreads and their lags are never significant to predict next day's CDS bid-ask. When I look at the VAR estimates with 1 or 2 lags and when I limit the sample to the days when CDS ad equity bid-ask spreads increase (unreported results), tomorrow's equity bid-ask spreads also appear largely affected by today's and past CDS bid-ask spreads.

All the analysis reported in this section confirms that negative firm-specific information and higher illiquidity appear to be incorporated first in the CDS market and then transmitted to the equity market, in particular during the crisis period of 2007–2009. This finding is consistent with the mechanism behind the 'hedging–arbitrage channel' described in section 3.2.

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