Essays on the informational efficiency of Credit Default Swaps

Paulo Miguel Pereira da Silva

Tese apresentada à Universidade de Évora
para obtenção do Grau de Doutor em Economia

Évora, Janeiro de 2017

ORIENTADOR (A/ES) : *Professora Doutora Isabel Maria Pereira Viegas Vieira*
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Essays on the informational efficiency of Credit Default Swaps markets

Abstract

This thesis contributes to the strand of the financial literature on credit derivatives, in particular the credit default swaps (CDS) market. We present four inter-connected studies addressing CDS market efficiency, price discovery, informed trading and the systemic nature of the CDS market. The first study explores a specific channel through which informed traders express their views on the CDS market: mergers and acquisitions (M&A) and divestitures activities. We show that information obtained by major banks while providing these investment services is impounded by CDS rates prior to the operation announcement. The run-up to M&A announcements is characterized by greater predictability of stock returns using past CDS spread data. The second study evaluates the incremental information value of CDS open interest relative to CDS spreads using a large panel database of obligors. We find that open interest helps predict CDS rate changes and stock returns. Positive open interest growth precedes the announcement of negative earnings surprises, consistent with the notion that its predictive ability is linked to the disclosure of material information. The third study measures the impact on CDS market quality of the ban on uncovered sovereign CDS buying imposed by the European Union. Using panel data models and a difference-in-differences analysis, we find that the ban helped stabilize CDS market volatility, but was in general detrimental to overall market quality. Lastly, we investigate the determinants of open interest dynamics to uncover the channels through which CDS may endanger the financial system. Although we find information asymmetry and divergence of opinions on firms' future performance as relevant drivers of open interest, our results indicate that systematic factors play a much greater influence. The growth of open interest for different obligors co-varies in time and is pro-cyclical. Funding costs and counterparty risk also reduce dealers' willingness to incur inventory risk.

JEL classification: E44, G12, G01, G12, G14, G15, G19, G28

Keywords: credit default swaps, CDS, market efficiency, open interest, price discovery.

Eficiência dos mercados de *Credit Default Swaps*

Resumo

Esta tese investiga o mercado de derivados de crédito, e em particular o mercado de *credit default swaps* (CDS). São apresentados quatro estudos interligados abordando temáticas relacionadas com a eficiência informacional, a existência de negociação informada no mercado de CDS, e a natureza sistémica daquele mercado. O primeiro estudo analisa a existência de negociação informada no mercado de CDS antes de operações de aquisição, fusões ou venda de ativos relevantes. A nossa análise mostra uma reação dos prémios de CDS antes do anúncio daqueles eventos, sendo em alguns casos mais imediata do que a reação dos mercados acionistas. O segundo estudo avalia o conteúdo informativo das posições em aberto no mercado de CDS utilizando dados em painel de diferentes empresas ao longo do tempo. Os resultados indiciam que as posições em aberto podem ajudar a prever variações futuras dos prémios de CDS e retornos acionistas. Em acréscimo, verifica-se um aumento estatisticamente significativo das posições em aberto antes da divulgação de surpresas negativas nos resultados das empresas. O terceiro estudo mede os efeitos da proibição de posições longas em CDS sobre entidades soberanas pertencentes ao Espaço Único Europeu sem a detenção do ativo subjacente pelo comprador. A análise mostra um efeito negativo da proibição sobre a qualidade do mercado, pese embora se tenha assistido em simultâneo à redução da volatilidade. Por fim, são analisados os determinantes dos montantes associados a posições em aberto, com o intuito de compreender como o mercado de CDS pode influenciar o risco sistémico. Os resultados indicam que a assimetria de informação e a divergência de opiniões dos investidores influenciam aqueles montantes. Todavia, fatores sistemáticos como risco de contraparte, aversão ao risco e risco de re-financiamento parecem ser ainda mais relevantes por via do efeito que exercem no risco do balanço dos intermediários financeiros.

Classificação JEL: E44, G12, G01, G12, G14, G15, G19, G28

Palavras-chave: *credit default swaps*, CDS, eficiência de mercado, posições em aberto, formação de preços.

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Introduction

Credit default swaps (CDS) help investors manage risk by enabling credit risk transfer of a reference entity to a third party for a pre-determined fee. The CDS market experienced a remarkable growth in the early 2000s, both in number of reference names available for trade and in market value of outstanding positions, becoming close to surpassing foreign exchange derivatives as the second largest segment in the global over-the-counter (OTC) derivatives market. In effect, CDS gross notional values ramped up from $1,000bn in 2001 to $62,000bn in 2007.

Prior to the 2008 financial meltdown, CDS were considered as essentially benign instruments due to their ability to enhance risk sharing amid economic agents while allowing trade credit risk as a separate asset class. However, from 2008 onwards, the reputation of these credit derivatives decayed, not only due to their direct involvement in the failures of Lehman Brothers, Bear Stearns and especially AIG, but also for their role in the credit bubble formation in the preceding years. Following greater pressure and scrutiny from financial regulators and the general public, notional amounts have been declining since then. Gross values plunged to $26,000bn in 2010. Nevertheless, it is worth noting that part of such decline is explained by "compression" (elimination of redundant positions) and by the inception of central clearing.

CDS are not redundant assets. The most important issue of CDS market's initiation is that it produced relevant changes in different areas of finance and in real economic activity. Corporate finance, credit supply and financial intermediation were altered by the existence of CDS. Most importantly, CDS have the capacity to affect real economic activity by changing economic agents' incentives (e.g., while altering the incentives of "empty creditors" in the wake of restructuring events) and through the price system, as a new barometer of credit risk.

This thesis seeks to improve current knowledge on two particular topics of the CDS literature: the informational efficiency of CDS spreads and the dynamics of open interest. During the last decade, the use of CDS spreads as credit risk barometers impacted several fields in finance and challenged the dominance of credit rating agencies. In effect, CDS have application as measures of counterparty risk, in credit valuation adjustment and debit value adjustment (CVA and DVA), and thus affect firms' balance sheets (e.g., most banks price CVA and DVA using current CDS valuation inputs, such as spreads, recovery rates and default probabilities); they are a real-time indicator of market discipline; market-implied default probabilities are utilized by supervisors to monitor the resilience of banks and other financial intermediaries; CDS have also contributed to more market-based (and less relationship-based) loan pricing, thereby impacting actual financing decisions. The inception of bank loans with borrowing costs linked to CDS spreads and corporate bonds issuance with coupon payments that depend on the evolution of CDS spreads illustrate such new trends.

The role of CDS spreads as credit risk barometers aggregating investors' individual beliefs about borrowers' risk profile raises several interesting questions. For instance, how efficient CDS spreads are in assimilating information? How did the inception of CDS trading change the process of gathering information and price discovery across related markets? Does CDS market activity reveal useful information about credit risk, not conveyed in other financial instruments' prices (e.g., stocks and bonds)? Understanding how CDS rates are formed and how they adjust to new information is important, given their relevance for various entities, including bond fund managers (especially for high-yield portfolios), rating agencies, credit market data vendors, speculators on credit quality, relative value traders and regulators, and for their current and future role in corporate finance and financial intermediation decisions.

This thesis compiles four interconnected studies addressing the existence of informed CDS trading, CDS rates informational efficiency and the systemic nature of the CDS market. Concerning the first two topics, the relevant research questions are:

- Is there informed trading prior to mergers and acquisitions (M&A, henceforth) and divestiture operations in the CDS market?
- Does CDS open interest reveal incremental information regarding CDS and stock prices?
- Did the ban on uncovered sovereign CDS buying, imposed by the European Union regulation 236/2012, affect CDS market quality?

Chapter two addresses the first question and empirically assesses alternative channels through which informed traders express their views in the CDS market: M&A and divestitures activities. In effect, while stock prices result from the interaction of a relatively large number of retail investors, the participants of the less liquid CDS market are primarily banks, hedge funds and other financial institutions, regarded as relatively well informed and sophisticated. Previous studies showed that private information obtained through banking services, such as loans and syndicated debt, is incorporated into CDS rates by large banks in their trading and quote revising activities. We show that information obtained by major banks while supplying M&A and divestiture investment banking services is also assimilated by CDS rates prior to the operation announcement. Our results also support the notion that CDS innovations have incremental predictive power over stock returns prior to M&A announcements. Such power may be improved if major dealers in the CDS market concomitantly act as investment bankers supplying services to one of the parts.

The second question is addressed in chapter three where an analysis of the information value of CDS open interest is developed using a large panel database. The results show that open interest innovations help in predicting subsequent raw and abnormal CDS rate changes, as well as raw stock returns. An abnormal open interest pattern is also associated to future disclosures of information: positive open interest growth precedes the announcement of negative earnings surprises. The analysis also suggests that the information content of open interest is related with proxies of investors' attention and slow moving capital.

In chapter four the effects of the ban on uncovered sovereign CDS buying imposed by the European Union regulation 236/2012 over the CDS market quality are evaluated. Regulation 236/2012 on *Short Selling and Certain Aspects of Credit Default Swaps* came into force in November 2012 with the aim of banning uncovered protection buying on European sovereign names. Previous research investigated the consequences of short selling restrictions in stock markets, but the literature is scarce on assessments of the effects of similar restrictions in the CDS market. Using panel data models and a difference-in-differences analysis, we find that the ban helped in stabilizing CDS market volatility, but was detrimental for liquidity, for the price delay in the adjustment to news and for price precision. Overall, we conclude that market quality was negatively affected by the ban.

Chapter five deals with the systemic nature of CDS. After the 2008 financial crisis, policy makers and regulators considered the CDS market as a threat to financial stability, due to the potential to induce contagion and systemic risk. Such concern lies in the counterparty risk and in the concentration of risk assumed by market participants, the binary nature of CDS (consubstantiated in the existence of jump-to-default risk) and the high sensitivity to the business cycle of these instruments' valuation. Therefore, a relevant research question is what factors drive the CDS market's inventory risk? In this chapter we analyze the determinants of open interest dynamics with the goal of shedding some new light on the channels through which CDS may endanger the financial system, and to provide some guidance for regulators in drawing new regulatory policies. Identifying the determinants of open interest (i.e., the maximum exposure of market participants) is thus relevant for understanding the risks of the CDS market for financial stability.

Our results suggest that although information asymmetry and divergence of opinions on firms' future performance help explaining the growth of net notional amounts of single-reference contracts, systematic factors have a much greater influence. The growth of net notional amounts for different obligors co-varies in time and is pro-cyclical. The open interest tends to expand following positive stock market performance and to fall when large negative (positive) jumps in stock (CDS) prices are perceived by investors. In line with the market microstructure theory, funding costs and counterparty risk reduce CDS market players' willingness to incur inventory risk, thus contracting gross notional amounts.

The remainder of this thesis is structured as follows: chapter one contextualizes the empirical assessments developed ahead and provides information on the history of CDS, definition of some relevant concepts and valuation. It also briefly surveys the various ramifications of the CDS market literature and, in particular, the market's influence on financial intermediation, related markets and corporate finance; chapter two investigates M&A and divestitures activities as alternative channels for informed traders in the CDS market; chapter three evaluates the information value of CDS open interest; chapter four examines the effects of the ban on uncovered sovereign CDS buying imposed by European Union regulation 236/2012 on CDS market quality; chapter 5 assesses the determinants of open interest dynamics. The last chapter concludes, with a brief summary of the main results and the respective policy implications.

1. An Overview of the Credit Default Swap Market

1.1. Definitions and relevant concepts

CDS contracts were created in the early nineties by J.P. Morgan to off-load its credit risk exposure to Exxon by paying a fee to the European Bank for Reconstruction and Development, who was willing to sell protection (Tett 2009). Since then, the number of underlying reference entities available to trade and the notional amounts outstanding boosted. The investor base has been expanding through time, and includes a diversity of players such as banks, brokerage firms, insurance companies, pension funds, financial guarantors, hedge funds and asset managers. The buy-side comprises institutional investors and other non-dealer financial institutions (retail investors are usually not involved in the CDS market). These buy-side market participants interact with dealers, as in other over-the-counter (OTC) markets, through bilateral arrangements, based on indicative and unbinding quotes posted on major data providers. Inter-dealer trades are used to manage or hedge transactions with end-user clients and reduce dealers' inventories.

This fixed income instrument is included in the broader definition of credit derivatives. It enables buyers to obtain insurance against a contingent credit event on an underlying reference entity – corporate or sovereign. In doing so, the protection buyer accords to pay a (quarterly) premium to the protection seller (referred to as CDS spread or rate) over the life of the contract, i.e., until maturity or a default event occurrence, whichever arrives first. In return, the failure of the reference entity to meet its obligations triggers a payment from the seller to the buyer equal to the difference between the notional of the contract and the value of the underlying reference obligation (referred to as the loss given default)[1]. The two cash flow streams of a CDS contract are typically termed as the fixed leg (the fixed periodic premium paid by the protection buyer) and the contingent or default leg (the payment contingent on the existence of a credit event). The CDS spread is quoted in basis points and represents the total fee paid per year by the protection buyer as a percentage of the notional principal.

The definition of credit event encompasses several occurrences including bankruptcy, failure to pay, obligation default or acceleration, repudiation or moratorium (for sovereign

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[1] This payment may occur through cash settlement of actual incurred losses or physical delivery (transfer of the obligation from the buyer to the seller in exchange for the notional amount of the contract). In a physically settled contract, the protection buyer has the right to deliver a set of deliverable obligations to the protection seller who in turn has the obligation to pay the full face value of the obligation. In a cash settled contract, the protection seller pays the difference between face and market value of the reference obligation to the protection buyer. In this latter case, the market value of the reference obligation is typically determined through an auction in that a number of participating dealers provide two-way prices on an agreed obligation, leading eventually to a final market price or recovery value of the obligation, which is used to cash settle all CDS contracts (Theis 2014).

entities) and restructuring. A bankruptcy takes place when the reference entity becomes insolvent or is unable to repay its debt (this situation must be confirmed by a judicial, regulatory or administrative proceeding or filing in order to be considered as a credit event). The failure to pay refers to a default on due payments, such as principal or interest, and is usually subject to a materiality threshold of $1 million (Theis 2014). Obligation acceleration occurs when an obligation of the reference entity has become due prior to maturity and has been accelerated because of default.

In a repudiation/moratorium event, the reference entity refuses or challenges the validity of its obligations or imposes a moratorium. Restructuring refers to a modification of the terms of a debt obligation that is materially unfavorable to creditors (e.g., lowering the coupon or lengthening the obligation maturity). In general, credit events include (i) a change in coupon rates, (ii) a change in principal amount (hair-cut), (iii) a postponement of interest or principal payment date, (iv) a change in ranking of priority, and (v) a change of the currency in which the obligation is denominated.

Under normal conditions, a CDS contract on a specific reference entity is terminated as a result of a credit event or because it has reached its maturity date. Nonetheless, its status may vary over time for several other reasons. The first is referred to as “novation”, and consists of the replacement of one of the two original counterparties of the contract with a third one. To put it simple, the position is terminated by entering into an offsetting transaction with a different counterparty, a procedure that however does not legally cancel the original contract (indeed, this type of exposure management is commonly used and helps explain the growing number of CDS trades). Other status changes may derive from early termination clauses, or to contract terminations due to compression mechanisms that allow market participants to cancel out redundant positions.

From a valuation point of view, CDS spreads are equivalent to par floating-rate spreads. The CDS buyer (protection buyer) has a similar credit risk exposure to selling a bond short and investing the proceeds in a risk-free asset. In the absence of a credit event both strategies result in the payment of a credit spread until the maturity of the contract; if a credit event occurs, the buyer receives the difference between the market value of the default-free floating rate note and the market value of the defaultable floating rate note (Duffie 1999; and Hull and White 2000). Hull and White (2001) extend that methodology to account for counterparty default risk and allow the payoff to be contingent on defaults by multiple reference entities. Nevertheless, this definition only accounts for the cash-flow involved in the operation, disregarding voting rights in the presence of distress or convenience yields that emanate from their use in regulatory arbitrage.

Like any other derivative instrument, CDS may be utilized to hedge, to speculate or to undertake arbitrage operations. In that respect, the onset of CDS trading in financial markets brought innumerous advantages to market participants:

- CDS allow transferring credit risk of a reference entity between two parties without transferring the underlying asset, isolating credit risk from funding[2];
- they constitute a new asset class where market participants may express a credit view on a reference name without entering into the bond or loan market directly; Cossin and Pirotte (2001) claim that credit derivatives make an important dimension of financial risk tradable, thereby enhancing market completion and risk allocation;
- CDS enable investors to trade and hedge credit risk with lower transaction costs (e.g., investors no longer need to buy and sell the bond to achieve their desired exposure or may avoid further transaction costs by reversing unnecessary positions). That is particularly relevant in the case of illiquid portfolios of bonds and loans;
- CDS allow reducing the exposure to certain borrowers while conserving the client relationship. In contrast, other typologies of credit risk transfer such as loan sales and loan syndication could have detrimental effects on lending relationship with borrowers;
- the higher level of standardization (at least in comparison with bonds) makes it easier to revert positions with other traders;
- CDS allow reducing credit exposure to particular borrowers or sectors without affecting on-balance sheet exposures. The ability to trade CDS is thus a key risk management tool for writers of protection to achieve a level of risk that they can be comfortable with;
- investors in general benefit from a new diversification channel and a widen investment opportunity set;
- CDS facilitate speculation involving negative views of a firm’s or a sovereign’s financial strength, most notably when some bonds are not readily available for short selling;

[2] Prior to the appearance of credit derivatives in the 1990s, credit risk management was limited to the use of traditional financial analysis, covenants and counterparty limits. In effect, financial institutions and large investors relied on the use of triggers and covenants, collateral and regular business review to manage their risk. The introduction of credit risk instruments such as CDS promoted credit risk management solutions built on the basis of complex statistical models. Before the onset of CDS trading, an investor not comfortable with its credit exposure to an entity had few protection options.

- the greater liquidity and risk transfer possibilities brought by CDS may reduce borrowing rates and enhance credit supply;[3]
- CDS spreads help improving banks' market discipline through real-time market monitoring. In fact, this additional real-time information influence banks' credit availability and funding costs (Norden and Weber 2012);
- CDS furnished banks with new risk management tools. Norden, Buston and Wagner (2014) claim that some of the banks' benefits were passed on to borrowers (their results indicate that banks with larger gross positions in credit derivatives charge significantly lower corporate loan spreads).

In spite of the aforementioned advantages, it has been acknowledged that large exposures to CDS can create substantial systemic risk (French et al. 2010). Brunnermeier et al. (2013) report that, in aggregate terms, major dealers are net sellers of CDS protection. Systemic risk arises because systemically important financial institutions that act as market-makers can be severely affected by unhedged positions when they are on the sell-side. On the one hand, the value of these derivative contracts is very sensitive to the economic environment because default rates, default correlation and recovery values are partially determined by the business cycle. That may increase the tail risk of financial institutions that act as dealers on the sell-side, especially when market conditions deteriorate. On the other hand, systemic risk may arise due to the multiple channels through which financial intermediaries are connected, and particularly due to counterparty risk (French et al. 2010).

The next subsection describes the evolution of the regulatory setup of credit risk markets.

1.2. The evolution of the regulatory framework

Prior to 2009, CDS were traded exclusively in un-regulated OTC markets through bilateral arrangements involving counterparty risk. This market was viewed as opaque and non-transparent due to the lack of information available about prices and transactions, and the existence of a highly complex network structure of existing positions. Despite that, CDS were perceived as benign instruments of financial innovation given their ability to provide effective tools to trade and manage credit risk. In that respect, former Federal Reserve Chairman Alan Greenspan stressed that "these increasingly complex financial instruments have contributed, especially over the recent stressful period, to the development of a far more flexible, efficient, and hence resilient financial system than existed just a quarter-century ago".[4] In reality, the off-

[3] In this regard, Stulz (2010) claims that they allow financial institutions to make loans they would not otherwise be able to make.
[4] From Greenspan's speech ''Economic Flexibility'' before Her Majesty's Treasury Enterprise Conference

balance sheet nature of credit derivatives was also regarded as an advantage. As argued by Shan, Tang and Yan (2014), regulators recognized CDS as important risk management tools that allowed banks to reduce their risk-weighted assets and raise regulatory capital ratio, thereby contributing to a more efficient use of capital.

Notwithstanding their opaque nature, credit derivatives markets grew remarkably until the onset of the 2008 financial crisis becoming close to surpass foreign exchange derivatives as the second largest segment in the global OTC derivatives market. From 2008 onwards, notional amounts have declined more or less steadily. The 2008 financial crisis, and especially the failure of AIG (a large international insurance company at the time), unveiled the problems caused by the misuse of CDS and deficiencies in market design and infrastructure where a few important players carried substantial credit risk without having the ability to manage it (Stulz 2010).[5] The view of policy makers and regulators about the role of these derivative instruments also changed and led to an unprecedented regulatory upsurge.

Prior to the 2008 financial crisis, regulatory reforms in OTC markets were initiated principally by participants and their corresponding associations (e.g., the International Swap and Derivative Association (ISDA)). ISDA undertook several reforms on CDS market architecture with the objective of enhancing contract standardization, facilitate back office and contract management operations, and reduce legal disputes. The first example is the Master Agreement (and a wide range of related documentation) produced in 1999 and revised in 2003, that applies to any OTC derivatives trades (including CDS), and ensures the enforceability of netting and collateral provisions. ISDA defined a standardized legal documentation and a format for trade confirmation (Master Confirmation Agreement on Credit Default Swaps) and predefined various optional variables in relation to the underlying reference entity. The codification of credit events and the definition of the liquidation process have been of paramount importance to reduce risk of potential legal disputes.[6]

In 2009, ISDA put forward a new Master Confirmation Agreement (the so called "Big Bang Protocol"), to which more than 2000 market participants (including banks, hedge funds and

(London, January 26, 2004).

[5] AIG had been very active prior to the crisis in the CDS market as a protection seller (with a short exposure in credit derivatives reaching USD 372 billion at September 30, 2008). The deterioration of credit conditions led to a credit rating downgrade of AIG, which subsequently brought about higher demands for collateral by AIG's counterparties and a liquidity shortfall. Systemic concerns by the Federal Reserve and the US government resulted in one of the major bailouts in the US history. The position of AIG as a "one-way seller" in the CDS market was viewed as systemically too relevant and too interconnected to fail given the complex chains of counterparty risk in the CDS market (ECB 2009).

[6] The ISDA Master Agreement contains information on: i) reference entity (underlying in form of a legal entity, indices or sovereign), ii) nominal value, iii) the maturity date (agreed tenor or by credit event), iv) the agreed premium/ coupon, v) credit event trigger (and related reference obligation), and vi) contract liquidation procedure in case of a credit event.

institutional investors) voluntarily adhered. The Big Bang Protocol introduced three important changes: (i) the creation of Determination Committees[7] which take binding decisions on whether a credit event occurs, replacing the previous bilateral negotiation; (ii) introduction of an auction mechanism to set the price of distressed bonds (binding for those parties that signed to the Protocol)[8] and promotion of financial liquidation; and (iii) strong contract standardization in terms of expiry dates and premiums, aimed at facilitating compression and promoting the growth of Central Counterparty (CCP) clearing.[9]

With the goal of clarifying unresolved issues in the Big Bang protocol relative to the absence of a common definition of Chapter 11 for European firms and to the qualification of restructuring events, ISDA presented in July 2009 the so called "Small Bang" protocol. This Supplement to the Master Agreement add to the auction hardwiring provisions of the Big Bang Protocol to restructuring credit events.

Recently, policy makers and regulators also added new legislation to the CDS trading activity. The Dodd-Frank Act in the US introduced *Made Available to Trade* (MAT) determinations, which implies that certain contracts will be subject to mandatory trade execution on Swap Execution Facilities (SEF) or designated contract markets (DCMs), and thus prohibited from OTC trading without an express exemption or exclusion from the CFTC.[10] The European Market Infrastructure Regulation (EMIR) also introduced a clearing obligation for eligible OTC derivatives, which will also produce effects on the level of transparency in this market in the EU.[11] Other important changes in the CDS market relate with their treatment in Basel III bank regulations (for instance, banks are now subject to greater capital charges for derivatives trading, including CDS so-called "incremental risk charge" – Shan, Tang and Yan 2014), the temporary

[7] The central decision-making body in the marketplace (Determination Committee) aims to determine whether an event occurred, the settlement procedure and the type of deliverable obligations (Chaplin 2010).
[8] The cash settlement emerged as the standard settlement procedure with the aim of avoiding short squeeze episodes that occasionally result in the bid up of deliverable bonds by protection buyers (Mengle 2007). As for the recovery rate, it is determined through a centralized auction in order to discover a single price that mirrors the fair recovery value after an event.
[9] For instance, CDS premiums were set at 100 or 500 basis points for US contracts and at 25, 100, 500 or 1000 basis points for European single name CDS. Hence, an upfront payment is required to compensate for the difference between the market price and the standardized premium set by the protocol (making the net present value of the contract worth zero at inception). In the market place, the CDS contract is still quoted on the basis of the fair CDS premium/running spread.
[10] Not all CDS contracts are eligible for CCP clearing as they are not sufficiently standardized. Nonetheless, a significant share of OTC credit derivatives will probably move to CCP, due to mandatory regulation and incentives.
[11] This procedure may present several advantages: (i) by acting as buyer to every seller and seller to every buyer of protection, the CCP isolates each participant from the default of other participants, thereby limiting contagion risk in the financial system; (ii) improved monitoring and risk management through membership (minimum capital), margin and collateral requirements (in the event of a default by a clearing member, the CCP may use different tools to absorb losses, such as margin calls and, if needed, a guaranty fund, to which clearing members contribute according to the risk of their position, and finally using its own capital). Proponents of central clearing claim that it increases market liquidity; improves risk management; and raises market confidence by increasing transparency in the market.

ban on naked CDS in Germany, and the permanent in the EU in 2011. This last event is carefully analyzed in Chapter 4.

1.3. The valuation of CDS

The pricing of CDS constitutes a central piece of academic research on the CDS market. Nevertheless, this strand of research cannot be dissociated from the broader field of research on credit risk determinants (e.g., Das 1995; Duffee 1999; and Duffie and Singleton 1999). Credit risk valuation models fall into two different categories: structural models and reduced form models. While the structural approach takes into account the firm's asset-liability evolution process, the reduced form deals with default as a stochastic event.

From a structural perspective, as in Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995) and Leland and Toft (1996), CDS are valued as deep out-of-the-money put options. In Merton (1974), the source of credit risk comes from the uncertainty about the future market value of the firm and the level of risky debt. Based on the option theory, risky debt is priced as the difference between a riskless bond and a short put written on the value of the assets of the firm. If the market value of the firm is higher than the face value of debt, bondholders will get their debt fully repaid and residual value will be assigned to shareholders. However, if the firm market value falls below the face value of debt, the bondholders will take over the firm, whereas shareholders will be wiped-out. In Merton (1974), credit spreads are determined by interest rates, asset volatility and leverage.

Black and Cox (1976) propose an extension wherein default occurs after firm value drops below a threshold level during the term of the loan. The existence of such threshold is justified with the existence of loan conditions such as covenants and guaranties. Geske (1977) extends the model with the introduction of coupon bonds. Ramaswamy and Sundaresan (1986) and Kim, Ramaswamy and Sundaresan (1993) allow for default not only at maturity but also on coupon payment dates and include stochastic instead of constant interest rates. Longstaff and Schwartz (1995) incorporate interest rate risk, and other aspects as the seniority of debt and recovery rates. Zhou (1997) develops a model where the dynamics of firm value depends on a jump-diffusion process with two components: a continuous component (similar to Merton's, 1974, diffusion type stochastic process) and a discontinuous jump component, which allows the firm value to change unpredictably and by a considerable size.[12]

[12] These models resulted in interesting applications for capital structure theory. For instance, Leland (1994) and Leland and Toft (1996) build on this framework to model the optimal maturity of the capital structure of a firm, balancing the effects of tax advantage of debt with those of bankruptcy and agency costs. In Fan

In the reduced form approach, default depends of latent factors, following the modeling approach used in Treasury and interest rate swap markets. These models disregard the evolution of assets and capital structure, and focus on the hazard rate itself (i.e., the probability that the reference entity will default at time t conditional on having survived to t-1). While the use of latent factors is extremely valuable (e.g., Doshi, Jacobs and Zurita 2014 find that they usually provide a good in-sample fit), they do not add intuition with respect to the economy wide and firm-specific determinants of credit risk. Reduced form models basically fall into three main types: default-based, rating-transition and spread models. Jarrow, Lando and Turnbull (1997), Duffie and Singleton (1999) and Hull and White (2000) provide detailed explanations of several well-known reduced form modeling approaches.

Default-based models consist of a jump diffusion process with jump intensity assumed to be either constant or time varying, whereas the recovery rate is assumed to be either a fraction of face value or market value of a risk-free security at termination. For instance, Jarrow and Turnbull (1995) represent default by a random stopping time with a stochastic or deterministic arrival intensity (hazard rate), whereas the recovery rate is usually assumed to be constant. Jarrow, Lando and Turnbull (1997) extend the preceding setup while developing a credit migration model. In lieu of a sudden and unexpected occurrence, credit migration models assume that credit spreads vary with the credit rating or the occurrence of other credit events besides default. Finally, Duffie and Singleton (1999) and Das and Sundaram (2000) price a defaultable bond as if it were risk-free by replacing a conventional risk-free interest rate process with a default-adjusted yield process on a risky debt instrument. The pricing process depends on the sum of three stochastic processes: the risk-free interest rate, default rate and (occasionally) the recovery rate.

Other developments in the reduced form approach include Houweling and Vorst (2005), who extend the Duffie-Singleton (1999) setup to CDS pricing; Chen et al. (2008), who improve reduced form models by allowing correlation between interest rates and default intensities; and Doshi et al. (2013), who introduce a reduced form, discrete-time, quadratic no-arbitrage model for CDS pricing, where the default intensity is driven by observable covariate (firm leverage and historical volatility).

With the development of theoretical pricing models, a vast empirical literature addressing their merits and disadvantages emerged. The consensus of the literature is that structural models do a poor job in empirically predicting credit spreads - the credit spread puzzle. Huang and Huang (2012) report that credit risk represents only a small portion of observed corporate credit spread. Huang and Zhou (2008) test several structural models using CDS spreads for 93 firms during

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and Sundaresan (2000), creditors and shareholders can renegotiate in distress to avoid inefficient liquidations, so that the default barrier is typically lower than in Leland (1994).

period 2002–2004. Using GMM-based specification tests, they examine the accuracy of five structural models: Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001) and Huang and Huang (2012). They show that Collin-Dufresne and Goldstein's (2001) model provides the best approximation. The models of Merton (1974), Black and Cox (1976) and Longstaff and Schwartz (1995) are strongly rejected by the data for failing to accurately capture time-series changes in spreads.

By the same token, Huang and Huang (2003) show that structural variables lack explanatory power for credit spread variation, and Eom, Helwege and Huang (2004) find that structural models overestimate (underestimate) credit risk of riskier (safer) firms, whereby there is a large pricing error for corporate bonds. Das, Hanouna and Sarin (2009) and Correia, Richardson and Tuna (2012) reduce prediction errors while adding accounting-based measures to structural models' variables as predictors. Bai and Wu (2013) show that distance-to-default and a long list of firm fundamental characteristics explain 77% of the cross-sectional variation in CDS spreads. Ericsson, Reneby and Wang (2006) examine the accuracy of the models of Leland (1994), Leland and Toft (1996) and Fan and Sundaresan (2000). They find that these models systematically under-predict bond spreads. CDS spreads, in contrast, include less non-default components. Feldhutter and Schaefer (2014) suggest that the credit puzzle stems from biased data (the use of historical default rates) and biased analysis (based on average coefficients from regressions).

Other authors have attempted to explain bond credit spreads and CDS spreads empirically using observable variables suggested by structural models, but under non-formal model specifications. Collin-Dufresne, Goldstein and Martin (2001) find that structural variables have limited power to fully explain credit spread changes. Zhang, Zhou and Zhu (2009) include volatility and jump risk measures (based on high-frequency equity returns) as explanatory variables of credit spreads. Their results suggest that high-frequency return based volatility and jump risk measures have significant explanatory power for the levels of CDS spreads. Galil et al. (2014) find that firm-specific variables consistent with structural models substantially explain spread changes. However, these variables lose explanatory power after controlling for common market variables and credit ratings.

Cao, Yu and Zhong (2010) investigate the explanatory power of option-implied volatility for CDS spreads, rather than historical volatility. They conclude that stochastic volatility and jumps help explain the level and time-series variation of CDS spreads, in particular for highly rated firms. Ericsson, Jacobs and Oviedo (2009) find that volatility and leverage explain a great portion of CDS spread variation. In addition, they find little evidence of the existence of an additional omitted common factor. Berndt et al. (2008) compare ratios of risk-neutral default intensities, implied from CDS spreads and from Moody's KMV expected default frequencies (EDFs), and find substantial variation of risk premia over time. Bharath and Shumway (2008) investigate the forecasting power of the distance-to-default measure computed from the Merton model on actual default probabilities, and report that its functional form is useful for forecasting defaults, despite the Merton model failure in predicting the probability of default accurately.

Regarding reduced form models, Duffee (1999) shows that the reduced form approach fits market prices well, but underperforms in the prediction of the level and slope of the credit curve for investment-grade bonds. Arora, Bohn and Zhu (2005) compare structural and reduced form models utilizing CDS. Their findings indicate that structural models outperform their counterparts except when there are many bonds trading in addition to CDS. Madan and Unal (2000) evaluate certificates of deposit using the reduced form approach and find that the estimated spreads are below (above) market spreads when the company is far from (close to) default.

All in all, the use of structural models depends on the existence of internal information about the firm balance sheet (disclosed quarterly to the public). Structural models are hard to calibrate and the estimation of the input parameters can be problematic. The process can be computationally burdensome as all liabilities senior to the corporate bond in question should be valued simultaneously (Jarrow and Turnbull 1995). Nevertheless, the structural approach is useful to price the credit risk of private firms using non-market information. In the reduced form approach, default is not directly dependent on the firm value or company-specific parameters but, instead, on market data. Consequently, it relies on the existence of traded debt and market prices which make it difficult to apply to private debt. This approach uses aggregated market data only and disregards company-specific risk.

In fact, the valuation of CDS by large financial institutions is performed using proprietary models. Among those, CreditGrades and KMV (now Moody's KMV or MKMV) are among the most popular. CreditGrades was developed by four leading institutions in the area of risk modeling, namely JP Morgan, Deutsche Bank, Goldman Sachs and RiskMetrics Group, and is based on the structural approach of Black and Cox (1976). Its modeling details are available for the general public. Bystrom (2006) demonstrates that theoretical CDS spreads generated by the CreditGrades model correlate with market CDS spreads, but the two spreads often differ. KMV is a modified version of Vasicek-Kealhofer's (VK) structural model. It is based on a specification of the default-risk-free rate, the market risk premium, liquidity premium and expected recovery.

1.4. Are CDS a pure measure of credit risk?

Even though a significant amount of research in this field were concentrated, at first, on the development of models to price credit risk, it rapidly expanded into other areas of financial economics, with a variety of ramifications. This was in part a result of the remarkable growth in importance of credit derivatives in the early 2000 and of the recognition of CDS spreads as a cleaner measure of credit risk than bond credit spreads. Indeed, CDS were commonly thought to be less affected by non-default factors, becoming an interesting source of data for evaluating models of default risk. The fact that they are constant-maturity-spread products with homogeneously defined contracts enables a much cleaner comparison in empirical work across companies and countries vis-à-vis bond yield spreads.

For example, Longstaff, Mithal and Neis (2005) use CDS spreads as a pure measure of credit risk. They claim that the CDS market is usually more liquid than the corporate bond market, whereby the non-defaultable component of CDS spreads is, in principle, lower than the non-defaultable component of bond credit spreads. Furthermore, CDS spreads are not affected by tax effects, covenants and embedded options. The separation of default and non-default components of credit spreads (using CDS information) suggests that liquidity has a strong effect on the non-default components.

Nevertheless, the use of CDS rates as a pure measure of credit risk has been challenged by recent empirical literature. Indeed, it has been demonstrated that the pricing of CDS may be influenced by third factors not related with the reference entity's credit risk, including counterparty risk, liquidity and the cheapest-to-delivery option.[13] The analysis of the cheap-to-delivery option implicit in CDS contracts is undertaken by Jankowitsch, Pullirsch and Veža (2008) for corporate CDS, and by Ammer and Cai (2011) for sovereign CDS.

The default risk of CDS counterparties may influence CDS pricing due to a reduction in the expected value of the insurance promised by the protection seller. Certainly, the protection buyer will not receive that payment if the default of the counterparty coincides with, or precedes, the credit event. Therefore, sellers with higher credit risk would tend to sell CDS contracts at lower prices compared to similar financially healthier counterparties. Counterparty risk became particularly problematic following the default of Lehman Brothers and the near default of AIG as those companies were key players in the OTC credit derivatives market. Nonetheless, it is also clear that the practice of posting collateral mitigates the effect of counterparty risk on CDS pricing and that the effect of counterparty risk inherent in CDS trades is lessened by the fact that trades

[13] The effect of the cheapest-to-deliver bond was substantially reduced with the introduction of Big and Small Bang Protocols and the modified-modified restructuring clause (MMR), which assign the delivery obligations into five maturity buckets.

take place between dealers of major institutions with relatively high credit ratings. Consistent with this premise, Arora, Gandhi and Longstaff (2012) report that counterparty credit risk is priced, but the magnitude of its effects is economically small. Jarrow and Yu (2001) model protection seller's counterparty risk as a reduction in the credit spread curve. Empirical findings by Morkoetter, Pleus and Westerfeld (2012) support the idea that protection seller's counterparty risk has a negative effect on CDS spreads, and this result holds before and after the financial crisis.

Amato (2005) claims that spreads represent a risk-adjusted expected loss, capturing not only expected loss given default, but also a risk premium compensating for undiversifiable systematic risk and the idiosyncratic jump-to-default risk.[14] Although CDS contracts are, in general, more liquid than reference bonds, CDS rates also reflect a liquidity premium. For instance, Tang and Yan (2007) report that liquidity is priced, and that higher illiquidity is associated with higher CDS rates (they estimate a liquidity premium earned by the protection seller of approximately 11% of the mid quote). Bongaerts, De Jong and Driessen (2011) introduce a formal equilibrium asset pricing model to investigate liquidity risk in the CDS market. Their empirical results indicate that CDS liquidity, captured by the bid-ask spread, significantly affects CDS rates. Qiu and Yu (2012) show that liquidity effects on CDS spreads are generally negative, because a greater number of CDS dealers suggests more information asymmetry and, consequently, higher CDS premia. Buhler and Trapp (2009) introduce a measure of CDS liquidity intensity into a reduced form model for CDS valuation allowing for correlation between liquidity and default risk. They report that the liquidity premium denotes 5% of mid-quotes and accrues for the protection seller.

Other important studies in this area include Shachar (2012), Gündüz, Nasev and Trapp (2013), Tang and Yan (2013) and Siriwardane (2015). The first shows that order imbalances of end-users may have an impact on prices depending on their direction relative to the sign of dealers' inventory. Gündüz, Nasev and Trapp (2013) show that informational and real frictions in the CDS market strongly affect CDS spreads. First, CDS traders adjust CDS rates in response to the observed order flow, which conveys information; second, transactions prompting higher inventory tend to trigger larger adjustment of rates. This evidence lends support to the idea that CDS traders charge to protect themselves against informational and real frictions. Tang and Yan (2013) demonstrate that excess demand and liquidity produce effects on CDS spreads.

Siriwardane (2015) demonstrates that dealers' risk-bearing capacity affects pricing and aggregate risk premia in the CDS market. Bao and Pan (2013) establish a link between illiquidity

[14] Berndt et al. (2008) document substantial variation of risk premia over time, and Berndt (2014) reports that, together, expected losses and credit risk premia account for less than 45% of the level of credit spreads.

in CDS and excess volatility relative to firm fundamental volatility in CDS returns. These empirical results agree with the predictions of models by Duffie, Gârleanu and Pedersen (2005, 2007), who relate search frictions and asset prices in OTC markets, and Zhu (2012), who reports that search costs affect asset prices through a dynamic model of opaque OTC markets.

1.5. CDS contracts and related markets

Some researchers relate the onset of CDS trading with market fragmentation and price discovery changes in related markets. Goldstein, Li and Yang (2014) provide a theoretical setup for examining the informational effects of derivative markets on the underlying market. Their model predicts that different derivative markets may produce different effects on the underlying market. The intuition is that market segmentation exists and investors trade a given asset for different purposes (e.g., speculation versus hedging), thereby responding differently to the same information. This affects the informativeness of the pricing system and the cost of capital.

Das, Kalimipalli and Nayak (2014) suggest that the beginning of CDS trading was detrimental for the bond market informational efficiency and for bond trading, given that large institutional traders moved from trading bonds to trading CDSs in order to achieve their desired exposure. In contrast, Massa and Zhang (2012) argue that the existence of CDS improves bond liquidity, as the new hedging tool diminishes fire-sale risk when bonds move to junk status. In the same vein, Ismailescu and Phillips (2015) demonstrate that in the aftermath of CDS trading, sovereign bonds become more informationally efficient and bond spreads decrease.

Li, Zhang and Kim (2011) study the implication of CDS-bond basis arbitrage for the pricing of corporate bonds. They show that arbitrageurs introduce new risks into the corporate bond market, which was dominated by passive investors before the existence of CDS. Ashcraft and Santos (2009) conjecture that the onset of CDS trading can have screening advantages. However, they find that the impact of CDS initiation rests on the borrower's credit quality: it reduces borrowing costs for creditworthy borrowers and increases them for risky and informationally opaque firms. Shan, Tang and Winton (2014) present results consistent with the notion that loan covenants are loosened after CDS initiation, although mostly for high-quality and transparent firms. Subrahmanyam, Tang and Wang (2016) examine whether trading in CDS elevates credit risk of reference entities. They present evidence that the probability of credit downgrades and bankruptcy increase after CDS inception because of CDS-protected lenders' reluctance to restructure.

Boehmer, Chava and Tookes (2015) study the effect of CDS trading on stock market quality, namely market liquidity and price efficiency. *Ex-ante*, CDS trading may enhance stock market liquidity due to the introduction of efficient tools for risk sharing, or reduce liquidity by virtue of a shift of informed traders to the CDS market. If investors choose CDS to express negative views, it may become more difficult for stock market-makers to learn from these trades. Boehmer, Chava and Tookes (2015) document significant negative effects on stock market liquidity and price efficiency following CDS onset, using a sample of corporate CDS during 2003–2007. They also show that these effects are state-dependent in that in bad states negative information spillovers dominate, while in good states, CDS seem to complement the stock market with net positive effects.

In what follows, we review the determinants of the differences between CDS spreads and bond credit spreads, informational flows between CDS, stock and bond markets, and the informational efficiency of CDS spreads.

1.5.1. The basis between CDS spreads and bond credit spreads

The cash-flow from CDS can be replicated in a no-arbitrage environment by means of long and short positions on the underlying obligation. Following Duffie (1999), if markets are frictionless and complete, credit risk should be priced similarly across cash and synthetic credit derivative markets, so that CDS spreads on a given risky company should equal the bond yield spread of a par floating-rate note in excess of the benchmark risk-free rate. The difference between CDS spreads and bond credit spreads – the CDS-bond basis - should be close to zero. On the one hand, if a negative basis arises, arbitrageurs may enter in a long position strategy in both cash bond and CDS protection, obtaining a positive excess return that is free of any default risk. On the other hand, arbitrageurs may profit from a positive basis while shorting the underlying bond and selling CDS protection. These arbitrage strategies should push the basis towards zero.

A natural question that arises is whether these arbitrage mechanisms also hold in non-frictionless markets. Blanco, Brennan and Marsh (2005), Hull, Predescu and White (2004), De Wit (2006), Nashikkar, Subrahmanyam and Mahanti (2011) and Fontana (2010) demonstrate that the basis was slightly positive before the crisis. Hull and White (2000) and Zhu (2006) show that although there were strong deviations between credit spreads and CDS in the short-run, the basis tended to zero in longer spans. These studies agree with the notion that arbitrage is, in general, not perfect. Blanco, Brennan and Marsh (2005) suggest that the difficulty in short-selling bonds and the cheapest-to-deliver option tend to drive the basis into the positive domain.

In the presence of bond lending fees, CDS spreads must equal the sum of the par floating-rate bond spread and the repo rate, which means that repo rates and the lack of bonds to borrow drive the basis up. In contrast, counterparty risk, bond illiquidity and funding risk tend to drive the basis into negative domain. Nashikkar, Subrahmanyam and Mahanti (2011) find that the basis is also influenced by both bond market and CDS market liquidity. Firms' credit risk characteristics (such as leverage and tangible assets), covenants and tax status also affect the basis.

The basis became remarkably negative following the 2008 financial meltdown (Fontana 2010; and Guo and Bhanot 2010). Mayordomo et al. (2014) analyze a panel of 49 European non-financial firms and 64 investment-grade bonds, and find persistent deviations between CDS rates and bond spreads over the period 2005-2009. However, after considering funding costs and trading costs, these departures do not lead to profitable arbitrage opportunities. Arce, Mayordomo and Peña (2013) find, instead, persistent deviations between bond spreads and CDS rates for 11 euro-area countries over the period January 2004 – October 2011. Arce, Mayordomo and Peña (2013) find that the basis is influenced by counterparty risk, financing costs, differential liquidity between bonds and CDS, and domestic and global risk premiums.

A prominent explanation for the non-zero basis is the existence of ‘limits to arbitrage’. Shleifer and Vishny (1997) predict that common wide shocks force arbitrageurs to unwind their leveraged positions and other investors with lower marginal valuations demand significant price discounts. As risk-capital from arbitrageurs becomes scarcer during financial distress, there is a de-coupling of bond credit spreads and CDS spreads. When the basis becomes negative, arbitrageurs implement a long position in the underlying bond and buy CDS protection. However, funding risk, sizing the long CDS position, liquidity risk, and counterparty risk may deter arbitrageurs from implementing a negative basis trade. This reasoning is illustrated in a model developed by Garleanu and Pedersen (2011), where leverage constraints can yield mispricing between two otherwise identical financial securities that differ in terms of margin requirements or hair-cuts. Mitchell and Pulvino (2012) show that funding risk may not only turn the basis negative, but also prevents arbitrageurs from exploiting such arbitrage opportunities. Duffie (2010) develops a model where there may be market frictions that hinder an immediate allocation of resources towards arbitrage strategies (the so called “slow-moving capital” hypothesis).

Fontana (2010) shows that, during the financial crisis, rising margin calls produced a negative and persistent effect on the basis, and Bai and Collin-Dufresne (2013) find that trading frictions can explain the basis during the crisis period, in particular funding risk, counterparty risk and collateral quality. Trapp (2009) shows that the basis depends on credit risk, liquidity and market conditions. However, Choi and Shachar (2014) present evidence contradicting the idea that deleveraging by dealers caused the negative CDS-bond basis, by showing that after the Lehman Brothers crash, dealers were actively providing liquidity to hedge funds that were running for the exit and unwinding basis arbitrage trades. Nevertheless, the authors concur that their activity was not sufficient to close the gap. Feldhutter, Hotchkiss and Karakas (2014) claim that the basis between bonds and CDS also emanates from a credit control premium in bond prices, particularly relevant for firms in distress.

1.5.2. Information flows between the bond and CDS

In efficient markets, the prices of different claims on a firm should adjust simultaneously to new information. Theoretical models, as in Duffie (1999), predict that CDS and bond spreads should follow co-integrated processes because prices are determined by the credit risk of the same company. However, structural differences between markets (organization, liquidity and type of participants) may result in a faster adjustment of the prices of one instrument. Different claims may assimilate new information at different paces if markets differ in the focus and characteristics of traders, the ability to short, and the cost of trading on private information.

The results of Blanco, Brennan and Marsh (2005) lend empirical support to the idea that CDS spreads led price formation of credit risk before the 2008 crisis. The synthetic nature of CDS makes that market a convenient venue to trade credit risk. In addition, there is a clientele effect of institutional investors, typically well informed, that trade in both cash and CDS markets, while retail investors trade mostly in the cash market. Zhu (2006) documents a long run co-movement of bond and CDS spreads. Still, in the short run, both spreads may deviate from their common pattern due to different responses to changes in credit conditions. The leadership of CDS with respect to price formation is more prominent for US entities.

Norden and Weber (2004) find that CDS spread changes ‘Granger cause’ bond spread changes for a higher number of firms than vice-versa in a sample with more than 1000 reference entities for the period from July 2, 1998 to December 2, 2002. Forte and Peña (2009) show that stock prices command CDS and bond prices more frequently than the other way round and that CDS spreads lead bond credit spreads. Nashikkar, Subrahmanyam and Mahanti (2011) document a liquidity spillover effect from CDS to bond markets in that CDS liquidity affects both bond liquidity and bond prices.

Dötz (2007) emphasize that both markets’ contributions to price formation change over time. Alexopoulou, Andersson and Georgescu (2009) and Coudert and Gex (2010) obtain qualitatively similar conclusions. The findings of Arce, Mayordomo and Peña (2013), Ammer and Cai (2011) and Coudert and Gex (2013) also suggest that price discovery is state dependent and a function of the relative liquidity in the two markets. Ammer and Cai (2011) report that CDS price leadership correlates positively with the bond-to-CDS ratio of bid-ask spreads, and negatively with the number of bonds outstanding. Coudert and Gex (2013) put on evidence the prominent role of CDS during the global financial crisis.

1.5.3. CDS and the equity market

Stock prices and CDS rates of a firm react to the same fundamental shocks on future cash flows. As mentioned earlier, Merton (1974) establishes a relationship between equity and bond markets using option-pricing theory. Debt and equity prices, and consequently their returns, are determined by the same company-specific information. In the absence of any frictions, debt and equity markets should be perfectly integrated. This no-arbitrage pricing relationship between equity prices and credit spreads should also apply to the relationship between equity prices and CDS spreads. The firm's liabilities constitute a barrier point for the value of assets, so that if the value of a firm's assets falls below the face value of debt, the firm would default. In that sense, equity and debt value should ramp up with firm value, whereas greater asset volatility should increase (decrease) the equity (debt) value.

Equity and bond prices are positively correlated because they depend of the firm's asset value. The degree of correlation depends positively on the debt-to-asset ratio. When default risk is a major concern, equity and bond returns should display higher correlations. Given the theoretical relationship between CDS and bonds, it is possible to conclude that there is also a price relationship between CDS spreads and equity prices. Friewald, Wagner and Zechner (2014) demonstrate that the market price of risk (Sharpe ratio) must be equal for all contingent claims written on a firm's assets in a Merton model setup, and hence risk premia in equity and credit markets must be related. Accordingly, they find a significant positive relation between credit risk premia and equity excess returns in portfolios sorted monthly, based on the estimated risk premia, using a sample of 491 US firms from 2001 to 2010.

An interesting question that emerges is which market assimilates material information about the firm first and hence commands price formation. On the one side, CDS are traded over-the-counter in a market regarded as opaque; only a few dealers provide quotes and the system of quotation is fragmented; further, there is not much information on actual transactions and investors' positions. On the other side, this market comprises primarily institutional investors who have better access to information and exhibit more sophisticated and rational trading behavior than the typical retail investor. It is also argued that CDS market participants pay more attention to factors that determine downside risk (particularly jump-to-default risk). In contrast, stock market investors own residual claims (with unlimited upside potential), whereby they tend to pay more attention to drivers related to long-term growth and cost of capital. Finally, CDS allow circumventing short-selling restrictions that prevail in stock markets.

Attending to the results of the empirical work of Acharya and Johnson (2007) and Asquith et al. (2013), informed trading is present in the CDS market, but not in the bond market (the former find evidence of informed trading in the CDS market, whereas the latter does not find evidence that bond sellers own private information). Asquith et al. (2013) also show that bonds with traded CDS tend to be more actively lent. The borrowing costs for bonds with traded CDS are lower, and although CDS contracts are statistically related to bond shorting, it is not a substitute for it.

Three sub-ramifications of the financial literature address the relationship between CDS and stock markets. The first evaluates the unconditional information spillover between equity and credit markets. Norden and Weber (2009) find that the stock market leads the CDS and bond markets. Their evidence also sustains the leading role of the CDS market with respect to the bond market. Forte and Lovreta (2015) analyze a sample of corporate CDS and stock prices from 2002-2004. They show that the lower the creditworthiness of the reference entity, the stronger the association between stock price implied-credit-spreads (ICSs) and CDS spreads. According to their results, price discovery in the stock and CDS markets seem to evolve over time, with slight informational dominance of the stock market. The intensity of stock market leadership is positively related to the level of credit risk. Forte and Peña (2009) find that stocks lead CDS and bonds more frequently than the reverse, in a sample of North American and European non-financial firms for 2001-2003. Fung et al. (2008) indicate that the direction of information flow across the CDS and stock markets rests on the credit quality of the reference entity. While in the case of high-yield firms there is mutual information feedback, for investment-grade firms the stock market leads the CDS market in terms of price discovery.

Wang and Bhar (2014) document significant information flow from the equity market to the CDS market under turmoil conditions for investment-grade firms and the reverse for non-investment-grade firms. The incremental information of positive CDS returns affects the equity market one day ahead. Narayan, Sharma and Thuraisamy (2014) find that the stock market contributes to price discovery in most sectors whereas the CDS market contributes to price discovery in only a few sectors. Narayan (2015) find that CDS return shocks are important in explaining the forecast error variance of sectoral equity returns in the US. Overall, the stock market drives the price discovery process more frequently than the CDS market, despite the stock market's declining leading role over time. This relationship is stronger for firms with higher levels of credit risk. The studies that investigate this interaction at the aggregate level obtain similar conclusions (Bystrom 2006; Bhar, Colwell and Wang 2008).

The second category of analysis addressing the relationship between CDS and stock markets comprises studies focusing on the information flow across equity and credit markets in the context of specific events. Acharya and Johnson (2007) document an information flow from the CDS market to the stock market, but only in days with negative credit news, and for firms that experience or are more likely to experience negative credit events. The evidence is stronger for firms with a greater number of banking relationships. Banks, who play a role as CDS market-makers, also act as insiders by virtue of their lending relationships with the reference names. By the same token, Qiu and Yu (2012) provide evidence that CDS rate changes command stock returns prior to major credit events and that the estimated magnitude climbs along with the number of quote providers. Berndt and Ostrovnaya (2014) demonstrate that information about bad news events such as an accounting scandal or a negative earnings surprise is incorporated faster in CDS spreads than in stock and option prices. Ni and Pan (2011) relate short-sale restrictions in the stock market with stock returns predictability by CDS spread changes in that negative information revealed in the CDS market slowly gets incorporated into equity prices.

Marsh and Wagner (2015) and Hilscher, Pollet and Wilson (2015) challenge the empirical conclusions that stock returns are driven by CDS spread changes. Hilscher, Pollet and Wilson (2015) do not find evidence that CDS returns command subsequent stock returns prior to adverse credit events. They attribute these findings to the larger transaction costs that investors face in the CDS market. Moreover, they show that CDS market participants pay more attention to stock market movements during earnings announcement periods rather than non-announcement days. Hilscher, Pollet and Wilson (2015) conclude that liquidity traders participate in the CDS market and that the stock market dominates price discovery more often than the CDS market. Marsh and Wagner (2015) analyze daily lead-lag relationship in equity and CDS markets and find that the equity market leads the CDS market. Han and Zhou (2015) report predictive power of the slope of the term structure of CDS spreads (measured as the difference between the five-year and one-year CDS spreads) on stock returns ahead. Schweikhard and Tsesmelidakis (2012) show that the CDS and equity markets for financial institutions decoupled during the recent financial crisis in the face of massive government intervention.

The third ramification in this literature debates the effect of limits to arbitrage on the integration of stock and credit risk markets. Hedge funds and private equity firms are active in the so-called capital structure arbitrage, attempting to take advantage from the relative mispricing across equity and credit markets. Duarte, Longstaff and Yu (2007) and Yu (2006) investigate the profitability of capital structure arbitrage, and find positive returns and high Sharpe ratios. Duarte, Longstaff and Yu (2007) suggest that the alpha of capital structure arbitrage strategies is amongst the highest across fixed income arbitrage strategies. Kapadia and Pu (2012) report that the cross-sectional variation in the correlation between firms' equity and credit markets is related to the heterogeneity of its investors, funding liquidity, market liquidity, and the idiosyncratic risk of the firm. Trutwein and Schiereck (2011) find that equity and credit markets (CDS) become more integrated during times of amplified stress.

1.5.4. *The informational efficiency of the CDS market*

The empirical research on credit derivatives lends support to the notion that the CDS market is highly efficient in processing credit-related information. Hull, Predescu and White (2004) provide evidence that CDS respond significantly prior to downgrades or negative watch-listings announcements by the major rating agencies. Norden and Weber (2004) document that CDS spreads anticipate rating reviews and downgrades earlier than stock prices do. Wang, Svec and Peat (2014) also find rising CDS spreads up to 90 days before a downgrade, review for downgrade and negative outlook event. Norden (2011) shows that spreads start changing earlier and more strongly before rating events for firms with greater media coverage.

Finnerty, Miller and Chen (2013) report that the CDS market anticipates favorable as well as unfavorable credit rating change announcements. Additionally, changes in CDS spreads for non-investment-grade credits contain information useful for estimating the probability of negative credit rating events. Galil and Soffer (2011) test CDS market reaction to rating announcements by Moody's and S&P during the period 2002-2006. The CDS market appears to respond to rating actions by one rating agency in spite of earlier similar action by other rating agencies.

While analyzing bankruptcies, Jorion and Zhang (2007) evaluate the effect of the deterioration of a firm's credit quality (Chapter 11 and Chapter 7 bankruptcies, as well as large jumps in CDS spreads) on the stocks and CDS spreads of industry peers. In doing so, Jorion and Zhang (2007) seek to disentangle contagion from competition effects through the sign of cross-asset correlations (a negative (positive) correlation among CDS spreads being indicative of competition (contagion) effects) using a sample of 820 obligors from 2001 to 2004. They find that Chapter 11 bankruptcies and jumps induce contagion, whereas Chapter 7 bankruptcies are more likely to prompt competition effects. Jorion and Zhang (2009) argue that counterparty risk may also generate credit contagion. Using a sample of 251 bankruptcy filings from 1999 to 2005, their results suggest that bankruptcy announcements of peers lead to lower stock prices and greater CDS spreads for creditors.

Looking at earning announcements, Batta, Qiu and Yu (2016) find that the CDS market offers greater incremental price discovery than the stock market in the case of firms with greater analyst forecast dispersion and other factors linked to the level of private information, as earnings-based loan covenants. Zhang and Zhang (2013) gauge the CDS market response to earnings announcements and find that while both stock and CDS markets seem to anticipate earnings announcements, the latter do not exhibit post-earnings announcement drift. Similarly, Franco, Vasvari and Wittenberg-Moerman (2009) show that CDS prices are responsive to debt analysts' reports, and Shivakumar et al. (2011) document a reaction of CDS spreads to management forecast news, stronger than to actual earnings news. Callen, Livnat and Segal (2009) and Das, Hanouna and Sarin (2009) find that accounting earnings are priced into the levels and changes in CDS spreads. Jenkins, Kimbrough and Wang (2016) observe that prior to the credit crisis the CDS market was efficient (there was no evidence of systematic relation between subsequent CDS returns and previously announced accounting information). During the credit crisis, there was an underreaction to both quarterly earnings surprises and quarterly accruals. After the crisis the CDS market overreacted to both measures, although the overreaction dissipates in later quarters.

1.6. The effect of CDS trading in corporate finance and financial intermediation

Another ramification of the CDS literature concerns the impact of CDS trading activity on corporate finance decisions, financial intermediation and credit supply. In a frictionless world, credit derivatives would be redundant assets. However, there are reasons to believe that CDS inception may produce real effects on the economy by changing the economic incentives of investors, managers and creditors. Accordingly, the change in the strategic behavior of these economic agents may produce effects on the capital structure, credit supply and bankruptcy risk. As argued by Augustin et al. (2015), such externalities, positive or negative, may affect operating performance, financing decisions and financial aspects of the company, as well as the cost of borrowing.

Before the inception of credit derivatives markets, risk mitigation and sharing was quite limited. The secondary market for corporate bonds was very illiquid and loan sales were rare. The new setup brought by CDS altered the risk-sharing mechanism and, consequently, economic agents' behavior. From a theoretical standpoint, Morrison (2005) predicts financial disintermediation and reduced bank monitoring after credit derivatives inception. By reducing credit and concentration risk through CDS trading, banks have lower monitoring incentives. That, in turn, reduces the firm's chances of obtaining cheaper bond market financing, as the bond investors will no longer benefit from the bank's role in certifying the firm's financial condition. Consistent with this view, Hakenes and Schnabel (2010) predict that CDS can reduce bank incentives to exercise their monitoring role, and raise the incentives to finance riskier projects. Parlour and Winton (2013) compare bank's decisions to lay off credit risk through loan sales vis-à-vis CDS protection buying, and conclude that CDS, as a risk transfer mechanism, are more likely to undermine the monitoring incentives of banks.

Another relevant topic in the intersection of CDS with corporate finance is the separation of creditors' cash flow rights from their control rights. To put this into context, lenders transfer their cash flow rights when hedging their exposures. Still, they are allowed to keep voting rights during a debt renegotiation process. In that sense, they become "empty creditors" (Hu and Black

2008), for they may use control rights to strategically force companies into bankruptcy if their insurance payment is more favorable than the debt renegotiation outcome. As argued by Bolton and Oehmke (2011), this issue is more prominent when creditors over-insure, leading them to enforce too many defaults. In effect, when the net present value of such projects in a going concern perspective is higher than their liquidation value (i.e., recovery value) there is a reduction of social welfare.

Campello and Matta (2013) argue that the empty creditor problem is pro-cyclical in that the consequences of CDS trading may vary over time. Feldhutter, Hotchkiss and Karakaş (2014) demonstrate that CDS rates reflect the cash flows of the underlying bonds, but not control rights. When firms' credit quality declines, the value of control rights increases since creditor control can affect managerial decisions. Control rights are valuable for they affect bond prices and liquidity. Feldhutter, Hotchkiss and Karakaş (2014) estimate the control premium to reach 6% by the time of default.

In a different vein, Che and Sethi (2014) develop a model where CDS are used by investors who are optimistic about a firm's prospects. These investors substitute lending by naked CDS positions lessening the firms' ability to obtain financing for their real investments. CDS impact negatively on credit supply, as those that are optimistic about a firm's prospects may sell protection through CDS in lieu of supplying credit. Conversely, Bolton and Oehmke (2015) stress the benefits of CDS, as they allow long-term investors to purchase credit protection on illiquid bonds, enhancing credit supply for those firms. Campello and Matta (2013) claim that in the presence of CDS trading, managers may shift their investment to riskier projects, raising the borrowers' probability of default.

At the empirical level, Saretto and Tookes (2013) document an increase of firm leverage and debt maturity following the onset of CDS trading, in a study focusing on non-financial S&P 500 firms. Those results concur with the notion that credit supply to firms is greater when lenders can hedge their credit exposures with CDS. These findings contrast with those of Hirtle (2009), who finds that CDS trading onset produced only modest effects on bank credit supply.

Ashcraft and Santos (2009) examine two channels through which CDS may reduce the cost of debt. The first is a diversification effect in that investors are allowed to improve hedging, risk sharing and diversification of their portfolios. The second effect is related to the signals of CDS spreads that reduce information asymmetries (e.g., creditworthy borrowers are easier to identify, reducing the "lemons problem") and improve the price discovery process. Nevertheless, the empirical evidence seems to cast doubts on the prediction that CDS onset lead to credit spread reduction. Ashcraft and Santos (2009) find that, in the wake of CDS trading, borrowing costs declined for low-risk borrowers. Still, opaque firms saw an increase of borrowing costs. Shan, Tang and Winton (2014) report that loan covenants are loosened after CDS trading, being that effect more pronounced for less opaque and with better credit quality firms.

Shim and Zhu (2010) document a positive impact of CDS trading on the cost of borrowing under normal market conditions, as well as on the liquidity of new bond issues in Asia. Subrahmanyam, Tang and Wang (2016) empirically test the effect of “empty creditors” on firm's life expectancy. Their results are in accordance with the notion that firms are more likely to be downgraded or to go bankrupt after CDS trading, in particular when contracts include restructuring as a credit event. They argue that the number of creditors increases with CDS trading, hampering creditors’ coordination, and thereby elevating the probability of bankruptcy. Peristiani and Savino (2011) also document a greater likelihood of bankruptcy following the inception of CDS trading. Subrahmanyam, Tang and Wang (2014) find that firms hold more cash after CDS trading suggesting that CDS trading elicits concerns about the empty creditor problem and debt rollover risk, raising firms’ incentives to hold more cash.

Bedendo, Cathcart and El-Jahel (2016) and Narayanan and Uzmanoglu (2012) do not find evidence that CDS influence restructuring outcomes. In effect, they claim that debt issuers coordinate their efforts strategically with selected creditors to mitigate the pressure from empty creditors. Danis (2012) assesses participation rates in the restructuring voting records from 2006 to 2011 and finds that fewer creditors voted for restructuring when there is a CDS contract referencing the bonds compared to a situation without a CDS. Arentsen et al. (2015) show that loan delinquency jumped by more than 10% during the financial crisis after CDS inception. In the light of their results, CDS facilitated the issuance of lower-quality securities, thereby increasing the overall default rate for all securities offered. Karolyi (2013) studies the effects of CDS trading on borrowers’ behavior and finds evidence consistent with increased risk taking.

The inclusion of CDS as hedging tools in regulatory capital directives also affects banks' strategic behavior, as it induces regulatory arbitrage. For instance, it has been acknowledged that banks and insurance companies get involved in mutual CDS transactions to circumvent regulatory restrictions. To that extent, banks buy CDS from insurance companies for regulatory capital relief, because insurance companies are not subject to a strict regulatory framework as banks. Based on this reasoning, Yorulmazer (2013) presents a model where CDS are traded at a price above their fair value, a deviation explained by the value of capital relief. Shan, Tang and Yan (2014) demonstrate empirically that banks use CDS to improve regulatory capital adequacy as stipulated by regulations, while engaging in more risky lending. Allen and Carletti (2006) highlight the benefits of credit risk transfer when banks face systematic demand for liquidity. Nevertheless, they claim that hedging via CDS may conduct to contagion episodes between the banking and real sectors, and could potentially intensify the risk of financial crises.

Hakenes and Schnabel (2010) and Biais, Heider and Hoerova (2016) develop theoretical banking models where CDS prompt excess risk taking. The former present a model wherein banks have an incentive to make unprofitable loans as their risks can be transferred to other parties via CDS, thereby raising aggregate risk and decreasing welfare. Biais, Heider and Hoerova (2016) show that weaker financial firms have an incentive to reduce their efforts to honor the contracts they sell. Duffee and Zhou (2001) highlight the potential downside of CDS trading for firms, given that banks' information advantage with respect to borrower credit quality can induce adverse selection and moral hazard concerns. Beyhaghi and Massoud (2012) document a higher likelihood of hedging with CDS when monitoring costs are high.

There is also interesting research on the effects of CDS trading for accounting and auditing. Martin and Roychowdhury (2015) document lower accounting conservatism (e.g., asymmetric timeliness of loss recognition) of borrowing firms' after the inception of CDS trading. They justify these results with lower monitoring incentives of lenders after CDS start trading, which causes firms to become more aggressive in their accounting practices. Du, Masli and Meschke (2013) argue that CDS inception, while weakening monitoring incentives of creditors, can increase firms' business and audit risk. As a result, they may face higher audit fees vis-à-vis non-CDS firms.-Finally, CDS onset has the potential to alter the payoff structure of corporate debt. For instance, Ivanov, Santos and Vo (2014) document a recent practice where corporate bonds and loans have coupon payments linked to the issuer CDS spreads.

1.7. The role of CDS contracts on the subprime financial crisis in 2008

The contribution of CDS to the 2008 US financial crisis has also generated keen interest among financial researchers. Stulz (2010) presents three reasons why CDS were considered dangerous and may have contributed to the crisis. First, CDS helped fuel the credit boom in the US. Second, the exposure of financial institutions in CDS (which totals trillions of dollars of notional amount) poses systemic risk. Third, the lack of transparency made it possible for participants to manipulate that market and constitutes a threat to the financial system stability. For all these reasons, the costs of CDS trading have to be taken as seriously as their benefits.

Prior to the financial crisis, the CDS market was largely un-regulated. By virtue of the lack of transparency about prices, trades and network exposure, it was seen as very opaque. For instance, transactions were taken through bilateral agreements, the disorganized clearing process posed substantial litigation risk, and the network exposure made it difficult for participants to manage counterparty risk. These problems were exacerbated by the massive growth of the CDS market before the onset of the financial crisis. Since then, regulators and policy makers attempted to improve CDS market regulation standards by dealing with three issues: counterparty risk exposure, concentration risk and jump-to-default risk.

Counterparty risk is among the regulators' primary concerns on these markets. Like other derivative instruments, CDS contracts do not imply a transfer of ownership. In the absence of a central counterparty, either party in a CDS contract is exposed to loss both through the performance of the underlying asset and through the potential default of the counterparty. The liquidity of the CDS market is supplied by dealer firms, who enter into transactions with end-clients even if they do not wish to retain the exposure. As stressed by Shachar (2012), to adjust exposures, dealers must enter into offsetting hedge transactions with other end-users or with other dealers. Over time, a large number of interdealer and other hedge transactions may emerge in an attempt to limit the dealers' inventory and exposure to market movements. It is clear that these hedge transactions eliminate, or at least reduce, credit risk exposure to the reference name, but they do not cancel any previous contract. In that sense, the CDS market contrasts with cash markets, where the transferring of inventory does not leave any residual obligations to the original seller or buyer. Until the termination of the contract, counterparty risk does not vanish, and it may actually increase with further offsetting transactions that aim at reducing the exposure to reference entities.

Zawadowski (2013) demonstrates that unhedged counterparty risk in OTC markets may trigger a systemic run of lenders in the event of a bank idiosyncratic failure. Acharya et al. (2009) emphasize the negative effects of the substantial risk externality entailed by one transaction on the risk exposures of other market players. Likewise, concerns about the collateral call risk and the lack of transparency are exacerbated when one counterparty enters in distress. In distress situations, other counterparties have the incentive to require additional collateral, thereby aggravating the liquidity position of the distress counterparty.

Acharya and Bisin (2014) claim that the lack of transparency can generate a counterparty risk externality where protection sellers excessively take short positions, thereby aggravating counterparty risk to all trades. In the same vein, Biais, Heider and Hoerova (2016) develop a theoretical model where a large exposure of a net seller brings about moral hazard problems due to their incentives to reduce efforts on risk-prevention and to speculate on the total assets of the firm, leading to endogenous counterparty risk. The underlying rationale is that the protection seller bears the full cost of the efforts to reduce the downside risk of his total assets, but some of those benefits accrue to the protection buyer, creating a moral hazard problem. This problem emerges when the protection seller finds that his CDS positions are likely to trigger large losses if bad news occur.

The counterparty risk inherent in the CDS market is exacerbated with concentration risk, i.e., a high concentration of dealers and sellers within the market, and with the huge web of interconnected exposures across financial institutions. The failure of a large and interconnected counterparty or of a large reference entity can quickly spread throughout the financial system, triggering the failure of other counterparties.[15] A survey by Fitch (2009) indicates that, at the end of the first quarter of 2009, 96% of credit derivative exposure of one hundred surveyed firms in the US was concentrated among JP Morgan, Goldman Sachs, Citigroup, Morgan Stanley and Bank of America.[16] More recently, Atkeson, Eisfeldt and Weill (2013) reach similar conclusions using data from OCC's Quarterly Report on Bank Trading and Derivatives Activities. The CDS market is highly concentrated, with only a small number of financial institutions acting as dealers (namely, HSBC, Bank of America, Citigroup, Morgan Stanley, Goldman Sachs, and J.P. Morgan Chase). Mengle (2010) shows that the ten most active traders account for 73% of CDS gross sales.

French et al. (2010) argue that important institutions may suffer substantial losses on large unhedged CDS positions. Those losses may constitute a systemic threat due to counterparty risk in that the failure of one important participant in the CDS market could destabilize the financial system by inflicting significant losses on many trading partners simultaneously. Large dealer failures, whether because of CDS losses or not, may endanger other counterparties with claims against the dealer that are not fully collateralized. Peltonen, Scheicher and Vuillemey (2014) show that the CDS market is highly concentrated around 14 dealers. In effect, the failure of a single dealer may trigger contagion effects and create systemic risk. Cont (2010) claims that the magnitude of financial contagion rests more on the market network structure than on the size of its largest participants.

Brunnermeier et al. (2013) report that the European CDS market is highly concentrated at the level of counterparties, where the top-ten most active traders account for more than 70% of gross protection bought or sold. They also find that major traders sell and smaller traders buy (net) CDS protection, and that concentration among counterparties is quite high. Consistent with this reasoning, Siriwardane (2015) presents evidence that the network has become even more

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[15] A large dealer default may trigger other large defaults due to a domino effect. Concentration risk brings about a higher probability that all banks will jointly fail (Liu 2011). In addition, there is also the case where a large reference entity default triggers large payments by protection sellers, raising the correlation of default among the highly interconnected group of dealers in the market. The opaque nature of CDS markets may fuel uncertainty among market participants when a large counterparty or reference entity defaults or finds itself in a run-up to default, increasing the probability for a severe liquidity dry-up. Thus, it becomes of paramount importance for market participants to also assess the level of distress of the counterparties' counterparties as well as the level of distress of the counterparties of the counterparties' counterparties, and so on. Network effects and the costs of information gathering may become unmanageable for dealers and other market participants, exacerbating uncertainty or even panic, and thereby conducting to withdrawals from loan commitments, higher margins and flight to quality.

[16] As a matter of fact, the failure of important dealer banks such as Lehman Brothers and Bear Stearns, raised dealer concentration, which became even more pronounced than prior to the crisis.

concentrated after the credit crisis. By means of a network-based measure of systemic risk, Cont and Minca (2014) demonstrate that in a CDS market where sellers lack the liquidity for credit event payments, default contagion and systemic risk will hike.

The binary nature of CDS contracts that materializes in jump-to-default risk also raises concerns for regulators. Although the market value of a CDS position (i.e. its replacement cost) at inception may be only a small fraction of the notional, the actual exposure upon default may represent a large fraction of the notional. Thence, sellers could suddenly be asked to pay large amounts of money and enter into financial distress. In order to reduce counterparty risk in OTC contracts, market participants may post collateral, with the goal of absorbing first losses in case of the counterparty default. Initial margins may also be required on initiation of the contract. Nevertheless, "jump-to–default" risk lessens the risk management effectiveness of CDS due to the price discontinuities it involves, which may result in under-collateralization or underestimation of additional collateral requests (variation margins). Credit events imply large swings in CDS contracts value, prompting a surge in the amounts required as collateral or to fund the settlement payment. As a result, the protection seller may face liquidity problems to honor its obligations (Brown 2010).

1.8. Sovereign CDS trading

Sovereign CDS constitute a special case within the broader class of single-name CDS contracts. While credit events of corporate CDS are usually triggered by bankruptcy, failure to pay, and if covered, restructuring, standard sovereign credit events usually consist of repudiation and moratorium. In addition to that, there are other relevant differences between corporate and sovereign CDS: (i) sovereign CDS tenors are less concentrated in 5 years (Chen et al. 2011) than corporate CDS; (ii) the currency of denomination of the sovereign contracts is not usually the domestic currency, in order to cover for currency depreciation risk (highly plausible after a default); and (iii) credit events are usually confined to debt issues in foreign currency, whereby default on domestic debt may not trigger a credit event (Augustin 2015). In view of the above, the pricing of sovereign contracts is more complicated than that of CDS written on corporate references.[17]

Sovereign CDS contracts have multiple applications, including speculation, hedging country risk and macro hedging, relative-value trading (e.g. a short position in country X and a long position in country Y), and arbitrage trading (e.g. government bonds vs. CDS). Ismailescu

[17] Another issue that introduces uncertainty into the pricing of sovereign CDS contracts is the possible existence of Collective Action Clauses (CAC) in that voluntary restructuring may be enforced by a majority of creditors in less favorable terms than the original debt claim without triggering a debt event.

and Phillips (2015) argue that sovereign CDS are efficient monitoring tools, helping reducing adverse selection costs for informationally opaque countries, allowing for enhanced risk sharing and boosting market participation.

The onset of sovereign CDS trading took place in the late 1990s, focusing on the debt of emerging market sovereigns. Those countries were amid the world's largest high-yield borrowers in terms of the number of bonds outstanding, longer maturities and larger issues.[18] The financial literature followed CDS inception, primarily focusing on price discovery between sovereign CDS and the underlying reference obligations. Bowe, Klimaviciene and Taylor (2009) examine price discovery between five-year tenor CDS and bonds utilizing daily CDS mid-quotes for eight emerging market countries (Brazil, Bulgaria, Colombia, Mexico, Romania, South Africa, Turkey, and Venezuela) over a 3.5 year sample period (2003 to late 2006) and conclude that CDS do not command price discovery in all countries. Chan-Lau and Kim (2004) assess price discovery between bonds and CDS in a sample of eight emerging market sovereigns using daily data for two years (where only one had speculative-grade credit ratings). Their results are mixed and sensitive to the measure of price discovery adopted.

Ammer and Cai (2011) evaluate price discovery for ten emerging markets using a daily sample covering the period from 2001 to 2005. Their findings indicate that of the seven countries wherein CDS and bond spreads are cointegrated, CDS dominates the price discovery in four, whereas bonds contribute most to information transmission in the remaining three cases. Levy (2009) finds that both counterparty risk and liquidity explain pricing discrepancies between emerging markets' bonds and CDS. Küçük (2010) shows that CDS-bond basis is explained by factors capturing bond and CDS liquidity, CDS market speculation, equity market performance, and global macroeconomic variables, using a sample of 21 emerging market countries over the period 2004-2008. Adler and Song (2010) find that the basis is larger than bid–ask spreads in Latin America countries, and relate that fact to the evolution of repo rates of bonds around episodes of credit quality deterioration.

Another ramification of the research on sovereign CDS concerns the determinants of CDS spreads. This field of research assumes particular relevance as the identification of the risk factors affecting sovereign yield spreads may help governments to reduce public borrowing costs and help financial professionals to obtain greater diversification benefits for their portfolios.[19] One

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[18] Packer and Suthiphongchai (2003) report that 90% of all sovereign CDS were written on emerging market sovereigns in 2003. In 2002, JPMorgan created the first Sovereign CDS Index - the TRAC-X index, which was formed almost exclusively by emerging market sovereigns (e.g., Mexico, Russia and Brazil add up to 37% of the index).

[19] Additionally, there is a strong relationship between sovereign and corporate spreads as governments have the discretion to expropriate corporate assets, raise taxes or impose foreign exchange controls. Accordingly, the borrowing conditions of firms are affected by the creditworthiness of the local government as sovereign borrowing rates represent a lower bound for domestic borrowing rates (the so-called sovereign ceiling).

interesting finding of this strand of research is that global risk factors assume paramount importance in explaining the dynamics of sovereign CDS spreads (Pan and Singleton 2008; Longstaff et al. 2011; and Augustin and Tédongap 2016).

The consensus in this literature is that sovereign CDS spreads co-move over time and jump jointly in the face of negative global events. Pan and Singleton (2008) provide evidence that sovereign CDS spreads correlate strongly with the VIX, the spread between the 10-year yield on US BB-rated industrial corporate bonds and the 6-month US Treasury bill rate, and the implied volatility of currency options. Augustin and Tédongap (2016) link consumption growth and macroeconomic uncertainty in the US with the first two principal components extracted from the entire term structure of CDS spreads of 38 countries.

Alternative explanations for the co-movement of sovereign CDS spreads are brought by Benzoni et al. (2015) and Anton, Mayordomo and Rodríguez-Moreno (2013). The former argue that the co-movement arises because agents revise their beliefs about the default probabilities of all countries when negative country-specific shocks take place, causing greater credit spread correlations than if spreads depended only of macroeconomic fundamentals. Anton, Mayordomo and Rodríguez-Moreno (2013) show that commonality in dealer quotes for sovereign CDS spreads is a powerful predictor of cross-sectional CDS return correlations. Since CDS trading takes place primarily among US dealers, this commonality would also explain the tight relationship of sovereign CDS spreads with US risk factors.

The relationship between sovereign CDS spreads and country-specific financial risk has also generated keen interest among researchers. Acharya, Drechsler and Schnabl (2014) demonstrate how the excessive debt burden from public bank bailouts may feed back into the financial sector by lessening the value of bank bailout guarantees and reducing the value of sovereign bond holdings by banks. Ang and Longstaff (2013) conclude that systemic risk originates in financial markets rather than in macroeconomic fundamentals. Kallestrup, Lando and Murgoci (2016) find that government implicit or explicit guarantees to the banking sector influence sovereign CDS spreads, and Kallestrup (2011) finds an association between sovereign credit risk and macro-financial risk indicators. Altman and Rijken (2011) apply credit scoring methods to estimate sovereign default probabilities based on public companies' balance sheet information and conclude that the financial health and profitability of a country's economy significantly influences default risk.

On balance, global risk factors and country specific information seem to explain sovereign credit spread dynamics. To sort out which type of factor dominates sovereign CDS spreads, Remolona, Scatigna and Wu (2008) decompose monthly 5-year emerging markets sovereign CDS spreads into a market-based proxy for expected loss and a risk premium. They conclude that global risk aversion is the primary determinant of the sovereign risk premium component, whereas country fundamentals and market liquidity are more material for default probabilities. Longstaff et al. (2011) find that global factors seem to play a greater role in explaining CDS spreads at higher frequencies, whereas country-specific fundamental risk factors often seem to dominate at lower frequencies. Augustin (2013) reports that spread changes are mainly driven by global risk factors in good times (a positive credit curve slope), and by country-specific shocks in bad times (a negative credit curve slope). On those grounds, the term structure of sovereign CDS spreads can be a useful indicator of the relative importance of the underlying sources of risk.

Ismailescu and Kazemi (2010) analyze the response of CDS spreads of 22 emerging economies to credit rating announcements. They show that CDS spreads of investment-grade countries are more reactive to negative credit rating events and usually adjust to those events before their announcement. Conversely, speculative-grade countries react strongly to (unanticipated) positive announcements. Afonso, Furceri and Gomes (2012) replicate the study of Ismailescu and Kazemi (2010) using a sample of 24 developed economies from the EU, and report a positive reaction of sovereign CDS spreads (on average, by 13 basis points) to a negative rating announcement or outlook.

The failure of Lehman Brothers in fall 2008 prompted a fundamental reassessment of the default risk of developed country sovereigns. The financial crisis motivated an upsurge of fiscal deficits in most countries to levels last seen after World War II (Fontana and Scheicher 2010), due to stimulus programs, bail-outs of financial institutions and reduced tax revenues. After a couple of years of increased budget deficits and worsening fiscal conditions, the level of the debt of most countries soared. The fiscal situation of developed countries started receiving considerable attention from the financial community. The increased default risk manifested itself in greater trading activity and spreads on certain sovereign CDS.

At the beginning of 2010, CDS and bond credit spreads of European sovereigns rapidly escalated, in particular those of Portugal, Italy, Ireland, Greece and Spain. These economies where characterized by very high debt-to-GDP ratios, exceptionally high deficits, a high ratio of net debt interest payments to GDP, negative balances of trade and fundamental structural economic problems, and for those reasons were at the center of the turmoil. Politicians and the media soon started to blame CDS market activity for artificially raising credit spreads, thereby worsening refinancing conditions of some European countries.

The findings of Coudert and Gex (2013), O'Kane (2012) and Fontana and Sheicher (2010) show that CDS play a leading role in price discovery for high-yield sovereigns, particularly during periods of turbulence, whereas bond market leads price discovery for countries with larger and more liquid bond markets and better ratings. Palladini and Portes (2011) show that CDS have a leading role in the price discovery for most euro-area sovereigns. Fontana and Sheicher (2010) also show that the sovereign credit risk repricing after 2008 in the CDS market seems mostly due to common factors, some of which proxy for changes in investor risk appetite. They report that the basis was positive as of September 2008, most likely because of 'flight to liquidity' effects and limits to arbitrage.

Arce, Mayordomo and Peña (2013) demonstrate that counterparty risk and differential liquidity between sovereign bonds and CDS (captured by the ratios of percentage bid-ask spreads in the two markets) partially explain the CDS-bond basis. Foley-Fisher (2010) investigates the association between bond and CDS spreads for ten EMU countries on the basis of a theoretical model of heterogeneous investors' expectations and shows that a non-zero basis is consistent with a relatively small dispersion in the beliefs of investors on the likelihood that certain European countries will default. Salomao (2014) relates uncertainty about the triggering of the default event, based on the judgment of the Credit Derivatives DC (e.g., the recent case of Greece), with a decay of the insurance value and the arising of negative sovereign basis. Pu and Zhang (2012a) show that after the temporary naked ban applied by Germany in 2010, the sovereign CDS and bid-ask spreads of Greece, Ireland, Italy, Spain and Portugal continued to hike, but sovereign CDS spread volatility declined.

Santis (2014) argues that the difference between the euro-dollar quanto CDS spread of a Eurozone member country and that of a benchmark country such as Germany may signal re-denomination risk, i.e., the risk that a country will leave the euro zone. Pu and Zhang (2012b) show that the differences between US dollar- and euro-denominated sovereign CDS spreads for ten Eurozone countries can help forecasting the bilateral euro-dollar exchange rate returns up to ten days.

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Chapter 2

M&A operations: further evidence of informed trading in the CDS market (*)

Abstract

Previous studies showed that private information gathered through banking services such as loans and syndicated debt is incorporated into CDS rates by large banks. Additionally, there is also evidence that innovations in CDS rates precede stock market returns prior to credit events. This paper adds to the literature by showing that the information obtained by major banks while providing M&A investment banking services is assimilated by CDS rates prior to the operation announcement. We also find strong supportive evidence that CDS innovations have incremental predictive power over stock returns before M&A announcements, and that this predictive power may be even greater when major dealers in the CDS market supplied investment banking services to one of the parts of the deal.

JEL Codes: G12; G13; G14; G20

Keywords: credit default swaps; information flow; informed trading; price discovery; M&A activity.

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1. Introduction

The credit default swap (CDS) market and other credit derivative markets have grown in importance and popularity over the last two decades. This trend, along with the fact that CDS rates constitute a cleaner measure of credit risk than bond credit spreads, raised academics' interest in knowing whether and how these derivatives contribute to price discovery. In the absence of market frictions, derivatives markets are, in general, redundant. However, in the real world there are frictions (such as limits to arbitrage, transaction costs, taxes, liquidity constraints and, no less important, information asymmetry), and therefore derivatives may have a role in price discovery.

The presence of an information flow from the CDS to the stock markets is well-documented in the financial literature. In a seminal article, Acharya and Johnson (2007) demonstrate an incremental information flow from the CDS to the stock markets around credit events, especially when the reference firm has a large number of banking relationships and during times of financial stress (i.e. credit rating downgrades). Large financial institutions are amongst the major players in the CDS market. As they provide different kinds of financial services to other firms, they possess a large amount of private information about their customers' activity. Acharya and Johnson (2007) argue that they take advantage of such privileged access and impound their superior information in CDS quote revisions, before such information is available to stock market participants.

This paper addresses the informational content of CDS rates and a particular channel of information flow between CDS and stock markets. Up to now, the financial literature has concentrated on a specific channel of information transmission based on the lending activities of major banks. In contrast to the previous literature, and as a novelty, we explore the channel of investment banking services related to mergers & acquisitions (M&A, henceforth) or divestiture (sell-offs) operations of listed firms.

The key idea is that dominant players in the CDS market, i.e., major investment banks, are also important players in M&A operations. This prompts the question of whether private information related to those deals is impounded into CDS rates before it is revealed to uninformed stock market participants. We address this issue by comparing the run-up effects in the assimilation of information and the interaction between CDS and stock markets prior to M&A announcements. To the best of our knowledge, this is the first study assessing the relevance of this channel of information flow.

The main objective of this paper is to ascertain the existence of informed trading in the CDS market and to explore some key issues regarding its nature. This research topic is relevant for several reasons. First, it contributes to the long-lasting debate on whether derivatives markets, and particularly the CDS market, are redundant for price discovery. Secondly, it sheds some new light on how stocks and CDS markets interact and helps in explaining spikes in the cross-correlation of the returns of the two financial instruments, which is of interest to risk managers using CDS to hedge their exposure in the stock market. Thirdly, analysis of the channels of information flows between the CDS and stock markets may be of interest to dealers seeking to manage their adverse selection risk, because the presence of informed traders in the CDS market may affect the profits and losses of their liquidity provision activity. Finally, regulators and policy makers may also benefit from having more information on the use of private information in the CDS market. If the information is gathered or used illegally, it may affect the overall integrity and efficiency of the market.

A natural starting point for the analysis is the appraisal of whether M&A announcements constitute material information for CDS and stock market participants. Using a large database of U.S. and European firms, we find that M&A and sell-off operations produce relevant wealth changes for stockholders and creditors; in effect, while M&A operations yield negative stock returns for the bidder, sell-offs generate positive returns for the seller. These results agree with those of Kaplan and Weisbash (1992), Asquith et al. (1990), Servaes (1991) and Schwert (2000), who report a negative (though modest) impact of M&A operations on bidders' stock prices, and with those of Klein (1986) and Lang et al. (1995), who find a positive effect of sell-off announcements on the stock prices of sellers. These results closely follow the predictions of the non-synergistic theory of corporate restructuring, which states that agency conflicts between management and shareholders drive M&A and divesting activity. In effect, if M&A are fueled by management entrenchment, empire building, and managerial hubris, and not by shareholder value, these transactions will likely have a negative impact on stock prices. In contrast, asset sell-offs reduce diversification and agency conflicts, and consequently are expected to produce positive effects on stock prices.

With respect to creditors' wealth, we find that, on average, CDS spreads increase with acquisition announcements, and decrease with assets sell-off announcements. Not surprisingly, the effects of such operations are greater for firms that lack creditworthiness than for financially sound firms. These results show that the effect of diversification and cash-flow volatility reduction brought about by M&A on the default probability of the acquirer is offset by the effect of subsequent changes in its capital structure that undermine creditors' prospects. In general, our results agree with those of Billett et al. (2004), Warga and Welch (1993) and Asquith and Wizman (1990). As both shareholders and creditors of firms that lack creditworthiness benefit from asset sell-offs, our results are also in line with those of Lang et al. (1995) and Datta and Iskandar-Datta (1996). Asset sell-offs appear to be value-enhancing, perhaps because they allow firms in financial distress to raise funds more cheaply than by alternative means (Shleifer and Vishny, 1992).

Subsequently, we focus on the information flow between CDS and stock markets. More precisely, we investigate the lead-lag relationship between CDS innovations and stock returns. First, we examine the unconditional information flow between the markets. Although seemingly irrelevant when the entire sample of firms is considered, it is statistically and economically relevant for high-grade non-financial firms. However, this latter result should be interpreted with care given that our sample is limited to obligors involved in M&A operations (a selection bias problem). More importantly, our findings reveal an incremental information flow from the CDS to the stock market prior to M&A announcements. CDS innovations appear to have predictive power over stock returns of speculative-grade financial and non-financial firms. Furthermore, the incremental information flow from the CDS to the stock market tends to be greater when at least one of the top CDS dealers supplied investment banking services to one of the parts of the M&A operation.

Finally, we assess how liquidity provision in the CDS market evolved around M&A events. By means of time series regressions, we investigate the bid-ask spread pattern in the M&A pre-announcement period. Intuitively, an abnormal increment of the bid-ask spread may signal asymmetry of information prior to M&A operations because liquidity providers tend to raise bid-ask spreads when they perceive that other traders hold superior information (Copeland and Galai, 1983; Bagehot, 1971). Our results show that the bid-ask spread tends to rise prior to M&A events when CDS dealers supply investment banking services to one of the parts involved in the M&A operations. This abnormal up-trend is consistent with dealers perceiving higher information asymmetry prior to M&A events. As transactions between dealers represent the largest share of the bulk of transactions in this market[20], other dealers may learn, from the trading behavior of the CDS dealer supplying investment banking services, that new information may arise soon.

Overall, our results, subjected to various robustness checks, reinforce previous evidence suggesting that, prior to M&A events, CDS quotes may convey private information not yet reflected in stock prices. They also confirm increasing information flows from CDS to stock markets prior to M&A announcements. These results complement those of Acharya and Johnson (2007), Batta et al. (2013), Berndt and Ostrovnaya (2008) and Qiu and Yu (2012), who focus on the credit channel as the main driver of the information flow from the CDS market to the stock market.

[20]Chen et al. (2011) report that more than half of all transactions occur between G14 dealers.

The remainder of the paper is organized as follows. Section 2 provides a review of the related literature and Section 3 develops the research hypotheses. Section 4 describes the data. The results of the empirical analysis are presented in Sections 5, 6 and 7. Section 8 concludes the study.

2. Related Literature

This study contributes to the literature on financial markets' efficiency by adding value to two strands of this body of research. The first investigates the roles of stock and CDS markets in price discovery processes. The second analyses the association between banking relationships and insider trading. In the first perspective, as CDS spreads are driven by the credit risk of the obligor, the topic of analysis is also included in the broader discussion on the interactions between the stock market and credit markets. Relevant developments for this discussion were provided by Blume et al. (1991), Cornell and Green (1991), Kwan (1996) and Hotchkiss and Ronen (2002), among others.

In the specific case of the relationships between CDS and stock markets, Longstaff et al. (2003) suggest that the stock and CDS markets lead price discovery. Zhang and Jorion (2007) show that CDS spreads anticipate credit quality downgrades before the stock market does, whereas Marsh and Wagner (2012) and Forte and Peña (2009) provide evidence that the stock market leads the CDS market. Norden and Weber (2009) show that the reaction of CDS rates to stock returns is influenced by the credit risk of the firm and by the liquidity of the bond market.

Acharya and Johnson (2007) provide empirical evidence of the existence of an information flow from the CDS market to the stock market, particularly for entities that have a larger number of bank relationships. This information flow is greater on days with negative credit news and when entities face, or are likely to experience, adverse credit events.

Examining the role of private information before quarterly earnings announcements, Batta et al. (2013) show that the speed of CDS price discovery is positively related to the dispersion of analysts' forecasts, to idiosyncratic volatility and to the presence of earnings-based covenants in obligors' syndicated loans. Berndt and Ostrovnaya (2008) document a significant increment in the flow of information from the CDS to the options market following adverse earnings announcements of speculative-grade firms. In addition, conditional spillovers from options to CDS markets are stronger for firms whose shares show greater volatility and surrounding accounting scandals or adverse earning announcements. Qiu and Yu (2012) show that the contracts of obligors with more banking relationships tend to present greater liquidity, suggesting endogenous liquidity provision. Focusing on the Japanese markets, Park et al. (2013)

report evidence of an unconditional information flow from the CDS market to the stock market, although primarily for keiretsu-affiliated firms. The flow of information from the CDS market to the stock market conditional on the existence of a future bad credit event appears to exist only in times of crisis and for keiretsu-affiliated firms. Silva (2015) finds that high open interest growth prior to the announcement of negative earnings surprises is linked to positive and significant CDS rate changes.

Our study is also related to the strand of literature assessing the association between banking relationships and insider trading. In this regard, Acharya and Johnson (2010) report that the insider activity prior to bid announcements of private-equity buyouts during the period 2000–2006 is related to the number of financing participants. Bushman et al. (2010) suggest that institutional investors involved in the syndicated loan market make use of their access to private information when trading in the stock market. Finally, Ivashina and Sun (2011) show that, as lenders, institutional investors routinely collect private information about borrowers, and concurrently trade in public securities. Their results indicate the existence of a positive link between superior information and outperformance in the stock market by such investors after the release of private information about the borrower.

Our analysis provides interesting additions to both these strands of the literature by examining a novel and distinct mechanism via which private information is assimilated by CDS spreads before its dissemination into stock prices. As investment banks obtain confidential information about their customers while supplying M&A investment banking services, and concomitantly act as dealers in the CDS market, we investigate whether some amount of private information is impounded into CDS rates before its disclosure to uninformed investors in the stock market. In the next section we develop the research hypotheses in greater detail.

3. Hypothesis Development and Framework of the Empirical Analysis

The financial literature is consensual on the fact that mergers, acquisitions and divestitures affect the wealth of stockholders and creditors of the companies involved. This influence stems from various channels that may lead to opposing effects on stockholders’ (and creditors’) wealth. The literature addressing this topic is vast and may be divided into two broad sets of theories of corporate restructuring: the non-synergistic and the synergistic theories (Mulherin and Boone, 2000).

The non-synergistic theory emphasizes the role of agency conflicts, such as management entrenchment, empire building, and managerial hubris, as drivers of corporate restructuring (principal-agent conflicts, between shareholders and managers, or between shareholders and creditors). The synergistic theory suggests that operating synergies may arise from such transactions, as a result of economies of scale, greater market power, or the elimination of duplicate functions, and have a positive effect on shareholders' wealth.

These theories lead to different predictions on the effects of acquisitions and divestitures on the wealth of stockholders and creditors, ultimately turning this issue into an empirical question. While the non-synergistic theory predicts that the combined bidder-target return in acquisitions will be negative, the synergistic theory foresees a positive effect. Indeed, proponents of the non-synergistic theory argue that larger acquisitions may have a detrimental impact on shareholders' wealth given greater management entrenchment (e.g., protecting management from market forces and by lessening corporate focus). The synergistic theory predicts that larger acquisitions will have positive effects on shareholder wealth as these operations are mainly a response to market conditions, such as changes in transaction costs, changes in regulation or the desire to eliminate industry overcapacity and increase market power (Jensen, 1993).

With regard to acquisitions, most empirical evidence shows they have a large impact on the wealth of the stockholders of the target firm, while the effect on bidders' wealth is unclear[21]. For instance, Mulherin and Boone (2000), Kaplan and Weisbash (1992), Asquith et al. (1990), Servaes (1991) and Schwert (2000), report large positive CARs for target firms around the bidding announcement and negative (though modest) CARs for bidders. Bradley et al. (1988) and Jarrell and Poulsen (1989) report small positive CARs for bidders and large positive CARs for target firms. Morck et al. (1990) document a negative reaction of stock prices to diversifying acquisitions and to acquisitions where the bidder's managers perform poorly prior to the operations.[22] Lang et al. (1991) report high stock market gains in tender offers when the bidder has a high Tobin's q and the target has a low q.

While reducing diversification and agency costs, divestitures may generate wealth for stockholders. That appears to be supported by the empirical literature, although some studies also show that the effect will ultimately relate to the motive for the divestiture. Schlingemann et al. (2002) suggest that corporate divestitures arise (i) because the firm owns specific assets that might be operated more efficiently by others (the efficiency explanation[23]); (2) to reduce the degree of

[21]According to Bruner (2002), more than ¾ of the previous empirical research documents large positive cumulative abnormal returns (CARs) for the target firm, and mixed results for the acquiring firm. In general, the results rest on how hostile the tender offer is.

[22] They claim that these results agree with the idea that M&A that are potentially motivated by managerial private benefits lead to a decline of shareholder wealth.

[23] Hite et al. (1987) argue that asset sales promote efficiency by allocating assets to better uses and sellers capture some of the resulting gains. In their view, firms only manage assets for which they have a comparative advantage and sell assets as soon as another firm can manage them more efficiently.

diversification and increase efficiency (the focusing explanation[24]); and (3) to relax credit constraints (the financing explanation[25]). Mulherin and Boone (2000), Lin and Rozeff (1993), Hite et al. (1987) and Jain (1985) document positive effects on the stock prices of divesting firms. In addition, Schipper and Smith (1986), Allen and McConnel (1998) and Vijh (1999) report positive CARs in the period surrounding the announcement of carve-outs, whereas Klein (1986) documents positive CARs in the period surrounding the announcement of asset sales. Lang et al. (1995) report significantly positive abnormal returns around sell-offs for firms expected to use the proceeds to pay off debt and insignificantly positive returns for firms expected to keep the proceeds within the firm[26]. John and Ofek (1995) report greater stock price reaction for focus-increasing sell-offs and show that the performance of such firms improves in the three years following the operation.

Bondholders are also affected by M&A and divestiture activity. However, the sign of the effect will depend on financial risk shifts, asset substitution and the prospects for future operating performance after restructuring. As stressed by Renneboog and Szilagyi (2008), these factors may have opposing effects on bondholders' wealth. From an asset portfolio perspective, these transactions have the merit of expanding or narrowing a firm's business. By doing so, they change the risk of the firm and the collateral available to creditors. Provided that the debt structure remains unaffected after the operation, M&A leaves bondholders better off if it leads to reduced bankruptcy risk through a co-insurance of cash flows, i.e. a decline of the cash flow variability in the combined firm (Galai and Masulis, 1976). By contrast, asset sales and spin-offs reduce bondholders' wealth by decreasing collateral and raising cash flow volatility, unless compensated for by improved operating performance[27].

[24] John and Ofek (1995) concentrate on the focusing explanation, arguing that eliminating negative synergies between divested assets and the firm's remaining assets should lead to better performance after the sell-off. In effect, they document a positive stock price response around sell-off announcements motivated by an increase in focus.

[25]Shleifer and Vishny (1992) and Lang et al. (1995) provide theoretical and empirical support to the financing explanation. Shleifer and Vishny (1992) claim that asset sales relate to the firm's debt capacity. In their view, asset illiquidity is a potentially important cost of debt, as un-leveraging and financial distress might imply selling assets at a discount. Lang et al. (1995) stress that management values firm size and control, and for that reason it is reluctant to sell assets for efficiency reasons alone. In effect, they put forward the explanation that management only sell assets when alternative sources of financing are too expensive. More importantly, they emphasize that the sale would not have occurred if the value of the asset turned out to be low, which leads to the conjecture that asset sales are good news for shareholders. Management may have to raise funds to reduce financial distress costs, to pay dividends or repurchase shares, or to engage in an investment policy that shareholders do not value. Alexander et al. (1984) and Maksimovic and Phillips (1998) show that firms in Chapter 11 tend to sell their most efficient plants, while other firms tend to sell their least efficient ones. Schlingemann et al. (2002) show that the liquidity of the market for assets plays an important role in determining which asset is divested.

[26]In spite of that, the authors argue that when the proceeds are kept within the firm by self-interested management, it could reduce shareholder wealth (due to the increase in agency costs between managers and stockholders).

[27]For instance, additional discipline on management may improve firm performance. For instance, in Jensen (1986), higher leverage commits the firm cash flow to re-paying debt.

Financial restructuring transactions may induce substantial wealth redistributions between shareholders and creditors. In Black and Scholes (1973), the equity of a firm is represented as a leveraged position on the firm's assets. Changes in the capital structure should transfer wealth between shareholders and bondholders. For instance, if M&A activity is financed through leverage-increasing debt issues or new loans, thereby generating greater probability of default, shareholders may reverse bondholders' benefits obtained through diversification and co-insurance of cash-flows. Additionally, bondholders' wealth is also affected by the relative pre-merger riskiness of bidder and target firms (Shastri, 1990).

Dennis and McConnell (1986) report negative cumulative daily returns for bonds of the acquiring and target firms during the 15-day period before the merger announcement. Their results are in accordance with those of Kim and McConnell (1977) and Asquith and Kim (1982). Eger (1983) reports significant bondholder gains in stock-for-stock deals and Walker (1994) presents evidence that bondholders are unaffected by M&A. Maquieira et al. (1998) find positive excess returns with stock-for-stock M&A non-conglomerate deals. Billett et al. (2004) document losses for the bondholders of acquiring firms, while the bondholders of target firms gain in junk-grade but lose in investment-grade firms. Renneboog and Szilagyi (2006) show that the effect of M&A on bondholders' wealth is influenced by cross-country variations in governance and legal standards. Warga and Welch (1993) and Asquith and Wizman (1990) reveal significant losses experienced by bondholders in leveraged buyouts, where leverage is substantially raised.

As for the effect of asset sales on bondholders' wealth, Galai and Masulis (1976) claim that these operations may expropriate collateral and liquidation value available to creditors, whereas John (1993) argues that they lead to a loss of co-insurance and diversification when the cash flows of the parent and the division are not perfectly correlated. Shleifer and Vishny (1992) highlight the importance of sell-offs as a way to resolve financial distress. The empirical findings of Datta and Iskandar-Datta (1996) indicate that sell-offs, on average, are firm value enhancing, as both stockholders and bondholders gain from such transactions.[28] Brown et al. (1994) document a wealth transfer from stockholders to bondholders of financially distressed firms if the proceeds are used to pay off debt. The findings of Gilson et al. (1990) indicate that increased creditor control during financial distress may lead to sell-offs that result in a wealth transfer from stockholders to bondholders, whereas Brown et al. (1994) show that the benefits from distressed sales seem to accrue to bondholders, consistent with increased creditor control during financial distress.

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[28] Nonetheless, they can also be wealth redistributing or value destroying, depending on the way the sale proceeds are distributed and the motive underlying the sell-off. The benefits from the sale of assets that do not strategically fit the firm's core business accrue primarily to stockholders, while benefits from distress-related sell-offs accrue to bondholders.

All in all, it seems clear that restructuring operations as M&A and asset sell-offs may be of paramount importance for shareholders and creditors. Still, the channels through which they influence the wealth of the former are rather complex. Motivated by these considerations, in a preliminary analysis we examine the effect of M&A deals in stock returns and CDS spread changes in our sample. Thereby, we gauge whether these events translate into changes in the wealth of firms' claimholders. The first hypothesis to be tested is:

H0: M&A announcements constitute material information for stockholders and CDS market participants, and hence constitute an opportunity for traders with private information to exploit.

Next, we proceed with the analysis of the timeliness of price discovery. In doing so, the sample of M&A announcements is divided according to the entities that supplied investment banking services. From this division two groups are formed. The first comprises M&A deals wherein major CDS dealers' affiliated firms supplied investment banking services to one of the parts of the operation. The second encompasses all the other deals not included in the first group. In what follows, the major dealers included in our sample are denoted as the G14 group.[29] These financial firms (or affiliated firms) play an important role in M&A investment banking activity. In effect, we find that members of the G14 group provided M&A services (to the acquirer, seller or target firm) in 39.2% of the operations in our restricted sample. As these financial institutions are major players in both financial services, we posit that M&A private information is impounded into CDS rates prior to the official announcements of the deals and then disseminated into stock prices.

H1: The pace of the assimilation of information is faster for deals where CDS market super-spreaders played a role as sponsors, brokers or consultants.

To examine H1, the timeliness of the assimilation of information of M&A announcements having G14 affiliated firms as advisors is compared with the timeliness of other M&A announcements. As the analysis of the interaction of CDS and stock markets is the main subject of our study, we proceed to analyze the information flow from the CDS market to the stock market. In a first step, the unconditional information flow from the CDS market to the stock market is examined.

[29]The G14 comprises the Bank of America-Merrill Lynch, Barclays Capital, BNP Paribas, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs & Co., HSBC Group, J.P. Morgan, Morgan Stanley, The Royal Bank of Scotland Group, Société Générale, UBS AG and Wachovia Bank. Chen, et al. (2011) report that these fourteen dealers account for 78% of trades as CDS protection buyers and 85% as protection sellers. Mengle (2010) documents that only 18% of the players are overall CDS net sellers, and that the top ten "super-spreaders" represent more than 73% of total gross sales. These dealers not only account for a large portion of the transactions in the CDS market, but are also important liquidity providers and have considerable market power in defining CDS quotes (Gündüz et al., 2013).

H2: There is an unconditional information flow from the CDS market to the stock market.

Subsequently, we examine the hypothesis of an upsurge of the information flow from the CDS market to the stock market before M&A announcements. Taking into account the results of previous research, and the fact that most operations are financed by external debt[30], it is expected that positive CDS innovations precede positive stock returns prior to acquisitions (higher leverage is associated with higher expected returns for stockholders and higher probability of default for debt holders in structural credit models such as Merton's (1974)), while negative CDS innovations precede positive stock returns prior to divestitures[31].

H3: The information flow from the CDS market to the stock market increases prior to M&A and asset sell-offs.

In order to improve our knowledge of the nature of the incremental informational flow from the CDS market to the stock market, we also investigate whether there are significant differences for investment-grade and speculative-grade firms. Intuitively, the impact of leverage or asset substitution on the wealth of credit holders should be greater for speculative-grade firms. In addition, the monitoring activity of credit holders is likely to be greater for speculative-grade than for investment-grade firms resulting in more private informed trading for the former firms.[32]

H4: The cross-correlation between CDS innovations and stock returns, conditional to M&A events, is stronger for speculative-grade firms.

To sort out the channels associated with the information flow, we also analyze whether the predictive power of CDS rate changes is greater when an important dealer in the CDS market (or affiliated firm) acts as advisor of the M&A or sell-off transaction. The intuition is that in the absence of perfect Chinese walls, information about M&A and divestures may leak from corporate finance divisions to other divisions, including CDS trading divisions. Accordingly, the latter may take advantage of that privileged access and impound their superior information in CDS quote revisions.

H5: The cross-correlation between CDS innovations and stock returns is stronger when major dealers' affiliated firms are involved as advisors in the M&A operations.

Finally, we investigate the pattern of CDS market liquidity prior to M&A announcements. The microstructure literature indicates that bid-ask spreads reflect information asymmetry, on top

[30] Bharadwaj and Shivdasani (2003) and Harford et al. (2009) report that most cash deals are financed with debt. Uysal (2011) provide preliminary evidence of the importance of leverage deficit in financing acquisitions.
[31]This observation is supported by the empirical findings of Datta and Iskandar-Datta (1996) that sell-offs benefit both stockholders and bondholders.
[32]For instance, Rauh and Sufi (2010) show that bank debt after a downgrade is more likely to contain restrictive covenants, such as dividend and capital expenditure restrictions.

of search costs, inventory costs and processing costs. Hence, ceteris paribus, an increase in bid-ask spreads is expected when CDS dealers perceive greater information asymmetry. We therefore expect bid-ask spreads to increase as CDS dealers anticipate M&A events before such information becomes public.

H6: There is an increase of bid-ask spreads of CDS contracts prior to M&A announcements.

The next section describes the data sample used in the analysis.

4. Data description and sources

The analysis is developed with information on M&A transactions over 100 million USD (including acquisitions and divestitures) involving U.S. and Western European listed companies, from January 2006 to October 2013, extracted from Bloomberg. We then remove the companies not listed in the stock market, and those whose CDS contracts were not actively traded in the CDS market during the period.

We use daily stock prices and CDS mid, bid and ask quotes from January 2006 to November 2013 collected from Bloomberg. For CDS contracts, we use benchmark CDS mid, bid and ask quotes of contracts on senior unsecured debt with maturity of 5 years. This maturity is usually the most liquid along the CDS curve (see Qiu and Yu, 2012). In addition to the information on prices and quotes, other fundamental information about the firms, such as market capitalization and the debt-to-equity ratio, is also extracted from Bloomberg.

Data on M&A includes information on the financial advisors of the acquirer, the seller and the target companies. Our initial sample conveys M&A deals involving companies domiciled in seventeen countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Holland, Luxembourg, Ireland, Italy, Portugal, Spain, Switzerland, Sweden, United Kingdom and USA. Concurrently, we also restrict the sample to the deals where the acquirer or the seller companies' stocks and CDS contracts were actively traded. Only M&A deals involving more than 100 million USD are included in the final sample, to ensure that the transaction may have a material impact on the wealth of the firm's claimholders. As these firms are usually large, small transactions would hardly affect stock prices or CDS rates as they would represent a tiny share of the firms' value.

We analyze 3,568 M&A events divided in acquisitions (26.3%) and divestitures (73.7%). The database comprises 720,669 observations and information on 443 firms. The average number of observations by firm is 1,627. The average CDS bid-ask spread of the obligors is 9% and the average premium is 154.2 basis points.

5. The pattern of CDS spreads and stock prices before M&A and sales announcements

The starting point of this study is the analysis of the patterns of CDS rates and stock prices in the periods surrounding M&A and sales announcements. We estimate the cumulative abnormal returns (CAR) for stocks and CDS contracts in this time span and evaluate their abnormal performance. As acquisitions and divestures impact CDS and stock returns differently, we divide the sample according to the type of operation.

Daily raw returns of stocks (CDS contracts) are calculated as the daily log changes of stock prices (CDS rates). Abnormal returns are computed as the difference between effective returns and expected returns. We estimate expected returns using the standard market model and an estimation window of 120 trading days ($[\mathrm{t}_{-189};\mathrm{t}_{-61}]$, where t_0 denotes the announcement date).

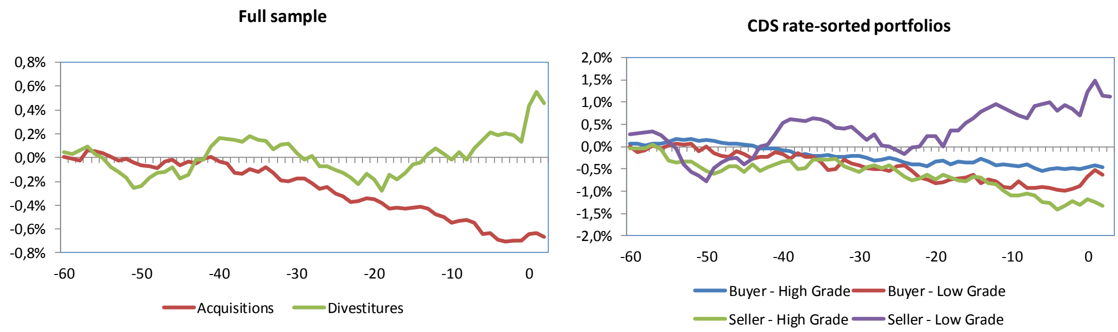
$$\mathrm{R}_{\mathrm{it}} = \alpha_{\mathrm{i}} + \beta\mathrm{i} \times \mathrm{R}_{\mathrm{mt}} \qquad \text{(EQ. 1)}$$

where R_{it} is the return on stock/CDS contract i on day t and R_{mt} is the market return on day t. The MSCI Europe and MSCI North America indices are used as proxies for the stock market returns in Europe and North-America, respectively. The iTraxx Europe and CDX North American Investment Grade indices are used as CDS market proxies for European and American firms, respectively. MSCI indices are well diversified and are often used in the financial literature to capture market movements. iTraxx Europe and CDX North American Investment Grade are amongst the CDS indices showing higher liquidity (Chen et al., 2011).

Figures 1 and 2 plot the evolution of average cumulative abnormal returns between t-60 and t2, with t0 as the announcement day. The stock market reaction to acquisitions contrasts with the reaction to divestitures: $CAR_{-60,2}$ is positive for seller companies (0.4%) and negative for buyer companies (-0.6%). Indeed, these results agree with those of Kaplan and Weisbash (1992), Asquith et al. (1990), Servaes (1991) and Schwert (2000), which report negative (though modest) CARs for bidders, and with the results of Klein (1986) and Lang et al. (1995), which document positive CARs in the period surrounding the announcement of asset sales.

CDS markets present an opposite pattern: acquisitions are preceded by a surge of CDS rates ($CAR_{-60,2}$ equals +2.9%), while divestitures are headed by a decline of rates ($CAR_{-60,2}$ equals -1.2%). As mentioned earlier, M&A operations could improve bondholders' situation insofar as they contribute to an increment of collateral and co-insurance of cash flows. Nevertheless, changes in the capital structure associated with the operation, such as leverage-increasing debt issues, may transfer wealth from creditors to shareholders. The results obtained are in line with these assertions and with the results of Dennis and McConnell (1986) Kim and McConnell (1977) and Asquith and Kim (1982).

Figure 1 – Cumulative abnormal returns of stocks around M&A announcements



The left hand chart depicts the average cumulative abnormal returns of stocks from the 60 trading days before an M&A announcement until day t. The sample is partitioned between acquisition and divestiture announcements. On the right hand side, acquisition and divestiture announcements are subdivided according to the firms' credit risk.

The findings from Billett et al. (2004), Datta and Iskandar-Datta (1996), Brown et al. (1994), and Gilson et al. (1990) suggest that the effect of these operations on creditors' wealth correlates with firms' creditworthiness. Following their insights and to sort out the influence of firms' credit risk on the behavior of the returns, the sample of events is sorted by firms' CDS rate prior to the announcement. Two bins are formed from the top (speculative-grade firms) and bottom (investment-grade firms) quintiles. Buyers (speculative-grade and investment-grade firms) experienced, on average, increases of CDS rates greater than 2%. In general, the effect of M&A events is greater for firms presenting greater credit risk.

Speculative-grade seller firms are the ones that benefit the most from divestitures in the stock market ($CAR_{-60,2}$ equals 1.1%) and in the CDS market ($CAR_{-60,2}$ equals -5.2%). In effect, these results are consistent with Lang et al. (1995) and Datta and Iskandar-Datta (1996) in that sell-offs, on average, are firm value enhancing, as both stockholders and bondholders gain from such transactions. It is important to bear in mind that the analysis covers a period characterized by a financial crisis and economic recession. In that sense, sell-offs of non-core assets to raise funds were of paramount importance as many firms were in financial distress or without alternative means of raising funds during most of the sample period.

Therefore, our hypothesis H0 is not rejected because, as conjectured, M&A operations impact CDS rates and stock prices.

Figure 2 – Cumulative abnormal returns of CDS contracts around M&A announcements

The left hand chart depicts the average cumulative abnormal returns of CDS contracts from the 60 trading days before an M&A announcement until day t. The sample is partitioned between acquisition and divestiture announcements. On the right hand side, acquisition and divestiture announcements are subdivided according to the firms' credit risk.

In order to assess H1, a measure of intra-period timeliness (IPT, hereafter) is calculated. Attention is on the 63-trading-days window beginning 60 trading days before the announcement and ending two trading days after. First, the proportion of the event window's CAR realized up to and including a particular day is computed. For day m, this is the cumulative buy-and-hold abnormal return from day -60 until day m, scaled by the cumulative buy-and-hold abnormal return for the entire period. IPT estimates the area under the cumulative abnormal returns curve for a given security, where greater values (areas) are a signal of timeliest price discovery.

$$IPT = \frac{1}{2} \times \sum_{m=-60}^{2} \frac{(CAR_{m-1} + CAR_m)}{CAR_2} = \sum_{m=-60}^{1} \frac{CAR_m}{CAR_2} + 0.5 \qquad \text{(EQ. 2)}$$

where $\mathrm{CAR_m}$ corresponds to the cumulative abnormal return from t_{-60} to m.

The sample of announcements is divided in two bins: M&A operations where major dealers also provide investment banking services to one part of the transaction, and other M&A operations. We average away random arrivals by forming portfolios from the two bins. As single-events can be extremely noisy, averaging the CAR of the two bins helps in debugging the influence of third factors and enhances the quality of the results.

The IPT is calculated from the average CAR of each 'portfolio', and afterwards a statistical test based on permutation analysis is performed. Under the null hypothesis, the order of arrival of the returns is irrelevant, because there should be no difference between the two 'portfolios' at the time of the arrival of news. As the order of the abnormal returns does not matter, the IPT difference of the portfolios' should equal 0. The alternative hypothesis is that price discovery is faster for M&A announcements that had G14 dealers as financial advisors of the operation. The permutation analysis is run as follows:

i) simulate the sequence of the 63 pair of returns (without re-sampling) and compute the test statistic (i.e. ΔIPT, the IPT difference of the two bins);

ii) repeat i) 10,000 times to derive the empirical density function of the test statistic;

iii) ascertain whether the null hypothesis is rejected.

Applying this procedure we obtain the empirical density function of ΔIPT. Then, we compare the 95th percentile of the empirical density function of ΔIPT with the ΔIPT calculated from the actual sequence of pairs of abnormal returns.

The results are reported in Table 1. Focusing firstly on the IPT in the stock market, we observe that the IPT of the bin comprising the M&A operations where G14 dealers acted as advisors is not statistically different from the IPT of other M&A operations. An equivalent analysis also reveals that the IPT of M&A operations of investment-grade and speculative-grade firms is also not statistically distinct.

The analysis of the IPT for the CDS market tells a different story. In the case of acquisitions by non-financial firms, the IPT is higher in operations where G14 dealers had a role as advisors in the deals (the IPT difference equals -20.8). This result is statistically significant at a 5% level. Another relevant outcome is the fact that the IPT is, in general, larger for investment-grade than for speculative-grade obligors.

Table 1 – Intra-period timeliness

Type of Firm	Operation	Clustering	P1	P2	IPT Dif for stocks	IPT Dif for CDS
Non-Financial	Buyer	G14	Others	G14	44.3	-20.8**
Non-Financial	Seller	G14	Others	G14	-9.4	18.7
Financial	Buyer	G14	Others	G14	-34.3	18.1
Financial	Seller	G14	Others	G14	15.1	29.4
All	Buyer	Grade	High-Grade	Low-Grade	-1.9	53.4*
All	Seller	Grade	High-Grade	Low-Grade	26.6	21.5

*The table displays the intra-period timeliness (IPT) for stock and CDS portfolios from 60 trading sessions before until two days after the M&A announcement (normalizing the CAR at t=-61 to zero and at t=2 to one). We compare the IPT of different portfolios around M&A announcements. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.*

In view of these results, we do not reject H1 and conclude that the CDS market assimilates the information faster when G14 dealers are also advisors of one of the parts involved in the operation (particularly in the case of acquisitions by non-financial firms). We do not obtain a similar result for the stock market.

6. The information flow from the CDS market to the stock market around M&A events

This section explores the cross-correlation between CDS and stock markets around M&A announcements. If informed traders use their superior knowledge to purchase credit protection or revise quotes, CDS rates will convey confidential information and may have the capacity to anticipate future stock returns before information becomes public.

To assess the interaction between CDS and stock markets, we follow Acharya and Johnson's (2007) approach based on the following two assumptions: (i) the stock market is efficient regarding the assimilation of publicly available information; (ii) the information flow from the CDS market to the stock market permanently impacts stock prices.

In a first step, CDS innovations are obtained by running time-series regressions for each firm:

$$\Delta(\ln CDS\,rate)_{i,t} = \alpha_i + \sum_{k=0}^{5}\left(\beta_{i,k} + \gamma_{i,k} \times \frac{1}{CDSrate_{i,t}}\right) \times Stockret_{i,t-k}$$

$$+ \textstyle\sum_{k=1}^{5}\left(\delta_{i,k} \times \Delta(\ln CDS\,rate)_{\,i,t-k}\right) + u_{i,t} \qquad \text{(EQ. 3)}$$

The interaction between the stock returns and the inverse of the CDS rates is included to account for the nonlinear dependence between the CDS rate changes and the stock returns (see Acharya and Johnson, 2007). CDS innovations reflect the component of CDS rate changes that are neither explained by past CDS rate changes, nor concurrent or past stock returns. The standardized residuals $\hat{u}_{i,t}$ capture "CDS innovations" for firm i on day t. They are a cleaner measure of the arrival of new information in the CDS market, which, at that time, is neither known to stock market investors nor captured by past stock returns or CDS rate changes. This residual component captures news specific to the CDS market on day t that may affect subsequent stock prices. In a second step, we evaluate the predictive power of CDS 'innovations' on future stock returns using the following empirical model:

$$Stockret_{i,t} = a + \sum_{k=1}^{5}\left(b_k + b_k^D \times CCD_{i,t}\right) \times StockRet_{i,t-k} + \sum_{k=1}^{5}\left(c_k + c_k^D \times CCD_{i,t}\right)$$
$$\times CDSinnovation_{i,t-k} + \varepsilon_{i,t}$$

(EQ. 4)

Besides Acharya and Johnson (2007), this model specification is also used by Berndt and Ostrovnaya (2007) and Qiu and Yu (2012). $\mathrm{CCD}_{i,t}$ is a credit condition dummy to which we assign the value of one in the 30 or 45 trading days prior to the M&A announcement, and zero otherwise. These pre-announcement windows are in line with other studies on M&A insider trading reported in the literature. Previous research on insider trading, such as Meulbroek (1992), Keown and Pinkerton (1981) and Dennis and McConnell (1986), analyze 20 trading days prior to M&A announcements, while Bris (2005) studies a 60-day period.

The coefficients $\sum_{k=1}^{5} c_k$ and $\sum_{k=1}^{5} c_k^D$ are of key importance to quantify the amount and significance of the information flow from the CDS market to the stock market. $\sum_{k=1}^{5} c_k$ measures the unconditional amount of information flow from the CDS market to the stock market, while $\sum_{k=1}^{5} c_k^D$ measures the incremental amount of information flow from the CDS market to the stock market conditional on the occurrence of a specific event.

As acquisition and divestiture episodes produce different effects on the cross-correlation between CDS rates and stock prices, we utilize different credit condition dummy variables to each type of event:

$$Stockret_{i,t} = a + \sum_{k=1}^{5}\left(b_k + b_k^{D,B} \times M\&A\_Buy_{i,t} + b_k^{D,S} \times M\&A\_Sell_{i,t}\right) \times StockRet_{i,t-k} + \sum_{k=1}^{5}\left(c_k + c_k^{D,B} \times M\&A\_Buy_{i,t} + c_k^{D,S} \times M\&A\_Sell_{i,t}\right) \times CDSinnovation_{i,t-k} + \varepsilon_{i,t} \qquad \text{(EQ. 5)}$$

where $M\&A\_Buy_{i,t}$ and $M\&A\_Sell_{i,t}$ take the value of one, in the 30 or 45 days windows before acquisitions and divestitures, and zero otherwise. The model is estimated running random effects panel data regressions using clustered standard errors and clustered bootstrapped standard errors to conduct statistical inference.

Table 2 reports the results of the estimations of (EQ. 5). $\sum_{k=1}^{5} b_k$ is negative and statistically significant. This outcome is not surprising, and reflects the negative serial correlation in stock returns documented by Lo and MacKinlay (1988), among others. $\sum_{k=1}^{5} c_k$ is not statistically significant, indicating that the CDS market unconditional incremental information flow to the stock market is not economically and statistically relevant. $\sum_{k=1}^{5} c_k^{D,B}$ is positive and statistically significant when using both 30 and 45 trading days as pre-announcement windows, suggesting that CDS innovations predict stock returns prior to M&A acquisitions. It is noteworthy that the cross-correlation is positive, in line with the notion that acquisitions have an opposite impact on the wealth of stockholders and creditors. In contrast, $\sum_{k=1}^{5} c_k^{D,S}$ is not statistically significant, which means that there is no increment in the information flow from the CDS market to the stock market around asset sell-offs. Thus, it can also be inferred from these results that the informational flow from CDS to stock markets is greater for acquisitions than for divestitures. Overall, these results support non-rejection of H3.

Table 2 – Information flow from the CDS market to the stock market

	Panel Data		Time Series Regressions	
	30 days' run-up window	45 days' run-up window	30 days' run-up window	45 days' run-up window
$\sum_{k=1}^{T} b_k$	-0.053(***/***)	-0.052(***/***)	-0.083***	-0.082***
	(-7.570/-7.367)	(-6.496/-6.403)	(-14.118)	(-13.860)
$\sum_{k=1}^{T} c_k$	0.001	0.001	0.010**	0.011**
	(0.307/0.323)	(0.341/0.339)	(2.308)	(2.140)
$\sum_{k=1}^{T} b_k^{D,B}$	-0.054(**/**)	-0.043	-0.022	-0.012
	(-2.437/-2.374)	(-0.711/-0.759)	(-1.149)	(-0.754)
$\sum_{k=1}^{T} b_k^{D,S}$	0.052	0.032	0.046	-0.029
	(1.089/1.086)	(0.718/0.737)	(0.434)	(-1.393)
$\sum_{k=1}^{T} c_k^{D,B}$	0.017(*/*)	0.029(***/***)	0.025	0.033**
	(1.836/1.862)	(3.004/3.140)	(0.839)	(1.964)
$\sum_{k=1}^{T} c_k^{D,S}$	0.012	-0.009	0.138	-0.001
	(0.798/0.830)	(-0.729/-0.724)	(0.963)	(-0.020)
N.º Obs.	715796	715796		

This table shows the results of panel regressions and time series regressions of daily stock returns on lagged CDS innovations and lagged stock returns (EQ.5) as follows:

$$\boldsymbol{Stockret_{i,t}} = \boldsymbol{a} + \sum_{\boldsymbol{k=1}}^{\boldsymbol{5}} \left(\boldsymbol{b_k} + \boldsymbol{b_k^{D,B}} \times \boldsymbol{M\&A\_Buy_{i,t}} + \boldsymbol{b_k^{D,S}} \times \boldsymbol{M\&A\_Sell_{i,t}}\right) \times \boldsymbol{StockRet_{i,t-k}} + \sum_{\boldsymbol{k=1}}^{\boldsymbol{5}} \left(\boldsymbol{c_k} + \boldsymbol{c_k^{D,B}} \times \boldsymbol{M\&A\_Buy_{i,t}} + \boldsymbol{c_k^{D,S}} \times \boldsymbol{M\&A\_Sell_{i,t}}\right) \times \boldsymbol{CDSinnovation_{i,t-k}} + \boldsymbol{\varepsilon_{i,t}}$$

*where $\boldsymbol{M\&A\_Buy_{i,t}}$ and $\boldsymbol{M\&A\_Sell_{i,t}}$ are dummy variables indicating whether there is an acquisition or a sell-off announcement within the next 30 or 45 trading days. The model is estimated using the full sample of firms and covers the time frame ranging from January 2006 to November 2013. The table reports the estimated coefficients and corresponding levels of significance. t-statistics for the joint significance are reported in parentheses. In the case of panel data estimation, clustered robust standard errors and bootstrapped clustered standard errors are reported. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.*

The use of panel data models assumes that all firms share the same dynamic properties, an assumption not present in time series regressions. Therefore, in order to ascertain the robustness of the previous results,(EQ5) is individually estimated for each firm. The estimated coefficients are saved and averaged across obligors. The results of these estimations are shown on the right hand side of Table 2. It is noteworthy that $\sum_{k=1}^{5} c_k^{D,B}$ is statistically significant in the 45 days run-up span and that $\sum_{k=1}^{5} c_k^{D,S}$ is not significant. Thus, the results from panel data regressions and individual time series regressions lead to similar conclusions regarding H3. We also estimate bootstrapped standard errors (clustered by firm) when using the panel data estimator.

The advantage of this method is that it increases the robustness of the results for data non-normality. The use of this alternative method to compute the standard errors does not qualitatively change the conclusions.

To gain further insight into the results, the sample is divided into financial and non-financial firms. There are two main reasons for making separate assessments of these two sectors. First, financial firms are more opaque than non-financial ones. Second, the sample encompasses the 2008 US financial crisis, in which financial firms were severely affected. It is well known that in some countries, such as the USA, governments and supervisors encouraged distressed financial companies to merge with more sound financial institutions during that period.

As the information content of M&A announcements differs for investment-grade and speculative-grade obligors, the sub-samples of financial and non-financial firms are subsequently separated according to the firm's implied credit risk. In doing so, we distinguish between events where the analyzed firms are in the top (speculative-grade) and in the bottom (investment-grade) terciles in terms of CDS rate levels. The results are presented in Table 3. $\sum_{k=1}^{5} c_k$ becomes statistically significant for investment-grade non-financial firms, but remains non-significant for speculative-grade non-financial firms and for investment-grade and speculative-grade financial firms. These results should be interpreted with caution because our sample is restricted to firms involved in M&A operations (a sample selection bias problem).

In turn, speculative-grade non-financial firms present a positive (negative) and statistically significant $\sum_{k=1}^{5} c_k^{D,B}$ ($\sum_{k=1}^{T} c_k^{D,S}$) when the pre-announcement window comprises 45 trading days. $\sum_{k=1}^{5} c_k^{D,B}$ is also positive and statistically significant for the subset of speculative-grade financial firms. These results corroborate the existence of an increment of the informational flow from the CDS market to the stock market prior to M&A announcements of speculative-grade firms. In the case of divestitures by speculative-grade non-financial firms, the cross-correlation between CDS rate changes and stock returns decreases prior to divestiture announcements. An obvious explanation is that in the aftermath of the divesture a decline of the leverage or asset volatility is anticipated.[33]

[33] Gilson et al. (1990) and Brown et al. (1994) argue that during financial distress, creditors obtain greater control of the firm. It is thus plausible that firms use the proceeds of the sell-off operation to reduce leverage.

Table 3 – Information flow from the CDS market to the stock market and firms' creditworthiness

	Non-Financial Firms			
	Investment-grade subsample		Speculative-grade subsample	
	30 days' run-up window	45 days' run-up window	30 days' run-up window	45 days' run-up window
$\sum_{k=1}^{T} c_k$	0.011***/***	0.012***/***	-0.014	-0.015
	(3.587/3.482)	(3.621/3.665)	(-1.330/-1.399)	(-1.331/-1.340)
$\sum_{k=1}^{T} c_k^{D,B}$	-0.009	-0.006	0.041	0.065***/***
	(0.832/-0.825)	(-0.723/-0.753)	(1.560/1.555)	(2.698/2.625)
$\sum_{k=1}^{T} c_k^{D,S}$	-0.014	-0.015	-0.070*	-0.074***/***
	(0.944/-0.981)	(-1.270/-1.314)	(-1.683/-1.709)	(-2.513/-2.609)
N.º Obs.	231169	231169	26547	26547

	Financial Firms			
	Investment-grade subsample		Speculative-grade subsample	
	30 days' run-up window	45 days' run-up window	30 days' run-up window	45 days' run-up window
$\sum_{k=1}^{T} c_k$	-0.007	-0.009	-0.030	-0.023
	(-0.432-/0.454)	(-0.535/-0.559)	(-1.551/-1.596)	(-1.370/-1.403)
$\sum_{k=1}^{T} c_k^{D,B}$	0.030	0.022	0.095***/***	0.160***
	(0.830/0.792)	(0.702/0.706)	(2.513/2.599)	(2.877/2.906)
$\sum_{k=1}^{T} c_k^{D,S}$	-0.031	0.022	0.105***/*	-0.007
	(-0.466/-0.392)	(0.163/0.146)	(2.013/1.879)	(-0.164/-0.162)
N.º Obs.	153082	153082	65992	65992

This table shows the results of panel regressions of daily stock returns on lagged CDS innovations and lagged stock returns (EQ.5) as follows:

$$\boldsymbol{Stockret_{i,t} = a + \sum_{k=1}^{5}\left(b_k + b_k^{D,B} \times M\&A\_Buy_{i,t} + b_k^{D,S} \times M\&A\_Sell_{i,t}\right) \times StockRet_{i,t-k}}$$
$$\boldsymbol{+ \sum_{k=1}^{5}\left(c_k + c_k^{D,B} \times M\&A\_Buy_{i,t} + c_k^{D,S} \times M\&A\_Sell_{i,t}\right) \times CDSinnovation_{i,t-k} + \varepsilon_{i,t}}$$

*where $\boldsymbol{M\&A\_Buy_{i,t}}$ and $\boldsymbol{M\&A\_Sell_{i,t}}$ are dummy variables indicating whether there is an acquisition or a sell-off announcement within the next 30 or 45 trading days. The sample is split into four subsamples: investment-grade financial firms; investment-grade non-financial firms; speculative-grade financial firms; and speculative-grade non-financial firms. The model is estimated for the various sub-samples of firms and for the time frame ranging from January 2006 to November 2013. Due to space restrictions, and for simplicity, only the coefficients associated with CDS 'innovations' are presented. The table reports the estimated coefficients and corresponding levels of significance. t-statistics for the joint significance are reported in parentheses, and are based on clustered robust standard errors and bootstrapped clustered standard errors. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.*

Acquisitions are usually financed by increased leverage. A positive association between CDS rate changes and stock returns surrounding the announcement is thus expected, because leverage raises the credit risk of the debt and the value of equity (Leland and Toft, 1996). For speculative-grade non-financial firms, the increment of the cross-correlation between CDS rate changes and stock returns prior to the announcement, corroborates the view that the information is assimilated first in the CDS market, and then spread to the stock market, so that CDS innovations predict subsequent returns. In the case of investment-grade firms, $\sum_{k=1}^{5} c_k^{D,B}$ and $\sum_{k=1}^{T} c_k^{D,S}$ are non-significant, probably because these events produce modest effects on stock prices (as seen in Section 5). As a consequence, we do not reject H4.

In order to identify possible justifications for the cross-correlation between CDS rate changes and stock returns around M&A announcements, we analyze the role of major dealers in the CDS market that also acted as consultants in certain M&A operations (directly or through affiliated firms) in the process of price discovery. We conjecture that confidential information on M&A deals flows from corporate finance departments to the CDS trading front-offices of these major dealers. An implication of this conjecture is the rise of the predictive power of CDS rate changes on subsequent stock returns prior to M&A announcements when a CDS dealer supplied investment banking services to one of the parts of the transaction.

Following this conjecture, (Eq. 5) is extended to distinguish operations where major dealers supplied investment services to one of the parts of the transaction. As previously, major dealers are defined as G14 dealers.

$$Stockret_{i,t} = a + \sum_{k=1}^{5}\left(b_k + b_k^{D,B} \times M\&A\_Buy_{i,t} + b_k^{D,S} \times M\&A\_Sell_{i,t} + b_k^{G14,B} \times M\&A\_Buy_{i,t} \times G14_{i,t-k} + b_k^{G14,S} \times M\&A\_Sell_{i,t} \times G14_{i,t-k}\right) \times StockRet_{i,t-k} + \sum_{k=1}^{5}\left(c_k + c_k^{D,B} \times M\&A\_Buy_{i,t} + c_k^{D,S} \times M\&A\_Sell_{i,t} + c_k^{G14,B} \times M\&A\_Buy_{i,t} \times G14_{i,t-k} + c_k^{G14,S} \times M\&A\_Sell_{i,t} \times G14_{i,t-k}\right) \times CDSinnovation_{i,t-k} + \varepsilon_{i,t} \tag{EQ.6}$$

where$G14_{i,t}$ is a dummy variable that assumes the value of one when at least one financial advisor of the M&A operation is concomitantly a G14 dealer.

The results of estimating (EQ.6) are reported in Table 4. Again, at a first stage, the sample is separated into financial and non-financial firms, and afterwards between investment-grade and speculative-grade firms. Regarding investment-grade non-financial companies, $\sum_{k=1}^{5} c_k^{G14,S}$ is negative and highly significant, but $\sum_{k=1}^{5} c_k^{D,S}$ is not. In addition, neither $\sum_{k=1}^{5} c_k^{G14,B}$ nor $\sum_{k=1}^{5} c_k^{D,B}$ have explanatory power. These results provide strong evidence that CDS rate changes precede stock returns prior to divestitures by investment-grade non-financial companies when an important CDS dealer or affiliated firm is involved in the M&A operation. Interestingly, $\sum_{k=1}^{5} c_k^{G14,S}$ is negative, which agrees with the idea that these types of operations created value for both stockholders and creditors. Indeed, investment-grade companies are not under pressure to sell assets at a discount. The result of the operation is likely to leave both stockholders and creditors better off. In contrast, we do not find a similar pattern around acquisition events.

Table 4 – Information flow from the CDS market to the stock market and the advisors on M&A deals

	Non-Financial Firms			
	Investment Grade		High Yield	
	30 days' run-up window	45 days' run-up window	30 days' run-up window	45 days' run-up window
$\sum_{k=1}^{T} c_k$	-0.070(**/**)	-0.048(*/**)	0.001	-0.033
	(-2.291/-2.325)	(-1.812/-2.137)	(0.008/0.754)	(-0.485/0.597)
$\sum_{k=1}^{T} c_k^{D,B}$	-0.015	-0.010	0.095(**/.)	0.113(***/.)
	(-1.270/-1.334)	(-0.872/-1.063)	(2.301/0.281)	(3.357/0.754)
$\sum_{k=1}^{T} c_k^{D,S}$	0.018	0.009	-0.064(*/.)	-0.064(**/*)
	(1.249/1.657)	(0.693/0.858)	(-1.842/-0.996)	(-2.150/-1.875)
$\sum_{k=1}^{T} c_k^{D,B} \times G14_{i,t}$	0.012	0.009	-0.066	-0.069(*/.)
	(0.572/0.618)	(0.526/0.592)	(-1.288/0.954)	(-1.674/0.788)
$\sum_{k=1}^{T} c_k^{D,S} \times G14_{i,t}$	-0.111(***/***)	(-0.072***/***)	-0.024	-0.034
	(-3.120/-3.272)	(-2.874/-2.432)	(-0.322/0.907)	(-0.648/1.247)
N.º Obs.	231169	231169	153082	153082

	Financial Firms			
	Investment Grade		High Yield	
	30 days' run-up window	45 days' run-up window	30 days' run-up window	45 days' run-up window
$\sum_{k=1}^{T} c_k$	0.090	0.092	0.043	0.172(*/**)
	(0.953/-0.083)	(0.938/-0.469)	(0.508/0.776)	(1.683/2.261)
$\sum_{k=1}^{T} c_k^{D,B}$	0.013(./**)	0.020	0.105(***/***)	0.140(***/**)
	(0.323/2.06)	(0.593/2.706)	(2.658/2.792)	(2.574/2.302)
$\sum_{k=1}^{T} c_k^{D,S}$	-0.091(./*)	-0.112*	0.040	-0.088
	(-0.949/-1.939)	(-1.866/-2.184)	(1.043/1.282)	(-1.160/-1.186)
$\sum_{k=1}^{T} c_k^{D,B} \times$	0.043	0.030	-0.041	0.015
	(0.629/-1.124)	(0.577/-1.32)	(-0.568/-0.62)	(0.175/0.026)
$\sum_{k=1}^{T} c_k^{D,S} \times$	0.597	1.154(*/.)	0.182	0.195(*/.)
	(1.167/-0.08)	(1.679/-0.343)	(1.489/1.2)	(1.700/1.303)
N.º Obs.	26547	26547	65992	65992

This table shows the results of panel regressions of daily stock returns on lagged CDS innovations and lagged stock returns (EQ.6) as follows:

$$\boldsymbol{Stockret_{i,t} = a + \sum_{k=1}^{5}\left(b_k + b_k^{D,B} \times M\&A\_Buy_{i,t} + b_k^{D,S} \times M\&A\_Sell_{i,t} + b_k^{G14,B} \times M\&A\_Buy_{i,t} \times G14_{i,t-k} + b_k^{G14,S} \times M\&A\_Sell_{i,t} \times G14_{i,t-k}\right) \times StockRet_{i,t-k} + \sum_{k=1}^{5}\left(c_k + c_k^{D,B} \times M\&A\_Buy_{i,t} + c_k^{D,S} \times M\&A\_Sell_{i,t} + c_k^{G14,B} \times M\&A\_Buy_{i,t} \times G14_{i,t-k} + c_k^{G14,S} \times M\&A\_Sell_{i,t} \times G14_{i,t-k}\right) \times CDSinnovation_{i,t-k} + \varepsilon_{i,t}}$$

where $\boldsymbol{M\&A\_Buy_{i,t}}$ *and* $\boldsymbol{M\&A\_Sell_{i,t}}$ *are dummy variables indicating whether there is an acquisition or a sell-off announcement within the next 30 or 45 trading days.* $\boldsymbol{G14_{i,t}}$*is a dummy variable indicating whether the financial advisor of the acquisition or sell-off operation is concomitantly a G14 dealer. The sample is split into four subsamples: investment-grade financial firms; investment-grade non-financial firms; speculative-grade financial firms; and speculative-grade non-financial firms. The model is estimated for the various sub-samples of firms and for the time frame ranging from January 2006 to November 2013. Due to space restrictions, and for simplicity, only the coefficients associated with CDS 'innovations' are presented. The table reports the estimated coefficients and corresponding levels of significance. t-statistics for the joint significance are reported in parentheses, and are based on clustered robust standard errors and bootstrapped clustered standard errors. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.*

The term $\sum_{k=1}^{5} c_k^{G14,S}$ is also significant for speculative-grade financial firms, but here the sum of the coefficients has a positive sign. One interpretation of this result is that the benefits of these sale operations accrued to the bondholders and not stockholders, probably because some of these sales were performed in a context of global financial crisis, where financial firms had limited capacity to raise funds and were forced to de-leverage. Selling assets (sometimes with a large discount) was the financial sector's solution to de-leverage, benefiting creditors at the expense of stockholders. Conversely, in the case of speculative-grade non-financial companies and investment-grade financial firms, the predictive power of CDS innovations does not increase when CDS dealers are consultants or sponsors of the M&A operation.

On balance, there is strong supporting evidence that CDS innovations have incremental predictive power over stock returns before M&A operations. CDS rates reveal private information and accelerate price discovery in the stock market, especially for speculative-grade firms. Concurrently, we also detect predictive power of CDS innovations in the case of investment-grade non-financial seller firms when CDS dealers supplied investment banking services to one of the parts in the transaction. We therefore do not reject H5.

7. The liquidity pattern surrounding M&A events

Our last analysis is an assessment of CDS market liquidity prior to M&A announcements. CDS bid-ask spreads, computed as percentage spreads, are used as a proxy for liquidity, since they are independent of the premium level. The microstructure literature suggests that bid-ask spreads reflect information asymmetry, in addition to search costs, inventory costs and processing costs. Hence, ceteris paribus, when CDS dealers perceive greater information asymmetry, this perception should be reflected in increasing CDS bid-ask spreads. We therefore expect increases in bid-ask spreads when CDS dealers anticipate M&A events before they become public knowledge. The pattern of the bid-ask spread of CDS contracts is captured with the following empirical model:

$$\mathrm{BAS_t} = \theta_0 + \theta_1 \times \mathrm{BAS}_t{}^{HQ} + \theta_2 \times \mathrm{BAS}_t{}^{LQ} + \sum_{k=1}^{10} \gamma_k \times \mathrm{BAS}_{t-k} + \varphi \times M\&A_t + \varepsilon_{i,t}$$

(EQ.7)

where $\mathrm{BAS_{i,t}}$ corresponds to the daily bid-ask spread of the CDS contract of obligor i on t; $\mathrm{BAS_t}^{\mathrm{HQ}}$ ($\mathrm{BAS_t}^{\mathrm{LQ}}$) denotes the average bid-ask spread of an equally-weighted investment-grade (high-yield) portfolio of CDS contracts, and $M\&A_{\mathrm{i,t}}$ is a dummy variable taking the value of one 120 days before acquisitions and divestitures, and zero otherwise. This model specification captures the reaction of individual CDS liquidity to the market-wide liquidity (Mayordomo et al., 2014). The introduction of these two different sets of contracts has the objective of capturing market liquidity and flight-to-quality (or search-for-yield) effects (which could make contracts on speculative-grade (investment-grade) obligors less liquid). $M\&A_{i,t}$ is our variable of interest and captures the bid-ask spread increment in the pre-announcement window.

Equation (7) is estimated using a sample of 240 trading days covering the span [-240; -1], where 0 represents the announcement date. We run time-series regressions on (EQ.7) for each M&A announcement in the sample. After that, the average $\widehat{\varphi}$ and the corresponding t-statistic are computed. The results, shown in Table 5, indicate that the average $\widehat{\varphi}$ equals 0,03% and is not statistically significant, and thus that bid-ask spreads do not change prior to M&A announcements.

Table 5 – Bid-ask spread evolution in the pre-announcement window

Coef.($\hat{\varphi}$)	All Sample	Non- G14	G14
Mean	0.03%	0.01%	0.07%
t-stat	1.469	0.425	1.691*
Inverse Normal Test	2.744***	1.121	2.935***

*The table reports the average estimated coefficients of (EQ.7) and corresponding t-statistics. The results are also divided according to the type of financial consultant (G14 and non-G14). ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.*

We also separate the results for the events in which major dealers had a role as financial advisors. Indeed, the average $\widehat{\varphi}$ stays positive and becomes statistically significant for the G14 group (at a 10% significance level). As the latter test does not control for the heterogeneity of the different obligors, we run a second test. Using the t-statistics and corresponding p-values associated with $\hat{\varphi}_i$ of the time series regressions, the following test is run

$$Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1}(p_i) \Rightarrow N(0,1). \qquad \text{(EQ. 8)}$$

where p_i denotes the p-value associated with $\hat{\varphi}_i$ and N is the number of cross-section regressions.

The results of this second test seem to reinforce the notion that bid-ask spreads increased in the pre-announcement window when major dealers were advisors of the operation. The average increase of the bid-ask spread in the pre-announcement window is statistically significant but quite small (0.07%) in comparison to the average bid-ask spread (9.13%) reported for the whole sample. In sum, the bid-ask spread analysis suggests the existence of information asymmetry prior to M&A announcements when major CDS dealers were consultants of the M&A operations. Therefore, we do not reject H6.

8. Conclusions

Banks and other institutional investors have access to private information about firms through their screening, monitoring and advisory activities. Previous analyses have shown that they trade using this confidential information in the CDS market. Our study adds to that body of research by assessing the information flow from the CDS market to the stock market, prior to M&A operations. Specifically, we analyzed the transmission of information between the CDS and the stock markets via consultancy, sponsoring and brokerage of M&A operations.

Our preliminary analysis indicated that M&A operations produce non-negligible wealth changes for stockholders and debt holders. On average, such wealth changes are greater for speculative-grade firms. We also analyzed the intra-period timeliness in CDS and stock markets. One major finding is that the CDS market processes the information more quickly when major CDS dealers are also financial advisors of the operation. This result is in line with the idea that major CDS dealers hold private information when providing advisory services to M&A deals and use it in the CDS market when revising quotes.

The unconditional lead-lag relationship between CDS innovations and stock returns seems to be, on average, negligible. Nonetheless, it becomes statistically and economically relevant for investment-grade non-financial firms. Prior to M&A operations, we observed an increase of the cross-correlation between CDS innovations and stock returns, particularly for speculative-grade financial and non-financial firms. CDS innovations also have predictive power over stock returns prior to divestiture deals of investment-grade non-financial firms when G14 dealers were financial advisors of the operation. Finally, we document an increase of the bid-ask spread prior to M&A announcements. The increment of the bid-ask spread is statistically significant for deals where major CDS dealers provided investment banking services to one of the parts of the transaction, but not for other M&A deals.

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Chapter 3

The information content of the open interest of credit default swaps (*)

Abstract

This article addresses the information content of the open interest of CDS markets. Using a panel database of 481 firms, I show that open interest innovations help to predict subsequent CDS rate changes and stock returns. The open interest dynamics appears to convey specific information on the reference entity and common information. On the one hand, there is evidence that positive open interest growth precedes the announcement of negative earnings surprises, and that high open interest growth prior to these events is linked to positive and significant CDS rate changes. This forecasting power relates with proxies of investors' attention and market frictions. The predictive power on CDS rates is larger for illiquid contracts and for entities with low credit risk, whereas the predictive power over stock returns is larger for entities that display greater open interest outstanding. On the other hand, this article also shows that the aggregate open interest growth has predictive power on the subsequent returns of CDS and bond main indexes, and to a lesser extent on stock market returns.

Keywords: Credit risk, credit default swap, information flow, informed trading, open interest measures.

JEL Codes: G12; G13; G14; G20

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1. Introduction

The consensus of the financial literature is that derivatives markets are not redundant in price discovery. The main reason is that informed investors may choose to trade in derivatives markets due to their higher leverage, lower funding costs and smaller transaction costs (Black 75). In the case of credit default swaps (CDS, henceforth) markets, Acharya and Johnson (2007) document an information flow from the CDS markets to the stock markets, especially for obligors with a large number of bank relationships and during times of financial distress (e.g., credit rating downgrade). The idea is that CDS markets are dominated by informed and sophisticated traders as major financial institutions. While acting as lenders, these large banks obtain access to private information about their clients' financial situations. Subsequently, that private information is impounded into CDS rates through their trading and quote updating, and then spread into stock markets. Similar findings are also documented by Batta et al. (2012), Berndt and Ostrovnaya (2008) and Qiu and Yu (2012).

In addition to prices, other trading data from CDS markets may convey private information. This paper investigates the informational content of CDS open interest data, and in particular its capacity to predict future movements in CDS spreads and stock prices. Open interest is a unique measure of derivatives markets that subsumes the speculative and hedging behavior of investors. One might question whether it is plausible that open interest or volume data help in predicting future CDS spread movements or even stock price movements. Indeed, there are several arguments in favor of that possibility. On the one hand, CDS markets are a trading venue for informed traders (Acharya and Johnson 2007). In effect, these contracts allow investors to obtain considerable leverage effects when trading (resembling out-the-money put options). They not only offer downside protection as they can be utilized by traders seeking to exploit informational advantages based on negative news. This way, CDS markets increase the completeness of financial markets, and particularly allow to overcome short-selling restrictions in stock markets that prevent bearish investors not owning the stock to bet on their beliefs. Finally, CDS contracts require lower funding costs than other financial instruments.

In the presence of private information, on the other hand, non-price data may convey information beyond that already existing on prices. As shown by Glosten and Milgrom (1985), prices adjust at once to the public information contained in the trading process, but may adjust only gradually to the private information owned by informed traders. Therefore, if CDS contracts are a trading venue for informed investors, open interest data may uncover private information about the obligors not instantaneously assimilated by prices, and predict future price movements.

The novelty of this paper is that it establishes an association between private information, CDS open interest dynamics and subsequent returns. Until now, very little effort has been made to examine the informational value of CDS trading volume data, and in special, open interest data, which is the central contribution of this paper. In analyzing whether or not CDS open interest data helps in predicting stock returns ahead, it also provides new insights about the information flow from CDS markets to stock markets. These topics are of obvious practical interest for academics and practitioners. It has important implications for market makers and dealers concerned with the risk management of adverse selection. CDS market participants, in general, may benefit from learning the signals about future price movements furnished by the open interest dynamics, which may be used in timing the market. Finally, the transparency and other regulatory issues of CDS markets are currently being debated by regulators and policy makers. In that sense, if open interest conveys information about future prices, further data on CDS transactions - such as intraday prices and volumes (along with a timely disclosure) - and more transparency could improve the informational efficiency of markets.

The main findings of this study can be outlined as follows. First, open interest growth contains private information that precedes CDS and stock price movements. Most of the statistical evidence regarding this issue comes from the cross-section of CDS and stock returns. Using a large panel dataset, I document a relationship between past open interest innovations, and concurrent raw CDS rate changes and stock returns. Interestingly, that association holds for abnormal CDS rate changes, but not for abnormal stock returns, suggesting that the explanatory power of open interest innovations decays when market-wide shocks are filtered from the analysis. Consistent with these results, I find that the open interest tends to increase before negative earnings surprises, and that high open interest growth prior to these events signals significant CDS rate changes. These results are in accordance with the hypothesis that open interest is driven by the private information of the investors.

In an attempt to gain further insight into the drivers of open interest informativeness, I investigate whether the predictive power is affected by the characteristics of the obligor and the features of the contract. Indeed, the predictive power on CDS rate changes increases with the illiquidity of the contract and declines with the credit risk level of the obligors. As for the predictive power of CDS open interest on stock returns, it seems to increase with the gross notional amount outstanding of the obligors.

Following the insight that the predictability of open interest tends to diminish when systematic shocks are filtered out from prices, I also investigate whether open interest dynamics relate to systematic information. Using several metrics of forecasting accuracy, I show that aggregate open interest growth foresees subsequent CDS market and bond market aggregate returns. There is also some ability to predict future returns of the stock market, but the results are not as robust as for CDS and bond indexes. From these results emerges the conclusion that CDS trading activity may be a useful additional predictor of future aggregate returns.

On balance, the findings of this paper are consistent with the presence of private information in CDS markets. The time that it takes to fully impound open interest innovations on prices and the cross-section of open interest informativeness suggest that the predictability is also fueled by the limited attention of market participants (and limited information processing capacity) and by market frictions. This conclusion stems from the evidence that CDS rates of contracts that probably receive less attention from CDS traders, as illiquid contracts and contracts on safer borrowers, present a higher degree of predictability than the others contracts. On the one hand, many investors might not pay attention to or be able to extract the information from the open interest dynamics. On the other hand, search costs for trading counterparties and execution costs are undoubtedly higher for illiquid contracts and are likely to hinder the assimilation of open interest information content.

The findings of this paper add to recent work on the flow of information between related markets and to the line of the literature that assesses the information content of derivatives trading volume data. There are several related papers that examine the information content of non-price trading data of options and futures, but only one of CDS contracts. Pan and Poteshman (2006) find that signed trading volume in the option market has predictive power over stock returns, whereas Ni et al. (2008) show that the option trading activity predicts future realized volatility. Easley et al. (1998) report that the volume of directional option trades leads the stock price changes, but the total option volume lacks predictive power. Hong and Yogo (2012) show that the open-interest growth of future contracts on commodities predicts commodity returns, bond returns and inflation. Roll et al. (2010) show that the ratio between options volume and stock trading volume (O/S) predicts lower abnormal returns after earnings announcements. There is also evidence that options volume contains material information prior to the announcement of important firm-specific news (see Amin and Lee 1997; and Cao et al. 2005).

While the information content of volumes data on options and future contracts trading has been extensively debated in the literature, the information content of the trading activity of CDS contracts is still unaddressed. Lee (2011) is the only paper exploring the informational value of the open interest data of CDS markets. This paper distinguishes from Lee (2011) in several ways: it uses a more comprehensive dataset, with a large number of obligors (U.S. and European) and a longer time span; it provides a different insight on how open interest relates with future prices by disentangling specific and systematic information; it assesses the pattern of open interest and CDS rates prior to the announcement of important firm-specific news; and it evaluates the predictive power of open interest on subsequent returns of market indexes using several metrics of forecasting evaluation.

The remainder of the paper is organized as follows. Section 2 details the hypotheses under analysis. Section 3 describes the data and provides summary statistics. Section 4 presents the empirical results and Section 5 outlines the main conclusions of the paper.

2. Hypotheses development

The central question addressed in this paper is whether or not open interest data has information beyond what is contained by CDS rates and stock prices. If markets were perfect, prices would fully impound all the present and past public information. However, in the presence of information asymmetry, non-price trading data may contain relevant information, because prices adjust at once to the public information contained in the trading process, but adjust gradually to the private information owned by informed traders (Glosten and Milgrom 1985). If informed investors use CDS markets as a trading venue, then volume and open interest data may convey information beyond that already existing on current prices.

In the first hypothesis under analysis, I examine whether open interest innovations reflect private information of investors, and whether they have predictive ability over CDS rate movements, such that private information embedded in open interest dynamics is only gradually assimilated by CDS rates. Concurrently, as positive innovations reflect higher demand for speculation on credit risk, I also posit that innovations climb together with CDS rate changes ahead.

H1: Open interest innovations predict subsequent CDS rate changes.

The second hypothesis under analysis focuses on the ability of the open interest innovations of an obligor to predict stock returns (after removing the information content of CDS rates). The informational content of CDS rates and the information flow between CDS markets and other markets was the subject of an intense debate in the financial literature. The ongoing consensus is that CDS markets are not redundant and that they contribute to price discovery. Up to now, the empirical analysis focused on the cross-correlation of stock returns and CDS rate changes, and concluded that past CDS rate changes preceded concurrent stock returns around negative events. This paper employs an alternative approach to appraise the informational content of CDS markets. If confirmed, the ability of open interest innovations to predict stock returns ahead provides additional supporting evidence that information flows from the CDS markets to the stock markets. Additionally, I posit that positive (negative) innovations are associated with subsequent negative (positive) stock returns, because higher buying pressure on CDS markets is related to worst prospects about the firm's future performance.

H2: Open interest innovations predict stock returns ahead.

CDS rate changes and stock returns are influenced by two types of information: specific information about the obligor and market-wide news that affects all firms (macroeconomic and systematic shocks on rates or prices). If CDS open interest conveys incremental specific private information about the obligors, that is, not yet impounded into rates, then innovations should predict the subsequent non-systematic component of returns.

H3: The predictive power of open interest innovations is linked to the specific information component of (a) CDS rate changes and (b) stock returns.

In a different vein, conventional wisdom says that bond and CDS traders pay special attention to downside risk and put great effort into detecting upward movements in credit spreads, because the upside potential to investors who have sold protection or have purchased bonds is limited in comparison with the downside potential losses. In addition, contrarily to stock markets where short-sale restrictions exist, CDS contracts allow trading on negative information. It is thus reasonable that informed traders use CDS markets (preferably) to exploit negative private information. H4 explores that hypothesis.

H4: The impact of open interest innovations of different signs on (a) CDS rate changes and (b) stock returns is symmetrical.

The degree of predictability of open interest may vary with the characteristics of the borrower and the contract. In that sense, I postulate that the predictive ability of open interest relates with proxies of investors' attention or institutional frictions that hinder price discovery. Limited attention of market participants and limited information processing capacity imply that the information is gradually disseminated on prices and may fuel the predictive capacity of open interest data. Search costs associated with illiquidity may also deter prices from fully absorbing information.

H5: The pace at which the open interest information content is assimilated by prices relates with proxies of investor attention and market frictions.

The final question under analysis concerns the predictive ability of CDS open interest data on the aggregate returns of stocks, bonds and CDS markets. To that end, the predictive power of open interest on the subsequent returns of three indexes (S&P500, iBoxx Liquid Investment-grade and Markit iTraxx Corporate Europe) is analyzed.

H6: Open interest growth has predictive power over market-wide returns.

In the next section, I proceed with the description of the sample and with the definitions of the main variables used in the analysis.

3. Data

Daily CDS quotes (bid, ask and mid-quotes), stock prices and other fundamental data (quarterly data on market capitalization and book debt; earnings announcement dates and quarterly earnings per share (EPS)) about the obligors are retrieved from Bloomberg. Regarding CDS quotes, the focus of the analysis is on 5-Yr maturity contracts traded in New York. Up to now, the 5-Yr tenor has been widely used in the empirical literature since it is the one that displays a higher trading volume among the different maturities[34] and it is a benchmark reference for practitioners.

In addition, data from the Depository Trust & Clearing Corporation (henceforth, DTCC) website on open interest (number of transactions, and gross and net notional amounts) is also used. DTCC is a trade repository for credit derivatives and has been publishing data on the amounts outstanding for the Top 1000 contracts since October 2008. DTCC covers 95% and 99% of the trading of CDS contracts on single-name references in terms of the number of contracts and total notional amounts, respectively (Gündüz et al. 2013). Two different proxies of open interest are analyzed: the gross notional amount outstanding (GNA, henceforth) and the net notional amount outstanding (NNA, henceforth). The NNA denotes the sum of net protection bought (sold) by counterparties that are net buyers (sellers) of protection for a particular obligor, which means that it captures the stock of credit risk transferred in the CDS markets (Oehmke and Zawadowski 2014).[35] This means that the NNA encompasses the maximum net exposure to the borrowers' credit risk. The gross notional amount, on the other hand, stands for the aggregate notional of all the CDS contracts open in the market. As a result, the gross notional amount is also driven by operations related to the management of counterparty exposures, such as portfolio compression cycles and novation.[36] The main goal of these operations is to maintain the same risk profile while reducing the number of contracts and GNA held by participants. This aspect is important since compression operations may produce noisy data affecting the results. On balance,

[34] For the U.S. market, Chen et al. (2011) report that the trading of 5-Yr maturity contracts represents 43% of the trading amongst single-name CDS.

[35] The Depository Trust & Clearing Corporation gives the following definition: "Net notional positions generally represent the maximum possible net funds transfers between net sellers of protection and net buyers of protection that could be required upon the occurrence of a credit event relating to particular reference entities. (Actual net funds transfers are dependent on the recovery rate for the underlying bonds or other debt instruments)."

[36] These compressions may also result from administrative transactions related to central clearing such as novations to central counterparties.

NNA variations uncover the hedging and speculative demand, whereas GNA variations are a measure close to the traded volume.

Table 1 – Descriptive statistics

Panel A

Domicile	# observations
Austria	522
Belgium	272
Switzerland	3,739
Germany	7,572
Denmark	510
Spain	2,104
Finland	1,616
France	10,211
Great Britain	10,842
Greece	263
Ireland	365
Italy	3949
Luxembourg	523
The Netherlands	2,753
Portugal	819
Sweden	2,439
US	68,639
Total	117,138

Panel B

Industry Sector	# observations
Basic Materials	9,794
Communications	11,852
Consumer, Cyclic	18,370
Consumer, Non-cyclic	22,556
Consumer, Diversified	270
Energy	9,048
Financial	19,845
Industrial	13,859
Technology	3,709
Utilities	7,835
Total	117,138

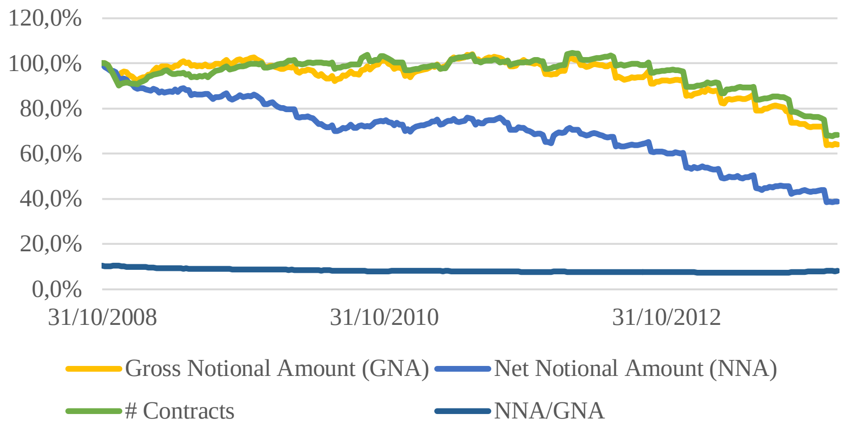
Panel C

	CDS Rates	Debt-to-Market Cap	Market Cap. (millions of USD)	GNA (millions of USD)	NNA (millions of USD)	# Contracts	Short and Long Term Debt (millions of USD)
Mean	211.9	2.0	27,059	16,000	1,130	2,381	23,196
Percentile 10	49.0	0.2	1,732	3,340	339	687	993
Percentile 50	119.0	0.5	11,960	12,800	895	2,076	4,649
Percentile 90	440.3	2.8	68,989	31,700	2,140	4,362	24,241
Interquartile	152.0	0.8	24,036	15,700	920	2,014	7,622
St. Dev.	354.0	7.2	41,465	13,200	898	1,483	94,112

Panel A and B tabulate the number of observations of the sample by the domicile and industry of the reference entity. The sample is collected from Bloomberg and the DTCC for the time frame that ranges from October 2008 to January 2014 (weekly data). Panel C presents descriptive statistics (average, median, standard deviation, percentiles 10 and 90, and interquartile range) of the sample in terms of the fundamental information on the obligors and their trading activity. More precisely, the variables analyzed are the CDS rate level, the debt-to-market capitalization ratio, market capitalization, gross notional amount (GNA), net notional amount (NNA), number of contracts (# Contracts), and short and long term debt.

DTCC reports the weekly CDS open interest of the 1,000 most relevant single-reference entities. Amid those obligors, I start by selecting the ones that are listed and active in the stock market, and the ones that display CDS quotes in Bloomberg. Next, I restrict the sample to the contracts over obligors domiciled in the U.S., the European Union and Switzerland. The sample comprises 117,138 weekly observations on 481 obligors and the span that ranges from October 2008 to January 2014. The observations of U.S. firms amount to 68,639, i.e. more than one half of the sample. The majority of the observations belongs to the firms of the sectors of consumer cyclic (18,370), consumer non-cyclic (22,556) and financials (19,845). The average GNA and NNA of the analyzed obligors are 16,000 millions of USD and 1,130 millions of USD, respectively. Each obligor has, on average, 2,381 contracts outstanding. The average CDS spread is 212 basis points and the debt-to-market capitalization is 2.0.

Figure 1 – The evolution of gross and net notional amount, number of contracts and the ratio between net notional amount and gross notional amount



The figure presents a line-plot of the path of gross notional amount, net notional amount, and number of CDS contracts (having as underlying single-reference entities, loans, and residential and commercial mortgage backed securities). Using a weekly frequency of data obtained from the DTCC, the plot covers the span that ranges between October 2008 and January 2014. The series are scaled as a function of their value on October 31, 2008, so that subsequent values are represented as a fraction of the starting point of the sample. The ratio between net notional amount and gross notional amount is also exhibited.

Figure 1 plots the aggregate gross notional amount outstanding, the aggregate net notional amount outstanding and the aggregate number of contracts on single-reference entities. The series are scaled so that they represent a fraction of the starting value (October 31, 2008). It can be seen that the three series witnessed a decline since October 31, 2008. The ratio between the aggregate net notional amount outstanding and the aggregate gross notional amount outstanding also saw a decline.

Two final notes. First, this study is performed using a weekly data frequency. As compared to the use of daily data, weekly data permits removing the effects of transient effects on prices and to concentrate on the information that moves prices permanently. In fact, the use of daily data may introduce noise in the estimation due to microstructure effects, such as the non-synchronicity between the dependent variable and the predictors. Second, open interest data is publicly disclosed in the DTCC website with a delay of one to two weeks. Hence, if open interest conveys private information it may take more than one week to be fully impounded in prices.

The next section proceeds with the empirical analysis.

4. Results

a. Open interest innovations and CDS rate changes

In order to evaluate the predictive power of open interest on CDS rate changes, I use a modified version of the model of Brennan and Subramanyam (1996). In a first stage, open interest 'innovations' are estimated by computing the standardized residuals of the regression of open interest growth on contemporaneous CDS rate changes, lagged CDS rate changes and lagged open interest growth.

$$\Delta V_t = \theta + \sum_{j=0}^{5} \delta_j \times r_{t-j}^{CDS} + \sum_{j=1}^{5} \varphi_j \times \Delta V_{t-j} + \tau_t \tag{1}$$

where ΔV_t denotes the weekly (log) growth of open interest and r_t^{CDS} stands for the weekly (log) change of CDS rates. The pre-whitening of open interest growth is important because this variable may respond to past information on CDS rate changes. For example, CDS spread changes may trigger strategies of hedgers that are dynamically rebalancing their portfolios, in that open interest changes derive from portfolio rebalancing and not from private information. Given that the contemporaneous correlation between open interest growth and CDS rate changes may not be zero, a predictive regression of CDS rate changes against past raw open interest growth could end up capturing the autocorrelation of the former and not material information.

In a second stage, the predictive power of these open interest 'innovations' is examined.

$$r_t^{CDS} = \gamma_0 + \sum_{j=1}^{5} \gamma_j \times r_{t-j}^{CDS} + \sum_{j=1}^{5} \Psi_j \times innovations_{t-j} + \varepsilon_t \tag{2}$$

with r_t^{CDS} as previously defined; $innovations_t$ denote the standardized residuals ($\hat{\tau}$) of equation (1). To put into context, for each firm, I run a regression of open interest growth on a constant, five lags of open interest growth, and the concurrent and five lags of CDS rate changes - see equation (1). The standardized residuals of the regressions ($\hat{\tau}$) are used as a proxy for unexpected open interest growth (or open interest innovations). Then, the predictive power of these open interest innovations on future raw rate changes of CDS contracts is examined, by estimating equation (2) for each obligor using time series regressions.

Table 2 tabulates the average estimated coefficients of equation (2), and corresponding t-statistics, using the (unexpected) growth of GNA and NNA as alternative measures of open interest. The average estimated coefficients are tabulated for the full sample of obligors and by the sector of the obligor (financial and non-financial firms), on the grounds that significant differences in the predictive ability of open interest may exist for different sectors.

Looking at Table 2, Panel A, we see that past open interest innovations, proxied by GNA innovations, have predictive power over raw CDS rate changes. $\sum_{j=1}^{5}\widehat{\Psi}_j$ is positive and significant, so that future CDS rate changes rise together with past unexpected GNA growth. Interestingly, the predictive power seems to be higher for financial firms than for non-financial firms if one attend to the average value of $\sum_{j=1}^{5}\widehat{\Psi}_j$. A closer inspection also reveals that the predictive power of innovations is concentrated on the second and third lags, which may relate with the fact that DTCC publishes open interest data with a delay of one to two weeks. The coefficient of the first lag is negative and statistically significant, in opposition to the other lags. The average R-squared of the time series regressions is below 10%.

Table 2, Panel B outlines the results of the time series regressions using NNA innovations as the predictor. The average $\sum_{j=1}^{5}\widehat{\Psi}_j$ is positive and significant, so that NNA innovations have predictive power over future CDS rates. The average R-squared (adjusted R-squared) of the time series regressions is 7.4% (1.5%) if the full sample is considered. In light of these results, H1 is not rejected. Open interest innovations seem to have predictive power over future rates. The conclusion is valid for both proxies of open interest.

Table 2 – Time series regressions of CDS rate changes on open interest innovations

Panel A

Dependent Variable	Raw CDS Rate Changes			Abnormal CDS Rate Changes		
	All Firms	Financial	Non-Financial	All Firms	Financial	Non-Financial
L.GNA_innovations	-0.002***	-0.002***	-0.002***	0.008*	0.017**	0.006
	(-7.098)	(-3.308)	(-6.317)	(2.030)	(2.367)	(1.322)
L2.GNA_innovations	0.001***	0.002**	0.001***	0.007	0.021*	0.004
	(4.290)	(2.443)	(3.582)	(1.237)	(2.273)	(0.631)
L3.GNA_innovations	0.002***	0.003***	0.002***	0.015***	0.020**	0.014**
	(8.141)	(5.421)	(6.607)	(3.581)	(2.995)	(2.896)
L4.GNA_innovations	0.000	0.002***	0.000	-0.006	-0.002	-0.007
	(1.428)	(3.241)	(0.181)	(-1.184)	(-0.185)	(-1.180)
L5.GNA_innovations	0.000*	0.002***	0.000	0.013***	0.014*	0.012***
	(1.881)	(3.497)	(0.540)	(3.706)	(2.084)	(3.194)
$\sum_{j=1}^{5}\widehat{\Psi}_j$	0.003***	0.008***	0.002*	0.036**	0.070***	0.029*
	(3.976)	(4.848)	(2.251)	(2.674)	(4.175)	(1.835)
Warner et al. (1988) procedure	5.046***	5.012***	5.009***	7.052***	7.046***	7.044***
Average R2	7.6%	7.5%	7.6%	7.7%	7.6%	7.8%
Average Adj. R2	1.9%	2.0%	1.9%	1.9%	2.1%	1.9%

Panel B

Dependent Variable	Raw CDS Rate Changes			Abnormal CDS Rate Changes		
	All Firms	Financial	Non-Financial	All Firms	Financial	Non-Financial
L.NNA_innovations	-0.001*	0.000	-0.001**	0.014***	0.042**	0.009*
	(-2.261)	(0.601)	(-2.697)	(3.480)	(5.146)	(1.897)
L2.NNA_innovations	0.001***	0.001	0.001***	0.012***	0.000	0.015***
	(3.467)	(0.787)	(3.500)	(3.267)	(-0.056)	(3.531)
L3.NNA_innovations	0.002***	0.002**	0.002***	0.014**	0.004	0.016**
	(6.005)	(2.525)	(5.477)	(2.929)	(0.561)	(2.894)
L4.NNA_innovations	0.001***	0.002***	0.001***	0.002	0.010	0.000
	(4.560)	(3.361)	(3.491)	(0.504)	(1.263)	(0.055)
L5.NNA_innovations	0.001*	-0.001	0.001**	0.006	-0.008	0.009*
	(1.854)	(-1.058)	(2.566)	(1.514)	(-1.155)	(1.975)
$\sum_{j=1}^{5}\hat{\Psi}_j$	0.004***	0.004**	0.004***	0.049***	0.047**	0.049***
	(6.111)	(2.972)	(5.404)	(4.076)	(2.481)	(3.544)
Warner et al. (1988)	7.874***	7.893***	7.871***	6.942***	6.944**	6.943***
Average R2	7.4%	7.6%	7.4%	7.7%	8.0%	7.7%
Average Adj. R2	1.5%	2.1%	1.4%	1.8%	2.5%	1.7%

*Panel A and B present results of forecasting (raw and abnormal) CDS rate changes in week t using five lags of open interest innovations (gross notional amount innovations [GNA_innovations] or net notional amount innovations [NNA_innovations] in Panel A and B, respectively). For each reference entity, I run predictive regressions of (raw and abnormal) CDS rate changes on five lags of open interest innovations and five lags of the dependent variable in the span that ranges from October 2008 to January 2014 (equation 2). The table reports results of cross-sectional averages of the estimated coefficients. Associated t-statistics for each average appear immediately beneath in parentheses. The results are reported for the full set of reference entities in the sample and for financial and non-financial firms separately. Due to space restrictions only the average coefficients of open interest innovations (and corresponding t-statistics) are tabulated. The R2s (Adj. R2) are cross-sectional averages of the R2 (Adj. R2) of the time-series regressions. The table also reports the cumulative effect of lagged open interest innovations on CDS rate changes ($\sum_{j=1}^{5}\hat{\Psi}_j$). Statistical inference is performed by averaging the estimated $\sum_{j=1}^{5}\hat{\Psi}_j$ across entities and computing the corresponding standard error. As an alternative, Warner et al. (1988) procedure is also employed. The t-statistics of $\sum_{j=1}^{5}\hat{\Psi}_j$ are summed across obligors and then divided by the square root of the number of obligors. The individual regression t-statistics are assumed to follow a unit normal distribution asymptotically. ***, ** and * denote one-side statistical significance at the 0.1%, 1% and 5% levels, respectively. L(i) is the lag operator of order i. t-statistics in parenthesis.*

In order to appraise H3 (a), the component of rate changes associated to specific information is isolated. Towards that end, the abnormal rate changes of CDS contracts are computed using a two-factor market model. In this model, CDS rate changes respond to the contemporaneous returns of investment-grade and speculative-grade portfolios of bonds. These two factors capture not only market-wide credit risk fluctuations, but also flight-to-quality (or search-for-yield) movements in the bond and CDS markets, that may raise the demand for investment-grade (speculative-grade) obligors. These effects are particularly relevant during crisis, when investors are more interested in high-quality assets and avoid the assets that convey greater risk[37].

[37] As an alternative to the two-factor model, I also used an one factor model calculated as the non-weighted average of CDS rate changes of obligors from the U.S., if firm i is domiciled in the U.S., and from the European Union (plus Switzerland) if firm i is domiciled in that area. The main conclusions do not change with this alternative procedure, and the results are available upon request.

$$r_{t,i}^{CDS} = \theta_0 + \theta_1 \times r_{t,i}^{HQ} + \theta_2 \times r_{t,i}^{LQ} + \upsilon_{i,t} \quad (3)$$

with r_t^{CDS} as previously defined; $r_{t,i}^{HQ}$ and $r_{t,i}^{LQ}$ denote the returns of investment-grade and speculative-grade portfolios of bonds, respectively. I proxy the high-grade portfolio and the speculative-grade portfolio using the iBoxx Liquid Investment-grade index and the iBoxx Liquid High-yield index, respectively. These indices are designed to represent the corporate investment-grade and high-yield bond markets using the most liquid issues available.

Investors are expected to own more private information about the idiosyncratic component of CDS rate changes than about the systematic component, whereby the predictability should be higher for idiosyncratic rate changes ($\hat{\upsilon}_t$) than for raw rate changes. Nonetheless, using abnormal rate changes as the dependent variable does not produce significant changes in the conclusions. It is true that the coefficients of the first three lags of NNA innovations are positive and significant when predicting abnormal rate changes (recall that the first lag coefficient is negative when predicting raw CDS rates). In spite of that, the average R-squared of time series regressions only improves slightly. A similar conclusion is obtained when analyzing the predictive power of GNA innovations on abnormal CDS rate changes. On balance, from these results emerges the conclusion that the predictive power of open interest innovations is linked to the specific information component of CDS rate changes, whereby H3 (a) is not rejected.

To gauge the sensitivity of the results to the aggregation method that was employed earlier, other statistical approaches are utilized. If the findings of these alternative estimation methods point in the same direction, there is evidence for the distinctness and robustness of the conclusions. Following Warner et al. (1988), the t-statistics of $\sum_{j=1}^{5} \widehat{\Psi}_j$ are summed across obligors and then divided by the square root of the number of obligors. This method assumes that the individual regression t-statistics follow asymptotically a unit normal distribution and are independent. The use of this alternative aggregation procedure leads to virtually identical results.

In parallel, Fama-MacBeth regressions and a panel data regression with random effects (using clustered robust and clustered bootstrapped standard errors) are also conducted. Table 3, Panel A reports the results using GNA innovations as the predictor. Using panel data regressions instead of time-series regressions does not produce significant changes in the conclusions ($\sum_{j=1}^{5} \widehat{\Psi}_j$ stays positive and significant). Nevertheless, applying Fama-MacBeth regressions has implications for the results. Even though $\sum_{j=1}^{5} \widehat{\Psi}_j$ remains positive and statistically significant for abnormal CDS spread changes, it turns non-significant for raw CDS spread changes. In contrast, time-series regressions and these alternative econometric techniques point towards similar conclusions with NNA innovations as the predictor (see Table 3, Panel B). The forecasting power of NNA innovations on raw and abnormal CDS spread changes is relevant, regardless of the econometric approach used.

Table 3 – Panel data regressions of CDS rate changes on open interest innovations

Panel A

	Raw CDS Rate Changes		Abnormal CDS Rate Changes	
	Panel Data	Fama-MacBeth	Panel Data	Fama-MacBeth
L.GNA_innovations	-0.002***/***	0.001	0.005	0.011
	(-8.370/-8.304)	(1.557)	(1.503/1.490)	(1.623)
L2.GNA_innovations	0.001***/***	0.000	0.015***/***	0.008
	(6.307/6.277)	(0.214)	(4.580/4.526)	(1.272)
L3.GNA_innovations	0.002***/***	0.000	0.023***/***	0.005
	(10.851 /10.924)	(0.633)	(7.879/7.819)	(0.618)
L4.GNA_innovations	0.000*/*	0.001	0.000	0.008
	(1.919 /1.923)	(1.306)	(0.022/0.022)	(1.270)
L5.GNA_innovations	0.000	0.000	0.012***/***	-0.004
	(1.118/1.114)	(-0.459)	(4.314/4.329)	(-0.661)
$\sum_{j=1}^{5} \widehat{\Psi}_j$	0.003***/***	0.002	0.055***/***	0.028*
	(5.139/5.138)	(1.510)	(7.146/7.029)	(1.838)
R2 Within	0.83%		0.51%	
R2 Overall	0.88%		0.52%	

Panel B

	Raw CDS Rate Changes		Abnormal CDS Rate Changes	
	Panel Data	Fama-MacBeth	Panel Data	Fama-MacBeth
L.NNA_innovations	-0.001***/***	0.001***	0.014***/***	0.021***
	(-3.222/-3.216)	(4.988)	(4.559/4.524)	(4.826)
L2.NNA_innovations	0.001***/***	0.001*	0.011***/***	0.010**
	(4.715 /4.694)	(2.269)	(3.704/3.710)	(2.680)
L3.NNA_innovations	0.002***/***	0.000	0.016***/***	-0.001
	(8.361/8.417)	(-0.528)	(5.342/5.422)	(-0.227)
L4.NNA_innovations	0.001***/***	0.001**	0.005*/*	0.012**
	(6.090/6.042)	(2.951)	(1.756/1.758)	(3.090)
L5.NNA_innovations	0.000*/*	0.000	0.004	0.002
	(2.094/2.108)	(1.082)	(1.538/1.543)	(0.670)
$\sum_{j=1}^{5} \widehat{\Psi}_j$	0.004***/***	0.003***	0.051***/***	0.044***
	(7.897/7.877)	(5.044)	(6.743/6.734)	(5.141)
R2 Within	0.75%		0.49%	
R2 Overall	0.79%		0.49%	

*Panel A and B present results of forecasting (raw and abnormal) CDS rate changes in week t using five lags of open interest innovations (gross notional amount innovations [GNA_innovations] or net notional amount innovations [NNA_innovations] in Panel A and B, respectively). In doing so, a random effects panel data model and Fama-MacBeth regressions are estimated. CDS rate changes are regressed on five lags of open interest innovations and five lags of the dependent variable in the span that ranges from October 2008 to January 2014 (equation 2). The table reports results for the estimated coefficients. Associated t-statistics appear immediately beneath in parentheses. Due to space restrictions only the coefficients (and corresponding t-statistics) of open interest innovations are tabulated. The table also reports the cumulative effect of lagged open interest innovations on CDS rate changes ($\sum_{j=1}^{5} \widehat{\Psi}_j$). In the case of the panel data models, clustered robust standard errors and clustered bootstrapped standard errors are used alternatively in the computation of the t-statistic. Fama-MacBeth t-statistics are corrected for autocorrelation using Newey-West standard-errors. ***, ** and * denote one-side statistical significance at the 0.1%, 1% and 5% levels, respectively. L(i) is the lag operator of order i. t-statistics in parenthesis (clustered robust s.e./clustered bootstrapped s.e).*

Next, I turn attention to H4, and investigate the presence of asymmetry in the predictive power of large innovations of different signs on subsequent rate changes. To examine that hypothesis, the following equation is estimated:

$$r_t^{CDS} = \gamma_0 + \sum_{j=1}^{5} \gamma_j \times r_{t-j}^{CDS} + \sum_{j=1}^{5} \phi_j \times D_{t-j}^{UP} + \sum_{j=1}^{5} \pi_j \times D_{t-j}^{DOWN} + \varepsilon_t \qquad (4)$$

with r_t^{CDS} as previously defined; D_t^{UP} is one when the open interest (NNA) innovation is higher than one standard deviation and zero elsewise; D_t^{DOWN} is one if the (NNA) innovation is lower than minus one standard deviation. The first dummy variable captures large positive open interest innovations, while the second captures large negative innovations. Equation (4) is estimated by means of the Fama-MacBeth two-step procedure with Newey-West standard-errors.

Table 4 displays the results with raw and abnormal CDS rate changes as dependent variables. With respect to raw CDS rate changes, $\sum_{j=1}^{5} \hat{\phi}_j$ is positive and not statistically significant, whereas $\sum_{j=1}^{5} \hat{\pi}_j$ is negative and significant. To further check the hypothesis of symmetry, the hypothesis that $\sum_{j=1}^{5} \phi_j + \sum_{j=1}^{5} \pi_j = 0$ is also assessed. Indeed, this test does not reject the hypothesis of symmetry (see the last row of Table 4). A similar procedure is conducted with abnormal CDS rate changes as the dependent variable. As expected, $\sum_{j=1}^{5} \hat{\phi}_j$ is positive, whereas $\sum_{j=1}^{5} \hat{\pi}_j$ is negative, and both are significant. Moreover, the hypothesis that $\sum_{j=1}^{5} \phi_j + \sum_{j=1}^{5} \pi_j = 0$ is not rejected. Put together, H4 (a) is also not rejected.

Table 4– The impact of large positive and negative (NNA) innovations on prices

	Raw CDS Rate Changes	Abnormal CDS Rate Changes	Raw Stock Returns	Abnormal Stock Returns
$\sum_{j=1}^{5} \phi_j$	0.003	0.060**	0.000	0.020
	(1.630)	(2.514)	(0.015)	(0.745)
$\sum_{j=1}^{5} \pi_j$	-0.006***	-0.069**	0.003**	0.055*
	(-3.103)	(-2.465)	(2.406)	(1.722)
$\sum_{j=1}^{5} \phi_j + \sum_{j=1}^{5} \pi_j$	-0.003	-0.009	0.003*	0.075*
	(-1.290)	(-0.245)	(1.832)	(1.802)

*The table presents the results of the estimation of equations (4) and (9) using Fama-MacBeth regressions in the span that ranges from October 2008 to January 2014. To start with, two dummy variables are created. The first (D_t^{UP}) assumes the value of one when the net open interest innovations are higher than one standard deviation and zero elsewise; the second (D_t^{DOWN}) assumes the value of one if the innovations are lower than minus one standard deviation and zero elsewise. The first dummy variable captures large positive open interest innovations, while the second captures large negative innovations. Then, I regress CDS rate changes (stock returns) against five lags of the dependent variable and five lags of each of the two dummy variables. To save space, I only report the cumulative effect of the lagged dummy variables ($\sum_{j=1}^{5} \phi_j$ and $\sum_{j=1}^{5} \pi_j$) and corresponding t-statistics, and not the estimated coefficients individually. To gauge whether there is symmetry in the effect of positive and negative innovations, I also test if $\sum_{j=1}^{5} \phi_j + \sum_{j=1}^{5} \pi_j = 0$. ***, ** and * denote one side statistical significance at the 0.1%, 1% and 5% levels, respectively. L(i) is the lag operator of order i. t-statistics in parenthesis.*

Communalities of open interest innovations and the predictive power over CDS rate changes

It is well known from the financial literature that the liquidity of financial instruments co-varies over time (see Chordia and Swaminathan 2000). Given that trading activity and liquidity are correlated amid firms, one may ask whether the open interest innovations of different borrowers are also correlated. To answer to that question, I investigate the communalities of open interest innovations for a sample of 277 obligors (those for which there is information for the entire time span).

The variance explained by the principal components is used to measure the size of the communalities of GNA innovations, NNA innovations and CDS rate changes. The first principal component of GNA innovations explains 72.2% of the variance of the series, whereas the first principal component of NNA innovations explains 26.6%. Indeed, the communalities of open interest innovations are higher for GNA than for NNA, which may be due to the fact that compression operations could be correlated amid the obligors. The communalities of CDS rate changes are also very high: the first principal component explains 47.5% of the variance of the CDS rate changes of the various obligors (see Table 5). To put into perspective, it appears that some kind of systematic factors drive GNA innovations, NNA innovations and CDS rate changes.

Table 5 – Variance explained by principal components

	PC	Proportion	Cumulative Proportion
GNA innovations	1	0.7218	0.7218
	2	0.0432	0.7650
NNA innovations	1	0.2660	0.2660
	2	0.0841	0.3501
	3	0.0638	0.4139
	4	0.0559	0.4698
	5	0.0466	0.5164
CDS Rate Changes	1	0.4752	0.4752
	2	0.0493	0.5245
	3	0.0240	0.5486
	4	0.0194	0.5679
	5	0.0185	0.5864

This table reports the variance explained by the principal components (PC) of the correlation matrix of weekly GNA innovations, NNA innovations and CDS rate changes. Note: Only the 277 reference entities that cover the entire time span of the analysis (from October 2008 to January 2014) are included.

Following these insights, it may be fruitful to disentangle the predictive power of open interest innovations into their idiosyncratic and systematic components. Using the average open interest (NNA) innovations across obligors in each period as a proxy for the systematic component of open interest innovations ($MKTinn_t$), the following equation is estimated:

$$r_t^{CDS} = \gamma_0 + \sum_{j=1}^{5} \gamma_j \times r_{t-j}^{CDS} + \sum_{j=1}^{5} \Psi_j \times \text{NNA}\, innovations_{t-j} + \sum_{j=1}^{5} \Theta_j \times MKTinn_{t-j} + \varepsilon_t \quad (5)$$

Table 6 reports the results of the estimation of equation (5) and shows that $MKTinn_t$ has predictive power over raw CDS rate changes.

As expected, the significance of NNA $innovations_t$ prevails after the inclusion of that variable, so that it continues to have predictive power over subsequent CDS rate changes. Without prejudice of that, $\sum_{j=1}^{5} \widehat{\Psi}_j$ is lower than $\sum_{j=1}^{5} \widehat{\Theta}_j$ (0.003 and 0.008, respectively) suggesting that a great portion of the predictability of open interest stems from the systematic component.

Table 6 – Systematic component of open interest innovations, CDS rate changes and stock returns

	Raw CDS Changes	Raw Stock Returns
L.NNA_innovations	0.001***	0.000
	(5.194)	(-1.217)
L2.NNA_innovations	0.000*	0.000
	(1.752)	(0.913)
L3.NNA_innovations	0.000	0.000**
	(0.048)	(-2.825)
L4.NNA_innovations	0.001***	0.000
	(3.262)	(-0.245)
L5.NNA_innovations	0.000	0.000
	(0.829)	(-1.037)
L.MKTinn	-0.016***	0.003***
	(-28.060)	(6.969)
L2.MKTinn	0.005***	-0.009***
	(9.091)	(-22.078)
L3.MKTinn	0.015***	-0.001**
	(28.798)	(-2.787)
L4.MKTinn	0.003***	-0.002***
	(4.747)	(-5.520)
L5.MKTinn	0.002**	-0.003***
	(2.752)	(-6.343)
$\sum_{j=1}^{5} \Psi_j$ [$\sum_{j=1}^{5} \emptyset_j$ in the case of stocks]	0.003***	-0.001*
	(5.105)	(-1.975)
$\sum_{j=1}^{5} \Theta_j$ [$\sum_{j=1}^{5} \vartheta_j$ in the case of stocks]	0.008***	-0.013***
	(5.843)	(-12.095)

The table reports the results of the estimation of equations (5) and (10) for the span that ranges from October 2008 to January 2014 by means of panel data regressions with clustered robust standard errors. To put it differently, I run a regression of raw CDS rate changes (stock returns) on five lags of net open interest innovations (NNA_innovations), five lags of the proxy of systematic net open interest changes (MKTinn), and five lags of the dependent variable. The proxy of systematic open interest changes is calculated as the average net open interest (NNA) innovations across obligors in each period. Due to space restrictions the results for other estimated coefficients aside from the open interest innovations (NNA_innovations) and the proxy of systematic open interest co-movement (MKTinn) are not tabulated. $\sum_{j=1}^{5} \Psi_j$ *and* $\sum_{j=1}^{5} \Theta_j$ ($\sum_{j=1}^{5} \emptyset_j$ *and* $\sum_{j=1}^{5} \vartheta_j$) *denote the accumulated effect of the five lags of net open interest innovations and of the five lags of systematic open interest changes, respectively on CDS rates (stock prices). ***, ** and * denote one-side statistical significance at the 0.1%, 1% and 5% levels, respectively. L(i) is the lag operator of order i. t-statistics in parenthesis.*

b. Open interest innovations and stock returns

This sub-section examines the predictive power of open interest innovations on subsequent stock returns. To that purpose, a procedure similar to that used in the previous sub-section is conducted. Here, however, open interest innovations are captured by the standardized residuals of a regression of open interest growth on past open interest growth, and concurrent and past stock returns and CDS rate changes.

$$\Delta V_t = \theta + \sum_{j=0}^{5} \delta_j \times r_{t-j}^{Stocks} + \sum_{j=1}^{5} \varphi_j \times \Delta V_{t-j} + \sum_{j=0}^{5} \alpha_j \times r_{t-j}^{CDS} + \tau_t \qquad (6)$$

with ΔV_t and r_t^{CDS} as previously defined; r_t^{Stocks} refers to the weekly stock returns on t. The underlying rational to include stock returns in the computation of these 'innovations' is that past stock returns may affect trading in CDS markets.[38] Further, past CDS rate changes are also included in the model specification because it is important to capture the incremental predictive power of CDS open interest beyond that already existing in CDS rate changes.

Using the residuals of (6) as a proxy for open interest innovations ($\hat{\tau}_t$), the following equation is estimated:

$$r_t^{Stocks} = \gamma_0 + \sum_{j=1}^{5} \gamma_j \times r_{t-j}^{Stocks} + \sum_{j=1}^{5} \emptyset_j \times innovations_{t-j} + \sum_{j=1}^{5} \omega_j \times r_{t-j}^{CDS} + \varepsilon_t \qquad (7)$$

Table 7, Panel A displays the average estimated coefficients of the time-series regressions and corresponding t-statistics with GNA innovations as the predictor. The results are tabulated for the full sample of obligors, and by the sector of the obligor (financial and non-financial firms). $\sum_{j=1}^{5} \widehat{\emptyset}_j$ is negative and significant, suggesting that positive (negative) GNA innovations precede negative (positive) raw stocks returns. The average R-squared of the time series regressions equals 10.1% for the full set of obligors, whereas the average adjusted-R-squared equals 2.2%. A closer look at the results also uncovers important differences between financial and non-financial firms: the predictive power exists for financial stocks, but not for non-financial stocks.

Unexpected NNA growth also precedes future raw stock returns. $\sum_{j=1}^{5} \widehat{\emptyset}_j$ is negative and significant, so that the variables move in opposite directions. In contrast with GNA innovations, the predictive power of NNA innovations is stronger for non-financial firms than for financial firms. The coefficients of the second and third lags are negative and statistically significant, while the first lag is not significant. Combining all these results, H2 is not rejected.

[38] When investors use CDS contracts to dynamically hedge their exposures in the stock market (as happens with capital structure arbitrageurs), stock price movements trigger portfolio rebalancing of CDS contracts.

Table 7 - Time series regressions of stock returns on open interest innovations

Panel A

Dependent Variable	Raw Stock Returns			Abnormal Stock Returns		
	All	Financial	Non-Financial	All	Financial	Non-Financial
L.GNA_innovations	0.001**	0.001	0.001**	0.000	-0.013	0.002
	(2.875)	(1.298)	(2.578)	(-0.112)	(-1.237)	(0.484)
L2.GNA_innovations	-0.002**	-0.004***	-0.002*	0.006	0.001	0.007
	(-2.916)	(-3.420)	(-2.050)	(0.749)	(0.080)	(0.747)
L3.GNA_innovations	0.000	-0.001	0.000	0.009**	-0.012	0.013***
	(0.658)	(-0.914)	(1.334)	(2.397)	(-1.273)	(3.251)
L4.GNA_innovations	0.000	-0.001*	0.000	-0.002	0.010	-0.005
	(0.099)	(-1.685)	(0.731)	(-0.490)	(1.020)	(-0.959)
L5.GNA_innovations	-0.001**	-0.002*	-0.001*	0.000	-0.001	0.000
	(-2.562)	(-2.009)	(-1.983)	(0.047)	(-0.076)	(0.093)
$\sum_{j=1}^{5}\hat{\emptyset}_j$	-0.002**	-0.006***	-0.001	0.013	-0.014	0.018
	(-2.546)	(-3.678)	(-1.060)	(1.259)	(-0.771)	(1.580)
Warner et al. (1988) procedure	-3.221***	-3.154***	-3.095***	2.631**	2.609**	2.637**
Average R2	10.1%	12.2%	9.7%	10.2%	12.5%	9.7%
Average Adj. R2	2.2%	3.8%	1.9%	2.3%	4.3%	1.9%

Panel B

Dependent Variable	Raw Stock Returns			Abnormal Stock Returns		
	All	Financial	Non-Financial	All	Financial	Non-Financial
L.NNA_innovations	0.000	0.000	0.000	0.003	-0.009	0.005
	(0.530)	(-0.378)	(0.892)	(0.737)	(-1.015)	(1.264)
L2.NNA_innovations	-0.001***	-0.001	-0.001***	0.010	0.020*	0.007
	(-3.991)	(-1.228)	(-4.051)	(1.612)	(2.202)	(1.081)
L3.NNA_innovations	-0.001**	-0.001	-0.001**	-0.007	-0.004	-0.007
	(-2.634)	(-0.848)	(-2.505)	(-1.132)	(-0.406)	(-1.060)
L4.NNA_innovations	0.000*	-0.001	0.000	0.006	0.001	0.007
	(-2.099)	(-1.611)	(-1.421)	(1.186)	(0.063)	(1.227)
L5.NNA_innovations	0.000	0.000	0.000*	0.004	0.017	0.001
	(-1.376)	(0.639)	(-2.029)	(0.612)	(1.506)	(0.166)
$\sum_{j=1}^{5}\hat{\emptyset}_j$	-0.003***	-0.003	-0.002**	0.015	0.025	0.013
	(-3.306)	(-1.493)	(-2.944)	(1.588)	(1.046)	(1.262)
Warner et al. (1988) procedure	-5.651***	-5.660***	-5.696***	1.242	1.248	1.141
Average R2	9.7%	11.6%	9.3%	9.9%	12.0%	9.4%
Average Adj. R2	1.7%	3.1%	1.5%	1.8%	3.9%	1.4%

*Panel A and B show the results of forecasting (raw and abnormal) stock returns in week t using five lags of open interest innovations (gross notional amount innovations [GNA_innovations] or net notional amount innovations [NNA_innovations] in Panel A and B, respectively). For each reference entity, I run predictive regressions of (raw and abnormal) stock returns on five lags of open interest innovations, five lags of CDS rate changes, and five lags of the dependent variable in the span that ranges from October 2008 to January 2014 (equation 7). The table reports results of cross-sectional averages of the estimated coefficients. Associated t-statistics for each average appear immediately beneath in parentheses. The results are reported for the full set of reference entities in the sample and for financial and non-financial firms separately. Due to space restrictions only the average coefficients of open interest innovations are tabulated. The R2s (Adj. R2) are cross-sectional averages of the R2 (Adj. R2) of the time-series regressions. The table also reports the cumulative effect of lagged open interest innovations on stock returns ($\sum_{j=1}^{5}\hat{\emptyset}_j$). Statistical inference is performed by averaging the estimated $\sum_{j=1}^{5}\hat{\emptyset}_j$ across entities and computing the corresponding standard error. As an alternative, Warner et al. (1988) procedure is also employed. The t-statistics of $\sum_{j=1}^{5}\hat{\emptyset}_j$ are summed across obligors and then divided by the square root of the number of obligors. The individual regression t-statistics are assumed to follow asymptotically a unit normal distribution. ***, ** and * denote one-side statistical significance at the 0.1%, 1% and 5% levels, respectively. L(i) is the lag operator of order i. t-statistics in parenthesis.*

The predictive power of open interest innovations on subsequent abnormal stock returns also merits attention. The idiosyncratic and the systematic components of returns are disentangled by means of the standard market model[39]:

$$r_{it}^{Stocks} = \alpha_i + \beta_i \times r_{mt} + \varepsilon_{i,t} \qquad (8)$$

where r_{mt} are the weekly market returns on t; and r_{it}^{Stocks} as previously defined. Two different proxies of market returns are used: the S&P500 index returns for U.S. companies and the DJ Eurostoxx 50[40] returns for European companies.

Table 7 - RHS details the results of the estimation of equation (7) with abnormal stock returns (residuals of equation (8)) as the dependent variable. Surprisingly, $\sum_{j=1}^{5}\widehat{\emptyset}_j$ becomes non-significant regardless of the proxy used to capture open interest innovations. These results elicit important questions. In effect, one may question whether the predictive power over stock prices stems from common information incorporated in open interest data rather than specific information. The robustness of the previous results is analyzed by means of alternative approaches. Table 8 tabulates the results using panel data models and Fama-MacBeth regressions. Even though the earlier conclusions are preserved when using panel data models, important changes emerge when using Fama-MacBeth regressions. Indeed, with the latter approach, the predictive power of (NNA and GNA) innovations on subsequent raw returns vanishes. As illustrated in Table 8, not only $\sum_{j=1}^{5}\widehat{\emptyset}_j$ loses significance, as the individual lags of open interest lack explanatory power.

Next, the presence of an asymmetric impact of positive and negative open interest innovations on stock returns is examined. Towards that end, the following equation is estimated:

$$r_t^{Stocks} = \gamma_0 + \sum_{j=1}^{5}\gamma_j \times r_{t-j}^{Stocks} + \sum_{j=1}^{5}\phi_j \times D_{t-j}^{UP} + \sum_{j=1}^{5}\pi_j \times D_{t-j}^{DOWN} + \sum_{j=1}^{5}\omega_j \times r_{t-j}^{CDS} + \varepsilon_t \qquad (9)$$

with r_t^{Stocks}, r_t^{CDS}, D_t^{UP} and D_t^{DOWN} as previously defined. Equation (9) is estimated using Fama-MacBeth regressions and Newey-West standard-errors - see Table 4 - RHS. The results of the regression of raw stock returns on lags of D^{UP} and D^{DOWN} indicate that while positive NNA innovations lack predictive power, negative innovations are significant. $\sum_{j=1}^{5}\hat{\pi}_j$ is positive, and therefore consistent with the notion that large decreases in open interest signal positive stock returns ahead. Further, the hypothesis that $\sum_{j=1}^{5}\phi_j + \sum_{j=1}^{5}\pi_j = 0$ is rejected, thereby corroborating the view that negative innovations take more time to be impounded into

[39] The analysis was also reproduced using Fama-French factors with no material changes in the conclusions.
[40] Although this index does not cover companies domiciled outside the EMU, it presents a very high correlation with other indexes in Europe, such as the FTSE 100, SMI, OMX and KFX.

prices than positive innovations. A possible interpretation of the results is that stock market investors pay less attention to negative innovations of open interest than to positive innovations, in accordance with the conventional wisdom that bad news flow faster than good news from credit markets to stock markets. These results hold when using abnormal stock returns as the dependent variable.

Table 8 – Panel data regressions of stock returns on open interest innovations

Panel A	Raw Stock Returns		Abnormal Stock Returns	
	Panel Data	Fama-MacBeth	Panel Data	Fama-MacBeth
L.GNA_innovations	0.001***/***	0.000	0.004	0.003
	(4.493/4.524)	(-0.237)	(1.236/1.239)	(0.420)
L2.GNA_innovations	-0.001***/***	0.000	0.000	0.004
	(-6.630/-6.667)	(1.430)	(-0.125/-0.125)	(0.633)
L3.GNA_innovations	0.000/	0.000	0.009**/**	0.007
	(0.687/0.689)	(0.446)	(2.786/2.785)	(1.141)
L4.GNA_innovations	0.000	0.000	0.000	0.003
	(-0.973/-0.982)	(0.066)	(-0.011/-0.011)	(0.558)
L5.GNA_innovations	-0.001***/***	0.000	0.005	0.001
	(-3.528/-3.521)	(-0.347)	(1.348/1.354)	(0.194)
$\sum_{j=1}^{5}\widehat{\emptyset}_j$	-0.001***/***	0.000	0.017**/**	0.019
	(-3.355/-3.411)	(0.459)	(2.407/2.433)	(1.331)
R2 Whithin	0.65%		0.07%	
R2 Overall	0.65%		0.07%	

Panel B	Raw Stock Returns		Abnormal Stock Returns	
	Panel Data	Fama-MacBeth	Panel Data	Fama-MacBeth
L.NNA_innovations	0.000	0.000	0.003	0.002
	(1.347/1.340)	(-0.077)	(0.978/0.975/)	(0.446)
L2.NNA_innovations	-0.001***/***	0.000	0.003	-0.002
	(-6.186/-6.222)	(-0.691)	(1.143/1.161)	(-0.392)
L3.NNA_innovations	-0.001***/***	0.000	-0.002	-0.002
	(-3.820/-3.851)	(-1.039)	(-0.802/-0.806)	(-0.600)
L4.NNA_innovations	0.000**/**	0.000	-0.002	0.004
	(-2.590/-2.572)	(0.617)	(-0.740/-0.749)	(1.121)
L5.NNA_innovations	0.000**/**	0.000	0.002	-0.002
	(-2.383/-2.376))	(-0.831)	(0.637/0.637)	(-0.404)
$\sum_{j=1}^{5}\theta_j$	-0.002***/***	0.000	0.004	0.000
	(-5.996/-6.048)	(-0.858)	(0.559/0.562)	(-0.010)
R2 Within	0.60%		0.06%	
R2 Overall	0.61%		0.06%	

Panel A and B present results of forecasting (raw and abnormal) stock returns in week t using five lags of open interest innovations (gross notional amount innovations [GNA_innovations] or net notional amount innovations [NNA_innovations] in Panel A and B, respectively). In doing so, a random effects panel data model and Fama-MacBeth regressions are estimated. Stock returns are regressed on five lags of open interest innovations, five lags of CDS rate changes, and five lags of the dependent variable in the span that ranges from October 2008 to January 2014 (equation 7). The table reports results for the estimated coefficients. Associated t-statistics appear immediately beneath in parentheses. Due to space restrictions only the coefficients (and corresponding t-statistics) of open interest innovations are tabulated. The table also reports the cumulative effect of lagged open interest innovations on stock returns ($\sum_{j=1}^{5}\widehat{\emptyset}_j$ *). In the case of the panel data models, clustered robust standard errors and clustered bootstrapped standard errors are used alternatively in the computation of the t-statistic. Fama-MacBeth t-statistics are corrected for autocorrelation using Newey-West standard-errors. ***, ** and * denote one-side statistical significance at the 0.1%, 1% and 5% levels, respectively. L(i) is the lag operator of order i. t-statistics in parenthesis.*

Communalities of open interest innovations and the predictive power over stock returns

As shown in sub-section 4.1, open interest innovations of different obligors co-vary over time. That gives rise to the hypothesis that the predictive power of open interest over raw returns may stem also from systematic information besides specific private information about the firm. To appraise that hypothesis, equation (10) is estimated:

$$r_t^{Stocks} = \gamma_0 + \sum_{j=1}^{5} \gamma_j \times r_{t-j}^{Stocks} + \sum_{j=1}^{5} \emptyset_j \times NNA\ innovations_{t-j} + \sum_{j=1}^{5} \omega_j \times r_{t-j}^{CDS} + \sum_{j=1}^{5} \vartheta_j \times MKTinn_{t-j} + \nu_t \qquad (10)$$

with $NNA\ innovations_t$, r_t^{Stocks} and r_t^{CDS} as previously defined, and $MKTinn_t$ denoting the average of NNA innovations across obligors at t. As shown in Table 6 (RHS), both $\sum_{j=1}^{5} \hat{\vartheta}_j$ and $\sum_{j=1}^{5} \hat{\emptyset}_j$ are negative and significant. $MKTinn_t$ appears to have information content on subsequent stock price movements. Likewise, $innovations_t$ continues to have predictive power, but it is clear that it decays with the introduction of $MKTinn_t$.

In short, the main conclusion of this sub-section is that open interest innovations help in predicting raw stock returns. However, contrarily to what was expected, that predictive power is not (solely) linked to idiosyncratic information conveyed in open interest data. Surprisingly, from the results of sub-sections 4.1 and 4.2 emerges the conclusion that CDS rates and stock prices may take up to five weeks to incorporate the incremental information content of CDS open interest. A lag of up to five weeks until volume information is fully reflected in CDS spreads appears, at a first glance, quite long. However, this time horizon is consistent with previous empirical findings in related studies: Hong and Yogo (2012) find that the information of open interest commodity futures might take several months until is fully impounded in the futures prices; Pan and Poteshman (2006) find that it takes several weeks for stock prices to adjust fully to the information embedded in option volume; and Fodor et al. (2011) find that the change in the call-to-put open interest ratio predicts equity returns over the following few weeks, even after controlling for traditional factors.[41] The next sub-section evaluates the open interest pattern and CDS rate dynamics prior to the disclosure of material information about the obligor in an effort to uncover the link between private information about the firm and open interest informativeness.

[41] There are also studies that report evidence that prices may take several weeks to impound information from past returns, including Menzly and Ozbas (2010), Hong et al. (2007), and Cohen and Frazzini (2008).

c. The pattern of open interest innovations prior to the disclosure of material information

To shed some additional light on whether open interest is driven by information asymmetry on the borrower's credit risk, I examine the pattern of open interest growth prior to the disclosure of material information and, after that, its relation with the abnormal performance of CDS contracts. Previous empirical research has shown that current earnings are a good predictor of future earnings (Finger 1994; Nissim and Penman 2001), future cash flows (Dechow et al. 1998; Barth et al. 2001) and stock performance (Dechow 1994). There is also evidence that stock and CDS prices react to earnings announcements (Chan et al. 1996; Zhang and Zhang 2013), in line with the idea that these events convey material information. As such, it is interesting to see how the open interest growth performs prior to earnings announcements, and whether it unveils private information. In doing so, I posit that there are signs of informed trading if the open interest systematically increases (decreases) prior to the disclosure of negative (positive) earnings surprises.

In order to measure the level of surprise associated to the quarterly earnings announcements, I compute the standardized unexpected earnings (SUE). This variable is calculated as in Chordia et al. (2009), Hou (2007) and Chan et al. (1996). This signifies that the firms' SUE is computed as the most recently announced quarterly earnings ($\mathrm{E_{iq}}$) minus the earnings four quarters earlier ($\mathrm{E_{iq-4}}$). That earnings difference is standardized by the standard deviation measured over the previous eight quarters (σ_{iq}).

$$\mathrm{SUE_{it}} = \frac{\mathrm{E_{iq}} - \mathrm{E_{iq-4}}}{\sigma_{\mathrm{iq}}} \tag{11}$$

I am interested in appraising whether the open interest growth prior to negative surprises diverges systematically from that of positive surprises and no surprises. Therefore, in a first pass, the open interest growth (and innovations) is summed for the four weeks prior to the disclosure (excluding the week of announcement). In parallel, the earnings announcements are grouped into three bins using two alternative methods. In the first method, group 1 (G1) encompasses the events wherein the SUE is less than minus one; group 3 (G3) comprises the events wherein the SUE is greater than one; and group 2 (G2) includes the remaining observations. In the second method, the sample of events is partitioned by the value of the SUE into three terciles. For each tercile of observations, a group is assigned. Therefore, G1* corresponds to the first tercile in terms of SUE, G2* corresponds to the second tercile, and G3* corresponds to the third tercile. The advantage of this alternative method to form the bins is that an equal number of observations are assigned to the three bins.

After the formation of the groups, the average and median (cumulative) NNA growth is calculated for each group of observations. The statistical inference is conducted by means of parametric and non-parametric tests. The average and median differences of the (cumulative) net notional amount growth between groups of observations are calculated. It should be noted that under the null hypothesis the average (median) difference between groups is zero, whereas under the alternative hypothesis a rise (decay) of open interest is expected to occur prior to a negative (positive) surprise.

The results are reported in Table 9, Panel A. I first test whether the mean of the cumulative NNA growth prior to the disclosure of negative earnings surprises (SUE lower than minus one) systematically exceeds that of positive earnings surprises (SUE greater than one). Under the null hypothesis the difference is zero, whereas under the alternative hypothesis the difference is positive. Looking at the t-statistic of the difference between the two means, it is apparent that the average of the NNA growth associated to G1 (negative surprises) exceeds that of G3 (positive surprises), in accordance with the conjecture that open interest conveys private information. In effect, both parametric (standard t-test and Satterthwaite-Welch t-test) and non-parametric tests (Wilcoxon/Mann-Whitney and Kruskal-Wallis) point towards the conclusion that open interest growth is higher prior to negative earnings surprises than to positive earnings surprises.

I also compare the difference of the average (and of the median) NNA growth of the observations that form G1 and G2, and G3 and G2. Indeed, both parametric and non-parametric tests reject the null hypothesis that the average (median) net notional amount growth is equal for bins G1 and G2. Nevertheless, that hypothesis is not rejected for bins G2 and G3. The results for the alternative method to form the bins are also tabulated in Table 9, Panel A (see column five). The alternative method used to form the bins does not produce changes in the results (the results of column three are virtually identical to those of column five).

For robustness check, the previous exercise is replicated using NNA innovations instead of raw NNA growth. The idea is to remove the influence of the effect of autocorrelation of open interest growth and of cross-autocorrelation with CDS spread changes and stock returns on the conclusions. While using the first method to form the bins of announcements, the results confirm that cumulative innovations of G1 are greater than cumulative innovations of G2. Yet, they do not confirm that the average (median) innovations of bins G1 and G3 are statistically different. Nevertheless, when using the second method to form the bins, the results for cumulative open interest innovations closely parallel those for cumulative raw open interest growth (using both the first and second methods to form the bins).

Table 9 – The pattern of open interest innovations and CDS rates prior to earnings announcements

Panel A

		Method 1		Method 2	
		Net notional amount growth	Net notional amount innovations	Net notional amount growth	Net notional amount innovations
G1 vs. G3	t-test	1.715*	1.532	2.106**	1.934*
	Satterthwaite-Welch t-test*	1.677*	1.514	2.109**	1.935*
	Wilcoxon/Mann-Whitney	1.751*	1.606	2.232**	1.868*
	Kruskal-Wallis	3.065*	2.579	4.982**	3.490*
G2 vs. G3	t-test	0.060	-0.173	-0.447	-0.152
	Satterthwaite-Welch t-test*	0.060	-0.174	-0.447	-0.152
	Wilcoxon/Mann-Whitney	0.126	0.246	0.299	0.544
	Kruskal-Wallis	0.016	0.060	0.089	0.296
G1 vs. G2	t-test	1.994**	1.938*	2.556**	2.124**
	Satterthwaite-Welch t-test*	1.843*	1.871*	2.556**	2.123**
	Wilcoxon/Mann-Whitney	1.849*	2.042**	2.508**	2.413**
	Kruskal-Wallis	3.420*	4.171**	6.290**	5.825**

The table traces out the pattern of net notional amount growth and net notional amount innovations prior to quarterly earnings announcements. First, the standardized unexpected earnings (SUE) associated to each earnings announcement is computed. The firms' SUE is computed as the most recently announced quarterly earnings minus the earnings four quarters earlier. That earnings difference is then standardized by the standard deviation measured over the previous eight quarters. Two methods are used to group earnings announcements into "good", "bad" and no surprises. In the first method, Group 1 (G1) encompasses the events wherein the SUE is less than minus one. Group 3 (G3) comprises the events wherein the SUE is greater than one. Group 2 (G2) includes the remaining observations. In the second method, the sample of events is partitioned by the value of their SUE into three terciles. For each tercile of observations, a group is assigned. Therefore, G1 corresponds to the bottom tercile in terms of SUE, G2 corresponds to the middle tercile, and G3 corresponds to the top tercile. Following that, I sum the net notional amount growth (innovations) over the four weeks prior to each event. Subsequently, the average and median of the cumulative net notional amount growth (innovations) is calculated for each group of observations. To perform statistical inference, I compare the mean and the median net notional amount growth (and net notional amount innovations) of the three groups of observations prior to the announcement. Two types of tests are run: parametric (t-test and Satterthwaite-Welch t-test) and non-parametric tests (Wilcoxon/Mann-Whitney and Kruskal-Wallis). The analysis is conducted for the span that ranges from October 2008 to January 2014.

Panel B

		Raw CDS rate	Abnormal CDS rate changes
Negative Surprise (G1)	Method 1	1.717*	2.387**
	Method 2	1.860*	2.231**
No Surprise (G2)	Method 1	-0.002	1.713*
	Method 2	-0.848	1.310
Positive Surprise (G3)	Method 1	-0.559	1.358
	Method 2	0.077	1.594

*The table presents the results of testing the hypothesis that cumulative (raw and abnormal) CDS rate changes in the three weeks prior to the earnings announcements are zero. The cumulative CDS rate changes of the events are weighted by the open interest change of the obligor in those three weeks prior to the earnings announcement. A numerical breakdown of the results by the type of surprise (G1, G2, and G3) and by the method of grouping the surprise is also provided to ascertain the robustness of the results. For simplicity, only the t-statistics (and corresponding level of significance) of the cumulative (raw and abnormal) CDS rate changes are presented. t-statistics are computed using the method of Boehmer et al. (1991). ***, ** and * denote two-side statistical significance at the 1%, 5% and 10% levels, respectively.*

Next, I investigate the reaction of CDS spreads near earnings announcements. If open interest conveys information surrounding these events, one should observe greater price dynamics for the events wherein the (absolute) open interest changes are greater. A sign of informed trading exists when open interest moves along with prices, conditional to the occurrence of a surprise. To check this hypothesis, I compute the raw and abnormal CDS rate changes in the three weeks prior to each earnings release. For the three groups of observations (G1, G2 and G3), the average cumulative (raw and abnormal) CDS rate changes is calculated. However, instead of computing an equally weighted average, I weight the relevance of the observations within the groups using the cumulative open interest change in the three weeks prior to the announcement. This signifies that a greater weight is assigned to the events in which changes in the open interest are larger.

$$\overline{\mathrm{CAR}}^{j} = \sum_{i=1}^{N} \mathrm{CAR_i} \times \mathrm{OI\ weight}_i \qquad (12)$$

where $\overline{\mathrm{CAR}}^{j}$ is the weighted average cumulative (raw or abnormal) CDS rate changes for group Gj (j=1, 2, 3); $\mathrm{CAR_i}$ is the cumulative (raw or abnormal) CDS rate changes associated with event i in the three weeks prior to the disclosure; and $\mathrm{OI\ weight}_i$ is computed as the ratio between the open interest change associated to event i and the total open interest change of group Gj (j=1, 2, 3)[42].

Table 9, Panel B shows the t-statistics of the average CAR associated with each group of observations. That t-statistic is computed using the method of Boehmer et al. (1991). The results are broken-down by the type of CDS rate change (raw or abnormal), and by the type of method utilized to group the observations into 'positive' and 'negative' surprises. In accordance with the earlier results, investing in CDS contracts with greater open interest changes prior to negative surprises would generate positive and significant (raw and abnormal) CDS rate changes. [43] Interestingly, this strategy would not yield abnormal performance prior to positive surprises, which means the information asymmetry is concentrated on negative information.

On balance, the results obtained above accord with the story that open interest growth systematically increases prior to "bad" news. Likewise, there is also evidence that spreads increase prior to negative announcements, consistent with the results of Zhang and Zhang (2013). To be more precise, greater open interest dynamics prior to negative announcements hint positive CDS spread movements. Both these results are consistent with the hypothesis that some informed investors anticipate the disclosure of negative material information taking positions in CDS contracts.

[42] Using open interest innovations to compute the weight instead of open interest changes does not alter the conclusions.

[43] Notice that using the current sample of negative earnings surprises, the unweighted average of abnormal CDS rate changes is not statistically significant.

d. The cross-section determinants of open interest predictive ability

It may be instructive to see whether the predictive power of open interest innovations is influenced by specific characteristics of the borrower or the liquidity of the CDS contracts. I start by focusing on four variables: the level of CDS rates (capturing the credit risk of the reference entity), CDS bid-ask spread (capturing the liquidity of the CDS contract), stock bid-ask spread (capturing the liquidity of the stock) and the ratio between the GNA and the firm's debt (proxing the investors' base of the contract). First, I rank the obligors according to the time series average value of each of the aforementioned variables. Then, the set of obligors is partitioned into terciles, so that three groups of obligors are formed for each of the variables. Here, the sample is restricted to non-financial firms on the grounds that the line of business and opaqueness of the banking sector makes a comparison with other sectors unreliable.

The time-series regressions with CDS rate changes, abnormal CDS rate changes, stocks returns and abnormal stock returns as dependent variables are again run for each obligor (equations (2) and (7)). After that, $\sum_{j=1}^{5} \widehat{\Psi}_j$ ($\sum_{j=1}^{5} \widehat{\emptyset}_j$ in the case of stock returns) is averaged for each bin of firms. The results are reported in Table 10.

A first striking result is that the predictive power of NNA innovations on subsequent raw CDS rate changes appears to be affected by the bid-ask spread of the contract. In effect, NNA innovations only have predictive power when the contract lacks liquidity. In the same vein, although the average of $\sum_{j=1}^{5} \widehat{\Psi}_j$ is positive and significant for the bottom and top subsamples in terms of the CDS rate and the GNA-to-debt ratio, it is higher for entities with lower credit risk and lower GNA-to-debt ratio. Notably, the conclusions are virtually the same when using abnormal rate changes as the dependent variable.[44]

The effect of characteristics and liquidity on the predictive power of open interest innovations over (raw and abnormal) stock returns is also evaluated. Although there is predictive power of NNA innovations on raw stock returns in the majority of the subsamples, the average of $\sum_{j=1}^{5} \widehat{\emptyset}_j$ is positive or non-significant in the various subsamples with abnormal stock returns as the dependent variable.

[44] The earlier procedure was reproduced using GNA innovations as the predictor, instead of NNA innovations. Non-tabulated results show that the predictive power of GNA innovations appears to be concentrated on the obligors with a lower ratio between GNA and debt.

Table 10 - Time series regressions of CDS rate changes and stocks returns on open interest innovations – results tabulated by firms' characteristics

	$\sum_{j=1}^{5}\widehat{\Psi}_j$				$\sum_{j=1}^{5}\widehat{\emptyset}_j$			
	CDS Raw Returns		CDS Abnormal Returns		Stocks Raw Returns		Stocks Abnormal Returns	
Subsample	1º T	3º T	1º T	3º T	1º T	3º T	1º T	3º T
CDS rate level	0.005***	0.002**	0.069*	0.018	-0.005*	-0.001*	0.023	0.020
CDS BAS	0.000	0.006***	-0.014	0.079**	-0.003	-0.004***	0.017	0.020
GNA-to-debt	0.005***	0.003***	0.078***	0.030*	-0.002*	-0.001	-0.003	0.010
Stock BAS	0.004**	0.002**	0.084**	0.004	-0.004*	-0.001*	0.018	0.016

*The table presents results of forecasting CDS rate changes (or stock returns) in week t using five lags of net notional amount innovations. For each reference entity, I run time series predictive regressions of CDS rate changes (or stock returns) on five lags of open interest innovations and five lags of the dependent variable in the span that ranges from October 2008 to January 2014. The table reports results of cross-sectional averages of the estimated coefficients, namely the average cumulative effect of lagged open interest innovations on CDS rate changes ($\widehat{\sum_{j=1}^{5}\Psi_j}$) and on stock returns ($\sum_{j=1}^{5}\widehat{\emptyset}_j$). Associated t-statistics for each average appear immediately beneath in parentheses. Several subsamples are analyzed separately. Specifically, the results are reported for the bottom and top terciles of firms in terms of stock and CDS bid-ask spread (BAS), CDS spread, and GNA-to-debt ratio. Statistical inference is performed by averaging the estimated $\sum_{j=1}^{5}\widehat{\Psi}_j$ and $\sum_{j=1}^{5}\widehat{\emptyset}_j$ for each bin and computing the corresponding standard error. ***, ** and * denote one-side statistical significance at the 0.1%, 1% and 5% levels, respectively. 1º T (3º T) – denotes the first (third) tercile of firms according to a characteristic.*

In short, the characteristics of firms and CDS contracts seem to affect the information content of past open interest data. To improve our knowledge on the cross-section determinants of the predictive ability, interaction variables are introduced in the regressions using the whole sample of obligors. The interaction of five variables with open interest innovations is examined: the level of CDS spread of the borrower ($\mathrm{CDS\_price}$), the percentage bid-ask spread of the 5-year CDS contracts (BAS), the level of the gross notional amount outstanding (Gna), the debt-to-market capitalization ratio ($\mathrm{D/E}$)[45], and the gross notional amount-to-debt ratio ($\mathrm{Gna\_debt}$). These variables aim to capture the default risk of the borrower ($\mathrm{CDS\_price}$ and $\mathrm{D/E}$), the liquidity of the CDS contract (BAS), and the level of notoriety of the borrower in the CDS markets ($\mathrm{Gna\_debt}$ and Gna).

A lower predictive power is expected for obligors with higher credit risk, on the grounds that creditors and CDS traders pay more attention to riskier obligors than to others borrowers. The idea is that since new information induces larger price movements on riskier obligors than others, investors have incentives to put more effort in monitoring the open interest dynamics of the formers. As a result, these contracts may assimilate the information faster. Open interest may also have higher predictive power for obligors with larger transaction costs, measured by bid-ask spreads. First, larger transaction costs lessen the ability to take advantage from the information content of open interest innovations. Second, contracts on obligors with lower transactions costs are likely to exhibit greater attention from investors, whereby the incremental information content

[45] In the case of D/E, the sample is restricted to non-financial firms.

of open interest may be lower, with prices adjusting to new information faster. Finally, the higher the number of investors exposed to the risk of an obligor, the lower the time to impound open interest innovations on CDS rates. Therefore, contracts with greater open interest or greater open interest-to-debt ratio should incorporate the information content of open interest faster into the CDS rates.

To see whether the credit risk of the borrower, the bid-ask spread of the contract or the gross maximum exposure of market participants to the obligor's credit risk influence the open interest informativeness, I add the aforementioned interaction variables (interaction_var) into the predictive regressions.

$$r_t^{CDS} = \gamma_0 + \sum_{j=1}^{5} \gamma_j \times r_{t-j}^{CDS} + \sum_{j=1}^{5} (\varphi_j + \emptyset_j \times \text{interaction\_var}_{t-j}) \times NNA\ innovations_{t-j} + \varepsilon_t \quad \text{(13a)}$$

$$r_t^{Stock} = \gamma_0 + \sum_{j=1}^{5} \gamma_j \times r_{t-j}^{CDS} + \sum_{j=1}^{5} \propto_j \times r_{t-j}^{Stock} + \sum_{j=1}^{5} (\varphi_j + \emptyset_j \times \text{interaction\_var}_{t-j}) \times \text{NNA}\, innovations_{t-j} + \varepsilon_t \quad \text{(13b)}$$

Equations (13a) and (13b) are estimated by means of Fama-MacBeth regressions. Table 11, Panel A details the effect of the various interaction variables in the predictive power of open interest innovations on raw CDS rates. When the interaction between CDS rates and open interest innovations is introduced in the main equation, $\sum_{\mathrm{j}=1}^{5} \widehat{\emptyset}_{\mathrm{j}}$ is negative and significant, so that the predictive power of innovations decays with the credit risk of the obligors. In contrast, the level of $\mathrm{D/E}$ and Gna_debt of the borrower do not seem to influence the informativess of NNA innovations, since the interaction of these variables with NNA innovations lacks predictive power. Importantly, in the case of BAS, $\sum_{\mathrm{j}=1}^{5} \widehat{\emptyset}_{\mathrm{j}}$ is positive and significant, whereas $\sum_{\mathrm{j}=1}^{5} \hat{\varphi}_{\mathrm{j}}$ lacks significance. It is also interesting to see that the main results are preserved with abnormal CDS rate changes as the dependent variable.

A similar procedure is conducted to gauge whether the characteristics affect the incremental informativeness of open interest on stock prices. A result that caught my attention is that the incremental information of past innovations on stock prices appears to be unrelated to the level of the credit risk of the borrower when measured by the CDS rate level. This conclusion applies to the equations that have stock returns and abnormal stock returns as the dependent variable. In contrast, the bid-ask spread of the CDS contracts seems to affect the informativeness of open interest innovations, such that the open interest from contracts that lack liquidity manifest lower ability to predict raw stock returns. It is also curious that the ability of innovations to predict (raw and abnormal) stock returns increases with the level of gross notional amount outstanding and with the level of credit risk measured by the D/E.

Table 11 – Cross-section determinants of the predictive ability of net open interest innovations on stock and CDS returns

Panel A	CDS rate changes		Abnormal CDS rate changes	
	$\sum_{j=1}^{5}\varphi_j$	$\sum_{j=1}^{5}\emptyset_j$	$\sum_{j=1}^{5}\varphi_j$	$\sum_{j=1}^{5}\emptyset_j$
CDS_price	5,921***	-2,411***	6,447***	-3,174***
BAS	-0,160	2,124**	-0,335	2,446***
Gna	2,733***	0,951	2,610***	1,238
D/E	3,695***	-0,918	3,835***	-1,421
Gna_debt	3,196***	-0,640	3,115***	-0,207

Panel B	Stock returns		Abnormal stock returns	
	$\sum_{j=1}^{5}\varphi_j$	$\sum_{j=1}^{5}\emptyset_j$	$\sum_{j=1}^{5}\varphi_j$	$\sum_{j=1}^{5}\emptyset_j$
CDS_price	0,430	-1,262	0,596	-1,289
BAS	-1,709*	1,685*	-0,873	0,983
Gna	1,396	-2,397**	1,618	-2,147**
D/E	0,886	-1,827*	1,501	-2,001**
Gna_debt	0,228	-0,232	1,865*	-1,488

*Panel A presents results of forecasting (raw and abnormal) CDS rate changes in week t using five lags of open interest innovations (net notional amount innovations) and five lags of an interaction variable (equation 13a). In doing so, Fama-MacBeth regressions are estimated using the span that ranges from October 2008 to January 2014. The interaction variable results from the multiplication of the net notional amount innovations with one of the following variables: CDS rate, CDS percentage bid-ask spread (BAS), gross notional amount (GNA), debt-to-equity ratio (D/E), and gross notional amount-to-debt ratio (Gna_debt). The table reports results for the t-statistics of the average sum of coefficients associated to the five lags of open interest innovations ($\sum_{j=1}^{5}\hat{\varphi}_j$) and for the t-statistics of the average sum of coefficients associated to the five lags of the interaction variable ($\sum_{j=1}^{5}\hat{\emptyset}_j$). Fama-MacBeth t-statistics are corrected for autocorrelation using Newey-West standard-errors. Panel B reproduces the procedure used in Panel A for (raw and abnormal) stock returns (equation 13b). ***, ** and * denote one-side statistical significance at the 0.1%, 1% and 5% levels, respectively.*

On balance, these findings suggest that the incremental information of open interest on future CDS spreads increases with the illiquidity of the CDS contracts and decays with the level of credit risk of the borrower. This evidence accords with the idea that CDS market players pay less attention to the open interest dynamics of safer obligors and illiquid contracts, whereby the information content of the open interest of those obligors takes more time to be impounded into rates. Likewise, it may also be that transaction costs unable investors from taking advantage from the knowledge gathered from the open interest dynamics. Regarding the incremental predictive power of open interest on stock prices, it is driven by other factors than those that affect the predictability of CDS rates. In particular, it is higher for entities with larger positions outstanding, i.e., the ones for which the production of information in the CDS market should be higher. A possible justification resides in the market segmentation between credit markets and stock markets or other institutional frictions that deter stock prices from timely adjusting to relevant information contained in the open interest dynamics.

e. Open interest and market returns

The findings from the previous sub-sections suggest that the predictive power of CDS open interest does not derive exclusively from specific information on the obligors. For instance, the predictive power of open interest innovations decays strongly when forecasting abnormal stock returns instead of raw stock returns. On the top of that, there is also evidence that the communalities of open interest innovations forecast future returns.

To gain a further insight on whether open interest data conveys systematic information, this sub-section investigates the predictive power of aggregate gross notional amount (GNA) growth of single-reference CDS contracts on the returns of three different indexes: the S&P 500, the Markit iTraxx Europe and the Iboxx Investment-grade Liquid Bonds[46]. To ensure the robustness of the conclusions, two types of tests are conducted: in-sample (IS) tests and out-of-sample (OOS) tests. The in-sample tests are based on the following predictive regression:

$$r_t^{Index} = \delta_0 + \sum_{j=1}^{\mathrm{U}} \gamma_j \times r_{t-j}^{index} + \sum_{j=1}^{\mathrm{H}} \theta_j \times \Delta V_{t-j}^{CDS} + \varepsilon_t \qquad (14)$$

where r_t^{Index} denotes the weekly return of the index and ΔV_t^{CDS} corresponds to the weekly growth of the aggregate open interest on single-reference entities. The predictive ability of ΔV_t^{CDS} is assessed by evaluating the significance of $\theta_j, \forall \mathrm{j} = 1, \dots, \mathrm{H}$ and the goodness-of-fit measure R-squared. Under the null hypothesis of non-predictability, $\theta_j = 0, \forall \mathrm{j} = 1, \dots, \mathrm{H}$. To remove the effect of autocorrelation on statistical inference, Newey and West (1987) standard errors are calculated. U and H are selected according to the AIC and BIC of the regressions, and may differ with the dependent variable under analysis.

Looking at Table 12, Panel A, the Iboxx Investment-grade Liquid Bonds is the index with a higher degree of predictability. The in-sample R-squared is 7.5%, and the adjusted R-squared equals 4.6%. The level of predictability of open interest growth only dies out after three or four weeks. With respect to the Markit iTraxx Europe, the in-sample R-squared equals 2.2%. The second lag of open interest growth has a positive and significant coefficient. Finally, the results also confirm the predictive power of open interest growth over the returns of the S&P500. The in-sample R-squared equals 1.2%. The second lag of open interest growth has a negative and statistically significant coefficient at a 10% level.

[46] The choice of the Iboxx Investment-grade Liquid Bonds is related to the fact that earlier results suggested that the predictive ability of open interest is greater amid investment-grade bonds.

Table 12 - Time series regressions of stocks, bonds and CDS indices returns with gross notional amount growth as the predictor

Panel A

	Iboxx Investment-Grade Liquid Bonds	ITraxx European Corporate	S&P 500
const	0.001**	-0.002	0.003*
	(2.121)	(-0.544)	(1.895)
L1. OI	0.029		
	(0.741)		
L2. OI	-0.012	0.574**	-0.167*
	(-0.431)	(2.106)	(-1.774)
L3. OI	-0.097***		
	(-2.662)		
L4. OI	-0.087***		
	(-2.679)		
L1. (Dep. Variable)	-0.103	-0.100*	-0.072
	(-1.311)	(-1.755)	(-1.394)
L2. (Dep. Variable)	0.124**	0.025	
	(2.086)	(0.386)	
L3. (Dep. Variable)	0.149		
	(1.574)		
L4. (Dep. Variable)	0.042		
	(0.652)		
R-squared	7.5%	2.2%	1.2%
Adjusted R-squared	4.6%	1.1%	0.5%
θ_j=0, ∀ j=1,.., H			
F-test	2.86**	4.44**	3.19*
Robust Wald test	11.46**	4.43**	3.15*
Bootstrap LR test p-value	3.70%	8.80%	15.60%

Panel B

		Adjusted Critical Value					
		1%	5%	10%	90%	95%	99%
Iboxx Investment-grade Liquid Bonds	L1.OI	-2.928	-2.127	-1.743	1.791	2.168	2.928
	L2.OI	-2.910	-2.130	-1.781	1.793	2.158	2.923
	L3.OI	-2.897	-2.164	-1.773	1.782	2.124	2.778
	L4.OI	-2.943	-2.108	-1.740	1.777	2.181	2.946
ITraxx European Corporate	L2. OI	-2.815	-2.083	-1.719	1.773	2.090	2.878
S&P 500	L2. OI	-2.906	-2.138	-1.783	1.744	2.111	2.826

*Panel A reports the estimates of time series predictive regressions of index returns on lags of the growth of aggregate gross notional amount (OI) of single-reference entities (see equation (14)). The dependent variables are the returns of three different indices: the Iboxx Investment-Grade Liquid Bonds, the ITraxx European Corporate Index and the S&P 500. The analysis is conducted using weekly data and the span that ranges from October 2008 to January 2014. The table reports the estimated coefficients. The associated t-statistics appear immediately beneath in parentheses, and are corrected using Newey-West standard-errors. The results of three additional tests are also presented in the table: a bootstrap LR test, a standard F-test and a Wald test calculated using the Newey-West covariance matrix. These three tests examine the null hypothesis that the growth of aggregate gross notional amount of single-reference entities has no predictive power over the indices returns. Panel B presents simulated Newey-West t-statistics under the hypothesis of non-predictability for various levels of significance. It aims to assess size distortions when using Newey-West standard errors and provide an alternative way of performing statistical inference taking into account the finite-sample properties of the estimator. ***, ** and * denote two-side statistical significance at the 1%, 5% and 10% levels, respectively. L(i) is the lag operator of order i.*

Several authors have demonstrated that standard t-statistics based on asymptotic theory can have poor finite sample properties or lead to severe small sample biases. The biases are larger when predictors are persistent and their innovations are highly correlated with the variable being predicted (see Nelson and Kim 1993; and Stambaugh 1999). Cavanagh et al. (1995) show that the standard t-test for predictability has an incorrect size, while Ang and Bekaert (2007) show that there are substantial size distortions with Newey-West t-statistics when forecasting stock returns with persistent predictors.

Motivated by these considerations, two additional exercises are performed. The first exercise follows Li and Yu (2012), and it is based on a Monte Carlo study to investigate whether Newey–West t-statistics are affected by size distortions. In doing so, I simulate pseudo-series of returns and open interest growth under the null hypothesis that open interest does not convey information on subsequent returns. Then, I re-estimate the predictive regression using these pseudo-series and construct a density function for Newey–West t-statistics. The Appendix A presents a detailed description of the procedure employed to run this exercise.

The simulated critical values of Newey-West t-statistics are presented in Table 12 – Panel B. Using adjusted critical values instead of asymptotic critical values does not produce significant changes in the conclusions. In the case of the Iboxx Investment-grade Liquid Bonds, the third and fourth lags of the predictor stay significant at a 5% significance level. In the cases of the Markit iTraxx Europe and the S&P500, the conclusions are virtually identical.

The second exercise follows Goyal and Welch (2008) and consists in computing a bootstrapped LR-statistics to gauge the in-sample significance of open interest growth. Annex B describes the procedure employed to carry out this test. Table 12, Panel A presents the results of this bootstrap LR test, along with a standard F-test and a Wald test that impose the null hypothesis of no predictability ($\theta_j = 0, \forall \mathrm{j} = 1, \ldots, \mathrm{H}$). The latter test is robust, in the sense that the Newey-West covariance matrix is considered to compute the Wald statistics. The three tests confirm the ability of open interest growth to predict the subsequent returns of the Iboxx Investment-grade Liquid Bonds and the Markit iTraxx Europe indices. There is no loss of significance when using the bootstrap LR test for the equation with the Iboxx Investment-grade Liquid Bonds returns as the dependent variable. In the case of the returns of the Markit iTraxx Europe index, the null hypothesis is rejected at 5% significance level under the standard F-test and the Wald test, and at a 10% significance level under the bootstrap LR test. In contrast, there is a loss of significance when using the bootstrap LR test for S&P500 returns.

The out-of-sample (OOS, hereinafter) accuracy of the predictive regression is also examined. Goyal and Welch (2003, 2008) and Butler et al. (2005) emphasize that predictive regressions of stock market returns have often performed poorly out-of-sample. Goyal and Welch

(2008) compare predictive regressions with historical average returns and find that the latter almost always produce superior return forecasts. OOS accuracy is not only important for the diagnosis of IS regressions, it is interesting to an investor who had used these models for timing the market. If the model is stable and well-specified, IS inference is preferable to OOS inference in evaluating the quality of the model (Inoue and Kilian 2005; and Clark and McCracken 2001). OOS inference is particularly important when discrete structural breaks exist (Chen 2005), or when the parameters change over time, thereby complementing the results obtained through IS inference.

Herein, the out-of-sample accuracy of the model is examined by means of recursive and rolling window schemes, and one-step-ahead forecasts (where the parameter vector is updated at each step forecast). An important methodological issue concerns the partition of the sample into in-sample (R) and out-of-sample (P) observations. In effect, two different partitions of the sample are used, one where P/R equals 1, and another where it equals 1/2.[47]

Equation (14) is estimated using the two alternative schemes of data partition. In parallel, one-step-ahead forecasts are performed utilizing recursive and rolling windows. After that, I compute the out-of-sample R-squared (OOS-R2). To conduct statistical inference, three alternative tests are employed: Clark and West test, $MSE - F$ test and $ENC - NEW$. For the sake of brevity, the procedures employed to run these tests and to calculate the OOS-R2 are not presented in the main body of the article. Nonetheless, interested readers may consult Appendix C to obtain further information on how to perform these tests.

All the aforementioned tests confirm the out-of-sample predictive ability of open interest growth on the returns of the Iboxx Investment-grade Liquid Bonds. The OOS-R2 equals 4.60% when conducting rolling regressions and when P/R equals 1 (see Table 13). Notably, elevating the number of IS observations (R) seems to increase the OOS-R2. This preliminary insight that open interest growth has predictive power over bond market returns is reinforced by the results of the Clark and West test, and the bootstrapped tests of MSE-F and ENC-NEW. All these tests point towards the rejection of the null hypothesis that open interest growth does not add predictive power to the restricted model. When using recursive regressions, the earlier conclusions survive in spite of the minor loss of significance in some of the tests.

The results also suggest that open interest growth has predictive power over Markit iTraxx Europe returns. The OOS-R2 increases with the number of in-sample observations (it equals

[47] As stressed by Clark and McCracken (2011), the literature is largely silent on the best way to determine the number of in-sample and out-of-sample observations. More out-of-sample observations (larger P) increase the amount of information to evaluate the accuracy of the forecasts. However, more in-sample observations (larger R) bring about more accuracy in the estimation of the coefficients, and probably conduct to more accurate forecasts.

4.88% and 4.17% when P/R equals 0.5, and when rolling regressions and recursive regressions are conducted, respectively). The Clark and West test and the bootstrapped tests of MSE-F and ENC-NEW also confirm the predictive power of open interest growth when P/R equals 0.5. When using a smaller number of in-sample observations, the OOS-R2 and the significance of the results fall, particularly when rolling regressions are used. That elicits an important issue: the reduction of the number of in-sample observations raises the estimation error, and diminishes the quality of the prediction.

Table 13 – Out-of-sample forecast accuracy

		P/R=100 % Rol. Reg.	P/R=100 % Rec. Reg.	P/R=50% Rol. Reg.	P/R=50% Rec. Reg
Iboxx Investment-Grade Liquid Bonds	Clark-West	2.685***	2.773***	2.255**	2.248**
	MSE-F	6.565***	6.200***	4.549**	2.513*
	ENC-NEW	7.298***	8.082***	5.220***	5.759***
	OUS-R2	4.60%	4.36%	4.76%	2.69%
ITraxx European Corporate	Clark-West	1.847**	2.410***	2.550***	3.016***
	MSE-F	1.008	2.616**	4.666***	3.963***
	ENC-NEW	1.587*	2.050*	3.466***	2.923**
	OUS-R2	0.74%	1.89%	4.88%	4.17%
S&P 500	Clark-West	1.268	1.556*	1.421*	1.474*
	MSE-F	-0.336	1.173*	3.458**	2.672**
	ENC-NEW	2.478**	2.137**	6.193***	3.926***
	OUS-R2	-0.25%	0.86%	3.66%	2.85%

*The table presents the results of out-of-sample accuracy tests to infer the predictive power of open interest growth on the returns of three different indices: the Iboxx Investment-Grade Liquid Bonds, the ITraxx European Corporate Index and the S&P 500. The analysis is conducted using weekly data and the span that ranges from October 2008 to January 2014. The results of four statistics are presented: OOS-R2, Clark-West test, MSE-F and ENC-NEW. The results are partitioned by the estimation scheme (rolling and recursive estimation scheme) and by the initial sample partition between in-sample and out-of-sample observations (P/R=100% and P/R=50%, where R is the in-sample number of observations and P is the out-of-sample number of observations). ***, ** and * denote one-side statistical significance at the 1%, 5% and 10%, respectively. Rol. Reg. –Rolling Regression; Rec. Reg. – Recursive Regression.*

Finally, the predictive power of open interest growth on the subsequent returns of the S&P500 is analyzed. Here, different tests drive to mixed conclusions. The OOS-R2 is positive in three of the regressions (it is positive apart from the rolling window estimation case where P/R equals 100%). The Clark and West test also rejects (at a 10% significance level) the null hypothesis in three of the regressions. Notably, this latter test and the bootstrapped MSE-F and ENC-NEW tests lead to qualitatively similar conclusions. To sum up, while some tests indicate the existence of predictive power of open interest growth over stock returns, others suggest the contrary. The results are influenced by the number of observations included in the in-sample (and out-of-sample), so that more in-sample observations contribute to better estimates and better forecast accuracy.

5. Conclusions

This paper represents one of the few attempts to analyze the informational content of CDS open interest data. Three major conclusions stand out from the analysis. First, CDS open interest growth has predictive power on CDS rate changes and stock returns ahead. As CDS open interest conveys information not readily impounded into stock prices, it can be concluded that CDS markets are an important venue for informed trading. Second, the predictive power of open interest on CDS rates increases with the illiquidity of the contract and falls with the credit risk of the reference entity, in accordance with the idea that it is partially fueled by investors' inattention and market frictions. There is also evidence that the predictive power of open interest on stock prices increases with the gross notional amount of the contract, a rough measure of traders' attention and information production in CDS markets. Third, the informativeness of open interest is related to both common and specific information. On the one hand, the open interest upsurges together with CDS rates before the disclosure of negative earnings surprises, in that high open interest growth triggers significant CDS rate changes. These results lend support to the idea that open interest conveys material information about a firm. On the other hand, I find that the aggregate open interest growth of single-reference contracts has predictive power over bonds, CDS and stock market returns, i.e. it conveys common information.

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Annex

Annex A -Size distortion in predictive regressions: a Monte Carlo study

To gauge whether the statistical inference of predictive regressions is well-specified, I conduct a Monte Carlo study. This study aims to investigate whether Newey–West t-statistics are affected by size distortions. To that end, the following VAR model is simulated:

$$r_t^{Index} = \delta_0 + \sum_{j=1}^{\mathrm{U}} \gamma_j \times r_{t-j}^{index} + \varepsilon_t \qquad \text{(A1)}$$

$$\Delta V_t = \theta + \sum_{j=1}^{\mathrm{L}} \varphi_j \times \Delta V_{t-j} + \epsilon_t \qquad \text{(A2)}$$

where r_t^{Index} and ΔV_t are the return of the index and the open interest growth on week t. The VAR model imposes the null hypothesis of no-predictability. To obtain the values of the parameters to initiate the simulation, (A1) and (A2) are estimated by OLS. The number of lag orders U and L are determined by the AIC of the regressions. The covariance matrix of the joint disturbance vector $(\varepsilon_t, \epsilon_t)$ is computed from the residuals of the estimation $(\hat{\varepsilon}_t, \hat{\epsilon}_t)$ and the error terms are assumed to be jointly normal. After estimating (A1) and (A2), OLS estimates are corrected using the Shaman and Stine (1988) bias-correction method.

10.000 pseudo-series, each with T+25 observations are simulated. For each time series, the first 5 observations are set equal to the original sample. Later, I drop the 25 start-up observations in order to randomize the first five observations used to initiate the simulation. For each combination of pseudo-series, the following regression is run and the corresponding Newey-West t-statistics are saved.

$$\tilde{r}_t^{Index} = \delta_0 + \sum_{j=1}^{\mathrm{U}} \gamma_j \times \tilde{r}_{t-j}^{index} + \sum_{j=1}^{\mathrm{F}} \theta_j \times \widetilde{\Delta V}_{t-j}^{CDS} + \varepsilon_t \qquad \text{(A3)}$$

where $\tilde{r}_t^{Index}$ and $\widetilde{\Delta V}_{t-j}^{CDS}$ correspond to pseudo-values of the series of returns of the index and open interest growth, respectively, under the null hypothesis. This procedure provides the distribution of the Newey-West t-statistics and corresponding adjusted critical values.

Annex B - A bootstrap simulation LR-based test

I follow Mark (1995), Kilian (1999) and Clark and McCracken (2011), and implement a bootstrap approach to ascertain the predictive power of open interest growth on the subsequent returns of bond, stock and CDS indices. To start with, (A1) and (A2) are estimated by OLS using all the available data. U and L are determined using the AIC of the regressions. Recall that (A1) imposes the null that open interest growth has no predictive power over the indices returns. The estimated coefficients and the residuals of the equations are saved $(\hat{\varepsilon}_t, \hat{\epsilon}_t)$.

Next, 10,000 bootstrapped time series are generated (with T+25 observations each) by drawing the residuals with replacement and using the autoregressive structures of the VAR equations to iteratively construct data. For each pseudo-time series, the first 5 observations are set equal to the original sample. The initial 25 observations are then dropped in order to randomize the first five observations used to initiate the simulation. It should be realized that the OLS residuals are drawn in tandem, in order to preserve the correlation between the disturbances in the original sample and the autocorrelation structure of the predictor. For each bootstrap replication, the restricted and unrestricted models [(A1) and (A3)] are estimated, and the corresponding LR statistics stored.

This procedure is run for the 10,000 pseudo-series allowing reproduction of the density function of the LR-statistics under the null hypothesis of no predictability, and to obtain the corresponding critical values for that statistic. Critical values are calculated as percentiles of the bootstrapped LR test statistics.

Annex C – OOS accuracy and the predictive power of open interest growth

The R^2_{OOS} is calculated as follows:

$$R^2_{OOS} = 1 - \frac{MSE_1}{MSE_0} \qquad \text{(C1)}$$

where MSE_1 and MSE_0 are the mean squared error of the unrestricted (equation 14) and restricted models (imposing $\theta_j = 0,\ j = 1, ..$ H), respectively. If R^2_{OOS} is positive, then the unrestricted predictive regression has lower mean squared forecast error than the restricted predictive regression, whereby the predictive ability of the extra-variables (lags of open interest growth) is important. The statistical inference is conducted by means of three different tests: Clark and West test, $MSE - F$ test and $ENC - NEW$. Clark and West test is run as follows:

$$CW = P^{1/2} \times \frac{P^{-1} \times \overline{d^*}}{\hat{\sigma}_{CW}(m)} \qquad \text{(C2)}$$

where $\hat{u}_{0,t}$ and $\hat{u}_{1,t}$ are the one-step-ahead forecast errors of the restricted and unrestricted models, respectively; $\overline{d^*} = \frac{1}{P} \times \sum_t^P d_t^*$, $d_t^* = \hat{u}_{0,t}^2 - \hat{u}_{1,t}^2 + (\hat{y}_{0,t} - \hat{y}_{1,t})^2$; $\hat{\sigma}_{DM}(m)$ is the non-parametric estimator of the long run variance of d_t^*; P is the number of out-of-sample observations; and finally, $\hat{y}_{1,t}$ and $\hat{y}_{0,t}$ are the one-step-ahead forecasts of the unrestricted and restricted models, respectively. The $MSE - F$ test and $ENC - NEW$ are calculated using the following expressions:

$$MSE - F = P \times \frac{P^{-1} \times \sum_t^P \hat{u}_{0,t+1}^2 - \hat{u}_{1,t+1}^2}{P^{-1} \times \sum_t^P \hat{u}_{1,t+1}^2} \qquad \text{(C3)}$$

$$ENC - NEW = P \times \frac{P^{-1} \times \sum_t^P \hat{u}_{0,t+1}^2 - \hat{u}_{1,t+1} \times \hat{u}_{0,t+1}}{P^{-1} \times \sum_t^P \hat{u}_{1,t+1}^2} \qquad \text{(C4)}$$

where $\bar{c} = P^{-1} \times \sum_t^P \hat{c}_{t+1}$ and $c_{t+1} = \hat{u}_{0,t+1}^2 - \hat{u}_{1,t+1} \times \hat{u}_{0,t+1}$. Statistical inference for $MSE - F$ and $ENC - NEW$ is conducted by means of bootstrapping techniques. In effect, equation (A3) is estimated from the pseudo-series computed beforehand (bootstrapped residuals of the VAR models under the null hypothesis) using recursive and rolling window schemes, and after that, the one-step ahead forecasts are saved. The procedure is employed for each of the 10,000 pairs of pseudo-series, from which the density function of $MSE - F$ and $ENC - NEW$ is computed (see Rapach and Wohar 2006; and West 2006 for further details).

Chapter 4

The EU Ban on Uncovered Sovereign Credit Default Swaps – Assessing Impacts on Liquidity, Volatility and Price Discovery (*)

Abstract

This paper addresses the effects of the prohibition of naked CDS buying implemented by the European Union (EU) in November 2012. Three aspects of market quality are analyzed: liquidity, volatility and price informativeness. Overall, our results suggest that the ban produced negative effects on liquidity and price informativeness. First, we find that while bid-ask spreads rose after the ban for contracts in the scope of the EU regulation, they fell for other countries outside its bounds. Open interest declined for both groups of sovereign reference names, but significantly more in the constraint group. Price delay increased more prominently for countries affected by the ban, whereas price precision decreased in these countries while increasing for CDS written on other sovereign references. Most notably, our findings indicate that these negative effects were more pronounced amid reference entities exhibiting lower credit risk. With respect to volatility, the evidence suggests that the ban was successful in stabilizing the CDS market in that volatility decreased, particularly for contracts written on riskier CDS names.

JEL Classification: G01, G12

Keywords: Credit Default Swaps, Uncovered CDS Buying, Volatility, Liquidity, Price Discovery

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Not yet fully recovered from the 2007-08 financial crisis, several peripheral countries in the Eurozone were hit by a severe sovereign debt crisis in 2010. High fiscal deficits and a growing debt-to-GDP ratio reduced investor confidence in Greece, Ireland, Italy, Portugal and Spain, and led to a series of downgrades by rating agencies. The bond yields and credit default swap (CDS) spreads based on euro-denominated government bonds soared in that period, threatening the Eurozone's overall financial system and its economy. At the same time, speculation through sovereign CDS, i.e. naked CDS buying operations betting on a contingent government default, was blamed for artificially driving Eurozone countries' sovereign borrowing costs upwards. The controversy surrounding the role of CDS during that crisis led Europe's policy makers to ban trading of "naked" sovereign CDS (i.e. buying CDS without holding the underlying sovereign debt).

First, in May 2010, the German financial regulator BaFin implemented a temporary prohibition of naked short sales of euro-denominated government bonds, naked CDS written on those bonds, and naked short-selling on stocks of Germany's ten leading financial institutions, with the objective of stabilizing the Eurozone sovereign debt market. Later, in November 2012, the European Union (EU) enforced a permanent ban on naked CDS protection buying. The EU ban reflects a delayed effort of coordination amongst its members. In fact, although the financial crisis prompted worldwide emergency measures restricting the practice of short selling, in the EU the lack of common rules to deal with these matters led to the adoption of heterogeneous procedures by the various national regulators. For the European Commission, such fragmentation of regulatory regimes was detrimental to the effectiveness of financial supervision in general, and of the measures imposed at the height of the crisis in particular (European Commission, [2010]).

The EU Regulation 236/2012 on Short Selling and Certain Aspects of Credit Default Swaps became applicable in the European Economic Area, comprising the 28 EU member states plus Iceland, Liechtenstein and Norway. One of the objectives of this ban was the reduction of certain risks, in particular those of negative price spirals for sovereign debt and of settlement failures caused by uncovered CDS buying (International Monetary Fund [2013]). While the proponents of these measures claim that banning speculation against borrowers, whether through CDS or outright short bond positions, promotes financial stability (e.g., Portes [2010]), others (such as Duffie [2010]) argue that regulations that severely restrict CDS speculation could have the unintended consequences of reducing the underlying market liquidity (raising trading execution costs for investors who are not speculating) and lowering the quality of information provided by CDS rates regarding the credit quality of bond issuers.

In this paper we assess some effects of EU regulation 236/2012 on CDS market quality. The impact of the EU prohibition on uncovered sovereign buying is relevant for several reasons.

Previous research showed that the CDS market is not redundant. It plays a leading role in the price discovery of credit risk of both corporate (Blanco et al. [2005]) and sovereign bonds (Ammer and Cai [2011]), and may contribute to reducing the liquidity component of bonds' (and other loans') credit spreads (Ashcraft and Santos [2009]). The model developed by Salomao [2014] suggests that, in equilibrium, markets for sovereign CDS reduce financing costs by increasing the default costs internalized by borrowers and thus incentivizing more efficient investment plans.

Sovereign CDS also expand investors' opportunity sets. For instance, while acting as a macro hedging device (a la Shiller [1998]), they provide protection against systematic risk. Furthermore, by improving risk sharing, reducing hedge adverse selection costs, and encouraging investors' information seeking, the CDS market increases the liquidity and price informativeness of the underlying bonds. Consistent with this view, Ismailescu and Phillips [2015] conclude that sovereign CDS initiation enhances market completeness and improves price efficiency in the underlying market, reducing risk premiums, particularly for investment-grade sovereigns. Therefore, restricting naked CDS buying may reduce the incentives of market players to produce new information about sovereign obligors and, ultimately, contribute to raising sovereign borrowing costs due to information uncertainty, adverse selection and higher illiquidity premiums, with the obvious negative consequences for tax-payers, social welfare and financial markets' stability.

Previous research on short selling constraints in the context of stock markets suggests that they lead to declines in markets' liquidity and efficiency, with evidence also pointing to an increase in the asymmetry of price adjustments (with stock prices responding more slowly to negative than to positive news). Research on the impact of such restrictions on the CDS market is still scarce. However, while there are reasons to anticipate similar qualitative effects to those identified in stock markets, at least two distinctive characteristics of the CDS market may suggest otherwise. First, CDS contracts are traded over-the-counter and their quotation system is fragmented, with only a few dealers providing quotes. Will the ban reduce liquidity in a context where net buying interest is almost entirely driven by hedging motives and adverse selection will presumably fall? Second, institutional investors, typically better informed and more sophisticated than retail ones, are the only players in CDS transactions. Additionally, CDS traders (along with bond traders) seem to pay more attention to downside risk than stock market investors do. Will the fact that CDS traders are more prone to identifying market downturns and overpriced securities reduce the impact of the ban on the process of price discovery?

In this study we assess the impacts of a permanent ban on naked CDS on the overall CDS market's quality. Closely related studies are Pu and Zhang [2012], Sambalaibat [2014], and Capponi and Larsson [2014]. Pu and Zhang [2012] investigate the 2010 temporary ban applied in

Germany, concluding that the sovereign CDS market's liquidity declined in peripheral EU countries (Greece, Ireland, Italy, Portugal and Spain) and that the ban has helped to stabilize the sovereign CDS market by reducing CDS volatility. Not least importantly, they show that the rise of CDS rates in these more risky EU members continued after the ban, in line with the view that the ban would not stop soaring borrowing costs in those countries.

Sambalaibat [2014] provides evidence suggesting that permanent and temporary bans on naked sovereign CDS trading may have contrasting impacts: while the EU permanent ban reduced bond markets' liquidity, Germany's 2010 temporary ban improved it. Additionally, a model developed by Capponi and Larsson [2014] anticipates that, provided that CDS speculators are risk averse and take positions that are small in comparison to the amount of outstanding debt, a ban on naked CDS trading will have a negligible impact on borrowing costs, albeit reducing sovereign debtors' borrowing capacities.

We investigate the impact of EU Regulation 236/2012 on Short Selling and Certain Aspects of Credit Default Swaps on CDS market quality, examining effects on liquidity, liquidity risk, volatility, delay in the incorporation of information, and price precision. We compare the patterns of these variables for the countries affected by the regulation, before and after its implementation and, to generate counterfactual and mitigate confounding effects, we contrast evidence for countries affected by the ban (treatment group) with that of countries outside the scope of the regulation (control group). In some cases, we also distinguish the countries by groups of risk, to verify whether the effects are greater for those with the highest CDS spreads. At a first stage, we compare the trends of the variables using mean and median tests. At a second stage, the effects of the ban are evaluated using two-way fixed effects panel data models. To reinforce the robustness of the analysis, we also evaluate the effects of the ban on some of the variables of interest with a random effects panel data model with control variables that capture unobserved factors related to changes in funding costs, systematic risk, risk aversion and other financial factors.

Overall, our results suggest that there was a decline in liquidity (and an increase of liquidity risk) after enforcement of the ban. In sharp contrast with the control group, EU obligors faced an increase of bid-ask spreads and liquidity risk. A fall in the amount of net notional open interest also occurred in the two groups, but the decline was more pronounced for EU obligors. Notably, the effects of the ban on liquidity and open interest are more pronounced for countries with higher creditworthiness than for countries in distress.

In line with Pu and Zhang [2012], our estimates indicate that the ban had negative impacts on volatility and on the frequency of extreme positive CDS rate changes, and thus that one of the ban's objectives (helping to stabilize the CDS market) was attained. The analysis of countries by groups of risk indicates that these effects are stronger for sovereigns with a higher level of credit risk.

In spite of its merits in reducing CDS market volatility, from the perspectives of price precision and delay in the assimilation of information, we find that the ban had a detrimental impact on market quality. In fact, although both the treatment and control group countries experienced, on average, an increment in price delay, the deferral in information assimilation was more pronounced for treatment group countries. Surprisingly, and in contrast with research on stock markets, we found no evidence of greater price delays for negative news.

It is also noteworthy that while price precision (measured by the variance ratio) declined after the ban's implementation in the treatment group, it increased for the countries outside the scope of the ban. A further inspection revealed that the ban had a greater impact on delay and price precision measures for sovereigns exhibiting lower credit risk. Overall, our results suggest the ban impacted the market quality of CDS written on sovereigns within its scope, in ways that cannot be explained by third factors that also affected outside countries.

To strengthen the robustness of our results, we carried out complementary tests controlling for the existence of a prior temporary ban in Germany, applied by BaFin in 2010, and for the fact that there was a lengthy period separating the European Commission's approval of Regulation 236/2012, in November 2011, and its enforcement in November 2012. This gap may have led market participants to anticipate the ban's effects long before its implementation. However, and in general, our main results are unchanged by these complementary tests.

The study is organized as follows: the next section develops the hypotheses to be tested; section three describes the variables employed in the empirical analysis and the data sources; section four outlines the empirical methods; section five analyses the effects of the ban on the sovereign CDS market's liquidity, volatility and price discovery; section six concludes, summarizing the main results and discussing their implications.

1. Hypotheses Development

Previous theoretical research suggests that short-sale restrictions in the stock market may hinder price discovery, especially in the event of negative news (Diamond and Verrecchia [1987]); lead to price inflation, by excluding the views of pessimistic investors who do not own the stock (Miller [1977]; Harrison and Kreps [1978]; and Duffie et al. [2002]); contribute to market crashes, following the accumulation of unrevealed negative information (Hong and Stein [2003]); and increase the information risk of uninformed market participants, due to the lower informative content of market prices (Bai et al. [2007]).

The empirical literature has shown that selling constraints reduce stock price efficiency (e.g., Saffi and Sigurdsson [2011]; Boehmer and Wu [2013]; Beber and Pagano [2013]; and Bris et al. [2007]), decrease market quality, by leading to larger spreads, higher price impacts, and augmented intraday volatility (Boehmer et al. [2013]), and cause liquidity disruptions, particularly for small-cap stocks (Beber and Pagano [2013]).

Following the results of the literature investigating the impact of short-sale constraints in the stock market, we ask whether EU Regulation 236/2012 on Short Selling and Certain Aspects of Credit Default Swaps is likely to produce similar effects on the liquidity, volatility, and price informativeness of the sovereign CDS market. Our first hypothesis concerns the effects on liquidity of the ban on CDS naked protection buying. According to Diamond and Verrecchia [1987], a ban on short-selling that is equally restrictive for informed and uninformed traders will raise information uncertainty about fundamentals which, in turn, will impact positively on the bid-ask spread. In line with this, Tang and Yan [2013] conjecture that banning naked CDS buying may both reduce net CDS buying interest and jeopardize the processes of information production and dissemination, thus reducing market liquidity and efficiency.

Nevertheless, as discussed by Beber and Pagano [2013], Diamond and Verrecchia's [1987] prediction rests on the hypothesis that the ban equally constrains informed and uninformed investors. However, if potential short-sellers have superior information and market-makers are relatively uninformed, a short-selling ban should reduce the component of the bid-ask spread associated with information asymmetry, thereby enhancing liquidity. This means that the effect of the ban on CDS naked protection buying on liquidity may rest on the levels of information held by major dealers and by end-users potentially engaging in this type of operation.

Furthermore, if the ban succeeds in reducing CDS rate volatility, major dealers' inventory costs will also decline, reducing bid-ask spreads. Therefore, whether the impact of CDS naked protection buying on liquidity is positive or negative is ultimately an empirical question.

H1: The ban on CDS naked protection buying does not impact liquidity and liquidity risk.

In addition to the effect on liquidity, enforcement of the new regulation may also impact volatility and tail risk of CDS returns, thereby having a role in stabilizing or destabilizing the market. With respect to the stock market, Boehmer et al. [2013] provide empirical evidence of increased intraday volatility following the 2008 short-selling ban in the US. Within the context of CDS, Pu and Zhang [2012] show that Germany's 2010 temporary ban on sovereign CDS reduced CDS volatility and helped to stabilize the market.

In a different vein, Hong and Stein [2003] demonstrate that the coexistence of dispersion of opinions and short-sales constraints deters bad news from being assimilated by stock prices and, as mentioned above, may increase the risk of market crashes (resulting from the build-up of undisclosed negative information). Abreu and Brunnermeier [2002, 2003] and Scheinkman and Xiong [2003] relate the existence of bubbles and excessive volatility with short sales restrictions. A plausible implication of a ban on naked protection buying is that the frequency of extremely positive returns may increase, and the skewness of returns may become more positive.

Motivated by the previous considerations, we examine the impact of the ban on CDS volatility, kurtosis, skewness and frequency of extremely positive returns:

H2: The ban on CDS naked protection buying does not affect volatility and tail risk of CDS returns.

The effect of the ban on CDS price informativeness is also assessed. Most theoretical developments on the stock market anticipate that short-selling constraints hamper price formation. For instance, Diamond and Verrecchia [1987] predict that short-sale restrictions may deter the assimilation of negative information by stock prices. These effects should be more pronounced if short sellers play a key role in the price discovery process. Theoretical models by Miller [1977], Harrison and Kreps [1978] and Duffie et al. [2002] suggest that short-sale restrictions produce price inflation, particularly when the dispersion of beliefs is wide. Contrasting views may be found in Goldstein and Guembel [2008] and Brunnermeier and Pedersen [2005], for whom short sellers' manipulative and predatory trading strategies result in less informative prices or price reversals.

Empirical analyses of the stock market have also produced mixed results. On the one hand, there is evidence that overpricing is reduced when short-selling operations are allowed (e.g., Danielsen and Sorescu [2001], Jones and Lamont [2002], Cohen et al. [2007] and Harris et al. [2013]) and that short-sellers are informed investors (Asquith et al. [2005], Desai et al. [2002] and Boehmer et al. [2008]). Beber and Pagano [2013] show that the bans imposed between 2007 and 2009 in a set of 30 countries reduced liquidity and slowed down the process of price discovery. On the other hand, Shkilko et al. [2012] document downward pressure on prices, even in the absence of negative information. We examine the following hypothesis in the context of the CDS market:

H3: The ban on CDS naked protection buying does not affect the assimilation of (negative) news by CDS spreads.

In the next section, we present the sample, the data sources and the variables utilized in the empirical analysis.

2. Data Sources and Variables Description

The study is developed using daily data from Bloomberg on CDS (bid, ask and mid-quotes), benchmark bond yields (bid, ask and mid-quotes) and swap rates. Data for the basis of CDS contracts was provided by Thomson Reuters. The DTCC website was the source for data on open interest (number of transactions, and gross and net notional amounts). The latter are available solely on a weekly frequency.

Data regarding control variables were also retrieved from Bloomberg. These variables are included to capture dealers' inventory costs, funding costs, counterparty risk, financial intermediaries' capacity to provide market liquidity and investor sentiment:

- the VIX index, frequently referred to as the "investor fear gauge", and used as a proxy for market sentiment and investors' risk aversion (see, for instance, Tang and Yan [2013]), represents the market's expectation of 30-day volatility and is based on the implied volatilities (of both calls and puts) of a wide range of S&P 500 index options. Market volatility affects dealers' capacity to supply market liquidity due to capital bindings and risk management restrictions;
- the stock market performance (S&P500) is included as a control variable to measure capital constraints faced by financial intermediaries. As Adrian and Shin [2010] show, asset price changes impact financial intermediaries' net worth. Therefore, assets' devaluation may prompt adjustment of the size of balance sheets and reduction of inventory. As stock market returns are an advanced proxy for changes in the net worth of financial intermediaries, it is also plausible that they capture the capital constraints of major dealers which are mainly US financial institutions (Chen et al. [2011]);
- the spread between repo rates having Mortgage Backed Securities (MBS) and Treasuries as collateral (following Gârleanu and Pedersen [2011], who used the

spread of the rates of uncollateralized and collateralized loans as a proxy for funding costs) is utilized as a proxy for funding costs. In periods of distress, financial intermediaries prefer Treasuries rather than MBS, as collateral, because the latter are riskier and display lower liquidity. As a result, the spread between the two repos (Repo spread) becomes wider during periods of turmoil (when funding risk is higher);

- counterparty risk is calculated as the average of CDS spreads for the 14 major dealers participating in the CDS market. A dry-up of liquidity is expected if counterparty risk increases;
- the difference between the rates of one-month top commercial paper and one-month US LIBOR captures risk aversion in money markets. This measure also proxies flight-to-quality or search-for-yield effects that may affect demand and supply of CDS contracts. In fact, market liquidity tends to dry up when markets are turbulent (see Brunnermeier and Pedersen [2009] on funding liquidity risk).

These control variables are based on US indicators for the following reasons: first, the fact that major CDS dealers are domiciled in the US, or have a strong relationship with the US markets; second, previous empirical research established a relationship between global and US risk factors and sovereign CDS spreads; third, the fact that US risk factors determine the inventory risk of major dealers, and hence the path in liquidity provision and price discovery.

Longstaff et al. [2011] uncover a link between sovereign credit risk dynamics and global factors (a single principal component explaining more than 50 percent of the variation in sovereign credit spreads). Moreover, they show that sovereign credit spreads are more related to US stock and high-yield markets than to local economic measures. Hilscher and Nosbusch [2010] also conclude that global factors are relevant in explaining sovereign spreads, particularly the VIX index which positively affects sovereign credit spreads. However, Augustin [2014] concludes that both global risk factors and country-specific fundamentals are important sources of sovereign credit risk.

Pan and Singleton [2008] find communalities in the risk premiums of Korea, Mexico, and Turkey, and show that they are cyclically related to the CBOE VIX option volatility index, the spread between the 10-year return on US BB-rated industrial corporate bonds and the 6-month US Treasury bill rate, and the volatility implied by currency options. Antón et al. [2013] find that dealer commonalities in quotes across countries are relevant for CDS spreads' changes.

The data sample covers CDS contracts on sovereign entities divided into two groups. A set including EU countries plus Iceland, Liechtenstein and Norway, designated as treatment group (these are the contracts under the scope of the ban), and a control group, encompassing sovereigns that are not under the influence of the ban. The list of reference entities is presented in Exhibit 1.

Exhibit 1: List of the reference entities included in the analysis

Treatment Group Country Name	Control Group Country Name
Czech Republic	Arab Republic of Egypt
Federal Republic of Germany	Argentine Republic
French Republic	Bolivarian Republic of Venezuela
Hellenic Republic	Canada
Hungary	Commonwealth of Australia
Kingdom of Belgium	Commonwealth of Puerto Rico
Kingdom of Denmark	Democratic Socialist Republic of Sri Lanka
Kingdom of Norway	Dominican Republic International Bond
Kingdom of Spain	Emirate of Abu Dhabi United Arab Emirates
Kingdom of Sweden	Emirate of Dubai United Arab Emirates
Kingdom of the Netherlands	Federal Republic of Nigeria
Portuguese Republic	Federation of Malaysia
Republic of Austria	Federative Republic of Brazil
Republic of Bulgaria	Hong Kong Special Administrative Region
Republic of Cyprus	Islamic Republic of Pakistan
Republic of Estonia	Japan
Republic of Finland	Kingdom of Bahrain
Republic of Iceland	Kingdom of Morocco
Republic of Ireland	Kingdom of Saudi Arabia
Republic of Italy	Kingdom of Thailand
Republic of Latvia	Lebanese Republic
Republic of Lithuania	New Zealand
Republic of Malta	Oriental Republic of Uruguay
Republic of Poland	People's Democratic Republic of Algeria
Republic of Slovenia	People's Republic of China
Romania	Republic of Chile
Slovak Republic	Republic of Colombia
United Kingdom of Great Britain and Northern Ireland	Republic of Costa Rica
	Republic of Ecuador
	Republic of El Salvador
	Republic of Ghana
	Republic of Guatemala
	Republic of India
	Republic of Indonesia
	Republic of Iraq
	Republic of Kazakhstan
	Republic of Korea
	Republic of Panama
	Republic of Peru
	Republic of Serbia
	Republic of Singapore
	Republic of South Africa
	Republic of Tajikistan
	Republic of the Fiji Islands
	Republic of the Philippines
	Republic of Turkey
	Socialist Republic of Vietnam
	State of Israel
	State of Kuwait
	State of Qatar
	Swiss Confederation
	Tunisian Republic
	Ukraine
	United Mexican States
	United States of America
	Russian Federation

This exhibit lists the CDS names covered in the analysis. Two groups of reference entities are formed to distinguish those under the scope of the ban (treatment group) from the remaining ones (control group).

The analysis covers the period between January 1, 2008 and December 31, 2015. The focus is on 3, 5, 7 and 10-year tenors, the ones presenting higher liquidity and visibility from the investors' perspective, as confirmed by Chen et al. [2011], who report that trading is concentrated on the 5-year tenor (representing 43% of the trading amongst single-name CDS), followed by the 3, 7 and 10-year tenors.

The sequence of events between the approval of the ban and its enforcement is relevant for our analysis. On October 18, 2011, the European Council and the European Parliament agreed on the proposed Regulation on Short Selling and Credit Default Swaps, which was subsequently voted by the European Parliament on November 16, 2011. It was published in the Official Journal in March 2012, but only became applicable on November 1, 2012. Taking this timeline into account, the sample is first divided into two subsets: the period between January 1, 2008 and October 31, 2012; and the treatment or enforcement period covering the time frame between November 1, 2012 and December 31, 2015. The treatment period covers the phase in which market players were legally forced to adopt a new conduct concerning sovereign CDS contracts written on obligors from the EU, Iceland, Liechtenstein and Norway. Later, as a robustness test and on the grounds that some market participants may have anticipated the effects of the ban and changed their behavior accordingly, we also check whether including the phase between the ban's approval and enforcement in the treatment period affects our conclusion.

3. Methodology

In order to assess the effects of the ban on liquidity, volatility and price efficiency, we examine whether the implementation of EU Regulation 236/2012 on Short Selling and Certain Aspects of Credit Default Swaps triggered changes in the pattern of our variables of interest, comparing results for reference entities under the scope of the ban with those obtained for entities outside its bound.

In a first stage, we use parametric and non-parametric tests to ascertain whether, after the ban, the change in the variables' average and median is similar for both groups. The main sample is divided in two partitions: one encompassing data for the period from January 01, 2008 to October 31, 2012; the other with data from November 01, 2012 to December 31, 2015. Subsequently, we compute the changes of each representative variable from the first to the second period, and aggregate (average and median) the results by group of reference names. To measure the effect of the ban, a t-test (corrected for unequal variances) and the Wilcoxon signed rank test are performed.

Although this is quite a straightforward procedure, it still presents some caveats. For instance, the sample is not balanced. For some countries, CDS trading initiation took place after January 01, 2008, while others left the sample before December 31, 2015 (e.g., Greece and Argentina, due to the existence of a default). In addition, this approach does not allow for the consideration of additional controls, such as global risk factors and investor sentiment, which may influence the conclusions.

To tackle both problems, we employ regression analysis. Specifically, we estimate the following models:

$$\mathrm{Y}_{i,t} = \alpha + \theta \times \mathrm{ENFORCEMENT}_t + \varphi \times \mathrm{ENFORCEMENT}_t \times BAN_i + \varepsilon_{i,t} \quad (1)$$

$$\mathrm{D.Y}_{i,t} = \alpha + \emptyset \times \mathrm{ENFORCEMENT}_t \times BAN_i + \sum_{k=1}^{5} \gamma_k \times CONTROL_{k,t} + \epsilon_{i,t} \quad (2)$$

where, $\mathrm{Y}_{i,t}$ stands for the representative dependent variable of interest for CDS contract i in period t; BAN_i is a dummy variable taking the value of one when the obligor is subject to the ban and zero if this is not the case; $\mathrm{ENFORCEMENT}_t$ is a dummy variable taking the value of one in the enforcement period (i.e., between November 01, 2012 and December 31, 2015); $CONTROL_{k,t}$ corresponds to control variable k at time t; and D is the differential operator.

With respect to equation (1), we follow the empirical model setup of Boehmer et al. [2008]. In doing so, we alternatively employ fixed effects for each contract, and fixed effects for each contract together with calendar effects. Coefficient φ represents the incremental change of the representative variable attributable to the ban's implementation. It allows the comparison of the representative variable's pattern for countries under the scope of the ban with the pattern it would display had the ban not been introduced. The pattern of the control group replicates the treatment group's expected behavior in the absence of the ban, thus allowing identification of the ban's marginal effect on the representative variable using the cross-section of entities, i.e., comparing the patterns of countries within and outside the scope of the ban, at the same moment, and across time, by contrasting trends before and after implementation of the ban.

To strengthen our conclusions, we also measure the effect of the ban using the alternative model specification (2) for certain representative variables. First, the baseline model is differenced. In addition, we also introduce a set of control variables in the baseline model, namely, changes in the VIX index, the stock market performance, changes in the spread between repo rates having MBS and Treasuries as collateral, changes in counterparty risk of major CDS dealers, and changes in the difference between the rates of one-month top commercial paper and one-month US LIBOR. These control variables aim to capture relevant changes in dealers' inventory risk, CDS market congestion associated with dealers' counterparty risk, changes in funding costs and changes in risk aversion that may have influenced the path of the dependent variables.

Equation (2) is estimated using GLS random effects for each contract, corrected for clustered robust standard errors as in Saffi and Sigurdsson [2011]. The scheme below summarizes the alternative model specifications.

Equation	Fixed/ Random Effects	Standard Errors	Control Variables
(1)	Cross-section (id) fixed effects	Clustered robust s. e. by id and Driscoll-Kraay [1998] s. e.	No
(1)	Cross-section (id) and time fixed effects	Clustered robust s. e. by id and time	No
(2)	GLS random effects	Clustered robust s. e.	Yes

4. Empirical Results

Effects of the ban on liquidity

We begin the assessment with examination of H1, i.e., measuring the impact of the ban on the liquidity of the CDS market. Liquidity is not directly observable and encompasses dimensions such as price impact, depth, immediacy and resilience of prices. The bid-ask spread is a measure of transaction costs and is commonly used as a liquidity indicator in the financial literature. The bid-ask spread is defined as the percentage difference between ask and bid rates, although it may also be calculated as an absolute spread.

The first row of Exhibit 2 reports average values for bid-ask spreads. For each contract (considering all contract tenors: 3, 5, 7 and 10-years and reference names), we first average the values of bid-ask spreads for the full sample period, and afterwards separately for the periods preceding and following implementation of the ban. Then, we average data according to the status of the CDS reference name with regard to the ban. When the full sample is considered, the bid-ask spread equals 12.1% and 7.4% for CDS names covered by the ban and for CDS names of the control group, respectively.

A first striking result is that, after the ban, the bid-ask spread of treatment group names and control group names evolved in opposite directions: while the average bid-ask spread of treatment group names climbed 5.8 percentage points, the average bid-ask spread of control group names dropped 1.1 percentage points. The average difference of the bid-ask spread change in the two groups equals 7.0% and is statistically significant under a standard t-test assuming unequal variances. Likewise, the median difference of the bid-ask spread change in the two groups equals 3.7% and is statistically significant with the Wilcoxon/Mann-Whitney non-parametric test.

Exhibit 2: Descriptive statistics for different proxies of liquidity, volatility and price informativeness

	Control Group			Treatment Group			Average diff. in variation for treatment and control group contracts	Median diff. in variation for treatment and control group contracts
	Before Ban [1]	After Ban [2]	Full Period [3]	Before Ban [4]	After Ban [5]	Full Period [6]	[7]	[8]
BAS (%)	7.9	6.8	7.4	9.1	14.9	12.1	7.0***	3.7***
Liquidity Risk (%)	1.6	1.0	1.4	1.7	3.0	2.4	1.9***	0.9***
Net Notional Amount (% change)	-0.1	-0.2	-0.1	-0.1	-0.4	-0.2	-0.3	-0.3**
Volatility (%)	4.9	2.9	4.0	3.8	2.9	3.3	1.0	-0.3**
Vol.$^-$ (%)	3.5	2.0	2.8	2.5	1.9	2.2	0.9	-0.2*
Vol.$^+$ (%)	3.1	1.9	2.6	2.7	2.0	2.3	0.6	-0.3**
Kurtosis	6.35	5.86	6.15	5.94	5.22	5.57	-0.22	-0.44
Skew	0.03	0.13	0.07	0.10	0.18	0.14	-0.02	-0.02
% of positive extreme obs.	3.3	1.6	2.6	2.9	2.2	2.6	1.0	-0.8**
% of positive extreme obs.	3.6	1.9	2.9	3.4	2.6	3.0	0.8	-0.4
SR	-0.98	-1.29	-1.11	-0.52	-2.17	-1.38	-1.33***	-0.96***
SR$^+$	-1.96	-2.12	-2.03	-1.36	-2.02	-1.71	-0.51**	-0.32**
SR$^-$	-1.68	-1.97	-1.80	-1.30	-2.68	-2.01	-1.08***	-1.10***
D1	0.27	0.33	0.30	0.17	0.45	0.31	0.22***	0.16***
D1$^+$	0.26	0.32	0.28	0.17	0.44	0.31	0.21***	0.14***
D1$^-$	0.25	0.31	0.27	0.16	0.45	0.30	0.24**	0.20***
|VR-1| (%)	52.5	30.3	43.0	20.2	39.6	30.3	41.5**	10.9***
Q (%)	86.4	83.5	85.3	90.9	76.8	86.0	-11.2	-3.3
Basis	-16.7	61.4	19.8	51.4	-0.7	30.4	-130.15**	-42.48***
D2	0.324	0.357	0.340	0.311	0.378	0.341	0.03	0.04
D2$^+$	0.327	0.305	0.317	0.300	0.390	0.340	0.11*	0.09**
D2$^-$	0.321	0.332	0.326	0.282	0.365	0.319	0.07**	0.10**

*Columns [1] to [6] present average values of representative variables of liquidity, volatility and price informativeness by group (treatment and control contracts) and by period (full sample period, period that precedes the ban and period that follows the ban). Column [7] presents the average difference in the change of the representative variable for treatment and control group contracts between periods, along with its statistical significance in light of a t-test assuming that the groups have unequal variances. Column [8] presents the median difference in the change of the representative variable for treatment and control group contracts between periods, along with its statistical significance in light of the Wilcoxon/Mann-Whitney non-parametric test. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.*

Variables definitions: ***BAS*** *is the bid-ask spread;* ***Liquidity risk*** *is the daily standard deviation of bid-ask spreads;* ***Net Notional Amount*** *(net open interest) is the sum of net protection bought (sold) by counterparties that are net buyers (sellers) of protection for a particular obligor;* ***Volatility*** *is the standard deviation of the continuously compound returns of CDS contracts, assuming a zero drift;* ***Vol.*** $^-$ *(**Vol.**$^+$) is volatility computed with the negative (positive) returns, and setting positive (negative) returns to zero;* ***SR*** *is the Synchronicity Ratio =* $ln(R^2/(1-R^2))$ *using the* R^2 *of the market model equation;* ***SR***$^+$ = $ln(R^{2+}/(1-R^{2+}))$ *with* $R_{it}=\alpha_i+\beta_i\times R_{mt}^+$ *to obtain* R^{2+}*;* $\boldsymbol{SR^-} = ln(R^{2-}/(1-R^{2-}))$ *with* $R_{it} = \alpha_i + \beta_i \times R_{mt}^-$ *to obtain* R^{2-}*;* ***D1*** *is a measure of delay in processing market-wide information;* $\boldsymbol{D1^+}$ *(*$\boldsymbol{D1^-}$*) reflect delay to negative (positive) market news;* ***|VR-1|*** *is the variance ratio, computed as the absolute value of the variance of two-day returns divided by two times the variance of daily returns, minus one;* ***Q*** *is the Hasbrouck's q (calculated as* $q = 1 - \sigma_s^2/\sigma_r^2$*), it reflects the risk of prices deviating from their efficient levels;* ***Basis*** *is the basis of the CDS contract and measures the difference between the CDS spread and cash-bond implied credit spread (reported in basis points);* ***D2*** *is a measure of delay in processing specific information embedded in bond credit spreads, with* ***D2***$^+$ *(**D2**$^-$) including solely positive (negative) changes of lagged bond credit spreads.*

To gain a further insight into these results, we also estimate equations (1) and (2) considering all contract tenors (3, 5, 7 and 10 years) and solely 5-year CDS contracts. It may be useful to obtain separate results for 5-year CDS contracts because they are usually more liquid than contracts with other maturities. The bid-ask spread is averaged for each contract on a monthly frequency. The regression estimates are presented in Exhibit 3, Panel A. The coefficient $\hat{\varphi}$ is positive and statistically significant, irrespective of model specification or sample (all contracts vs. 5-year contracts). Using the results of a two-way fixed effects models as baseline, the bid-ask spread of contracts written on treatment group names increased, on average, 4.6 percentage points more than those of contracts written on control group names.

Estimation of equation (2) produced qualitatively similar outcomes, thus supporting the notion that factors capturing dealers' inventory costs, funding costs, counterparty risk, capacity of financial intermediaries to provide market liquidity and investor sentiment are not, *per se*, capable of explaining these results.

In addition to analysis of the average bid-ask spread, we also analyze the daily standard deviation of bid-ask spreads in a monthly frequency. This variable aims to capture changes in the liquidity risk of the CDS market. Dick-Nielsen et al. [2012] use a similar approach to measure liquidity risk by taking the standard deviation of daily observations of the Amihud measure in order to gauge whether the price impact of trades' variability changed in the aftermath of the subprime crisis. The second row in Exhibit 2 shows that liquidity risk declined 0.6 percentage points among reference names of the control group, while increasing 1.3 percentage points for those of the treatment group. The reported results for the standard t-test (assuming unequal variances) and the Wilcoxon/Mann-Whitney non-parametric test indicate that both the average and median differences in the path of the two groups are statistically significant.

The results of the regression analysis are presented in Exhibit 3, Panel B. They suggest that the ban had an impact on liquidity risk, particularly when all contract tenors are accounted for. Considering the estimates of equation (1), including all observations, the standard deviation of the bid-ask spread increased 1.2 percentage points. These conclusions are robust for the introduction of control variables in equation (2). We also estimate equations (1) and (2) with observations for 5-year contracts only. The conclusions are preserved when considering the results of estimation of equation (1). However, the variable $\mathrm{ENFORCEMENT}_t \times BAN_i$ becomes non-significant with the introduction of control variables in equation (2), in line with the idea that other factors may have driven up the liquidity risk of 5-year CDS contracts under the scope of the ban.

Next, we turn our attention to the path of open interest of CDS contracts following the ban's implementation. The open interest of CDS contracts reflects market participants' willingness to take positions. If the open interest of a CDS contract is reduced, market opportunities for that contract are limited. Thus, a higher open interest signals both price fairness and relatively small bid-ask spreads.[1]

Exhibit 3: The impact of the ban on liquidity

Panel A - Bid-ask spread (%)

	All Contracts			5 – YR contracts		
	BAS	***BAS***	***D.BAS***	***BAS***	***BAS***	***D.BAS***
Enforcement	-0.135		-0.087***	-0.700 /*		-0.011
	(-0.60/-0.41)		(-3.95)	(-1.64/-1.91)		(-0.28)
Ban*Enforcement	4.225***/***	4.577***	0.368***	4.741***/***	4.669***	0.372***
	(6.87/7.17)	(5.77)	(5.22)	(4.98/5.15)	(4.02)	(4.75)
r2	7.7%	60.1%		7.3%	61.4%	
N	13,026	13,026	12,703	4,927	4,927	4,837
FE (Id)	Yes	Yes	No	Yes	Yes	No
FE (Calendar)	No	Yes	No	No	Yes	No
GLS - RE(Id)	No	No	Yes	No	No	Yes
Control Variables	No	No	Yes	No	No	Yes
Clustered S.E.	Id/D-K	Id and time	Id	Id//D-K	Id and time	Id
Frequency	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly

Panel B – Liquidity risk (%)

	All Contracts			5 – YR		
	LR	***LR***	***D. LR***	***LR***	***LR***	***D. LR***
Enforcement	-0.377***/***		-0.050***	-0.646***/***		-0.042***
	(-2.96/-2.98)		(-4.71)	(-4.05/-5.17)		(-2.58)
Ban*Enforcement	1.174***	1.243***	0.162*	1.720***/***	1.703***	0.021
	(6.10/4.53)	(3.80)	(1.92)	(6.16/7.12)	(5.42)	(1.07)
r2	1.6%	23.4%		3.7%	21.0%	
N	12,917	12,917	12,595	4,900	4,900	4,811
FE (Id)	Yes	Yes	No	Yes	Yes	No
FE (Calendar)	No	Yes	No	No	Yes	No
GLS - RE(Id)	No	No	Yes	No	No	Yes
Control Variables	No	No	Yes	No	No	Yes
Clustered S.E.	Id/D-K	Id and time	Id	Id/D-K.	Id and time	Id
Frequency	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly

Panel C – Log Net Notional Amount (All Contracts)

	NNA	**NNA**	**D.NNA**
Enforcement	0.052***		-0.002**
	(0.62/3.06)		(-2.29)
Ban*Enforcement	-0.609***	-0.610***	-0.003***
	(-5.40/-20.62)	(-5.29)	(-3.74)
r2	24.6%	92.5%	
N	21,023	21,023	20,957
FE (Id)	Yes	Yes	No
FE (Calendar)	No	Yes	No
GLS - RE(Id)	No	No	Yes
Control Variables	No	No	Yes
Clustered S.E.	Id/D-K	Id and time	Id
Frequency	Weekly	Weekly	Weekly

*Panels A-C report results of regressing representative variables of liquidity, liquidity risk and trading activity on $ENFORCEMENT$ (a binary variable that assumes the value of one after the ban's implementation and zero otherwise) and $ENFORCEMENT \times BAN$ (BAN is a binary variable that equals one for CDS names under the scope of the ban and zero otherwise). Three alternative model specifications are considered: (i) a fixed-effects model by contract with clustered standard errors or Driscoll-Kraay [1998] (D-K) standard errors; (ii) a two-way error components model (fixed-effects and clustered standard errors by contract and time); and (iii) a GLS random effects model on first differences with control covariates. In panels A and B, the estimation is run using monthly data for the period 2008M1 to 2015M12. Two samples are considered: (i) the full sample of contracts (3, 5, 7 and 10 year contracts) and (ii) 5-year contracts. In panel C, the estimation is run using weekly data for the period 2008M10 to 2015M12. All contract tenors are considered. T-statistics appear in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variables definitions: **BAS** is the bid-ask spread; **Liquidity risk** (LR) is the daily standard deviation of bid-ask spreads; **Net Notional Amount** (net open interest) is the sum of net protection bought (sold) by counterparties that are net buyers (sellers) of protection for a particular obligor.*

We concentrate on the net notional amount, which denotes the sum of net protection bought (sold) by counterparties that are net buyers (sellers) of protection for a particular obligor, and captures the stock of credit risk transferred in the CDS market (Oehmke and Zawadowski [2016]). Accordingly, long and short positions held by the same market participant on the same contract cancel each other out and are not accounted for in net notional amount figures. Other definitions of open interest (such as, the gross notional amount and the number of contracts outstanding) are noisy, in the sense that they are influenced by the existence of inter-dealer operations, compression operations and novations of contracts to central counterparties. These operations do not reflect the capital at risk, given that some risk transfer operations may be accounted for several times due to interdealer operations.

The average weekly log growth of the net open interest by status of reference names (for the complete time span and for the periods preceding and following enforcement of the ban) is shown in row 3 of Exhibit 2. The net open interest of both groups diminished, on average, during the full analyzed period. It is noteworthy that both groups present a similar rate of decline prior to the ban's implementation, while afterwards net open interest declined more quickly for the treatment group CDS names. The difference in the log growth of the two groups (in the period following implementation of the ban) is statistically significant for the Wilcoxon/Mann-Whitney non-parametric test, but not for the standard t-test assuming unequal variances.

Next, we use weekly data to regress the logarithm of net notional amount against the variable $\mathrm{ENFORCEMENT}_t \times BAN_i$ with fixed effects and a two-way error component model (equation (1)). A semi-log model is estimated and the coefficient associated with the variable $\mathrm{ENFORCEMENT}_t \times BAN_i$ represents a semi-elasticity. We also estimate equation (2) with the log change of net notional amount as dependent variable. Exhibit 3, Panel C, displays the results for the alternative model specifications. The estimated coefficient associated with the variable $\mathrm{ENFORCEMENT}_t \times BAN_i$ is negative and statistically significant regardless of model specification, indicating that, after the ban, market participants became less eager to take positions in CDS contracts.

An interesting question is whether the latter results hold in an analysis that differentiates the level of credit risk of CDS names. We assess whether the impact of the ban was more pronounced for riskier sovereigns by disaggregating the results by level of credit risk (calculated as the obligor's average CDS spread during the whole sample period). The sample of obligors is thus divided into three bins, each encompassing a tercile of obligors in terms of average CDS spreads. For the sake of brevity, only the estimates and statistical significance of the coefficient for the variable $\mathrm{ENFORCEMENT}_t \times BAN_i$ of equation (1), obtained with a two-way fixed effects model, are reported.

The results of this estimation are presented in Exhibit 4. The bid-ask spread, $\text{ENFORCEMENT}_t \times BAN_i$, presents a positive and statistically significant coefficient, regardless of the analyzed sub-sample. However, the value of the estimated coefficient is substantially higher for lower credit risk CDS names. This suggests that the ban was especially detrimental for the liquidity of CDS contracts on more creditworthy sovereigns. The results also indicate that this group of CDS names presents the greatest increment of liquidity risk as measured by the standard deviation of the bid-ask spread, whereas the liquidity risk of CDS contracts written on riskier obligors was only slightly affected.

Exhibit 4: The impact of the ban on liquidity by level of creditworthiness of the sovereign

		Ban*Enforcement	
		Coef.	**t-stat**
BAS (%)	1st Tercile by CDS spread level	7.460***	(4.67)
	2nd Tercile by CDS spread level	2.255*	(1.91)
	3rd Tercile by CDS spread level	4.594***	(5.40)
LR (%)	1st Tercile by CDS spread level	2.354***	(4.28)
	2nd Tercile by CDS spread level	0.787**	(2.24)
	3rd Tercile by CDS spread level	0.634	(1.52)
Log NNA	1st Tercile by CDS spread level	-0.796***	(-4.91)
	2nd Tercile by CDS spread level	-0.730***	(-4.72)
	3rd Tercile by CDS spread level	-0.430*	(-1.85)

*This exhibit presents the results of regressing representative variables of liquidity, liquidity risk and trading activity on $ENFORCEMENT \times BAN$. The regression includes fixed-effects and clustered standard errors by contract and time. Results are desegregated by the level of credit risk of the sovereign entity (1st tercile corresponds to the lowest credit risk).The full sample of contracts (3, 5, 7 and 10 year contracts) is considered. T-statistics appear in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variables definitions: **BAS** is the bid-ask spread; Liquidity risk (**LR**) is the daily standard deviation of bid-ask spreads; Net Notional Amount (**NNA**) is the sum of net protection bought (sold) by counterparties that are net buyers (sellers) of protection for a particular obligor.*

There was a decline in net notional amounts for the three sub-sets of CDS names, but again more pronounced for sovereigns with a higher level of creditworthiness. Therefore, demand for CDS protection declined after the ban for all classes of risk, but this impact was smaller for sovereigns with a higher credit risk, thus suggesting that investors continued using the CDS market for hedging purposes.

Overall, the estimates indicate that enforcement of the ban had a negative impact on liquidity (a positive impact on bid-ask spreads) and net notional amount, and raised liquidity risk, and as such, we can reject our first hypothesis H1. The results hold for a variety of model specifications and when control variables are included to remove the influence of other factors that may also affect liquidity.

Effects of the ban on volatility

We now examine H2 and assess whether the ban contributed to stabilizing the CDS market, or had a counterproductive destabilizing impact, by analyzing the behavior of various proxies of volatility and tail risk:

Standard volatility (Vol) – measured as the daily standard deviation of the continuously compound returns of CDS contracts, assuming a zero drift, and estimated on a monthly basis.

Upside volatility (Vol+) and downside volatility (Vol-) - the upside volatility (Vol+) is calculated with the positive returns (and setting negative returns to zero), while the downside volatility (Vol-) is computed with the negative returns (and setting positive returns to zero). Both are estimated on a monthly basis.

Skewness (Skew) – to measure the degree of asymmetry of the daily CDS returns' distribution (estimated on a quarterly basis).

Frequency of Positive (Negative) Extreme Events – calculated as the fraction of trading days with daily returns (of a CDS contract) standing two standard deviations above (below) zero (estimated on a quarterly basis).

Kurtosis (Kurt) – to measure the tail risk of the daily CDS returns' distribution (estimated on a quarterly basis).

The log change of CDS mid-rates is used as a proxy for CDS "returns", because the percentage change in the credit spread approximates the return on holding credit protection well (see Hilscher et al. [2015] and Wang and Bhar [2014]).

We begin with the analysis of some descriptive statistics on each of the above mentioned variables. The results, shown in Exhibit 2, indicate that the daily volatility of CDS contracts declined after the ban. On average, the reduction in volatility was more pronounced for control group contracts (2 percentage points and 0.9 percentage points for control and treatment groups, respectively). The difference in the mean change of volatility between the two periods is not statistically significant for the two groups (with a standard t-test assuming unequal variances). However, analysis of the median change of volatility tells a different story. Indeed, that difference is negative and statistically significant when the Wilcoxon/Mann-Whitney non-parametric test is considered, in line with the idea that treatment group names experienced a sharper decline in volatility following implementation of the ban. Analysis of the upside and downside volatilities leads to nearly identical conclusions.

The kurtosis and frequency of (positive and negative) extreme events declined after the ban's enforcement in the two groups. Parametric and non-parametric tests indicate that the change in kurtosis for the two groups is not statistically different. While similar results are obtained for the frequency of negative extreme events, the results of a Wilcoxon/Mann-Whitney non-parametric test suggest that the drop in the frequency of positive extreme events is higher for treatment group contracts. Regarding skewness, the results of parametric and non-parametric tests suggest that, after the ban, it evolved in a similar way in the two groups.

We now use regression analysis to assess the impact of the ban on standard volatility and estimate equations (1) and (2). We focus on this variable for the sake of brevity. Exhibit 5 displays the qualitatively identical results for estimations with the full sample of contracts (including all tenors) and with 5-year CDS contracts only. The estimation of equation (1) with a fixed effects model (with the introduction of binary variables by contract) shows that, after implementation of the ban, volatility declined for both treatment and control group contracts, particularly in the sub-sample of 5-year CDS contracts.

Exhibit 5: The impact of the ban on volatility

	All Contracts			**5 – YR contracts**		
	Volatility (%)	***Volatility (%)***	***D. Volatility (%)***	***Volatility (%)***	***Volatility (%)***	***D. Volatility (%)***
Enforcement	-0.187		-0.057***	-0.665***/**		-0.063**
	(-0.66/-0.46)		(-2.75)	(-2.95/-2.02)		(-2.32)
Ban*Enforcement	-1.000***/***	-0.999***	-0.088***	-0.652**/***	-0.688**	-0.056**
	(-3.25/-2.61)	(-2.67)	(-3.86)	(-2.43/-2.82)	(-2.16)	(-2.16)
r2	1.1%	31.6%		4.1%	40.5%	
F	48.392	18.689		45.374	19.696	
N	12,909	12,909	12,593	4,889	4,889	4,798
FE (Id)	Yes	Yes	No	Yes	Yes	No
FE (Calendar)	No	Yes	No	No	Yes	No
GLS - RE(Id)	No	No	Yes	No	No	Yes
Control Variables	No	No	Yes	No	No	Yes
Clustered S.E.	Id/D-K	Id and time	Id	Id/D-K	Id and time	Id
Frequency	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly

*This exhibit reports the results of regressing volatility on $ENFORCEMENT$ (a binary variable that assumes the value of one after the ban implementation and zero otherwise) and $ENFORCEMENT \times BAN$. Three alternative model specifications are considered: (i) a fixed-effects model by contract with clustered standard errors or Driscoll-Kraay [1998] (D-K) standard errors; (ii) a two-way error components model (fixed-effects and clustered standard errors by contract and time); and (iii) a GLS random effects model on first differences with control covariates. The estimation is run using monthly data for the period 2008M1 to 2015M12. Two samples are considered: (i) the full sample of contracts (3, 5, 7 and 10 year contracts) and (ii) 5-year contracts. T-statistics appear in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Volatility is the standard deviation of the continuously compound returns of CDS contracts, assuming a zero drift.*

The coefficient of $\text{ENFORCEMENT}_t \times BAN_i$ is negative and statistically significant, which is consistent with the notion that the reduction of volatility was sharper for contracts under the scope of the ban. On average, the decline of volatility was one percentage point higher for sovereigns of the treatment group than for those in the control group. Using a two-way fixed-effects model, or introducing control variables in a random effects setup on the first differences, produces virtually identical outcomes.

We also examine impacts by class of sovereigns' risk. In order to do so, the results are disaggregated according to level of credit risk, calculated as the average of the CDS spread of the obligor during the whole sample period. The method used in the previous subsection is also utilized here, and the results are presented separately for each tercile of sovereigns (in terms of credit risk). It is striking that the ban had a greater impact on the volatility of more risky obligors (see Exhibit 6). The coefficient of $\mathrm{ENFORCEMENT}_t \times BAN_i$ is negative and statistically significant (equals -2.3 percentage points) for the third tercile of sovereigns, but is not significant for the first and second terciles. These results suggest that the ban succeeded in stabilizing the CDS market, particularly for riskier obligors.

Exhibit 6: The impact of the ban on volatility and tail risk, global and by level of credit risk of the reference name

	All Contracts		**5-YR Contracts**		**1st Tercile**		**2nd Tercile**		**3rd Tercile**	
Vol. (%)	-0.999***	(-2.67)	-0.688***	(-2.16)	-0.162	(-0.55)	-0.441	(-1.15)	-2.277***	(-2.77)
Vol^{+} (%)	-0.744***	(-2.69)	-0.551**	(-2.30)	-0.164	(-0.70)	-0.377	(-1.34)	-1.602***	(-2.71)
$Vol.^{-}$ (%)	-0.558**	(-2.20)	-0.341	(-1.54)	0.060	(0.29)	-0.224	(-0.81)	-1.471***	(-2.62)
$Vol.^{+}$ (%)-$Vol.^{-}$ (%)	-0.187	(-1.43)	-0.211	(-1.33)	-0.224	(-1.38)	-0.152	(-1.00)	-0.131	(-0.69)
Kurtosis	-0.364	(-0.59)	0.463	(0.69)	-0.191	(-1.23)	0.186	(-0.86)	-0.101	(-0.39)
Skew	0.006	(0.05)	0.042	(0.34)	0.817	(-0.78)	-0.108	(-0.12)	-1.767	(-1.45)
Positive Ext. Events	-0.025*	(-1.72)	-0.042***	(-3.06)	0.025	(-1.37)	-0.003	(-0.15)	-0.031	(-1.53)
Negative Ext. Events	-0.008	(-0.51)	-0.019	(-1.38)	0.013	(-0.68)	-0.023	(-1.05)	-0.052**	(-2.46)

*This exhibit presents the results of regressing representative variables of volatility and tail risk on $ENFORCEMENT \times BAN$. The regression includes fixed-effects and clustered standard errors by contract and time. The full sample of contracts (3, 5, 7 and 10 year contracts) and solely 5-year contracts are alternatively considered. Results are also desegregated by the level of credit risk of the sovereign entity. T-statistics appear in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Positive extreme events computed as $ln(\,P^{+}/(1-P^{+})$, with P^{+} standing for the fraction of positive extreme events in a quarter. Negative extreme events computed as $ln(\,P^{-}/(1-P^{-})$, with P^{+} standing for the fraction of negative extreme events in a quarter. Other variables' definitions are provided in the caption to Exhibit 2.*

Exhibit 6 also summarizes the results for the other proxies of volatility and tail risk. Interestingly, the coefficients of $\mathrm{ENFORCEMENT}_t \times BAN_i$ are negative and statistically significant for both upside and downside volatilities, when the full sample of contracts is used. Nevertheless, significance is lost in the case of downside volatility for the subsample of 5-year contracts. Another result that stands out is that only the contracts written on riskier obligors (third tercile in terms of CDS spread) appear to have been significantly affected by the ban, a result also obtained for standard volatility.

Given that the ban only affected naked CDS protection buying, its impact should be higher for upside than for downside volatility. Intuitively, as demand for CDS is constrained by the reference name's amount of debt, the ban should have put a ceiling on buying (but not on selling) pressure. Accordingly, buy side order imbalance should occur less often, reducing major positive movements of CDS spreads. To examine this hypothesis, we regress the difference between upside and downside volatility against $\mathrm{ENFORCEMENT}_t \times BAN_i$, time and cross-section fixed effects. Even though the coefficient of $\mathrm{ENFORCEMENT}_t \times BAN_i$ is negative (and therefore consistent with the idea that the reduction of upside volatility was more pronounced than that of downside volatility), it is not statistically significant.

A lower skew and kurtosis are also expected following the ban's enforcement. In fact, the ceiling on buying pressure should have reduced the frequency of major positive movements, and hence also skew and kurtosis. However, the results presented in Exhibit 6 cast some doubt on that hypothesis, as the coefficients of $\mathrm{ENFORCEMENT}_t \times BAN_i$ are non-significant for models with skewness or kurtosis as dependent variables.

We also analyze the effect of the ban on the frequency of positive (negative) extreme events. To this end, for each quarter, we first compute the fraction of trading days with daily returns (of a CDS contract) standing two standard deviations above (below) zero and, subsequently, perform a logit transformation as follows: $\mathrm{F.Extreme\ Events} = \ln\left(\frac{P}{1-\mathrm{P}}\right)$ (with P standing for the fraction of positive, or negative, extreme events in a quarter). The results of the regression of this variable against $\mathrm{ENFORCEMENT}_t \times BAN_i$, time and cross-section fixed effects (Exhibit 6) show that the ban reduced the frequency of positive, but not of negative, extreme events. This effect was greater for 5-year contracts.

Overall, the assessment suggests that implementation of the ban produced negative effects on volatility and tail risk, more pronounced for contracts written on sovereigns with lower creditworthiness. H2 is thus rejected and we conclude that the ban has helped to stabilize the CDS market.

Effects of the ban on price informativeness

In this subsection we focus on H3 and examine the impact of EU Regulation 236/2012 on price informativeness by performing a number of tests on the following variables, using daily data:

Synchronicity Ratio (SR) – Roll [1988] introduces non-synchronicity as an indicator of the specific information disseminated into market prices. The assumption underlying non-synchronicity is that relatively more efficient markets display a higher ratio of idiosyncratic risk. The ratio between idiosyncratic and market information should be larger in rich informational environments, where investors are able to quickly obtain and use cheap information. Roll [1988] captures synchronicity using the R2 of the market model equation.

We assume that spreads' informational relevance increases when CDS returns become less correlated with global sovereign CDS returns. Our focus on the latter follows the insights of recent research on the role global factors play in the dynamics of sovereign CDS spreads. In this regard, Longstaff et al. [2011] show that most sovereign credit risk can be linked to global factors, and report that a single principal component explains 64 percent variance in sovereign credit risk. Hilscher and Nosbusch [2010] also conclude that global factors are relevant determinants of sovereign credit risk dynamics, whereas for Augustin [2014] both global and country-specific factors determine sovereign credit risk.

We take advantage of this communality of sovereign CDS spreads with global factors to examine the impact of the ban on price discovery. Since a global CDS index for sovereign entities is not available, an equally-weighted global CDS market index is formed using the set of 5-year CDS contracts in our sample. Then, for each individual contract, we regress daily CDS returns on a constant and on the returns of the global CDS market index and save the R^2:

$$R_{it} = \alpha_i + \beta_i \times R_{mt};\ \text{to obtain } R_i^2$$

whereR_{it} is the return of contract i at t; R_{mt} is the market return at t. Following Bris et al. [2007], we also exploit non-synchronicity with respect to positive and negative market information. The down (up) R2 is derived from a regression of the returns of CDS contracts on market returns, conditional on the latter being negative (non-negative). To this end, the following auxiliary regressions are run:

$$R_{it} = \alpha_i + \beta_i \times R_{mt}^- \text{; to obtain } R^{2-}$$

$$R_{it} = \alpha_i + \beta_i \times R_{mt}^+ \text{; to obtain } R^{2+}$$

whereR_{it} is the return of contract i at t; $R_{mt}^+(R_{mt}^-)$ is the positive, or zero, (negative) market return at t. Next, we perform a logistic transformation change in order to turn the indicators into continuous variables with a more normal distribution:

$$SR = \ln(R^2/(1 - R^2))$$

$$SR^- = \ln(R^{2-}/(1 - R^{2-}))$$

$$SR^+ = \ln(R^{2+}/(1 - R^{2+}))$$

Delay– Diamond and Verrecchia [1987] argue that prices adjust slowly to negative market news in the presence of short selling constraints. As in Bris et al. [2007] and Beber and Pagano [2013], delay in price adjustments to common information is utilized to capture informational inefficiency. Here, delay is computed in a two-step procedure regression analysis.

First, the unrestricted model (with the lagged market returns as explanatory variables) is estimated with daily data, separately for each contract, and the corresponding R2 ($R^2_{Unrestricted}$) is saved:

$$R_{it} = \propto_i + \beta_i \times Rm_t + \sum_{k=1}^{5} \phi_{k,i} \times Rm_{t-k} + \varepsilon_{it}$$

Next, a restricted model, with $\phi_{k,i}$ (k=1,..,5) set to zero, is estimated and the corresponding R2 is also saved ($R^2_{Restricted}$).

$$R_{it} = \propto_i + \beta_i \times Rm_t + \varepsilon_{it}$$

The delay measure is then computed as

$$D1 = 1 - \left(\frac{R^2_{Restricted}}{1 - R^2_{Unrestricted}}\right)$$

A larger D1 indicates that a greater portion of return variation is captured by lagged market returns, and thus that a longer delay exists in the response to global-wide news. Boehmer and Wu [2013] suggest a variant to distinguish between delays to positive and to negative market news. First, the following unrestricted equations are estimated:

$$R_{it} = \alpha_i + \beta_i \times R_{mt} + \sum_{k=1}^{5} \varphi_{k,i} \times R^+_{mt-k} + \varepsilon_{it}$$
$$R_{it} = \alpha_i + \beta_i \times R_{mt} + \sum_{k=1}^{5} \varphi_{k,i} \times R^-_{mt-k} + \varepsilon_{it}$$

whereR^+_{mt} (R^-_{mt}) equals R_{mt} if non-negative (negative) and zero otherwise. Then, the restricted version of the previous equations ($\varphi_{k,i} = 0$, k=1,..,5) is estimated and two delay measures are computed:

$$D1^+ = 1 - \left(\frac{R^2_{Restricted}}{1 - R^2_{+unrestricted}}\right)$$
$$D1^- = 1 - \left(\frac{R^2_{Restricted}}{1 - R^2_{-unrestricted}}\right)$$

The main advantage of these indicators is their ability to identify delays in price adjustment to positive and to negative information.

In addition to synchronicity risk and delay, we also assess the pattern of three other variables: the variance ratio, price precision, and the basis of CDS contracts:

Variance ratio - The variance ratio (|VR-1|) is computed on a quarterly basis and is defined as the absolute value of the variance of two-day returns divided by two times the variance of daily returns, minus one.

$$|VR - 1| = \left|\frac{Var(R_t)}{2 * Var(r_t)} - 1\right|$$

where Var (R_t) is the variance of two-day returns and $Var(r_t)$ is the variance of one-day returns. In both cases, a zero drift is assumed in computation of the variance. A higher |VR-1| indicates lower efficiency, as the return process deviates more from a random walk. Less resilient markets exhibit higher short-term volatilities and more transitory price changes when new information arrives. Therefore, |VR-1| should tend to zero when permanent price changes occur with minimum transitory changes.

Price precision - The accuracy of CDS prices and market quality prior to, and after, the introduction of the ban is assessed using a measure proposed by Hasbrouck [1993]. The author defines the pricing error ($\mathrm{s_t}$) of a security as the difference in its (log) transaction price ($\mathrm{p_t}$) and its efficient (log) price ($\mathrm{m_t}$). Therefore, returns may be decomposed into permanent price changes and transitory price changes.

$$r_t = (m_t - m_{t-1}) + (s_t - s_{t-1})$$

The permanent change is provided by the first expression on the right. Because m_t is a random walk, its first difference is a white noise. Therefore, the relative importance of transitory movements is provided by the ratio between the variance of the pricing error and the total variance of the returns(σ_s^2/σ_r^2). The assimilation of information in efficient markets is well-timed and accurate when transitory movements are rare. Hasbrouck's q, defined below, equals one minus this ratio. It reflects the risk of prices deviating from their efficient levels. This occurs when q departs from one towards zero.

$$q = 1 - \sigma_s^2/\sigma_r^2$$

In order to estimate q, the following MA(1) process (without intercept) is estimated and the pair $\{a, \sigma_e^2\}$ is used in the computation of q:

$$r_t = e_t - a \times e_{t-1}$$

$$q = \frac{\sigma_e^2 - 2a \times cov(e_t, e_{t-1})}{\sigma_e^2 + a \times \sigma_e^2 - 2a \times cov(e_t, e_{t-1})} \in (0,1)$$

As transaction prices are not available, mid-quotes are used to compute r_t. The objective is to detect the relevance of transitory movements and price reversal in mid-quotes other than the traditional bid-ask bounce. The q that follows from Hasbrouck's model is calculated on a quarterly basis and using daily data. In this analysis, only 5 and 10 year contracts are utilized.

All the aforementioned measures are calculated in quarterly time frames using daily data on CDS spreads.

Basis of the CDS contract– measures the difference between the CDS spread and cash-bond implied credit spread. When the basis is positive, the CDS spread is larger than the bond spread. An investor could then short the bond and sell CDS protection to capture the basis. When the basis is negative, the CDS spread is smaller than the bond spread, so that the basis could be captured through a long position in the bond, combined with CDS protection buying. We use the relative pricing errors between the two instruments as a measure of market efficiency. In this analysis, only 5 and 10 year contracts are used. Daily data on the basis is aggregated into quarterly time frames.

We begin by examining how SR, SR^{-} and SR^{+} evolved after the ban's implementation, in both treatment and control groups. In a first step,SR, SR^{-} and $SR^{+}$are estimated for each contract using two alternative time windows: January 2008 to October 2012, and November 2012 to December 2015. Then, we compare the change of the variables in the two groups utilizing parametric and non-parametric tests (see Exhibit 2). After the ban, the averages of SR, SR^{-} and SR^{+}declined in the two groups. The decline was more pronounced for contracts included in the treatment group, with a statistically significant difference between the two groups, according to a standard t-test assuming unequal variances and to the Wilcoxon/Mann-Whitney non-parametric test.

These results are, in general, similar to those obtained with regression analyses. For each contract, we estimate the representative variables (SR, $SR^{-}$and SR^{+}) in quarterly time windows, in order to form a panel dataset. We analyze the effects of EU Regulation 236/2012 on CDS price informativeness by regressing each representative variable against $\mathrm{ENFORCEMENT}_t \times BAN_i$, time and cross-section fixed effects. We alternatively utilize the full sample of contracts, a sample with 5-year contracts only, and the disaggregation by classes of credit risk. The results are presented in Exhibit 7.

Exhibit 7: The impact of the ban on price informativeness

	All Contracts		5-YR Contracts		1st Tercile		2nd Tercile		3rd Tercile	
SR	-0.851***	(-3.42)	-1.084***	(-3.21)	-2.069***	(-4.77)	-0.560**	(-2.10)	0.121	(0.39)
SR^{+}	-0.698**	(-2.42)	-0.881**	(-2.39)	-1.888***	(-3.66)	-0.455	(-0.91)	0.138	(0.52)
SR^{-}	-1.065***	(-3.53)	-1.244***	(-3.43)	-1.608***	(-3.68)	-0.545	(-1.45)	-0.784	(-1.35)
SR^{+}- SR^{-}	0.365	(1.04)	0.364	(1.14)	-0.280	(-0.63)	0.089	(0.13)	0.919**	(2.03)
D1	0.089**	(2.12)	0.118***	(2.72)	0.242***	(3.72)	0.060	(0.99)	-0.062	(-1.20)
$D1^{+}$	0.089*	(1.85)	0.121***	(2.86)	0.213***	(3.33)	0.042	(0.68)	-0.030	(-0.47)
$D1^{-}$	0.112***	(3.51)	0.124***	(2.90)	0.251***	(3.98)	0.098*	(1.91)	-0.044	(-0.95)
$D1^{+}$- $D1^{-}$	-0.023	(-0.86)	-0.004	(-0.20)	-0.038	(-1.15)	-0.056**	(-2.40)	0.015	(0.43)
|VR-1|(%)	6.113*	(1.86)	5.116	(1.17)	18.196***	(-4.15)	8.784*	(-1.66)	-7.637	(-1.60)
Q^{a}(%)	-0.470	(-0.20)	-0.455	(-0.13)	1.022	(0.43)	7.685**	(2.11)	-3.017	(-0.78)
Basis[a]	-79.707**	(-2.06)	-73.099	(-1.22)	-15.923	(-0.96)	-38.384**	(-2.47)	-107.257	(-1.20)
D2	0.032	(0.98)	0.005	(0.14)	-0.057	(-0.97)	0.101**	(2.54)	0.075*	(1.79)
$D2^{+}$	0.119*	(1.71)	0.175	(1.37)	-0.048	(-0.65)	0.131**	(2.30)	0.286*	(1.74)
$D2^{-}$	0.075**	(2.40)	0.076**	(2.23)	-0.046	(-0.60)	0.135***	(3.21)	0.145**	(2.38)
$D2^{+}$- $D2^{-}$	0.044	(0.68)	0.099	(0.84)	-0.001	(-0.05)	-0.004	(-0.15)	0.142	(0.98)

*This exhibit details the results of regressing representative variables of market quality on $ENFORCEMENT \times BAN$. The regression includes fixed-effects and clustered standard errors by contract and time. The full sample of contracts (3, 5, 7 and 10 year contracts) and solely 5-year contracts are alternatively considered. Results are also desegregated by the level of credit risk of the sovereign entity. T-statistics appear in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. [a] Only 5 and 10-year contracts are considered in the analysis. Variables definitions are provided in the caption to Exhibit 2.*

If the ban prevented the assimilation of idiosyncratic information into prices, an increment in R2 (SR) is expected. However, the results appear to challenge this expectation for synchronicity actually declined after enforcement of the ban. The coefficients of $\mathrm{ENFORCEMENT_t} \times \mathrm{BAN_i}$ are negative and statistically significant when SR, SR^{-} and SR^{+} are the dependent variables. A further inspection of the results disaggregated by classes of credit risk indicates that the decline of synchronicity is more pronounced within sovereigns with higher creditworthiness and did not occur for riskier sovereigns.

In efficient markets, $\mathrm{SR}^{+} - \mathrm{SR}^{-}$ should be close to zero, indicating a symmetric adjustment to news with a positive and negative impact. We run a regression of $\mathrm{SR}^{+} - \mathrm{SR}^{-}$ against $\mathrm{ENFORCEMENT}_t \times BAN_i$, time and cross-section fixed effects. Remarkably, the coefficient for $\mathrm{ENFORCEMENT}_t \times BAN_i$ is not statistically significant in either the full sample of contracts or the subset of 5-year contracts. However, it is positive and statistically significant in the subsample comprising the sovereigns with lower creditworthiness.

Overall, for contracts in the treatment group, synchronicity decreased after implementation of the ban. This effect was more pronounced for sovereigns displaying lower levels of credit risk and analysis of the path of $\mathrm{SR}^{+} - \mathrm{SR}^{-}$ indicates it was mainly induced by the decline in price synchronicity associated with positive news.

We now assess the delay of price responsiveness in the assimilation of market news. This delay is proxied by D1 and Boehmer and Wu [2013] delay measures ($\mathrm{D1}^{+}$and $\mathrm{D1}^{-}$). Again, we begin by estimating the measures in two time frames, January 2008 to October 2012 and November 2012 to December 2015. A first striking result is that, after implementation of the ban, D1 (and $\mathrm{D1}^{+}$and $\mathrm{D1}^{-}$) increased in both groups of contracts, although more noticeably in the treatment group (Exhibit 2). The standard t-test and the Wilcoxon/Mann-Whitney test indicate that the difference in the average and median changes of the two groups is statistically significant, in line with the expectation that the ban would increase the delay in incorporating common-wide information.

For each contract, we estimate the above-listed representative variables of delay in quarterly time windows, in order to form a panel dataset. The results of the regression of D1(D1+ and D1-) against $\mathrm{ENFORCEMENT}_t \times BAN_i$, time and cross-section fixed effects confirm that contracts subjected to the ban experienced a greater increase in the delay of assimilation of (positive and negative) common-wide information (Exhibit 7). In the regressions run on D1, $\mathrm{D1}^{+}$ and $\mathrm{D1}^{-}$, the coefficient for $\mathrm{ENFORCEMENT}_t \times BAN_i$is positive and significant, both for the complete sample and for the sub-sample of 5-year contracts. The three variables increased following implementation of the ban for the sovereigns affected by this regulatory measure.

The results of regressions run on D1, $D1^{+}$ and $D1^{-}$ taking into account the level of credit risk of CDS names produce estimates for $\text{ENFORCEMENT}_t \times BAN_i$ that are positive and statistically significant for sovereigns with low credit risk (1st tercile of sovereigns ranked by CDS spread level), but not for sovereigns with high credit risk (3rd tercile of sovereigns sorted by CDS spread level). These results suggest that the delay in assimilation of common-wide information increased more for sovereigns in the treatment group, especially for those with a higher level of creditworthiness.

To further investigate the presence of asymmetry of delay for positive and negative common-wide news, we regress the difference of $D1^{+}$ and $D1^{-}$ against $\text{ENFORCEMENT}_t \times BAN_i$, time and cross-section fixed effects. It is noteworthy that $\text{ENFORCEMENT}_\text{t} \times \text{BAN}_\text{i}$ presents a negative, though not significant, coefficient when the full sample of obligors is considered, for this is not consistent with the reasoning that the delay increased more for negative news. Taken together, these results suggest that the delay increased after the ban for sovereigns affected by it. However, there is no evidence that the increment of the delay is mainly associated with the adjustment of CDS spreads to negative common-wide news.

We now examine the effect of the ban on price precision proxies, namely the (transformed) variance ratio and Hasbrouck's q, which measure the existence of transitory movements in prices. We first estimate the (transformed) variance ratio and Hasbrouck's q for each contract in the same two time frames (January 2008 to October 2012 and November 2012 to December 2015). We then compare how the variables evolved before and after the ban in the two groups.

The lower the $|\text{VR} - 1|$, the higher the level of market efficiency. Exhibit 2 shows that, after implementation of the ban, $|\text{VR} - 1|$ increased for treatment group contracts and decreased for the control group. The representative variable q declined in the two groups. Differences in the change of $|\text{VR} - 1|$ for the two groups are statistically significant (with a standard t-test assuming unequal variances and the Wilcoxon/Mann-Whitney non-parametric test) but differences in the change of q are not statistically different from zero.

To increase the robustness of our conclusions, we utilize the model setup associated with equation (1) to assess the impact of the ban on market quality, and run regressions of $|\text{VR} - 1|$ and q on $\text{ENFORCEMENT}_t \times BAN_i$, time and cross-section fixed effects. With respect to $|\text{VR} - 1|$, $\text{ENFORCEMENT}_t \times BAN_i$ presents a positive and statistically significant coefficient for the full sample but not for the sample of 5-year contracts (Exhibit 7). Most notably, the analysis by class of risk of sovereign names suggests that the effect of the ban is strong for the first and second terciles, but not for the riskier ones.

Regarding q, $\text{ENFORCEMENT}_t \times BAN_i$ presents a negative (but non-significant) coefficient both for the full sample and for the 5-year sample. Surprisingly, the coefficient of $\text{ENFORCEMENT}_t \times BAN_i$ is positive and statistically significant only for sovereign names in the second class of credit risk. The results thus point to a negative effect of the ban on price precision, particularly within the sovereigns in the treatment group exhibiting a higher level of creditworthiness.

Finally, we analyze the path of the basis of CDS contracts before and after implementation of the ban. The close relationship between CDS spreads and credit spreads of traded bonds constitutes an alternative set-up to examine the implications of regulation EU 236/2012. The information in Exhibit 2 shows that the basis increased, on average, 78 basis points for contracts not subjected to the ban, and dropped 52 basis points for contracts included in the treatment group. The difference in the change of the basis of the contracts of the two groups is negative and statistically significant according to the results of the above-mentioned parametric and non-parametric tests.

We also estimate equation (1) using the basis as the dependent variable and including time and cross-section fixed effects. A result that deserves attention is that the coefficient of $\text{ENFORCEMENT}_t \times BAN_i$ is negative and statistically significant when all contracts are considered. After implementation of the ban, and in relation to the evolution of the basis of CDS contracts on control group entities, the basis for treatment group entities declined, on average, 80 basis points.

Our interpretation of these results is that by prohibiting naked protection buying, the EU regulation also limited the fraction of investors holding relatively pessimistic default beliefs that could effectively trade CDS contracts. That ceiling on buying pressure of CDS drove the basis down. A breakdown of the results by tenor and class of sovereign risk shows that the effect of the ban on the basis is concentrated on contracts with maturities of 10-years and contracts on sovereigns that belong to the mid-class of credit risk.

Robustness check: Sovereign bond spreads and delay

An alternative to the evaluation of delay on market-wide information is the assessment of delay with respect to specific information embedded in bond credit spreads. As demonstrated by Duffie [1999] and Hull and White [2000], CDS and bond markets are close substitutes in that arbitrage forces the co-movement of CDS premiums and credit spreads. This result is also supported by the findings of Blanco et al. [2005], Norden and Weber [2009], De Wit [2006] and Zhu [2004], who report a long-run relationship between CDS spreads and credit spreads. These authors do not find evidence of arbitrage opportunities in the long run, suggesting that information on credit risk is incorporated in the prices in both markets, although considerable price deviations may occur in the short run (Adler and Song [2010] show that deviations may also occur for some emerging market sovereign spreads).

We take advantage of the tight relationship between CDS spreads and bond credit spreads to gauge whether the ban on naked CDS buying reduced the pace at which specific information about the reference entity is assimilated by CDS spreads. To that end, the following equation is estimated in quarterly time frames:

$$\Delta \mathrm{CDS}_{\mathrm{it}} = \alpha_i + \sum_{\mathrm{K}=0}^{5} \theta_{i,k} \times \Delta \mathrm{BCS}_{\mathrm{it-k}} + \sum_{\mathrm{K}=1}^{5} \emptyset_{i,k} \times \Delta \mathrm{CDS}_{\mathrm{it-k}} + u_{\mathrm{it}}$$

where $\Delta \mathrm{BCS}_{\mathrm{it}}$ ($\Delta \mathrm{CDS}_{\mathrm{it}}$) represents changes in bond credit spreads (CDS spreads) for reference entity i at time t. In this analysis, only 5 and 10 year contracts are utilized.

We split the main sample into quarterly subsets of observations. Afterwards, for each contract and for each time frame, we estimate the above equation and save the corresponding R2 ($\mathrm{R}^2_{Unrestricted}$) in order to form a panel dataset. In a second step, a restricted model where θ_k (k=1,..,5) are set to zero is estimated and the corresponding R2 saved ($\mathrm{R}^2_{Restricted}$).

$$\Delta \mathrm{CDS}_{\mathrm{it}} = \alpha_i + \theta_{i,0} \times \Delta \mathrm{BCS}_{\mathrm{it}} + \sum_{\mathrm{K}=1}^{5} \emptyset_{i,k} \times \Delta \mathrm{CDS}_{\mathrm{it-k}} + u_{\mathrm{it}}$$

The delay measure is computed as

$$\mathrm{D2} = 1 - \left(\frac{\mathrm{R}^2_{Restricted}}{1-\mathrm{R}^2_{Unrestricted}}\right)$$

We also compute variants of the former measure by including solely positive or negative changes of lagged bond credit spreads (${\mathrm{BCS}^+}_{\mathrm{it}}$or ${\mathrm{BCS}^-}_{\mathrm{it}}$, respectively) in the unrestricted model. $\mathrm{D2}^+$and $\mathrm{D2}^-$ are then computed using the same approach as D2.

We begin by comparing the average and median values of D2, $\mathrm{D2}^+$ and $\mathrm{D2}^-$ before and after the ban in our two groups of interest (Exhibit 2). The three indicators increase following the ban for treatment group CDS names. A comparison of the pattern of the variables between treatment and control group CDS names shows that delay (measured by $\mathrm{D2}^+$and $\mathrm{D2}^-$) increased by a greater extent in treatment group CDS names, this conclusion being supported by the results of parametric and non-parametric tests.

We also regress D2, $\mathrm{D2}^+$, $\mathrm{D2}^-$ and $\mathrm{D2}^+ - \mathrm{D2}^-$ against $\mathrm{ENFORCEMENT}_t \times BAN_i$ and time and cross-section fixed effects. Exhibit 7 shows that the ban produced effects on the delay in the adjustment to positive and negative specific information by CDS spreads of contracts written on names affected by the EU regulation. In effect, $\mathrm{ENFORCEMENT}_t \times BAN_i$ displays a positive and statistically coefficient when $\mathrm{D2}^{+}$and $\mathrm{D2}^{-}$ are dependent variables and when the full sample of sovereigns and tenors is considered. A careful inspection of the results by the class of risk of the reference entity suggests that the effect was strong among references with greater credit risk, but modest or non-existent for references with greater creditworthiness. Finally, analysis of the regression of $\mathrm{D2}^{+} - \mathrm{D2}^{-}$ against $\mathrm{ENFORCEMENT}_t \times BAN_i$ and time and cross-section fixed effects does not lend support to the idea that delay became more asymmetric with respect to negative or positive news.

All in all, these results corroborate the hypothesis that delay in the assimilation of information increased after the ban implementation for sovereigns under the scope of EU Regulation 236/2012. Notwithstanding, some differences in the conclusions also emerge when comparing the impact on the delay of common and specific information by class of risk. Indeed, while sovereigns with greater creditworthiness were particularly affected concerning the delay in the adjustment to common-wide (global) information, higher risk sovereigns were more affected by the delay in the assimilation of specific information embedded in bond credit spreads.

Robustness check: Anticipation of the effect of the ban between approval and implementation

EU Regulation 236/2012 became applicable on November 1, 2012 but became known to market participants long before its enforcement. On October 18, 2011 the European Council and the European Parliament reached agreement on the regulation's proposal. The Regulation was voted and accepted by the European Parliament on November 16, 2011 and published in the Official Journal in March 2012. Implementation of the ban was therefore expected by market participants, and an interesting question that emerges is whether its effects were anticipated after its approval by the European Commission or by the European Parliament.

To address this question, we replicate the earlier approach using an alternative timeline to measure the effects of the ban. In lieu of regressing representative variables on $\mathrm{ENFORCEMENT}_t \times BAN_i$ and time and cross-section fixed effects, we regress the representative variables on $\mathrm{APPROVAL}_t \times BAN_i$ and time and cross-section fixed effects, wherein $\mathrm{APPROVAL}_t$is a dummy variable for which the value is one from October 19, 2011 to December 31, 2015. A summary of the main results is reported in Exhibit 8, columns [1]-[2].

In general, the main conclusions are preserved when using the alternative timeline. With regard to the bid-ask spread, the value of the coefficient associated with $\text{APPROVAL}_t \times BAN_i$ is positive and significant, although of a smaller magnitude compared to the value of the coefficient associated with $\text{ENFORCEMENT}_t \times BAN_i$ in equation (1) (0.028 versus 0.042, respectively). A similar conclusion can be obtained with respect to our proxy of liquidity risk (0.007 versus 0.012), the (log) of net open interest (-0.460 versus -0.609), volatility (-0.008 versus -0.010) and delay (for D1, D1+ and D1-). In the case of |VR-1|, the coefficient associated with $\text{APPROVAL}_t \times BAN_i$ is not significant, contrary to the positive and significant coefficient associated with $\text{ENFORCEMENT}_t \times BAN_i$ in equation (1).

Exhibit 8: Robustness tests

	Approval		**Enforcement**[a]	
	Coef. [1]	**t-stat [2]**	**Coef. [3]**	**t-stat [4]**
BAS (%)	2.765***	3.69	4.241***	(5.16)
LR (%)	0.772***	3.08	1.147***	(3.49)
Log NNA	-0.460***	-4.17	-0.480***	(-4.76)
Volatility (%)	-0.799***	-2.76	-1.058***	(-2.72)
Vol^{+} (%)	-0.685***	-3.15	-0.789***	(-2.75)
Vol.- (%)	-0.346*	-1.75	-0.584**	(-2.20)
Vol. Up (%) minus Vol. Down (%)	-0.339***	-2.67	-0.205	(-1.42)
Kurtosis	-1.238**	-2.57	-0.044	(-0.07)
Skew	-0.305***	-2.61	0.052	(0.40)
Positive Extreme Events	-0.025**	-2.45	-0.024	(-1.60)
Negative Extreme Events	0.001	0.07	-0.009	(-0.53)
SR	-0.658***	-3.08	-0.836***	(-3.14)
SR^{+}	-0.667**	-2.11	-1.100***	(-3.21)
SR^{-}	-0.575**	-2.44	-0.659**	(-2.28)
SR^{+}- SR^{-}	0.108	0.35	0.438	(1.22)
D1	0.074**	2.34	0.097**	(2.19)
$D1^{+}$	0.081***	2.89	0.113***	(3.30)
$D1^{-}$	0.076**	2.24	0.097*	(1.93)
$D1^{+}$- $D1^{-}$	-0.005	-0.27	-0.016	(-0.56)
|VR-1|(%)	3.028(.)	1.35	6.258(*)	(1.87)
Q(%)	0.698(.)	0.37	-0.768(.)	(-0.30)
Basis	95.840	0.78	-82.200**	(-2.12)
D2	0.029	0.90	0.023	(0.80)
$D2^{+}$	0.117*	1.87	0.113	(1.62)
$D2^{-}$	0.095**	2.51	0.071**	(2.00)
$D2^{+}$- $D2^{-}$	0.022	0.48	0.042	(0.64)

*Columns 1 and 2 detail the results of regressing representative variables of liquidity, volatility and market quality on $APPROVAL \times BAN$ (where $APPROVAL$ is a binary variable that assumes the value of one after the ban approval and zero otherwise; and BAN is a binary variable that equals one for CDS names under the scope of the ban and zero otherwise). Columns 3 and 4 detail the results of regressing representative variables of liquidity, volatility and market quality on $ENFORCEMENT \times BAN$. In this latter case, we exclude the period May 2010 to April 2011. The regressions include fixed-effects and clustered standard errors by contract and time. The full sample of contracts (3, 5, 7 and 10 year contracts) is considered. T-statistics appear in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. [a] Excluding the time period covered by the German ban. Variables definitions are provided in the caption to Exhibit 2.*

In sum, the effect of the ban is greater when considering the period from the ban implementation onwards than when analyzing the period beginning with the ban approval.

Robustness check: Controlling for the 2010 German temporary ban

Another important issue that may potentially affect our results is the 2010 German temporary ban. On May 19, 2010, the German Federal Financial Supervisory Authority (BaFin) prohibited naked short sales of euro-denominated government bonds and naked CDS based on those bonds. These prohibitions were set to expire on March 31, 2011. Previous research by Pu and Zhang [2012] shows that the temporary ban implemented by Germany helped stabilize the CDS market, particularly CDS volatility. However, they also document a reduction in CDS market liquidity for euro area countries subjected to financial distress.

Our above analysis does not control for this temporary ban that only applied to Germany's jurisdiction. Indeed, most CDS trading involving European CDS names takes place in London. Nevertheless, it is of interest to control the analysis for this previous temporary ban and to ascertain whether it affects our conclusions. We therefore re-estimate equation (1) for each representative variable using a two-way fixed effects model (fixed effects by contract and time), but exclude the period from May 2010 to April 2011 from the estimation. The main results of this alternative procedure are tabulated in Exhibit 8, columns [3]-[4].

In general, the main conclusions survive when excluding the period associated with the temporary ban that only applied to Germany's jurisdiction. Most notably, in the cases of the bid-ask spread, the liquidity risk proxy, the volatility proxies (volatility, upward volatility and downward volatility), the variance ratio and the delay measures (D1, D1+, D1-), we find close estimated coefficients associated with $\mathrm{ENFORCEMENT}_t \times BAN_i$using the full and restricted samples.

A result worth mentioning are the differences in the magnitude of the coefficient of $\mathrm{ENFORCEMENT}_t \times BAN_i$ when the (log) of net open interest is used as the dependent variable. The estimated value becomes considerably smaller when the May 2010 to April 2011 period is excluded from the estimation. This signifies that the ban enforced by BaFin had a relevant impact on CDS trading of Euro sovereigns. Combining all the results, exclusion of the period marked by the temporary ban on Germany's jurisdiction does not qualitatively change our conclusions.

5. Conclusions

The objective of this study is to contribute to a better understanding of the impacts of short selling restrictions. Whereas most previous analyses assessed prohibitions imposed on stock markets, we evaluate the implications of EU Regulation 236/2012, which ruled out buying uncovered sovereign CDS protection. We use panel data models to investigate the possible effects of the ban over three aspects of market efficiency, namely liquidity, volatility and price discovery. In order to enhance the robustness of the research, the analysis includes a control group of obligors not affected by the ban and, to rule out influences other than those related to the regulation, controls for some macroeconomic and financial factors that could have also affected the variables of interest.

The results suggest, firstly, that the regulation contributed to a decline in liquidity. After the regulation's implementation, bid-ask spreads rose for contracts on obligors subjected to the ban and decreased for control group CDS-names. In addition, both groups experienced a decline of net notional amounts (open interest), more relevant for treatment group names. Secondly, the evidence indicates that the ban was successful in stabilizing the CDS market. There was a decline in volatility, more pronounced for contracts under the scope of the ban, and particularly for the more risky obligors. Thirdly, as regards the process of price discovery, our analysis overall suggests that the EU's short-selling ban had a negative effect on price informativeness. There is evidence of an increase in price delay, significantly more prominent for the countries affected by the short-selling ban. Price precision declined in the countries under the regulation's constraints, but increased for those outside its scope. These effects on both price delay and price precision are more pronounced for the more creditworthy sovereigns.

All these results hold for different model specifications and when other factors, such as factors that influence inventory costs and capital constraints of financial intermediaries are accounted for. The results are also robust when delay in the appraisal of information is assessed with respect to specific information embedded in bond credit spreads, when the effect of the ban is anticipated to the moment when it was approved and known to market participants, and also when we control for the temporary ban on naked short-selling of euro-denominated sovereign bonds and CDS on those bonds enforced by the German authorities in 2010.

The identified impact of the ban on liquidity and price discovery may have implications beyond financial market efficiency. In fact, the CDS market plays a relevant role in credit risk price discovery and, at least theoretically, contributes to a decrease in the risk premiums of the underlying bonds. Given that CDS rates are also used as references for loans and other credit claim rates, EU Regulation 236/2012 also runs the risk of affecting sovereign borrowing rates and thus resource allocation and social welfare. Future research should focus on the possible links between bonds' liquidity premiums and CDS market trading, and try to uncover the implications of the short selling ban for the former.

ENDNOTES

[1] Volume based measures are commonly used to assess the liquidity of equity markets. However, the data on the number of traded contracts and corresponding turnover available in DTCC is censored. The weekly report on trades and turnover of a reference name is disclosed if trades (in that week) exceed 50. We use open interest as a proxy for realized liquidity.

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Chapter 5

The Determinants of CDS Open Interest Dynamics (*)

Abstract

It has been argued that the CDS market may be a threat to financial stability. Such concern may stem from the counterparty risk assumed by market participants and the high sensitivity of these instruments to the business cycle. The open interest of the CDS market mirrors investors' maximum exposure and captures aggregate inventory risk, liquidity risk, and trading activity. In this paper, we aim at identifying the main determinants of the dynamics of two alternative measures of open interest, the gross and net notional amounts. Our results suggest that both asymmetry of information and divergence of opinions on firms' future performance help explain the growth of the net notional amount of single-reference contracts, but systematic factors play a much larger influence. Net notional amount growth of different obligors' co-varies in time and the dynamics of open interest is pro-cyclical. The CDS market expands following a positive stock market performance and contracts when large negative (positive) jumps in stock (CDS) prices are perceived by investors. In line with the market microstructure theory, funding costs and counterparty risk reduce CDS market players' willingness to incur in inventory risk, thus contracting gross notional amounts.

JEL Codes: G12; G13; G14; G20
Keywords: Credit default swaps; open interest; inventory risk; counterparty risk.

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1. Introduction

In the last two decades, credit default swaps (CDS) have emerged as important derivative instruments. Mainly traded by sophisticated investors, such as banks, hedge funds, insurance companies, and asset management firms, CDS spreads are now viewed as barometers of creditworthiness for corporate and sovereign borrowers. Most transactions take place in over the counter platforms, but the CDS market became a trading venue for informed investors and is thus relevant for the price discovery process (Acharya and Johnson 2007). However, the market's growing importance has not been matched by comparable improvements in transparency. It continues to be regarded as opaque and badly regulated. Information on prices, transactions or volumes is scarce and, until recently, there were no formally established clearing and settlement mechanisms. Despite regulators' efforts, more transparency, with full disclosure of real time information on prices and transactions, is probably a long way away.

A first step to enhance transparency was taken in November 2008, when the Depository Trust & Clearing Corporation (DTCC) started reporting data on single-name CDS volumes and open interest. Until then, the lack of public information meant that the analysis of non-price trading data, such as volumes and open interest, was outside the scope of academic research. Therefore, very few studies have until now investigated the determinants of such variables. Our objective is to take advantage of the currently available data and contribute to improve existing knowledge on investors' motives to take positions and trade in the CDS market, by developing a comprehensive assessment of the main factors driving the dynamics of CDS net and gross open interest.

Both the efficient markets theory and easier access to reliable data may justify the predominance of price based studies in the financial literature. Yet, many researchers have long concluded that non-price data also provide relevant information that prices alone do not supply (see for instance Blume et al. 1994). The analysis of non-price data may be particularly useful in markets where search costs, heterogeneous bargaining power and limits to the leverage of agents affect optimal risk allocation. That is the case of CDS markets, where most transactions come from bilateral agreements and where dealers behave strategically and exhibit quasi-monopolistic market power (Gündüz et al. 2013).

The rich literature on CDS pricing, thoroughly surveyed by Augustin et al. (2014), suggests that market knowledge may be improved by the development of studies utilizing non-price data. Likewise, the conclusions of previous analyses for other markets suggest that investigating the dynamics of CDS open interest and attempting to identify its main determinants may improve the knowledge on the functioning of the CDS market. In the case of option markets, Fodor et al. (2011)

highlighted the importance of analyzing open interest changes, and Launois and Van Oppens (2005) showed that open interest data is superior to volumes when the objective is to detect informed trading. Focusing on futures, Bessembinder and Seguin (1993) argued that unexpected open interest is a proxy for the willingness of traders, in aggregate, to risk capital.

Although CDS are insurance contracts, the rapid growth of the CDS market is a result of its versatility. Investors trade CDS contracts to hedge exposure to the underlying assets (or to assets with correlated payoffs), but also to speculate and to implement arbitrage strategies (Oehmke and Zawadowski 2014). CDS contracts allow creditors to hedge and diversify credit risk, a possibility that may have wide-reaching benefits. As CDS are generally more liquid than bonds (Bessembinder et al. 2009), credit risk transfers between investors in the CDS market have lower price impacts and lower transaction costs. Both the banking system, in particular, and society, as a whole, benefit from the financial stability promoted by a broader diversification of risks across investors. Moreover, CDS transactions allow the preservation of the costly capital of financial firms which may than be allocated to other financing activities.

The other side of the coin is that large exposures to CDS can create substantial systemic risk (French et al. 2010). In this regard, Brunnermeier et al. (2013) reported that, in aggregate terms, major dealers tend to sell and end-clients tend to buy (net) CDS protection. Systemic risk arises because systemically important financial institutions can be severely affected by unhedged positions when they are on the sell-side. On the one hand, the value of these derivative contracts is very sensitive to the economic environment because default rates, default correlation, and recovery values are influenced by the business cycle[48], which may increase the tail risk of financial institutions that act as dealers in the sell-side, especially when market conditions deteriorate. On the other hand, systemic risk may upsurge due to the multiple channels through which financial intermediaries are connected, and particularly due to counterparty risk (French et al. 2010). Indeed, deficiencies in market design and infrastructure allowed the misuse of CDS and intensified the 2008 financial meltdown. A well-known example is provided by AIG's substantial losses that forced a bail out by the US government in an attempt to prevent financial contagion to other major US financial institutions.

Academic research plays a role in the improvement of market efficiency, namely by investigating relationships involving relevant specific and systematic variables, and providing insights into the strategic behavior of agents faced with changing market conditions. In this study, we

[48] Altman et al. (2005) and Acharya et al. (2007) found out that macroeconomic and industry conditions at the time of default are robust determinants of the recovery rate. Giesecke et al. (2011) showed that default rates are persistent and tend to cluster over time.

develop a thorough investigation of the main determinants of the dynamics of CDS net and gross notional amounts outstanding. The scarcity of studies using non-price CDS data provides academic justification for the analysis, but it is also of interest for financial professionals and for regulators and policy makers, aimed at improving the CDS market architecture. More specifically, the assessment of possible relationships between open interest changes and the counterparty risk of major dealers may be relevant for the current discussion on the creation of a central counterparty (CCP), or for the improvement of clearing and settlement mechanisms. As the maximum exposure of market participants to CDS contracts is subsumed by their aggregate outstanding positions, or open interest, new insights on the drivers of this variable's dynamics may improve knowledge on the strategic behavior of CDS market players and on the potential threat posed by the market in terms of systemic risk. In addition, the identification of such determinants is important to assess market players' capacity, and especially that of the dealers, for managing risk in adverse market conditions and promoting efficient risk sharing among economic agents. Finally, as changes in open interest have been shown to be good proxies of trading activity, the analysis of their determinants may help explain the time patterns of liquidity risk in the CDS market.

Our study focuses on two different measures of open interest: the net notional amount and the gross notional amount. The former is the sum of net protection bought (sold) by counterparties that are net buyers (sellers) of protection for a particular obligor, and captures the stock of credit risk transferred in the CDS market (Oehmke and Zawadowski 2014). The gross notional amount is the aggregate notional of all the CDS contracts open in the market and is also driven by operations related to the management of counterparty exposure, such as portfolio compression cycles and novation. We utilize weekly data on 537 obligors from the US, European Union (EU), and Switzerland, to develop an empirical evaluation in three steps. First, we perform an exploratory assessment of the commonalities of open interest. Then, we carry out regression analyses, using a variety of estimation methods for robustness, to evaluate the impact of specific factors (the credit risk of the obligor and differences of opinion) on the dynamics of the net notional amounts. The limited explanatory power of these factors, and the results obtained with the principal components analysis, justify the subsequent focus on systematic determinants (market conditions – market performance, risk aversion and systematic volatility – changes in funding costs and in the creditworthiness of major dealers, and market liquidity). Finally, we investigate whether CDS dealers and end-users respond differently, in terms of the gross notional amounts held, to changing market conditions.

In what concerns specific factors, we mentioned above that hedging the credit risk of a reference entity and speculating on specific information about the future performance of a firm are plausible motives for taking positions in CDS contracts. Chordia et al. (2007) argued that trading may be induced by asymmetric information. Thus, investors that use the CDS market to explore their private information will take positions that are reflected in the amount of open interest outstanding. It is hence expected that a relationship exists between changes in the credit risk of an obligor and the pattern of open interest changes. Higher credit risk could also induce risk adverse investors to seek more credit risk protection, impacting open interest as well. These issues are explored in our assessment of how changes in the credit risk of an obligor interact with the CDS market anatomy.

Information uncertainty and investors' heterogeneous expectations concerning the future prospects of an obligor may also promote the trading activity in the CDS market and thus the amount of outstanding positions. The underlying rationale is that if many investors disagree about the future prospects of a firm, more will trade and take offsetting positions in CDS contracts. It is thus expected that information uncertainty and heterogeneous expectations rise together with open interest. In fact, Bessembinder and Seguin (1993) used the open interest in the futures market to measure differences of opinion.

The obtained results suggest that the evolution of the obligors' credit risk is a significant determinant of the CDS net notional growth, in line with the notion that credit risk increases the demand for protection through CDS contracts. Surprisingly, the results indicate that information uncertainty and divergences of opinion have a negative impact on the changes of CDS net positions outstanding. Nevertheless, the explanatory power of these idiosyncratic factors for the dynamics of the open interest is very low - the R-squared of time series regressions of open interest growth against proxies of credit risk and divergences of opinion averages 3.5%.

The initial exploratory principal components analysis of the series of obligors' open interest growth unveils the interesting fact that the first principal component explains almost 20% of the series' variance, prompting the question of whether the open interest dynamics of single reference entities is driven by common factors. Therefore, after concluding that specific factors play a relatively small role in this context, we also concentrate on systematic features, exploring several possible lines of reasoning. The first relates to the impact of portfolio rebalancing following changes in market conditions.

When the business climate deteriorates, or when risk aversion intensifies, investors may increase the demand for credit risk protection with CDS contracts. Such demand increment is driven by common factors and will subsequently affect the open interest of the various CDS-names. A second explanation relates to the supply-side of the CDS market and to its liquidity. As open interest is a main determinant of dealers' inventories, open interest co-variation may be induced by comovements in optimal inventory levels and systematic factors, such as market risk and interest rates. Adrian and Shin (2010) showed that the leverage of financial intermediaries is pro-cyclical, following the capital and margin requirements that these entities face. Hence, following market downturns, CDS dealers may have to adjust the size of their balance sheets and limit their inventories. It is therefore plausible that CDS dealers diminish their open interest when market performance deteriorates. Likewise, an increase in systematic volatility may affect the willingness of liquidity providers to take additional risks and, therefore, also impact the behavior of the aggregate amount of net open interest.

Our analysis suggests that stock market returns, stock market volatility, and risk aversion are relevant determinants of the growth of open interest. The regression analyses confirm the procyclicality of open interest amounts, as they increase (decrease) with positive (negative) stock market returns. These results are in line with the idea that stock market returns influence the leverage capacity of financial intermediaries and their propensity to incur in additional risks. Therefore, when large negative stock market movements are perceived, open interest decreases. This confirms the intuition that liquidity providers and sellers try to limit their exposure when large (positive) movements in CDS spreads are perceived because they lead to undesirable margin calls and collateral reinforcements (Brunnermeier et al. 2013).

To shed some additional light on the impact of financial intermediaries' capital constraints, the association between the growth of open interest and funding costs is analyzed. The results suggest that funding costs have limited power to explain the dynamics of the net notional amount, but are a relevant explanatory variable for the gross notional amount held by dealers (funding costs in the interbank market) and by end-clients (funding costs in the repo market). Not surprisingly, gross open interest and funding costs are inversely related.

Counterparty risk also influences the dynamics of open interest. Our findings suggest that the counterparty risk of major dealers affects their ability to reallocate inventory risk in the inter-dealers market. Counterparty risk has a negative impact on net open interest, perhaps because it hampers the reallocation of risks across dealers (it limits the risk sharing capacity in the inter-dealers market). Overall, our findings support the view that counterparty risk is an important determinant of the gross open interest held by dealers and end-clients. They also support the hypothesis of a negative connection between financial markets' liquidity and open interest. Interestingly, accounting for unspecified unknown common factors increases the R-squared of our models from 10.1% to 22.7%, thus suggesting that factors other than those commonly used in empirical research drive the open interest dynamics.

The study is concluded with an examination of the role played by the above mentioned systematic factors as determinants of the overall gross notional amount, and of the gross amounts held by dealers and by end-clients. Some of the findings were already mentioned above. We conclude that the gross notional amount responds differently to changes in market performance. Dealers reduce their maximum (sell-side) exposure following market downturns, in opposition to end-clients, whose sell-side inventories are countercyclical. The effect of funding costs on the gross notional amount is also distinct for dealers and for end-clients. The former respond negatively to shocks in the interbank and repo markets, whereas the latter are positively affected by shocks in the inter-bank market and negatively affected by shocks in the repo market. Counterparty and systematic jump risks have a negative impact on the gross notional amounts held by dealers and by end-clients.

The overall conclusions of the analysis have significant implications. We conclude that major CDS dealers react to adverse market conditions, and in particular to increases in counterparty risk. It can therefore be argued that the creation of a CCP could help mitigate market frictions resulting from upsurges in dealers' counterparty risk. Such frictions limit credit risk smoothing amongst dealers and also between dealers and end-clients. Furthermore, when end-clients perceive that a counterparty is in distress, they seek to close their positions with that counterparty, or engage in novation operations with other dealers (Duffie 2010), thus causing disruption in the CDS market.

Activity in the CDS market decreases when the stock market falls, as a consequence of the attempts of major dealers to readjust balance sheets and inventory risk to the new market conditions. Such behavior is sub-optimal. It inhibits hedgers from covering their exposure to borrowers in the aftermath of market downturns, thus hindering efficient risk sharing. It may also have implications for investment decisions, if the hedging of credit risk exposures is critical for the development of such projects, thus making investment decisions also pro-cyclical.

Our study adds to the relatively scarce body of research on the CDS market that explores the informational content of non-price trading data. Chen et al. (2011), Berg and Streitz (2012), Shachar (2012), Brunnermeier et al. (2013), and Oehmke and Zawadowski (2014) are recent empirical studies that also investigated CDS positions or transaction data. Chen et al. (2011) analyzed three months of global CDS transactions and presented stylized facts on the market composition, trading dynamics and level of standardization. Berg and Streitz (2012) assessed the determinants of the sovereign CDS market's scale using information on 57 countries. Brunnermeier et al. (2013) assessed the risk of contagion stemming from CDS exposures and found out that the market activity is concentrated on a group of highly interconnected global derivative dealers, which they designate as "super-spreaders".

Within this group of studies, the analysis we develop is closer to the work produced by Shachar (2012) and by Oehmke and Zawadowski (2014). In common with them, we use CDS net notional values to empirically evaluate a variety of features from the market microstructure literature in the context of the CDS market. The three studies are, however, substantially distinct. They differ in terms of the econometric methodologies adopted, the samples of data utilized, the research questions underlying the tested hypotheses and the incremental contributions to improve existing knowledge on the functioning of a still relatively opaque financial market.

Shachar (2012) used dealer specific data on 35 North American reference entities (financial firms), from February 2007 to June 2009, to examine the effect of counterparty risk on the activity of dealers as liquidity providers and also to assess the price impact of end-users' order imbalances. She concluded that interdealer market congestion raises inventory risk aversion and limits intermediation.

Unlike Shachar (2012), our study and Oehmke and Zawadowski's (2014) are developed with data on individual reference entities' positions. Such data, which only became available from DTCC in 2008, is cruder than that utilized by Shachar but, on her own words, "allows a broader picture of the CDS market activity" (Shachar 2012, p. 26). Whereas Oehmke and Zawadowski (2014) worked with monthly data on US obligors, from October 2008 to September 2012, we use weekly data from October 2008 to October 2014 and included US and European obligors. In comparison with Shachar's, these two samples have the advantage of encompassing the 2009 'Big Bang' Protocol, implemented by ISDA with the objective of standardizing contracts and settling procedures. However, our sample gains in diversity for it is the only one containing information on both US and European obligors and covering a period of time characterized by the generalized use of CCP clearing facilities (from 2012 onwards).

Both we and Oehmke and Zawadowski (2014) investigate possible determinants of the net notional outstanding (focusing on growth and levels, respectively), but our analysis encompasses a larger set of potential variables, clearly distinguishing between idiosyncratic and systematic factors. Oehmke and Zawadowski (2014) concluded that speculation and hedging, the search for alternatives to direct bond trading and the exploitation of arbitrage opportunities explain both the level of net notional and the existence of the CDS market. In view of such evidence, we turned our attention to the dynamics of the net notional amounts outstanding and investigated the importance of microstructure factors found to be relevant in the context of other financial markets.

The remainder of the study is organized as follows. The hypotheses under investigation are established in Section 2; Section 3 describes the dataset and provides the data's summary statistics; Section 4 presents the empirical results; Section 5 concludes the analysis.

2. Hypothesis Development

Our study addresses the time series determinants of the growth of CDS market's open interest. Like other non-price trading variables, open interest results from the hedging and speculative activities of investors. These may be motivated by idiosyncratic and systematic factors. We first address the relevance of specific issues (hypotheses 1 and 2) and, subsequently, focus on systematic influences. In what follows, we describe the motivation and then state each of the empirical hypotheses underlying the subsequent empirical analyses.

As asymmetry of information exists, open interest growth is expected to be related to changes in the credit risk of obligors. When informed investors perceive a higher credit risk for a borrower, they increase the demand for credit risk protection and buy CDS contracts. Speculation over changes in obligors' credit quality should thus affect trading activity in the CDS market. In fact, short-selling restrictions and price impacts in the bond market render the price discovery process in this market less likely. Furthermore, changes in the credit risk of the obligors may also trigger hedge rebalancing, again impacting open interest amounts.

Dealers are, on average, net-sellers of CDS (Brunnermeier et al. 2013). It is thus reasonable to argue that speculative trades are mainly buyer-initiated and that net open interest should increase with credit risk. Indeed, Tang and Yan (2010b) concluded that the price impact of net buying interest results from the information content of future changes in CDS spreads, whereas the net selling interest appears to have little information content (the price impact of negative net buying imbalances is quickly reversed). Gündüz et al. (2013) suggested that asymmetric information and inventory risk are only relevant for trades with buy-side investors.

The first hypothesis is thus:

H1: Changes in the credit risk of the obligor are an important determinant of the dynamics of the net maximum exposure of investors.

The relationship between trading activity and informational flows is highlighted in several theoretical and empirical studies. For instance, Chordia et al. (2007) stated that trading is induced by asymmetric information. Mitchell and Mulherin (1994) showed that trading volumes and measures of public information are connected. Bessembinder et al. (1996) concluded that trading volumes correlate with empirical proxies for information flows.

Another idiosyncratic factor that can help explain the pattern of open interest growth is therefore investors' divergence of opinions. Indeed, there is extensive theoretical and empirical literature establishing a link between differences of opinion and trading activity. The theoretical model of Harris and Raviv (1993) associated trading volumes and volatility, since both reflect divergences of investors' opinions and speculative trading. Opinion divergence may result from differentiated access to private information or from distinct interpretations of publicly available information. Kandel and Pearson (1995) developed a model in which investors interpret public signals differently, which was consistent with the patterns of volume-return observed in empirical data. Cao and Ou-Yang (2009) analyzed the effects of differences of opinion on the dynamics of trading volumes in stocks and options markets. They demonstrated that disagreements about the meaning of the current and next-period public information lead to trading in stocks in the current period. Bamber et al. (1997 and 1999) provided evidence indicating that distinct interpretations are an important motivation for speculative trading. Chordia et al. (2000) found out that differences of opinion induce trading activity prior to macroeconomic announcements. Foster and Viswanathan (1993) showed that heterogeneous beliefs lead to trading in reaction to public information.

These considerations elicit a central question: are investors' differences of opinion related with CDS trading data and, specifically, with the dynamics of open interest? Intuitively, the greater the divergence of opinions, the higher the willingness of investors to trade and to take offsetting positions based on their expectations. Hence, it is expected that:

H2: Differences of opinion positively influence the dynamics of the net maximum exposure of CDS market players.

In what concerns the impact of common factors, a number of arguments support the hypothesis that systematic variables have an effect on the dynamics of open interest. The first is of an empirical nature. The principal components analysis developed below uncovers commonalities in the open interest growth of different obligors. Other researchers have also acknowledged the existence of commonalities in liquidity and trading activity in stock and bond markets. For instance, Chordia et al. (2000) showed that illiquidity co-varies across different securities and asset classes. Hasbrouck and Seppi (2001) showed that order flows in the stock market are characterized by common factors. We also assume that the commonalities of the open interest changes result from a reaction to common factors.

From a theoretical perspective, it is important to distinguish the impact of systematic factors on the provision of liquidity and on financial intermediaries' inventory risk, and also on the speculation and hedging activities of end-clients in the CDS market. Intuitively, changing market conditions may lead end-clients to rebalance their portfolios. The deterioration of market conditions is expected to increase the demand for insurance against credit risk. In fact, even in the absence of contracts for some borrowers, end-clients may purchase contracts for reference names whose fundamentals are correlated with those of the actual borrowers. Another common practice is to use CDS contracts to implement macro hedging strategies. Consequently, new market conditions may force investors to rebalance their positions, particularly when risk is dynamically managed.

Notwithstanding the reaction of hedgers and speculators to adverse market conditions, liquidity providers tend to reduce liquidity in the aftermath of market downturns or in periods of systematic risk upsurges. Adrian and Shin (2010) showed that when asset prices fall, the net worth of financial intermediaries decreases, forcing these entities to un-leverage, i.e. to reduce the size of their balance sheets and inventory risks. Gârleanu and Pedersen (2007) argued that tighter risk management reduces the maximum position an institution can take and, consequently, the amount of liquidity it can supply to the market. Hence, the reactions of liquidity suppliers, market downturns and systematic risk should reduce the amounts of CDS open interest outstanding.

The impacts from hedging and speculation by end-clients and from liquidity suppliers' inventory risk may affect the dynamics of open interest differently. Such impacts may even offset each other. In our empirical analysis, we aim to determine which one prevails.

H3: Changes in market conditions (market performance, risk aversion, and systematic volatility) impact the dynamics of open interest.

The funding costs faced by financial intermediaries, and in particular by CDS dealers, may influence these entities' capacity to absorb liquidity shocks. In fact, they may react with larger bid-ask spreads and CDS premiums to higher funding costs. Additionally, they also affect the capacity to replicate the payoffs of CDS contracts using bond markets. Brunnermeier and Pedersen (2009) showed market liquidity and funding risk are mutually reinforcing and lead to liquidity spirals, so that funding risk moves *pari passu* with market liquidity. Gârleanu and Pedersen (2011) developed a theoretical model where funding risk is priced in "bad times", as margin requirements are hit. Open interest is connected to inventory risk. When the margin requirements are hit and the shadow cost of capital climbs, intermediaries tend to deleverage their balance sheets and to reduce the risk of their portfolios, with the objective of decreasing their regulatory capital requirements. This may also affect the amount of open positions in the CDS market, leading to a negative relationship between funding costs and open interest.

H4: Changes in funding costs (negatively) impact open interest.

Another factor affecting the liquidity supply-side is counterparty risk. Shachar (2012) suggested that counterparty risk, measured by the level of exposure in the inter-dealer market, limits the willingness of dealers to provide liquidity and thus restricts intermediation in the CDS market.

When dealers pass the end-user's trade, the exposure to the underlying is unaffected, but the counterparty exposure between dealers increases (Shachar, 2012). Therefore, an increase of the default risk of major CDS dealers makes the reallocation of inventory among them unappealing. In fact, in addition to credit exposure to the underlying borrower, a new exposure between a pair of dealers emerges from each trade in the interdealer market. As in Reiss and Werner (1998), inter-dealer trade is expected to facilitate inventory risk sharing among dealers. Inter-dealer transactions are used for hedging operations and to reallocate inventory risk. To assess the relevance of counterparty risk in the context of the CDS market, we examine whether changes in dealers' creditworthiness produce effects on the open interest dynamics.

H5: Changes in the creditworthiness of major CDS dealers impact the dynamics of open interest.

The effects of systematic liquidity on open interest changes are also evaluated. Illiquidity may increase search and transaction costs for hedgers and speculators, lowering trading activity and net outstanding positions in the CDS market (see Duffie et al. (2007), for over the counter markets in general). Furthermore, illiquidity affects the financial intermediaries' shadow cost of owning assets and may influence their optimal inventory level. Accordingly, it is also plausible that market-wide illiquidity influence the growth of net open positions of CDS contracts.

H6: Market illiquidity and open interest move in opposite directions.

Finally, to get a detailed picture of how CDS dealers and end-clients react when market conditions change, the relationship between systematic factors and the dynamics of gross notional amounts held by seller-clients and seller-dealers is examined at the industry level.

H7: The response of CDS dealers to changing market conditions distinguishes from that of end-clients.

The study proceeds with the detailed description of the data, data sources and variables utilized in the empirical analysis, and with an exploratory analysis of the commonalities of open interest.

3. Data

3.1 Data sources and empirical variables

The dataset comprises weekly data for a six-year period from October 31, 2008 to October 10, 2014, retrieved from DTCC and Bloomberg. DTCC collects data directly from major derivative dealers and is the most comprehensive source of data on CDS trades, covering, according to their own information, 95% of globally traded CDS. DTCC provides data on CDS gross notional amounts, net notional amounts and number of contracts outstanding. The gross and net amounts outstanding[49] distinguish themselves by the fact that the former encompasses the total amount outstanding, whereas net notional amounts reflect the maximum exposure of CDS market participants to the credit risk of the reference names. Long and short positions on the same contract held by the same market participant cancel out and are not accounted for on net notional amount figures.

The data available from DTCC is censored for the top 1,000 reference entities with the highest gross notional amount outstanding in each week. However, these represent, on average, over 98% of the global gross notional amount in DTCC. The dataset comprises 317 US obligors (82,787 weekly observations) and 210 obligors from Europe (56,976 weekly observations). The data from the DTCC website is matched with data from Bloomberg on the 5-year CDS spreads[50] of the obligors (bid, ask and mid), stock prices, stock trading volumes, fundamental data on the obligor (debt, debt-to-market cap ratio), and business-cycle and macro data.

The study assesses the impact of idiosyncratic and of systematic variables on the open interest of single-reference contracts. According to previous research, trading in the CDS market may be motivated by portfolio rebalancing, liquidity shocks of market participants, asymmetric information, and opinion divergence (Bessembinder et al. 1996). We firstly examine whether hedging and speculation over the credit risk of the obligors are positively related with the dynamics of the net notional amount. In doing so, we assume that speculation and hedging are motivated by changes in the credit risk of the obligor. As asymmetric information on credit risk signifies that one of the parties in a transaction has superior information about future changes in the credit risk of the obligor, trading and new positions on CDS contracts should also be related to changes in proxies of credit risk.

CDS rate changes are a proxy for credit risk. However, this variable and net notional amount changes might be endogenously determined by third variables. As such, in order to avoid econometric bias, stock returns' volatility, the debt-to-equity ratio and stock returns are used as proxies for credit risk. The first two variables are associated to credit structural models, which directly link the value of credit risk instruments to the economic determinants of default risk and loss given default.

[49] DTCC provides the following definition: "Net notional positions generally represent the maximum possible net funds transfers between net sellers of protection and net buyers of protection that could be required upon the occurrence of a credit event relating to particular reference entities. (Actual net funds transfers are dependent on the recovery rate for the underlying bonds or other debt instruments)."
[50] Average prices are computed intraday at about 6 p.m. in New York. The notional amount of contracts is denominated in USD.

Structural models predict that the likelihood and severity of a default are a function of financial leverage, assets' volatility, and the risk-free term structure. In fact, an increment of leverage decreases the distance to the default boundary, thereby raising the probability of default. Leverage is computed as the ratio between the book-debt (sum of long-term debt and debt in current liabilities of the firm) and the market value of the equity of the firm. The volatility of stock returns reflects the assets' volatility and the leverage of the firm and also correlates positively with credit risk. Finally, stock price changes convey information about firms that may affect credit spreads. In this respect, Collin-Dufresne et al. (2001) and Shaefer and Strebulaev (2008) argued that stock price changes encapsulate all fundamental information related to the default risk of a firm. Accordingly, we use stock returns as a proxy for credit risk.

The effect of differences of opinion on the path of open interest is also analyzed. Differences of opinion are captured by the CDS rate volatility and by changes in stock trading volumes. More opinion divergence is expected when trading volumes and the CDS rate volatility climb.

A detailed description of these idiosyncratic variables is provided below:

$stock\ ret_{i,t}$	Log weekly change of stock prices
$\Delta stock\ trading\ volume_{i,t}$	Log weekly change of trading volume in the stock market
$\Delta Leverage_{i,t}$	Weekly change of the D/E of the firm
$\Delta stock\ vol_{i,t}$	Weekly change of the stock price volatility (90-days' historical returns)
$\Delta CDS\ rate\ vol_{i,t}$	Weekly change of the CDS rate volatility (5-days' historical rate changes)
$Excess\ stock\ ret_{i,t}$[51]	Weekly stock returns minus the weekly stock market returns

Systematic factors might influence the path of open interest via different channels. We divide these factors into four categories. Stock market returns, systematic jump risk, VIX, the volatility premium, the yield curve slope, the 10-year spot rate, the spread between rates of one-month top commercial paper and one-month US Libor, and the excess returns of speculative-grade bonds over investment-grade bonds are included in a first category. These variables affect the hedging and speculative behavior of end-clients and the inventory risk of CDS dealers. Given that the expected reaction of end-clients and dealers to changing market conditions might lead to different dynamics of open interest, the sign of the impact of these variables is *a priori* unknown.

[51] The market model was also used to obtain $Excess\ stock\ ret_{i,t}$ without producing relevant changes in the final conclusions of the article.

The business climate influences the default risk and the loss given default of borrowers, and the correlation risk of portfolios (Altman et al. 2005; Acharya et al. 2007; and Giesecke et al. 2011). Long-term interest rates and the slope of the yield curve are utilized as proxies for the business climate. In fact, interest rates are often associated with macroeconomic conditions and the business cycle. Long-term interest rates correlate with expected consumption growth and decrease during economic recessions. The slope of the yield curve also conveys information on future spot rates and economic conditions.[52]

Another factor that may drive open interest changes is volatility. The volatility of financial markets is proxied by VIX (VSTOXX), which plays a relevant role in explaining changes of corporate CDS spreads and is a pervasive factor in explaining sovereign CDS spreads (Pan and Singleton 2008). On the one hand, it is reasonable to anticipate that the demand for hedging and portfolio rebalancing increases with the systematic risk perceived by investors. On the other hand, an increase of the expected risk may change the behavior of CDS liquidity suppliers due to a higher expected inventory risk, making the latter reluctant to increase their exposures. Concurrently, potentially large positive movements in CDS spreads may lead to margin calls and collateral reinforcements (Brunnermeier et al. 2013) and thus, when they are perceived, liquidity providers and sellers may attempt to limit exposures and inventories. Systematic jump risk is utilized to capture the likelihood of large negative (positive) jumps in stock prices (in CDS rates). As in Tang and Yan (2010), systematic jump risk is calculated as the slope of the implied volatility surface of put options written on stock market indices.

Risk aversion is also expected to have a role in driving changes in the demand and supply of CDS contracts. Here, risk aversion is measured by three alternative variables: volatility premium, excess returns of speculative-grade bonds over investment-grade bonds, and spread between the rates of one-month top commercial paper and one-month US LIBOR. The volatility premium is calculated as the difference between the three-month implied volatility of at-the-money options on the S&P 500 (DJ Eurostoxx 50) and the three-month historical volatility of the S&P 500 (DJ Eurostoxx 50). The volatility premium is used because the stock market volatility varies over time. The volatility premium denotes the compensation required by investors to bear variance risk. Therefore, it is a measure of investors' risk aversion, considering that a higher volatility premium implies a higher compensation warranted by investors for taking variance risk. The excess returns of speculative-grade

[52] Harvey (1988) showed that the slope of the yield curve has a positive association with future consumption. Estrella and Hardouvelis (1991) claimed that a positive slope predicts an increase of real economic activity, measured by consumption, consumer durables and investment. Estrella and Mishkin (1998) examined the power of various financial variables in probit models to predict recessions and found that, among all the variables analyzed, the slope of the yield curve has the largest explanatory power (a decline in the slope increases the probability of a recession).

bonds over investment-grade bonds increase when investors are less risk averse, thereby representing changing risk aversion in the bond market. This variable closely relates to the difference between the rates of one-month top commercial paper and one-month US LIBOR.

Finally, stock market performance is included in the model as a forward-looking indicator of business climate and market sentiment, and as a measure of capital constraints faced by financial intermediaries. Regarding this last aspect, Adrian and Shin (2010) concluded that asset price changes affect the net worth of financial intermediaries. They suggested that these entities adjust the size of their balance sheets and reduce inventory risk following assets devaluation. Thus, as stock market returns are an advanced proxy for changes in the net worth of financial intermediaries and major CDS sellers and liquidity providers are financial institutions (Chen et al. 2011), it is also plausible that they capture major dealers' capital constraints. Greater market volatility also implies capital bindings, risk management restrictions, and less capacity to supply liquidity to the markets.

It is also relevant that CDS spreads are likely to become more correlated during periods of financial turmoil. Growing correlations may result from fundamental factors and from intermediaries' capital constraints. In the first case, the default rates and the loss given default rise during economic recessions, turning credit spreads more correlated. In the second, contagion induced by capital constraints from financial intermediaries leads to larger correlations[53]. The latter reduce the benefits of diversification and increase dealers' inventory risk, making them less available to supply liquidity to other market participants.

A second category of factors aims to capture funding costs and capital constraints of financial intermediaries and, in particular, of dealers. The spread between repo rates having Mortgage Backed Securities and Treasuries as collateral[54], and the spread between the one-month US Libor and OIS are used as proxies for funding costs. With regard to the former, it is well-known that financial intermediaries prefer Treasuries as collateral rather than Mortgage Backed Securities, since the latter are riskier and display lower liquidity in periods of financial turmoil. This implies that the spread between the two repos (Repo spread) becomes wider during such periods (when funding risk is higher). The third category includes a measure of aggregate counterparty risk, namely the average CDS spread of the G14 group of major dealers in the CDS market. Finally, two measures of market-

[53] In this respect, Acharya et al. (2007) showed that in the normal regime, the correlations across assets are primarily driven by correlations in fundamentals. However, during crises, intermediaries' capital constraints induce a correlation that is higher than that induced by fundamentals. Because the benefits of risk diversification diminish, higher correlations originate higher shadow capital costs and higher inventory risk for intermediaries.
[54] This measure follows Gârleanu and Pedersen (2011), which used the spread of the rates of uncollateralized and collateralized loans as a proxy for funding costs.

wide liquidity are included in the fourth category: the average weekly bid-ask spread in CDS markets and the average weekly bid-ask spread in stock markets.

A detailed description of these systematic variables follows:

SMR_t	Log weekly change of stock market prices (S&P 500 and DJ Eurostoxx 50 for US and European firms, respectively)
ΔJR_t	Changes of the systematic jump risk. The systematic jump risk is proxied by the difference between the implied volatility measured at the strike-to-spot ratio of 90% and the strike-to-spot ratio of 110%. Options written on the S&P 500 and on the DJ Eurostoxx 50 are used to compute this indicator (for US and European firms, respectively)
ΔVIX_t	Weekly change of the VIX (VSTOXX in the case of European obligors)
ΔYCS_t	Changes of the yield curve slope, defined as the difference between the 5-year and 2-year spot rates (US and Germany benchmarks)
$\Delta 10YR_t$	Changes of the 10-year spot rate (US and Germany benchmarks)
$\Delta Vol\_premium_t$	Changes of the volatility premium, defined as the difference between the three-months' implied volatility and the three-months' historical volatility of the S&P 500 (for US obligors) and of the DJ Eurostoxx 50 (for European obligors)
BRA_t	Excess returns of speculative-grade bonds over investment-grade bonds (proxied by the Iboxx High-Yield Liquid Bond and Investment-Grade Liquid Bond indices, respectively)
$\Delta Repo\ spread_t$	Changes of the spread of the repo rates having as collateral Mortgage Backed Securities and Treasuries
$\Delta G14$	Changes of counterparty risk, proxied by the average 5-year CDS spreads of the G14 main dealers of the CDS market
ΔBAS_CDS_t	Average change of the CDS percentage bid-ask spread (aggregated by the domicile of the firm, i.e. European and US obligors)
ΔBAS_stocks_t	Average change of the stocks percentage bid-ask spread (aggregated by the domicile of the firm, i.e. European and US obligors)
ΔCPS_t	Change of the spread between the rates of 30-days' top commercial paper and one-month US Libor
$\Delta LOIS_t$	Change of the spread between the rates of one-month US Libor and OIS – overnight indexed swap

Some descriptive statistics of the sample are provided in Table 1, Panel A. In order to shed some light on the differences between CDS written on US and European borrowers, a numerical breakdown of the results by domicile is displayed. The average (median) CDS rate is 300.2 (153.4) for European obligors, and 302.8 (142.8) for US obligors. Both subsamples are skewed, with the average exceeding the median by a large extent, meaning that the subsamples comprise a set of firms displaying very large CDS rates. The average net notional amount by borrower for the entire sample equals 945 million USD, whereas the average number of contracts is 2062.3. The average market capitalization of the firms included in the subsamples is 21,555 million EURO for non-US obligors and 25,130 million USD for US obligors. Taken jointly, the sample mainly covers very large firms. The average (median) net debt is 14,931 (3,236) million USD for US obligors.

Restricting the sample to non-financial obligors, the average (median) interest rate coverage is 8.4 (4.5), whereas the average (median) debt-to-equity ratio equals 1.0 (0.5), which signifies that, on average, borrowers have the capacity to fulfill their obligations in the short-run. The average (annualized) stock returns volatility (obtained through 90 day's historical rolling windows) is near 40%, whereas the average (annualized) volatility of the CDS rate percentage changes equals 38.7%. The percentage bid-ask spread of the CDS contracts equals, on average, 7.9%. The weekly trading volume of stocks is 189 million of USD for US obligors and 610 millions of EURO for European obligors.

Table 1, Panel B, traces out the correlation structure of the systematic variables. It is noteworthy that ΔVIX and $\Delta Vol\, premium$ present a very high correlation (0.85), which suggests they should not be included simultaneously in the same empirical model. The same applies to ΔYCS and $\Delta 10YR$, and to $\Delta LOIS$ and ΔCPS. As $\Delta G14$ and SMR also exhibit a large correlation (-0.62), further controls are implemented when both are simultaneously considered as explanatory variables.

Table 1 – Descriptive statistics

Panel A - Sample statistics	European			US			Total		
	Mean	Std.	Median	Mean	Std.	Median	Mean	Std.	Median
CDS rate	300.2	443.4	153.4	302.8	518.9	142.8	301.6	484.5	147.8
Daily stock trading volume ($)(*)	610	1,906	130	189	239	113			
CDS contracts net notional amount (**)	996	744	783	907	870	699	945	820	732
# Contracts	2,217.5	1,395.3	2,001.6	1,949.4	1,311.1	1,632.8	2062.3	1352.8	1771.4
Market capitalization(*)	21,555	24,770	12,071	25,130	38,722	11,579			
Debt-to-equity ratio	1.0	1.7	0.5	0.9	2.9	0.4	1.0	2.5	0.5
Interest rate coverage	7.6	14.7	4.0	8.8	15.5	4.8	8.4	15.2	4.5
Stock price vol. (annualized)	38.3%	22.5%	32.7%	40.9%	29.1%	35.1%	39.9%	26.7%	34.6%
Net debt(*)	6,123	12,108	2,684	14,931	61,345	3,236			
Bid-ask spread of CDS contracts	7.7%	2.8%	7.3%	8.0%	3.1%	7.4%	7.9%	2.9%	7.3%
CDS volatility (annualized)	45.7%	30.4%	37.0%	32.3%	11.2%	30.8%	38.7%	23.3%	33.7%
Bid-ask spread daily vol.	1.0%	0.6%	0.9%	0.6%	0.4%	0.5%	0.8%	0.6%	0.7%

Panel B - Correlation analysis	$\Delta LOIS$	ΔCPS	SMR	ΔJR	ΔVIX	ΔVol Prem.	ΔYCS	$\Delta 10YR$	$\Delta Repo$ spread	$\Delta G14$	BRA	ΔBAS CDS	ΔBAS stocks
$\Delta LOIS$	1.00												
ΔCPS	0.74	1.00											
SMR	0.13	-0.02	1.00										
ΔJR	0.04	0.01	-0.14	1.00									
ΔVIX	0.04	0.10	-0.79	0.25	1.00								
$\Delta Vol\ premium$	0.07	0.15	-0.73	0.23	0.85	1.00							
ΔYCS	0.05	-0.02	0.44	-0.07	-0.43	-0.36	1.00						
$\Delta 10YR$	0.08	0.00	0.47	-0.10	-0.40	-0.32	0.89	1.00					
$\Delta Repo\ spread$	0.39	0.32	0.07	0.05	-0.02	-0.04	0.06	0.03	1.00				
$\Delta G14$	0.02	0.04	-0.62	0.25	0.55	0.52	-0.30	-0.36	0.00	1.00			
BRA	-0.12	-0.13	0.56	-0.14	-0.43	-0.37	0.47	0.62	-0.08	-0.55	1.00		
ΔBAS_CDS	-0.02	0.00	0.17	-0.01	-0.12	-0.11	0.12	0.13	-0.01	-0.18	0.19	1.00	
ΔBAS_stocks	0.00	0.01	-0.09	-0.05	0.06	0.09	0.01	0.00	-0.09	0.06	-0.06	-0.01	1.00

Panel A reports summary statistics for the reference entities of CDS contracts included in the sample. Mean, median and standard deviation statistics are presented for several variables namely CDS rates, daily stock trading volume, net notional amount of CDS contracts, number of CDS contracts outstanding, stock market capitalization, debt-to-equity ratio, interest rate coverage, stock returns volatility based on the prior 90 trading days, net debt, stocks bid-ask spread, CDS daily volatility, and CDS bid-ask spread daily volatility. The results are tabulated for the whole sample of obligors and by the domicile of the obligor. The analysis covers the span that ranges from October 31, 2008 to October 10, 2014. Panel B presents the correlation matrix of the systematic variables used in the analysis. (*) Data in local currency (USD for US firms and EURO for European firms). (**) Data in USD.

3.2 An exploratory analysis of the commonalities of open interest

In addition to the analysis of the data sample's descriptive statistics, an exploratory analysis of the commonalities of open interest of different obligors is also developed. Previous studies have shown that CDS rates and bid-ask spreads of CDS contracts appear to co-vary over time. Berndt and Obreja (2010) claimed that there is a common omitted factor that explains CDS spread changes. Such factor is not related to standard market risk factors. Mayordomo et al. (2012) presented evidence suggesting the existence of significant liquidity commonalities in the corporate CDS market.

Table 2 – Principal components analysis and the co-movement of net notional amount growth, CDS rates, and bid-ask spreads amid obligors

US	Growth of Net Notional Amount of CDS Contracts		CDS rate percentage changes		CDS bid-ask spread changes	
Factors	Proportion	Cumulative Proportion	Proportion	Cumulative Proportion	Proportion	Cumulative Proportion
1	15.3%	15.3%	49.7%	49.7%	13.5%	13.5%
2	4.0%	19.4%	3.4%	53.1%	4.3%	17.8%
3	3.2%	22.6%	2.3%	55.4%	3.8%	21.6%
4	3.1%	25.6%	1.8%	57.3%	3.1%	24.6%
5	2.3%	27.9%	1.7%	59.0%	2.7%	27.4%
6	2.2%	30.1%	1.6%	60.5%	2.6%	30.0%
7	2.1%	32.2%	1.3%	61.9%	2.4%	32.4%
8	1.9%	34.1%	1.2%	63.1%	2.4%	34.8%
9	1.8%	35.9%	1.1%	64.2%	2.3%	37.1%
10	1.7%	37.6%	1.1%	65.3%	2.2%	39.3%
# Obligors	179		179		174	

EU	Growth of Net Notional Amount of CDS Contracts		CDS rate percentage changes		CDS bid-ask spread changes	
Factors	Proportion	Cumulative Proportion	Proportion	Cumulative Proportion	Proportion	Cumulative Proportion
1	25.3%	25.3%	58.4%	58.4%	35.2%	35.2%
2	3.2%	28.5%	4.2%	62.6%	4.8%	39.9%
3	2.8%	31.2%	2.1%	64.6%	3.0%	42.9%
4	2.6%	33.8%	1.8%	66.4%	2.4%	45.3%
5	2.4%	36.2%	1.6%	68.0%	2.1%	47.4%
6	2.2%	38.4%	1.6%	69.6%	1.8%	49.2%
7	2.0%	40.4%	1.2%	70.8%	1.7%	50.9%
8	2.0%	42.4%	1.1%	71.9%	1.6%	52.4%
9	1.9%	44.3%	1.0%	72.9%	1.5%	53.9%
10	1.7%	46.0%	0.9%	73.8%	1.4%	55.3%
# Obligors	146		146		145	

This table displays the results of a principal component analysis on the time series of net notional amount growth of the obligors. For simplicity, only the proportion of the variance explained by each factor is presented. Since the open interest of obligors from Europe and from the US are driven by different factors, the results are tabulated by the domicile of the obligor. The previous exercise is replicated for the time series of CDS rate percentage changes and CDS bid-ask spread changes. The analysis covers the span that ranges from October 31, 2008 to October 10, 2014.

Motivated by these considerations, we ask whether changes in the net notional amount of the different obligors also co-vary over time, and perform a principal components analysis to extract the commonalities from the series of the net notional growth. We replicate the procedure for the series of CDS rate percentage changes and for changes of the bid-ask spread. As different factors may explain the correlations of US and European obligors, the sample is divided according to the obligor's domicile. The results are displayed in Table 2.

With regard to US obligors, the first principal component of net notional amount growth explains 15.3% of the variance of the series. The first principal component of CDS rate changes (bid-ask spread changes) explains 49.7% (13.5%) of the variance of the series. For European obligors, the first principal component of the net notional amount growth explains 25.3% of the variance of the series, whilst the first principal component of CDS rate changes (bid-ask spread changes) explains 58.4% (35.2%) of the variance of the series. These results suggest that at least one common factor drives net notional amount changes of CDS contracts. It is also relevant that the co-variation of the growth of European CDS net notional amounts and bid-ask spread changes is larger than that of US borrowers. We infer from such results that common factors may determine how open interest evolves in time, and assess this possibility in the empirical analysis described in section 4.

4. Research design and results

4.1 The dynamics of net notional amount

The first hypothesis assessed in this study (H1) establishes a relationship between changes in the credit risk of borrowers and the pattern of the net notional amount of CDS contracts written on their debt. This hypothesis builds up on the notion that speculation and hedging on the credit risk of an obligor are related to the dynamics of net notional amounts. The credit risk of a borrower, however, is not directly observable, i.e. is a latent variable. We rely on three alternative variables to capture the credit risk of an obligor: debt-to-market capitalization ratio, stock returns volatility, and stock returns. Divergences of opinion are also expected to be related to the dynamics of net notional amount. CDS rate volatility and stock trading volumes are used as proxies for differences of opinion, so that opinion divergence climbs along with the former variables. To examine the possible association between the variables, we estimate the following model:

$$\Delta \log(V_{i,t}) = \theta_i + \delta_{1,i} \times \Delta Leverage_{i,t} + \delta_{2,i} \times \Delta stock\ vol_{i,t} + \delta_{3,i} \times stock\ ret_{i,t} + \delta_{4,i} \times \Delta stock\ trading\ volume_{i,t} + \delta_{5,i} \times \Delta CDS\ rate\ vol_{i,t} + \tau_t \quad [1]$$

where $\Delta\log(V_t)$ is the weekly (log) change of CDS net notional amount of entity i on week t; $Leverage_{i,t}$, $stock\ vol_{i,t}$, and $stock\ ret_{i,t}$ represent the debt-to-market capitalization ratio, stock returns volatility and stock returns of entity i on t, respectively; and $\Delta stock\ trading\ volume_{i,t}$ and $\Delta CDS\ rate\ vol_{i,t}$ are the weekly (log) changes of the stock trading volume of entity i on t and the weekly changes of the CDS rate volatility of entity i on t, respectively.

The estimation of equation [1] poses important econometric challenges, namely the poolability of individual series of obligors and the cross-dependence of the residuals. The poolability of the series requires slope homogeneity, i.e. the parameters of interest are assumed to have common values across panel units, an assumption that may not hold. Assuming that the disturbances of a panel model are cross-sectionally independent is also often unsuitable. However, provided that the unobservable common factors are uncorrelated with the explanatory variables, the parameters' estimates, although inefficient, are still consistent.

Equation [1] is estimated with the Pesaran and Smith (1995) Mean Group (MG) estimator. This estimator assumes slope heterogeneity, but disregards cross-section dependence. Cross-correlation is tackled later on with additional robustness tests. The equation is estimated for each panel member i and, subsequently, the estimated coefficients are averaged across panel members. To mitigate the heterogeneity across panel units, the net notional amount growth, the (changes of the) debt-to-market capitalization ratio, the (changes of the) stock returns volatility, stock returns, the (changes of the) stock trading volume and the (changes of the) CDS rate volatility are standardized by obligor.

Table 3 reports the outputs of the regression (see column (1)) indicating that both credit risk and opinion divergence seem to affect the dynamics of net notional amount. Indeed, $\Delta stock\ vol$, $stock\ ret$, and $\Delta stock\ trading\ volume$ have explanatory power on the dependent variable. The former displays a positive coefficient, so that credit risk and net open interest rise together as expected. Surprisingly, $\Delta stock\ trading\ volume$ ($stock\ ret$) presents a negative (positive) coefficient. As for the remaining explanatory variables, they lack explanatory power. In light of these results, H1 is not rejected, but H2 is. However, we have to be cautious in drawing conclusions from these results. Since systematic variables are still not included in the model, an omitted variables' problem may be biasing these preliminary estimates, as may be suspected from the very low R-squared.

To avoid endogeneity arising from omitted variables, we introduce systematic factors in the model. Indeed, the results from the principal component analysis displayed in Table 2, and discussed above, confirm the co-variation of the net notional amounts of different obligors, and suggest that systematic factors may drive the dynamics of net open interest. To examine whether systematic factors affect the growth of the net notional amount, the following variables are introduced in the empirical model: (i) changes in the 10-year treasury rates ($\Delta 10YR_t$), (ii) changes of the slope of the yield curve (ΔYCS_t), (iii) changes of the VIX index or Vstoxx index (ΔVIX_t), (iv) changes in the jump-size risk (ΔJR_t), (v) stock market returns (SMR_t), (vi) changes in the volatility premium ($\Delta Vol\_premium_t$), (vii) excess return of speculative-grade bonds over investment-grade bonds (BRA_t), and (viii) difference between the rates of one-month top commercial paper and one-month US LIBOR (CPS_t). In addition, raw stock returns are replaced by the excess of the returns of the stocks of the borrower over the stock market returns ($excess\_stock\ ret_{i,t}$). In order to avoid multicollinearity, two alternative model specifications are considered:

$$\Delta\log(V_{i,t}) = \theta_i + \delta_{1,i} \times \Delta Leverage_{i,t} + \delta_{2,i} \times \Delta stock\ vol_{i,t} + \delta_{3,i} \times excess\_stock\ ret_{i,t} + \delta_{4,i} \times \Delta stock\ trading\ volume_{i,t} + \delta_{5,i} \times \Delta CDS\ rate\ vol_{i,t} + \alpha_{1,i} \times SMR_t + \alpha_{2,i} \times \Delta JR_t + \alpha_{3,i} \times \Delta VIX_t + \alpha_{4,i} \times \Delta YCS_t + \alpha_{5,i} \times BRA_t + \tau_t \qquad [2]$$

$$\Delta\log(V_{i,t}) = \theta_i + \delta_{1,i} \times \Delta Leverage_{i,t} + \delta_{2,i} \times \Delta stock\ vol_{i,t} + \delta_{3,i} \times excess\_stock\ ret_{i,t} + \delta_{4,i} \times \Delta stock\ trading\ volume_{i,t} + \delta_{5,i} \times \Delta CDS\ rate\ vol_{i,t} + \alpha_{1,i} \times SMR_t + \alpha_{2,i} \times \Delta JR_t + \alpha_{3,i} \times \Delta Vol\_premium_t + \alpha_{4,i} \times \Delta 10YR_t + \alpha_{5,i} \times BRA_t + \alpha_{6,i} \times \Delta CPS + \tau_t \qquad [3]$$

The results of the estimation of equation [2] reveal the importance of stock market returns to explain how net notional amounts evolve in time (column (2) of Table 3). The coefficient of SMR is positive and statistically significant, so that stock market performance and the growth of the net notional amount move *pari passu*. This is in line with the assumption that the inventory risk and capital bindings of liquidity providers lessens their capacity to expand open interest when asset prices decline, making net notional amount growth pro-cyclical. In contrast, the excess stock returns lack significance. This means that the positive sign presented by $stock\ ret$ in equation [1] results from the correlation between individual returns and market returns, and not from specific information on the borrower. BRA is not statistically significant, but ΔJR and ΔVIX are. It is interesting that the coefficients of ΔJR and ΔVIX display opposite signs. Changes of VIX (VSTOXX) positively affect the growth of the net notional amount, according to the view that, when investors perceive greater uncertainty, they increase the demand for protection against default risk. Still, the likelihood of large positive CDS rate jumps produces a negative impact upon the dynamics of open interest, reflecting the fact that sellers and liquidity providers respond negatively to the perspective of suddenly having to pledge larger margins and more collateral.

Table 3 – Regressions of net notional amount growth on specific and systematic determinants

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
$stock\ ret$	0.043***						
	(3.156)						
$\Delta stock\ vol$	0.013***	0.015***	0.017***	0.016***	0.018***	0.005	0.004
	(3.276)	(3.428)	(4.100)	(3.613)	(3.953)	(0.505)	(0.478)
$\Delta Leverage$	0.015	0.013	0.010	0.022	0.021	-0.006	-0.006
	(0.873)	(0.717)	(0.542)	(0.892)	(1.007)	(-0.333)	(-0.336)
$\Delta stock\ trading\ volume$	-0.012***	-0.011***	-0.009**	-0.013***	-0.013***	-0.007	-0.006
	(-3.065)	(-2.698)	(-2.101)	(-3.323)	(-3.336)	(-1.531)	(-1.463)
$\Delta CDS\ rate\ vol$	0.007	-0.015***	-0.015***	-0.017***	-0.019***	0.004	0.004
	(0.297)	(-3.000)	(-3.064)	(-3.467)	(-4.048)	(0.882)	(0.889)
$excess\_stock\ ret$		0.001	-0.002	0.009	0.006	-0.018*	-0.018*
		(0.134)	(-0.158)	(0.476)	(0.383)	(-1.918)	(-1.911)
SMR		2.255***	2.458***	0.740	0.620	-0.691	0.607
		(6.089)	(6.319)	(1.539)	(1.440)	(-1.402)	(1.152)
ΔVIX		0.006***		0.008***	0.010***	0.008***	0.005**
		(2.993)		(4.693)	(5.463)	(3.984)	(2.376)
ΔYCS		-0.282***		-0.249***	-0.231***	-0.236***	-0.280***
		(-4.183)		(-3.715)	(-3.448)	(-3.776)	(-4.545)
ΔJR		-0.018***	-0.018***	-0.009*	-0.008	-0.009	-0.019***
		(-3.254)	(-3.242)	(-1.687)	(-1.588)	(-1.351)	(-3.056)
BRA		0.742	-0.162	-0.211	0.574	-0.794	0.897*
		(1.462)	(-0.310)	(-0.439)	(1.342)	(-1.597)	(1.914)
$\Delta Vol\_premium$			0.012***				
			(5.583)				
$\Delta 10YR$			0.066				
			(1.623)				
ΔCPS			-0.046				
			(-0.759)				
$\Delta LOIS$				0.009***	0.008***	0.008***	0.007***
				(3.958)	(3.140)	(2.676)	(2.585)
$\Delta Repo\ spread$				0.000	0.022	0.235	0.228
				(0.000)	(0.158)	(1.604)	(1.551)
$\Delta G14$				-0.006***	-0.006***	-0.006***	
				(-13.766)	(-13.358)	(-11.790)	
$\Delta G14\_res$							-0.066***
							(-13.211)
ΔBAS_CDS					-4.898***	-3.591**	-3.548**
					(-4.041)	(-2.349)	(-2.319)
ΔBAS_stocks					-5.823	-28.861**	-
					(-0.560)	(-2.280)	(-2.648)
_cons	0.002*	0.003	0.004*	0.008***	0.006**	0.008***	0.005*
	(1.669)	(1.298)	(1.804)	(2.622)	(2.184)	(2.724)	(1.774)
N	136352	136341	136341	136341	136341	136,323	136,323
R2(1)	3.5%	6.8%	7.5%	9.0%	10.1%	22.7%	22.7%

*This table shows the regression results of the estimation of equations [1] to [7]. The estimation of equations [1] to [5] is carried by means of Pesaran and Smith (1995) procedure, whereas equations [6] and [7] are estimated by means of Pesaran (2006) Mean Group Common Correlated Effects (MGCCE). The full sample of obligors is included in the estimation. The analysis covers the span that ranges from October 31, 2008 to October 10, 2014. ***, ** and * denote two-side statistical significance at the 1%, 5% and 10%, respectively. (1) Average R2 from time-series regressions.*

Equation [3] introduces three alternative explanatory variables in the analysis: changes of the volatility premium, changes of the ten-year risk-free spot rate, and changes of the spread between one-month top commercial paper and one-month US-LIBOR. To avoid multicollinearity, ΔVIX and ΔYCS are excluded from the main specification. Indeed, $\Delta Vol\_premium$ is statistically significant, but $\Delta 10YR$ and ΔCPS are not. The growth of the net notional amount is positively related with the volatility premium, in line with the anticipation that risk aversion fuels the demand for credit risk protection. The statistical significance of SMR and ΔJR is preserved under this model specification, whereas BRA remains non-significant (see column (3) of Table 3).

In summary, the estimations' results corroborate the expectation that net notional amount growth is pro-cyclical. In fact, stock market returns (systematic jump risk) are positively (is negatively) associated with the net notional amount growth. The estimates also reveal the existence of a positive association between net notional amount growth and risk aversion (or volatility expectation), such that risk aversion (uncertainty) fuels the demand for credit risk protection and the open interest dynamics. It is worth noting that the average R-squared of the empirical model increases from 3.5% to 7.5% with the introduction of the systematic factors. The hypothesis that the growth of the net notional amount of single-reference entities responds to market conditions (H3) is confirmed by the regression results.

Next, we examine the influence of funding and counterparty risks on the dynamics of the net notional amount. According to hypothesis H4, changes on funding costs are expected to affect the dynamics of the net notional amount of CDS contracts. Two proxies of funding costs are used in the empirical analysis: the spread of the rates of repo agreements on Mortgage Backed Securities and on Treasuries, and the spread between one-month US-LIBOR and OIS ($\Delta LOIS$)[55]. Counterparty risk is also expected to affect the growth of the net notional amount in the CDS market. Accordingly, a decline in the growth of the net notional amount is expected when counterparty risk mounts (see hypothesis H5). Counterparty risk is proxied by the average 5-year CDS spreads of the G14 main dealers[56] of the CDS market ($\Delta G14_t$). To gauge the effects of counterparty risk of major dealers and of funding costs on the dynamics of net notional amounts, $\Delta G14_t$, $\Delta LOIS_t$ and $\Delta Repo\ spread_t$ are added as explanatory variables to the empirical model:

$$\Delta \log(V_{i,t}) = \theta_i + \delta_{1,i} \times \Delta Leverage_{i,t} + \delta_{2,i} \times \Delta stock\ vol_{i,t} + \delta_{3,i} \times stock\ ret_{i,t} + \delta_{4,i} \times \Delta stock\ traded\ volume_{i,t} + \delta_{5,i} \times \Delta CDS\ rate\ vol_{i,t} + \alpha_{1,i} \times SMR_t + \alpha_{2,i} \times \Delta JR_t + \alpha_{3,i} \times \Delta VIX_t + \alpha_{4,i} \times \Delta YCS_t + \alpha_{5,i} \times BRA_t + \alpha_{6,i} \times \Delta Repo\ spread_t + \alpha_{7,i} \times \Delta LOIS_t + \alpha_{8,i} \times \Delta G14_t + \tau_t \quad [4]$$

Table 3 (column (4)) reports the outcomes of the estimation. $\Delta LOIS$ and $\Delta G14$ seem to produce effects on the dynamics of the net notional amount. $\hat{\alpha}_8$ is negative and statistically significant, in line with the expectation that higher counterparty risk of CDS dealers contracts the net notional amount of single reference CDS contracts. While $\Delta Repo\ spread$ lacks explanatory

[55] This variable is used as a proxy for funding risk. However, other authors have used this variable as a measure of credit risk in the financial system.

[56] These dealers are net-sellers and account for the majority of the transactions in inter-dealer markets (Shachar 2012 and Chen et al. 2011).

power, it is surprising that $\Delta LOIS\ spread$ presents a positive and statistically significant coefficient. This latter result challenges H4. The introduction of funding costs and counterparty risk in the empirical model increases the average R-squared of the regressions from 7.5% to 9.0%. Yet, adding $\Delta G14$ to the model specification diminishes the explanatory power of stock market returns. It is shown later that after removing the commonality between SMR and $\Delta G14$, the former also becomes significant. In contrast, ΔVIX, $\Delta stock\ vol$, $\Delta CDS\ rate\ vol$, and $\Delta stock\ trading\ volume$ are statistically significant. These results lead to the rejection of H4, but not of H5.

Finally, the effect of systematic illiquidity on the dynamics of the net notional amount is assessed by including two additional variables that reflect market-wide movements in illiquidity. The first variable (ΔBAS_CDS_t) denotes the changes of the average bid-ask spread of CDS contracts, whereas the second (ΔBAS_stocks_t) represents the changes of the average bid-ask spread of stocks. Both averages are computed using the entire sample of obligors in the database, divided by domicile. As the database comprises a large number of obligors, the averages are expected to capture the time-series of the commonalities in liquidity.

$$\begin{aligned}\Delta\log(V_{i,t}) = \theta_i + \delta_{1,i} \times \Delta Leverage_{i,t} + \delta_{2,i} \times \Delta stock\ vol_{i,t} + \delta_{3,i} \times stock\ ret_{i,t} + \delta_{4,i} \times \\ \Delta stock\ traded\ volume_{i,t} + \delta_{5,i} \times \Delta CDS\ rate\ vol_{i,t} + \alpha_{1,i} \times SMR_t + \alpha_{2,i} \times \Delta JR_t + \alpha_{3,i} \times \Delta VIX_t + \\ \alpha_{4,i} \times \Delta YCS_t + \alpha_{5,i} \times BRA_t + \alpha_{6,i} \times \Delta Repo\ spread_t + \alpha_{7,i} \times \Delta LOIS_t + \alpha_{8,i} \times \Delta G14_t + \alpha_{9,i} \times \\ \Delta BAS\_CDS_t + \alpha_{10,i} \times \Delta BAS\_stocks_t + \tau_t \end{aligned} \qquad [5]$$

The results of the estimation of equation [5] (Table 3, column 5) reveal that liquidity is a relevant determinant of the net open interest's dynamics. $\hat{\alpha}_9$ and $\hat{\alpha}_{10}$ are both negative, though only the former is statistically significant, confirming that CDS open positions decline in the aftermath of negative liquidity shocks. Based on these results, H6 is not rejected.

4.2 Robustness tests

The results presented in sub-section 4.1 are obtained utilizing the MG estimation procedure. Specifically, Pesaran and Smith (1995) proposed a heterogeneous-slope panel data estimator, with no adjustment for cross-correlation. To account for the latter, we adopt the procedure developed in Pesaran (2006). Pesaran (2006) introduced the Common Correlated Effects Mean Group (CCEMG) estimator as an alternative for the estimation of panel time series models with heterogeneous slopes. The CCEMG procedure takes cross-section dependence into account and consists of approximating the linear combinations of the unobserved factors while introducing cross-sectional averages of the dependent and explanatory variables in the main equation (Chudik and Pesaran 2013). Under slope heterogeneity, the CCEMG approach assumes a random coefficients panel data model. The method has the advantages of not requiring prior knowledge of the cross-sectional dependence type and being consistent for large panels, as is the case in our own empirical analysis.

Equation [5] is estimated using this more robust estimator and the results, displayed in Table 3, column (6), do not confirm the relevance of opinion divergences to explain the growth of the net notional amount. Nevertheless, the conclusions regarding the effects of counterparty risk, systematic liquidity, VIX (VSTOXX) and changes of the spread between one-month US Libor and OIS remain unchanged. Indeed, counterparty risk and liquidity shocks are negatively linked to the growth of open interest, while the risk perceived by market participants (ΔVIX) and funding costs (proxied by $\Delta LOIS$) have a positive association with the dependent variable. The estimated coefficient of the excess returns of the stocks of the borrower becomes negative and significant when the no cross-correlation assumption is relaxed, in line with the notion that credit risk impacts the dynamics of open interest positively. Interestingly, accounting for these unspecified common factors increases the R-squared to 22.7%.

The validity of the empirical hypotheses is also assessed under the assumption of data poolability. Again, variables that are specific to each obligor, e.g. net open interest growth, (excess) stock returns, changes of the leverage, changes of the stock return volatility, changes of the trading volume, and changes of the CDS rate volatility, are standardized by obligor, with the objective of eliminating heterogeneity across obligors. Three types of standard error are computed: standard errors clustered by time and panel ID, as in Petersen (2009); Driscoll-Kraay standard errors corrected for AR(1) disturbances and cross-correlation[57]; and Beck and Katz (1995) panel-corrected standard errors (PCSEs), corrected for specific AR(1) disturbances and cross-correlation.

Surprisingly, the results from the pooled regressions using alternative standard errors (not displayed, but available upon request) are virtually identical. The estimated coefficient of $\Delta CDS\, rate\, vol$ is statistically significant under the hypothesis of poolability, but that of $\Delta stock\ trading\ volume$ is not. SMR coefficient turns out as not statistically significant when the poolability assumption is relaxed. Notably, the results for ΔVIX, $\Delta G14$ and ΔBAS_stocks hold when the estimation is run with this less flexible estimator.

To sum up, employing different estimation techniques produces some changes in the conclusions. However, regardless of the estimation procedure employed, counterparty risk, risk aversion and uncertainty, and illiquidity movements in financial markets remain significant. The fact that SMR loses explanatory power when counterparty risk and funding risk proxies are

[57] We thank Daniel Hoechle for providing the code to compute the Driscoll-Kraay standard errors in Hoechle (2007).

introduced in the estimating model prompts the question of whether the latter variables encompass the effect of market returns on open interest growth. This is examined by introducing the residual effect of counterparty risk changes in the empirical model, instead of $\Delta G14$. To this end, the following two-stage procedure is developed. First, we regress $\Delta G14$ on the set of systematic variables included in equation [5], and save the residuals. The residuals denote the effect of counterparty risk changes not conveyed by the remaining systematic variables. Then, $\Delta G14$ is replaced by this residual variable ($\Delta G14$_res) in equation [5]. The estimation results under the CCEMG approach are presented in Table 3, column (7). Notably, $\Delta G14$_res is significant, whereas SMR remains not significant.

A similar procedure is used to capture the residual effect of stock market returns on the dynamics of net open interest. The residual effect of stock market returns is significant under the various specifications (again, for the sake of brevity, the results not shown, but are available upon request). These residual variables have opposite effects on the path of the net notional amount: while the residual effect of stock market returns displays a positive coefficient, consistent with the pro-cyclicality of the growth of open interest, the residual effect of counterparty risk is negative, suggesting that higher counterparty risk reduces net notional amount growth.

4.3 The determinants of parameter heterogeneity

The previous empirical assessments, which allowed for heterogeneous coefficient slopes across panel members, expose the average reaction of the dynamics of CDS net open interest to changes in credit risk, opinion divergence, and systematic factors. Nevertheless, as it is also of interest to investigate the sources of parameter heterogeneity, in what follows we examine whether the domicile and the creditworthiness of the borrower help in explaining slope differences across obligors.

Equation [5] is first estimated separately for US and for European obligors. For reasons of space and simplicity, only the results of the Pesaran and Smith (1995) MG estimation are presented. The results in Table 4 reveal that the coefficients of $\Delta CDS\ rate\ vol$, ΔBAS_CDS and $\Delta G14$ are negative and statistically significant in both subsamples, in accordance with the earlier results obtained for the full sample. ΔBAS_stocks, ΔVIX, ΔJR, $\Delta Repo\ spread$ and SMR are statistically significant in the subsample of European obligors. In contrast, $\Delta stock\ trading\ volume$, $\Delta stock\ vol$, $\Delta LOIS$ and ΔYCS are statistically significant for US borrowers only.

Another noteworthy result is the fact that changes in risk aversion in the bond market appear to produce asymmetric effects for US and European borrowers. Indeed, whereas the former present a positive coefficient, European reference entities have a negative coefficient. Thus, when risk aversion in bond markets increases, the net open interest of contracts on US borrowers declines, whereas the net open interest of contracts on European obligors increases.

These results reinforce the notion that counterparty risk and systematic liquidity shocks are important drivers of changes in the net open interest. Indeed, these variables affect both US and European obligors' net notional amount changes. The growth of the net open interest of European and US borrowers is affected by systematic variables and business climate proxies (albeit not exactly by the same variables). Credit risk proxies do not produce effects on the growth of European obligors' open interest, but opinion divergence does.

Subsequently, we address the role of creditworthiness as a source of slope heterogeneity. The intuition is that the sensitivity of open interest changes to idiosyncratic and systematic variables may vary with the creditworthiness of the borrower. To assess this conjecture, equation [5] is estimated separately for borrowers with a level of credit risk below and above average. In each period, borrowers are sorted by their CDS rate. Then, two bins are formed. The first encompasses the top 40% obligors in terms of CDS rate, while the second comprises the bottom 40% obligors. The top (bottom) bin encompasses the group of riskier (safer) obligors.

The results of these estimations are shown in Table 4, columns (3) and (4). The estimates indicate that $\Delta G14$, ΔVIX, $\Delta LOIS$, and ΔBAS_CDS appear to drive the growth of the net notional amount of both safer and riskier borrowers. However, it is curious that the growth of the net open interest of riskier obligors appears to be insensitive to changes in the credit risk and to changes in opinion divergence, in contrast to that of safer obligors.

On balance, the partition of the sample uncovers the fact that the growth of the open interest of US and European obligors is driven by different systematic factors. In addition, there is supporting evidence that solely the growth of the net open interest of riskier obligors appears to be insensitive to changes in the credit risk and to changes in divergences of opinion. Not less importantly, the empirical findings identify counterparty risk and systematic liquidity shocks as key determinants of the dynamics of net notional amounts in the distinct analyzed subsamples.

Table 4 – Regressions of net notional amount growth on specific and systematic determinants, tabulated by the domicile and creditworthiness of the obligors

	US Obligors	European Obligors	Bottom CDS rate borrowers	Top CDS rate borrowers
$\Delta stock\ vol$	0.027*** (4.346)	0.004 (0.622)	0.026** (2.285)	-0.006 (-0.730)
$\Delta Leverage$	0.019 (0.603)	0.025 (0.999)	-0.034 (-0.538)	-0.030 (-0.471)
$\Delta stock\ trading\ volume$	-0.023*** (-4.236)	0.001 (0.131)	-0.009 (-1.117)	-0.005 (-0.610)
$\Delta CDS\ rate\ vol$	-0.015** (-2.308)	-0.025*** (-3.729)	-0.019** (-2.093)	-0.013 (-1.167)
$excess\_stock\ ret$	0.007 (0.267)	0.005 (0.413)	-0.016 (-0.622)	0.011 (0.307)
SMR	-0.199 (-0.309)	1.845*** (4.015)	-0.371 (-0.513)	-0.090 (-0.084)
ΔVIX	0.003 (1.185)	0.021*** (7.376)	0.010** (2.330)	0.015* (1.848)
ΔYCS	-0.509*** (-6.582)	0.185 (1.615)	-0.150 (-0.979)	-0.551*** (-3.043)
ΔJR	-0.004 (-0.515)	-0.016* (-1.939)	-0.023 (-1.572)	0.008 (0.362)
BRA	2.573*** (4.168)	-2.414*** (-5.155)	-1.233 (-1.295)	1.637 (1.362)
$\Delta LOIS$	0.014*** (3.906)	-0.002 (-0.502)	0.012** (2.292)	0.012* (1.691)
$\Delta Repo\ spread$	-0.305 (-1.509)	0.511*** (3.122)	0.223 (0.607)	-0.180 (-0.324)
$\Delta G14$	-0.003*** (-6.151)	-0.010*** (-14.427)	-0.009*** (-9.907)	-0.009*** (-5.812)
ΔBAS_CDS	-5.293*** (-2.782)	-4.308*** (-4.174)	-6.353** (-2.248)	-8.021** (-2.093)
ΔBAS_stocks	20.488 (1.201)	-45.162*** (-14.549)	1.390 (0.048)	2.678 (0.061)
_cons	0.012*** (2.975)	-0.004 (-1.498)	0.009 (1.320)	0.000 (0.026)
N	80,289	56,052	53,913	54,076
R2[(1)]	9.5%	11.2%	11.1%	12.2%

*This table shows the results of the estimation of equation [5] using alternative subsamples, namely for US and European obligors, and for investment-grade and speculative-grade obligors. For simplicity, only the results for Pesaran and Smith (1995) Mean Group (MG) estimator are reported. The analysis covers the span that ranges from October 31, 2008 to October 10, 2014. ***, ** and * denote two-side statistical significance at the 1%, 5% and 10%, respectively. (1) Average R2 from time-series regressions.*

4.4 Gross notional amount held by dealers and end-clients and the effect of systematic variables

The results obtained so far indicate that systematic factors, and particularly the counterparty risk of dealers, affect the dynamics of net notional amounts. Although variables that are specific to each obligor, such as credit risk and divergences of opinion, are statistically significant under some model specifications, they have little explanatory power for the dynamics of net notional amounts (average R-squared of 3.5%).

In this subsection, we investigate whether systematic factors affect the dynamics of the (sell-side) gross notional amounts held by dealers and end-clients in a similar way. Besides providing data on the net notional amount of single reference contracts, DTCC also supplies weekly data on gross notional amounts held by dealers and by end-clients aggregated by industry. The following nine industries are covered: basic materials, consumer goods, consumer services, energy, financials, healthcare, industrials, technology and telecom, and utilities. In order to gain further insight on the commonalities of gross notional amount changes of these industries, a principal components analysis is conducted. This exploratory analysis is developed for the growth of the total gross notional amount and, separately, for the growth of the sell-side gross notional amount held by dealers and by end-clients.

The results, not shown, suggest that a strong commonality exists. The first principal component explains 96.5% of the variance of the distinct industries' gross notional amount growth. A split-up by type of seller reveals that the first principal component explains 96.1% and 92.4% of the variance of the growth of the gross notional amount held by dealers and end-clients, respectively. These results reinforce the earlier conclusion that commonalities explain a large portion of open interest changes. The previous regression analyses are replicated for the gross notional amount of the nine industries, the gross notional amount of CDS on loans, commercial mortgage backed securities, residential mortgage backed securities, and sovereign borrowers. The percentage of variance explained by the first principal component remains above 90% in the case of total gross notional amounts and gross notional amounts held by dealers. As for the gross notional amount held by end-clients, the percentage of variance explained by the first principal component falls to 70%.

To assess the relevance of systematic variables to explain the dynamics of the total gross notional amount, of the (sell-side) gross notional amount held by dealers and of the (sell-side) gross notional amount held by end-clients, the following equation is estimated[58]:

$$\Delta \log\left(GNA_{\,t,i}\right) = \beta_{0,i} + \beta_{1,i} \times \Delta SMR_t + \beta_{2,i} \times \Delta VIX_t + \beta_{3,i} \times \Delta YCS_t + \beta_{4,i} \times \Delta JR_t + \beta_{5,i} \times BRA_t + \beta_{6,i} \times \Delta Repo\ spread_t + \beta_{7i} \times \Delta LOIS_t + \beta_{8,i} \times \Delta G14_t + \varepsilon_t \quad [6]$$

where $GNA_{t,i}$ denotes the gross notional amount aggregated by industry i on t (total, held by dealers or held by end-clients on week t). The remaining variables are as previously defined.

Equation [6] is estimated with Pesaran (2006) CCE estimation procedure, Pesaran and Smith (1995) MG procedure and, under a pooled data framework, with Driscoll-Kraay standard

[58] In an alternative specification, the returns and volatility of industry indices were also included in the model. However, these variables turned out not to be statistically significant and we do not display such results.

errors. The growth of total gross notional amount is first used as the dependent variable. The results displayed in Table 5 show that the Pesaran (2006) CCE estimated coefficients for SMR and ΔVIX are positive and statistically significant at the 10% level. These results are in line with the above discussed procyclicality of open interest and with its positive relation with expected stock market volatility. On the other hand, ΔJR, $\Delta Repo\ spread$, $\Delta LOIS$ and $\Delta G14$ have a negative influence on the dynamics of the gross notional amount. Although these results are preserved when using the Pesaran and Smith (1995) MG estimator, SMR, $\Delta Repo\ spread$ and $\Delta LOIS$ lose statistical significance under a pooled data framework using Driscoll-Kraay standard errors. Funding costs (stock market performance) appear to affect the open interest dynamics of the various industries differently but, on average, the effect is negative (positive).

We next turn our attention to the dynamics of the gross open interest held by dealers (sell-side). Not surprisingly, because the sell-side gross notional amounts stem mainly from dealer operations, the results are very similar to those described above. However, the results for the dynamics of the (sell-side) gross notional amount held by end-clients unveil a different story. In fact, while the gross notional amount held by dealers is strongly pro-cyclical, the gross notional amount held by end-clients is countercyclical. It correlates negatively with stock market returns and with excess returns of high-yield bonds over investment-grade bonds. The gross notional amount held by end-clients also responds negatively to ΔJR, $\Delta Repo\ spread$ and $\Delta G14$, and positively to $\Delta LOIS$. It is surprising that the reaction to $\Delta Repo\ spread$ contrasts with that of $\Delta LOIS$, and thus that problems in alternative funding channels produce idiosyncratic effects on the dependent variable.

All in all, the earlier results reinforce the idea that funding costs, counterparty risk, stock market performance, and systematic risk influence the dynamics of open interest. The willingness of dealers to expand their inventory appears to be partially determined by the counterparty risk of other dealers. The gross notional amount held by dealers and the gross notional amount held by end-clients respond differently to changes in the stock and bond markets' performance. Dealers reduce their maximum exposure following market downturns, in opposition to end-clients whose inventories correlate negatively to stock and bond markets' performances.

The effect of funding costs on the gross notional amount also differs for dealers and end-clients. The gross notional amount held by the former responds negatively to shocks in the interbank market and in the repo market, in contrast with the gross notional amount held by the latter that is positively affected by changes in the spread between one-month LIBOR and OIS, and negatively affected by changes in the spread between repo rates. Accordingly, the empirical evidence supports the notion that end-clients and dealers react differently to changes in systematic factors and in the financial intermediaries' funding costs and, consequently, H7 is not rejected.

Table 5 – Gross Notional Amount Dynamics and Systematic Factors

	Gross Notional Amount			Gross Notional Amount Held by Dealers			Gross Notional Amount Held by End-Clients		
	CCEMG Pesaran (2006)	Mean Group (MG)	Pooled Data Driscoll-Kraay s. e.	CCEMG Pesaran (2006)	Mean Group (MG)	Pooled Data Driscoll-Kraay s. e.	CCEMG Pesaran (2006)	Mean Group (MG)	Pooled Data Driscoll-Kraay s. e.
SMR	0.619*	0.630*	0.630	0.993***	1.004***	1.004	-2.400***	-2.399***	-2.399*
	(1.907)	(1.938)	(0.462)	(2.696)	(2.725)	(0.721)	(-3.761)	(-3.759)	(-1.949)
ΔVIX	0.024***	0.024***	0.024*	0.026***	0.026***	0.026**	-0.002	-0.002	-0.002
	(8.237)	(8.223)	(1.862)	(8.060)	(8.048)	(2.108)	(-0.515)	(-0.526)	(-0.176)
ΔYCS	-0.002	-0.003	-0.003	-0.040	-0.041	-0.041	0.261***	0.259***	0.259
	(-0.015)	(-0.024)	(-0.004)	(-0.322)	(-0.330)	(-0.065)	(6.115)	(6.072)	(0.356)
ΔJR	-0.199***	-0.199***	-0.199*	-0.209***	-0.209***	-0.209*	-0.055***	-0.055***	-0.055
	(-14.906)	(-14.902)	(-1.702)	(-14.671)	(-14.666)	(-1.793)	(-3.411)	(-3.416)	(-0.615)
BRA	0.805	0.783	0.783	1.338	1.314	1.314	-3.176***	-3.170***	-3.170
	(0.924)	(0.899)	(0.278)	(1.480)	(1.453)	(0.446)	(-9.706)	(-9.687)	(-0.673)
$\Delta Repo\ spread$	-1.171***	-1.171***	-1.171	-1.069***	-1.069***	-1.069	-1.407***	-1.403***	-1.403
	(-5.055)	(-5.051)	(-1.050)	(-4.360)	(-4.359)	(-0.969)	(-10.300)	(-10.269)	(-1.453)
$\Delta LOIS$	-0.003***	-0.003***	-0.003	-0.004***	-0.004***	-0.004	0.003***	0.003***	0.003
	(-3.228)	(-3.238)	(-1.217)	(-4.012)	(-4.014)	(-1.443)	(2.876)	(2.830)	(0.788)
$\Delta G14$	-0.005***	-0.005***	-0.005**	-0.004***	-0.004***	-0.004**	-0.007***	-0.007***	-0.007*
	(-16.809)	(-16.801)	(-2.503)	(-17.916)	(-17.909)	(-2.260)	(-12.381)	(-12.368)	(-1.720)
_cons	-0.030***	-0.030***	-0.030	-0.029***	-0.029***	-0.029	-0.026***	-0.026***	-0.026
	(-5.385)	(-5.398)	(-0.386)	(-4.876)	(-4.890)	(-0.373)	(-9.597)	(-9.597)	(-0.408)
N	2,790	2,790	2,790	2,790	2,790	2,790	2,790	2,790	2,790
R2	95.8%(1)	1.0%(1)	0.8%	95.2%(1)	0.9%(1)	0.8%	86.0%(1)	3.1%(1)	0.8%

*This table shows regression results for linear pooled regressions of Gross Notional Amount growth on systematic factors. A numerical breakdown by type of market participant (dealer and end-client) is also displayed. The analysis covers the span that ranges from October 31, 2008 to October 10, 2014. ***, ** and * denote two-side statistical significance at the 1%, 5% and 10%, respectively. (1) Average R2 from time-series regressions.*

5. Conclusions

The specific nature of the market's architecture is a source of concern for academics and policy makers who view it as a potential threat to financial stability. Such fears are fueled by the counterparty risk assumed by market participants but also by the sensibility of CDS to market conditions and the business cycle, which may, in a crisis, severely affect financial institutions with large concentration of (sell-side) unhedged positions.

The open interest of the CDS market reflects the maximum exposure faced by investors and is a proxy for the inventory risk incurred by market participants. It also captures the market's trading activity and liquidity risk. As such, investigating the determinants of changes in open interest may help improve knowledge on the functioning of this relatively opaque market. In this study, we assessed the main idiosyncratic and systematic factors influencing the dynamics of two alternative measures of open interest: the gross and net notional amounts. We concluded that firms' credit risk and opinion divergence over their future performance help in explaining the open interest dynamics of single reference contracts. Nevertheless, common factors seem to have a much larger impact than idiosyncratic variables upon the open interest dynamics.

Our empirical analysis shows that the series of the different obligors' net notional growth exhibit commonalities (in line with the view that they co-vary in time) and that the dynamics of open interest is pro-cyclical. Accordingly, the CDS market expands following a positive performance in the stock market and contracts when large negative jumps in asset prices are perceived by investors. Risk aversion also appears to play a role in explaining the dynamics of open interest. *Ceteris paribus*, the expectation of higher risks in the stock market generates net and gross open interest increases. We also identified a negative association between systematic liquidity and the growth of open interest.

The shadow cost of capital faced by liquidity providers has a strong negative effect upon gross open interest, but only a moderate one over the net open interest dynamics. In fact, the influence of funding costs on gross open interest is distinct for dealers and for end-clients. The gross notional amount held by dealers reacts negatively to shocks in the interbank and repo markets, in contrast with the gross notional amount held by end-clients which is negatively (positively) affected by shocks in the repo (interbank) market. The counterparty risk of major CDS dealers exerts a negative influence upon open interest growth, confirming the anticipation that it decreases the willingness of these players to incur in greater inventory risk. The fact that open interest reacts to changes in the credit risk of major dealers suggests that the creation of a CCP could help mitigate frictions deriving from upsurges of dealers' counterparty risk, which dissuade such players from supplying liquidity in periods of financial distress. CDS traders' objective to limit their aggregate exposure reduces the scope for concerns over their contribution for systemic risk. Yet, the attempt of major dealers to adjust their balance sheets and inventory risk to adverse market conditions is likely to compromise the CDS market's capacity to absorb shocks. This sub-optimal behavior inhibits hedgers from covering their exposure to borrowers in the aftermath of market downturns, thus hindering efficient risk sharing.

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Conclusion

CDS are one of the most important (and controversial) innovations in financial markets of the last two decades. Given its impact over the financial system and its role in the 2008 financial crisis, academic researchers have devoted great attention to the CDS market. An important consequence of the onset of this market respects its role in the process of gathering information and price discovery in credit markets. Clearly, these derivative instruments have altered the price discovery process across related markets and CDS spreads are now viewed as credit risk barometers with applications in multiple areas of finance.

This thesis extends the thriving literature on the CDS market in various ways. We undertook four interconnected assessments on CDS market efficiency and on the dynamics of the open interest. In common, all these studies focus on a large sample of reference entities and an extensive period of analysis. In addition, our results are subjected to multiple controls to strengthen the robustness of the conclusions. Nevertheless, we agree that most of our results derive from the analysis of a specific time frame - the post-2008 financial crisis period, which constitutes a breaking point for the financial industry and for regulation.

Our first studies addressed the informational role of CDS spreads and open interest, and the presence of informed trading in that market. Overall, the findings lend support to the idea that both CDS rates and open interest convey important information derived from the presence of informed traders. Accordingly, despite its over-the-counter setup, the CDS market was able to attract informed investors.

On the one hand, our assessment indicates that CDS rates react before the announcement of M&A and divestitures operations. Notably, not only the effects of such corporate events are assimilated by CDS rates before the announcement of the operation, but they are more substantive when one of the main CDS dealers is involved in the operation as a consultant or financial adviser. The new information channel uncovered in this study adds to other channels highlighted in previous literature like screening and monitoring lending operations. In common with those assessments, we find that financial intermediaries obtain confidential information while providing banking (or investment) services, and take advantage of it when trading CDS.

On the other hand, open interest helps predict future CDS rate changes and stock returns. The predictive power of open interest is apparently fueled by the existence of market frictions and investor's inattention. Not least importantly, there is evidence that open interest tends to increase prior to the announcement of negative idiosyncratic news, such as negative earnings surprises.

The conclusions of both assessments may have interesting applications for hedgers and market makers by showing that adverse selection risk in CDS trading is relevant. Regulators and policy makers may also benefit from having more information on the use of private information in the CDS market. If the information is gathered or used illegally, it may affect the overall integrity and efficiency of the CDS and related markets. CDS market participants, in general, may benefit from learning the signals about future price movements supplied by the open interest dynamics, which may be used in timing the market. Finally, if open interest conveys information about future prices, further data on CDS transactions - such as intraday prices and volumes (along with a timely disclosure) - and more transparency, could improve the informational efficiency of markets.

We also analyzed the effects of the introduction of trading constraints in the CDS market. European Union regulation 236/2012, prohibiting uncovered sovereign CDS buying, came into effect on November 2012, in an attempt to reduce speculation and stabilize the sovereign debt market. Our results indicate that banning uncovered sovereign CDS buying had unintended consequences for overall market quality (liquidity, price formation and price efficiency), albeit accomplishing a stabilization of CDS spread volatility. In line with similar studies undertaken in the stock market context, these results highlight the detrimental effect of trading constraints and regulatory intervention over market efficiency.

Finally, we assessed the determinants of CDS open interest, a proxy of the aggregate inventory risk taken by the participants in the CDS market. Our findings show that information asymmetry and divergence of opinions on firms' future performance are relevant drivers of CDS open interest. Nevertheless, systematic factors play a much greater influence than specific factors. Most notably, the growth of open interest for different obligors co-varies in time and is pro-cyclical (expanding with positive stock market performance and declining when large negative (positive) jumps in stock (CDS) prices are perceived by investors). Funding costs and counterparty risk also affect the level of inventory risk taken by market participants. This study informs the current debate about the regulatory framework of CDS markets and may be of use for the design of new policies, aimed at preventing contagion effects triggered by participants' exposures and adverse economic shocks.

The CDS market has been subjected to multiple regulatory changes after the 2008 financial crisis. The effects of such changes in CDS's and related markets' efficiency raise challenging research questions and open avenues for future research. For instance, it would be of interest to investigate whether the introduction of central clearing and the onset of central counterparty and organized exchanges on CDS contracts has reduced systemic risk; if the greater transparency produced by organized exchange platforms has decreased the fees charged by dealers and liquidity providers; Or what was the impact of European Union regulation 236/2012 on uncovered sovereign CDS on related markets (e.g., sovereign bond markets). We anticipate that such questions will shape the financial literature on this topic in the near future. Not least important, the future availability of new and higher quality data on the CDS market (e.g., intraday data, positions of market participants, etc.) will also help clarify open questions on the benefits and costs of this market.