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De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

CDS market structure and risk flows: the Dutch case*

Anouk Levels [a], René de Sousa van Stralen [a], Sînziana Kroon Petrescu [a] and Iman van Lelyveld [a,b]

[a] *De Nederlandsche Bank, Amsterdam, The Netherlands*
[b] *VU University Amsterdam, Amsterdam, The Netherlands*

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Abstract

Using new regulatory data, this paper contributes to the growing literature on derivatives markets and (systemic) risk, by providing a first account of the Dutch CDS market, investigating the factors that drive buying and selling of credit protection ('flow-of risk'), and analysing the impact of Brexit. We find that the CDS market has a 'core-periphery' structure in which Dutch banks are CDS sellers while insurance firms and pension funds (ICPF's) and ´other financial institutions' (OFIs) are buyers. When the volatility of a reference entity increases, the propensity to sell CDS decreases for banks and increases for ICPFs and OFIs. This hints at procyclical behaviour by banks and countercyclical behaviour by ICPFs and OFIs. The 'core-periphery' structure of the CDS market became more pronounced around Brexit events, making the CDS market more vulnerable to shocks emanating from 'systemic' players. Banks reduced net buying and selling of CDS protection on UK reference entities, while OFIs and investment funds became more dominant. This underpins the importance of adequate buyers for systemic institutions and extending the regulatory perimeter beyond banking.

Keywords: EMIR, trade repositories, CDS markets, Brexit.
JEL classifications: G15, G18.

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1. Introduction

The credit default swap (CDS) market has grown from an exotic niche market to a large and active market for credit risk transfer making it one of the most significant financial innovations of the last decades (Oehmke and Zawadowski (2015)).[1] In the run-up to the financial crisis, the global CDS market grew substantially, from USD 6.4 trillion in 2004 to 58.2 trillion in 2007 (BIS (2017)).

The rise of the CDS market in the 1990s and early 2000s can be attributed to the fact that CDS was meeting market participants' hedging, speculation, and arbitrage needs. Oehmke and Zawadowski (2015) show that CDS markets function as 'alternative trading venues' for hedging and speculation. Similarly, Acharya et al. (2016) show that a banks used CDS to rapidly increase their sovereign exposure in the sovereign debt crisis in Europe while reducing their risk just as swiftly later on. Kenny et al. (2016) find that CDS markets were widely used prior to the crisis due to their liquidity relative to the reference entity's bonds, and their leverage which enables the build-up of large positions with relatively small capital invested. CDS contracts were also used to hedge risk and to reduce a bank's required regulatory capital or as a part of a tax or accounting strategy to alter the treatment of a particular asset (Yorulmazer (2013)).

Notwithstanding the benefits for the financial sector and the real economy, the CDS market has proven to be a potential source of (systemic) risk as well. The near-collapse of Bear Stearns, the default of Lehman Brothers, and the bail-out of AIG in 2008 highlighted the fact that Over-the-Counter (OTC) derivatives in general and credit derivatives in particular carry systemic risk (EC (2009), p.5). The systemic risk of the CDS market stems from the inherent leverage in CDS contracts and the high level of market concentration and interconnectedness among major players (Coudert and Gex (2010), Kenny et al. (2016)). These characteristics, in combination with a lack of market transparency, resulted in excessive risk taking by major dealers prior to the crisis and a sudden deleveraging and liquidity drain when concerns about counter-party credit risks

[1] A credit default swap is essentially an insurance product: The protection seller agrees to make a payment to the protection buyer in case of a (pre-specified) credit event of a reference entity. In exchange for this insurance, the protection seller receives an upfront fee or periodic payments from the protection buyer. Credit events include for example bankruptcy, non-payment of debt, and, in some CDS contacts, debt restructuring (Oehmke and Zawadowski (2015), p.1, Mengle (2007)).

soared following losses in the sub-prime mortgage market.

Since 2007, economists have come to realize that the structure of the CDS market affects financial stability. The opaque over-the-counter nature can hide dangerous concentrations of risk. To make the CDS market safer, the G20 made a commitment in 2009 to increase transparency by mandating reporting of all derivatives transactions to trade repositories[2], increasing margin requirements for OTC derivatives, and mandating central clearing for the most standardized products. In the EU, these G20 commitments are implemented in the European Markets Infrastructure Regulation (EMIR).[3]

However, the link between the financial market structure and financial stability is yet to be fully understood (Peltonen et al. (2014)). On the one hand, connectivity in financial markets enhances financial stability because more links imply more risk diversification. On the other, connectivity increases the potential for contagion (Glasserman and Peyton Young (2015)). In addition, not only the overall level of connectivity, but also the distribution of connections matters for financial stability. The consensus is that financial markets that are characterised by a few highly connected market participants and many sparsely connected participants, are robust to random disturbances but susceptible to shocks to the 'core' participants (Haldane (2009), Acemoglu et al. (2015), Allen and Gale (2000)). This phenomenon has been termed 'robust-yet-fragile'. Empirical evidence shows that CDS markets exhibits such a potentially fragile 'core periphery' or 'scale free' structure.

Using new regulatory (EMIR) data, this paper contributes to the growing literature on derivatives markets and (systemic) risk, by giving a first account of the Dutch CDS market, investigating the factors that drive buying and selling of credit protection ('flow-of risk'), and analysing the impact of Brexit on the structure of the CDS market for UK underlyings. We are among the first to use the regulatory EMIR data as a daily time-series dataset instead of a one day cross-sectional snapshot.[4] We find that the CDS market has a 'core-periphery' structure in which banks are CDS sellers while insurance companies

[2]This commitment is part of 20 recommendations aiming to improve financial stability analysis (http://www.g20.utoronto.ca/2009/2009communique0925.html, cf. Heath and Goksu (2013)).

[3]See Art. 9 of EMIR (http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32012R0648).

[4]See Schimmel et al. (2018) for an extensive analysis of Brexit using our data set.

and pension funds (ICPFs) and other financial institutions (OFIs) are buyers. When the volatility of a reference entity increases, the propensity to sell CDS decreases for banks and increases for ICPFs and OFIs. This hints at procyclical behaviour by banks and countercyclical behaviour by ICPFs and OFIs. The core-periphery structure of the CDS market became more pronounced around Brexit events, making the CDS market more vulnerable to shocks emanating from systemic players. Banks reduced net buying and selling of CDS protection on UK reference entities, while OFIs and investment funds became more dominant. This underpins the importance of adequate buffers for systemic institutions and extending the regulatory perimeter beyond banking.

The set-up of our paper is straightforward. Section 2 provide an overview of the relevant literature. Section 3 gives a description of the data. Section 4 to 6 provide, respectively, a first overview of the Dutch CDS market, an analysis of the drivers of the 'flow-of-risk' in the Dutch CDS market, and a case study of the impact of Brexit on the structure of the CDS market for UK underlyings.

2. Literature Review

This paper relates to three strands of literature. Firstly, it relates to the literature on the social costs and benefits of CDS.[5] The issue of social costs and benefits of CDS came to the fore in the 2008 financial crises when CDS and other derivative contracts were seen as the prime culprit. Stulz (2010) gives an account of the role of the CDS market in the crisis and concludes that although there are legitimate concerns, the CDS market was not the fundamental cause of the crisis. He argues that credit default swaps increase economic welfare by facilitating risk-sharing, by improving price discovery, and by making the allocation of capital more efficient. The fundamental cause of the financial crisis was the underestimation of real estate risk and the excessive use of leverage. However, the CDS market exacerbated these vulnerabilities. According to Kenny et al. (2016), the systemic risk of the CDS market stems from the inherent leverage in the CDS contracts and the high level of market concentration and interconnectedness among major players. Leverage arises because market participants can replicate the exposure of a bond portfolio for only a fraction of the costs. This allows

[5]See Atkeson et al. (2015) for a theoretical model that shows that banks might be entering the market at an above socially optimal level.

market participants to significantly increase their risk exposure. The AIG case exemplifies this: the mono-line insurer sold too much CDS protection on mortgage backed securities and was not able to honour its obligations when defaults in the sub-prime real estate market became more frequent. Market concentration and interconnectedness exacerbate contagion when a shock hits the market. Even though Bear Stearns and Lehman Brothers held matched CDS positions and seemingly manageable risks, the shock in the real estate market caused market participants' to question Bear Stearns' and Lehman's credit worthiness. The subsequent withdrawal of funding is what ultimately led to the demise of both institutions. The opaqueness of the market and lack of transparency about the positions of major players added to their problems.

Secondly, this paper relates to the literature on financial networks and systemic risk. Early theoretical studies found mixed results regarding the relation between connectivity in financial networks and stability. Allen and Gale (2000) and Freixas et al. (2000) show that more connected financial systems are less prone to contagion. These findings were based on the assumption of homogeneous financial networks which does not hold for the scale free or core-periphery structures that are observed empirically. Others, argue that interconnectedness increases the likelihood of contagion. Later studies, e.g. Gai and Kapadia (2010) and Acemoglu et al. (2015), establish a consensus by pointing out the "robust-yet-fragile" nature of financial networks: Gai and Kapadia (2010) find a lower probability of contagion for more connected financial systems. However, contagion is more widespread if it occurs in connected networks. Acemoglu et al. (2015) find that more connected networks are better able to cope with small shocks, but also that highly connected networks are more prone to contagion when hit by a large shock. Squartini et al. (2013) show that the dynamics of financial networks can provide early signs of imminent financial crises. Financial network studies have focused mostly on interbank markets, although the literature on CDS markets has grown over the past few years. Markose et al. (2012) provide an empirical reconstruction of the US CDS market and shows that the market is dominated by a few core players. The authors argue for a 'super spreader tax' based on centrality to price in the negative externalities of interconnectedness (See also Haldane (2009)). Cont and Minca (2015) show that liquidity problems can cause systemic risk in the CDS market, and that central clearing can help mitigate this risk if core players are a clearing member of a Central Couterparty (CCP).

Finally, the paper relates to the growing stock of empirical research into the CDS network structure. Multiple studies show that CDS markets are characterised by a scale-free distribution of market participants, and evidence the CDS market's potential to destabilize the financial system (e.g. Peltonen et al. (2014), Abad et al. (2016), Ali et al. (2016), Kenny et al. (2016), Brunnermeier et al. (2013)). Peltonen et al. (2014) study the aggregate CDS network and find that core players hold large but matched positions while peripheral players are net buyers of CDS protection. The amount of CDS protection traded is related to the volume of debt issued by the reference entities and the risk characteristics of the debt. This is in line with hedging and speculation motives (See also Oehmke and Zawadowski (2015, 2017)). Abad et al. (2016) use EMIR data to study the European derivatives market and find similar evidence for a highly concentrated market, where a few dealers dominate the market and in which most trades relate to only a few reference entities. The dealers act as intermediaries. Together with banks, the dealers are net sellers of CDS protection. Other financial institutions (including hedge funds and mutual funds), non-financial corporations, as well as insurance and pension funds are generally net buyers of protection. Due to their interconnectedness, the large dealers are often described as 'too-interconnected to fail' or 'super spreaders'. Brunnermeier et al. (2013) note, however, that some of the non-bank market participants also have 'super-spreader' potential (cf Kenny et al. (2016)). Obviously, contagion in the CDS market is more likely if the core market participants have small capital and liquidity buffers relative to their exposures (Ali et al. (2016), Brunnermeier et al. (2013), Markose et al. (2012), Siriwardane (2016)).

3. Data

We use CDS transaction data provided by DTCC, the largest Trade Repository (TR) authorised under EMIR.[6] According to the ESRB, DTCC covers 80 percent of the EU CDS market (Abad et al. (2016)). This amounts to EUR 7,123 bn. in gross notional outstanding (December 2015), of which EUR 3,660 bn. pertains

[6]Currently six TRs are in operation, namely CME Trade Repository Ltd., DTCC Derivatives Repository Ltd., ICE Trade Vault Europe Ltd., Krajowy Depozyt Papierów Wartościowych S.A., Regis-TR S.A., and UnaVista Limited.

to single name CDS and the remainder to index CDS. Our analysis covers only the Dutch segment of the CDS market, which means that the data set contains trades for which the underlying reference entity is registered in the Netherlands and/or one (or both) of the counterparties in the trade is a Dutch entity. In line with the ESRB (Abad et al. (2016)), we exclude intragroup transactions. In contrast to the ESRB, we keep trades for which we do not have mark-to-market information (roughly 20% of observations). This results in total gross notional of the 'Dutch' CDS market of approximately EUR 4,000 bn. of which EUR 140 bn (4 %) are accounted for by single name CDS. Our data sample is predominantly made up of index CDS transactions because among the constituents of the underlying CDS index there is often a Dutch entity.

We use DTCC's daily 'trade state' reports from 1 December 2015 to 31 December 2016. These reports contain transaction-level information on the stock of all outstanding CDS contracts at a given date. They include information on the counterparties, the notional amount and market value, the underlying of the contract, the currency of the contract, and relevant contractual dates, along with other characteristics. TRs also provide 'trade activity' reports containing the daily flow. We did not use the daily 'trade activity' reports by TRs as their interpretation is complicated.[7]

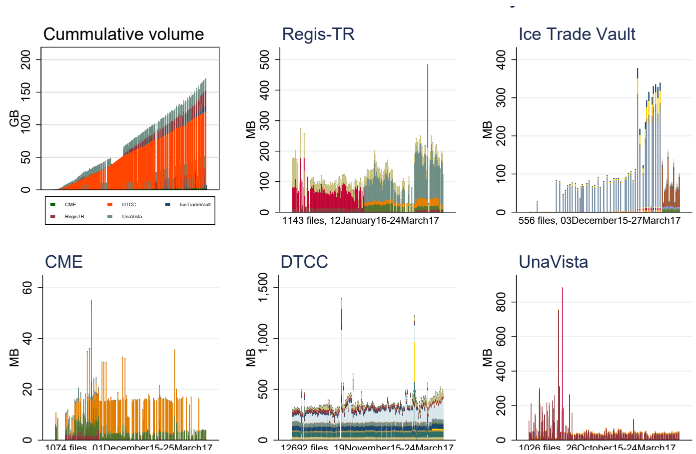
Because the EMIR dataset is new and untested, proper data cleaning and documentation thereof are important. To give an impression of the size and complexity of the EMIR data we plot the volume of the EMIR data files for the five European TRs De Nederlandsche Bank collects data from in Figure 1. The top left panel shows the total while the other five panels focus on the five relevant TRs.[8] Using the naming convention used by the TRs, we assign unique colours for each of the different types of files. The exact conventions (colours) are not relevant, except to note that each TR uses its own reporting templates, occasionally changing naming conventions or reporting setup. This makes data consolidation a daunting task and explains why recent studies – including this one – have focussed on the largest TR, DTCC.

The left pane of Figure 2 provides an overview of the data cleaning steps that

[7]For example, at this stage it is not possible to build up the trade state reports from the trade activity reports, because multiple updates to the same trade can be reported using a single time stamp. Since the order of updates is unknown, the end result is undetermined.

[8]We do not collect data from Krajowy Depozyt Papierów Wartościowych S.A. since it is not used by Dutch market participants.

Figure 1: The volume of files



The files have been grouped and coloured by the structure of the naming used. For example, DTCC's "trade state" files for CDS are structured as *OTC_CR_Trade_State_Report.D171005.T0030153*. This tells us it is a zip file for OTC credit trade state files reported on 5 November 2017. The last component is a version indicator. The TRs also provide many more files on, *inter alia*, trade flow, matching and collateral.

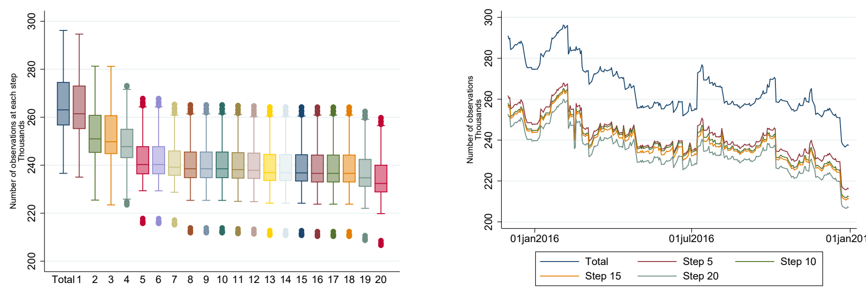
we applied, showing the distribution of remaining observations after applying each consecutive check. On average, the daily trade state reports contain 260,000 observations. During the cleaning process, around 20,000 observations are dropped, mostly due to missing or negative notional amounts, incorrect reporting of the underlying of the CDS or of maturity dates.

To enrich the data after the aforementioned cleaning steps, we augment the CDS trade state reports with the following data sets: First, GLEIF for information on counterparty name, LEI, and domicile of counterparties.[9] Second, we use the ECB's Centralised Securities Database (CSDB) for counterparty sector domicile, underlying name, and sector country.

The right hand pane of Figure 2 shows the number of observations remaining after selected cleaning steps over time. It is clear that the number of observations is trending downwards. Furthermore, it seems that the quality is constant over time.

[9]The Global Legal Entity Identifier Foundation (GLEIF) is set up to support the implementation and use of the Legal Entity Identifier (LEI).

Figure 2: The cumulative effect of data quality checks



(a) Over cleaning steps

(b) Over time

1) invalid cpa LEI 2) invalid cpb LEI 3) the notional amount should not be missing or negative 4) the reference entity should not be missing 5) non-ISIN should be removed, but keep Index CDS 6) the maturity date should be larger than the effective date 7) the maturity date should be larger than the execution date 8) termination date should not be prior to fileDate (we only want active contracts) 9) double reports are dropped 10) triplicates are dropped 11) inconsistent notionals are dropped 12) inconsistent counterparty ID 13) inconsistent counterparty side 14) inconsistent maturities 15) inconsistent reference entities 16) inconsistent intragroup flags 17) keep only one observation. 18) mtmEur/notiEur *and* notiEur should not be disproportional. 19) mtmEur winsorized at the top 1% 20) notiEur winsorized at the top 1%

4. Overview of the Dutch CDS market

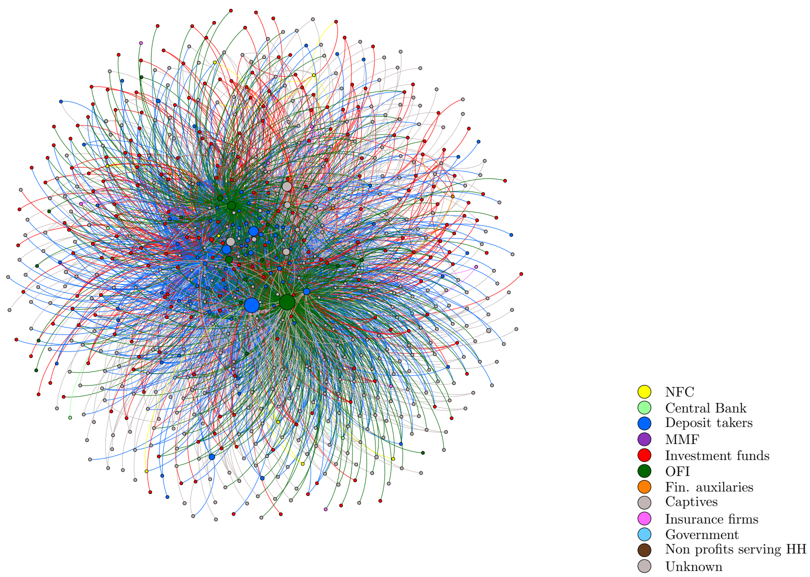
This section gives a first account of the Dutch segment of the CDS market. It provides an overview of the overall market structure, the size of the market, the total risk transferred, the underlying reference entities, and the ultimate protection buyers and sellers.

We start with the network structure of the Dutch CDS market in Figure 3. The nodes represent the counterparties in the network while the links indicate CDS exposure between two counterparties. The size of the nodes represents the net notional exposure taken on by each counterparty. The colour of the nodes signals the sector of each counterparty. The network includes both single name and index CDS as underlying. Thus, Figure 3 provides the most aggregated overview of the CDS market.[10] In line with Abad et al. (2016), we find that large banks (dealers) and several 'other financial intermediaries' (OFIs) play a central role. Peripheral players are mostly other banks and non-MMF investment funds.

The network graph shows the complexity of the Dutch segment of the CDS

[10]Note that to keep the graph tractable we only include nodes with a net notional CDS exposure above EUR 100 million.

Figure 3: Net exposures, above 100 million, 30^{th} June 2016



Note: The figure shows Net exposures above EUR 100 million. The links are coloured according to their source (i.e. the buyer).

market. To examine the structure of the network in more detail we plot four key descriptives in Figures 4 and 5 for the sample including and excluding indices, respectively.[11] The metrics are the number of nodes, connections (also dubbed edges or degrees), the density, and assortativity. Density is the number of connections as a percentage of all possible connections, i.e. (number of edges/(n*(n-1)). Assortativity is a measure of whether parties connect to counterparties that are similar in terms of connections. A high positive assortativity coefficient indicates that nodes with a similar degree tend to connect. For the total market including indices, the number of counterparties in the network averaged around 3,800 creating on average 8,000 connections. Over time the participation varied both over the intensive and extensive margin. The lion's share of the counterparties in our data set trade in index CDS only. Looking at just single name CDS, we

[11]Note that there is a reporting issue in October 2016 which – if uncorrected – would show market participants shifting their portfolio drastically

observe a much smaller number of active market participants: around 790 on average. In terms of connectivity, both the aggregate market (including indices) and the single name CDS market exhibit a low density level (on average 0,0008 and 0,0055, respectively) and a negative assortativity coefficient (on average -0,61 and -0,59, respectively). This is indicative of a 'core-periphery' market structure with small number of well connected core players and a larger set of peripheral players with fewer connections.

Figure 4: Network metrics over the sample, including indices

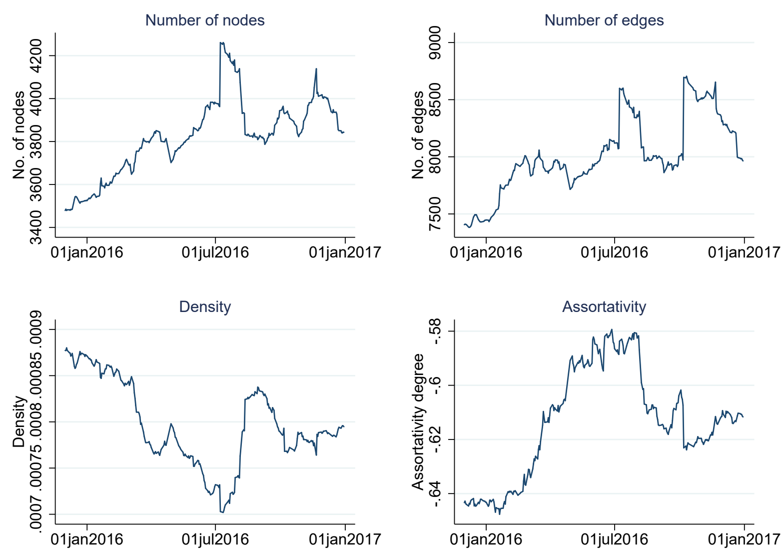


Figure 6 provides a sectoral breakdown of the market participants involved. As is clear from the graph, the number of market participants per sector remains quite stable over the observed period. For those participants where we observe the sector, the non-MMF investment funds are the most numerous, closely followed by banks.

The gross notional amount outstanding, as depicted in Figure 7, represents the absolute sum of the notional value of all single name CDS contracts bought and sold. The gross notional amount is a measure for the size of the CDS market and can also be regarded as an upper bound measure for risk. The gross notional amount will substantially overstate the risk exposure because (i) the notional amount is usually larger than the potential payout on the CDS contract – which

Figure 5: Network metrics over the sample, excluding indices

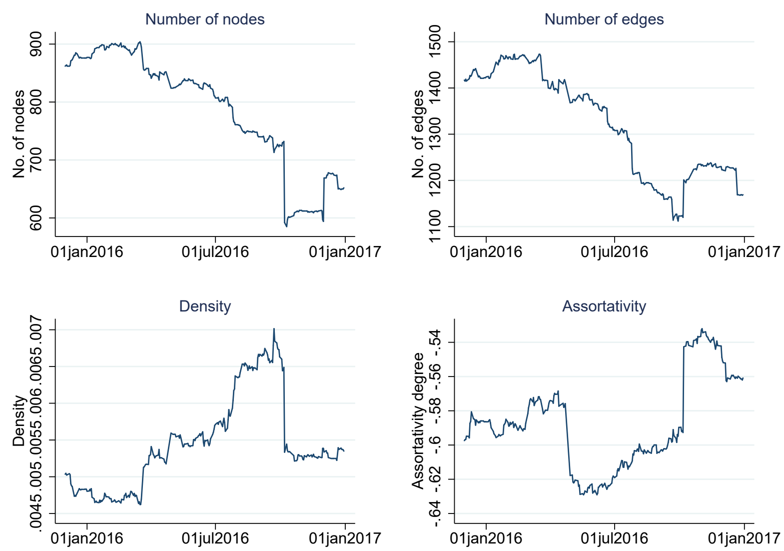
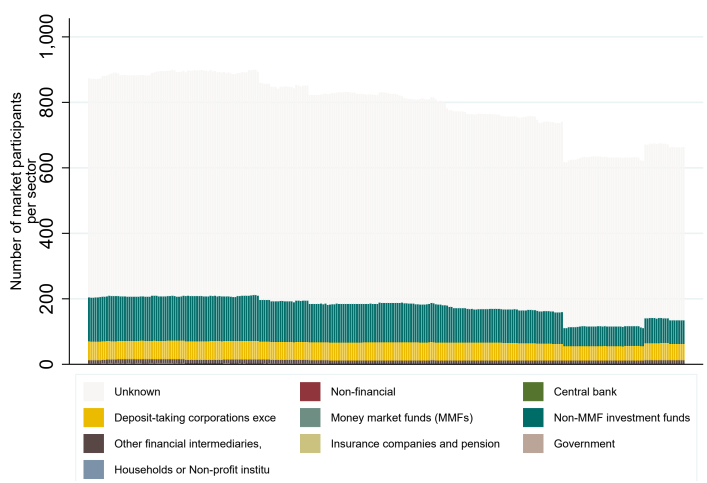


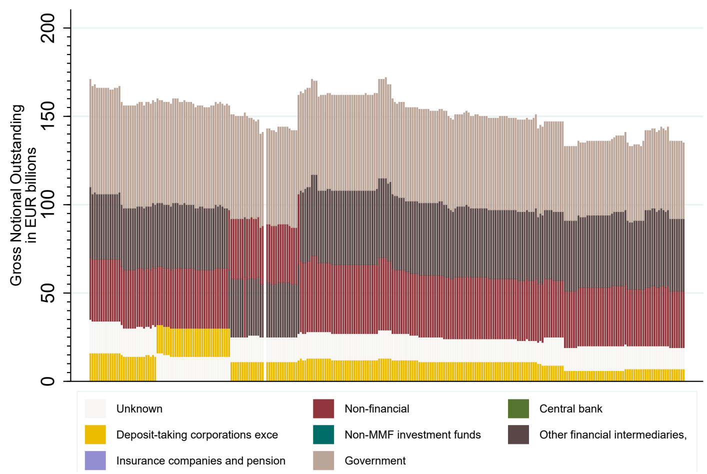
Figure 6: Number of unique counterparties per sector



is the notional value minus the recovery rate – and (ii) netting arrangements are not taken into account. From a macro perspective, however, gross notional exposure is a useful measure for upper bound risk in the case of a financial crisis, when recovery rates are low and netting sets may break down due to defaults.

The volume of the market averaged around EUR 150 billion between December 2015 and December 2016. About 34% of the CDS are written on government securities; 33% pertain to banks and other financial intermediaries; and 23% of the CDS are written on non-financial companies. An overwhelmingly large share of CDS contracts is denominated in USD and EUR, followed at a distance by a much smaller share of contracts denominated in JPY or GBP. These descriptives corroborate the results of Abad et al. (2016).

Figure 7: Gross notional amount outstanding, with breakdown of underlying sector



To get a feeling for the level of concentration in the market for single name CDS contracts, we plot the market share of the top 5 net CDS protection buyers and sellers in Figure 8. The computation is in line with Siriwardane (2016). First, the market share of each counterparty in a given reference entity is computed as the proportion of net selling (or buying). The aggregate share of net selling (buying) by each counterparty is the size-weighted average share across all reference entities. The top five sellers (buyers) are those with the largest aggregate share. It is clear from Figure 8 that the Dutch single name CDS market is highly concentrated: on both the buy and sell side the top five participants account for approximately 40 percent of the market. Compared to the US data studied by Siriwardane (2016), we find a higher level of CDS buyer concentration and a slightly lower CDS seller concentration (25 and around 50 percent, respectively). There is a strong persistence in the counterparties that make up the top 5 net CDS buyers and sellers (See Figure 9). When index CDS

Figure 8: Market share of Top 5 buyers and sellers

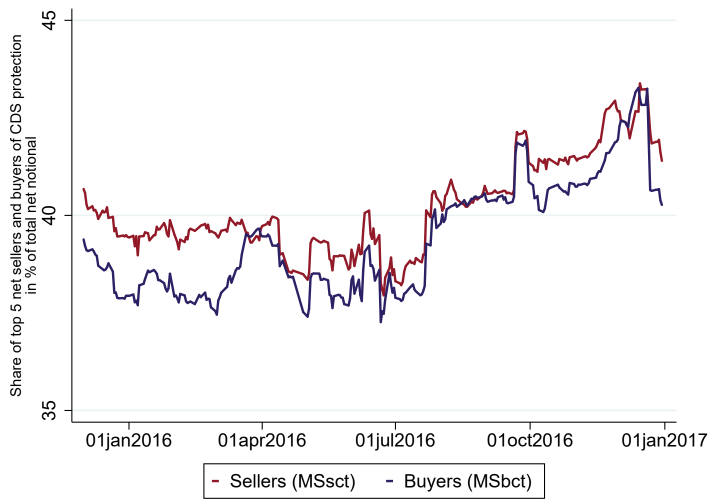
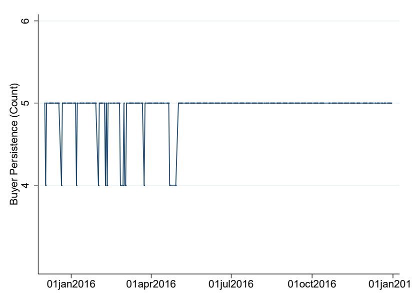
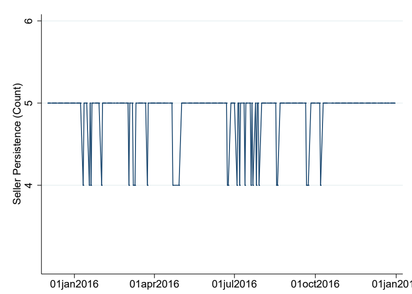


Figure 9: Persistence of top 5 sellers of CDS protection



(a) Buyers

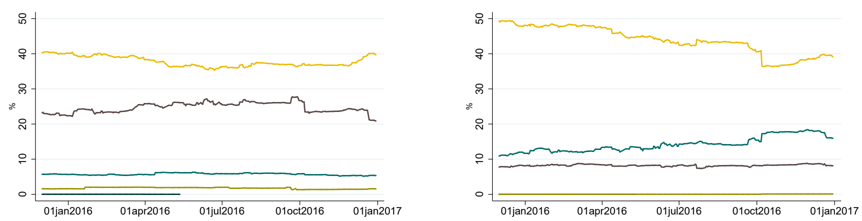


(b) Sellers

are also considered, we find an even larger concentration: the top five net CDS buyers and sellers account for 60 and 75 percent of the market, respectively.

To better understand which market participants are net sellers or buyers of CDS protection, we plot a sectoral breakdown of net CDS protection sold and bought in Figure 10. The computation of the market share for each type of counterparty follows a similar procedure as in Figure 8. For each reference entity, we compute the market share for each counterparty and then aggregate over counterparty sectors. To obtain the overall sectoral market shares in net selling and buying, we calculate the size-weighted average across all reference entities.

Figure 10: Net protection bought and sold per sector (as % total net protection bought or sold)



(a) Protection bought

(b) Protection sold

Banks
Insurance corporations and pension funds (ICPF)
Other financial institutions (OFI)
Non-Money market funds
Non-financial corporates

Banks are the major net sellers of CDS protection although in 2016 their market share dropped from 50 percent to 40 percent. Non-MMF investment funds are the second largest group of sellers of CDS protection, with a market share that increased from 10 to 20 percent over 2016. Note that a large share of CDS selling is done by counterparties for which we cannot observe their sector (most likely, these are large broker dealers outside the EU). Banks also account for the largest share – around 40 percent – of net CDS protection buying, followed by other financial intermediaries.

In sum, we observe on average 3,800 market participants in our dataset of which 790 hold single-name CDS positions with a notional value around EUR 150 billion. The single name CDS contracts are written on governments (34%), financials (33%) and non-financial corporations (23%). The CDS market has a core-periphery structure and is very concentrated. The top five buyers and sellers account for 40% of the single-name CDS market. Looking at the sectoral level, we observe that banks are the major net single-name CDS sellers and buyers, investment funds are the second largest group of sellers, and other financial institutions are the second largest group of buyers.

5. Drivers of the flow-of-risk in the Dutch CDS market

CDS contracts allow market participants to transfer credit risk, creating a 'flow-of-risk' from the CDS buyer to the CDS seller. The 2007-09 financial crisis showed that the CDS market can contribute to the build-up of systemic risk, which motivated the G20 to mandate the reporting of transactions so that authorities can monitor the flow-of-risk. In this section we investigate the factors that drive the flow-of-risk in the Dutch segment of the CDS market by means of logistic regressions. In our regression model, we aim to explain the probability of a market participant being a net CDS protection seller, based on characteristics of the market participant (i.e. its size and sector), the volatility of the underlying reference entity and the volatility in financial markets in general. Table 1 provides summary statistics of these explanatory variables. The selection of the independent variables is motivated by the literature, as discussed below.

An important driver of CDS use is the sector of the counterparty. D'Errico et al. (2018), for instance, find evidence for a 'bow-tie' structure of the global CDS markets (aggregated over all underlying names), in which large dealers form an interconnected core that is surrounded by peripheral players that are either ultimate risk buyers or sellers. The authors find that hedge funds are generally the largest CDS sellers, while asset managers and smaller banks are the largest CDS buyers. The authors note that these findings show more heterogeneity when the analysis is conducted at the level of the individual reference entity but it seems clear that different sectors have different needs and follow inherently different strategies and therefore take different positions in the CDS market. For our analysis of the Dutch market, we distinguish three sectors namely 1) banks, 2) other financial institutions (OFIs), and 3) pension funds and insurance companies (ICPF). Other sectors are too small to be included in the analysis.

Given their long term investment strategies, we expect pension funds and (life) insurance companies to be CDS buyers in general. For banks, the "natural" position is less clear because some banks are intermediaries while others take on only one side, for instance to hedge an exposure (e.g., a syndicated loan participation. Cf Shan et al. (2014)). Due to the specificities of the Dutch market, the OFI sector consists for a large part of asset managers that invest on behalf of pension funds. Because of their link with pension funds, we expect these entities to be CDS buyers as well. Of course, other types of OFIs, such as hedge funds, could be CDS sellers.[12]

We use the size of market participants, measured as total assets in billion USD, as a general control for the sophistication of participants. We use the Global Ultimate Owner (GUO) information from ORBIS. Missing values are substituted with total assets from annual reports.

The general tendency of market participants of a certain sector to be CDS sellers or buyers can change if market circumstances change. For instance, market participants could choose to buy more CDS protection to hedge an underlying asset that has become more volatile or to hedge general market uncertainty. Alternatively, some market participants may take on a larger intermediating or speculative position under these circumstances, especially when traditional players leave the market. Therefore – in various specifications of our model – we include the volatility or log price change of the underlying reference entity and a measure for the overall volatility of the market (VIXX, VSTOXX) as control variables. Since we have not yet been able to include information on market participants holdings of the reference entities underlying their CDS contracts, we cannot empirically identify hedging, speculation or intermediation at the individual market participant level. From a macro perspective, however, it is still relevant to find patterns in the flow of risks from CDS positions, as this can help identify and understand channels for contagion between sectors under different market circumstances.

Table 1: Summary statistics independent variables

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Underlying price	302,892	105.9	18.64	0.0500	377.9
Underlying price volatility	302,892	0.589	1.543	0	40.97
Underlying price change	302,892	-3.58e-05	0.0248	-2.331	2.862
VIX index	302,892	16.14	3.963	11.34	28.14
VIX index volatility	302,892	16.27	3.286	12.12	24.24
VSTOXX index	302,892	23.81	5.020	14.88	39.90
VSTOXX index volatility	302,892	23.97	4.001	16.39	32.15
Total assets	289,944	373.8	514.2	0	2,189

[12] Investment funds with a LEI were included in the ICPF category, because their market share was too small to be included separately in the analysis. The reason behind their small share in our sample could be that investment funds are not required to have an LEI.

Table 2: Distribution of counterparties across sectors

Sector	Frequency	Percent	Cumulative
Unknown	265	0.09	0.09
Non-financial corporations	346	0.11	0.20
Banks	99,329	32.79	33.00
Non-MMF investment funds	7,278	2.40	35.40
OFI	129,530	42,76	78.16
ICPF	66,144	21.84	100.00
Total	302,892	100.00	-

We define the dummy variable *netSellDummy* as the dependent variable, which equals 1 (0) if a market participant is a net seller (buyer) of CDS protection. To construct *netSellDummy*, we first generate a measure for net selling of CDS protection. This continuous variable – *netSell* – measures the net CDS protection sold for each Dutch counterparty in our sample per underlying reference entity at each date, relative to the counterparty's total exposure to the reference entity on that date. It is thus given by:

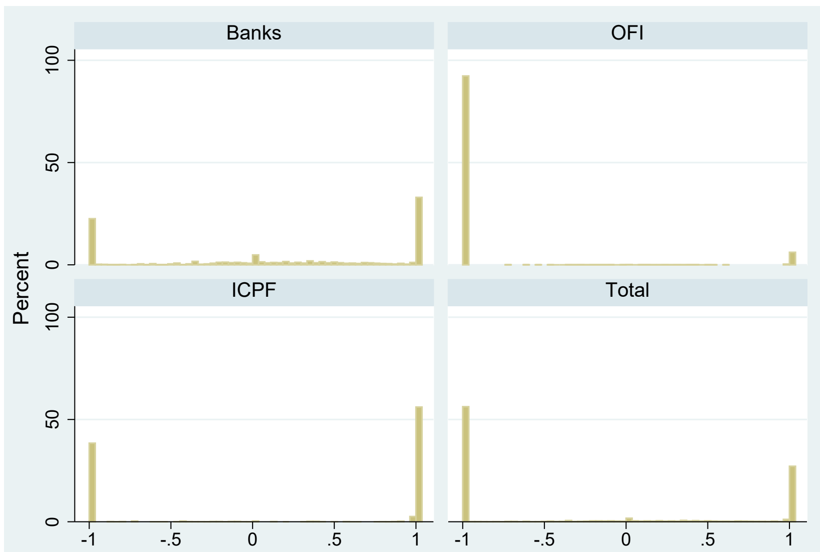
$$netSell_{i,r,t} = \frac{\sum_{j=1}^{N} CDSprotectionsold_{i,j,r,t} - \sum_{j=1}^{N} CDSprotectionbought_{i,j,r,t}}{\sum_{j=1}^{N} CDSprotectionsold_{i,j,r,t} + \sum_{j=1}^{N} CDSprotectionbought_{i,j,r,t}}$$

where subscript i and j denote the counterparties (with $j \neq i$), r is the reference entity, and t is the date. *netSell* ranges from -1 to 1. This measure is subsequently transformed into a dummy variable that indicates whether a counterparty is a net CDS protection seller for a given reference entity on a particular date:

$$netSellDummy_{i,r,t} = \begin{cases} 1 \text{ if } netSell_{i,r,t} > x \\ 0 \text{ if } netSell_{i,r,t} < -x \end{cases}$$

with $0 < x < 1$. This indicator function allows us to exclude market participants with balanced positions (e.g. if they act as intermediaries) from the regression, in order to focus the analysis on net buying and selling. This dummy variable will serve as the dependent variable in our logistic regression model, where we have set the threshold value x to equal 0.1. Figure 11 shows the distribution of *netSell* per sector. Overall, Dutch market participants have more buying positions than selling positions (note that our measure does not take into account the size of the position). Other financial institutions (OFIs) have the largest share of buying positions, followed by insurance companies and pension funds. There are a few market participants, most notably banks, that seem to fulfil an intermediary role indicated by *NetSell* values around zero.

Figure 11: Distribution of *NetSell* in the Dutch CDS market



The results of our logistic regression analysis are presented in an overview table (Table 3), a table with the average prediction probability (Table 4), and figures with marginal effects over selected explanatory variables (Figures 12 and 13). (Table 3) displays coefficients as odds ratios. For ease of interpretation, we discuss our results based on the marginal effects plots.

We find that banks are generally net CDS seller while ICPFs and OFIs are net CDS buyers. Table 3 shows that a market participant's sector is both a statistically and economically significant factor in all specifications, indicating that banks have a higher probability of being CDS sellers than ICPFs and OFIs. Table 4 shows the average predicted probabilities of being a net CDS seller for each sector (conditional on the mean of all covariates). It indicates that banks are generally net sellers of CDS protection (with probabilities above 50%), although this result is less pronounced if only the top 10 underlying reference entities are considered (Model 2). The other sectors (OFIs and ICPFs) are on average net buyers of CDS protection (with probabilities below 50%) although the probability of being a seller is higher for the most active reference entities.

Table 3: Logistic regression results (coefficients as odds ratios): explaining the flow-of-risk

	(1)	(2)	(3)	(4)
	Baseline		Variations	
	Underlying and VIX volatility	Top 10 underlyings	Underlying log returns	Quadratic underlying log returns and VIX
OFI	0.0040***	0.0010***	-5.5370***	-5.5370***
	(0.0004)	(0.0000)	(0.0773)	(0.0772)
ICPF	0.4110***	1.0810	-0.8560***	-0.8550***
	(0.0243)	(0.3650)	(0.0506)	(0.0506)
Total assets	0.9990***	0.9990***	-0.0008***	-0.0008***
	(2.15e-05)	(0.0001)	(2.15e-05)	(2.15e-05)
OFI • Total assets	1.0120***	1.1750***	0.0120***	0.0120***
	(8.19e-05)	(0.0235)	(8.00e-05)	(8.00e-05)
ICPF • Total assets	0.9950***	0.9910***	-0.0052***	-0.0052***
	(0.0003)	(0.0006)	(0.0003)	(0.0003)
ISIN volatility	0.9780***	0.5480***		
	(0.0041)	(0.0438)		
OFI • ISIN volatility	1.1150***	1.4130***		
	(0.0091)	(0.1400)		
ICPF • ISIN volatility	1.1460***	2.9420***		
	(0.0126)	(0.3150)		
VIX volatility (1mma)	0.9990	0.9690**		
	(0.0021)	(0.0135)		
OFI • VIX volatility (1mma)	0.9840***	1.1480***		
	(0.0051)	(0.0294)		
ICPF • VIX volatility (1mma)	1.0040	1.0740***		
	(0.0033)	(0.0191)		
log ISIN price			0.2420	0.4280
			(0.2670)	(0.3250)
OFI • log ISIN price			-0.2020	-0.3200
			(0.4350)	(0.5070)
ICPF • log ISIN price			-0.2630	-1.2780
			(0.6800)	(0.9060)
VIX			-0.0019	-0.0122
			(0.0018)	(0.0108)
OFI • VIX			-0.0096**	-0.0096**
			(0.0043)	(0.0043)
ICPF • VIX			0.0073***	0.0073***
			(0.0027)	(0.0027)
log ISIN price squared				0.4100**
				(0.1790)
VIX squared				0.0003
				(0.0003)
Constant	3.8460***	1.3460***	1.4350***	3.3460***
	(0.1610)	(0.0369)	(0.0988)	(0.9490)
Observations	279,646	279,646	279,646	12,918
Pseudo R-squared	0.368	0.368	0.368	0.371

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The statistical and economic significance of the other independent variables in our model depend on the specification. For ease of interpretation, Figure 12 and Figure 13 show – for our two baseline specifications – the predicted probabilities per sector for representative values of the independent variables. The figures show that the probability of being a net CDS seller decreases as banks' size (in terms of total assets) increases. The same result emerges for ICPFs. On the other hand, larger OFIs seem to have a higher probability of being a net seller if they are larger.

In the baseline specification, we see that banks are less inclined to be sellers of CDS protection if the volatility of the underlying reference entities increases. ICPF and OFIs on the other hand, seem to have an increased probability of CDS selling at higher volatilities: if we compare the (hypothetical) case of equally and average sized banks, ICPFs, and OFIs, the latter two sectors would even have an equal or larger probability of being a net CDS seller compared to the banks. This could be a reflection procyclical investment behaviour by banks and countercyclical behaviour by ICPFs and OFIs [13]. An explanation could be that banks limit their trading activities or withdraw from the CDS market when volatility is high because they have capital utilization constraints and strict limits to risk measures (i.e. VaR limits) while other types of financial companies have more room to manoeuvre due to smaller capital constraints and less regulatory scrutiny on their risk limits. However, it should be noted that the results are influenced by the assumption of average sized institutions (ICPFs and OFIs are on average smaller – in terms of total assets – than the total sample's average). The volatility of the market, as measured by the volatility of the VIX, seems to have no effect on the probability of being a CDS seller. This interesting and surprising result could be caused by the overall low level of market volatility in the observation period.

In the second baseline specification, we run our model for the top 10 underlying reference entities only (top 10 in terms of total notional outstanding in the market). Again, banks (ICPFs) propensity to sell CDS decreases (increases) as the volatility of the underlying reference entity increases. In contrast to the general baseline case, OFIs now have a lower probability of being a net CDS seller as the underlying volatility increases. Interestingly, net selling of CDS protection on the top 10 underlying reference entities is more sensitive to market

[13]Note that our results could be interpreted both along the time series and cross sectional dimension. In other words, our findings could indicate that the propensity to sell CDS on a reference entity decreases (increases) for banks (ICPF and OFIS) if the volatility of a single reference entity increases over time. Alternatively, our findings could suggest that banks have a relatively higher propensity to sell CDS on less volatile reference entities, while ICPF and OFIs have a relatively higher propensity to sell CDS on more volatile reference entities. It goes beyond the scope of this paper to disentangle these two dimensions.

Table 4: Average predicted probabilities per sector

		Banks	OFI	ICPF
Model 1	Baseline: underlying and VIX volatility	0.739	0.394	0.193
Model 2	Baseline: top 10 underlyings	0.476	0.00	0.366
Model 3	Variation: underlying log return & VIX	0.739	0.392	0.181
Model 4	Variation: quadr. log returns & VIX	0.739	0.391	0.180

volatility, possibly because of a higher correlation with the market. ICPFs and OFIs have a higher probability of being CDS sellers if market volatility increases (although for OFIs the effects are small). On the other hand, banks' probability of being a net CDS seller drops if market volatility increases. Again, these results may hint at procyclical beaviour by banks and countercyclical strategies by ICPFs and OFIs.

When considering the alternative specification with log returns for the underlying reference entities and the VIX index (Model 3), we again find that market volatility has no effect on position taking in the CDS market. In addition, banks have a lower probability of being a net seller if negative returns are observed for the underlying reference entity. ICPFs and OFIs do not seem responsive to returns. This is in line with the results of our baseline model. When quadratic effects are considered (Model 4), a non-linear relation emerges for the effect of the underlying return. For all sectors, the probability of being a net CDS seller is higher when returns are in the tails of the distribution. This could indicate that all sectors to some extent use CDS for hedging and speculative purposes. Note, however, that these results are estimated with more uncertainty (as it can be seen from the confidence interval bars in Figure 12 and Figure 13 and the statistical insignificance of the regression coefficients in Table 3, Column 3).

We conducted various robustness checks but overall our results seem to hold up. First, we estimated the model for different values for x, ranging between 0.1 and 0.3, and found that the results did not change significantly (which also is evident from Figure 11). We also analysed if our results were sensitive to including other benchmarks for market volatility by replacing the VIX measure by VSTOXX (a European stock market index) and found no effect. Finally, we examined if the results would change if only the contracts on the most important underlying for each market participant were considered (i.e. if the notional

Figure 12: Model 1: Baseline: underlying and VIX volatility - Average probabilities at representative values

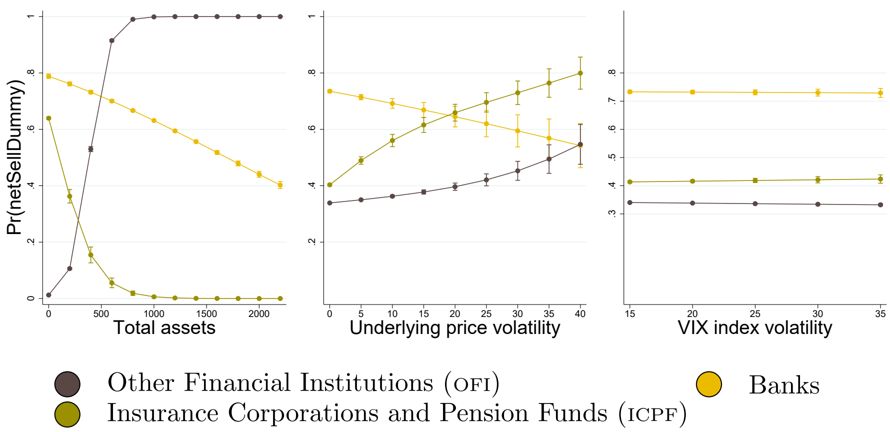
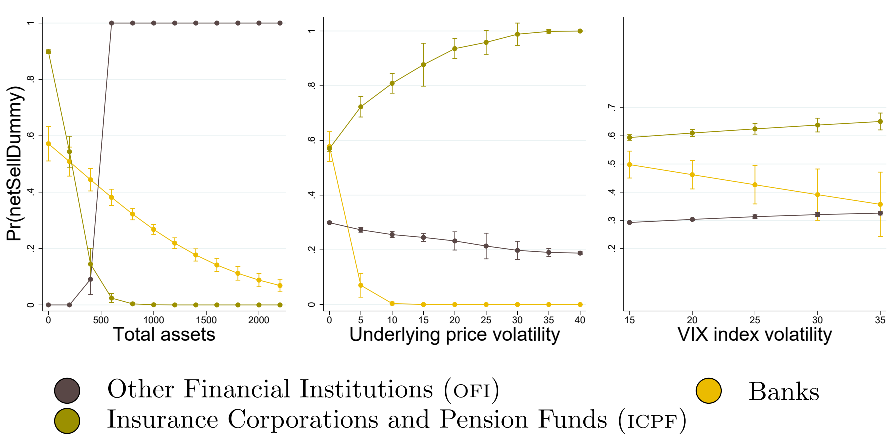


Figure 13: Model 2: Baseline: top 10 underlyings - Average probabilities at representative values



amount on a certain underlying exceeded 5% of the total notional CDS position of the market participant). Since the portfolios of Dutch market participants are not concentrated enough, this leaves too few observations to run our regression.

In sum, when focussing on Dutch counterparties only, we find that banks are on average CDS protection sellers while ICPFs and OFIs are CDS buyers. Looking within sectors, we observe that the probability of being a seller is lower for larger banks, and higher for larger OFIs. ICPFs and OFIs seem to increase CDS selling if the volatility of the underlying reference entities increases, while banks reduce CDS selling. This may hint at procyclical behaviour by banks and a- or countercyclical behaviour by ICPFs and OFIs. Although not statistically significant, we observe for all sectors that CDS selling increases when returns on the underlying are at either tail of the distribution, which might be an indication that all sectors, at least to some extent, use CDS for both hedging and speculative purposes.

6. Impact of Brexit: a case study for the Dutch CDS market

Brexit ranks among the most significant events in recent years in terms of political and economic consequences. On 23 June 2016, the United Kingdom (UK) held a referendum to decide whether the UK should remain in the European Union or leave. Against expectations, the "Leave" camp won by 51.9% to 48.1%. This unexpected outcome caused substantial market turmoil. On 24 June, the value of the British pound dropped by more than 8% against the US dollar. In addition, the main European equity indices fell sharply. The FTSE250, an important indicator for the performance of British business, lost more than 7%. Similarly, the Dutch AEX dropped by 5.7% and the Eurozone Eurostoxx50 by 8.6%. The equity market losses were particularly severe for European banks. Share price losses were even worse than those after Lehman's bankruptcy filing. CDS spreads also increased, but less than after Lehman's default (Schiereck et al. (2016)).

Given the substantial impact of Brexit on other financial markets, it is worthwhile to investigate the impact of Brexit on the structure of the CDS market. We do so by providing an overview of the development of several common network metrics (number of 'nodes' and 'links', the 'density' of the network, and its 'assortativity'[14]) as well as an overview of changes in net selling and buying of CDS on UK reference entities by Dutch market participants over the course of 2016. Note that this case study gives a first descriptive account of the impact of Brexit. Further research is needed to evaluate the econometric significance of the trends we observe around Brexit.[15]

[14] The density of the network measures the fraction of actual links in the network relative to all possible links, i.e. (number of edges/(n*(n-1)) while the assortativity measure indicates how similar interacting counterparties are. A high positive assortativity coefficient indicates that nodes with a similar degree tend to connect. High degree nodes thus connect with other high degree nodes and nodes with very few degrees connect with other low degree nodes.

[15] See Schimmel et al. (2018) for an econometric analysis of Brexit using the same data set.

We expect market participants to place bets and hedges in the run up to major Brexit dates, which we expect to be reflected by an increase in the number of nodes (market participants entering the CDS market) and and increase in the number of links (signalling new trading connections). Moreover, we expect that new market participants that enter the market are mostly 'peripheral' players that buy or sell CDS protection via 'core' dealers. We therefore expect to observe a decrease in the density of the network, as well as a decrease in assortativity. Finally, drawing on the finding from Chapter 5 that banks might exhibit procyclical trading behaviour and non-banks may act countercyclically, we expect that banks will take on a relatively smaller role, and non-banks a relatively larger role, in selling CDS.

The results of our analysis corroborate our expectations. At first sight, as indicated by Figure 14 the network of the Dutch CDS market for UK reference entities does not seem to change around the Brexit vote. A different picture emerges, however, when the development of the network metrics are considered over a longer time window (Figure 15): after the referendum date, we observe a small drop in the number of counterparties (reaching a minimum in August) followed by a sharp increase starting in September and accelerating in October. The October jump may be explained by Theresa May's announcement to enact Article 50 of the Treaty on European Union, thereby officially starting the process to exit the EU. The increase in the number of links between counterparties in the run up to the referendum date, and again around May's announcement in October, may be indicative of market participants 'placing their bets' on the outcome (i.e., taking hedging, speculative, or arbitrage positions).

In addition, we observe that the density of the network is generally low: only 4-5% of all possible links are active in the first half of 2016. The assortativity of the network is negative, indicating that most connections are between dissimilar counterparties. These observations are in line with the characteristics of the core-periphery structure of the CDS market, in which a few well connected core players act as intermediaries for many less connected peripheral market participants (cf. Anand et al. (2018) also find a core-periphery structure for UK and US CDS markets). After the Brexit vote, a small increase and subsequent sharp decrease

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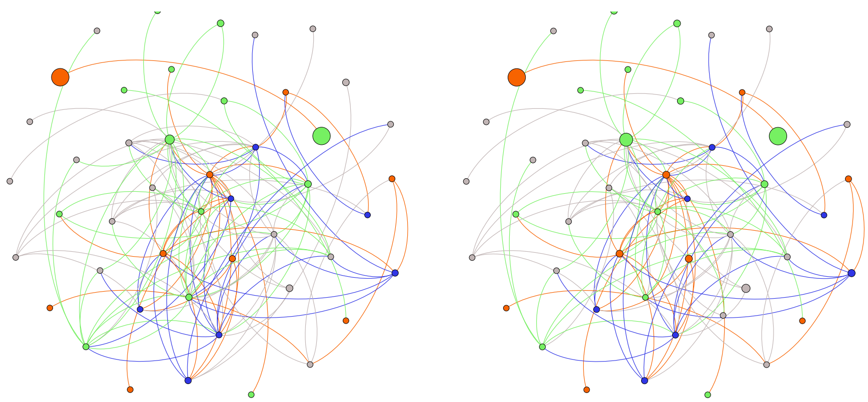
Using extensive break tests, the authors find no significant change around any of the important dates.

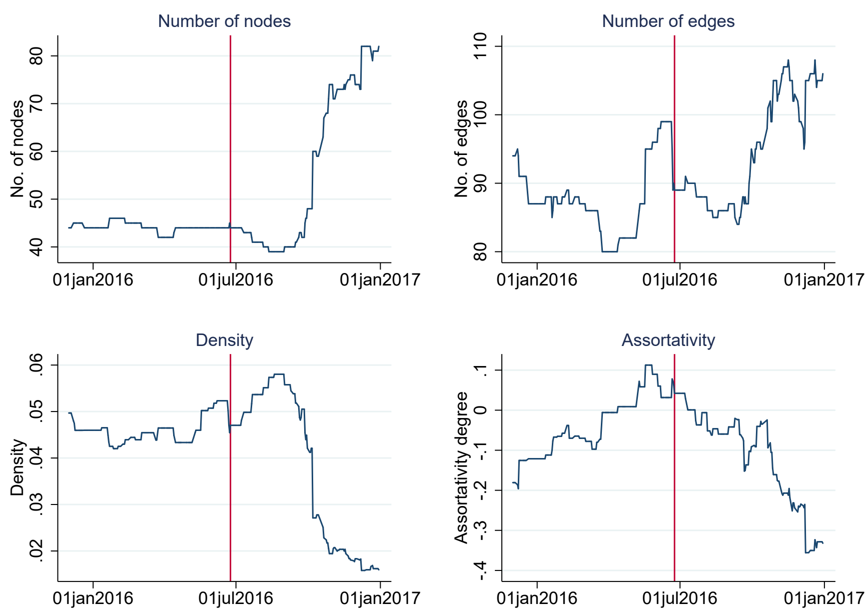
Figure 14: No changes in network structure around Brexit vote



(a) 16 June 2016 (b) 30 June 2016

Note: UK underlying only. Orange dots are Dutch reporting firms, blue dots are Great Britain, green dots are other countries, and grey dots are unknown. The links are coloured according to their source (i.e. the buyer).

Figure 15: Network metrics for the CDS market for UK underlyings

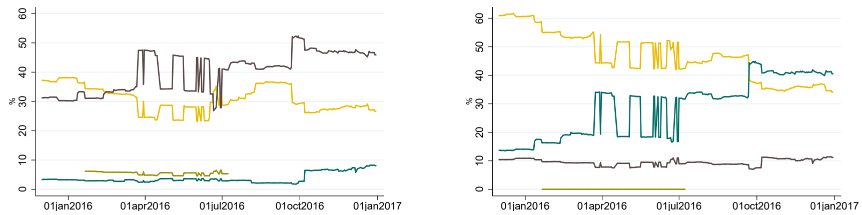


in the density of the network is visible. The assortativity coefficient turns slightly positive around the Brexit vote, but drops noticably afterwards, reaching even more negative levels than before the referendum date. The observed decrease in the density of the network, as well as the decrease in assortativity may indicate that the new market participants that entered the market are likely peripheral players that buy or sell CDS protection via core dealers.

Figure 16 shows the development of net CDS buying and selling behaviour per counterparty sector (analogous to Figure 10). Substantial variation can be observed in the run-up to the Brexit referendum, especially for banks, non-MMF investment funds and other financial intermediaries. In addition, pension funds and insurance companies seem to enter the market for the purpose of hedging their UK exposure. These observations corroborate the dynamics in the network metrics and indicate that these market participants are placing bets and hedges. Interestingly, investment funds become the most dominant sellers of CDS protection around the time of Theresa May's announcement in October; the market share of banks as net sellers of CDS protection decreases. Banks also lose market share in terms of net buying of CDS protection, while the predominance of other financial intermediaries increase.

Synthesizing the findings of existing literature on network theory, one could argue that the more pronounced core-periphery structure due to the Brexit event makes the market more vulnerable to shocks emanating from core players. This stresses the importance of ensuring that core or systemic market participants are robust and hold adequate buffers. The increased activity by non-banks around the Brexit events underpins the importance of expending the regulatory perimeter beyond banking.

Figure 16: Net protection bought and sold per sector (as % total net protection bought or sold), UK underlyings only



(a) Protection bought

(b) Protection sold

Banks
Insurance corporations and pension funds (ICPF)
Other financial institutions (OFI)
Non-Money market funds
Non-financial corporates

7. Conclusions and discussion

The 2007-09 financial crisis showed that the CDS market can contribute to systemic risk. Using new regulatory (EMIR) data, this paper aims to contribute to the growing literature on derivatives markets and (systemic) risk. To this end this paper provides a first account of the Dutch CDS market, investigates the factors that drive the flow-of-risk using logistic regression, and analyses the impact of Brexit on the structure of the CDS market for UK underlyings.

Over the course of 2016, we observe on average 3,800 market participants in our dataset of which 790 hold single-name CDS positions with a notional value around EUR 150 billion. The single name CDS contracts are written on governments (34%), financials (33%) and non-financial corporations (23%). The CDS market has a core-periphery structure and is very concentrated. The top five buyers and sellers account for 40% of the single-name CDS market. Looking at the sectoral level, we observe that banks are the major net single-name CDS sellers and buyers, investment funds are the second largest group of sellers, and other financial institutions are the second largest group of buyers.

Focussing on Dutch counterparties only, we find that banks are on average CDS protection sellers, while insurance companies and pension funds (ICPFs) and other financial institutions (OFIs) are CDS buyers. Within sectors, the probability of being a seller is lower for larger banks, and higher for larger OFIs. ICPFs and OFIs seem to increase CDS selling if the volatility of the underlying reference entities increases, while banks reduce CDS selling. This hints at procyclical behaviour by banks and countercyclical behaviour by ICPFs and OFIs. Although not statistically significant, we observe for all sectors that CDS selling increases when returns on the underlying are at either tail of the distribution, which might be an indication that all sectors, at least to some extent, use CDS for both hedging and speculative purposes.

Using common network metrics, we find that Brexit did not disrupt the market for UK reference entities. We observe that the core-periphery structure of the CDS market for UK underlyings became more pronounced as market participants placed bets and hedges around Brexit events, arguably making the CDS market more vulnerable to shocks emanating from systemic players. Also, banks reduced net buying and selling of CDS protection on UK reference entities, while OFIs and investment funds became more dominant CDS buyers and sellers. This underpins the importance of adequate buffers for systemically important market participants and extending the regulatory perimeter beyond the banking sector.

The EMIR data are extremely rich and can be used to inform micro- and macroprudential supervision and policy. This paper showed that EMIR data can give insight into the developments derivatives market structures and risk flows among banks as well as non-bank financial institutions. Future research could be geared towards increasing our understanding of speculative or hedging behaviour by analysing derivatives transaction data in conjunction with data on asset holdings. Also, to further improve our understanding of financial market structures and financial stability, future research could investigate the factors that drive changes and/or persistence in market structures and the implications for financial stability. An important question in this regard is whether non-banks can act as shock-absorbers. Combining EMIR data with other granular supervisory data is key to answering these questions but also time consuming as managing such large volume data sets is not a trivial matter.

8. Annex

Figure 17: Model 3: Variation: underlying log return & VIX - Average probabilities at representative values

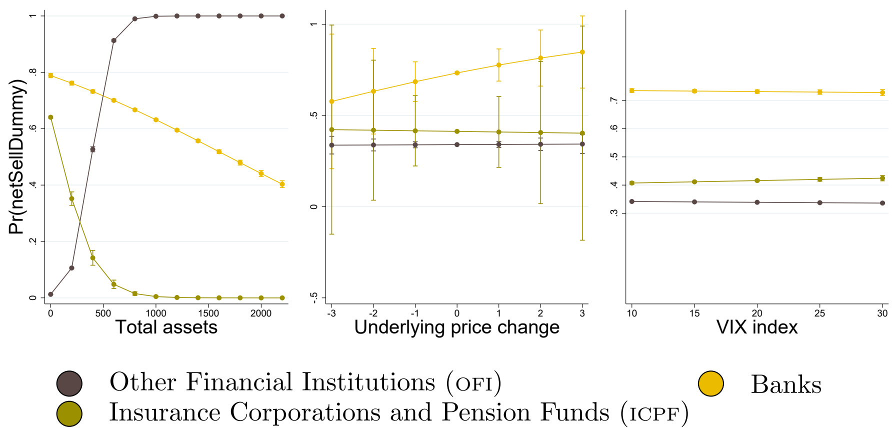
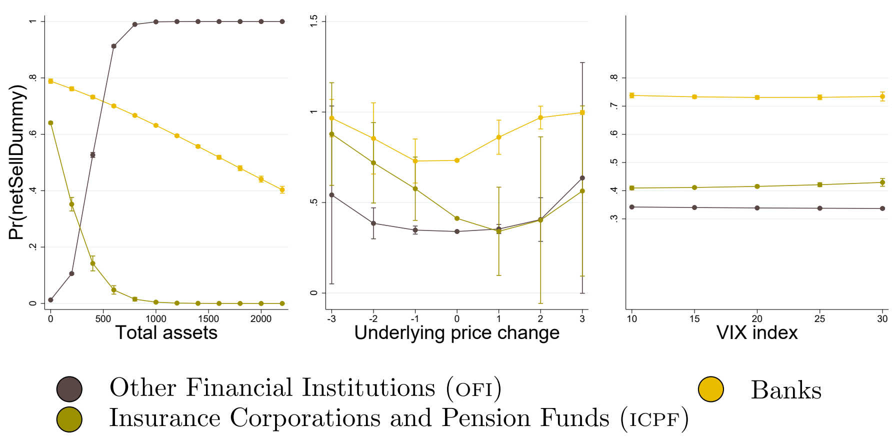


Figure 18: Model 4: Variation: quadr. log returns & VIX - Average probabilities at representative values



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Postbus 98, 1000 AB Amsterdam
020 524 91 11
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