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Resilience of trading networks: evidence from the sterling corporate bond market

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Abstract

We study the network structure and resilience of the sterling investment-grade and high-yield corporate bond markets. Using proprietary, transaction-level data, first we analyse the key properties of the trading networks in these markets. We find that the trading networks exhibit a core-periphery structure where a large number of non-dealers trade with a small number of dealers. Consistent with dealer behaviour in the primary market, we find that trading activity is particularly concentrated for newly issued bonds, where the top three dealers account for 45% of trading volume. Second, we test the resilience of these markets to the failure or paralysis of a key dealer, or to bond rating downgrades. We find that whilst the network structure has been broadly stable and the market broadly resilient around bond downgrades over our 2012–2017 sample period, the reliance on a small number of participants makes the trading network somewhat fragile to the withdrawal of a few key dealers from the market.

Key words: Corporate bond market, financial networks.

JEL classification: G10, G20.

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1 Introduction

The corporate bond market plays a vital role in the global financial system by providing funding to the real economy. Such market-based finance has grown increasingly important since the Global Financial Crisis (Baranova et al. (2017)). Whilst this brings the benefit of diversifying an overreliance on bank funding, this shift has raised the importance of understanding the resilience of market-based finance.

Our main contribution to the literature is to analyse the structure and resilience of the sterling corporate bond market, a key OTC market for the provision of market-based finance in the UK. We believe this is the first paper to set this out for the sterling corporate bond market. We conduct an in depth analysis of the network of trading relationships and test the resilience of the network to the exit of dealers, and to bond downgrades.

We use proprietary transaction-level data to map the sterling corporate bond market trading network to understand first its structure, and then second its resilience. The transaction data – the Zen database provided by the UK Financial Conduct Authority – allow us to identify both counterparties in each trade (Czech and Roberts-Sklar (2017)), enabling a full analysis of the trading network. We group counterparties into broad sectors: dealer banks, other banks, asset managers, insurance companies and hedge funds. We separately examine the markets for investment-grade (IG) and high-yield (HY) bonds. The monthly volume for IG bonds is on average around 7 times higher than for HY bonds.

The resilience of the corporate bond trading network is essential for corporates' ability to issue new debt, either to refinance existing debt or raise new finance. We therefore separately consider the trading networks for newly issued bonds and older bonds. For both IG and HY bonds, the trading volume for a given bond is highest in its month of issuance, dropping by 78% in the following month. As found in the US market by Goldstein and Hotchkissm (2007), we find that dealers tend to be net sellers of newly issued bonds in the secondary market. For older bonds, dealers tend to be net flat in the secondary market, intermediating flows between customers.

In line with the theory and empirical evidence for fixed income (Di Maggio et al. (2017), Li and Schürhoff (2019)) and other OTC markets (Abel and Silvestri (2017), Abad et al. (2016)) we find that the sterling corporate bond market trading network is very sparse, with only around 1% of possible connections existing on average. Consistent with that, we find that there is a core-periphery structure, with a core of highly interconnected dealers and a periphery of customers (mainly insurance companies and asset managers, with some hedge funds and other banks). We find that the network structure of the sterling corporate bond trading network has been relatively stable over our sample period of January 2012 to June 2017.

A resilient corporate bond market provides predictable access and liquidity for funding, investing, saving and risk transfer (Anderson et al. (2015)). So far, most of the existing work has focussed on the liquidity of corporate bonds (Adrian et al. (2017)). In this paper we assess the resilience of the corporate bond market by conducting an in-depth analysis of the network of trading relationships. The sterling corporate bond market is an over-the-counter (OTC) market, with almost all trading intermediated by dealers. The trading network of OTC markets has been explored in theoretical and empirical literature. Hugonnier et al. (2014) develop a model of OTC markets where intermediation chains arise between buyers and sellers and where a core-periphery trading network – i.e. a core of highly interconnected dealers and a periphery of customers – emerges endogenously in the equilibrium. Wang (2016) develops a model of trading network formation in OTC markets where a core-periphery structure arises due to dealer trade competition and inventory risk.

A market where trading volume is concentrated in a small number of participants is fragile to the failure of one of those participants. We find that the sterling corporate bond market is quite concentrated, so is reliant on a relatively small number of firms. On average, the top 3 dealers account for around 20% of volume, and the top three non-dealers account for around 10% of volume. The market is particularly concentrated for newly issued bonds, where the top three dealers account for 45% of trading volume. Moreover, end investors tend to interact with only a fairly small number of dealers: whilst there are 15 dealers in our sample, each asset manager and insurance company interacts with only 3 or 4 dealers on average. These links seem to be fairly persistent, with a high probability of the same trading relationship happening in consecutive months. As one would expect in opaque OTC markets new trading relationships are relatively rare, accounting for only 6% of links in the IG trading network each month on average.

We test the resilience of the trading network along two dimensions: stress to participants (i.e. exit of a major dealer from the market), and stress to the instrument traded (i.e. bond downgrade). We test the resilience of the trading network to dealer exits by following the methodology employed by Albert et al. (2000) and Li and Schürhoff (2019), deleting nodes and analysing the effect on the trading network. Given the high level of concentration in the market we find that when we delete counterparties with the highest trading volume, the network collapses relatively quickly. For instance, only two or three dealers need to be deleted to remove 25% of the trading volume in the network on average over time. We also employ a risk based scenario, where we delete the riskiest dealers first, proxied by their CDS spread. Under this scenario, usually more dealers (four to five) need to be deleted to remove 25% of the trading volume in the network. By comparing the results obtained under the two scenarios described above we can infer: a) how vulnerable the network is to stress, and b) given the perceived riskiness of dealers, how close we currently are to this worst-case scenario. However, our resilience test is limited in that it does not model how the network would respond to the removal of a node, e.g. by reallocating exposures to another counterparty.

For bonds that have been downgraded, we find that trading volume increases in the month of and immediately after a downgrade, and falls slightly thereafter. Unsurprisingly, hedge funds are particularly active around bond downgrades, exhibiting some signs of purchasing downgraded bonds when their prices are low with a view to later selling when prices have normalised. We also find that insurance companies increase their sales around bond downgrade, in line with Ellul et al. (2011) who show that regulatory constrained insurers can be forced into sales when a bond is downgraded, which can have a material impact on price.

Our results have important financial stability implications. Whilst the sterling corporate bond trading network has had a relatively stable structure over our sample period, we find that its resilience is reliant on a relatively small number of participants. The withdrawal of a small number of dealers could, therefore, have a significant impact on the function of this market, which could in turn affect the provision of market-based finance in the UK economy. Our work provides some indicators authorities can use to monitor the resilience of the network. Such indicators go beyond simple measures of market concentration. For example, we propose analysing the impact of removing both the biggest dealers and those with the highest perceived credit risk. Our findings can also be used to inform design of future potential policy interventions, such as market maker of last resort facilities or monetary policy implementation through corporate bond purchases.

The paper is organised as follows. Section 2 provides a short summary of the related academic literature. Section 3 describes the data we used in our analysis. Section 4 provides a description of the sterling corporate bond market, and Section 5 of the results of the analysis of structure of the corresponding trading networks. Section 6 presents the results of the analysis of the resilience of the market and Section 7 concludes.

2 Related literature

This paper relates to existing work investigating frictions, liquidity and resilience in the corporate bond and other OTC markets.

Pioneering work by Duffie et al. (2005) and Duffie et al. (2007) investigates how liquidity is affected by frictions such as the search for intermediaries, limited access to multiple market makers and limited bargaining in OTC markets.

More recently, Hugonnier et al. (2014) develop a model of OTC markets where intermediation chains arise between buyers and sellers and where the core-periphery trading network emerges endogenously in the equilibrium. Wang (2016) develops a model of trading network formation in OTC markets where a core-periphery structure arises due to dealer trade competition and inventory risk.

There is a large body of work investigating the properties of OTC markets. The existence of a core-periphery structure has been investigated in some OTC derivatives markets, such as UK CDS market by Abel and Silvestri (2017) and European interest rate, foreign exchange and credit derivatives by Abad et al. (2016). Other studies have investigated the core-periphery structure of networks associated to fixed income markets and how this affects dealer trading behaviour.[1] For instance, Di Maggio et al. (2017) and Li and Schürhoff (2019) respectively find that the US corporate bond market and US municipal bonds exhibit a core-periphery structure and find that dealers profit more when trading with peripheral clients. They also examined the resilience of these markets. Di Maggio et al. (2017) find that after the default of a major dealer in 2008 intermediation chain lengthened and dealers were unwilling to take on more inventories. Li and Schürhoff (2019) find that the US municipal bond market is resilient to the targeted and random exit of dealers as other dealers can act as substitutes. We investigate both whether the sterling corporate bond market exhibits a similar core-periphery structure, and the network's resilience to the targeted removal of key dealers.

Several papers have studied market liquidity and trading relationships in fixed-income markets, in light of concerns that regulatory changes might have reduced dealers' ability and willingness of intermediate markets.Benos and Zikes (2016) study how UK gilt market liquidity is affected by dealer balance sheet constraints, funding costs and risk sharing in the interdealer market. Bicu et al. (2017) study how the leverage ratio has affected the liquidity of UK gilt and repo markets. Adrian et al. (2017) analyse a range of measures

[1] Hollifield et al. (2017) find a core-periphery structure in the interdealer network of the US securitisation market but their findings on the relationship between bid-ask spreads and dealer positions are in contrast with Di Maggio et al. (2017) and Li and Schürhoff (2019).

of liquidity in the US corporate bond market without finding any deterioration after the introduction of the new regulation. Adrian et al. (2017) investigate the relationship between the liquidity of the US corporate bond market and dealer balance sheet finding that institutions that are more impacted by regulation are less able to intermediate. Choi and Huh (2017) find evidence that customers have been providing liquidity in the US corporate bond market as the fraction of customer trades matched by dealers has increased over time and as shown by liquidity measures when this is accounted for.

Finally, our work is related to papers investigating the behaviour of trading investors after different types of shocks in the corporate bond markets. Czech and Roberts-Sklar (2017) and Timmer (2016) investigate which investors sell and buy corporate bonds whose price has been falling after a shock. Ellul et al. (2011) examine (forced) selling behaviour after bond downgrades by insurance companies with binding regulatory constraints.

3 Data

Our analysis of the sterling corporate bond market is based on the Zen database maintained by the Financial Conduct Authority (FCA). [2] The Zen database contains transaction-level information on trading in sterling corporate and government bonds for all firms regulated in the UK, or branches of UK firms regulated in the EEA. Our analysis focusses exclusively on corporate bonds. Each transaction report includes the date, time, quantity, price, International Securities Identification Number (ISIN), a buyer/seller flag, trading capacity information, the reporting firm, and in most cases, the identity of their counterparty.

The dataset covers the period between January 2012 and June 2017. We clean the data by dropping trades that are implausibly large or small, or have prices very far from the end-of-day prices recorded by Bloomberg. We also drop trades executed on an agency basis[3] (i.e. we only include principal trades). Finally, we remove duplicates by matching trades which have been reported by both counterparties, and dropping one of them. Our cleaned dataset contains only transactions in the secondary market.

Using a unique hand-collected dataset, we are able to attribute an investor type to each firm identity. Doing so, we are able to know which counterparty of the trade is an asset manager, insurance company, hedge fund, dealer bank or other bank. All other investor types are classified as "others". One drawback of our dataset is that we can capture who executes the trade, but not necessarily who the beneficial owner is. For example, an asset manager might execute a trade on behalf of a pension fund. In our dataset, we would not be able to distinguish this from an asset manager trade originating from, for instance, an open-ended investment fund.

In our analysis we exclude trades where the same firm is reported as both buyer and seller (i.e., internal trades) and those where one of the counterparties is not reported. We also exclude trades involving the Bank of England as part of the Corporate Bond Purchase Scheme (Belsham et al. (2017)) that started at the end of September 2016 and ended in April 2017.

[2] This dataset has also been used by Czech and Roberts-Sklar (2017), Aquilina and Suntheim (2016) and Benos and Zikes (2016), although the latter analyse gilts rather than corporate bonds.

[3] Agency trades are those where dealers act on behalf of a client to purchase or sell bonds in the market. Dealers do not hold any inventory on their balance sheet as a result of their activity in agency trades.

We match the transaction data to publically available information on the corresponding bonds from Bloomberg. This allows us to attribute each bond with its issuance date, maturity date, amount issued, coupons, ratings and issuer identity. For bonds where a 'Bloomberg composite' rating is unavailable (such as matured bonds), we look at ratings from individual agencies (Fitch, S&P and Moodys) and attribute this where possible. Our analysis focuses only on rated bonds that we group into investment-grade and high-yields (i.e., we exclude from the scope of our analysis unrated bonds).

4 Key properties of the sterling corporate bond market

In this section we provide an overview of the sterling investment-grade (IG) and high-yield (HY) corporate bond markets. We analyse the key properties of these markets, including: structure, concentration, participants and trading relationships. Understanding these properties is essential in analysing the resilience of the trading network. Moreover, we believe such analysis has not yet been carried out for sterling-denominated corporate bonds, and so plugs a vital gap in the literature.

Currently OTC trading volume accounts for 80% of total trading volume.

As shown by the summary statistics of Table 1, the number of unique counterparties trading IG corporate bonds in each month is larger than that of counterparties trading HY corporate bonds. The number of trades in each month is much larger for IG than HY corporate bonds, but on average around half of the trades in both IG and HY have sizes between £100,000 and £1mn.

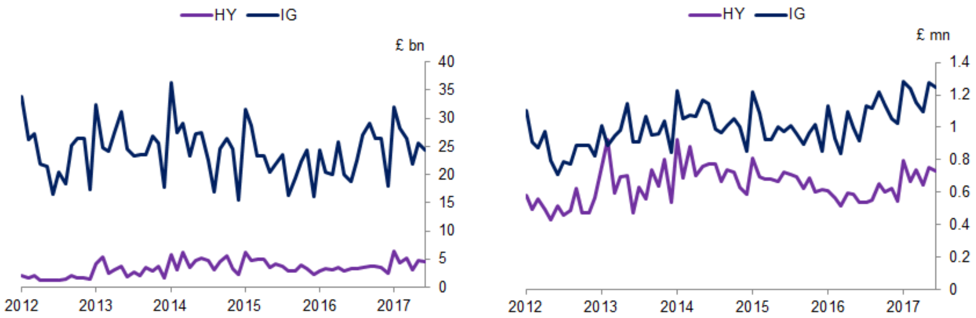
Quantity	Investment-grade	High-yield
Amount outstanding (£bn)	468.7	66.3
Average number of counterparties (monthly)	746	497
St. dev. number of counterparties (monthly)	56	68
Average number of trades (monthly)	24,077	5,104
St. dev. number of trades (monthly)	3,421	1,387

Table 1: Summary statistics for the sterling investment-grade (IG) and high-yield (HY) corporate bond market.
Note: amount outstanding data refer to end June 2017 and are from Thomson Reuters DBI (Deals Business Intelligence).

As shown by Figure 1a monthly trading volume in IG is much larger than that in HY, with the former fluctuating over time between £36bn and £15bn and the latter between £6.4bn and around £1.2bn. The majority of the trading activity is between dealers and their clients, as total interdealer volume corresponds to just 9% and 7% of the total trading volume in IG and HY, respectively. In both IG and HY markets, the average trade size has increased slightly over time as shown by Figure 1b. Interestingly, the average trade size has increased more for IG bonds than HY, causing a divergence.

4.1 Newly issued bonds

For both IG and HY bonds, trading activity is concentrated in the month of issuance and in the two following months as shown by Figure 2. Drawing on this evidence, for



(a) Monthly trading volume **(b)** Monthly average trade size

Figure 1: Monthly trading volume (left) and average trade size (right) in sterling investmen-grade (IG) and high-yield (HY) corporate bond market.

each month in our dataset we define the set of 'newly issued bonds' as those bonds issued in that month and in the previous two months. Newly issued bonds account for 4% and 3% respectively of unique IG and HY bonds traded each month, as shown in Figure 3. Newly issued bonds account for a larger proportion of trading volume, up to 49% in the HY market, as shown in Figure 3b.

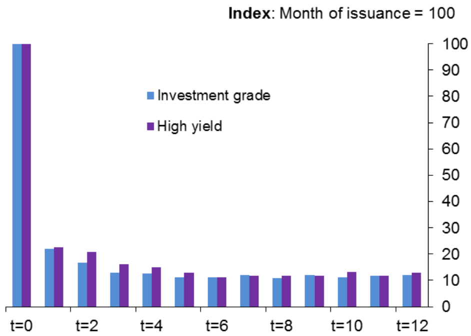
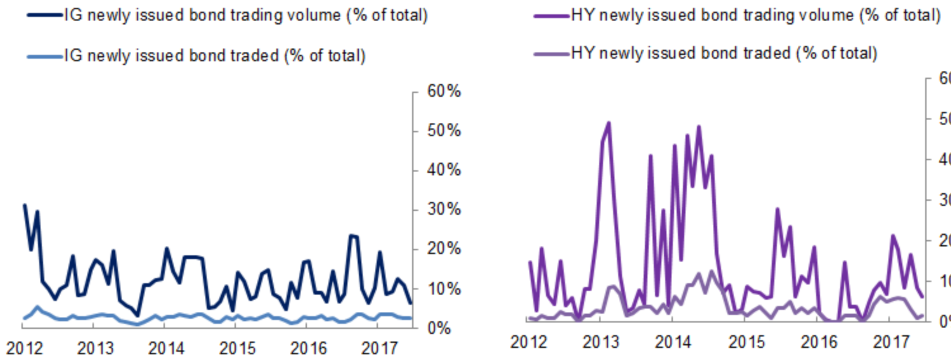


Figure 2: Trading volume of IG and HY corporate bonds in the month of and months following issuance (index: month of issuance = 100).

The volume of newly issued IG bonds fluctuates between 3% and 31%, and we observe a sharp increase corresponding to August 2016, the month when the MPC announced that the Bank of England would buy £10 billion of sterling-denominated corporate bonds over 18-month period (i.e., Corporate Bond Purchase Scheme).

In the rest of our analysis, we will show results for newly issued IG and HY corporate bonds and other bonds when relevant. The resilience of trading activity of newly issued bonds is important for firms raising finance through the corporate bond market. But the resilience of trading activity of other bonds is also important from a financial stability prospective as disruption in the trading activity of these bonds could negatively affect market prices and trigger feedback loops that could lead to amplification of initial price falls and ultimately impair primary issuance.



(a) Investment-grade

(b) High-yield

Figure 3: Trading volume of newly issued IG and HY corporate bonds as a fraction of total trading volume, and number of unique IG and HY newly issued bonds traded as a fraction of unique bonds traded in each month.

4.2 Investor base

Understanding the investor base helps us understand how participants may react to stress, for example given their different objectives and constraints. The composition of the investor base in each month is summarised in Table 2 for all sterling IG and HY corporate bonds as well as for newly issued and other IG and HY corporate bonds. For sterling IG corporate bonds we find that 15 dealers trade all bonds, as well as newly issued and other bonds. On average, 14 dealers trade newly issued HY bonds. The majority of non-dealer counterparties trading in IG and HY are either other banks or asset managers. On average there are more insurance companies, other banks and asset managers trading IG than HY corporate bonds in each month. Interestingly, on average there is a similar number of hedge funds trading both HY and IG corporate bonds each month.

	Investment-grade						High-yield					
	all bonds		newly issued bonds only		other bonds only		all bonds		newly issued bonds only		other bonds only	
Number of	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev
Dealers	15	0	15	0	15	0	15	0	14	2	15	0
Other banks	312	27	111	34	296	23	187	25	48	39	176	22
Insurance companies	36	4	17	4	35	4	18	3	5	4	18	2
Hedge funds	44	8	15	9	37	7	47	11	16	12	41	7
Asset managers	258	17	95	28	247	14	188	25	49	34	177	24
Others	78	9	18	11	71	12	38	12	7	8	34	12
Total	746	56	273	80	705	46	497	68	141	94	464	62

Table 2: Summary statistics of the composition of investor types in the sterling investment-grade (IG) and high-yield (HY) corporate bond market for all bonds and when all bonds are split between newly issued and other bonds.

As we would expect in a OTC market, on average dealers account for around 50% of the monthly volume sold and bought in both IG and HY. In IG other banks and asset managers account for around 17% (18%) and 19% (23%) on average of the volume sold (bought), respectively. This is similar in the HY market. Insurance companies account for around 9% and 5% of volume sold and bought in IG and HY, respectively. Hedge funds account for around 6% on average of the amount bought and sold in HY, and for less than 1% of volume bought and sold in IG. This is in line with Czech and Roberts-Sklar (2017) that use similar data to investigate investor behaviour.

4.3 Investor behaviour

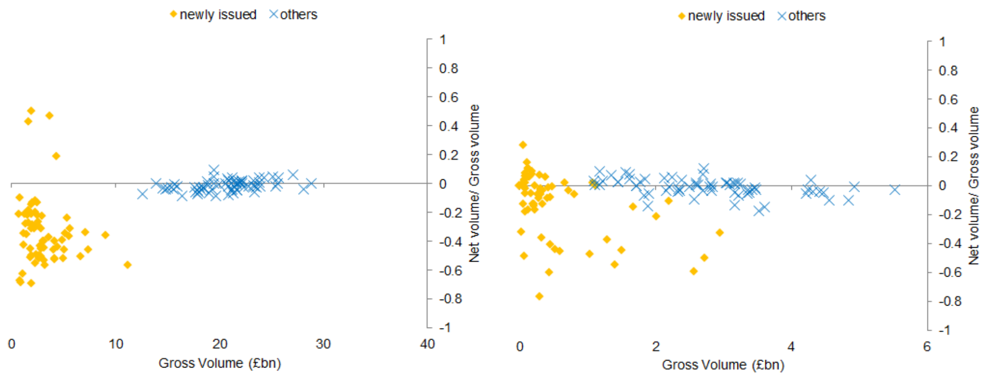
It is also important to understand the behaviour of different investor types, in particular who is demanding and supplying liquidity. We investigate the buying and selling behaviour across investor types first by analysing the average net volume (i.e., difference between amount bought and sold) for different investor types. Table 3 summarises the net volume averaged over time across investor types.

	Investment-grade						High-yield					
	all bonds		newly issued bonds only		other bonds only		all bonds		newly issued bonds only		other bonds only	
Average net volume (£mn)	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev
Dealers	-93.0	93.1	-74.6	77.5	-18.5	51.1	-12.5	22.8	-9.9	21.2	-3.6	11.4
Other banks	0.8	1.6	1.1	2.5	0.5	1.4	0.1	0.4	0.1	0.8	0.1	0.3
Insurance companies	1.0	14.0	16.2	16.5	-7.3	12.5	-0.4	4.7	2.3	6.7	-1.6	3.8
Hedge funds	0.1	1.8	0.2	2.8	-0.1	1.8	0.0	1.3	0.0	1.9	0.0	1.3
Asset managers	3.4	3.4	6.2	5.5	1.1	2.5	0.8	1.2	1.3	2.3	0.3	0.8

Table 3: summary statistics for the average monthly net volume (£mn) across investor types for all IG and HY corporate bonds and when these are split into newly issued and other bonds.

We investigate further the buying and selling behaviour of different investor types by analysing their total net volume and total gross volume. Figure 4 shows this relationship for dealers only by showing gross volume traded on the x axis and net:gross ratio on the y axis. Therefore, a dealer that is buying and selling similar amounts of bonds will be represented by a point close to 0 on the y axis. In most months we find that, unsurprisingly, dealers are net sellers of newly issued IG and HY bonds. This reflects their role in buying newly issued bonds from corporates (primary market), and selling them on to end investors (hence they tend to be net sellers in the secondary market that we capture in our analysis). For older bonds, dealers' gross volume is much larger than that of newly issued and dealers tend to sell and buy similar amounts in each month (i.e. net:gross ratio is close to zero) given that they act as intermediaries between buyers and sellers.

Figure 5 shows the same relationship for other major investor types- namely, other banks, asset managers and insurance companies. We find that the total gross volume of both newly issued bonds and other bonds is larger for bonds rated as investment-grade than high-yields. We find that insurance companies and asset managers are net buyers of newly issued IG bonds for most of the months in scope. This is consistent with a business model of buy-side investors, who buy newly issued bonds. For other IG corporate bonds, all types buy and sell similar amounts of IG bonds in all months



(a) Investment-grade **(b)** High-yield

Figure 4: Relationship between the total gross volume of dealers and the ratio between the net volume and gross volume of dealers for newly issued and other IG and HY corporate bonds. Dots correspond to volumes aggregated across all dealers in each month comprised in our dataset.

in scope, i.e. a net:gross ratio close to zero. We find that insurance companies' total gross volume of newly issued HY bonds is smaller compared with other investor type. They tend to be net sellers of other bonds most of the months in scope. This might be driven by regulatory requirements that disincentivise them to invest in lower rated bonds. Asset managers are most of the time net buyers of newly issued HY corporate bonds. Asset managers and banks buy and sell similar amounts of HY bonds that are other than newly issued.

5 Analysis of the trading network

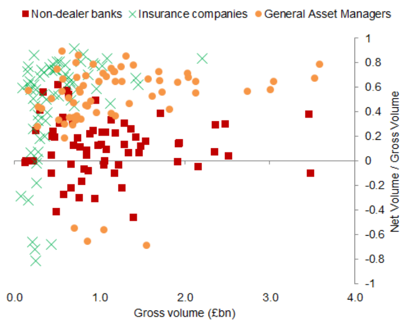
5.1 Methodology

Understanding the trading network tells us about the interconnectedness of the market, and as a result tells us both about the potential impact of stress, and the ability for market participants to reallocate following the exit of a dealer. We use the transaction level data described in Section 3 to build trading networks that describe trading relationships between different counterparties over time. These are directed networks, where transactions between any two counterparties are modelled as links (arrows) pointing from the seller to the buyer. For example, if a hedge fund were to buy from a dealer, a link would be created pointing from the dealer to the hedge fund. The volume underlying this transaction is modelled as weights attached to these links.[4]

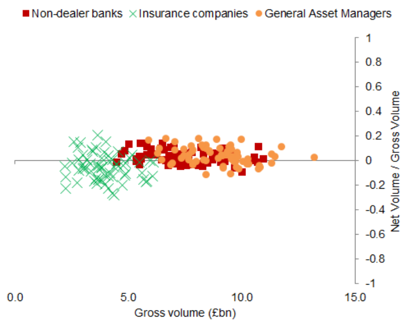
Formally, for each point in time we define the trading network as $T = (V, \mathbf{W})$, where $V = \{V_1, \ldots V_N\}$ is the set of vertices corresponding to financial institutions trading in the market, and $\mathbf{W}$ is a $N \times N$ matrix where the generic element W_{ij} denotes the total volume of corporate bonds that financial institution i sold to financial institution j. A stylised representation of this network is shown in Figure 6.

It is possible to investigate the trading behaviour of different counterparties by looking at the distribution of the elements of $\mathbf{W}$ as well as at the total amount sold S_i and bought B_i by each counterparty i that can be evaluated as the sum of the elements across the

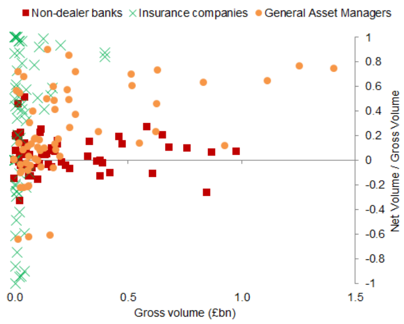
[4] Newman (2010) provides an introduction to network analysis.



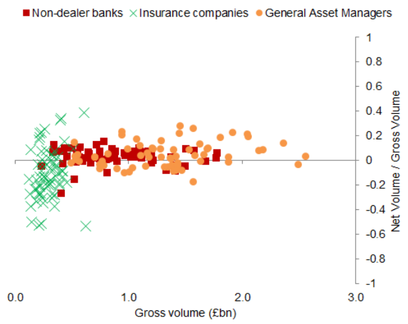
(a) Investment-grade, newly issued bonds



(b) Investment-grade, other bonds



(c) High-yield, newly issued bonds



(d) High-yield, other bonds

Figure 5: Relationship between total gross volume and the ratio between net and gross volume for newly issued and other IG and HY corporate bonds for other banks, insurance companies and asset managers. Dots correspond to volumes aggregated across investor types in each month comprised in our dataset

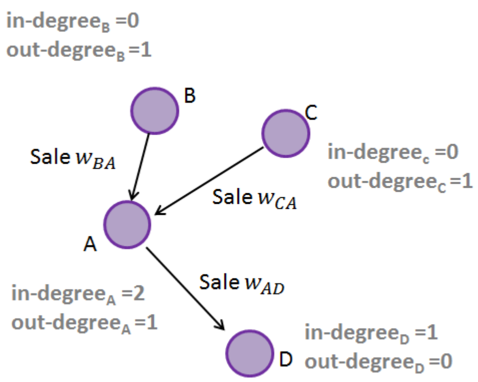


Figure 6: Stylised representation of the trading network.

rows and the columns of $\mathbf{W}$, respectively:

$$S_i = \sum_{j=1}^{N} W_{ij} \tag{1}$$

$$B_i = \sum_{j=1}^{N} W_{ji}. \tag{2}$$

The structure of the market can be investigated by looking at the how connections are distributed within the trading network. We define the adjacency matrix $\mathbf{A}$ that contains information on the presence or absence of links as

$$A_{ij} = \begin{cases} 1, & \text{if} \quad W_{ij} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Summing up across rows and columns of **A** it is possible to evaluate the number of unique counterparties on the sell and buy side, the in- and out-degree shown in Figure 6:

$$\text{out-degree}_i = \sum_{j=1}^{N} A_{ij} \tag{4}$$

$$\text{in-degree}_i = \sum_{j=1}^{N} A_{ji}. \tag{5}$$

We analyse the structure of the market by looking at the distribution of in- and out-degree as well as if more connected financial institutions are connected to less connected financial institutions ('dissassortativity' property) or vice versa ('assortativity' property).

We analyse the density of the network: that is the number of existing links out of all possible links that can be computed as

$$d = \frac{\sum_{ij} A_{ij}}{N(N-1)} \tag{6}$$

Network density can be a useful summary statistic to help understand the existence of trading relationships and structure of the trading network.

5.2 Results

We start with looking at the density of the networks corresponding to all bonds, newly issued and other bonds for IG and HY separately.

As shown by Table 4 the sterling IG and HY corporate bond trading networks have low network density, with on average around 1% of possible connections. This suggests that IG and HY corporate bond markets exhibit a very sparse network structure. This is true if we look at the density of the trading networks corresponding to all bonds, newly issued and other bonds. This is what we would expect from an OTC market because of the existing frictions faced by market participants as summarised in Section 2. This is also consistent with the findings of other papers that study the structure of other OTC markets (Di Maggio et al. (2017), Abel and Silvestri (2017) and Abad et al. (2016)).

	Investment-grade			high-yield		
	all bonds	newly issued bonds only	other bonds only	all bonds	newly issued bonds only	other bonds only
average	0.8%	1.1%	0.9%	0.8%	1.9%	0.9%
st. dev.	0.1%	0.2%	0.1%	0.1%	1.2%	0.1%

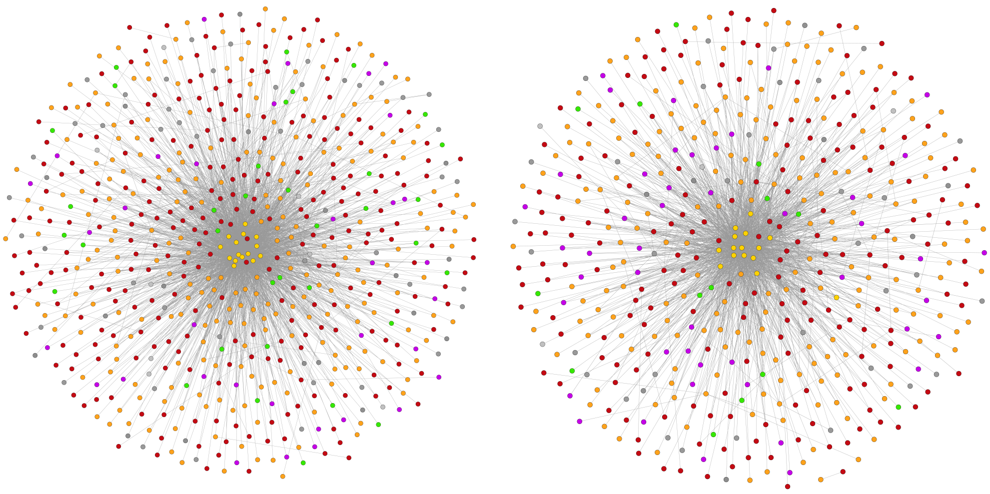
Table 4: Summary statistics of the density of monthly trading networks corresponding to all, newly issued and other sterling IG and HY corporate bonds.

Dealer trading relationships with both other dealers and clients differ for IG and HY bonds. The density of the interdealer market is 68% and 92% for HY and IG bonds respectively, telling us that there is greater interdealer activity in the IG market. Dealers have a large number of trading relationships with their clients each month. On average they have 53(48) unique non-dealer counterparties when selling (buying) HY bonds. This is larger for IG bonds, when they have on average 117(110) unique clients when selling (buying).

5.3 Core-periphery structure

As explained in Section 4 most of the trading in sterling corporate bonds is done OTC, and as a consequence we would expect the network to exhibit a core-periphery structure. This means that the network has a core composed of a small number of highly interconnected counterparties (dealers), and periphery composed of a large number less interlinked of counterparties (dealer clients). This structure means that the resilience of the trading network hinges on a small set of dealers.

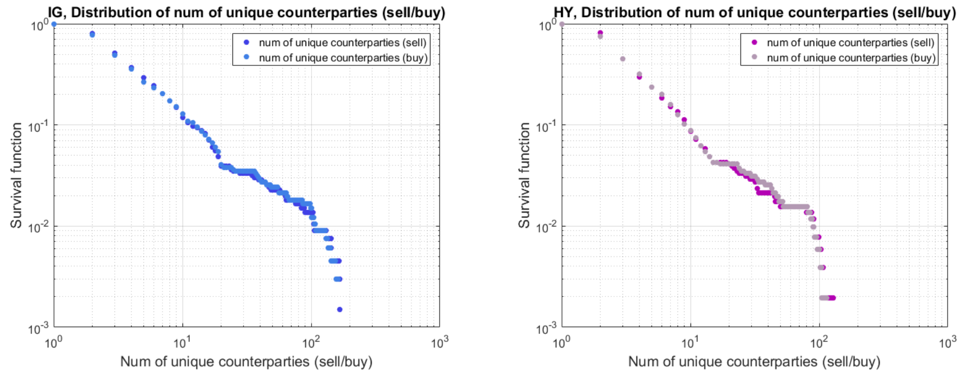
The existence of a core-periphery structure seems also clear from the visualisation of the trading networks of IG and HY corporate bonds corresponding to June 2017 in Figure 7, where dealers (yellow nodes) appear to have a large number of connections with different types of less interconnected clients.



(a) Investment-grade **(b)** High-yield

Figure 7: Visualisation of the network of sterling IG and HY corporate bonds in June 2017. Yellow nodes correspond to dealers, red to other banks, green to insurance companies, orange to asset managers, purple to hedge funds and grey to other investor types.

Following existing work (Abel and Silvestri (2017)), we test this hypothesis by studying the distribution of the number of unique counterparties (connections) for sales and purchases in the trading network. Specifically, this means analysing whether the distributions of in- and out-degree are fat-tailed. Fat-tailed distributions suggest that while the majority of counterparties have a small number of trading relationships, there are few counterparties with a large number of trading relationships. The survival distributions of the in- and out-degree are shown in Figure 8 for IG and HY corporate bonds for one month only (June 2017) for illustrative purposes. The survival distributions of in- and out-degree show a linear decay in the tails suggesting fat-tailed distributions.



(a) Investment-grade **(b)** High-yield

Figure 8: Distribution of the number of unique counterparties when buying (in-degree) and selling (out-degree) sterling IG corporate bonds in June 2017. Distribution is shown in terms of the survival function and both axes are in log scale.

To empirically test the existence of the core-periphery structure, we use the methodology proposed by Clauset et al. (2009) to fit power-law distributions to the tails of the distributions[5] of in-and out-degrees for each monthly snapshot of the trading network. Table 5 provides a summary of the results of the power-law fit over time for IG and HY separately. On average results are similar for investment-grade and high-yield bonds and for connections corresponding to sales and purchases. However, the percentage of significant results is lower for the investment-grade corporate bond market.[6]

	Investment-grade		high-yield	
	sales	purchases	sales	purchases
Average power-law coefficient	2.01	2.06	1.93	1.99
St dev of power law coefficient	0.11	0.10	0.09	0.09
Percentage of significant fit	62%	62%	89%	91%

Table 5: Summary of the results of the power-law fit over time in the sterling investment-grade (IG) and high-yield (HY) corporate bond market.

We further investigate the core-periphery structure by analysing if trading networks satisfy the disassortativity property, according to which more connected financial institutions are connected to less connected financial institutions. Specifically, this corresponds to a negative assortativity coefficient corresponding to connections for purchases and sales. We find negative assortativity coefficient of $-0.12(-0.12)$ and $-0.12(-0.13)$ for connections corresponding to sales (purchases) in investment-grade and high-yield corporate bonds, respectively, confirming that the corresponding trading networks satisfy this property over time.

[5] Mathematically, a power-law distribution has the form $P(x) = Cx^{-\alpha}$, where the power-law coefficient α is called scaling parameter.

[6] Given the limited number of investors in the trading network of newly issued bonds, we weren't able to fit power law distributions into the distributions of in- and out-degree.

Markets in which volume is concentrated in a small number of participants are more vulnerable to the failure of one of those participants (Di Maggio et al. (2017)). To test the concentration of the sterling corporate bond market, in Table 6 we report the summary statistics for the share of trading volume corresponding to top 3 dealers and top 3 non-dealers in IG and HY, respectively. We find that the volume purchased and sold in both IG and HY is quite concentrated in a few players. On average top 3 dealers account for around 20% (17%) and 22% (18%) of the volume sold (bought) of IG and HY corporate bonds, respectively. On average top 3 non-dealers account for 11% (11%) and 9% (9%) of the volume sold (bought) of IG and HY corporate bonds, respectively.[7] We find that selling volume of newly issued IG and HY bonds is quite concentrated on top 3 dealers, as on average they account for 45% and 35% of IG and HY trading volume respectively. This shows that the network is heavily concentrated in a small number of dealers, meaning there are potential risks is one of these key market makers were to fail. This risk is analysed in more detail in section 7. Furthermore, the concentration in a relatively small number of non-dealers shows the importance of a small number of institutional investors in supplying and demanding liquidity in the market.

	Investment-grade						High-yield					
	all bonds		newly issued bonds only		other bonds only		all bonds		newly issued bonds only		other bonds only	
	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev
Top 3 Dealers (sales)	20%	3%	45%	13%	19%	2%	22%	5%	35%	17%	20%	3%
Top 3 Non-dealers (sales)	11%	2%	11%	6%	12%	2%	9%	3%	18%	9%	9%	3%
Top 3 Dealers (purchases)	17%	2%	16%	9%	18%	2%	18%	2%	23%	10%	19%	2%
Top 3 Non-dealers (purchases)	11%	1%	17%	7%	11%	1%	9%	2%	22%	12%	9%	2%

Table 6: Summary statistics of the concentration of trading volumes across dealers and non-dealers for all, newly issued and other investment-grade (IG) and high-yield (HY) corporate bonds.

5.4 Number of unique dealers

We investigate further the frictions faced by different types of dealer customers by analysing the distribution of the number of unique dealers with whom they trade. We do so by looking at the number of unique dealers that, on average, each investor type trades with each month. This is essential to our resilience assessment, since the more dealers each particpant uses each month, the more options they have to move trading activity if one dealer is unable or unwilling to trade with them. As a result, the impact of a single dealer exiting the market will be lower. Table 7 shows the average and maximum of the number of dealers to whom the main investor types have been selling sterling IG and HY corporate bonds over time. We find that customers have trading relationships with a limited number of dealers in both IG and HY and that different investor types face different frictions. Compared to other investor types, insurance companies trade with the largest number of dealers on average over time in both IG and HY corporate bonds. In contrast, hedge funds trade with only one dealer on average over time in both IG and HY corporate bonds. The table shows also that this behaviour is consistent when we

[7] Top 3 non dealers consist mostly of insurance companies and asset managers.

consider transactions at monthly, quarterly and half-yearly frequency. This behaviour is also consistent when looking at the number of unique dealers from whom major investor types buy corporate bonds (not shown).

Results for the average number of unique dealers are slightly different for newly issued bonds. On average insurers, asset managers and hedge funds have trading relationships with one or two unique dealers when trading newly issued IG and HY bonds. This is in line with our finding of large concentration in the volume of newly issued bonds in the top 3 dealers as this might affect the number of dealers with which clients are able to trade newly issued bonds. The maximum number of unique dealers over time indicates again that insurance companies have trading relationships with a larger numbers of dealers compared to asset managers and hedge funds. These results suggest a degree of persistency in trading relationships between dealers and their clients that we further investigate later in this paper and that can affect the resilience of the market. These results correspond to trading relationships where a transaction took place. It doesn't tell us about the ability of non-banks to create new dealer relationships.

	Asset Manager		Insurer		Hedge fund	
	average	max	average	max	average	max
Investment-grade (sales)						
Monthly	3	3	3	4	1	2
Quarterly	3	3	4	5	2	2
Half-yearly	3	4	4	5	2	3
High-yield (sales)						
Monthly	2	2	3	3	1	2
Quarterly	2	3	3	4	2	3
Half-yearly	3	3	4	4	2	3

Table 7: Summary statistics of the number of unique dealers to whom different customer types sell sterling investment-grade (IG) and high-yield (HY) corporate bonds.

5.5 Persistence of trading relationships

In order to understand investor trading activity in the corporate bond market, we study how often investors trade IG and HY corporate bonds in two consecutive months.[8] Such analysis enables us to investigate whether investors have "dormant" relationships that they may be able to draw on in stress. Table 8 shows the average number of common investors with the previous month as a fraction of the total number of investors in that month. We find that on average 77% and 72% of investors trading HY and IG bonds in a given month were also trading in the previous month, respectively. We investigate newly issued bonds separately from other IG and HY bonds. In both cases the fraction of common investors is larger for non-newly issued bonds. We find also that the percentage of common investors in HY corporate bond market is smaller than that in the IG corporate bond market. This could be driven by the fact that trading activity of HY corporate bonds is less frequent and therefore investors are less likely to trade in

[8]Here we do not focus on investors trading the same bond in two consecutive months but investors trading at least one IG or HY corporate bond in two consecutively months.

two consecutive months. In the following we explore if these common investor use always the same trading relationships or not.

	Investment-grade						High-yield					
	all bonds		newly issued bonds only		other bonds only		all bonds		newly issued bonds only		other bonds only	
	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev
Common investors with the previous month (%)	77%	3%	63%	13%	78%	6%	72%	6%	51%	27%	73%	8%

Table 8: Summary statistics for the number of investors that are common with the previous month as percentage of the number of investors in that month in the trading network of all sterling IG and HY corporate bonds, and when these are split between newly issued and other bonds.

Trading relationships between dealers and customers account for the majority of links in the trading network of both IG and HY corporate bonds. To try and understand whether customers use the same set of dealers, or forge new links with other dealers, we analyse the tendency of customers to trade using the same established trading relationships by looking at the persistence of trading relationships in the dealer-customer network. In each month we split trading relationships in the network into those that are in common with the previous month and those that are new. Given that more than half of investors are common with the previous month as shown by Table 8, we then split new trading relationships into new trading relationships between common counterparties and new trading relationships between new counterparties. Table 9 provides summary statistics of the number of common links with the previous month and the number of new links between common counterparties for all IG and HY bonds and when these are split into newly issued and others, respectively in each month.

As one would expect from the analysis of common investors, for the trading networks corresponding to both IG and HY bonds we find that new trading relationships between new counterparties account only for 6% and 11% of links in the trading network on average, respectively. This is due to the fact that common trading relationships and new trading relationships between common counterparties account for 59% (41%) and 35% (49%) for IG (HY), respectively. Common trading relationships and new trading relationships between common counterparties account for the majority of trading relationships in each month for all bonds excluding the newly issued ones both for those rated IG and HY. For the newly issued ones, new links between new counterparties account for a larger share of trading relationships.

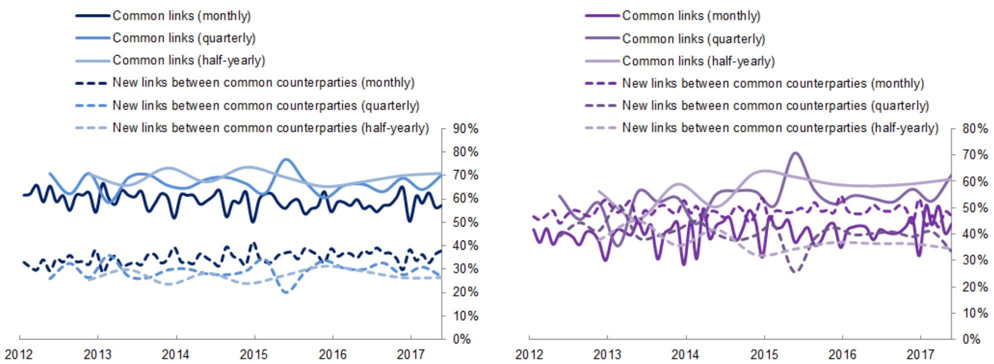
Figures 9 shows the fraction of trading relationships that are common with the previous month and the fraction of new trading relationship between dealers and clients that were already trading in the previous month for all IG and HY corporate bonds, respectively. For IG corporate bonds the proportion of common trading relationships between common counterparties is higher than the proportion of new trading relationships between common counterparties (as shown by Figure 9a). These results remain fairly stable over time and if we increase the lookback window to include all transactions happening in the previous quarter or half year. For HY corporate bonds results are quite different, as shown by Figure 9b. At monthly frequency the number of common trading relationships between common counterparties account for less than 50%, whereas new trading relationships between common counterparties account for slightly more. As we increase

	Investment-grade						High-yield					
	all bonds		newly issued bonds only		other bonds only		all bonds		newly issued bonds only		other bonds only	
	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev	mean	st. dev
Common links with the previous month (%)	59%	4%	27%	9%	59%	3%	41%	5%	14%	10%	40%	18%
New links between common counterparties (%)	35%	3%	50%	5%	35%	3%	49%	3%	40%	18%	49%	3%

Table 9: Summary statistics for the number of common links with the previous month and new links between common counterparties with the previous month, for all, newly issued and other IG and HY corporate bonds.

the lookback window to include all transactions happening in the previous quarter or half-year the proportion of common links between common counterparties increases to be more than 50% and the proportion of new links decreases to account for less than 50%. This might be due to the lower trading activity in the HY corporate bond market compared to the IG corporate bond market.

This implies that counterparties have dormant existing relationships that they do not use every month, but they can draw on if needs be. This is relevant to the next section where we assess the resilience of the sterling corporate bond market to dealer exit, as it implies that investors can shift their trading to these ‘dormant’ links instead of losing access to the market.



(a) Investment-grade **(b)** High-yield

Figure 9: Number of common and new links between common counterparties as a fraction of the total number of links in the trading network of dealers and customers only for different frequencies.

6 Resilience of trading networks

Given the characteristics of the sterling corporate bond market studied so far, in this section we now look at how ‘resilient’ the network is in the face of different types of stress. We focus on two types of stress to the network:

1. stress to the participants (i.e. withdrawal of a major dealer from the market);

2. stress to the instruments traded (i.e. bond downgrades).

We test how the market responds to these types of stress and whether they lead to significant changes to the structure and characteristics of the trading network.

6.1 Resilience to counterparty stress

To test the resilience of the trading network to the removal (failure) of a counterparty, we follow the methodology employed by Albert et al. (2000) and Li and Schürhoff (2019). Starting with the full network, we remove a particular node. We then look at the largest connected subnetwork remaining (i.e. we remove any nodes only connected via the deleted node) and calculate the remaining volume left in this subnetwork. This can be repeated until the network has 'collapsed' (i.e. no connections exist).

We consider two different ways of removing nodes:[9]

- *Worst case scenario* [10]: remove the counterparty with the highest trading volume (Figure 10).
- *Risk-based scenario*: remove the counterparty with the highest default risk (e.g. using CDS premia as proxies).

Figure 10: Stylised example of network resilience test for the worst case scenario.

Using these scenarios, we can analyse the number of nodes that need to be deleted to remove a significant proportion – such as 25% given the concentration of trading volume in the sterling corporate bond network presented in section 5 – of trading volume. Going forward we will now refer to removing 25% of trading volume to 'collapsing the network'. In this paper we focus on comparing the worst case scenario and the risk-based scenario, to assess a) how potentially susceptible the network is to stress of key counterparties and b) given current dealer default risk (as implied by CDS premia), how close we are to that worst case scenario.

This test simulates how resilient the network is to the failure of systemically significant counterparties. It does not, however, explain how the network would respond to the removal of a node. For example, we would expect that most counterparties would have

[9] We also removed a node at random and, due to the core-periphery structure and the small number of key participants, we found that the network was resilient to these removals.

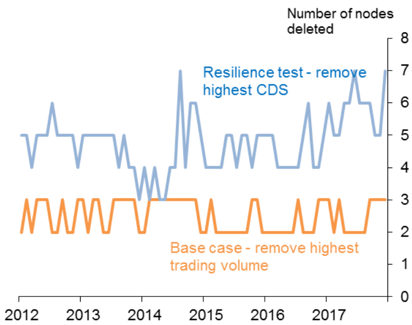
[10] We also ran a slightly altered worst-case scenario in which we removed the counterparty with the most connections to other nodes. This yielded very similar results to our standard 'worst-case scenario', with around 2-3 dealers needing to be removed to collapse the network.

relationships with multiple dealers (even if unused) and so they would be able to draw on these were their main dealer to fail.

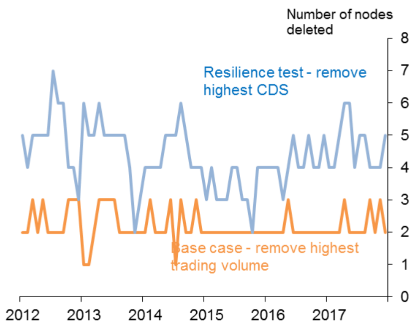
Our 'worst-case' scenario involves removing the counterparty that has the highest trading volume, at each iteration. This gives an idea of how fragile the network is to stress. A key factor here is the concentration of trading volume. As shown in section 5 trading volume is concentrated in a few counterparties so we would expect it to be more fragile to the removal of one of those counterparties.

In our risk-based scenario, we remove the dealer which is currently the most likely to default, proxied by their CDS premium. This gives us an idea how of resilient the network is to current market-implied risk levels.

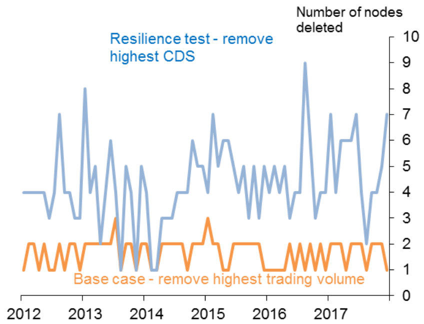
We identify months when the resilience of the market was low as those months when the worst-case scenario and the risk-based scenario yield the same results. In other words, this would be when the dealers with the highest market-implied default risk are also those that are most 'important' to the network. In order to assess this, Figure 11 compares the number of nodes that need to be deleted to collapse the network in the worst-case and risk-based scenarios. As the spread between the two lines decreases it tells us that the dealers that are most important to the market (i.e. control the highest proportion of trading volume) are also the most vulnerable (have the highest default risk). Therefore, a widening spread indicates increasing resilience.



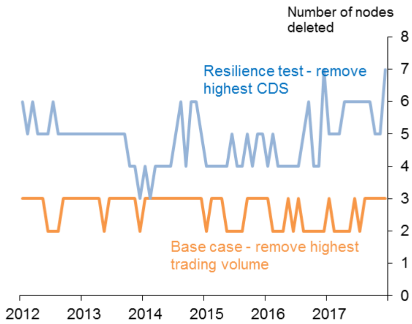
(a) Investment-grade, all bonds



(b) High-yields, all bonds



(c) newly issued bonds, IG and HY



(d) other bonds, IG and HY

Figure 11: Number of counterparties that need to be deleted to remove 25% of trading volume, both in the worst case scenario and risk-based scenario for both all IG and HY bonds, as well as newly issued and other older bonds (both IG and HY).

The number of dealers that need to be removed to see a reduction of 25% of the trading volume under a risk-based scenario for IG bonds has steadily been increasing since 2014, up to 7 from as low as 3, as shown by Figure 11a. As a result, the spread between the two scenarios has increased, implying that the dealers with the highest default risk are no longer those most important to the market. We observe that 2014 was a point of low resilience for the IG trading network when the spread between the scenarios reached 0.

There have been two key points where resilience was low in the high-yield network, in October 2013 and October 2015, when the spread between the two scenarios reached 0, as shown by Figure 11b. Since end-2015, however, the risk-based scenario has increased steadily, showing increased resilience in the HY market.

This test of resilience is far more volatile when we look at newly-issued bonds. Figure 11c shows that the number of dealers needing to be removed to delete 25% of the trading volume under the CDS stress varies greatly, for example moving from 2 to 7 over the space of 6 months. Despite this volatility there appears to be evidence that, since a period of low resilience in late 2013, resilience appears to have picked up slightly. This increased resilience is highlighted by the average spread between the two lines increasing from just 2 dealers for the period 2012-2014 to over 3 in 2015-2017. Non-newly issued bond resilience is far more stable (shown in Figure 11d), and again appears to have been increasing following a month of low resilience in late 2013.

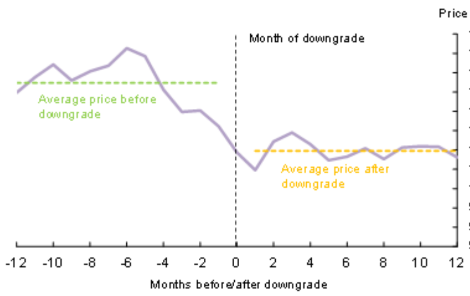
By looking at the network on a monthly basis, our analysis may overestimate the fragility of the network by ignoring trading relationships that exist but are less frequently used. To test for this, we have also run similar simulations using a half-yearly network. Doing so gave us vey similar results to the monthly network analysis, implying that there are few 'dormant' dealer-client relationship (at least over the six months horizon).

6.2 Resilience to bond downgrades

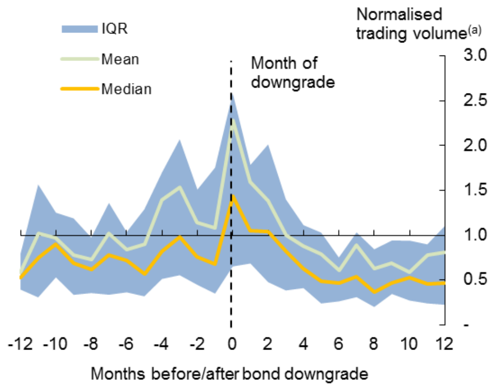
To test how the network reacts to downgrades, we selected 27 corporate bonds that had been downgraded from investment-grade to high-yield in the period January 2013 to December 2016. With this subset of bonds we were then able to analyse how network characteristics changed in the 12 months before and after the downgrade.

Before a bond is downgraded, rating agencies tend to place them on 'negative watch', which aims to provide investors with an indication of the likely direction and timing of future credit rating changes. The underpinnings of this decision is to inform investors of the rating agency's opinion that the credit quality of the underlying bond/firm may be deteriorating, thus reducing price volatility by moving credit ratings in a gradual/predictable fashion (see Chiyachantana et al. (2014)). As a result, when a firm is placed on negative watch, it signals that it is underperforming and can cause the price of a bond to fall up to 6 months before a ratings decision has been finalised. This price effect is analysed by Hite and Warga (1997), who show downgraded bonds experience significant negative 'abnormal returns' in the 6 months before the downgrade. Figure 12a shows the average clean price of downgraded bonds in the 12 months before and after downgrade. We find that prices fall dramatically in the 6 months prior to downgrade, reach their trough around 1 month after, and settle at their 'new normal', around 3% lower than before.

Figure 12b shows the normalised gross trading volume for this subset of bonds. To normalise trading volume, we divide volume in each month by the average volume in the 12 months before the downgrade. Volume traded increases markedly around 4 months before the downgrade month and again in the month of the downgrade, reaching volumes around 1.5 and 2.5 times average respectively.



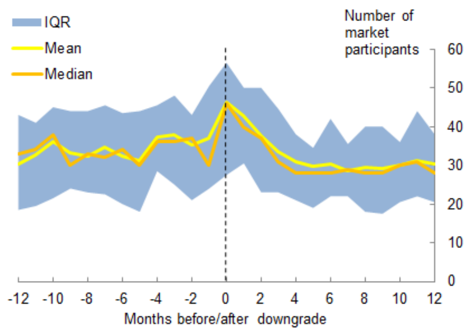
(a) Prices



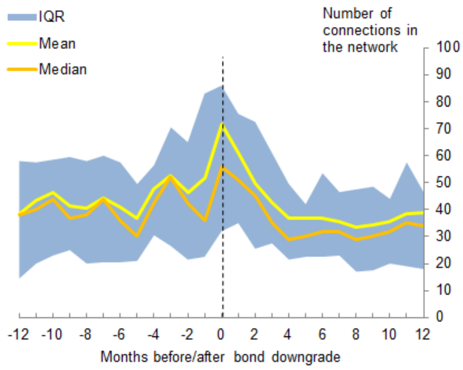
(b) Volume

Figure 12: Average price of corporate bonds before and after their downgrade (on the left). Distribution of the total normalised gross trading volume around bond downgrades (on the right).

To assess how the trading network is impacted by a bond downgrade we look at the number of market participants and number of connections in the months around the bond downgrade. Figure 13a shows that the number of market participants trading these downgraded bonds increases by around 25% in the month of the downgrade compared with the previous month. As a consequence also the number of connections in the network increases as shown in Figure 13b.



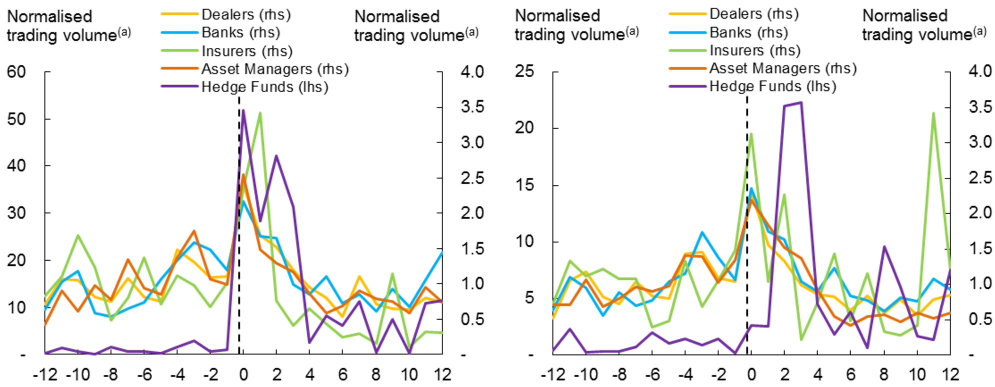
(a) Number of market participants



(b) Number of connections

Figure 13: Distribution of the number of market participants in the networks corresponding to trading activity of downgraded bonds (on the left). Distribution of the number of connections in the trading network of downgraded bonds around bond downgrades (on the right).

We explore buying and selling behaviour of the major investor types by looking at the normalised purchases and sales by different investor types (Figure 14), to see how investment behaviour changed in response to a downgrade. We find that hedge funds increase bond purchases markedly in the month of/following a downgrade, when prices are at their lowest (Figure 12a), followed by increased sales around 2-4 months after the downgrade. This could be indicative of hedge funds purchasing the bond when prices are low in order to make a quick profit when prices normalise, as shown in Figure 12a.



(a) purchases

(b) sales

Figure 14: Normalised trading volume by major investor types around the downgrade.

We analyse this by looking at the net and gross positions of hedge funds in these downgraded bonds in the 12 months before and after downgrade. We would expect the net position in each bond to be lower than the gross, as the initial purchases are offset by the sales. This relationship is shown in Figure 15, in which each dot on the scatter represents a hedge funds gross/net position in a specific bond. The dots on the 45 degree line represent those in which net and gross volume are equal and have not experienced any offsetting trades. On the other hand, any dots below the 45 degree line represent any positions that have experienced some form of offsetting (and thus net is less that gross). Around 50% of all positions taken by hedge funds in this period have experienced some form of offsetting, with 25% being completely offset, meaning the final net position is close to 0.

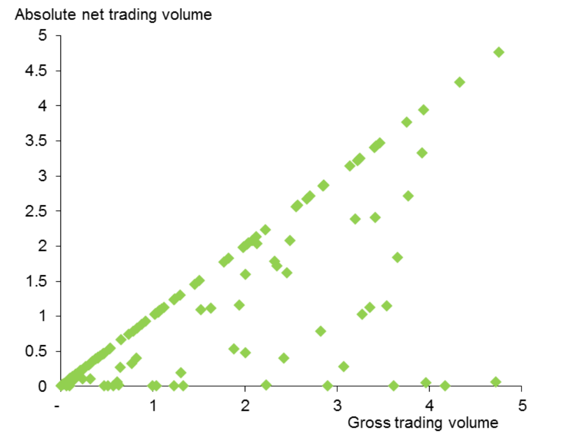


Figure 15: Relationship between gross and net trading volume by hedge funds for each downgraded bonds in the 12 months before and after the downgrade.

We also find that insurance company's sales of downgraded bonds increase by around 3 times in the month of downgrade (Figure 14b). This is consistent with Ellul et al. (2011) that show how insurance companies that are relatively more constrained by regulation are more likely to sell downgraded bonds. For example, firms that are nearing their NAIC risk-based capital ratio or their SR risk-adjusted capital ratio may be forced to sell downgraded bonds in order to avoid a breach. Given that insurance companies hold around 1/3 of outstanding investment-grade corporate bonds, these sales may have material impact on the price of these bonds and is consistent with the price movements shown in Figure 12a. However, Figure 14a also shows that insurance company's purchases also increase following a downgrade. This tells us that whilst regulatory constrained insurers may be forced into sales and thus force the price below fundamentals, other firms have the ability to purchase these bonds when the prices are low and thus reap the benefits of such fire selling.

7 Concluding remarks

In this paper we have analysed the resilience of the sterling corporate bond market by undertaking an in-depth study of the structure of the associated trading network, and by assessing the consequences of dealer withdrawal from the market and studying investor behaviour around bond downgrades. In order to capture the differences across corporate bonds we considered separately the trading networks corresponding to corporate bonds rated as investment-grade and high-yield and split them into newly issued and older bonds.

We have found that the trading networks associated to different sets of sterling corporate bonds are sparse and that major investor types have trading relationships with a limited number of dealers. Trading networks of sterling IG and HY corporate bonds exhibit a core-periphery structure, where there is a core comprised of highly interconnected counterparties (dealers) and a periphery of less interconnected counterparties (dealer clients). Trading volume is largely concentrated in few players - the top 3 dealers and top 3 non-dealers. We observe a high degree of commonality of investors trading in consecutive months and a large degree of persistency in trading relationships between dealers and clients.

These characteristics can affect the resilience of trading activity in the sterling corporate bond market, whose smooth functioning allows corporates to access funding for their investments. Also disruption in trading activity in the corporate bond market can negatively affect prices and lead to destabilising feedback loops that could further amplify the initial fall in prices.

We assessed the resilience of the trading network by simulating the removal of dealers accounting for the largest traded volume and also experiencing the largest level of financial stress. We identified months when the withdrawal of such a dealers from the market could lead to a reduction of 25% of the trading volume.

We observe prices falling around the months when corporate bonds are downgraded from IG to HY. We investigate the trading behaviour of investor types around the downgrade and find that insurance companies tend to sell downgraded bonds the month of the downgrade. We find that hedge funds tend to buy downgraded bonds the month they are downgraded and that insurance companies might also be likely to buy downgraded bonds in the months following the downgrade. In order to fully understand the resilience of the corporate bond market around downgrades, further research is needed to understand the drivers of insurance companies' behaviour taking into account balance sheet characteristics and regulatory constraints.

Using unique proprietary data on the sterling corporate bond market our paper contributes to the existing literature on frictions and resilience of the corporate bond market. By shedding light on the structure and the resilience of the corporate bond market, our work is relevant for policy makers when designing future potential policy interventions (e.g., market maker of last resort facilities) or monetary policy implementation through corporate bond purchases.

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