

# Contagion in Dealer Networks

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## Abstract

Using granular data about government bonds, we find that dealer networks undergo significant changes after the arrival of new public information. Following the release of macroeconomic data, dealer intermediation increases, the dealers' inventory changes and more bonds circulate through the networks, and dealer networks become larger. However, the incidence of contagion also increases. Contagion occurs when a failure by one trader to deliver securities for settlement cascades through the network. Together, these changes that networks undergo around news events suggest that larger dealer networks create a tradeoff between intermediation benefits and counterparty risk.

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I have nothing to disclose.

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I have nothing to disclose.

# Introduction

Networks of dealers operate in large over-the-counter (OTC) markets where trading is bilateral and decentralized. These networks play an essential role, overcoming search and informational frictions to intermediate trades between buyers and sellers.<sup>1</sup> Using granular trade data, an emerging empirical literature has documented structural features that are important to understand dealer networks. For instance, [Li and Schürhoff \(2019\)](#) show that peripheral investors in the US municipal bond market pay a markup to transact with dealers that have a more central position in the network, enabling faster execution.

We study how the network of trades between dealers and investors evolves over time. We focus on government bonds, for which it is well known that the release of new macroeconomic data can trigger large and rapid bond price adjustments together with surges in bond trading volume that last for a prolonged period ([Ederington and Lee, 1993](#); [Fleming and Remolona, 1999](#)). Although government bond markets are among the largest and most important OTC markets, and although these events are closely followed by bond investors because of their large impact, little is known about how the network of trades intermediated by dealers changes following the release of economic news.

We find that dealer networks undergo significant changes when new information arrives using event studies around the release of macroeconomic data. First, we find that a larger volume of bonds circulates through dealer networks after new economic data is released. Second, networks expand and become more complex: a larger number of dealers and clients are connected by networks, either directly or indirectly, and connections between dealers and clients are more numerous.

However, the additional intermediation benefits come with a tradeoff. As the flow of bonds increases and as the complexity of dealer networks rises, the probability of contagion also increases after the news events. Contagion occurs when a failure by one trader to deliver securities to settle its trade cascades through the flow of transactions in the network and affects downstream counterparties. The 99th percentile for the size of such a contagion is about \$2B, which corresponds to five standard deviations in the full sample. In the cross-section of bonds, the changes in the structure of dealer networks and in the incidence of

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<sup>1</sup>See, e.g., the review in [Duffie, 2011](#). A recent rich theoretical literature analyzes network formation in OTC markets. [Glode and Opp \(2016\)](#) show that longer paths of intermediaries may be needed because of information asymmetries. [Sambalalbat \(2018\)](#) study the formation of core-periphery network that arises due to specialization in a search-based model. [Colliard and Demange \(2017\)](#) provide a strategic model of trading via intermediation chains with relationships and information asymmetry.

contagion are concentrated in those most liquid and actively traded bonds. This underpins the empirical relevance of the tradeoff that we document.

Our analysis is based on a unique granular panel dataset that includes detailed proprietary and regulatory information on all spot and repo trades in the Government of Canada bonds market, including information about counterparties. For each bond and each day, we construct the network where each node is a dealer or a bond investors and where each link between any pair of nodes is the net settlement exposure for that bond at the end of the trading day. This produces more than 24,000 observations of dealer networks with large time series and cross-sectional variations in size. This construction includes both spot and repo trades since repos are used to source securities for settling a spot trade. For each network observation, we compute NETWORK VOLUME as the sum of the settlement volume, which is differs from trading volume due to netting between counterparties. We also compute COMPLEXITY as the first principal component of the number of links, the number of paths, the average path length, and the length of the longest path in a network (the diameter). Higher COMPLEXITY is associated with bonds that have benchmark status, more trading activity and which are more expensive to borrow in the repo market.<sup>2</sup> Other, older, less actively traded bonds exhibit low COMPLEXITY.

After the release of key macroeconomic data, we find that the NETWORK VOLUME for that day increases by \$750M, around 0.25 standard deviations, and that the COMPLEXITY for that day increases by around 0.4 standard deviations, on average for benchmark bonds.<sup>3</sup> Several pieces of evidence suggest that dealer networks accommodate a shift in investors' demand for intermediation services after the news release. First, we find that the effects are concentrated in benchmark bonds and that other non-benchmark bonds exhibit much smaller changes. This is intuitive since traders motivated by macro news should select bonds with lower transaction costs. Second, we find that dealers earn higher markups on news days. The increase in markups is significant statistically but the magnitude is small. Third, dealers' aggregate inventory of bonds declines by close to \$150M on the day of the release and by close to \$225M on the day after. The effect is large relative to the increases in NETWORK VOLUME. Since the change of markups is small and the change of inventory is large, dealers' supply of intermediation appears elastic with respect to prices. Intuitively, dealers increase their short positions, selling bonds that they do not own, to accommodate

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<sup>2</sup>Analogous to on-the-run treasuries in the US, benchmark bonds are the most liquid and active bonds.

<sup>3</sup>We focus on the release on GDP, unemployment, retail sales and inflation data as well as the release of monetary policy announcements.

the larger trading activity. Finally, dealers do not seem to be trading in the direction of the news: the estimates are not statistically different in sub-sample of news events where the bond yield goes up or down, suggesting the rise in trading by dealers is driven by increased demand for intermediation.

However, the probability of contagion, in the form of settlement fails, also rises following news events. Settlement fails are common but unanticipated delays that occur when counterparties do not deliver securities against cash in spot or repo trades. In many OTC markets, contracts that govern bilateral trades are flexible regarding the timing of delivery of securities. If a settlement fails on the scheduled date, then, by convention, the exchange is simply attempted again the next day, and the terms of the trade remain unchanged. This contractual feature emerged endogenously over time. Because of this lenient treatment, episodes of contagion are common.<sup>4</sup>

We document additional stylized facts consistent with the contagion of fails through networks. First, fails in repo and spot markets are highly correlated. This is intuitive since dealer networks involve a combination of spot and repo trades, where the latter are used to source bonds for a short period of time to settle short positions or to finance the purchase of bonds. Second, most fails tend to persist for several days, which would be unlikely if fails were localized between two counterparties. Third, the distribution of fails exhibits a fat tail. The average share of settlement volume that fails is only 0.5 percent, but it frequently spikes to as much as 10 to 20 percent. Finally, using simulations of fails in the population of observed trades, we show that a correlation between fails is needed to match the frequency of contagion that we observe as well as the mass of observations of zero fails.

Using event studies around the same macro news announcements where we studied changes in dealer networks, we find that contagion from settlement fails is more likely immediately following news releases. The median for the increase in fail is essentially zero, but the 90th, 95th and 99th percentile is \$200M, \$400M and \$2,000M, respectively, which corresponds to increases of 0.5, 1 and 5 standard deviations in the full sample. The effect is also nonlinear in relation to trading activity: the increase in fails at the 99th percentile is more than two times the increase in the flow of bonds in the network. In the cross-section the effect is concentrated in benchmark bonds, which exhibit the lowest transaction costs, the highest trading activity and the more complex networks.

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<sup>4</sup>In a discussion of fails in the US Treasury market, [Fleming and Garbade \(2005\)](#) describe these spikes as “daisy chains” of fails. The US equity and bond markets impose explicit but relatively small penalties for failing to deliver.

In quantile regressions for the change in fails around news events, the coefficient estimates for COMPLEXITY are large, significant and robust to including bond-specific characteristics such as liquidity, fixed effects, and to including controls for the trading activity and the scarcity of the bonds, two known determinants of fails (Fleming and Garbade, 2005; Boni, 2006; Corradin and Maddaloni, 2019). The evidence supports the simple interpretation that the complexity of a dealer network increases the probability of contagion beyond the simple effect of the larger volume.

We address and set aside the possibility of reverse causality in which a higher probability of contagion ex-ante causes networks to become more complex. This could arise if traders divert trades from central dealers to reduce or diversify exposures to contagion. Instead, we find that network centrality increases by around 0.35 standard deviations after news, on average, inconsistent with diversification. Furthermore, we find that centrality increases by 0.55 standard deviations for the most central dealers.

We ask if novation and netting by a central counterparty (CCP) may reduce the prevalence of contagion by reducing the complexity of dealer networks. In our sample, dealers have the option to clear their spot and repo trades through a CCP. To check the effect of the CCP on the network, we run the following counterfactual experiment. We disconnect the CCP node from our network, re-assign trades across bilateral links between dealers and recompute all network statistics. The results show that, if anything, the CCP makes the network slightly more complex in practice. Duffie and Zhu (2011) show that multilateral netting may not effectively reduce exposures through netting if the CCP clears only a fraction of these trades. Consistent with this prediction, we find that for most observations, the CCP covers less than 25 percent of trades.

Overall, the evidence shows that dealer networks change significantly after news events. It also suggests that the lenient treatment of settlement fails involves a tradeoff. If fails were treated as contractual defaults, dealers would only sell securities they currently held, limiting their ability to provide immediacy. In contrast, when settlement fails are allowed, dealers can sell bonds that they don't hold by borrowing or purchasing securities after a sale. However, this means that a higher level of counterparty risk is tolerated when fails arise.<sup>5</sup> While this risk may be benign most of the time, counterparty risk can sometimes rise rapidly and severely hinder intermediation. Garbade et al. (2010) show that daily settlement fails

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<sup>5</sup>Counterparty risk arises because, in case of a default, market participants would face market risk as they search for a new counterparty to establish equivalent trades.

in the US Treasury market averaged above \$200 billion and often exceeded \$350 billion for several weeks after the 2008 Lehman Brothers insolvency.<sup>6</sup>

## Related Literature

In an important work, [Corradin and Maddaloni \(2019\)](#) show that higher scarcity in the Italian repo market due to purchases by the European Central Bank leads to a higher probability of settlement fails. We confirm in our sample that scarcity is a key determinant for the likelihood and quantity of fails.

Empirical work on fixed-income fails is scarce. The literature on settlement fails in equity markets focuses on the interaction with short-selling and a debate persists around the costs and benefits of fails. Raising the costs of fails to reduce counterparty risk may limit short-selling and reduce liquidity and price discovery ([Evans, Geczy, Musto, and Reed 2009](#); [Fotak, Raman, and Yadav 2014](#); [Liu, McGuire, and Swanson 2017](#)). However, high levels of fails could result in mispricing and increased volatility ([Stratmann and Welborn 2012](#); [Autore, Boulton, and Braga-Alves 2015](#)). In contrast with equity markets, fail volume is much larger and concentrated in the most liquid and largest bonds.

Adding to [Li and Schürhoff \(2019\)](#), [Di Maggio, Kermani, and Song \(2017\)](#) and [Hollifield, Neklyudov, and Spatt \(2017\)](#) also study the markups of central dealers in the market for US corporate bonds and asset-backed securities, respectively. The seminal work in [Ederington and Lee \(1993\)](#) and [Fleming and Remolona \(1999\)](#) shows the large impact that the arrival of public information has on prices and trading activity the bond market. We build on both streams of literature to study how dealer networks change around news.

Theoretical guidance is thin regarding a tradeoff involving settlement fails in OTC markets. [Khapko and Zoican \(2019\)](#) analyze a tradeoff between settlement speed and market quality. They focus on the optimal contract in a static, two-sided market. Our results suggest that allowing for settlement delays allows the formation of larger and more complex networks between dealers and investors, which opens a channel for the contagion of counterparty risk across the dealer network.

The architecture of interbank networks is the focus of a large literature, where contagion takes the form of default and is relatively rare. For instance, [Elliott, Golub, and Jackson](#)

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<sup>6</sup>[Garbade et al. \(2010\)](#) also describe several policy responses that were taken to alleviate contagion. The Federal Reserve initially relaxed the terms of its securities-lending program, the US Treasury reopened several off-the-run Treasury notes and the Treasury Market Practices Group adopted changes in market practices.

(2014) study cascades of failures in a network of interdependent financial institutions where there is a tradeoff between network diversification and integration and the risk of contagion. Cabrales, Gottardi, and Vega-Redondo (2017) investigate the socially optimal design of financial networks and the tradeoff between risk sharing and contagion. Farboodi (2014) and Hugonnier, Lester, and Weill (2018) study how bilateral exposures and the core-periphery network emerge endogenously. In contrast with rare default events, contagion is common across the OTC dealer networks in our sample. This should offer a useful ground to compare models.

Section 1 provides details about our data from the market on Government of Canada bonds. Section 2 documents how dealer networks change around the release of economic data. Section 3 covers settlement fails and documents larger clusters of fails around news. Section 4 explores the impact of netting by the CCP. Section 5 concludes.

## 1 Network Data

This section describes several sources, including proprietary and regulatory data, that we use to construct a rich panel dataset that describes trading activity for Government of Canada bonds for the years 2016 and 2017. Our dataset includes information about trades and counterparties, so that we can construct 24,000 bond-day observations, where each observation describes one network of transactions. For reference, Table 2 provides the short names, descriptions and sources of every key variable. Data and variables related to settlement fails are introduced in section 3.

### 1.1 Bond Data

In contrast with studies of the municipal or corporate bonds, and most studies of government bonds, our data cover both the spot and the repo markets for bonds. To thoroughly observe the network of settlements, it is essential to cover both markets because of the prevalence of short-selling. A large share of trading and fails volume for government bonds involves bonds that are borrowed in the repo market to cover short sales on the spot market. We restrict the sample to bonds denominated in Canadian dollars and ignore inflation-linked bonds and Treasury bills.

We first compute basic market variables for each bond and each day. The repo spread is defined as the difference between the Bank of Canada's target overnight interest rate and the repo rate. It is a measure of bond scarcity: it measures how costly it is to borrow the

bond. We also compute a proxy for the velocity of a bond in the securities-lending market: the ratio of the par value being loaned to the quantity of bonds outstanding (i.e., the float).<sup>7</sup> Finally, we compute the daily average bid-ask spread on the Canddeal dealer-to-client trading platform, which we use as a proxy for a bond’s liquidity.

Table 3, Panel (A) reports summary statistics of these bond-level metrics for benchmark bonds and non-benchmark bonds, respectively. A Government of Canada bond achieves benchmark status when its amount outstanding reaches a certain level following several reopenings.<sup>8</sup> Benchmark bonds are more liquid than other bonds, analogous to on-the-run treasury bonds in the United States, they have smaller bid-ask spreads, are more expensive to borrow on the repo market and have higher velocities, relative to non-benchmark bonds.

## 1.2 Network Data

We reconstruct the dealer network for each day and each bond, using trade-by-trade data. Dealers in the Government of Canada bond market report spot and repo market trades to the Market Trade Reporting System (MTRS). This dataset includes details of the trades as well as anonymous counterparty identifiers.

To construct the network for a given bond and a given day, we first assign one node to each dealer, each client and the CCP. We draw a link between every pair of nodes where the net settlement volume of this bond on this day is not zero.<sup>9</sup> Links are directed based on which counterparty owes securities (as opposed to owing cash). For some client trades, the unique counterparty identifier is not available. When this happens, we create, for each dealer, one node that groups all of its clients for which we are missing a unique identifier. This construction produces more than 24,000 bond-day observations, each describing one core-periphery network of transactions.

We define a directed path between two nodes as a sequence of links for which the flow of securities between the nodes goes in one direction. To illustrate, a path with two links has

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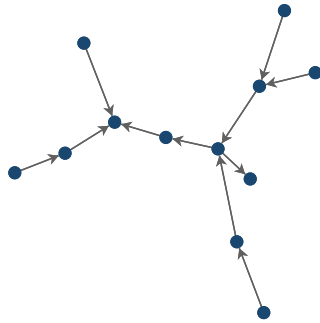
<sup>7</sup>The velocity label is appropriate because of the analogy to fractional-reserve banking. The number of settlement claims on a specific bond may expand beyond the stock of bonds of the same issue. In the analogy, the quantity outstanding for this bond represents base currency and settlement claims represent demand deposits. Changes in velocity make the bond supply elastic.

<sup>8</sup>Government of Canada bonds typically become benchmark a few months after the initial issuance, with the number of months depending on the maturity. The age of a benchmark bond is around nine months, on average. See [Bulusu and Gungor \(2017\)](#) for more information about the life-cycle of Government of Canada bonds.

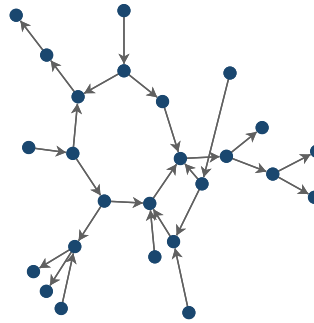
<sup>9</sup>Bonds with no trade on a given day are treated as missing values.

**Figure 1: Dealer Networks**

Representation of the settlement networks for one Government of Canada bond on two dates, before and after the release of GDP data: 29 February 2016 (Panel A) and the date of the news release, 1 March 2016 (Panel B). GDP growth was 0.5 percent relative to the median analyst forecast of 0 percent. Each node represents either a dealer, a client or a group of clients. Each arrow represents the direction of net obligations to deliver bonds between any two nodes. On the day preceding the news, the network has 12 counterparties, 11 links and 31 distinct paths, and the diameter has 4 links. After the news, the network has 25 counterparties, 26 links, 130 distinct paths and the diameter has 7 links.



(A) Before the news



(B) After the news

counterparty A delivering bonds to counterparty B, who is then delivering bonds to counterparty C. With this definition in hand, we compute the number of distinct paths (PATHS), the average path length (AVGPATH) and the length of the longest path (DIAMETER), measured in number of links. Finally, for each day and each bond, we compute the sum of the net settlement volume across all links (NETWORK VOLUME). This measures the flow of bond in each network as well as the volume of settlements that could potentially fail.<sup>10</sup>

Figure 1 shows the network for one bond on two different days, before and after a data release. This illustrates a typical dealer network Government of Canada bonds. One common feature in the sample is the low share of links relative to the number of all potential links. This number is typically close to zero which is indicative of a core-periphery network intermediated by a few central dealers. Figure 1 also illustrates that networks can change substantially around news. We introduce several standard metrics to characterize the changes.

The two dates in Figure 1 are 29 February and 1 March 2016, the day before and the day of a release of GDP data. On the day preceding the news, the network has 12 counterparties, 11 links and 31 distinct paths, and the longest path (diameter) has 4 links. On the day of the news, the network has 25 counterparties, 26 links, 130 distinct paths, and the longest path (diameter) has 7 links. This illustrates how the network can change rapidly following the release of new data.

Panel (B) of Table 3 reports the summary statistics for the network data separately for benchmark and non-benchmark bonds. It documents the large diversity of network structures. Focusing on the number of LINKS, the inter-quartile range is from 8 to 29 for non-benchmark bonds and from 83 to 107 for benchmark bonds. Hence, the network in Figure 1 exhibits an increase in the number of links around the news release that is almost the size of the interquartile range.

Since these metrics are highly correlated with each other, we summarize them with their first principal component, which we call COMPLEXITY. The standard deviation of COMPLEXITY is normalized to one. Figure 2 shows the time series of COMPLEXITY for the 10-year benchmark bond and for a bond that was originally issued with 10 years to maturity but that is not a benchmark bond in our sample. The COMPLEXITY is much higher for the

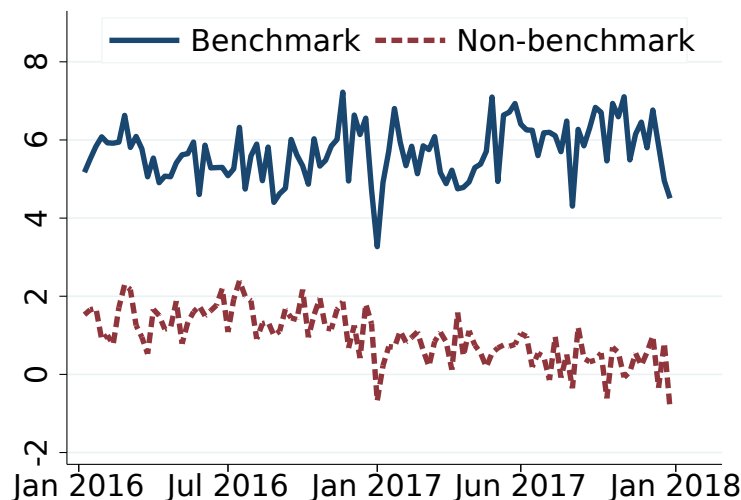
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<sup>10</sup>Note that we do not identify sequences of trades by using time stamps arranged as a continuous sequence. This identification strategy has been used by Green, Hollifield, and Schürhoff (2007); Li and Schürhoff (2019). It performs well for bonds that trade infrequently, like municipal bonds. However, in the government bond markets, dealers frequently make round-trip trades and trade with multiple clients on a given trading day making identification of distinct trade sequences impossible.

benchmark bond, which means that dealer networks tend to be bigger and more complex for bonds that are more liquid.

**Figure 2: Time Series of COMPLEXITY**

Weekly average COMPLEXITY for the 10-year benchmark bond, which tracks different bonds because the benchmark status changes over time, and an old bond with 6 years to maturity at the beginning of the sample. COMPLEXITY is the first principal component of the network metrics in [Table 3](#). Data are for the Government of Canada bond market for the years 2016 and 2017.



## 2 Dealer Networks and News

The arrival of public information in the bond market sets off episodes where prices adjust quickly and trading volume surges for a prolonged period ([Ederington and Lee, 1993](#); [Fleming and Remolona, 1999](#)). We ask whether dealer networks that provide intermediation in these markets adjust to the release of new public information. We collect information about the following Canadian data releases: inflation, unemployment, retail sales, GDP and monetary policy announcements, which are the most significant news releases. The timing for each release follows a pre-announced schedule and bond investors closely follow each release.<sup>11</sup>

Panel (A) of [Figure 3](#) shows the average change in COMPLEXITY around the news releases. Since the news releases are exogenous, the evidence can be interpreted as causal. We distinguish between the response for benchmark bonds and for non-benchmark bonds.

<sup>11</sup>We drop observations with overlapping news releases that occur within four business days of each other. This produces 78 distinct news release events in our sample.

We find that COMPLEXITY increases significantly for benchmark bonds on the day of the news, by 0.4 standard deviations, and the increase persists to the next day. The increase in COMPLEXITY can be due to an increase in bilateral trades between neighbours in the network, the creation of longer chains of trades between ultimate buyers and sellers, or a combination of these. By contrast, COMPLEXITY increases by 0.1 standard deviations for non-benchmark bonds.

In addition, the flow of bonds through the network increases. Panel (B) of Figure 3 shows that NETWORK VOLUME increases by \$750M for benchmark bonds on average after a news release, which is around 0.25 standard deviations. By contrast, the impact is small for non-benchmark bonds.

As a robustness check, Panels (C)-(D) of Figure 3 show the results from the same exercise, but we use the median of COMPLEXITY two days before the news to split the sample. For bonds with more complex networks, we find that COMPLEXITY increases by 0.25 standard deviations and NETWORK VOLUME increases by \$225M for dealer networks in the high-COMPLEXITY category. The results are similar, but the magnitudes are smaller, presumably because benchmark bonds attract most of the trading activity.

## 2.1 Centrality Premium

Figure 3 shows that dealer networks change significantly around news releases, especially for bonds that are very active before the news, which is precisely where investors face the lowest costs of trading. Overall, this suggests that dealer networks adapt and COMPLEXITY increases to accommodate a higher demand for intermediation. We check whether dealers markups and inventory changes around news releases.

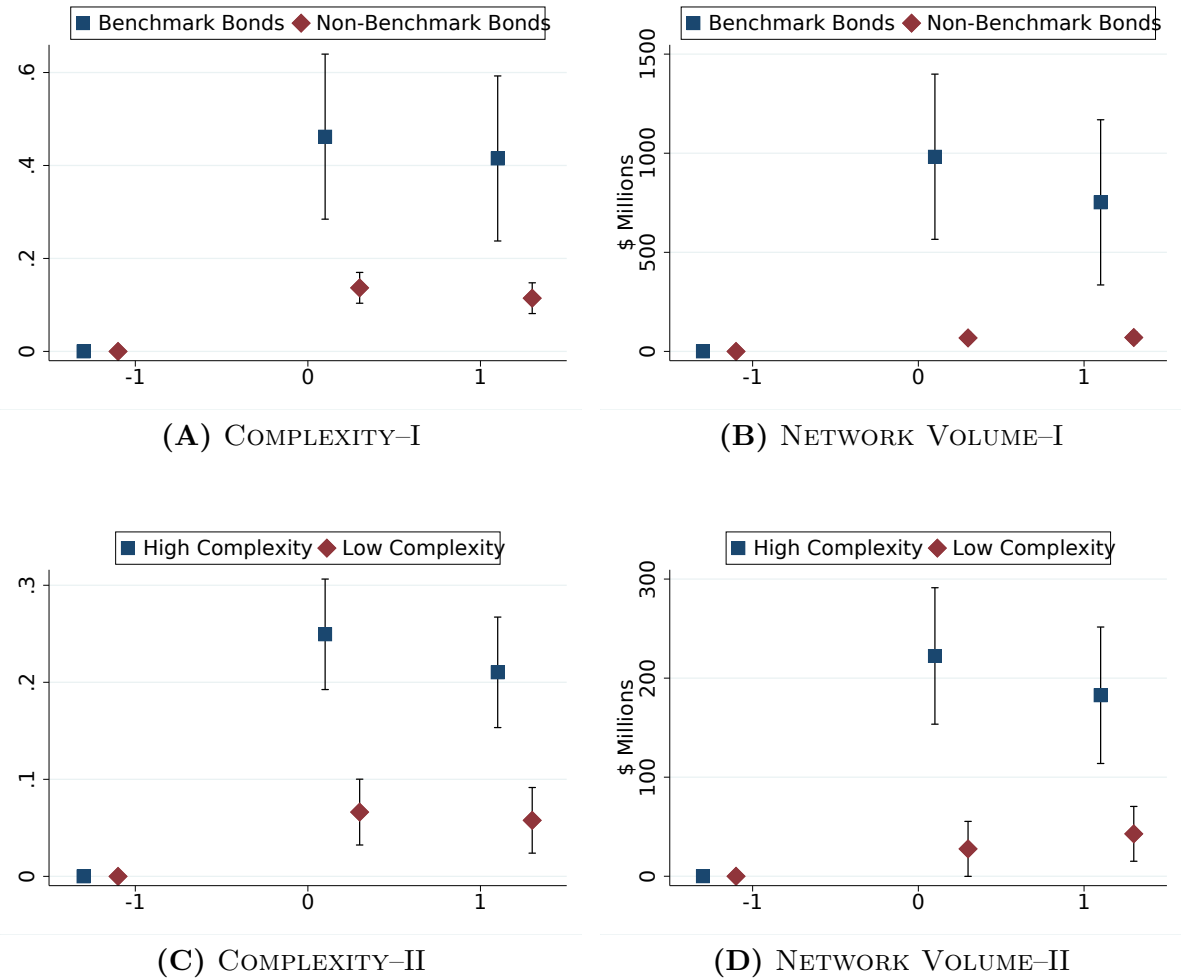
Li and Schürhoff (2019) show that dealers with a more central position in a network earn a higher markup to provide immediacy to peripheral clients. We first confirm similar results in our sample and then inspect what happens around news releases. Following Li and Schürhoff (2019), we compute several centrality metrics that we summarize with the first principal component CENTRALITY.<sup>12</sup> Table 4 reports centrality summary statistics for benchmark and non-benchmark bonds, respectively. The CENTRALITY of dealers is higher for benchmark bonds, which is a reflection that these networks are also more complex. Next, we compute the average SPOT MARKUP and REPO MARKUP between each dealer-client

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<sup>12</sup>The centrality metrics are IN-DEGREE, OUT-DEGREE, EIG-CENTRALITY, BETWEENNESS, CLOSENESS and CLUSTERING. For definitions, see Table 2.

**Figure 3: Dealer Networks and News**

Average changes in COMPLEXITY and NETWORK VOLUME in the days around economic news releases. Panels (A)-(B) report results separately for benchmark and non-benchmark bonds. Panels (C)-(D) report results separately for bonds with low and high complexity before the event. For each bond and for each event, we compute the change in COMPLEXITY and NETWORK VOLUME as the difference between their values after the release and their values on the day before. Time is normalized so that 0 is the day of a news release and all variables are zero at time -1 by construction. The vertical lines show a 90 percent confidence interval. Data are for the Government of Canada bond market for the years 2016 and 2017. Table 2 provides all variable definitions.



pair for spot and repo trades, respectively.<sup>13</sup> Given these measures, we ask if markups are higher for more central dealers.

Table 5 reports the results from regressions of markups on centrality measures. The control variables include COMPLEXITY NETWORK VOLUME, REPO SPREAD, VELOCITY, B/A SPREAD, FLOAT and AGE. The coefficient estimates on the control variables (unreported) are intuitive: the markup is lower for benchmark bonds, bonds that are more liquid, or bonds that are less expensive to borrow.

The results show that markups are higher for dealers that are more central and higher for clients that are less central. One natural way to combine information about the centralities of a dealer and a client is to use the difference between the two,  $\Delta$ CENTRALITY. We find that this difference predicts a higher SPOT MARKUP and REPO MARKUP with statistically significant estimates. Incrementing  $\Delta$ CENTRALITY from its first to its last sample decile corresponds to a change of around 4 cents in SPOT MARKUP and around 3 basis points in REPO MARKUP. In line with Li and Schürhoff (2019), the magnitude of the change in SPOT MARKUP is similar to the average bid-ask spread (see Table 3).

## 2.2 Markups and News

Panel (A) of Figure 4 reports the average change of SPOT MARKUP after news releases, similar to the results presented in Figure 3. The results show a significant increase, but only on the day of the news and only for benchmark bonds. Next, we ask whether dealers accommodate the higher demand for intermediation by changing their inventories.<sup>14</sup> Panel (B) shows that dealers inventory of benchmark government bonds decreases significantly, on average. The average decline of benchmark bond inventory is close to \$150M on the day of the release and close to \$225M on the day after. The aggregate decline is economically significant. For instance, the NETWORK VOLUME in Figure 3 increases by \$750M and \$500M, respectively, for these days. The changes are small and insignificant for non-benchmark bonds.

The results are consistent with dealers earning higher profits from trading benchmark bonds around news releases: the markups are higher and the NETWORK VOLUME is markedly higher. However, the estimated effect on markups is small relative to a typical bid-ask spread

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<sup>13</sup>We compute markups for each bond and for each day, as the average difference between all transaction prices for a given client-dealer pair and the average price for that bond for that day, in absolute value. We repeat for spot and repo market transactions, separately. This produces a measure of half-spread that we multiply by two to obtain SPOT MARKUP and REPO MARKUP, which are comparable to the bid-ask spread.

<sup>14</sup>For each bond and each dealer, we aggregate all spot transactions on the day of and the day after the news to compute the net change in inventory, relative to the day before the release.

though. If we interpret the change in network complexity and trading volume as a shift in the demand for intermediation services, then the results suggest that dealers' supply or intermediation is elastic with respect to prices, at least in this period with benign financial conditions.

The reduction in the inventory of benchmark bonds that we document after news releases is due to a higher level of short-selling by dealers. In separate calculations, we find that in aggregate, dealer almost always hold a short position in benchmark bonds on news days. The estimates are noisy, but the median aggregate short position is around \$10B, which is also the average FLOAT for these bonds (see [Table 3](#)). The results mean that dealers accommodate higher intermediation demand and trading volume on news days by increasing the effective supply of bonds available for trading. They do so by selling bonds that they do not own and using a reverse repo transaction to find the bonds that they need for settlement. The effective supply increases because the lenders of bonds have continued interests in the coupon and principal payments.

One natural question is whether the lower inventory of benchmark bonds is related to the direction of news. The evidence suggests that the answer is no. We cannot reject the null hypothesis that the decline is the same on average in sub-samples when yield changes are positive or negative ( $p$ -value of 0.67).<sup>15</sup> Then what is the motive underlying the higher level of trading activity around news days? One possible motive for trading that is unrelated to the direction of the news is the acquisition of information ([Leach and Madhavan, 1993](#)). [Branaccio, Li, and Schürhoff \(2017\)](#) characterize how investors use their own trading activity to acquire information in the decentralized market for U.S. municipal bonds. In the context of a government bond market, negotiating and trading with others after the data release can provide valuable information on how the news affects other investors' valuation of the asset and, more generally, about the overall state of the market. This motive can also explain why the increase in trading volume is concentrated in benchmark bonds, where the costs of trading are the lowest.

### 3 Contagion in Dealer Networks

This section documents that dealer networks are more likely to experience large clusters of settlement fails after news events, especially for bonds in dealer networks with higher

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<sup>15</sup>There are 799 bond-day observations for which the observed yield declines (bond price increases) after the news release and 1479 for which the observed yield rises (bond price decreases).

complexity. This provides evidence of a tradeoff between the costs due to settlement fails and the benefits of intermediation services on a dealer network.

### 3.1 Settlement Fails Data

For each bond and each day, we aggregate the volume of transactions that fail to settle.<sup>16</sup> The appendix provides details of the computation. In this section, we establish three important stylized facts that connect settlement fails with the configuration of dealer networks. First, fails in repo and spot markets are closely related, which is consistent with a trading network that integrates both markets. Second, fails exhibit persistence and can run for several days. Finally, correlation between fails can account for the very fat tails that we observe in the distribution of fails, which is consistent with the idea that fails can cascade through the trading network.

The summary statistics in Panel (C) in [Table 3](#) show that the volume of fails is evenly split between repo and spot market trades. This is confirmed in Panel (A) of [Figure 5](#), which shows the share of settlement volume that fails for the 10-year benchmark bond, separately in the repo and spot markets. These observations tell us that fails in spot and repo markets are closely related, most likely dealers simultaneously use both markets. This is because some of them do not hold the bond in their inventory at the time of a sale but borrow the bond later with a repo. The ability to sell securities short in such a way is essential, and settlement fails are not simply a side effect but a key feature of these markets. If a settlement fail was treated as a contractual default, then dealers could only sell securities that they hold.

Fails tend to persist over time. Once fails occur for a given bond-day, it can take a few days for the failed volume to return to zero. To see this, Panel (B) shows the histogram of the length of continuous runs of days with fails. The majority of observations run for more than one day, rarely ever longer than 10 days.<sup>17</sup>

The summary statistics of fails show that the distribution of fails is highly asymmetric, with observations clustering around zero and with a fat tail of large fails (Panel C in [Table 3](#)). This is also apparent in Panel (A) of [Figure 5](#), which shows that share of trading volume that fails tends to cluster close to zero or in the range of 5 to 10 percent. This pattern corresponds to the qualitative description in [Fleming and Garbade \(2005\)](#) of “daisy chains” of fails cascade through the settlement network, which we label contagion.

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<sup>16</sup>We aggregate data on fails since our network data and fails data

<sup>17</sup>A standard test of serial independence using these runs of fails produces a  $p$ -value that is essentially zero (unreported).

## 3.2 Correlation between Fails

One interpretation of these fat tails of fails is that whether one trade will fail is correlated with other trades. To quantify the importance of the correlation between fails, we can simulate fails in the population of trades. The first simulation assumes that fails are not correlated. The second simulation assumes a fixed pairwise correlation, which corresponds to the idea of a cascade.

The first simulation assumes that any given spot trade (1,189,012 observations) will fail with a fixed probability  $p$  and that any trade fails independently of other trades. The parameter  $p$  is calibrated to match the average percentage of failed trades, which is 0.54 percent. The simulation yields a binomial distribution of fails  $B(n, p)$  for each bond-day where  $n$  is the number of trades.

The second simulation uses the same probability  $p$  but also assumes a fixed pair-wise fail correlation  $\rho$  between trades. By design, this generates a beta-binomial distribution with parameters  $n$ ,  $p$  and  $\rho$ , nesting the binomial case when  $\rho = 0$ . The correlation parameter  $\rho$  is calibrated to match the unconditional variance of the fraction of failed trades ( $\rho = 0.037$ ).

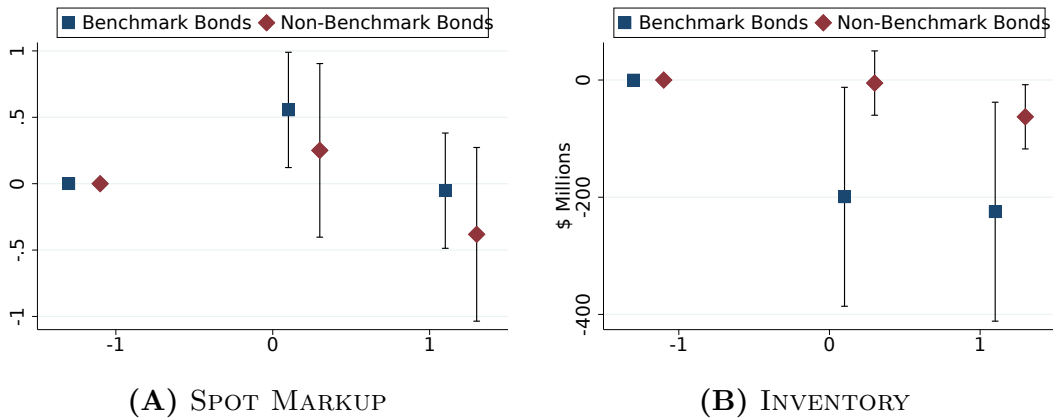
**Table 6** reports summary statistics for the observed and simulated distributions: the number of bond-days with zero fails (the left tail), the mean and variance of fails volume, as well as the 95th and 99th quantiles (the right tail). The key message is that allowing for correlation closely matches the observed distribution in both the number of bond-day observations with zero fails and in the right tails with very large fractions of failed trades. By contrast, simulating without correlation generates the wrong distribution. The dispersion is too small and the observations with zero fails or with large fails are both too infrequent. This is robust evidence that correlation is a key stylized fact of fails. One mechanism for this correlation is that fails propagate through settlement networks.

## 3.3 Settlement Fails and News

**Table 1** lists five dates with large economic surprises together with the share of the volume that failed in that week. This confirms that several of the spikes in **Figure 5** occurred around economic news. In this section, we characterize empirically the increase of fails around news releases. To do this, we compute, for each bond, the quantity of fails on the days of a news as well as over the next two days and we report the average difference relative to the day before this news. It is important to include days after the news release because the settlement of bond trades can happen on any of these days, depending on the type of trades.

**Figure 4: Markups, Inventory and News**

Averages changes on days with or after economic news releases, separately for benchmark and non-benchmark bonds. Panel (A) reports results for the price markup on the spot market. Panel (B) reports results for the aggregate dealers inventory. Time is 0 on the day of a news release and all variables are zero at time -1 by construction. The vertical lines show a 90 percent confidence interval. Data are for the Government of Canada bonds for the years 2016 and 2017. Table 2 provides all variable definitions.



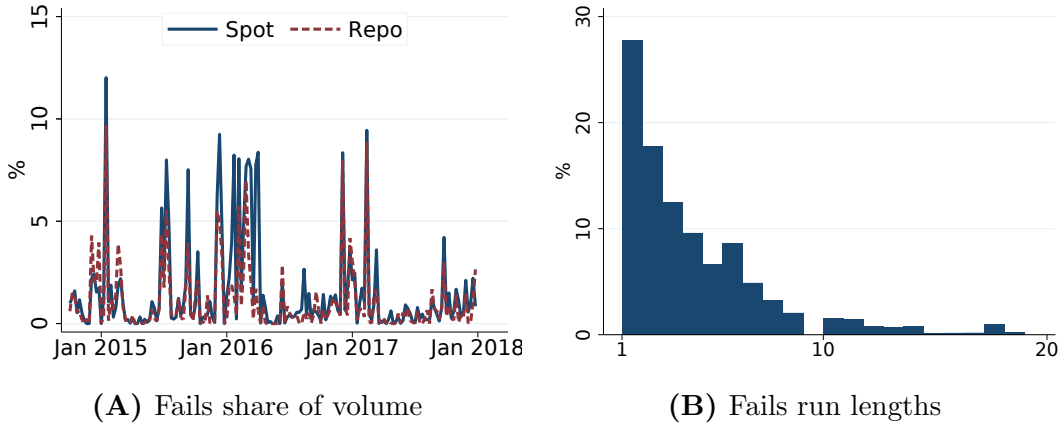
**Table 1: Episodes of Fails after Large News Surprises**

Select news release dates and the percentage of the settlement volume that fails for the 10-year benchmark bond during the corresponding week. We select the date with the largest surprise as measured by the deviation from the median analyst forecast for each of unemployment, retail sales, GDP and CPI news releases, respectively, as well as the largest surprise interest-rate change by the Bank of Canada.

Week Starting	Fails share of volume (%)	Event
19 Jan 2015	4.1	Interest rate cut
31 Aug 2015	1.3	Unemployment above forecast
18 Jan 2016	3.0	Retail Sales above forecast
29 Feb 2016	7.4	GDP above forecast
13 Feb 2017	5.1	CPI above forecast

**Figure 5: Settlement Fails**

Panel (A): weekly average of FAILS as a percentage of settlement volume for spot and repo market trades for the 10-year benchmark bond. Panel (B): full-sample histogram of run lengths. A run is defined as a continuous sequence of days where a given bond has FAILS greater than zero. Data are for the Government of Canada bond market for the years 2015 to 2017.



**Event study** Panel (A) of Table 7 reports the quantiles of these changes, separately for benchmark bonds and non-benchmark bonds (the 50th, 75th, 90th, 95th and 99th percentiles). For benchmark bonds, the increase in fails is \$400M and \$2,000M at the 95th and 99th percentile, respectively, which corresponds to 1 and 5 standard deviations. This means that the asymmetry increases and the tail becomes larger in the fails distribution after the news.<sup>18</sup> The impact for non-benchmark bonds is \$50M and \$260M, which corresponds to increases of 0.5 and 2.5 standard deviations.

For robustness, Panel (B) reports results for the same exercise but where we use the median COMPLEXITY to split the sample. The sub-sample with high COMPLEXITY includes the benchmark bonds (see, e.g., Figure 2). The results are qualitatively similar. The 95th and 99th percentile increases by \$170M and \$530M, respectively, for bonds with high COMPLEXITY. Overall, Table 7 shows that the impact of news on fails is highest for bonds with the benchmark status and with higher network COMPLEXITY.

**Quantile regressions** We estimate the coefficient on COMPLEXITY using quantile regressions around the news, so that we can control for other variables such as benchmark status, trading activity (e.g., settlement volume) and scarcity (e.g., repo spread) that are correlated

<sup>18</sup>There is no outward shift on the other side of this distribution.

with COMPLEXITY.

Table 8 presents results of quantile regressions targeting the 95th percentile. We include the same controls as in Table 5. The baseline regression (Column 1) includes the dummy variable AFTER with a value of 1 on the day of the news and the two following days. Again, we group these days because trades on the day of a news can settle T+1 and T+2. The AFTER coefficient estimate is positive and significant. The 95th quantile of fails is shifted by \$200M on days after news releases, which is around half the result for benchmark bonds in Table 7. The coefficient estimates of the control variables have the expected signs, indicating that bonds with higher volume, scarcer bonds and bonds that are more liquid exhibit more fails.

Next, we add either a BENCHMARK dummy or the dealer networks' COMPLEXITY to the baseline (Columns 2 and 3). Consistent with the results in Panel 7A, both coefficient estimates are significant and positive. Finally, we augment the baseline with both of these variables (Column 4). The coefficient estimate for COMPLEXITY is essentially unchanged and remains highly significant. By contrast, the coefficient estimates for BENCHMARK and NETWORK VOLUME are much smaller and become insignificant.

The results provide strong evidence that the increase in fails around news releases is much higher for dealer networks that are more complex, even after accounting for the possible mechanical increase due to a higher volume or to higher velocity. The evidence also suggests that the COMPLEXITY of dealer networks subsumes both BENCHMARK status, NETWORK VOLUME and VELOCITY. This suggests that the dealer network is the mechanism that connects the news to the increase in large fails.

The evidence unveils an important trade-off between trading immediacy and the counterparty risk in dealer networks. On the one hand, dealer networks become more complex around news releases because they accommodate the higher demand for intermediation. The settlement volume increases and dealers use more short positions, for which they must borrow bond to settle trades. On the other hand, the contagion of fails is more likely in complex dealer networks, which is a plausible mechanism because networks can lead to contagion when localized fails cascade through a sequence of transactions.

Note the close connection between the costs and benefits around news releases. If a settlement fail was a contractual default, the risk for dealers of selling bonds that they do not hold would be too high. Presumably, the costs of expanding the supply of intermediation

services would be higher than the small mark-ups increases documented above. A structural model would be needed to assess this conjecture, which we leave for future research.

### 3.4 Reverse Causality

We interpret the causal chain going from a news release to the expansion of dealer networks, and *then* resulting in increases in the incidence of contagion. However, the presence of central dealers opens the possibility of reverse causality from fails to changes in network complexity. In this alternative interpretation, the change in the complexity of a network after a news release could reflect a desire by investors to avoid counterparty risks associated with a counterparty's settlement fails. Traders may reduce the likelihood of incurring fails by diverting their trades from certain central dealers, either to diversify their exposures or because trading with less central dealers implies a lower risk. Under this hypothesis, the news causes a diversion of trades, which *then* causes the dealer network to become more complex. In this case, the increase in fails after news is simply the realization of the risk perceived by traders ex-ante.

We can test this interpretation. The key implication under this hypothesis is that the most central should become less central either in absolute terms or relative to other dealers. Panel (A) of Figure 6 reports the average change of centrality around news releases across all dealers. Centrality increases significantly for benchmark bonds after the news releases, by around 0.35 standard deviations, but not does increase significantly for non-benchmark bonds. This means that dealers' centrality increases as networks become more complex. Next, Panel (B) shows the same exercise but for the three most central dealers. If reducing the exposures to potential settlement delays is the primary motive for trading after the news releases, we should see that these dealers become less central. Instead, the centrality of these dealers increases by around 0.55 standard deviations. We checked that a similar result emerges if you use the number of outward links or the size of dealers' settlement obligations to identify those dealers with a higher probability of fails (unreported). Hence, we can set aside this reverse causality mechanism as a primary driver underlying our results.

### 3.5 Settlement Fails and Dealer Networks

The previous section measured exogenous variations in dealer networks around economic news releases. In the following, we use all bond-day observations to measure the strength of the relationship between dealer network complexity and settlement fails. To be clear, we do

not interpret this as causal evidence, but the results are useful to understand the empirical relevance of dealer networks to the propagation of fails.

We first estimate a logit model for the occurrence of some fails ( $> 0$ ) conditional on network metrics and other controls. This measures the relationship between the state of the dealer network and the likelihood of at least some fails. [Table 9](#) reports the results. We find that the likelihood of FAILS increases with the number of LINKS, PATHS, the AVGPATH and the DIAMETER. The effect is statistically significant even after controlling for market activity, bond scarcity, liquidity and bond characteristics. The signs of the estimated control coefficients are as expected; settlement fails are more likely for bonds that are more actively traded, scarce and liquid. However, the coefficient estimates for NETWORK VOLUME and BENCHMARK become insignificant when COMPLEXITY is also present in the regression. This is consistent with the previous results in Column 4 of [Table 8](#); the complexity of the network subsumes the information content of trading volume or benchmark status that is relevant to predict fails.

Panel (A) of [Figure 7](#) illustrates the partial effect on the likelihood of fails implied by the estimated Logit regression as we vary the value of each network metric between its first and last sample deciles, but holding all other variables to their median values. We find that COMPLEXITY has the largest impact on the predicted probability. Increasing the value of COMPLEXITY from its lowest to its highest decile raises the probability of fails from 20 percent to above 40 percent. We find similar results for LINKS, PATHS, AVGPATH and DIAMETER. Our results are also consistent with [Corradin and Maddaloni \(2019\)](#), who find that 1-basis-point change in the repo spread increases the probability of some fails by 0.32 percent. We find a similar but slightly stronger result: 1 basis point increases the probability by 0.8 percent. One reason for the difference is that our results are for Canada, while [Corradin and Maddaloni \(2019\)](#) study the bond market in Italy. Another reason is that we include data on both spot and repo trades.

We then estimate a linear model by ordinary least squares for the volume of settlement fails, conditional on the occurrence of some fails. [Table 10](#) shows that the complexity of dealer networks also predicts a higher volume of fails, conditional on some fails. Increasing COMPLEXITY from its first to last decile is associated with an increase in the expected volume of fails from around \$11M per bond to above \$34M, on average. The results are significant and robust. As expected, we also find that scarcity, trading volume and velocity predict a larger volume of fails volume, with significant estimates. Again, the coefficient for

the BENCHMARK dummy variable is not significant when COMPLEXITY is present in the regression.

We are particularly interested in relationship between COMPLEXITY and the tails of settlement fails, and not just on average volume, because of the potential for contagion to result in cascades of fails. Table 11 reports the coefficient estimates for COMPLEXITY from quantile regressions for the 75th, 90th, 95th and 99th percentiles. The regressions are otherwise identical to the specification in the fourth column of Tables 9-10. Panel (B) of Figure 7 illustrates the relationship between COMPLEXITY and each of these percentiles. As expected, the shift in the larger percentiles is much greater: the 95th percentile increases by \$120M from the first to last sample decile of COMPLEXITY.<sup>19</sup>

## 4 Clearing Trades

### 4.1 Central Counterparty

Our central result is that size and complexity of a dealer network are important amplifiers of contagion. The presence of a central counterparty (CCP) can shrink and simplify the network, potentially mitigating this mechanism. By providing multilateral netting, the CCP has the effect of replacing many interconnected settlement obligations fewer obligations and, in the extreme case where all trades are cleared by the CCP, the number of links and paths in the network would be the same as the number of counterparties, and the network diameter is two links.

Bond dealers in Canada have the option, but not the obligation, to clear spot and repo trades via a CCP. However, since the CCP's coverage of the market is partial, its effect on complexity may be small or it may even increase complexity.<sup>20</sup> We can assess the impact of CCP clearing by reconstructing counterfactual networks without a CCP.<sup>21</sup> Table 12 reports the summary statistics of the metrics. The left column reports the sample network statistics

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<sup>19</sup>Corradin and Maddaloni (2019) find that an increase in the repo spread of 1 basis point increases the share of the trading volume that fails by 0.05 percent. Repeating the regression in our sample but substituting the share of trading volume that fails as a dependent variable, we find that the effect of 1 basis point is 0.09 percent.

<sup>20</sup>See Deloitte (2018) for details about the evolution of the CCP for repo and spot transactions in Canada.

<sup>21</sup>This analysis focuses on just dealer-to-dealer trades because dealers were the only participants with access to the CCP in our sample period. We therefore limit construction of networks to just the dealer-to-dealer segment of the market. This does not affect the direction of the results, since dealer-to-client trades are unaffected in the counterfactual. We also limit our analysis to over-the-counter trades, since we are not able reconstruct the counterfactual network for trades done on trading platforms due to their anonymous nature. This does not affect the direction of our results as brokered trades are not more likely to be cleared.

and the right column reports counterfactual statistics computed after having replaced all links to the CCP with links to the original counterparties. The results show small but *positive* differences between the actual data and the counterfactual data, showing that, if anything, the CCP makes the network slightly larger and more complex. For instance, the CCP increases the number of LINKS from 4.5 to 5.3, the number of PATHS from 8 to 11 and the NETWORK VOLUME from \$278M to \$324M.

The main reason for the counterintuitive effect of the CCP is that it clears a relatively small share of trades, on average.<sup>22</sup> Table 13 reports the number of observations in sub-sample where the CCP handles less than 25 percent, 25 to 50 percent, 50 to 75 percent, or more than 75 percent of trades. For most of all bond-day observations ( $N \approx 23,000$ ), the CCP handles less than 25 percent of all trades. However, there are around 9,000, 6,000 and 2,000 observations in the next three sub-samples. Table 13 also reports a few summary statistics to look for a composition effect across these buckets. We find only small differences in VOLUME, REPO SPREAD, VELOCITY, B/A SPREAD, AGE and FLOAT across sub-samples.<sup>23</sup>

Duffie and Zhu (2011) examine the benefits from multilateral netting, showing that these decline rapidly if the CCP only clears a fraction of trades. The results here provide a case in point. It is interesting to note that dealers choose to direct only a small share of their trades to the CCP. This choice reflects the costs and benefits from clearing trades at the CCP (one of the costs is the higher margin requirements and one of the benefits is anonymity). This limits how much the CCP reduces the network complexity and the volume of settlement fails. In particular, in the absence of a coordination mechanism, an individual dealer’s decision to direct more trades to the CCP is unlikely to reduce settlement fails. Even if dealers as a group clear all of their trades, this does not maximize the netting benefits because a large segment of market participants are not members of the CCP.

## Conclusion

We analyze a unique dataset of trades, settlements, fails and counterparties in a large government bond market. Across more than 17,000 dealer settlement networks, we find that

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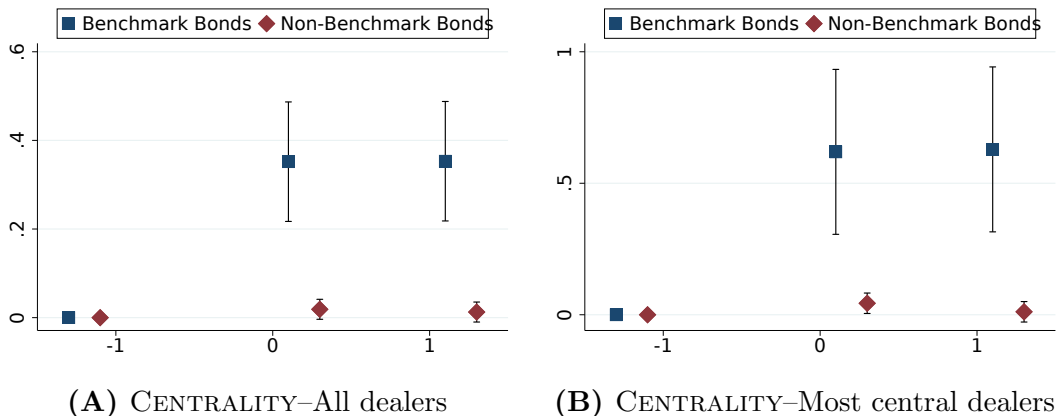
<sup>22</sup>In addition, Table 13 shows that where the CCP has larger coverage, networks tend to be smaller and the multilateral netting benefits also tend to be small.

<sup>23</sup>The analysis focuses on just inter-dealer trades because dealers were the only participants with access to the CCP in our sample period. This does not affect the direction of the results, since dealer-to-client trades are unaffected in the counterfactual. We also limit our analysis to over-the-counter trades, since we are not able to reconstruct the counterfactual network for trades done on trading platforms. This does not affect the direction of our results as brokered trades are not more likely to be cleared.

larger and more-complex network are associated with larger markups, higher probability of fails and a larger volume of fails. Following news events, we show that as the complexity of dealer networks increases, the intermediation quantity increases, and incidences of large cascades of settlement fails also increase. The evidence suggests that larger dealer networks create tradeoffs between intermediation benefits and counterparty risk. It also points to an important explanation for the emergence of market designs that allow a relatively benign penalty for settlement fails. Without this design feature, it could be too risky or too costly for dealers in large or complex networks to provide liquidity. The government bond market provides a rich environment for future research to study network formation, intermediation benefits and the propagation of counterparty risk.

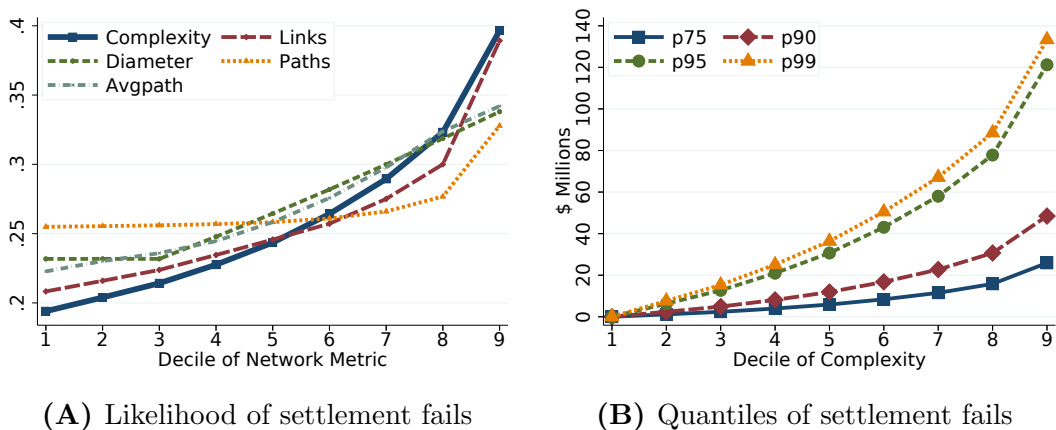
**Figure 6: Dealer Centrality and News**

Panels (A)-(B) report the average changes of dealers centrality on days with or after economic news releases, separately for benchmark and non-benchmark bonds. Time is 0 on the day of a news release and all variables are zero at time -1 by construction. The vertical lines show a 90 percent confidence interval. Data are for the Government of Canada bonds for the years 2016 and 2017. Table 2 provides all variable definitions.



**Figure 7: Dealer Networks and Settlement Fails**

Panel (A): partial effects of varying individual network metrics on the likelihood of fails, estimated with a logit regression. Each network metric varies between the first and last sample decile values, keeping all other variables at their respective sample median values. Panel (B): partial effects of varying individual network metrics on the quantile of fails volume estimated with quantile regressions. Each network metric varies between the first and last decile values, keeping all other variables at their respective sample medians. Data are for the Government of Canada bond market for the years 2016 and 2017. Table 2 provides all variable definitions.



# A Appendix

## *Settlement Data*

We label each trade in the Canadian Deposit for Securities (CDS) data either as a repo or spot trade, and we collect both the traded par value and the planned settlement date. There is one settlement order for each spot trade and two settlement orders for each repo trade. The first order is for the initial exchange of securities for cash, and the second order represents the return of the bond in exchange for the principal and interest. Together, these data represent the “trades” dataset. For each settlement fail, we collect the par value to settle, the planned settlement date and whether it was a spot or a repo trade. This represents the “fails” dataset. For each bond-day, we then combine the trades and the fails data sets to construct the total settlement volume: the sum of both the new and older failed settlement orders. The settlement fail date occurs after the planned settlement date, then this trade had failed on a prior date and failed again at a new delivery attempt. In this case, we deem the settlement failure an old fail. We exclude observations of settlement fails that are outstanding for more than five days.

For each day in our sample, the settlement volume includes both new trades and the previous day’s failed settlements:  $\text{Total volume}_t = \text{New settlement}_t + \text{Failed settlement}_{t-1}$ . We aggregate all trades by settlement date (and not by trade date) to compute the new settlement volumes for each bond-day. We provide a hypothetical example in the table below. Each record represents a new settlement order generated by a new trade. Note that there are two settlement orders for Trade ID 3 because it is a repo trade. Then bond ABC has 800 new settlement orders for May 3rd and 900 for May 4th.

ISIN	TradeID	Trade type	Trade date	Settlement date	Par value
ABC	1	Cash	May 1	May 3	100
ABC	2	Cash	May 1	May 3	200
ABC	3	Repo	May 3	May 3	500
ABC	3	Repo	May 4	May 4	500
ABC	4	Cash	May 2	May 4	400

We then sum all failed settlements for each bond-day, aggregating by fail date. We provide a hypothetical example below. Each record represents a settlement fail. In this example, the repo market settlement failure on May 4 indicates that the counterparty had failed to return bond ABC exchanged as collateral in a repo trade initiated on May 3. The fail volume for bond ABC was 100 for May 3rd and 500 for May 4th.

ISIN	Trade type	Trade date	Settlement date	Fail Date	Par value
ABC 1	Cash	May 1	May 3	May 3	100
ABC 3	Repo	May 4	May 4	May 4	500

Combining the aggregated trades dataset and the aggregated fails dataset, we have:

ISIN	Date	New	Failed	Prior days failed	Total volume
ABC	May 3	800	100	0	800
ABC	May 4	900	500	100	1000
ABC	May 5	0	0	500	500

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Table 2: **Description of Data**

Short name	Description	Unit	Source
<b>Bond Variables</b>			
REPO SPREAD	Target rate less repo rate	bps	CDCC
VELOCITY	Securities loan as a share of float	%	Markit
B/A SPREAD	Average daily bid-ask spread	cents	Candeal
SPOT MARKUP	Average dealer markup for spot trades	cents	MTRS
REPO MARKUP	Average dealer markup for repo trades	bps	MTRS
FLOAT	Bonds outstanding	Log-\$M	Thomson Reuters
AGE	Time since issuance	Years	CDS
BENCHMARK	Benchmark status dummy (2-, 5-, 10-, 30-year)	[0,1]	Bank of Canada
PRE-BENCHMARK	Pre-benchmark status dummy	[0,1]	Bank of Canada
<b>Network Variables</b>			
COUNTERPARTIES	Number of counterparties in network		
LINKS	Number of links in network		
PATHS	Number of paths in network		MTRS
AVGPATH	Average path length		
DIAMETER	Longest path length		
COMPLEXITY	First principal component of network variables		
<b>Volume and Fails Variables</b>			
NETWORK VOLUME	Sum of net link volumes	\$M	MTRS
FAILS	Daily failed volume	\$M	CDS
<b>Centrality Variables</b>			
IN-DEGREE	Average number of incoming links		
OUT-DEGREE	Average number of outgoing links		
EIG-CENTRALITY	Eigenvector centrality		
BETWEENNESS	Betweenness centrality		MTRS
CLOSENESS	Closeness centrality		
CLUSTERING	Clustering coefficient		
CENTRALITY	First principal component of centrality variables		
<b>Other Variables</b>			
GC	Bank of Canada target GC rate	bps	Bank of Canada

Note: Sources include the Canadian Depository for Securities (CDS); the Canadian Derivatives Clearing Corporation (CDCC); the DEX dataset on Canadian bond yields from FTSE TMX; and the Canadian bond dealers Market Trade Reporting System (MTRS).

Table 3: **Summary Statistics**

Summary statistics of bond data, network measures, volume and fails data. Table 2 provides the variable definitions and units. *Corr.* is the correlation with the first principal component, COMPLEXITY. Data are for the Government of Canada bond market for the years 2016 and 2017. Table 2 provides all variable definitions.

(A) Bond Data												
	Benchmark Bonds						Non-Benchmark Bonds					
	Mean	Std	p25	p50	p75	Corr.	Mean	Std	p25	p50	p75	Corr.
REPO SPREAD	8.5	9.5	2.1	5.4	11.6	0.25	3.8	7.1	0.0	1.8	5.1	0.30
VELOCITY	23.7	10.1	16.8	21.9	29.5	0.30	12.1	8.4	6.6	10.7	15.4	0.58
B/A SPREAD	2.9	1.6	1.1	3.0	3.8	0.46	4.6	4.3	1.0	2.9	8.3	0.01
SPOT MARKUP	9.4	8.3	3.0	7.0	13.6	0.44	15.0	23.4	2.0	5.8	17.7	0.16
REPO MARKUP	6.7	2.8	4.9	6.2	7.8	0.27	5.1	3.9	2.7	4.5	6.5	0.25
FLOAT	9.5	0.2	9.5	9.5	9.6	-0.13	8.9	1.0	9.0	9.2	9.5	0.47
AGE	0.8	0.4	0.4	0.7	1.2	0.41	7.4	7.8	1.9	4.0	9.4	-0.33
INVENTORY	-12.5	3.6	-15.0	-12.7	-10.2	-0.31	-3.9	4.4	-6.3	-2.8	-0.6	-0.60

(B) Network Measures												
	Benchmark Bonds						Non-Benchmark Bonds					
	Mean	Std	p25	p50	p75	Corr.	Mean	Std	p25	p50	p75	Corr.
LINKS	94.8	19.8	82.0	94.0	106.0	0.91	21.3	18.8	8.0	16.0	29.0	0.96
PATHS	1491.5	556.0	1118.0	1426.0	1799.5	0.97	133.7	281.9	12.0	34.0	120.0	0.83
AVGPATH	3.4	0.3	3.3	3.4	3.6	0.41	2.0	0.8	1.3	1.8	2.6	0.94
DIAMETER	7.5	1.1	7.0	7.0	8.0	0.21	4.2	2.3	2.0	4.0	6.0	0.91
COMPLEXITY	4.8	1.3	4.0	4.8	5.6	1.00	-0.3	1.7	-1.6	-0.7	0.7	1.00

(C) Volume and Fails												
	Benchmark Bonds						Non-Benchmark Bonds					
	Mean	Std	p25	p50	p75	Corr.	Mean	Std	p25	p50	p75	Corr.
NETWORK VOLUME	7316.1	3266.6	4881.8	6712.9	9201.0	-0.01	932.3	1216.8	211.1	586.7	1222.6	0.59
FAILS	148.1	415.8	0.0	1.1	110.0	0.15	19.2	103.6	0.0	0.0	0.0	0.21
SPOT FAILS	97.9	280.6	0.0	0.0	74.5	0.14	12.4	67.9	0.0	0.0	0.0	0.21
REPO FAILS	50.2	154.5	0.0	0.0	29.9	0.12	6.8	45.4	0.0	0.0	0.0	0.15

Table 4: **Centrality Summary Statistics**

Summary statistics of dealer centrality measures for benchmark and non-benchmark bonds, respectively. The last column reports the correlation between each measure and the first principal component CENTRALITY.

	Benchmark Bonds					
	Mean	Std	p25	p50	p75	Corr
IN-DEGREE	3.68	2.64	2.00	3.00	5.00	0.85
OUT-DEGREE	3.58	2.61	2.00	3.00	5.00	0.87
EIG-CENTRALITY	0.18	0.09	0.12	0.18	0.24	0.77
BETWEENNESS	165.02	171.13	45.04	118.09	226.88	0.94
CLOSENESS	0.39	0.05	0.37	0.40	0.42	0.72
CLUSTERING	0.05	0.10	0.00	0.00	0.05	0.10
CENTRALITY	2.63	2.74	0.70	2.19	3.90	1.00
	Non-Benchmark Bonds					
	Mean	Std	p25	p50	p75	Corr
IN-DEGREE	1.44	1.41	1.00	1.00	2.00	0.68
OUT-DEGREE	1.47	1.39	1.00	1.00	2.00	0.69
EIG-CENTRALITY	0.25	0.17	0.12	0.22	0.34	0.52
BETWEENNESS	23.96	63.38	0.00	2.00	18.00	0.76
CLOSENESS	0.40	0.15	0.31	0.38	0.44	0.49
CLUSTERING	0.01	0.06	0.00	0.00	0.00	0.27
CENTRALITY	0.47	1.39	-0.48	0.19	1.07	1.00

Table 5: **Price Markup and Centrality**

Regression of the price markups clients paid or received on the centrality metrics in the spot market (left panel) and the repo market (right panel). The regressions include fixed effect as well as control variables: COMPLEXITY NETWORK VOLUME, REPO SPREAD, VELOCITY, B/A SPREAD, FLOAT and AGE. The symbols \*, \*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 percent level, respectively, in a test of the null hypothesis that the true parameter is zero. Standard errors are clustered by date. Data are for the Government of Canada bond market for the years 2016 and 2017. Table 2 provides all variable definitions.

	Spot			Repo		
	(1)	(2)	(3)	(1)	(2)	(3)
DEALER CENTRALITY	0.22** (2.51)			0.019 (0.087)		
CLIENT CENTRALITY		-0.84*** (-11.2)			-0.61*** (-3.00)	
$\Delta$ CENTRALITY			0.46*** (26.6)			0.25*** (20.9)
Observations	329243	328613	316845	168951	136456	132816
Adjusted $R^2$	0.26	0.27	0.27	0.08	0.10	0.09

Table 6: **Moments of Settlement Fails**

Summary statistics for the fraction of trades that fails, in percentage terms, for the empirical distribution and two simulations. Binomial assumes that settlement fails are independent of each other, with the probability calibrated to the average rate of settlement failure; and the binomial assumes that settlement fails are correlated with the correlation parameter  $\rho$  calibrated to match the variance of the settlement fails. We exclude bond-days with fewer than 10 trades. Zeros report the number of bond-days in the sample where there are no failed settlement. Data are for Government of Canada bonds market for Q4 2014 to Q4 2017. Table 2 provides all variable definitions.

	Zeros	Mean	Variance	p75	p95	p99	N
Empirical	12450	0.54	3.71	0.00	3.57	8.33	15013
Beta-binomial $\rho \neq 0$	12851	0.54	3.70	0.00	3.85	9.52	15013
Binomial $\rho = 0$	10831	0.54	1.70	0.42	3.08	6.25	15013

Table 7: **Settlement Fails and News**

Quantiles of the change in settlement fails. The change in fails for each bond as the difference in the level of fails on the day prior to the release and the level of fails for the day of the release and the following two days. Panel (A) shows the quantiles for benchmark and non-benchmark bonds. Panel (B) shows the quantiles for bonds with high and low COMPLEXITY, respectively, relative to the median COMPLEXITY value on the day before the news release. \*,\*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 percent level, respectively, in a test of the null hypothesis that the quantile of the changes is zero. Data are for Government of Canada bonds market for the years 2016 and 2017. Data are for Government of Canada bonds market for the years 2016 and 2017. Table 2 provides all variable definitions.

Panel (A) Status

		Benchmark Bonds				
		p50	p75	p90	p95	p99
Change in Fails		0.0	31.2**	210.8***	407.0***	1965.5***
		Non-Benchmark Bonds				
		p50	p75	p90	p95	p99
Change in Fails		0.0	0.0	5.4***	51.0***	259.0***

Panel (B) COMPLEXITY

		High COMPLEXITY				
		p50	p75	p90	p95	p99
Change in Fails		0.0	0.2*	56.8***	170.4***	531.7***
		Low COMPLEXITY				
		p50	p75	p90	p95	p99
Change in Fails		0.0	0.0	0.0	5.0***	87.0***

Table 8: News, Dealers Network and Fails – Quantile Regressions

Quantile regressions of the change in settlement FAILS around news releases at the 95th percentile, including control variables. The independent variable is the change in fails around economic new releases, computed for each bond and for each news release as the difference in the level of fails between the day prior and the day of the news as well as the following two days. AFTER is the baseline increase in these three days. \*, \*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 percent level, respectively, in a test of the null hypothesis that the true parameter is zero. Standard errors are clustered by date. Data are for Government of Canada bonds market for the years 2016 and 2017. Table 2 provides all variable definitions.

	(1)	(2)	(3)	(4)
AFTER	215.5*** (4.35)	83.6 (1.39)	471.0*** (11.2)	421.3*** (7.91)
BENCHMARK		226.4*** (2.70)		84.5 (1.50)
COMPLEXITY			37.2*** (10.8)	32.5*** (7.86)
NETWORK VOLUME	3.57*** (3.93)	0.48 (0.33)	-0.51 (-0.70)	-0.78 (-1.07)
REPO SPREAD	1010.4*** (6.53)	837.8*** (10.5)	483.7*** (8.60)	509.5*** (5.00)
VELOCITY	3.93*** (8.87)	3.13*** (4.64)	0.92* (1.86)	1.12** (2.33)
B/A SPREAD	497.5*** (5.15)	360.6*** (3.24)	-15.8 (-0.29)	37.7 (0.57)
FLOAT	-22.8*** (-4.60)	-7.86 (-1.19)	-41.1*** (-10.0)	-36.6*** (-7.29)
PRE-BENCHMARK	-13.1 (-0.77)	20.2 (0.87)	-53.1*** (-2.92)	-49.7*** (-3.15)
AGE	-3.95*** (-5.72)	-2.16*** (-3.07)	-2.15*** (-5.14)	-2.24*** (-4.62)
Observations	5314	5314	5314	5314
$R^2$	0.00	0.00	0.00	0.00

Table 9: The Likelihood of Fails and Dealer Networks

Regression of the log-odds of the dummy variable  $D_{FAILS_{i,t}}$  that takes the value of 1 if FAILS are not zero for bond  $i$  and date  $t$  on the network variables, bond variables and bond fixed effects. Columns (1)-(3) provide baseline results based on control variables. Columns (4)-(8) provide results adding one network metric at a time. \*, \*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 percent level, respectively, in a test of the null hypothesis that the true parameter is zero. Standard errors are clustered by date. Data are for Government of Canada bonds market for the years 2016 and 2017. Table 2 provides all variable definitions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COMPLEXITY				0.20*** (10.1)				
LINKS					0.016*** (9.27)			
DIAMETER						0.090*** (7.86)		
AVGPATH							0.26*** (8.03)	
PATHS								0.00054*** (6.99)
NETWORK VOLUME	0.13*** (6.09)			0.026 (1.09)	0.036 (1.50)	0.076*** (3.15)	0.070*** (2.90)	0.088*** (3.78)
REPO SPREAD		0.046*** (20.7)		0.031*** (6.66)	0.032*** (6.67)	0.035*** (7.40)	0.034*** (7.29)	0.033*** (6.95)
VELOCITY			0.022*** (9.08)	0.0085** (2.48)	0.0087** (2.50)	0.013*** (3.86)	0.012*** (3.60)	0.012*** (3.47)
BENCHMARK	0.56*** (6.19)	0.84*** (13.6)	0.72*** (11.5)	-0.078 (-0.78)	-0.25** (-2.18)	0.38*** (4.17)	0.34*** (3.73)	-0.075 (-0.66)
B/A SPREAD	2.43 (1.14)	2.54 (1.56)	4.15*** (2.92)	1.26 (0.55)	1.48 (0.64)	0.37 (0.16)	0.56 (0.24)	0.68 (0.30)
FLOAT	0.17 (1.37)	0.61*** (7.55)	0.35*** (4.27)	-0.00054 (-0.0041)	-0.0094 (-0.073)	0.11 (0.83)	0.11 (0.84)	0.075 (0.58)
PRE-BENCHMARK	-0.63*** (-3.83)	0.017 (0.16)	-0.27** (-2.56)	-0.36** (-2.09)	-0.35** (-2.03)	-0.35** (-2.06)	-0.34** (-2.00)	-0.29* (-1.70)
AGE	0.15*** (3.03)	0.22*** (9.01)	0.092*** (3.82)	0.17*** (3.27)	0.16*** (3.06)	0.14*** (2.72)	0.14*** (2.78)	0.13** (2.51)
Observations	18191	31083	33509	17704	17704	17704	17704	17704
Pseudo $R^2$	0.10	0.12	0.12	0.11	0.11	0.10	0.10	0.10

Table 10: **Fails Size and Dealer Networks—OLS**

OLS regression of log failed volume  $FAILS_{i,t}$  conditional on bond  $i$  exhibiting at least one failed trade at date  $t$ , including controls and bond fixed effects. Columns (1)-(3) provide baseline results based on control variables. Columns (4)-(8) provide results adding one network metric at a time. \*, \*\*, and \*\*\* indicate statistical significance at the 10, 5 and 1 percent level, respectively, in a test of the null hypothesis that the true parameter is zero. Standard errors are clustered by date. Data are for Government of Canada bonds market for the years 2016 and 2017. Table 2 provides all variable definitions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COMPLEXITY				0.19*** (5.26)				
LINKS				0.016*** (6.19)				
DIAMETER				0.071*** (3.12)				
AVGPATH							0.24*** (3.65)	
PATHS								0.00050*** (4.46)
NETWORK VOLUME	0.32*** (7.92)			0.23*** (4.80)	0.22*** (4.74)	0.29*** (6.29)	0.28*** (5.94)	0.28*** (6.36)
REPO SPREAD		0.067*** (18.8)		0.065*** (8.93)	0.065*** (8.86)	0.069*** (9.42)	0.068*** (9.28)	0.066*** (9.09)
VELOCITY			0.034*** (6.93)	0.011 (1.63)	0.0096 (1.43)	0.016** (2.35)	0.014** (2.18)	0.014** (2.07)
BENCHMARK	0.74*** (4.56)	0.89*** (8.35)	0.75*** (6.57)	0.085 (0.47)	-0.13 (-0.68)	0.47*** (2.85)	0.44*** (2.67)	0.053 (0.28)
B/A SPREAD	1.47 (0.36)	-0.76 (-0.23)	0.12 (0.041)	1.20 (0.27)	1.75 (0.40)	0.37 (0.084)	0.58 (0.13)	0.76 (0.17)
FLOAT	-0.97*** (-4.09)	0.049 (0.31)	-0.36** (-2.18)	-0.92*** (-3.64)	-0.95*** (-3.73)	-0.80*** (-3.16)	-0.81*** (-3.19)	-0.87*** (-3.44)
PRE-BENCHMARK	-1.68*** (-5.48)	-0.46** (-2.34)	-0.82*** (-4.19)	-0.98*** (-3.21)	-0.97*** (-3.17)	-1.00*** (-3.24)	-0.99*** (-3.23)	-0.96*** (-3.10)
AGE	-0.039 (-0.48)	-0.30*** (-6.49)	-0.54*** (-11.2)	-0.0066 (-0.078)	-0.0098 (-0.12)	-0.045 (-0.54)	-0.037 (-0.44)	-0.047 (-0.57)
Observations	5529	8536	8639	5486	5486	5486	5486	5486
Adjusted $R^2$	0.13	0.18	0.15	0.15	0.15	0.14	0.14	0.14

Table 11: **Fails Sizes and Dealer Networks—Quantile Regressions**

Quantile regression of  $FAILS_{i,t}$  on  $COMPLEXITY$  at the 75th, 90th, 95th and 99th percentiles, including controls as in Table 9 and bond fixed effects. The \*,\*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 percent level, respectively, in a test of the null hypothesis that the true parameter is zero. Standard errors are clustered by date. Data are for the Government of Canada bond market for the years 2016 and 2017. Table 2 provides all variable definitions.

	p75	p90	p95	p99
COMPLEXITY	0.15*** (3.98)	0.11*** (3.50)	0.11*** (3.75)	0.080*** (2.91)
Observations	5487	5487	5487	5487
$R^2$	0.14	0.13	0.12	0.11

Table 12: **Central clearing and network complexity**

Mean of network measures for inter-dealer trades both in the actual data and for the counterfactual where we disconnect the CCP, in the column labelled CCP and No CCP, respectively. The last column reports the difference between the means. The symbols \*,\*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 percent level, respectively, in a test of the null hypothesis that difference  $\Delta$  is zero. Data are for the Government of Canada bond market for the years 2016 and 2017. Table 2 provides all variable definitions.

	CCP	No CCP	$\Delta$
COMPLEXITY	0.27	-0.27	0.54***
COUNTERPARTIES	6.78	6.22	0.56***
LINKS	5.27	4.53	0.74***
DIAMETER	2.29	1.90	0.39***
PATHS	11.15	8.02	3.13***
AVGPATH	1.39	1.25	0.14***
NETWORK VOLUME	324.21	277.99	46.22***

Table 13: **Central Clearing Summary Statistics**

Summary statistics of inter-dealer trades in sub-samples defined by the share of transactions centrally. Data are for the Government of Canada bond market for the years 2016 and 2017. Table 2 provides all variable definitions.

	0%-25%	25%-50%	50%-75%	75%-100%
NETWORK VOLUME	301.11	379.15	240.76	111.93
REPO SPREAD	0.03	0.04	0.04	0.03
VELOCITY	15.37	17.29	14.48	12.24
B/A SPREAD	0.04	0.03	0.03	0.03
FLOAT	9.33	9.41	9.32	9.17
AGE	5.21	4.22	5.22	5.48
Observations	23098	9298	6088	1896