OTC Intermediaries

Andrea L. Eisfeldt
Anderson School of Management, University of California, Los Angeles
andrea.eisfeldt@anderson.ucla.edu

Bernard Herskovic
Anderson School of Management, University of California, Los Angeles
bernard.herskovic@anderson.ucla.edu

Sriram Rajan
Office of Financial Research
sriram.rajan@ofr.treasury.gov

Emil Siriwirawane
Harvard Business School, Harvard University
esiriwardane@hbs.edu

The Office of Financial Research (OFR) Working Paper Series allows members of the OFR staff and their coauthors to disseminate preliminary research findings in a format intended to generate discussion and critical comments. Papers in the OFR Working Paper Series are works in progress and subject to revision.

Views and opinions expressed are those of the authors and do not necessarily represent official positions or policy of the OFR or Treasury. Comments and suggestions for improvements are welcome and should be directed to the authors. OFR working papers may be quoted without additional permission.
OTC Intermediaries*

Andrea L. Eisfeldt†, Bernard Herskovic‡, Sriram Rajan§, Emil Siriwattane¶

Current Draft: May 28, 2020

Abstract

We estimate the systemic effects of exit by a key over-the-counter (OTC) intermediary. In our model, risk-averse traders are connected by a core-periphery network. If traders are also averse to concentrated bilateral exposures then the incomplete network prevents full risk sharing. We quantify the impact of the network structure on prices using the closed-form solution to our model and proprietary data on all credit default swap (CDS) transactions in the U.S. from 2010-2013. There are a small number of key OTC intermediaries whose exit can move markets dramatically. Eliminating one of these leads credit spreads to increase over 20%.

Keywords: OTC markets, networks, intermediaries, dealers, systemic risk, credit default swaps

*The Office of Financial Research (OFR) Working Paper Series allows members of the OFR staff and their co-authors to disseminate preliminary research findings in a format intended to generate discussion and critical comments. Papers in the OFR Working Paper Series are works in progress and subject to revision. Views and opinions expressed are those of the authors and do not necessarily represent official positions or policy of the OFR or U.S. Department of the Treasury. Comments and suggestions for improvements are welcome and should be directed to the authors. OFR working papers may be quoted without additional permission.

We are very grateful to the Macro Financial Modeling Project at the Becker Friedman Institute for generous grant funding. We thank participants at the Laboratory for Aggregate Economics and Finance OTC Conference, Laboratory for Aggregate Economics and Finance Women in Macroeconomics Conference, Society for Economic Dynamics, Conference on OTC Markets and Their Reform by the SNSF, NBER Conference on Financial Market Regulation, Chicago Booth Recent Advances in Empirical Asset Pricing conference, the Macro Financial Modeling Annual Meeting, Rome Junior Finance Conference, Lubrafin, the Maryland Junior Finance Conference, NBER 2018 Summer Asset Pricing Meetings, Junior Workshop in New Empirical Finance at Columbia University, FMA Conference on Derivatives and Volatility, and Western Finance Association. We also thank seminar participants at the UCLA Macro Finance lunch, UCLA Finance Brown Bag, Pontifical Catholic University of Rio de Janeiro (PUC-Rio), University of Washington, Central Bank of Chile, Federal Reserve Bank of Dallas, Federal Reserve Board, and Office of Financial Research for helpful comments and suggestions.

†Finance Area, Anderson School of Management, University of California, Los Angeles, and NBER, e-mail: andrea.eisfeldt@anderson.ucla.edu
‡Finance Area, Anderson School of Management, University of California, Los Angeles, e-mail: bernard.herskovic@anderson.ucla.edu
§Office of Financial Research, United States Department of the Treasury, e-mail: sriram.rajan@ofr.treasury.gov
¶Finance Unit, Harvard Business School, Harvard University, Boston, e-mail: esiriwardane@hbs.edu
1 Introduction

A substantial portion of global financial assets are traded in over-the-counter (OTC) markets, including virtually all corporate bonds, sovereign fixed-income instruments, and swaps (e.g. interest rate, currency, and credit). The distinctive feature of trade in OTC markets is that it occurs bilaterally between pairs of counterparties who are connected through a network, one that typically features a small set of central intermediaries or dealers. During the 2008 Global Financial Crisis, the financial distress of these dealers – most notably Lehman Brothers – seemingly impacted the functioning of many OTC markets (see Figure 1 for a timeline of events affecting key OTC intermediaries in the credit default swap (CDS) market). These events raised important questions about how trading frictions in OTC markets impacts prices and whether it is possible to estimate in real-time how markets would respond to the loss of a systemically important OTC intermediary.

To address these questions, we build a tractable model of OTC markets and calibrate it using transaction-level data in the CDS market. A key feature of our model is that traders are connected by an incomplete network, meaning trade cannot occur between every pair of possible counterparties. This assumption reflects the fact that most OTC networks are characterized by a core-periphery structure, in which a core set of interconnected dealers trade with each other and with a peripheral set of clients. Traders in the network are risk averse over future payoffs and are endowed with different exposures to aggregate default risk. Endowing traders with varying exposure to fundamental default risk is our way of modeling, say, ex-ante cash positions in risky bonds or loans. Consequently, traders are heterogeneous in their effective willingness to bear default risk in the CDS market.\(^1\) Agents can trade away from their initial risk exposure by entering into bilateral CDS contracts with their connected trading partners.

Another key assumption in our setup – and one that we confirm empirically – is that traders prefer to spread their positions across multiple counterparties, as opposed to building up large, concentrated bilateral exposures. In practice, there are several reasons why traders may wish to spread trades across counterparties, including risk-management requirements (e.g., position limits) or the desire to conceal private information.\(^2\) In the model, this assumption means that traders must balance their desire to hedge aggregate default risk at the best possible price against relying too much on a single trading partner.

When the network is core-periphery, we show that there is a closed-form equilibrium mapping between our model’s structural parameters and easily observable moments in the data. We take advantage of this tractability when calibrating the model using a proprietary dataset covering virtually all CDS trades in the United States from 2010 to 2013. The data is provided to the Office of Financial Research (OFR) by The Depository Trust & Clearing Corporation (DTCC).

Before using the data to calibrate the model, we first verify that our model’s main assumptions

---

\(^1\) Aversion to overall exposure to aggregate risk factors can be motivated by standard risk management practices (see Dynkin, Dor, Deslee, Guan, Hyman, Konstantinovsky, Maitra, Ng, Phelps, and Polbennikov (2016), and many others). In the Internet Appendix, we show that disagreement can also be used to generate trade in our model.

\(^2\) See, for example, Saita (2007).
are likely to hold in the CDS market. Consistent with our treatment of the network in the model, we show that the U.S. CDS network is well-described by a core-periphery network, with fourteen core dealers facilitating trade for the entire market. Furthermore, the network is extremely persistent, meaning new connections between the institutions that trade CDS are rarely formed and existing connections are rarely broken – in a given week, the probability of either event happening is less than 1%. Importantly, we also provide direct evidence supporting the assumption that CDS traders are averse to concentrated bilateral exposures, i.e. that they prefer to spread bilateral exposures across multiple counterparties. In particular, we show that traders afford larger price concessions to counterparties with whom they have relatively low existing concentration, while demanding better terms from counterparties with whom they already maintain large positions. Again, there are several reasons for this, including the difficulty of making new connections on short notice, hold-up costs, and costs of information release.

After we provide empirical support for our main assumptions, we then measure two key properties of the data that we use to calibrate the model. Here, we leverage the fact that our model has a closed-form solution when the network is core-periphery. In particular, we infer the structural parameters governing aversion to aggregate risk and concentrated bilateral exposures based on: (i) the net CDS position of dealers and (ii) price dispersion, defined as the difference between CDS spreads in dealer-dealer transactions and dealer-customer transactions. In our sample, we find that dealers are on average net sellers of credit protection in the CDS market, providing roughly $0.04 of notional insurance on aggregate credit risk for each dollar of their equity. Moreover, net selling of CDS protection is extremely concentrated, with a handful of dealers providing the bulk of credit protection. In terms of pricing, we estimate that CDS spreads in dealer-dealer transactions are five percent lower than spreads in dealer-customer transactions.

We then use the calibrated model to answer two important questions. First, what is the quantitative effect of the incomplete network on the level and dispersion of CDS spreads? Second, what is the systemic effect of removing a key OTC intermediary from the network?

We answer the first question by benchmarking our economy against a complete network, in which all agents can trade with each other. We estimate that the average level of credit spreads in customer-dealer trades is three percent lower than it would be if the network were complete, or if there was no aversion to bilateral concentration. This distortion arises because the incomplete network prevents the market from fully sharing risks, as long as there exists aversion to bilateral concentration. Because dealers are at the core of the network, equilibrium spreads are more sensitive to their relative risk-bearing capacity than they would be if the network were complete. During our sample, dealers are net sellers overall, indicating that they have high risk-bearing capacity compared to the customer sector. Thus, spreads are lower than in the complete network case because dealers are more willing to take on credit risk. As we show later in our stress tests, removing a few key dealers from the core can move the dealer sector from being a net supplier to a net demander of credit insurance. When this happens, spreads are instead distorted upward relative to the complete network benchmark. More generally, this analysis suggests that OTC intermediaries play a key role
in pricing aggregate credit risk.

Our framework also provides one explanation for the observed price dispersion in the data, and in particular, why dealer-dealer trades occur at lower CDS spreads than customer-dealer trades. From the perspective of the model, the fact that dealers are typically net sellers of CDS protection implies that they have lower pre-trade exposure to aggregate credit risk than customers. If risk-sharing were perfect, then dealers would sell enough CDS protection to customers such that both groups would have equal overall post-trade exposure to aggregate credit risk. In our setting, risk-sharing is limited because agents trade off the costs of concentrated bilateral exposures against the benefits of default insurance. Imperfect risk sharing means that the post-trade exposure of dealers to aggregate credit risk remains less than that of customers. In turn, dealers pay lower spreads when purchasing credit protection from other dealers in equilibrium because, as a group, they would prefer to take more credit risk in the CDS market, not hedge it. By our estimates, credit spreads in dealer-dealer trades are nearly five percent lower than those in customer-dealer trades and almost seven percent lower than the average level of spreads that would prevail in a fully-connected economy. Though there are certainly other potential sources of price dispersion, such as market power, empirically, we provide evidence that a sizable portion of the observed price dispersion in the data is unlikely to be caused by strategic pricing. In our calibration, we use only this portion of price dispersion to infer traders’ aversion to concentrated bilateral exposure.

In the second application of our model, we return to our motivating question of what happens to OTC markets when a key intermediary fails. Akin to a market-wide stress test, we remove a dealer from the economy by exogenously breaking all of its connections with other agents, effectively removing that dealer’s risk-bearing capacity and ability to intermediate. Then, we re-equilibrate the model to obtain new prices and allocations. A persistent challenge in the study of systemic risk has been to quantitatively measure and model the ability of remaining traders to reallocate risk after a key intermediary is lost. Our core-periphery model allows us to overcome this challenge and present quantitative results of pricing effects conditional on equilibrium reallocation.

Empirically, dealers’ net positions vary widely, and we find that removal of a dealer from the model network has very different effects on prices depending on the specific dealer’s net position. The data show that the distribution of dealer risk bearing capacity is highly skewed, with the majority of net insurance provided by small number of key OTC intermediaries. When the largest net seller among the dealers fails, the average credit spread in dealer-dealer trades increases roughly 31 basis points, more than a 20 percent increase over the average observed spread of 133 basis points in the data. In contrast, we find that the failure of a dealer with median risk bearing capacity has a minimal effect on prices, both in the dealer-dealer market and the customer-dealer market. Furthermore, the failure of a dealer who is a net buyer of CDS can actually lead to lower spreads upon removal. This is intuitive, as removing this dealer’s net insurance demand, and their high marginal cost of bearing credit risk, allows the remaining dealers to price the remaining risk at lower spreads.

The large effects of a key OTC intermediary exiting depend entirely on OTC market frictions.
That is, it is not the removal of a key OTC intermediary’s risk-bearing capacity alone that leads to a large increase in credit risk prices. Instead, the incomplete nature of the network, plus the fact that within the dealer sector risk sharing is imperfect, prevents other other agents in the network from being able to step in and counter the effects of a failed dealer. To show this, using our estimated parameters, we document that in the counterfactual world in which the network is complete, there is almost no effect on prices when the dealer that is the largest net seller fails. The effect of removing a key dealer is essentially fully alleviated in the complete network case because everyone can trade with each other directly, so risk is reallocated relatively easily across all agents. A similar intuition holds when agents have very little aversion to concentrated bilateral exposures. In that case, risk sharing is improved across the entire network, thereby dampening the impact that the failure of a single dealer has on the level of CDS spreads.

Overall, these stress tests highlight why connectivity alone provides an incomplete view of which dealers are systemically important—one must also consider net exposures when thinking about systemic importance. Put differently, accounting for the interplay between the network structure and the distribution of risk-bearing capacity is crucial for identifying whether the failure of a dealer has a material impact on asset prices. Dealers’ accumulated positions provide information about their equilibrium risk-bearing capacities, as well as their role in reallocating risk through the core-periphery network. Intuitively, systemically important dealers are both highly connected and provide a large share of credit insurance.

Our paper contributes to several strands of research in systemic risk measurement and asset pricing. The specific modeling technique that we use in this paper is closely related to two recent papers on OTC markets and networks. Our objective function and endowment structure build on the model in Atkeson, Eisfeldt, and Weill (2015), though their market setup is very different. In their search-based model, all institutions are fully connected whereas we model a network trading structure with an emphasis on the role of limited connections. Moreover, while Atkeson, Eisfeldt, and Weill (2015) also study equilibrium dealer entry and exit decisions in OTC markets, our study is complementary in that it provides quantitative measures of market resilience. Our network structure is also related to interbank network modeled in Denbee, Julliard, Li, and Yuan (2014), but again with important differences. In particular, a key difference is that our model features endogenous bilateral quantities and endogenous market-clearing prices. Also, while Denbee, Julliard, Li, and Yuan (2014) focus on estimating the degree of strategic complementarity in the U.K.’s interbank borrowing market, we study on the role of core dealers in CDS market pricing and systemic stability.

The broad motivation for this paper draws on a large body of work that examines systemic risk in financial networks. We advance this literature by asking how network frictions impact OTC asset prices in times of stress, as opposed to how liquidity and default spirals propagate through the banking system (see Allen and Gale (2000), Eisenberg and Noe (2001), and Acemoglu,

---

3Both models generate price dispersion from imperfect risk sharing. Our approach has the advantage of leading to a smooth objective function, and to variation in trade sizes. Furthermore, in our framework, agents are price takers and we solve for a competitive equilibrium with market clearing prices instead of Nash bargaining.
Our network model provides a practical framework for policy makers to evaluate systemically important institutions in OTC markets, one that can be implemented in real time and could also be easily extended to other OTC markets. In particular, our paper suggests that regulators only need to measure a few simple properties of the data — the shape of the network, the degree of price dispersion, and the net positions of core intermediaries — in order to use our model to quantitatively assess the effect on prices from the loss of a systemically important dealer. We also contribute to the debate on the identity of systemically important financial institutions by arguing that the risk bearing capacity of a dealer plays a crucial role in determining whether it is systemically important, not just its level of connectivity or centrality. In our model, systemically important financial institutions are both in the core of the network, and are large net providers of credit protection.

In addition to providing guidance for how OTC markets might respond in times of stress, we also provide insights on how network frictions — the combination of the incomplete network plus aversion to concentrated exposures — impact the level of CDS spreads during normal times. In doing so, we bridge the literature on systemic risk to the literature on asset pricing in financial networks. In normal times, we find that spreads in the customer-dealer and dealer-dealer markets are respectively 3% and 7% lower than they would be if the trading network were complete. An early example of structural estimation of OTC market pricing is Gavazza (2016), which studies a structural search model estimated using aircraft transaction data. That paper also finds that prices are lower than their Walrasian counterpart. The fact that network frictions distort equilibrium credit spreads in normal times is a relatively new mechanism that is highlighted by our model, and one that is transparent because our equilibrium admits closed-form solutions for prices and quantities. Moreover, if dealers are net sellers of CDS protection and are more likely to exit in times of stress, then our calibrated model indicates that spreads will be counter-cyclically higher than in a complete network during periods of stress, but lower during normal times. In this respect, we also add to a long literature on the determinants of credit spreads (see Augustin, Subrahmanyam, Tang, and Wang (2016) for a recent survey).

In the asset pricing literature, OTC markets have been traditionally studied through the lens of search-theoretic models (Duffie, Gârleanu, and Pedersen 2005, Lagos and Rocheteau 2009). We depart from this tradition by explicitly incorporating a core-periphery network into our model, as this is a key feature of OTC markets in practice (e.g., Hollifield, Neklyudov, and Spatt (2017) or Peltonen, Scheicher, and Vuillemey (2014)). We incorporate the network into our model because

---

4 In related work in mathematical finance, Cont and Minca (2016) use publicly available aggregate CDS data and a random graph framework to ask how liquidity shocks cascade through derivatives networks. The fixed point they study is the number of nodes that fail after a liquidity shock, whereas we focus on equilibrium asset pricing effects.


6 The large literature on network formation started with the work by Jackson and Wolinsky (1996) and Bala and Goyal (2000). More specifically, the emergence of core-periphery networks have been widely studied, including the
it allows us to more directly measure how the failure of a core dealer impacts market outcomes. Stress tests of this kind are harder to conduct in the standard search framework because dealers are typically homogeneous in those models. Relatedly, the intermediary asset pricing literature emphasizes the role of dealers in asset pricing, but typically analyzes intermediaries at a sectoral rather than individual level.\footnote{Recent examples of asset pricing research on intermediaries includes He and Krishnamurthy (2013), Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017), and Siriwardane (2018).} However, as we document, the distribution of net selling within the dealer sector is highly skewed. In our simulations, heterogeneity across dealers is why the response of the market to a dealer failure is highly dependent on the specific dealer that we remove.

Another salient feature of our OTC network model is price dispersion, which in our context means that dealer-dealer trades occur at lower CDS spreads than customer-dealer trades. The prevailing explanations for price dispersion in OTC markets generally center around inventory holding costs Colliard, Foucault, and Hoffmann (2018) or market power Di Maggio, Kermani, and Song (2017). In our model, average holding costs increase with total credit exposure, consistent with risk management considerations. With respect to market power, we show that dispersion exists even in a subset of transactions between dealers and customers in the top 10\% of trading volume. Thus, we argue that heterogeneity in risk bearing capacity (holding costs), combined with an aversion to trading too much with any one counterparty, is a quantitatively important driver of observed price dispersion.

Price dispersion exists in equilibrium in our model because the incomplete network and aversion to bilateral concentration prevent agents from equating their marginal costs of risk bearing or fully exploiting observed price dispersion across counterparties. Indeed, our finding that price concessions depend on the relative size of bilateral exposures refines the traditional notion of counterparty risk in OTC markets. Researchers have used a counterparty’s financial health to measure its risk as a trading partner (Arora, Gandhi, and Longstaff (2012)). Intuitively, though, traders are less likely to worry about the financial health of their counterparties if they have a small exposure to them. Thus, as both the model and the data suggest, the pricing effects of counterparty risk should scale with the relative size of bilateral exposures. Moreover, our paper highlights that aversion to large bilateral exposures manifests in quantities as well, consistent with the findings of Du, Gadgil, Brody, and Vega (2017).

The remainder of the paper is organized as follows. In Section 2, we present our theoretical model. In Section 3, we verify that several of the model’s main assumptions are likely to hold in the CDS market. We then measure the net position of dealers and the degree of price dispersion in the market, which we use to calibrate the model in Section 4. Using the calibrated model, in Section 4 we also quantify the impact of network frictions on equilibrium prices and study how the CDS market would respond if a central dealer were to fail. Section 5 concludes.
2 Model

In this section, we outline our model of OTC trading. We start by presenting the most general form of the model in which risk-averse traders are connected in an arbitrary network. We make an important assumption that traders prefer to spread their transactions across multiple counterparties, as opposed to building up large, concentrated bilateral exposures. We show in Section 3.3 that this is indeed the case in the CDS market. Finally, in Subsection 2.2, we focus on the special case of a core-periphery trading network, which we eventually show is a natural lens to model the CDS network.\(^8\)

2.1 Setup

There are \(n\) agents in the economy and one asset with random payoff given by \((1 - D)\), where \(D\) is a default component with mean \(\mu\) and variance \(\sigma^2\). An agent \(i\) is initially endowed with an exposure, \(\omega_i\), to the underlying asset. There is a market in which agents trade CDS contracts before aggregate default is realized. A CDS contract between agents \(i\) and \(j\) specifies that agent \(i\) promises to pay \(D\) to agent \(j\), and, in exchange, agent \(j\) makes a payment of \(R_{ij}\) to agent \(i\). The so-called CDS ‘premium’ or ‘spread’ in the contract, namely \(R_{ij}\), is determined in equilibrium.

Let \(\gamma_{ij}\) be the number of contracts agent \(i\) sells to agent \(j\). The amount \(\gamma_{ij}\) can be positive or negative depending on whether agent \(i\) is selling to or buying insurance from agent \(j\). A positive \(\gamma_{ij}\) means that agent \(i\) sells insurance and takes additional exposure to aggregate default risk in the underlying asset.

There is a network of trade connections specifying which agents can bilaterally trade together. The network is exogenous and given by an \(n\) by \(n\) matrix \(G\) of zeros and ones, in which each entry \((i, j)\) is given by \(g_{ij} \in \{0, 1\}\). If agents \(i\) and \(j\) can trade, then \(g_{ij} = 1\), and, if they cannot trade, then \(g_{ij} = 0\). If two agents are not allowed to trade, then it must be that they hold a zero bilateral position with each other, that is, we have \(\gamma_{ij} = 0\) whenever \(g_{ij} = 0\). Furthermore, the network is symmetric, i.e., \(g_{ij} = g_{ji}\) for every \(i\) and \(j\), which means that if agent \(i\) can trade with agent \(j\), then \(j\) can also trade with \(i\). We assume that \(g_{ii} = 1\) for every \(i\), without loss of generality.\(^9\) The exogenous trade structure is consistent with our finding in Section 3.2.1 that these connections are highly persistent over time in the data. Although the trading network is exogenous, the quantities traded (\(\gamma\)'s) are endogenously determined in equilibrium.

Agents possess mean-variance preferences and their optimization problem is given by:

\[
\max_{\{\gamma_{ij}\}_{i=1}^{n}} \omega_i(1 - \mu) + \sum_{j=1}^{n} \gamma_{ij}(R_{ij} - \mu) - \frac{\alpha}{2} (\omega_i + z_i)^2 \sigma^2 - \frac{\phi}{2} \sum_{j=1}^{n} \gamma_{ij}^2
\]

\(^8\)In the Internet Appendix ??, we present a three-agent example to highlight key features behind the model’s equilibrium.

\(^9\)The equilibrium allocation is identical whether we set \(g_{ii} = 0\) or \(g_{ii} = 1\).
subject to $\gamma_{ij} = 0$ if $g_{ij} = 0$, and

$$z_i = \sum_{j=1}^{n} \gamma_{ij}$$

(2)

where $z_i$ is agent $i$’s net position in the CDS market, $\alpha > 0$ is a risk aversion parameter and $\phi > 0$ is aversion to bilateral concentration.\(^{10}\) The first restriction guarantees that agent $i$ can trade with agent $j$ if they are connected. The parameters $\alpha$ and $\phi$ play distinct roles in the model. Risk aversion represented by the parameter $\alpha$ measures aversion to total post-trade exposure to the underlying asset, namely $\omega_i + z_i$, while the parameter $\phi$ measures aversion to concentrated bilateral positions. In practice, we observe that institutions diversify their exposures to any one counterparty, and maintain multiple dealer connections. Counterparty diversification can be driven by efforts to minimize information leakage, to reduce hold-up problems, to ensure the ability to trade in case of a counterparty failure, and to diversify relationship capital.\(^{11}\) In our model, the parameter $\phi$ summarizes all (net) incentives to smooth trades across counterparties. Later, in Section 3.3, we provide empirical evidence that institutions prefer to spread their trades out across multiple counterparties, i.e. $\phi > 0$.

In our framework, agents are identical except for their initial pre-trade exposures and their trading connections, and in equilibrium how much exposure agent $i$ wants to sell to agent $j$ has to be equal to how much agent $j$ wants to buy from agent $i$. Hence our model features bilateral clearing conditions for any two counterparties:

$$\gamma_{ij} + \gamma_{ji} = 0 \quad \forall i, j = 1, \ldots, n.$$  

(3)

Finally, we assume no transaction costs between counterparties, which means that a payment agent $i$ receives from selling to agent $j$ is exactly the amount agent $j$ pays for such contract. In addition, there is no strategic pricing in our model, so dealers do not explicitly have monopolist or oligopolistic power over customers. While market power is certainly an interesting and realistic feature of OTC markets (Hau, Hoffmann, Langfield, and Timmer (2018)), we chose not to model it in order to maintain focus on how network frictions impact equilibrium pricing.\(^{12}\)

Formally, these assumptions mean that prices satisfy the following condition:

$$R_{ij} = R_{ji} \quad \forall i, j = 1, \ldots, n.$$  

(4)

We solve this model for a competitive equilibrium, in which agents optimize taking prices as

\(^{10}\)In the Internet Appedix, we present a version of our theoretical model with asymmetric costs of holding concentrated positions and find similar result. For readability, we opt for a model with identical preference parameters.

\(^{11}\)See Balasubramaniam, Gomes, and Lee (2019) for an explicit model of the net benefit of access to multiple counterparties in times of market stress.

\(^{12}\)In the Internet Appendix, we present a version of our theoretical model allowing agents to take into account their impact on equilibrium prices. We show that our analysis holds in an environment with price impact as well. In addition, we address the potential for strategic pricing in the empirical estimates we use in our calibration.
given, and all markets clear, using the following equilibrium concept.

**Definition.** An economy consists of a finite number of agents $n$, a trading network $G$, preferences described in Equation (1), and pre-trade exposures given by $\{\omega_i\}_{i=1}^n$. A competitive equilibrium with no transaction costs consists of spot market prices $\{R_{ij}\}_{i,j=1,...,n}$ and traded quantities $\{\gamma_{ij}\}_{i,j=1,...,n}$ such that: (i) agents optimize, taking the network of trading connections and prices as given (Equation 1); (ii) markets clear (Equation 3); and (iii) there are no transaction costs (Equation 4).

2.1.1 Equilibrium

In this subsection, we fully characterize the equilibrium of the model. Details of the model’s solutions are in Appendix A.1. To characterize the equilibrium, we first solve agents’ optimization problem, taking price as given. If agent $i$ can trade with agent $j$, i.e., $g_{ij} = 1$, then agent $i$’s first-order condition with respect to $\gamma_{ij}$ is:

$$R_{ij} - \mu = \phi \gamma_{ij} + \hat{z}_i,$$

where

$$\hat{z}_i = (\omega_i + z_i)\alpha \sigma^2.$$  

Equation (5) specifies agent $i$’s optimal exposure to aggregate default risk as a function the contract premium, $R_{ij} - \mu$, along with an additional term, $\hat{z}_i$. We interpret this last term as the shadow price of aggregate default risk for agent $i$, since it is the Lagrange multiplier on the constraint given by equation (2). Hence, $\hat{z}_i$ is agent $i$’s willingness to pay to insure against one additional unit of exposure to aggregate default.$^{13}$

Agent $i$’s first-order condition equalizes the marginal benefit of selling insurance to its own shadow cost of risk bearing combined with the marginal cost associated with bilateral concentration. The risk aversion parameter, $\alpha$, determines how much agent $i$ values net positions through the shadow cost of risk bearing, while the aversion to concentrated bilateral positions parameter, $\phi$, determines how much agent $i$ values bilateral contracts individually. In other words, $\alpha$ drives total net positions, while $\phi$ defines how much agents sell to and buy from each counterparty. Agent $i$ will buy CDS from agent $j$ at a higher spread than from agent $k$ in order to avoid an overly concentrated position with agent $k$, implying that connected agents only exploit price dispersion up to the extent that the benefits from attractive spreads outweigh the costs of concentrated

$^{13}$In equilibrium, agents trade because they have different pre-trade exposures and want to share risk, consistent with risk management considerations. Alternatively, one can set up the model with heterogeneous beliefs about aggregate default, i.e. $\mu_i$. In this case, there would be another motive for trade as agents hold different views about aggregate default, giving agents an speculative motive for trade. However, such formulation leads to exactly the same equilibrium allocation in terms of prices and quantities. Specifically, Equation (5) would become $R_{ij} - \mu_i = \phi \gamma_{ij} + (\omega_i + z_i)\alpha \sigma^2$. As a result, if $\mu_i + \omega_i\alpha \sigma^2$ is the same in both specifications, then the equilibrium allocations in the benchmark model and this alternative specification would be identical since they would both satisfy the equilibrium definition. Hence, the specific motive for trade is not critical for our results, and for this reason assume agents trade for risk-sharing motives alone. See the Internet Appendix for more details.
bilateral positions. They will still trade more with counterparties offering more attractive pricing, but only up to the point at which the marginal benefit of better pricing is exactly offset by the marginal cost of a concentrated exposure with one particular counterparty. In practice, we observe trades being spread out amongst counterparties in all OTC markets, from repo to CDS, and we see unexploited price dispersion amongst connected agents. The reasons are many, and include risk management considerations such as the cost of reallocating trades if a trading partner is lost and avoiding hold-up problems, as well as incentives to avoid information leakage and/or maintain communication regarding market conditions. These considerations apply on both sides of CDS transactions, and symmetry allows us to solve our model in closed form. However, we show that our main result holds for asymmetric $\phi$'s in the Internet Appendix.\footnote{Asymmetric $\phi$ can be microfounded in a mean-variance setting, in which the the actual payment of a CDS contract between $i$ and $j$ is given by $D + \varepsilon_{ij}$. The term $\varepsilon_{ij}$ is independent and identically distributed mean preserving spread. The non-contractible payoff risk is diversifiable across counterparties, but not across trades within a bilateral relationship. The counterparty-specific payoff can be a benefit (positive $\varepsilon_{ij}$), such as growth in relationship capital or access to market color. Alternatively, the trade may carry a cost such as payment delay or information release (negative $\varepsilon_{ij}$). These bilateral, non-contractible, payoffs become an additional source of risk and aversion to such risk is measured by $\phi$. See Sagi (2017) for empirical evidence of transaction-specific risk in non-exchange settings.}

By combining the first-order condition in Equation (5) with the counterparty clearing conditions in Equation (3) and the no-transaction cost assumption in Equation (4), we can write equilibrium prices as a linear combination of counterparties’ shadow prices of insurance:

$$R_{ij} - \mu \cong \frac{\hat{z}_i + \hat{z}_j}{2}, \quad (7)$$

for every $i$ and $j$ who can trade, i.e., $g_{ij} = g_{ji} = 1$.

The contract premium, which is the contract price in excess of the expected default in the underlining asset, depends on agents’ shadow prices of insurance. Therefore, a contract premium depends on post-trade exposures to default risk, along with the variance of aggregate default and preferences parameters. As a result, whenever there are differences in post-trade exposures, there is price dispersion in the cross section of agents in equilibrium, even if agents have identical preferences.

The CDS premium in Equation (7) is a function of the shadow prices of risk, which are determined in equilibrium. We can use Equations (2), (5), (6), and (7) to solve for equilibrium net positions as a linear combination of initial exposures and the net positions of other agents:

$$z_i + \omega_i = (1 - \lambda_i) \omega_i + \lambda_i \sum_{j=1}^{n} \tilde{g}_{ij} (z_j + \omega_j) \quad \forall i = 1, \ldots, n, \quad (8)$$

where $\tilde{g}_{ij} = \frac{g_{ij}}{K_i}$, $K_i = \sum_{j=1}^{n} g_{ij}$, and $\lambda_i = \frac{K_i \alpha \sigma^2}{K_i \alpha \sigma^2 + 2 \phi} \in (0, 1)$.

Agent $i$’s post-trade exposure to aggregate default risk is given by $z_i + \omega_i$. In equilibrium, $i$’s post-trade exposure is a convex combination of her pre-trade exposure, i.e. $\omega_i$, and a network-weighted average of agent $i$’s neighbors’ equilibrium post-trade exposures. The weight $\lambda_i$ defines how close agent $i$ is to the average of her neighbors’ post-trade exposures, and it makes a clear
distinction between risk aversion, $\alpha$, and aversion to bilateral concentration, $\phi$. Risk aversion increases agents’ willingness to diversify risk away and makes agent $i$’s post-trade exposures closer to her neighbors, by increasing $\lambda_i$. Aversion to bilateral concentration, however, makes agents less willing to concentrate trade with their counterparties at the expense of lower risk sharing. As a result, $\phi$ decreases $\lambda_i$, which leads to lower risk diversification.

The expression for post-trade exposures in Equation (8) has implications for agents not directly connected to each other as well. Since $\lambda_i \in (0, 1)$, the pre-trade exposure of an agent in the network has less and less influence on the post-trade exposure of other agents the farther away from each other trading partners are in the trading network. This decaying influence of pre-trade exposures on post-trade exposures becomes clear if we write post-trade exposures as a function of pre-trade exposures:

$$z_i + \omega_i = (1 - \lambda_i)\omega_i + \lambda_i \sum_{j=1}^{n} \tilde{g}_{ij}(1 - \lambda_j)w_j + \sum_{j=1}^{n} \sum_{s=1}^{n} \lambda_j \tilde{g}_{ij}\tilde{g}_{js}(1 - \lambda_s)w_s + \sum_{j=1}^{n} \sum_{s=1}^{n} \lambda_j \lambda_s \tilde{g}_{ij}\tilde{g}_{js}\tilde{g}_{sk}(1 - \lambda_k)w_k + \ldots$$  \hspace{1cm} (9)

The equilibrium condition from equation (8) as well as the equation above shows that the equilibrium net position of agent $i$ depends on the post-trade exposure of its neighbors. However, agent $i$’s neighbors’ post-trade exposures also depend on their own neighbors’ post-trade exposures, and so on. These equilibrium conditions imply a system of equations that we can solve for equilibrium exposures. In Appendix A.1, we characterize equilibrium quantities by rewriting Equation (8) in matrix notation and solving for $z$’s.

### 2.1.2 Risk-sharing benchmark: complete network

In this subsection, we consider the model when the trading network is complete, i.e., $g_{ij} = 1$ for every $i$ and $j$. We consider this risk-sharing benchmark because the trading network itself does not impose any additional trading frictions. In Appendix A.1, we show that, under the complete network benchmark, the post-trade exposure of agent $i$ in equilibrium is given by $z_i + \omega_i = (1 - \lambda)\omega_i + \lambda \left( \frac{1}{n} \sum_{j=1}^{n} w_j \right)$, where $\lambda = \frac{n\alpha\sigma^2}{n\alpha\sigma^2 + 2\sigma}$.

The equilibrium post-trade exposures are a convex combination of the agents’ pre-trade exposure and the perfect risk-sharing allocation. The coefficient $\lambda$ measures how far the equilibrium allocation is from perfect risk sharing due to aversion to bilateral concentration. As $\phi$ goes to zero, we have that $\lambda$ goes to one, and perfect risk sharing is achieved. Alternatively, as $\phi$ goes to infinity, we have that $\lambda$ goes to zero, and autarky is achieved in equilibrium. These two limiting cases are discussed in Appendix A.1 for a more general network structure.
Under the complete network benchmark, the average prices in equilibrium would be:

\[ \overline{R}_{\text{Complete Network}} \equiv \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} R_{ij} = \sigma^2 \alpha \overline{\omega} + \mu, \quad (10) \]

where \( \overline{\omega} = \frac{1}{n} \sum_{i=1}^{n} \omega_i \).

In Appendix A.1, we also show that when \( \phi = 0 \), there is perfect risk sharing and all equilibrium spreads are equal to \( \sigma^2 \alpha \overline{\omega} + \mu \), whenever any two agents are connected through a sequence of links. Hence, the complete network economy features an average equilibrium price that is the same as the one in an economy with perfect risk sharing. The difference between these two cases is that the complete network still has price dispersion in the cross section whenever \( \phi \neq 0 \) and pre-trade exposures are heterogeneous.

### 2.2 Core-periphery networks

In this subsection, we consider a core-periphery trading network and solve the model for equilibrium exposures and prices in closed form.\(^{15}\) To start, we formally define a core-periphery network as follows:

**Definition.** A core-periphery trading network consists of two groups of agents, a core and a periphery, in which (i) all agents in the core are connected to all other core agents, and all peripheral agents, and (ii) peripheral agents are connected to all core agents, and no other peripheral agents.

Specifically, let \( n_d \) be the number of members in the core ("dealers"), and \( n_c = n - n_d \) the number of agents in the periphery ("customers"). We use subscripts \( d \) and \( c \) to denote dealers and customers. Without loss of generality we set agents \( i = 1, \ldots, n_d \) to be core agents. Hence, a core-periphery trading network is defined as:

\[
G_{\text{core-periphery}} = \begin{bmatrix}
1_{n_d}1_{n_d}' & 1_{n_d}1_{n_c}' \\
1_{n_c}1_{n_d}' & 1_{n_c}1_{n_c}'
\end{bmatrix},
\]

where \( 1_{n_d} \) is a column vector of ones with \( n_d \) elements and \( 1_{n_c}1_{n_c}' \) is an \( n_c \times n_c \) identity matrix. The core-periphery \( G \) matrix with \( n_d \) dealers consists of blocks of ones along the top \( n_d \) rows, and left-most \( n_d \) columns. These ones represent the complete connections of core agents. The upper left \( n_d \) by \( n_d \) square of ones represents the full connections with the core. The remaining blocks of ones along the top and left of the matrix represent the core’s full set of connections to all periphery agents. Finally, the bottom right identity matrix represents the periphery agents' customer connections only to themselves.

Next, we characterize the market equilibrium when the trading network is core-periphery. Appendix A.2 contains the detailed derivation of the model in this special case. In the core-periphery

\(^{15}\)In Internet Appendix ??, we consider an example with three agents in order to provide intuition and to highlight key features of our framework. In addition, in the Internet Appendix ??, we provide a core-periphery example with the smallest possible number of agents (five).
economy, there are two interconnected markets: a dealer-to-dealer market and a customer-to-dealer market. For simplicity, we call them dealer and customer markets, respectively.

In the dealer market, the average post-trade exposures of dealers is given by:

\[
\bar{z}_d + \bar{\omega}_d \equiv \frac{1}{n_d} \sum_{i=1}^{n_d} (z_i + \omega_i) = (1 - \lambda_d) \bar{\omega}_d + \lambda_d \bar{\omega}. \tag{12}
\]

where \(\bar{\omega}_d = \frac{1}{n_d} \sum_{i=1}^{n_d} \omega_i\) and

\[
\lambda_d = \frac{n_d \alpha \sigma^2}{n_d \alpha \sigma^2 + 2\phi}. \tag{13}
\]

Equation (12) is derived from Equation (8) applied to dealers and taking an average across all dealers. The average post-trade exposures of dealers are a convex combination of their own average pre-trade exposure, i.e., \(\bar{\omega}_d\), and the average pre-trade exposure in the economy, i.e., \(\bar{\omega}\). Notice that since \(\lambda_d \in (0, 1)\), dealers are net sellers of protection on average, i.e., \(z_d > 0\), if, and only if, dealers are less exposed to aggregate default risk, i.e., \(\bar{\omega}_d < \bar{\omega}\).

Moreover, the average price in the dealer market, i.e., \(\bar{R}_d\), is given by:

\[
\bar{R}_d \equiv \frac{1}{n_d} \sum_{i=1}^{n_d} \sum_{j=1}^{n_d} R_{ij} = \mu + \alpha \sigma^2 \bar{\omega} - (1 - \lambda_d) \alpha \sigma^2 (\bar{\omega} - \bar{\omega}_d). \tag{14}
\]

If dealers are, on average, less exposed to the underlying default risk (\(\bar{\omega}_d < \bar{\omega}\)), then prices in the dealer market are lower than the complete network benchmark as derived in Equation (10).

In the customer market, the average post-trade exposures of customers are given by:

\[
\bar{z}_c + \bar{\omega}_c = \lambda_c \bar{\omega} + (1 - \lambda_c) \bar{\omega}_c - \lambda_c(1 - \lambda_d)(\bar{\omega} - \bar{\omega}_d), \tag{15}
\]

where \(\lambda_c = \frac{n_d \alpha \sigma^2}{n_d \alpha \sigma^2 + 2\phi}\), and the average price in the customer market, i.e., \(\bar{R}_c\), is given by:

\[
\bar{R}_c = \mu + \alpha \sigma^2 \bar{\omega} - \frac{1}{2} \alpha \sigma^2 (\bar{\omega} - \bar{\omega}_d) \left[(1 + \lambda_c)(1 - \lambda_d) - \frac{n_d}{n - n_d}(1 - \lambda_c)\right], \tag{16}
\]

where the last term in brackets is positive if, and only if, \(\frac{n_d}{n} < \frac{1}{2}\).

We can write the average price in the customer market as a function of the average price in the dealer market as follows:

\[
\bar{R}_c = \bar{R}_d + \frac{1}{2} \alpha \sigma^2 (1 - \lambda_c) \left[1 + (1 - \lambda_d) \frac{n - n_d}{n_d}\right] \frac{n_d}{n - n_d}(\bar{\omega} - \bar{\omega}_d). \tag{17}
\]

The next proposition compares the average price in the dealer market, the average price in the customer market, and the average price in the complete network benchmark.

**Proposition 1.** In the core-periphery model with \(\frac{n_d}{n} < \frac{1}{2}\), the average pre-trade exposure of dealers
is lower than the average exposure in the economy, i.e., \( \bar{\omega} > \bar{\omega}_d \), if, and only if,

\[
\mu + \alpha \sigma^2 \bar{\omega}_d < \bar{R}_d < \bar{R}_c < \bar{R}_{\text{Complete Network}},
\]

where \( \bar{R}_{\text{Complete Network}} = \mu + \alpha \sigma^2 \bar{\omega} \) as in Equation (10). Alternatively, \( \bar{\omega} < \bar{\omega}_d \) if, and only if, \( \mu + \alpha \sigma^2 \bar{\omega}_d > \bar{R}_d > \bar{R}_c > \bar{R}_{\text{Complete Network}} \).

Proof. This is a direct implication of Equations (14), (16) and (17).

Proposition 1 presents two interesting results. First, it shows that if dealers are less exposed to the underlying asset, the average price in the dealer market is lower than in the customer market. The intuition is that dealers are less exposed to the underlying risk and in equilibrium, they are still less exposed post-trade. As a result of their lower shadow costs of risk bearing, the dealers trade at a lower price among themselves.

The second result is more subtle. It shows that if the number of dealers is sufficiently small, the average price in both the dealer and the customer markets is below the complete network benchmark average price. The intuition reflects two considerations. First, dealers are less exposed post-trade when compared to customers. Second, there is a smaller number of dealers in the economy. The core-periphery structure implies that customers have to trade with dealers but are increasingly averse to trading with a small number of them because of agents’ aversion to bilateral concentration. As a result, risk sharing is imperfect and a wedge remains between customer and dealer sector exposures post trade. Prices are tilted towards dealers’ shadow costs of risk bearing because of their key role as intermediaries. Moreover, equilibrium prices must be attractive enough for customers to incentivize them to trade and to ensure market clearing.

2.2.1 Comparative statics

In this subsection, we analyze how equilibrium prices depend on risk aversion and aversion to holding concentrated position risk. The following proposition shows how equilibrium prices and spreads depend on \( \alpha \) and \( \phi \).

Proposition 2. If \( \frac{d}{n} < \frac{1}{2} \) and \( \bar{\omega} > \bar{\omega}_d > 0 \), then the following comparative statics hold:

\[
(i) \quad \frac{\partial}{\partial \phi} \bar{R}_d < 0, \quad \frac{\partial}{\partial \phi} \bar{R}_c < 0, \quad \frac{\partial}{\partial \phi} \bar{R}_{\text{Complete Network}} = 0, \quad \frac{\partial}{\partial \phi} (\bar{R}_{\text{Complete Network}} - \bar{R}_d) > 0,
\]

\[
\frac{\partial}{\partial \phi} (\bar{R}_{\text{Complete Network}} - \bar{R}_c) > 0, \quad \text{and} \quad \frac{\partial}{\partial \phi} (\bar{R}_c - \bar{R}_d) > 0,
\]

\[
(ii) \quad \frac{\partial}{\partial \alpha} \bar{R}_d > 0, \quad \frac{\partial}{\partial \alpha} \bar{R}_c > 0, \quad \frac{\partial}{\partial \alpha} \bar{R}_{\text{Complete Network}} > 0, \quad \frac{\partial}{\partial \alpha} (\bar{R}_{\text{Complete Network}} - \bar{R}_d) > 0,
\]

\[
\frac{\partial}{\partial \alpha} (\bar{R}_{\text{Complete Network}} - \bar{R}_c) > 0, \quad \text{and} \quad \frac{\partial}{\partial \alpha} (\bar{R}_c - \bar{R}_d) > 0.
\]

The proof consists of taking these derivatives using Equations (10), (14), (16), and (17). In this proposition, we assume dealers to be less exposed to the underlying default risk, i.e., \( \bar{\omega} > \bar{\omega}_d \), which implies dealers as net sellers in equilibrium, i.e., \( \bar{\zeta}_d > 0 \). This is consistent with the evidence presented in Section 3.4.
Aversion to bilateral concentration has no effect on the complete network benchmark average price and has a negative effect on the average price in the dealer and customer markets (item i). As $\phi$ increases, agents are more averse to trading too much with one counterparty. Hence, there is less risk sharing in the equilibrium with a higher $\phi$, which means that both customer and dealer post-trade exposures are closer to their pre-trade exposures. When dealers are net sellers of protection, this implies lower post-trade exposures for dealers and higher post-trade exposures for customers when $\phi$ increases.

The deterioration in risk sharing caused by an increase in $\phi$ changes equilibrium prices. For average customer prices, $\phi$ has two offsetting effects. On the one hand, it increases customer exposures which increases customer prices. On the other hand, because dealers absorb less risk from the customer sector, they have lower post-trade exposures to aggregate default risk, which pushes customer prices down. Given that dealers are small in number relative to customers, market clearing implies that the average post-trade exposure of dealers decreases by more than the increase in average post-trade exposure of customers. As a result, equilibrium prices in both the dealer and customer markets then decline. Intuitively, equilibrium prices are lower in the customer market to offset the higher costs of holding concentrated positions. Note that, in the dealer market, both lower post-trade exposures, and the burden of higher marginal costs of bilateral concentration, drive prices down. Since the two effects work in the same direction, average prices in the dealer market decrease by more than in the customer market. As a result, the gap between CDS premiums in customer-dealer and dealer-dealer trades widens.

Risk aversion increases the average price in both dealer and customer markets, as well as the complete benchmark price (items ii). As agents become more risk-averse, protection against aggregate default risk becomes more expensive. Similar to the effect of an increase in $\phi$, risk aversion also increases the spread between the average price in the dealer and customer markets. However, the economic mechanism behind the comparative statics for $\alpha$ is entirely different.

If risk aversion goes up, agents with high exposures have a higher demand for aggregate default risk protection and as a result there will be more risk-sharing in equilibrium. Given the improved risk reallocation, the dealer sector absorbs more risk from the customer sector. Dealers will trade at a higher price because of their higher average post-trade exposures. Customers will also trade at a higher price not only because risk aversion per se is higher but also because the average post-trade exposure of dealers increases by more than the decline in customers’ average post-trade exposure, due to their smaller number. This means that contracts between dealers and customers will be executed at higher prices on average.

Risk aversion increases both dealer and customer markets’ average prices. However, it increases the average price more in the customer market than in the dealer market. An increase in aversion to aggregate default risk also increases the spread in prices across dealer versus customer trades. There are two distinct offsetting effects driving this result. First, there is the direct effect of an increase in risk aversion on shadow prices of risk. More risk-averse agents have a higher shadow price of risk bearing for a given net exposure. Comparing the effect on dealers versus customers,
the fact that dealers are less exposed to the underlying asset than customers means that their shadow cost of risk bearing is less sensitive to changes in risk aversion. The effect of higher risk aversion on shadow prices of risk increases average prices in the customer market by more than in the dealer market, due to imperfect risk sharing. The second effect is more subtle and is dominated by the first one. The higher demand for risk sharing resulting from higher risk aversion implies that market participants become more similar in their post-trade exposures. Less dispersion in post-trade exposures implies less dispersion in the average prices observed in dealer versus customer markets. However, Proposition 2 shows that the first effect dominates the second one. Thus, as risk aversion increases, the spread between the average price in dealer and customer markets widens.

3 Empirical Evidence

In the first part of this section, we argue that the model’s key assumptions are likely to hold in the CDS market. We start by documenting that the network of trading in the CDS market is extremely persistent – new connections between the institutions that trade CDS are rarely formed and existing connections are rarely broken. We then reinforce previous research on the structure of OTC networks by showing that the CDS network is well-described by a core-periphery structure, where a periphery set of customers trades exclusively with a core-set of dealers. In addition, we provide evidence supporting our assumption that the institutions that trade CDS are averse to concentrated bilateral exposures. This last finding supports our modeling of preferences and implies that the parameter governing aversion to bilateral concentration is positive ($\phi > 0$).

After we provide empirical support for the model’s main assumptions, we then measure two key properties of the CDS market that we ultimately use to calibrate the model in Section 4. Our analysis is guided by the fact that the CDS network is core-periphery. As shown in Section 2.2, when the network is core-periphery we can easily infer the model’s structural parameters based on: (i) the net CDS position of dealers and (ii) the difference between CDS spreads in dealer-dealer transactions and dealer-customer transactions. As we show below, dealers are on average net sellers of credit protection in the CDS market and dealer-dealer transactions typically occur at lower CDS spreads than dealer-customer transactions.

3.1 Data Description

Before preceding to our main analysis, we start with a basic description of the data used throughout the remainder of the paper. Our primary data on CDS transactions and positions come from DTCC, which provides the data to the U.S. Treasury Department’s Office of Financial Research (OFR) under a license agreement. The data are derived from the DTCC’s Trade Information Warehouse (TIW) and include CDS transactions and positions reported to DTCC. Transactions represent flows in CDS, and positions represent stocks. The DTCC converts transactions to open positions before delivering both to the OFR. Positions data are updated at the end of each week. DTCC data
have been used previously by Oehmke and Zawadowski (2016), Siriwardane (2018) and Du, Gadgil, Brody, and Vega (2017).

For both transactions and positions, we observe complete information on the identities of the counterparties in the trade, pricing terms, size, and all contract details. When working with transactions, we follow industry practice and infer CDS spreads based on the the International Swaps and Derivatives Association standard pricing model. The DTCC provides the OFR with data on transactions or positions that meet at least one of two conditions: (i) the underlying firm covered by the swap is U.S. based or (ii) at least one of the counterparties in the swap is U.S. registered. In addition, the DTCC CDS data include all North American index swap transactions and positions (i.e. the index family is “CDX.NA.”). The data therefore capture most of the CDS market for U.S. firms.\(^{16}\) This is the key difference between the DTCC data from the OFR vs. from the Federal Reserve Banks; the network coverage from the OFR is more comprehensive in the sense that it covers more than just entities regulated by the Fed.

We focus on data from January 1, 2010 through December 31, 2013, when central clearing of single names was rare.\(^{17}\) In our data, we do not observe the ultimate counterparty for contracts that are centrally cleared. For example, a centrally cleared trade between Hedge Fund A and Dealer B will appear in our data as a trade between Hedge Fund A and the central clearing party, plus another (unlinked) trade between the central clearing party and Dealer B. This feature of the data matters only when we estimate the difference between inter-dealer prices and customer-dealer prices, as we must observe the ultimate counterparty type. For this reason, when analyzing CDS spreads, we use only single-name transactions on U.S. firms from 2010 to 2013, a time period that pre-dates central clearing of single name but not index contracts. By contrast, we use all trades when we estimate total net bilateral exposures and credit positions.

More generally, the introduction of central clearing does not disrupt the key economic forces in our model. Our model applies whenever agents have an aversion to concentrated bilateral exposures. Such an aversion is likely to persist even with central clearing, since diversifying across trading relationships can reduce the spread of information and can also reduce the risk of hold-up problems, or costly execution delay in the case of counterparty exit. Thus, it is plausible that our model’s main implications are relevant even for markets with central counterparties. However, we leave a full analysis of the impact of central clearing to future work. We also note that, in practice, a large portion of swaps markets (e.g. interest rate, FX, single name and many index CDS) are still cleared bilaterally, and that our model can be easily modified to study these other markets.

\(^{16}\)We refer to the underlying company whose default is covered by a CDS contract as the “firm” or “underlying firm”. The underlying firm is also often referred to as the reference entity or “name” in the swap.

\(^{17}\)Central clearing of single-name contracts was not prevalent until 2014. See https://www.theice.com/article/cds-growth?utm_source=Insights&utm_medium=tile.
3.2 The Persistence and Shape of the CDS Trading Network

3.2.1 How Does the CDS Network Change Over Time?

In the model of OTC markets in Section 2, we assumed that the trading network was static, which in turn means that we can treat it as exogenous when characterizing the model’s equilibrium. In this subsection, we argue that this simplifying assumption is a reasonable one, at least in the context of CDS trading.

Continuing with our notation from the model, we empirically represent trading relationships in the CDS market in at date $t$ through the matrix $G_t$, where $t$ is measured at a weekly frequency. Specifically, we code element $G_{i,j,t}$ as a one if counterparties $i$ and $j$ have an open position with each other at the end of week $t$ and we code it as zero otherwise. As a simple way to study network dynamics, we then compute the likelihood of new connections being established or current connections being broken. Formally, we first compute the number of counterparty-pairs that are or are not connected at $t$:

$$N^l_t = \sum_{i=1}^{n} \sum_{j=i+1}^{n} 1 (g_{i,j,t} = l), \quad l = 0, 1$$

where $n$ is the total number of counterparties in the market. $1 (g_{i,j,t} = l)$ is an indicator variable based on connection status. Next, conditional on connection status at $t$, we count the number of connected and unconnected counterparties at time $t + 1$:

$$N^{l,m}_{t+1} = \sum_{i=1}^{n} \sum_{j=i+1}^{n} 1 (g_{i,j,t} = l \text{ and } g_{i,j,t+1} = m), \quad l, m = 0, 1$$

So, for instance, $N^{0,0}_{t+1}$ counts the number of counterparties who are not connected at time $t$ and remain unconnected at time $t + 1$. We then map these counts to fractions of new and broken connections as follows:

$$p^{l,m}_{t+1} = \frac{N^{l,m}_{t+1}}{N^l_t}, \quad l, m = 0, 1$$

Extending the previous example, $p^{0,0}_{t+1}$ is the fraction of counterparties who were not connected at time $t$ and remain unconnected at time $t + 1$. Finally, we compute these connection transition probabilities for each period and then average over all periods.

Panel A of Table 1 shows the outcome of this exercise. Over our sample, conditional on no connection in week $t$, two counterparties have a 0.01% chance of making a new connection in the following week. Similarly, if two counterparties are connected in the current week, the probability that they remain connected next week is 99.09%. These statistics indicate that the CDS trading

---

$^{18}$We define $n$ as the total number of counterparties in our sample. For counterparties that enter at different points in the sample, we set all of their corresponding elements in the $G$ matrix to zero prior to their entry.
network is incredibly persistent – new connections in the CDS market are rarely formed and existing connections are rarely broken.

Panel B of Table 1 provides an alternative way of quantifying the persistence of the CDS network. For each counterparty $i$ and date $t$, we compute two standard measures of $i$’s centrality in the network: degree centrality and eigenvector centrality. Degree centrality $c_{d,i,t}$ simply counts the number of counterparties with whom $i$’s trades:

$$c_{d,i,t} = \sum_{j \neq i} g_{i,j,t}$$

Eigenvector centrality $c_{e,i,t}$ is defined recursively, based on the centrality of $i$’s trading partners:

$$c_{e,i,t} = \lambda^{-1} \sum_{j \neq i} g_{i,j,t} \times c_{e,j,t}$$

Intuitively, counterparty $i$ has a large eigenvector centrality if it is connected to other connected counterparties.\(^{19}\)

Next, at each date $t$, we compute the cross-sectional percentiles of each centrality measure. For instance, we compute the 10th percentile of degree centrality for each date in our sample. We then fit an AR(1) process to the time-series of 10th percentile of degree centrality. The estimated AR(1) statistics measure the stability of the centrality distribution through time. The results in Panel B of Table 1 indicate that a counterparty’s position in the CDS network is generally persistent, at least as measured by degree or eigenvector centrality. In short, the least central counterparties in the network stay that way, as do the most central counterparties.

It is important to note that we have likely overstated the extent to which the CDS network changes during our sample. To see why, recall that our construction of $G_t$ means that $i$ and $j$ will appear to have broken their connection if their existing positions mature without replacement, despite the fact that $i$ and $j$ are still likely to have the infrastructure (e.g., ISDA agreements) to trade at time $s > t$. In this sense, our analysis of how often connections are broken and formed is probably somewhat overstated. Despite this bias, we still find that the structure of the CDS network is highly persistent, thereby supporting our treatment of it as exogenous in the model.

### 3.2.2 The Shape of the CDS Network

It is well-established that many OTC trading networks are characterized by a core-periphery structure in which a central set of dealers trades with a periphery set of customers (e.g., Li and Schürhoff (2018), Peltonen, Scheicher, and Vuillemey (2014), or Hollifield, Neklyudov, and Spatt (2017)). We now confirm that this is the case in the U.S. CDS market as well. To simplify the analysis, we use the entire sample to define a constant network matrix $G$. Specifically, we set $G_{i,j}$ equal to one if counterparties $i$ and $j$ have any outstanding CDS positions open with each other over our

\(^{19}\)Formally, it is the $(n \times 1)$ vector $c^e_t$ that solves the system $G_t c^e_t = \lambda c^e_t$, where $\lambda$ is the largest eigenvector of $G_t$. 

19
sample. This simplification is motivated by our preceding results showing that the CDS network is relatively static, meaning \( G_t \approx G \).

Figure 2 presents a graphical depiction of the empirical \( G \) matrix of counterparty connections in the CDS market. Replacing ones with black squares and zeros with white space, it is clear that the network in the data is closely approximated by a core-periphery network. The black square in the upper left represents the full connections within the core. The remaining black bars across the top and left represent the core’s connections to periphery agents. The white area with a diagonal black line through it highlights the fact that direct connections between periphery agents are extremely rare. These broad patterns confirm that, like many other OTC markets, the CDS market is core-periphery. We will take advantage of the core-periphery structure in Section 4 when we calibrate the model using observed prices and net exposures of dealers. The calibration also requires us to designate which of the members of the network are dealers and which are customers. In Appendix B, we use a minimum-distance algorithm for dealer classification. This algorithm generates a counterparty network with 14 dealers, though the figure is already highly suggestive of who is and who is not a dealer.20

3.3 Are Traders Averse to Concentrated Bilateral Exposures?

A third assumption in our model from Section 2 is that institutions prefer to spread their trades out across multiple counterparties (i.e., \( \phi > 0 \) in the model). There are several reasons why traders may wish to spread trades across counterparties, including risk-management requirements (e.g., position limits) or the desire to conceal private information. Regardless of the precise microfoundation, assuming that institutions are averse to concentrated bilateral exposures is critical for generating limited risk sharing and price dispersion when the trading network is incomplete, as it is in practice. Using bilateral positions and individual transactions, we now test whether this assumption is supported empirically.

3.3.1 Measuring Bilateral Exposures

We begin by constructing a measure of bilateral CDS exposure between two counterparties, \( i \) and \( j \), at time \( t \). At any given point in time, \( i \) and \( j \) may have several outstanding CDS contracts with each other that cover different firms and maturities. We therefore aggregate \( i \) and \( j \)’s bilateral exposures by casting each individual CDS contract in terms of its exposure to aggregate credit risk. This approach to aggregation also accords with our model, where default risk is defined as exposure to a single aggregate risk factor. We provide a detailed account of our methodology in the Internet Appendix, though we briefly describe the key elements now. Specifically, we proceed in three steps. First, we define the aggregate credit risk factor. Second, we compute each bilateral

20The DTCC also classifies traders based on its list of registered dealer members. In single-name transaction data, the DTCC’s set of dealers is responsible for nearly 86 percent of gross volume. The 14 counterparties who we label as a dealer are responsible for about 83 percent. We provide robustness checks for our main results to the DTCC dealer designation.
position’s exposure to this aggregate credit risk factor. Finally, we aggregate positions simply by summing the computed exposures from Step 2.

**Step 1: Defining an Aggregate Credit Risk Factor**  On each date $t$, we define our aggregate credit risk factor as the cross-sectional equal-weighted average of all five-year CDS spreads for U.S. firms in the Markit Ltd. database. We have separately confirmed that this index is a close approximation to the first principal component of credit spreads across all maturities (i.e. a level factor). However, our simpler index is much better at dealing with missing data, which can be an issue for firms with lower volumes of CDS trading. Figure 3 shows that our aggregate credit risk factor evolves as one might expect, peaking at nearly 1000 basis points during the 2007-09 financial crisis. Relative to other measures of credit conditions, our factor is over 90 percent correlated with both the 5-year CDX investment grade and high yield indices. The average of our index is a little over 200 basis points, so it is between the investment grade and high yield indices in terms of average credit spread.

**Step 2: Measuring the Exposure of a Single Contract to Aggregate Credit Risk**  Next, we compute the exposure of an arbitrary CDS position $p$ to our aggregate credit risk factor. On date $t$, suppose that the position is written on firm $f$ and has $m$ remaining years till maturity. We first assign each position to a “maturity bucket” $b$ based on its maturity $m$ as follows:

$$b = \begin{cases} 
1 & \text{if } m \in [0, 2) \\
3 & \text{if } m \in [2, 4) \\
5 & \text{if } m \in [4, 6) \\
7 & \text{if } m \geq 6 \end{cases}$$

Then for each position $p$, we match it to the Markit CDS spread database based on the underlying firm $f$ and maturity bucket $b$. Markit provides constant maturity CDS spreads for maturities ranging from 6 months all the way to 10 years. We match each position’s maturity bucket $b$ to the closest constant maturity spread in Markit. For instance, if we observe a position on Ford Motor Co. that has a maturity bucket $b = 3$, we obtain Ford’s history of three-year CDS spreads up to date $t$ from Markit.\(^{21}\) Next, we compute the position’s underlying beta with respect to changes in our aggregate credit risk factor via the following rolling regression:

$$\Delta CDS_{f,b,s} = \alpha + \beta_{p,t} \times \Delta \text{CDS Index}_s + \varepsilon_{f,b,s}, \quad s \in [t - 2 \text{ years}, t]$$

where CDS Index$_s$ is our aggregate credit risk factor on date $s$. The regression is run using weekly data over a rolling window of two years. The position’s beta $\beta_{p,t}$ gives us a gauge of how sensitive the underlying CDS spread of the position is to movements in this index.

\(^{21}\)We also match positions to Markit using the documentation clause and underlying currency of the position.
We compute $\beta_{p,t}$ for every position contained in our database sourced from DTCC. Importantly, we account for both index and single name CDS positions. Selling protection on an index is equivalent to selling protection on the individual firms that comprise the index. This distinction is particularly important in the CDS market because index positions are nearly half of the net notional outstanding for the entire CDS market during our sample (Siriwardane (2018)). To account for this fact, we follow Siriwardane (2018) and disaggregate CDS indices into their individual constituents and then combine these “disaggregated” positions with any pure single name positions. We then estimate $\beta_{p,t}$ for every position and date in this disaggregated data. The Internet Appendix provides more details on how we compute $\beta$’s.

**Step 3: Aggregation** To compute a position’s overall sensitivity to aggregate credit risk, we simply multiply the estimated $\beta_{p,t}$ by the notional value $\text{Notional}_{p,t}$ of the position. Formally, we define $E_{p,t} \equiv \beta_{p,t} \times \text{Notional}_{p,t}$ as the position’s exposure to aggregate credit risk. In some applications, we instead define $E_{p,t}$ by multiplying $\beta_{p,t}$ by what is referred to in practice as a position’s “DV01”. DV01 refers to how much the market value of the position changes in response to a one-basis point move in the credit spread of firm $f$ – it is similar to the concept of “delta” in options markets. Thus, scaling $\beta_{p,t}$ by DV01 measures how much the position will change in market value for a one-basis point change in the aggregate credit risk factor. \(^{22}\)

Having defined a position’s exposure to aggregate credit risk, $E_{p,t}$, aggregation is straightforward. For example, define $S_{i,j,t}$ as the set of positions where $i$ is a seller to $j$, and $B_{i,j,t}$ as the set of positions where $i$ is a buyer from $j$, both as of time $t$. We define the net and gross notional exposures to aggregate credit risk between counterparty $i$ and $j$ as follows:

$$\text{Net}_{i,j,t} \equiv \sum_{p \in S_{i,j,t}} E_{p,t} - \sum_{p \in B_{i,j,t}} E_{p,t}$$

$$\text{Gross}_{i,j,t} \equiv \sum_{p \in S_{i,j,t}} E_{p,t} + \sum_{p \in B_{i,j,t}} E_{p,t}$$

By construction, positive values of $\text{Net}_{i,j,t}$ mean that $i$ is a net seller of CDS protection on aggregate credit risk to $j$.

**3.3.2 A Measure of Bilateral Concentration**

From $i$’s perspective, $j$ is a concentrated counterparty if most of $i$’s gross-notional exposure occurs with $j$. Thus, a natural measure of bilateral concentration is:

$$\kappa_{i,j,t} \equiv \frac{\text{Gross}_{i,j,t}}{\sum_k \text{Gross}_{i,k,t}}$$

\(^{22}\)We describe the computation of and calculation of sensitivity to DV01 in the Internet Appendix.
Intuitively, $\kappa_{i,j,t} \in [0,1]$ and $\sum_j \kappa_{i,j,t} = 1$. In the extreme case, if all of $i$'s positions are with $j$, then $\kappa_{i,j,t} = 1$. On the other hand, if $i$ does not have a lot of open positions with $j$, then $\kappa_{i,j,t}$ will tend towards zero.

Table 2 provides some basic summary statistics of $\kappa_{i,j,t}$, broken out by whether $i$ is a dealer or not. When interpreting these summary statistics, it is important to note that our model does not predict that traders will spread their trades equally out across their counterparties in equilibrium. The model only suggests that traders must be compensated through prices for higher concentration, which is the prediction that we will test below. Indeed, the exact distribution of concentration depends how averse traders are to bilateral concentration and the distribution of pre-trade exposures ($\omega$).

With that said, Table 2 indicates that the median customer does appear to spread their trades somewhat equally across trading partners. Based on the actual degree distribution, an equally-weighted benchmark would predict a $\kappa$ of 7% for the median customer, while we observe a $\kappa$ of about 9%. There are of course some customers that have more concentrated exposures on average, with the 75th percentile customer trading about 16% of its gross exposure with a single counterparty. As mentioned, this skewness reflects the underlying distribution of $\omega$'s and the fact that some customers have less connections than others. Because dealers are inherently more connected than customers, they naturally face more counterparties and so their average bilateral concentration is somewhat smaller at 2%.

3.3.3 A Measure of Bilateral Price Concessions

If agent $i$ is averse to concentrated bilateral exposures, then $i$ should be less willing to concede in price (offer a relatively attractive price) to $j$ on new trades when $\kappa$ is already large. To test this hypothesis in the data, we need to construct a measure of price concession between counterparties $i$ and $j$ in week $t$. Let us now walk through a stylized example of how we do so.

Suppose that the CDS market consists of contracts for only one firm and one maturity. Define $S_{i,t}$ as the minimum CDS spread paid by $i$ in transactions where $i$ bought protection in week $t$. Similarly, $\bar{S}_{i,t}$ is defined as the maximum CDS spread received by $i$ in transactions where $i$ sold protection in week $t$. Next, consider a single trade that is indexed by $k$ between $i$ and $j$ in week $t$ and suppose that the CDS spread in that trade was $S_{k,i,j,t}$. Then the amount that $i$ concedes in price to $j$ on the trade is naturally measured as:

$$\text{PriceConcession}_{k,i,j,t} = \begin{cases} S_{k,i,j,t} - S_{i,t} & \text{if } i \text{ buys from } j \\ \bar{S}_{i,t} - S_{k,i,j,t} & \text{if } i \text{ sells to } j \end{cases}$$

Intuitively, if $i$ purchases protection from $j$ at a high spread relative to other trades where $i$ bought protection, then $i$ is conceding more in price to $j$. And, if $i$ sells to protection to $j$ at a low spread relative to other trades where $i$ sold protection, then $i$ is also conceding in price. We aggregate our measure of price concession across all of the trades between $i$ and $j$ in week $t$ in two different ways.
First, we take an equal-weighted average of \( \text{PriceConcession}_{k,i,j,t} \) across the trades \( k \) between the two counterparties. We call this metric \( \text{PriceConcession}^{EW}_{i,j,t} \). Second, we take a notional-weighted average across their trades, where the weights are defined by the notional in each trade. We call this metric \( \text{PriceConcession}^{NW}_{i,j,t} \).

While the preceding example focused on defining our measure of price concession when there is CDS traded on only one firm and one maturity, the logic of our approach generalizes in a straightforward way to account for trades on different firms and of different maturities. Table 2 provides some basic summary statistics of price concession (\( \text{PriceConcession} \)), again broken out by whether \( i \) is a dealer or not. Here, it is readily apparent that there is substantial variation in how much traders concede in price to their counterparties. Our goal in this subsection is to test whether this variation lines up with bilateral concentration.

### 3.3.4 Results

Next, we run the following regression to flesh out the relationship between bilateral concentration and price concession:

\[
\text{PriceConcession}_{i,j,t} = \psi_{i,t} + \beta \times \kappa_{i,j,t-1} + \varepsilon_{i,j,t}
\]

(18)

where \( \text{PriceConcession}_{i,j,t} \) is either \( \text{PriceConcession}^{EW}_{i,j,t} \) or \( \text{PriceConcession}^{NW}_{i,j,t} \) and \( \psi_{i,t} \) is an \( i \)-by-\( t \) fixed effect. The coefficient of interest in this regression is \( \beta \). Because of the fixed effect \( \psi_{i,t} \), it is identified purely off of variation in \( \text{PriceConcession}_{i,j,t} \) across \( i \)'s counterparties in trades that occur in week \( t \). Intuitively, our assumption that traders are averse to bilateral concentration means that we expect \( \beta < 0 \): if \( i \) is already highly concentrated to \( j \) coming into week \( t \), then \( i \) will concede less in price in any trades that occur with \( j \) during the week. In the Internet Appendix, we show more formally that the parameter governing aversion to concentrated bilateral exposures (\( \phi \)) is positive if and only if \( \beta < 0 \). This is the sense in which the regression tests whether one of our model’s primitive assumptions is justified empirically.

Table 3 contains the results from running several variants of regression (18). In column (1), we use \( \text{PriceConcession}^{EW}_{i,j,t} \) as our measure of price concession. The estimated \( \beta \) in this case is -5.43 and we can reject the null hypothesis that it is equal to zero with 95% confidence. The negative coefficient implies that traders concede less in price when facing counterparties with whom they have large pre-existing exposures. The magnitude of the point estimate indicates that a one-standard deviation increase in bilateral concentration (\( \kappa \)) is associated with about 0.8 basis point less in price concessions. As a point of reference, the average of \( \text{PriceConcession}^{EW}_{i,j,t} \) is 3.4 basis points. Note that if traders with a “relationship” have a high \( \kappa_{i,j,t-1} \) on average, any price concessions to favored counterparties would cut against finding a negative coefficient.

In column (2), we run the regression for the subset of the data where \( i \) is a dealer, which sheds some light on whether dealers are also averse to concentrated bilateral concentration. The estimated \( \beta \) is once again negative and measured with statistical precision, implying that dealers
charge their counterparties more when they have concentrated pre-existing positions with them. In terms of magnitudes, the point estimates in column (2) are comparable to column (1) because, as shown in Table 2, $\kappa_{i,j,t}$ is less volatile for dealers than non-dealers.

Columns (3) and (4) contain the results using $\text{PriceConcession}_{i,j,t}^{NW}$, which puts more weight on price concessions that occur on large trades. We again observe a similar pattern in that larger bilateral concentration is associated with less price concession. In columns (5)-(8), we repeat the analysis using a different approach to constructing $\kappa_{i,j,t-1}$. We redefine a position $p$’s exposure to aggregate credit risk based on its DV01, which as previously discussed provides a gauge of how much the position will change in market value if our aggregate credit risk factor increases by 1 basis point. We then aggregate positions in the same way as before to arrive at $\kappa_{i,j,t-1}$. Intuitively, when $\kappa_{i,j,t-1}$ is defined in this manner it measures how much of $i$’s potential margin payments go to or come from $j$ (see both Section 3.3.1 and the Internet Appendix for more details). As columns (5)-(8) show, the negative relationship between bilateral price concessions and concentration is robust to this alternative approach to construction of $\kappa$.

Overall then, the evidence in Table 3 supports our assumption that CDS traders prefer to spread their trades out across multiple counterparties. In the model, this is equivalent to assuming that $\phi > 0$. Moreover, our analysis of dealers in Table 3 also suggests that they too will pay to avoid concentrated bilateral exposures. One concern might be that dealers have market power over some of their counterparties, particularly the ones with whom they have large concentrated exposures. While this mechanism would explain why dealers appear to concede less in price to more concentrated counterparties, it would also predict that overall dealers offer lower average price concessions than non-dealers. However, the summary statistics in Table 2 do not support this. Thus, we interpret the results in column (2) as suggesting it is safe to assume that $\phi > 0$ for dealers. We revisit the issue of market power in Section 3.4.2.

3.4 Dealer Exposures and Dealer-Dealer versus Dealer-Customer Spreads

We have established that the CDS trading network has a stable, core-periphery structure and that CDS traders appear averse to concentrated bilateral exposures. Given that these results support our model’s main assumptions, we now explore a more careful calibration of the model, which we will ultimately use to quantify the impact of network frictions on prices. As demonstrated in Section 2.2, mapping the model to the data is much more straightforward when the CDS network is core-periphery. In this special case, there is a direct mapping between the model’s structural parameters and two easily observable objects in the data: (i) the net CDS position of dealers and (ii) the average difference between CDS spreads in dealer-dealer transactions and dealer-customer transactions. Our goal in this subsection is to estimate both.

---

---

\[23\text{While the preceding analysis is suggestive that } \phi > 0, \text{ it provides less guidance on the magnitude of } \phi. \text{ Indeed, in the Internet Appendix we show that the estimated } \beta \text{ from regression (18) is a somewhat complicated function of } \phi \text{ and the other underlying structural parameters of our model. This means we cannot easily recover the model’s structural parameters from this regression, which motivates an alternative estimation approach that we explore in subsequent sections.} \]
3.4.1 The Net CDS Position of Dealers

In Section 3.3.1, we denoted the net amount of CDS protection that \( i \) has sold to \( j \) on date \( t \) by \( \text{Net}_{i,j,t} \). Recall that \( \text{Net}_{i,j,t} \) is positive if \( i \) is a net seller to \( j \) of CDS protection on aggregate credit risk. Summing this metric across all \( j \) yields a measure of \( i \)'s net overall exposure to aggregate credit risk:

\[
\text{Net}_{i,t} \equiv \sum_j \text{Net}_{i,j,t}.
\]  

To define the net exposure of dealers, we first compute \( \text{Net}_{i,t} \) for each of the 14 dealers in our sample. In the model, net exposure is defined as fraction of total wealth, so we then scale each dealer’s net CDS exposure by its market capitalization:

\[
z_{i,t} \equiv \frac{\text{Net}_{i,t}}{\text{MktCap}_{i,t}}.
\]  

To isolate lower-frequency movement in equity, we compute \( \text{MktCap}_{i,t} \) by taking a quarterly moving average of end-of-week market capitalizations. Here, we use \( z_{i,t} \) to denote this scaled-exposure measure to match the notation used in the model.

A key quantity for our mapping between the model and the data is the cross-sectional average exposure of dealers (see Section 2.2), which is computed as follows:

\[
\bar{z}_{d,t} \equiv \frac{1}{n_d} \times \sum_{i \in D} z_{i,t}
\]

where \( n_d = 14 \) is the number of dealers and \( D \) is the set of dealers. Table 6 indicates that the average \( \bar{z}_{d,t} \) is about 0.045 across all dates in our sample. One way to interpret this number is as follows: on average, dealers sell $0.045 of net notional CDS protection on the aggregate credit risk factor for each dollar of their equity. The observed positive \( z_d \) reflects the net credit risk absorbed by the dealer sector due to their net provision of credit insurance through trade in single name and index CDS contracts. Total credit exposure is the sum of the exposure from CDS trading, and pre-trade exposure to aggregate credit risk from other credit positions.

In that Internet Appendix, we explore an alternative way of defining dealer exposure by computing how the market value of each dealer’s CDS portfolio responds to movements in our aggregate credit risk factor. As previously mentioned, this is often referred to as a portfolio DV01 in practice. By this metric, dealers lose money on average if the factor increases, indicating that they are net sellers of protection on the index to their customers. Thus, regardless of the metric, it appears that dealers are on average net sellers of protection to customers from 2010 through 2013 — a fact that is also consistent with dealer behavior in U.K. markets (Morrison, Vasios, Wilson, and Zikes 2018).

Within the core set of dealers, net selling of CDS protection is itself very concentrated. To visualize this fact, Figure 4 plots the distribution of \( z_i \) within the dealer sector for our sample period. The first thing to notice is that much of the mass is concentrated around zero, meaning
many intermediaries have roughly zero net exposure (Atkeson, Eisfeldt, and Weill 2015). Still, the highly concentrated nature of net credit provision is clear from the plot, as the right tail shows that a handful of dealers have substantial positive net positions, indicating that they are large net sellers. As we argue later in Section 4.3, the fact that a few key dealers provide most of the credit insurance is one of the big reasons that a single dealer’s failure can have a very large effect on the level of CDS spreads.

### 3.4.2 CDS Spreads in Dealer-Dealer versus Dealer-Customer Trades

In the case of a core-periphery network, the second piece of information that is needed to calibrate the model is the difference between CDS spreads in dealer-dealer transactions and dealer-customer transactions. To empirically estimate this average spread differential, we use all single name transactions on U.S. firms from 2010 through 2013, excluding those with CDS spreads greater than 1000 bps. We further focus on transactions where the tier of debt in the contract is senior unsecured, and the so-called “doc-clause” that determines CDS trigger events is XR (no restructuring), the most commonly used clause. In addition, we match each transaction in our sample to an associated 5-year spread in the Markit database based on the date and underlying firm of the contract. We winsorize both the transaction spreads and Markit spreads at their 5 percent tails, but have confirmed that our main conclusions are robust to alternative methods for dealing with outliers.

Table 4 displays some simple summary statistics on our transaction panel. We construct the reported statistics by first grouping transactions into buckets based on the underlying firm and week \((f, w)\) of the transaction. Within each firm-week bucket, we calculate, for instance, the average transaction spread. The reported statistic in the table is simply the average across all \((f, w)\) buckets. To develop a sense of the characteristics of contracts written on more actively traded firms, we also compute a liquidity-weighted average across \((f, w)\) buckets, with the weights determined by the number of trades in each bucket. To this end, we also compute statistics for a subset of our sample where there is a minimum number of trades in an \((f, w)\) bucket.

Table 4 shows that the average transaction spread for our sample is roughly 133 basis points, though this increases for the most actively traded names. We also merge our transaction data with Moody’s expected five-year default frequency (EDF) data, and the average EDF for our sample of firms is 65 basis points.\(^{24}\) Relatedly, the average loss-given-default (from Markit) is 60.6%. We use the both the average EDF and loss-given-default to calibrate expected losses in the quantitative application of our model in Section 4.

Our next task is to estimate the average difference in spreads between DD and DC transactions. We do so by running variants of the following generic regression:

\[
Spread_{k,f,t} = \text{FEs} + \theta \times 1_{k,t}(\text{Customer-Dealer}) + \\
\beta_1 \times \text{MarkitSpread}_{f,t} + \beta_2 \times \log(\text{Notional}_{k,t}) + \epsilon_{k,f,t}
\]  

\(^{24}\)For firms that do not have a match in Moody’s, we use the average EDF for the set of firms with the same rating during that week.
where FEs denote a series of fixed effects that we describe below. In terms of notation, we use \(k\) to index each transaction and we roll transaction characteristics (e.g. seller, buyer, maturity, etc.) into \(k\). As before, \(f\) denotes the underlying firm in the CDS transaction and \(t\) denotes the date of the trade. The key variable in regression (21) is \(1_{k,t}(\text{Customer-Dealer})\), which is just a dummy variable for whether the transaction is between a customer and a dealer. The estimated coefficient \(\theta\) in the regression therefore provides an estimate of the average difference between spreads in the customer-dealer market versus the dealer-dealer market, which we denote by \(\bar{R}_c - \bar{R}_d\).

Our estimate of \(\theta\) will be biased if dealer-customer trades are concentrated in riskier firms or maturities. The ideal way to address this issue is to estimate \(\theta\) based on trades on the same firm, day, and maturity via a firm-date-maturity fixed effect. However, the frequency of trade in our data does not afford us enough statistical power to implement this strategy. Instead, we control for the 5-year CDS spread as reported by Markit, who produces daily CDS spread data based on information provided to them by dealers. Still, if dealers on average trade with customers on the longer end of the maturity spectrum for all firms, then \(\theta\) would be potentially biased by common movements in the term structure of credit across firms. To alleviate this concern, we include a fixed effect based on the interaction of a firm’s rating class (i.e. investment grade or high-yield), maturity bucket, and week.\(^{25}\) Similarly, the firm fixed effect in the regression accounts for time-invariant differences in \(\text{Spread}\) across firms, which would bias our estimation if customer-dealer trades are somehow concentrated in a given name. The 5-year Markit CDS spread should largely subsume the firm fixed effect, but, we include it to be conservative. Finally, we include the notional amount of the trade to account for any size effects on spreads.

Table 5 presents the results from running regression (21) on various subsamples of our data. Columns (1)-(4) of the table all use our definition of dealers from Section 3.2.2. Column (1) of the table runs the regression for our full sample and provides our baseline estimate of \(\theta = 6.14\) bps. The point estimate is measured precisely in a statistical sense and implies that, on average, customer-dealer trades occur at 6.14 bps higher than dealer-dealer trades. In terms of economic magnitude, 6.14 bps is a large amount of price dispersion considering that the average level of spreads in our transaction is 133 bps. We provide additional context for the magnitude of \(\theta\) when we use it to calibrate \(\phi\) our model in Section 4.

As previously discussed, our estimate of \(\theta\) could potentially be biased if customer-dealers trades are concentrated in a specific maturity of CDS that has systematically different CDS spreads. The fixed effect based on ratings class by maturity bucket and week should alleviate most of these concerns. Nonetheless, as an alternative way to address this issue, we focus only on trades that have between four and six years to maturity in column (2). The most important takeaway is that the estimated \(\theta\) of 6.40 bps in this subsample is quite comparable to our baseline estimate in column (1), suggesting that our estimate of \(\theta\) is not biased by unobservable maturity-effects.

\(^{25}\)Our estimate of \(\theta\) could still be biased if dealer-customer activity correlates with movements in a firm’s term structure that are orthogonal to common term structure movements for firms in the same ratings class and also orthogonal to movements in that firm’s own 5-year Markit CDS spread. While unlikely, for robustness we analyze a subsample of transactions with 4-6 years maturity to eliminate any potential term structure effects.
Market Power A central motivation behind our model in Section 2 is to understand how network frictions – the combination of a sparse network and aversion to bilateral concentration – interact with price dispersion in equilibrium. However, in reality there are certainly other mechanisms that could generate a gap between CDS spreads in dealer-dealer and dealer-customer trades. One natural candidate is market power: if dealers have market power over their customers, then they might sell CDS at higher spreads to customers relative to other dealers.

In column (3) of Table 5, we attempt to strip out the potential impact of market power on our estimate of $\theta$ by running regression (21) on a subset of transactions where prices are more plausibly competitive. To do so, we filter our transaction panel to include only dealer-dealer trades and trades between dealers and large customers, where large customers are defined as those whose share of gross volume is in the top 10% for our sample period. Further, we require that the Markit depth for the firms in the panel is at least eight. Markit depth is a data field provided by Markit and gives an indication of how many dealers provide quotes on a given firm and date. The cutoff of eight was chosen because it is the top 10% of Markit depth for our sample of trades. The fact that many dealers are providing quotes to large customers supports the idea that dealers are unlikely to possess monopolistic pricing power in this subset of trades. The estimate of $\theta = 5.12$ bps that emerges from this regression is not markedly lower than our estimate from column (1), indicating that a sizable portion of our baseline estimate of $\theta = 6.14$ bps is due to forces that are distinct from strategic pricing. Indeed, a crude decomposition suggests about 17% ($= 1 - 5.12/6.14$) is attributable to market power. Nonetheless, to ensure that strategic pricing does not influence our results, we take a conservative approach and use $\theta = 5.12$ when we calibrate the model in Section 4.

Additional Robustness The remaining columns in Table 5 display the results when using the DTCC’s definition of dealers, as opposed to our custom definition based on the algorithm discussed in Section 3.2.2. In this case, the point estimates on the dealer-dealer dummy are quite consistent with the ones we obtain when using our custom dealer definition. Thus, our choice of dealers is largely unimportant when estimating differences in dealer-dealer versus dealer-customer pricing.

4 Calibration and Dealer Removal

In this section, we use the estimates from Section 3.4 to calibrate our core-periphery model of OTC markets. After interpreting the magnitude of the implied structural parameters, we then use the calibrated model to answer two questions. First, how much does the incomplete network impact the level and dispersion of CDS spreads? Second, and motivated by the events of the 2008 Global Financial Crisis, how are equilibrium prices impacted by the removal of a central OTC intermediary?
4.1 Calibration and Interpretation

Our goal is to map the data to the two structural risk aversion parameters $\alpha$ and $\phi$ in our model. Table 6 presents the data estimates we use for our calibration, along with the resulting parameter values. To generate the calibrated parameter values, we first rearrange equations (12), (14), and (16) to express $\alpha$ as a function of observable quantities in the data:

$$\alpha = \frac{1}{\sigma^2 \omega} \left[ \bar{R}_d - \mu + (\bar{R}_c - \bar{R}_d)2 \left(1 - \frac{n_d}{n}\right) \right].$$

(22)

This equation says that the parameter describing aversion to the aggregate credit risk factor is mainly identified by the level of equilibrium spreads in the dealer market in excess of expected default, i.e., $\bar{R}_d - \mu$. A higher average spread indicates that agents are willing to pay a higher price for insurance against aggregate default risk. Table 6 summarizes the inputs we use to calibrate $\alpha$. We set $\mu = 0.39\%$ and $\sigma = 4.87\%$ based on our estimates of loss-given-default and the probability of default from Section 3.4.2.\footnote{Given a probability of default given by $p = 0.0065$ and a loss-given-default given by $L = 0.6060$, we have $\mu = Lp = 0.0039$ as the unconditional expected default and $\sigma^2 = L^2p(1-p) = 0.0024$ as the unconditional variance of aggregate default.} Our estimates of $\bar{R}_d = 133$ bps and $\bar{R}_c - \bar{R}_d = 5.12$ basis points also come from the analysis in that section. To be conservative about the amount of price dispersion which results from network frictions alone, we use the estimate which is based only on dealer-dealer trades and trades between dealers and large customers, where large customers are defined as those whose share of gross volume is in the top 10% for our sample period (see Table 5). We set the number of dealers $n_d = 14$ and the total number of counterparties in the CDS market to $n = 723$, the latter of which is based on our sample of transactions. The only variable on the right-hand side of Equation (22) that we do not observe is $\omega$, which is the economy-wide exposure to the underlying default risk. We assume that, on average, agents have one unit of exposure to default risk by normalizing $\omega$ to one. This leads to an estimated aversion to aggregate default risk of $\alpha = 4.37$.\footnote{We show that our main results hold for other values of $\bar{\omega}$ in the Internet Appendix.}

Next, to calibrate the parameter measuring aversion to bilateral concentration, $\phi$, we combine Equations (13), (14), and (16) to obtain:

$$\phi = \left(n - n_d\right) \left(\frac{\bar{R}_c - \bar{R}_d}{\bar{z}_d}\right).$$

(23)

This equation says that the inference of $\phi$ depends on the number of customers, $n - n_d$, the customer-dealer spread, $\bar{R}_c - \bar{R}_d$, and the average exposure of dealers, $\bar{z}_d$. Higher price dispersion ($\bar{R}_c - \bar{R}_d$) coincides with larger values of $\phi$, as agents are less willing to build up concentrated bilateral exposures. Conversely, because dealers are net sellers of protection in the data ($\bar{z}_d > 0$), when they sell more protection it reflects better risk sharing in equilibrium, and hence a lower $\phi$. In Section 3.4.1, we computed that $\bar{z}_d = 0.045$, which leads to a value of $\phi = 8.00$ in our calibration (see Table 6).
The comparative statics in Proposition 2 provides further intuition for the mapping between \( \phi \) and \( \alpha \) and observable data. Intuitively, \( \alpha \) is mainly identified from the level of credit spreads, while \( \phi \) is mainly identified by the dispersion in spreads.

**Interpretation** To provide a sharper interpretation for the magnitude of \( \phi \), we start from agents’ first-order conditions. They imply that when agent \( i \) trades with agent \( j \), the marginal benefit of selling insurance to agent \( j \) has to be equal to its marginal cost. Specifically, Equation (5) shows that the spread collected from agent \( j \) \( (R_{ij}) \) equals the sum of the expected default, the marginal cost of increasing a concentrated position with \( j \) \( (\phi \gamma_{ij}) \) and the shadow cost of insurance \( (\hat{z}_i) \). To contextualize the magnitude of the parameter \( \phi \), we can take Equation (5) and average across all of agent \( i \)’s connected counterparties:

\[
\bar{R}_i = \mu + \phi \frac{1}{K_i} \sum_{j: g_{ij} = 1} z_i + \alpha \sigma^2 (z_i + \omega_i),
\]

where \( \bar{R}_i \equiv \frac{1}{K_i} \sum_{j: g_{ij} = 1} R_{ij} \) is the average price faced by agent \( i \). The term \( \phi \frac{1}{K_i} z_i \) is the average marginal cost of bilateral concentration. If agent \( i \) is a net seller \( (z_i > 0) \), then the average marginal cost of bilateral concentration is positive, increasing the average price at which agent \( i \) is willing to sell additional insurance. Similarly, if agent \( i \) is a net buyer \( (z_i < 0) \), then the average marginal cost of bilateral concentration is negative, decreasing the average price at which agent \( i \) is willing to buy additional insurance. Using the benchmark calibration, dealers’ average marginal cost of bilateral concentration is \( \phi \frac{1}{n} \bar{z}_d \approx 5 \) basis points on average.

A marginal cost of 5 basis points represents about 3.8% of the average spread in the dealer market (5 out of 131 basis points). It is important to highlight, however, that this is the average cost of a marginal increase in concentrated exposure and is therefore greater than the average cost associated with the holding of concentrated positions. We can measure average costs using agents’ preferences. Specifically, the term \( \frac{\phi}{2} \sum_j \gamma_{ij}^2 \) measures the total cost of trading with all the counterparties, and \( \frac{\phi}{2K_i} \sum_j \gamma_{ij}^2 \) measures the average cost per trade. To get an idea of the magnitude of average trading costs that could be compared to, for example, bid-ask spreads, we provide a parsimonious calculation using our model to infer dealers’ average per-trade cost of holding a concentrated positions with other dealers.\(^{28}\) In this case, the average cost of holding concentrated positions is 0.04 basis points per trade when dealers trade with other dealers. Hence, the model-implied average per-trade cost for an average dealer resulting from aversion to bilateral concentration is much smaller than average bid-ask spreads, which are on the order of one or two basis points.\(^{29}\) Indeed, even if even we focus on the largest net seller dealer, its average total cost of holding concentrated positions with other dealers is only 0.27 basis point per trade.

We emphasize that the structure of the core-periphery network means that even a small friction can lead to quantitatively important effects on prices and risk sharing. The network amplifies the

---

\(^{28}\) We use Equation (8) applied to dealers to infer \( \hat{z}_i \), and Equations (5), (6) and (7) to compute \( \gamma_{ij} \) for every dealer pair \( (i,j) \). Then, for every dealer \( i \), we compute \( \frac{\phi}{2} \gamma_{ij}^2 \) and average across dealers \( j \).

\(^{29}\) See Adrian, Fleming, Shachar, and Vogt (2017).
effect of a small per-trade friction due to the fact that each unit of risk can be essentially re-traded multiple times across connected counterparties (see Equation (9)). As a result, the small per-trade cost induced by bilateral concentration aversion leads to sizable price dispersion in our model \(\bar{R}_c - \bar{R}_d = 5.12\) bps. It also leads to a substantial deterioration in risk sharing. If risk sharing were perfect, dealers’ post-trade exposures to the credit risk factor would equal the economy-wide average exposure, implying that \(\lambda_d = 1\). Table 6 shows that in the calibrated model, \(\lambda_d = 0.32\). This implies that dealer post-trade exposures put about two-thirds weight on their own pre-trade exposures, and only one third weight on the economy-wide average exposure.

4.2 How Much Do Network Frictions Impact Prices?

Using our calibrated model, we now quantify the impact that the incomplete network has on equilibrium prices. A natural way to do so is to compute equilibrium prices if the network were instead complete, meaning all agents are connected. Rearranging Equation (22) yields the complete network benchmark price as a function of observables:

\[
\bar{R}_{\text{Complete Network}} = \alpha \sigma^2 \bar{\omega} + \mu = \bar{R}_d + (\bar{R}_c - \bar{R}_d)2 \left(1 - \frac{n_d}{n}\right).
\]

(24)

Importantly, Equation (24) allows us to infer what the complete network benchmark price would be based solely on observed prices and the number of counterparties in the network. Based on the parameters in Table 6, we infer that the average CDS spread would be \(\bar{R}_{\text{Complete Network}} = 143\) bps if the CDS trading network were complete.

We can then use the implied \(\bar{R}_{\text{Complete Network}}\) to quantify the size of network frictions in the market. From Table 6, we see that in the core-periphery network customer-dealer trades occur at spread of about \(\bar{R}_c = 138.12\) bps. Thus, credit spreads in the customer-dealer market are about 3.4% lower than they would be if the network were complete. Intuitively, spreads in trades between dealers and customers reflect the average post-trade exposures of dealers and customers, but are tilted towards dealers’ marginal cost of risk bearing because of their central role as OTC intermediaries. Since, empirically, dealers are net sellers of credit protection (indicating a higher capacity to bear credit risk than that of customers), spreads are depressed downward from the perfect risk-sharing benchmark. Moreover, in equilibrium, these lower prices reflect the fact that customers must be incentivized to purchase protection from a concentrated set of dealers.

Similarly, we estimate average dealer-dealer spreads in the core-periphery network to be \(\bar{R}_d = 133\) bps, nearly 7% lower than they would be if the network were complete. Again, in our model, the empirical fact that dealers are net sellers of credit protection in equilibrium implies that they start with less ex-ante exposure to aggregate credit risk than customers. However, aversion to concentrated exposures prevents dealers from selling as much protection as they would like because all agents trade off the costs of concentrated bilateral exposures against the benefits of default insurance (and exploiting price dispersion). As a result, the model suggests that the post-trade exposure of dealers to aggregate credit risk remains less than that of customers, i.e. that there is
imperfect risk sharing. In turn, dealers pay lower spreads when purchasing credit protection from other dealers in equilibrium because, as a group, their lower ex-ante exposure results in a higher risk-bearing capacity and a lower shadow cost of risk bearing.

More broadly, the fact that CDS spreads in both the interdealer and customer-dealer markets are lower than the complete network benchmark reflects worse risk sharing in equilibrium, and a tilt toward dealers’ (who are net sellers of CDS) lower marginal costs of risk bearing. The lower premiums can be interpreted as compensation for concentrated bilateral exposures – absent these costs, agents would compete away any price dispersion.

These results provide further evidence that a small per-trade cost of bilateral concentration, combined with the core-periphery network, can have large effects. In addition to driving price dispersion $R_c - R_d$ of 5.12 bps, network frictions lead to customer prices that are 4.88 bps lower, and dealer prices that are 10bps lower than in the complete network benchmark. In the next section, we build on the results in Proposition 1 and use our calibrated model to show that the direction of the price distortion depends crucially on the shadow cost of risk bearing in the dealer core relative to the customer periphery. If the dealer sector’s ability to bear aggregate default risk falls below that of the customer sector, for example due to dealer exit, then prices become distorted upward.

4.3 What Happens if a Dealer Fails?

Core-periphery networks are often thought to be susceptible to systemic risk. As a concrete example, many accounts of the 2008 financial crisis claim that the failure of Lehman Brothers led to a freezing of several OTC markets, including the CDS market. Indeed, the CDX Investment Grade Index rose by nearly 25% immediately following the collapse of Lehman Brothers. Motivated by these events, in the last part of the paper, we use our model to assess how the CDS market would respond to the failure of a central dealer in the network.

To preview, we find that removing the most systemically important OTC intermediary leads to a 23% increase in CDS spreads in the interdealer market, an increase on par with observed changes in the CDX Investment Grade Index following the exit of of Lehman Brothers. The increase in spreads occurs despite the fact that there is no default or default contagion in our model, and, in addition, we allow institutions to reallocate risk following dealer removal. We show that the increase in spreads is driven entirely by network frictions. Spreads are essentially unchanged following dealer exit in the complete network benchmark.

4.3.1 Simulating Dealer Failure in the Model

To quantitatively evaluate systemic risk in our network, we start from the calibrated core-periphery model in Section 4.1. We then remove one dealer from the core, without changing any other model parameters or remaining agents’ pre-trade exposures, and evaluate how prices and quantities change
in the new equilibrium.\textsuperscript{30} However, we do allow all remaining agents in the model to re-trade in the CDS market following the removal of a dealer. This is a key strength of our quantitative model; the extent to which agents in the network can reallocate risk following dealer exit is calibrated to match empirical price and quantity data. Because we allow reallocation of risk through CDS trading, but do not allow agents to make any changes to their pre-trade exposures to credit risk, it is natural to view this exercise as a stress test with a focus on medium-term outcomes. That is, we ask the policy-relevant question of how markets would respond if a failed dealer’s CDS positions needed to be distributed among the remaining market participants before they were able to change the fundamental exposures that drove their original net CDS demand (e.g., a pre-existing bond exposure). Even without the default contagion that has been previously emphasized in the literature on systemic risk, we find that these effects can be sizable.

4.3.2 Results and Discussion

We provide several sets of results. First, we show the effects of removing dealers with different roles within the core using our baseline calibration. We emphasize the heterogeneity in various dealers’ roles in the CDS market, as evidenced by the right skewness in Figure 4. Then, we trace out the effects of removing the dealer which is the largest net seller of protection for various assumptions about the amount of price dispersion that is due to aversion to bilateral concentration. Varying the degree of price dispersion essentially varies the calibrated value of $\phi$, with larger dispersion corresponding to higher values for $\phi$. Finally, we show that only in the core-periphery network, the increase in spreads from removing the largest net seller of protection is magnified if $\alpha$ or $\phi$ increase as well. It seems reasonable that aversion to aggregate credit risk, and aversion to bilateral concentration would increase upon the exit of a key dealer. However, removing a key dealer in a complete network has almost no effect on prices, for any values of $\phi$ or $\alpha$.

Table 7 displays the results for the baseline calibration in Column (1), and the effects of dealer removal in Columns (2)-(5). In Column (2) we remove the dealer that is the largest net seller of credit protection. In Column (3), we remove a dealer at the 90\textsuperscript{th} percentile of dealers’ net position. In Column (4), we remove a dealer with the median net position in the benchmark case. Finally, in Column (5), we alternatively remove the dealer that is the largest net buyer in the baseline model.

Removing the largest net-seller dealer has a large systemic effect on CDS prices in the core-periphery network, increasing equilibrium spreads in the dealer market by 31 basis points from 133 to 164 basis points, a 23\% increase. The intuition for this result can be seen by combining Equations (12) and (14):

$$R_d = \mu + \alpha \sigma^2 \varpi - (1 - \lambda_d) \alpha \sigma^2 \frac{\varpi_d}{\lambda_d}. \tag{25}$$

Ignoring the small effect on $\lambda_d$ from reducing the number of dealers, the change in spreads in the interdealer market resulting from dealer removal is negatively linearly related to the resulting

\textsuperscript{30}See Equations (14) and (16) for prices, and Equations (A6) and (A7) from the Appendix for dealer’s net positions.
change in $\bar{z}_d$. Removing the largest net seller of credit protection dramatically changes the amount of net protection the dealer sector is willing to provide. In fact, as seen in Figure 4, most dealers are net buyers of protection, and, accordingly, removing the largest net seller changes the sign of $\bar{z}_d$, indicating that without this dealer the entire dealer sector becomes a net demander of credit protection. The core dealer sector still plays an important role in reallocating credit risk, but it is no longer willing to absorb aggregate credit risk from the customer sector on net. As a result, spreads adjust to reflect the reduced risk bearing capacity of the dealer sector. Indeed, because the dealer sector becomes a net buyer of protection, spreads are now distorted upward relative to their complete network benchmark. This result highlights how the distortion in spreads resulting from network frictions is driven by the risk-bearing capacity of OTC intermediaries. When dealer risk-bearing capacity is relatively high, spreads are distorted downward. Conversely, when dealer risk bearing capacity falls below that of customers, credit spreads are distorted upward. If dealer risk bearing capacity is relatively low in times of stress, as emphasized by the intermediary asset pricing literature (see He and Krishnamurthy (2013), Adrian, Etula, and Muir (2014), and He, Kelly, and Manela (2017)), then network frictions can lead to higher credit spread volatility, and countercyclical amplification of credit spreads.

The fact that the dealer sector becomes a net demander of credit protection following the loss of the largest net-seller dealer has another surprising effect. Dealer-customer prices also increase, but by only 11%. As a result, they are now lower than prices in the inter-dealer market. The fact that interdealer prices now exceed dealer-customer prices reflects dealers’ injured risk bearing capacity, and the higher shadow cost of risk bearing of the remaining dealers. The effect can be seen by combining Equations (12) and (16):

$$R_c = R_d + \frac{1}{2} \alpha \sigma^2 (1 - \lambda_c) \left[ 1 + (1 - \lambda_d) \frac{n - n_d}{n_d} \right] \frac{n_d}{n - n_d} \bar{z}_d. \quad (26)$$

As shown in Proposition 1, only when the customer sector becomes a net insurance provider to the dealer sector ($\bar{z}_d < 0$), which happens in the CDS market if the largest net-seller dealer is removed, do prices in the inter-dealer market exceed those between dealers and customers.

Another key result is that there is essentially no effect of removing a key dealer if the network is complete, or if risk sharing is perfect. This finding is important, as it shows that the effect on prices is not from removing risk bearing capacity from the market overall, but results only from removing a key dealer in the presence of network frictions. The reason can be seen in Equation (24). The only effect of removing the largest net-seller dealer is to change $\bar{\omega}$ by a very small amount. Even though the largest net-seller dealer is important to the dealer sector’s net position, it is not important for the economy’s credit risk exposure overall. As a result, the second row of Table 7 shows almost no change in complete network spreads from removing any dealer.

The importance of dealer heterogeneity can be seen by studying what happens when we remove dealers who play different roles in the dealer sector, i.e. who are drawn from various points in the
distribution in Figure 4. Column (3) presents results for removing a dealer at the 90th percentile of the $z_d$ distribution. This dealer is a small net seller and hence not crucial in determining the sign of the aggregate dealer sector’s position. Removing this dealer leads to an increase in spreads, but since the effect on $\bar{z}_d$ is smaller, so is the effect on prices. Next, we study a large dealer who buys and sells protection, but does not change their net exposure through the CDS market. The results appear in Column (4) of Table 7. In this case, there is almost no effect on the level of CDS spreads in the economy, both in the dealer-dealer market and the customer-dealer market. The intuition can again be seen in Equation (26), which highlights the key role of $\bar{z}_d$, the average net credit exposure dealers accrue from trading in CDS. This average net exposure captures the risk bearing capacity of the dealer sector; when dealers are net sellers of CDS ($\bar{z}_d > 0$) OTC intermediary risk-bearing capacity is relatively high, and when dealers demand insurance ($\bar{z}_d < 0$) intermediary risk-bearing capacity is low. Removing an intermediary who takes a net neutral credit exposure in CDS does not significantly affect the risk-bearing capacity of the dealer sector given the calibrated number of dealers, and the calibrated value for aversion to concentrated bilateral exposures.

Our results regarding the varying effects of removing intermediaries with different roles are relevant for the findings in the intermediary asset pricing literature, much of which relates to OTC traded assets. Like in that literature, what primarily drives the pricing of aggregate risk is the risk-bearing capacity of the dealer sector, and intermediary risk bearing capacity is essentially determined by aggregating the risk bearing capacity of the fully-connected dealers. Although $\phi$ limits risk sharing, at its calibrated value dealers share risk between their fully connected core counterparties fairly well. Different from standard intermediary asset pricing models, however, our model emphasizes that intermediary risk bearing capacity can be heavily influenced by a small number of key dealers. In this sense, our results connect the intermediary asset pricing literature to the literature on systemic risk; while the former has emphasized the pricing role of the aggregate dealer sector, the latter emphasizes, as do we, that large price swings can result from the deterioration of a single key OTC intermediary’s balance sheet.

Building on these results, in column (5), we show what happens if we remove the dealer who is the largest net buyer of protection. Removing this dealer actually leads to lower average spreads in both dealer and customer markets. The reason is that removing a large buyer of protection from the dealer sector increases the available risk bearing capacity of the remaining dealers. The main takeaway is that removing a connected counterparty (i.e., a dealer) from the network has very different effects depending on that counterparty’s net position. This observation suggests that policy makers aiming to regulate systemic risk need to look at more than size and number of connections to determine systemic importance. We do acknowledge, however, that, in order to focus on heterogeneity in dealer risk-bearing capacity, we have abstracted from other potentially

---

31 In the Internet Appendix, we also use our framework to study the impact of a customer removal on the CDS market. We find more muted effects from removing a customer—even one who is a large net seller—because they are not as central to the network. We also provide results for different values of $\bar{\omega}$, and for the set of dealers designated as such by the DTCC, and show that the results for dealer removal are very similar under these alternative assumptions.

32 See (He, Kelly, and Manela 2017) and (Haddad and Muir 2018).
important roles of core dealers, such as in information revelation.\textsuperscript{33}

Our calibration uses the price dispersion $R_d - R_c$, which is observed between dealers and customers in the top 10% of the trading volume distribution. However, we acknowledge that there may still be other drivers of price dispersion in that estimate besides network frictions. In Figure 6, we plot the sensitivity of our results on the impact of removing the largest net-selling dealer from the network against the amount of price dispersion caused by network frictions. A smaller price dispersion estimate leads to a lower value of $\phi$ in our calibration. Consistent with our argument that a small friction limiting bilateral positions can have large effects in a core-periphery network, Figure 6 shows that even if only half (roughly 2.5 basis points) of the observed 5.12 bps of price dispersion in the data is attributable to network frictions, removing the largest net-seller would still increase the level of spreads by about 15 basis points, or over 10%.

As the 2008 crisis showed, when a dealer fails and is no longer able to trade with other counterparties, it is likely that the rest of the economy is also under stress. It is therefore reasonable to assume a dealer failure might be accompanied by an increase in aversion to both aggregate default risk ($\alpha$) and concentrated bilateral exposures ($\phi$). Simultaneously increasing both parameters in our stress tests further amplifies the effects of removing a dealer. In Panel A of Figure 5, we plot the average dealer market spreads as a function of both $\phi$ and $\alpha$, without removing any dealer. In Panel B, we show the same plot after removing the largest net-seller dealer. Aversion to aggregate default risk, $\alpha$, increases equilibrium spreads with and without the dealer removal. However, the effects of dealer removal on average dealer market spreads are further amplified by higher risk aversion.

The effects of changing the aversion to concentrated bilateral exposures, $\phi$, on equilibrium spreads before and after the dealer removal are more subtle, and highlight the key role of $\overline{z}_d$ in the sign of network distortions of prices relative to the complete network or Walrasian benchmark. Panel A shows that the parameter $\phi$ lowers the average spreads in the dealer market.\textsuperscript{34} A higher $\phi$ leads prices to be more representative of agents’ pre-trade exposures than of the economy-wide average benchmark that would be achieved with perfect risk sharing. The observed fact that net sellers of protection ($z_d > 0$), implies that they are relatively less exposed to aggregate default risk before trading (that is, $\overline{\omega}_d < \overline{\omega}$). As a result, increasing $\phi$ decreases the average spread in the dealer market, driving it closer to the lower bound identified in Proposition 1.\textsuperscript{35} In Panel B, however, the parameter $\phi$ increases the average spreads in the dealer market. After removing the largest net-seller dealer from the economy, dealers become net buyers of protection on average. The same logic applies, but now dealers are on average more exposed to aggregate default risk. Consequently, a higher $\phi$ increases the average spreads in the dealer market, which is what we observe in Panel B.

Figure 5 also shows that network frictions are the main reason why we observe such large pricing

\textsuperscript{33}See Babus and Kondor (2018), Glode and Opp (2016), and Glode, Opp, and Zhang (2017).

\textsuperscript{34}See also Proposition 2.

\textsuperscript{35}Formally, $\phi$ lowers $\lambda_d$, which from Equation (14) lowers the average spreads in the dealer market, as observed in Panel A.
effects when removing a dealer from the network. In particular, Panel C of Figure 5 plots the average spreads under the complete network benchmark as a function of both $\phi$ and $\alpha$, without removing any dealer. In Panel D, we make a similar plot, but remove the largest net-seller dealer. Panels C and D are almost identical, which means that dealer removal has almost no effect on average spreads if the network of trading connections is complete, and there is no interaction between dealer removal and changes in risk aversion, or aversion to bilateral concentration. The punchline then is that removing the largest net-seller dealer has significant effects on average spreads only when the trading network is incomplete, and that, in this case, effects can be amplified by increases in $\alpha$ or $\phi$.

In summary, our stress tests find that the failure of a dealer that is also a large net seller of CDS protection can significantly disrupt the market. This effect does not rely on imperfect contracting or contagion. Instead, due to the fact that the network is incomplete, and agents are averse to large bilateral positions, the core-periphery network cannot effectively aggregate the risk-bearing capacity in the network that remains after a dealer fails. Moreover, the loss of the largest net selling dealer’s risk bearing capacity is not solely responsible for the increase in credit spreads. If the network is complete, but agents remain averse to large counterparty exposures, we show that the effect of removing a key intermediary is close to zero. We conclude that network frictions are therefore critical for assessing systemic risk in OTC markets.

5 Conclusion

We develop a model of pricing in OTC markets. We emphasize two key trading frictions, namely, network incompleteness (i.e. a core-periphery structure), and traders’ aversion to accumulating large concentrated positions with any one counterparty. We show that the model’s main assumptions are supported in the data using detailed transaction and position-level data from the DTCC on credit default swaps. We then use the key pricing and quantity equations from the closed-form solution to our model in equilibrium to calibrate our model to this data. Our calibrated model then allows us to answer two important questions in OTC asset pricing quantitatively.

First, we show how network frictions distort OTC prices away from their Walrasian, or complete network, benchmark. As long as the network is incomplete, and aversion to concentrated bilateral positions limits risk sharing, there is always a distortion. However, the sign depends on the relative risk bearing capacity of OTC intermediaries, or the dealer sector of our core-periphery network. If the dealer has a higher risk-bearing capacity than the customer sector, then network frictions distort prices downward, toward dealers’ shadow price of risk. By contrast, if the risk-bearing capacity of the OTC intermediary sector becomes impaired, for example through the loss of a key dealer, then prices are distorted upward. As a result, we argue that network frictions can lead to changes in credit spreads that do not rely on changes in parameters governing risk or risk aversion.

Second, we use our calibrated model as a laboratory for regulators to evaluate the systemic importance of key OTC intermediaries. We measure the impact of dealer removal on prices and
risk sharing in the OTC network. We show that the loss of a systemically important dealer causes a large increase in credit spreads, on the order of magnitude of that observed during Lehman’s failure. Crucially, this systemically important dealer is not only identified by its centrality as defined by measures of connectedness, as all dealers are fully connected to all other agents in our model. The key features of the most systemically important dealer in our model are that they are both a dealer (fully connected) and a large net provider of credit insurance. We find empirically that different dealers play very different roles within the intermediary sector. A small number of dealers are responsible for the fact that the dealer sector as a whole is a net provider of credit insurance, while many dealers maintain net neutral positions or are net buyers of protection. The effect of dealer removal on prices depends critically on their net position, and removing a net demander of insurance can actually lead to lower prices. Importantly, we show that the effects of dealer removal on prices are entirely due to network frictions. If the network is complete, or if there is no aversion to bilateral concentration, then there is no effect of removing any dealer on prices or risk sharing.
References


40


41


Figures

Figure 1: CDS Markets During the 2008 Global Financial Crisis

Notes: This figure plots the 5-year CDX Investment Grade Index from June 1, 2006 through January 31, 2010. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Notes: This figure plots the matrix $G$ where element $G_{i,j}$ equals one if $i$ and $j$ have an open position with each other in our sample, for all counterparties with an open position in the investment grade index. If $i$ and $j$ do not have an open position, $G_{i,j}$ equals zero. Counterparties are ordered by their total number of connections, highest to lowest. Theoretically, a core-periphery network has a structure as in Definition 2.2, with ones along the diagonal, a core of dealers each represented by a columns and row of ones, and zeros elsewhere. This plot shows the close approximation in the data to the theoretical core-periphery structure. Dealers are represented by the left-most columns, and top-most rows, and customers are connected to these dealers, but not each other. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Figure 3: Aggregate Credit Risk Factor

Notes: This figure plots our aggregate credit risk factor from 2002 through 2013. We construct the factor on each date by taking a cross-sectional average of 5-year CDS spreads for all U.S. firms. CDS spreads are obtained from Markit Ltd.
Figure 4: The Distribution of Post-Trade Net Exposures, $z_i$ for Dealers

Notes: This figure plots the distribution of dealer exposure to aggregate credit risk, scaled by their equity, for the period 2010-01-04 through 2013-12-31. We compute each dealer’s notional exposure to aggregate credit risk across all of its bilateral positions using the methodology described in Section 3.4.1. The aggregate credit risk factor we use is the cross-sectional average of 5-year CDS spreads for all U.S. firms from the Markit database. We then scale each dealer’s notional exposure to aggregate credit risk by the market value of their its to obtain $z_i$ on each date. The plot shows the distribution of the average $z_i$ across dealers for our sample. Positive values of $z_i$ indicate that dealer $i$ is a net seller of credit protection on the aggregate credit risk factor. For readability, we’ve scaled the $y$-axis so that the probability distribution integrates to 1000, not 1. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Figure 5: Dealer Removal

Panel A: $\overline{R}_d$ without dealer removal
Panel B: $\overline{R}_d$ with dealer removal
Panel C: $\overline{R}_{Complete\ Network}$ without dealer removal
Panel D: $\overline{R}_{Complete\ Network}$ without dealer removal

Notes: This figure plots the average spreads, levels of risk aversion, $\alpha$, and aversion to counterparty risk, $\phi$. The lowest $\phi$ and $\alpha$ plotted in both graphs are the benchmark calibrated parameters, also available in Table 6. Panel A plots the average spread in the dealer market, $\overline{R}_d$, while Panel B plots $\overline{R}_d$ after the removal of the highest-net-seller dealer. Panel C plots the model-implied complete network average spread, $\overline{R}_{Complete\ Network}$, while Panel D plots $\overline{R}_{Complete\ Network}$ after the removal of the highest-net-seller dealer. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Figure 6: Dealer Removal Effect for Different Dealer-Customer Spread Estimates

Notes: This figure plots the change in the average dealer market spreads upon the removal of the largest net-seller dealer. On the x-axis, we vary the customer-dealer spread, namely $R_d - R_c$, which in turn change the model-implied values for $\alpha$ and $\phi$. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Table 1: Dynamics of the CDS Trading Network

Panel A: The Probability of Breaking and Forming Connections

<table>
<thead>
<tr>
<th></th>
<th>No Connection$_{t+1}$</th>
<th>Connection$_{t+1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Connection$_t$</td>
<td>99.99%</td>
<td>0.01%</td>
</tr>
<tr>
<td>Connection$_t$</td>
<td>0.91%</td>
<td>99.09%</td>
</tr>
</tbody>
</table>

Panel B: Measuring the Persistence of the Network

<table>
<thead>
<tr>
<th></th>
<th>Degree Centrality</th>
<th>Eigenvector Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AR-Coefficient</td>
<td>t-statistic</td>
</tr>
<tr>
<td>p10</td>
<td>1.0*</td>
<td>-</td>
</tr>
<tr>
<td>p20</td>
<td>0.80</td>
<td>19.67</td>
</tr>
<tr>
<td>p40</td>
<td>0.92</td>
<td>32.25</td>
</tr>
<tr>
<td>p60</td>
<td>0.92</td>
<td>33.85</td>
</tr>
<tr>
<td>p80</td>
<td>0.90</td>
<td>25.65</td>
</tr>
<tr>
<td>p90</td>
<td>0.92</td>
<td>35.47</td>
</tr>
</tbody>
</table>

Notes: Panel A of this table compute the likelihood of breaking or forming a new connection in the CDS trading network at time $t + 1$, conditional on connection status at time $t$. At time $t$, we count the number of counterparty pairs that are not connected, where connection status is determined by whether or not there is an open position between two counterparties. For the set of counterparties that are not connected at time $t$, we then compute the fraction that remain unconnected and the fraction that become connected at time $t + 1$. We repeat the same exercise for the set of counterparties that are connected at time $t$. We then average these proportions over all dates in our sample to produce Panel A. Panel B of the table contains a complimentary way to understand the dynamics of the CDS network. On each date $t$, we compute both the degree centrality and eigenvector centrality of every counterparty in the network. Let $c_{p,t}$ denote the $p$-th percentile of centrality metric $c$ across all counterparties on date $t$. Next, we model each $c_{p,t}$ as an AR(1) process, i.e. $c_{p,t+1} = \eta_p + \phi_p c_{p,t} + \varepsilon_{p,t+1}$. The table shows the estimated $\phi_p$ and its associated t-statistic for each percentile of the given centrality metric. See Section 2 for more details on the specific centrality measures. The (*) for the row in p10 means that the degree centrality of the 10th-percentile takes the same value for the entire sample, so estimating an AR(1) process is not feasible. The sample is weekly and runs from 2010-01-04 to 2013-12-31. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Table 2: Summary Statistics of Bilateral Concentration and Price Concessions

<table>
<thead>
<tr>
<th></th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>Mean</th>
<th>StdDev</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\kappa_{i,j,t}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Dealers</td>
<td>0.03</td>
<td>0.09</td>
<td>0.18</td>
<td>0.16</td>
<td>0.21</td>
</tr>
<tr>
<td>Dealers</td>
<td>0.00</td>
<td>0.01</td>
<td>0.03</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>All</td>
<td>0.00</td>
<td>0.02</td>
<td>0.07</td>
<td>0.07</td>
<td>0.14</td>
</tr>
<tr>
<td>$PriceConcession^{EW}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Dealers</td>
<td>0.00</td>
<td>0.00</td>
<td>2.48</td>
<td>2.93</td>
<td>8.53</td>
</tr>
<tr>
<td>Dealers</td>
<td>0.00</td>
<td>0.74</td>
<td>3.21</td>
<td>3.61</td>
<td>9.99</td>
</tr>
<tr>
<td>All</td>
<td>0.00</td>
<td>0.51</td>
<td>3.01</td>
<td>3.41</td>
<td>9.58</td>
</tr>
<tr>
<td>$PriceConcession^{NW}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Dealers</td>
<td>0.00</td>
<td>0.00</td>
<td>2.32</td>
<td>2.90</td>
<td>8.58</td>
</tr>
<tr>
<td>Dealers</td>
<td>0.00</td>
<td>0.70</td>
<td>3.13</td>
<td>3.62</td>
<td>10.12</td>
</tr>
<tr>
<td>All</td>
<td>0.00</td>
<td>0.49</td>
<td>2.96</td>
<td>3.40</td>
<td>9.69</td>
</tr>
</tbody>
</table>

Notes: This table presents summary statistics of bilateral concentration and weekly price concessions between counterparties. $\kappa_{i,j}$ measures the fraction of $i$’s total gross exposure to aggregate credit risk is with $j$ as of the end of week $t$. $PriceConcession_{i,j,t}$ is the average amount of basis points that agent $i$ conceded in price to agent $j$ over their trades in week $t$. The superscript on $PriceConcession$ indicates whether it is computed using an equal-weighted (EW) or notional-weighted (NW) average over the trades between $i$ and $j$ in week $t$. We winsorize both measures at their 99% tails. See Section 3 of the paper for more detail on how we construct $PriceConcession$, $\kappa$, and the aggregate credit risk factor. Dealers are defined according to the algorithm in Appendix B. The sample size of the panel with both concentration and price concession measures is 45,074. The sample runs from 2010-01-04 to 2013-12-31. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Table 3: Are Traders Averse to Concentrated Bilateral Exposures?

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>$\text{PriceConcession}_{i,j,t}$ (bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Notional-Based $\kappa$</td>
<td>EW</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\kappa_{i,j,t-1}$</td>
<td>-5.43**</td>
</tr>
<tr>
<td>Sample</td>
<td>Full</td>
</tr>
<tr>
<td>Overall $R^2$</td>
<td>0.16</td>
</tr>
<tr>
<td>$N$</td>
<td>45,074</td>
</tr>
</tbody>
</table>

Notes: This table presents regressions of the following form:

$$\text{GiveUp}_{i,t,t} = \psi_{i,t} + \beta \times \kappa_{i,j,t-1} + \epsilon_{i,j,t}$$

where $\text{PriceConcession}_{i,j,t}$ is the average (equal or notional-weighted) amount of basis points that agent $i$ conceded in price to agent $j$ over their trades in week $t$. $\kappa_{i,j,t-1}$ measures the fraction of $i$’s total gross exposure to aggregate credit risk is with $j$ as of the end of week $t - 1$. See Section 3 of the paper for more detail on how we construct $\text{PriceConcession}$, $\kappa$, and the aggregate credit risk factor. $\psi_{i,t}$ is an $i \times t$ fixed effect. Columns (1)-(4) run the regression when $\kappa$ is defined using notional values. Columns (5)-(8) run it when $\kappa$ is defined using DV01s with respect to aggregate credit risk, which measure the amount of margin payments that $i$ would make or receive if our aggregate credit risk index were to go up by one basis point. See Section 3 of the paper for more detail on how we construct $\text{GiveUp}$, $\kappa$, and the aggregate credit risk factor. To be included in the regression, $i$ must have at least five trades in week $t$. We also winorize the price concession variables at their 1% tails. In all regressions, we report standard errors that are clustered by $i$ below point estimates. * indicates a $p$-value of less than 10% and ** indicates a $p$-value of less than 5%. The full sample runs from 2010-01-04 to 2013-12-31. The dealer subsample spans the same period, but runs the regression only for the subset where $i$ is a dealer. Dealers are defined according to the algorithm in Appendix B. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Table 4: Summary Statistics of Spreads by Firm-Week Buckets

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>≥ 5 per (f,w)</th>
<th>≥ 10 per (f,w)</th>
<th>≥ 20 per (f,w)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EW</td>
<td>LW</td>
<td>EW</td>
<td>LW</td>
</tr>
<tr>
<td># Trades</td>
<td>8</td>
<td>23</td>
<td>14</td>
<td>27</td>
</tr>
<tr>
<td>Avg. Spread (bps)</td>
<td>133</td>
<td>153</td>
<td>150</td>
<td>159</td>
</tr>
<tr>
<td>Avg. EDF (bps)</td>
<td>65</td>
<td>77</td>
<td>68</td>
<td>78</td>
</tr>
<tr>
<td>Avg. Loss-Given-Default (%)</td>
<td>60.6</td>
<td>60.3</td>
<td>60.4</td>
<td>60.2</td>
</tr>
<tr>
<td>Avg. Maturity (Years)</td>
<td>3.7</td>
<td>4.0</td>
<td>4.1</td>
<td>4.1</td>
</tr>
<tr>
<td>Avg. Notional (mm)</td>
<td>6.3</td>
<td>5.7</td>
<td>5.9</td>
<td>5.6</td>
</tr>
<tr>
<td>% Trades Dealer-to-Dealer</td>
<td>76</td>
<td>76</td>
<td>74</td>
<td>76</td>
</tr>
<tr>
<td>% Notional Dealer-to-Dealer</td>
<td>77</td>
<td>77</td>
<td>75</td>
<td>77</td>
</tr>
<tr>
<td># of (f,w) groups</td>
<td>56,409</td>
<td>56,409</td>
<td>25,053</td>
<td>25,053</td>
</tr>
</tbody>
</table>

Notes: This table presents summary statistics of spreads and trading activity across firm-week pairs (f,w). Within each (f,w) group, we compute each statistic (e.g., average spread). We then average these statistics across (f,w) groups using equal weights. We also liquidity-weight (LW) across groups, where a groups’ liquidity weight is determined by the number of trades in that (f,w) group. For the % of dealer-dealer trades, we define use our definition of dealers from Appendix B. Notional values are reported in $ millions and CDS spreads are reported in basis points. Our sample contains only single name transactions on firms that are domiciled in the United States. In addition, we consider trades that are in denominated in USD, have documentation clause XR (no restructuring), and are for senior unsecured debt (tier = SNFOR). We also drop contracts between nondealers and nondealers (only 0.31% of total) and those whose fair-value spread is above 1000 basis points. We then winsorize fair-value transaction CDS spreads at their 5% tails. The average EDF (bps) row corresponds to the 5-year expected default frequency from Moody’s. For transactions where the underlying firm does not have a match in Moody’s EDF database, we fill in the missing value with the average EDF for firms in the same rating during the week of the trade. The loss-given-default data comes from Markit. The sample runs from 2010-01-04 to 2013-12-31. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Table 5: Dealer and Customer Prices

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Fair-Value CDS Transaction Spread (bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Robust Dealer Selection</td>
</tr>
<tr>
<td></td>
<td>Full Sample</td>
</tr>
<tr>
<td>Markit Spread (bps)</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>0.82**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>1 (Customer-Dealer)</td>
<td>6.14**</td>
</tr>
<tr>
<td></td>
<td>(1.12)</td>
</tr>
<tr>
<td>Overall $R^2$</td>
<td>0.92</td>
</tr>
<tr>
<td>$N$</td>
<td>424,485</td>
</tr>
</tbody>
</table>

Notes: This table presents regressions of the following form:

$$Spread_{k,f,t} = FE(Firm) + FE(IG \times Mat\, Bucket_k \times Week) + \theta_1 \times MarkitSpread_{f,t} + \theta_2 \times \log(Notional_{k,t}) + \Phi \times 1_{k,t}(Customer-Dealer) + \epsilon_{k,f,t}$$

$Spread_{k,f,t}$ is the fair-value spread (in basis points) for transaction $k$, written on firm $f$, and executed on date $t$. $MarkitSpread_{f,t}$ is the 5-year CDS spread from Markit’s singlename database that is associated with firm $f$ on date $t$. $Notional_{k,t}$ is the notional amount in the transaction. $1_{k,t}(Customer-Dealer)$ is a dummy variable that equals 1 if the transaction is between two dealers and is zero otherwise. In columns (1)-(4), dealers are defined according to the algorithm in Appendix B and in columns (5)-(8) we use the DTCC’s labeling of dealers. $FE(Firm)$ is a fixed effect based on the underlying firm $f$ in the transaction. $Firm(IG \times Mat\, Bucket_k \times Week)$ is a fixed effect based on the interaction of whether the firm in the trade is rated as investment grade, the maturity bucket of the trade, and the week of the trade. To define a maturity bucket, we first group transactions into one of the following four buckets based on their maturity: (i) 0-2 years; (ii) 2-4 years; (iii) 4-6 years; and (iv) 7+ years. Column (1) runs the regression for the full sample of transactions. Column (2) uses transactions whose maturity is between four and six years. Column (3) uses transactions where Markit’s liquidity factor (the number of dealers providing quotes) for the firm on date $t$ is at least eight (the 10% of tail of Markit depth for the full sample). In addition, column (3) focuses on dealer-dealer trades and trades between dealers and large customers, where large customers are defined as those in the top 10% of gross transaction volume for our sample period. Columns (4)-(6) mirror the filters used in columns (1)-(3), except these regressions use the DTCC’s definition of dealer. Our main sample contains only single name transactions on firms that are domiciled in the United States. In addition, we consider trades that are in denominated in USD, have documentation clause XR (no restructuring), and are for senior unsecured debt (tier = SNFOR). We also drop contracts between nonealers and nonealers (only 0.31% of total) and those where the fair-value spread is over 1000 basis points. We then winsorize fair-value transaction CDS spreads and 5-year CDS Markit spreads at their the 5% tails. The credit ratings used to determine whether a firm is investment-grade fixed effect come from Markit. Standard errors, which are double clustered by year and firm, are listed below point estimates. * indicates a p-value of less than 10% and ** indicates a p-value of less than 5%. The sample runs from 2010-01-04 to 2013-12-31. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Table 6: Calibration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{z}_d$</td>
<td>0.045</td>
<td>DTCC Data 2010-2013</td>
</tr>
<tr>
<td>$\bar{R}_c - \bar{R}_d$ (bps)</td>
<td>5.12</td>
<td>DTCC Data 2010-2013</td>
</tr>
<tr>
<td>$\bar{R}_d$ (bps)</td>
<td>133.00</td>
<td>DTCC Data 2010-2013</td>
</tr>
<tr>
<td>$n$</td>
<td>723</td>
<td>DTCC Data 2010-2013</td>
</tr>
<tr>
<td>$n_d$</td>
<td>14</td>
<td>DTCC Data 2010-2013</td>
</tr>
<tr>
<td>$L$ = Loss-Given-Default</td>
<td>60.60%</td>
<td>Markit</td>
</tr>
<tr>
<td>$p$ = Probability of Default</td>
<td>0.65%</td>
<td>Moody’s</td>
</tr>
<tr>
<td>$\lambda_d$</td>
<td>0.32</td>
<td>Model Implied</td>
</tr>
<tr>
<td>$\alpha \sigma^2 \bar{w} + \mu$</td>
<td>143.04</td>
<td>Model Implied</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>4.37</td>
<td>Model Implied</td>
</tr>
<tr>
<td>$\phi$</td>
<td>8.00</td>
<td>Model Implied</td>
</tr>
</tbody>
</table>

Notes: This table shows parameters used to calibrate the model. $\bar{z}_d$ is the time-series average of dealer exposure. For each week, we compute the average dealer $\bar{z}_d$ across dealers, then report the time-series average for the full sample in the table. Section 3.4.1 contains a full description of this procedure. Dealers are those identified by the algorithm described in Appendix B. $\bar{R}_c - \bar{R}_d$ is the estimate that comes out of a regression of transaction spreads on a dummy variable for if the transaction is a customer-dealer trade (see Table 5 for complete details). $\bar{R}_d$ is the average transaction spread in the CDS market from Table 4. $n$ is the total number of counterparties in the network. $n_d$ is the number of dealers. $L$ and $p$ are the physical loss-given-default and probability of default for the firms that are included in our estimation of $\bar{R}_c - \bar{R}_d$. See Table 5 for more details on this set of firms. The remaining parameters in the table are implied by our structural model. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
<table>
<thead>
<tr>
<th></th>
<th>Benchmark</th>
<th>Top</th>
<th>90\textsuperscript{th} prc.</th>
<th>Median</th>
<th>Bottom</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of dealers</td>
<td>14</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>Complete network $\bar{R}$ (bps)</td>
<td>143.04</td>
<td>143.88</td>
<td>143.21</td>
<td>143.02</td>
<td>142.81</td>
</tr>
<tr>
<td>$\bar{R}_d$ (bps):</td>
<td>133.00</td>
<td>164.06</td>
<td>138.54</td>
<td>131.40</td>
<td>123.25</td>
</tr>
<tr>
<td>$\bar{R}_c$ (bps):</td>
<td>138.12</td>
<td>153.78</td>
<td>140.92</td>
<td>137.32</td>
<td>133.21</td>
</tr>
<tr>
<td>$z_d$</td>
<td>0.045</td>
<td>−0.091</td>
<td>0.021</td>
<td>0.052</td>
<td>0.088</td>
</tr>
</tbody>
</table>

Notes: This table reports the number of dealers, the average spreads under the complete network, the average spreads in the dealer market, the average spreads in the customer market, and the average net position of dealers. We define dealers precisely in Section 3.2.2. Column (1) reports our benchmark calibration. In Column (2) reports the results after removing the largest net-seller. Column (3) reports results after removing one dealer at the 90\textsuperscript{th} percentile. Column (4) reports results after removing the dealer with the median net position, and Column (5) reports results after removing the dealer that is the largest net buyer in the baseline model. Source: Authors’ analysis, which uses data provided to the OFR by The Depository Trust & Clearing Corporation.
Appendix

A Model Derivations

A.1 Solving the Model

Agent $i$'s optimization problem is given by Equation (1):

$$\max_{\{\gamma_{ij}\}_{j=1}^{n}} \quad w_i(1 - \mu) + \sum_{j=1}^{n} \gamma_{ij}(R_{ij} - \mu) - \frac{\alpha}{2} (w_i + z_i)^2 \sigma^2 - \frac{\phi}{2} \sum_{j=1}^{n} \gamma_{ij}^2$$

subject to

$$\gamma_{ij} = 0 \text{ if } g_{ij} = 0,$$

and

$$z_i = \sum_{j=1}^{n} \gamma_{ij},$$

Agent $i$'s first-order conditions give us:

$$\gamma_{ij} = \begin{cases} \frac{1}{\phi} (R_{ij} - \mu) - \frac{1}{\phi} \hat{z}_i & \text{if } g_{ij} = 1 \\ 0 & \text{if } g_{ij} = 0 \end{cases} \quad (A1)$$

where

$$\hat{z}_i = (w_i + z_i)\alpha \sigma^2,$$  

$$z_i = \sum_{j=1}^{n} \gamma_{ij} = \frac{1}{K_i} \sum_{j=1}^{n} g_{ij}(R_{ij} - \mu) - \alpha w_i \sigma^2,$$  

and

$$K_i = \sum_{j=1}^{n} g_{ij}. \quad (A4)$$

We can derive Equation (8) by combining Equations (2), (6), and (7). Furthermore, to fully characterize the equilibrium, we solve for equilibrium quantities by rewriting Equation (8) in matrix notation as follows:

$$z + w = (I - \Lambda)\omega + \Lambda \tilde{G}(z + \omega),$$

where $z = [z_1, \ldots, z_n]'$ and $w = [w_1, \ldots, w_n]'$ are column vectors of net positions and pre-trade exposures, $\Lambda$ is a diagonal matrix with the $i$th element given by $\lambda_i$, and $\tilde{G}$ is a $n \times n$ matrix with the $ij$th entry given by $\tilde{g}_{ij}$.

We can solve the system of equations for the equilibrium net positions and post-trade exposures:

$$z + w = (I - \Lambda \tilde{G})^{-1}(I - \Lambda)w, \quad (A5)$$

which fully characterize the solution of the model. Equation (A5) defines the map between agents’ pre-trade exposures to the underlying asset on the right-hand side and their post-trade exposures on left-hand side. The right-hand side of the equation depends only on exogenous parameters of the model.

A.1.1 Complete Network

Under the complete network benchmark, we have $g_{ij} = 1$ for every $i$ and $j$. In this case, $K_i = n$ for every $i$, and $\gamma_{ij} = \frac{1}{n}$ for every $i$ and $j$. Also, $\lambda_i = \frac{n \alpha \sigma^2}{n \alpha \sigma^2 + 2 \phi} \equiv \lambda$ for every $i$, and the matrix $\tilde{G}$ becomes idempotent.
Therefore, the vector of net positions becomes:

\[ z + \omega = (I - \Lambda \tilde{G})^{-1}(I - \Lambda)w \]
\[ = (1 - \lambda)(I - \lambda \tilde{G})^{-1} \omega \]
\[ = (1 - \lambda) \left( I + \frac{\lambda}{1 - \lambda} \tilde{G} \right) \omega \]
\[ = (1 - \lambda) \omega + \lambda \tilde{G} \omega. \]

Specifically, the post-trade exposure of agent \( i \) is given by:

\[ z_i + w_i = (1 - \lambda)w_i + \lambda \left( \frac{1}{n} \sum_{j=1}^{n} w_j \right). \]

The average prices in equilibrium becomes:

\[ \bar{R}_{\text{Complete Network}} \equiv \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} R_{ij} = \frac{\alpha \sigma^2}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{1}{2} (\hat{z}_i + \hat{z}_j) + \mu \]
\[ = \frac{\alpha \sigma^2}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{1}{2} (z_i + \omega_i + z_j + \omega_j) + \mu \]
\[ = \sigma^2 \alpha \bar{\omega} + \mu, \]

where \( \bar{\omega} = \frac{1}{n} \sum_{i=1}^{n} \omega_i \).

### A.1.2 Equilibrium properties

Although the model features closed-formed solutions, the equilibrium variables still depend on the entire trading network. In this subsection, we exploit some limiting cases of the model. First, we define what it means for two agents to be path-connected.

**Definition A1.** Two players \( i \) and \( j \) are path-connected if there is a sequence of agents \( \{s_1, s_2, \ldots, s_k\} \) such that:

\[ g_{is_1} = g_{s_1 s_2} = \ldots = g_{s_{k-1} s_k} = g_{skj} = 1. \]

The following proposition shows that when there is no counterparty-specific risk aversion, i.e., \( \phi = 0 \), then there is perfect risk sharing among path-connected agents. The corollary following the proposition shows that if all agents are path-connected, then perfect risk sharing among all agents is achieved in equilibrium.

**Proposition A1.** If \( \phi = 0 \) for every \( i = 1, \ldots, n \), then any two path-connected agents have the same post-trade exposure:

\[ (z_i + w_i) = (z_j + w_j) \]

for any \( i \) and \( j \) who are path connected.

**Proof.** Suppose players \( i \) and \( j \) are path-connected, but

\[ (z_i + w_i) \neq (z_j + w_j). \]

Then, there are two agents, say \( s \) and \( l \), that are directly connected with each other (i.e., \( g_{sl} = 1 \)) and have different post-trade exposure (i.e., \( z_s + w_s \neq z_l + w_l \)). If both agents are maximizing and their first-order conditions hold with equality, then we have that:

\[ R_{sl} - \mu = \alpha (z_s + w_s) \sigma^2 = \alpha (z_l + w_l) \sigma^2 \implies z_i + w_i = z_j + w_j. \]
Corollary A1. If \( \phi = 0 \) for every \( i = 1, \ldots, n \), and all agents are path connected, then there is perfect risk-sharing in equilibrium, i.e.,

\[
z_i + w_i = \frac{1}{n} \sum_j w_j,
\]

and equilibrium prices are given by:

\[
R_{ij} - \mu = \sigma^2 \omega \quad \forall i, j,
\]

where \( \omega = \frac{1}{n} \sum_{i=1}^{n} \omega_i \).

Proof. We know that:

\[
z_i + w_i = z_j + w_j = \omega,
\]

where \( \omega \) is a constant. We also know that

\[
\sum_j z_j = 0,
\]

from the clearing conditions.

Finally, the next proposition shows that when counterparty-specific risk aversion goes to infinity, then the equilibrium features autarky, regardless of the trading network in place.

Proposition A2. If \( \phi \to \infty \) for every \( i = 1, \ldots, n \), then there is no trade in equilibrium, regardless of the network structure.

Proof. From the first-order conditions, we get that \( \gamma_{ij} = 0 \) for any two agents \( i \) and \( j \).

A.2 Model with Core-Periphery Network

A.2.1 Dealer market

Applying Equation (8) to dealers gives us the following expression for the post-trade exposures of dealers:

\[
z_i + \omega_i = (1 - \lambda_d) \omega_i + \lambda_d \omega \quad \forall i = 1, \ldots, n_d,
\]

where

\[
\lambda_d = \frac{na\sigma^2}{na\sigma^2 + 2\phi}
\]

and \( \omega = \frac{1}{n} \sum_{j=1}^{n} \omega_j \). Hence, dealers’ post-trade exposures are a convex combination of their own pre-trade exposure, i.e., \( \omega_i \), and the average pre-trade exposure in the economy, i.e., \( \omega \).

The average post-trade exposure in the dealer market is given by:

\[
\overline{z_d} + \overline{\omega_d} = \frac{1}{n_d} \sum_{i=1}^{n_d} (z_i + \omega_i) = (1 - \lambda_d) \overline{\omega_d} + \lambda_d \overline{\omega}.
\]

The equilibrium price of a contract between dealers \( i \) and \( j \) is given by:

\[
R_{ij} - \mu = \alpha \sigma^2 \left[ \lambda_d \omega + (1 - \lambda_d) \frac{\omega_i + \omega_j}{2} \right],
\]

and the average price in the dealer market, i.e., \( \overline{R_d} = \frac{1}{n_d^2} \sum_{i=1}^{n_d} \sum_{j=1}^{n_d} R_{ij} \), is given by:

\[
\overline{R_d} - \mu = \alpha \sigma^2 \omega - (1 - \lambda_d) \alpha \sigma^2 (\omega - \overline{\omega_d}),
\]

where \( \overline{\omega_d} = \frac{1}{n_d} \sum_{i=1}^{n_d} \omega_i \).
A.2.2 Customer market

Applying Equation (8) to customers gives us the following expression for their post-trade exposures:

\[ z_i + \omega_i = (1 - \bar{\lambda}_c)\omega_i + \bar{\lambda}_c \frac{1}{n_d + 1} \sum_{j=1}^{n_d} (z_j + \omega_j) + z_i + \omega_i \quad \forall i = n_d + 1, \ldots, n, \]

where \( \bar{\lambda}_c = \frac{(n_d + 1)\alpha\sigma^2}{(n_d + 1)\alpha\sigma^2 + 2\sigma^2} \). We can use Equation (12) to write the post-trade exposures as follows:

\[ z_i + \omega_i = \lambda_c \omega_i + (1 - \lambda_c)(\omega - \omega_d) \quad \forall i = n_d + 1, \ldots, n, \quad (A7) \]

where \( \lambda_c = \frac{n_d\alpha\sigma^2}{n_d\alpha\sigma^2 + \sigma^2} \).

The equilibrium price of contract between a customer \( i \in \{n_d + 1, \ldots, n\} \) and a dealer \( j \in \{1, \ldots, n_d\} \) is given by:

\[ R_{ij} - \mu = \alpha\sigma^2 \left( \frac{z_i + \omega_i + z_j + \omega_j}{2} \right) = \alpha\sigma^2 \omega - \frac{\alpha\sigma^2}{2} \lambda_c(1 - \lambda_d)(\omega - \omega_d) + \frac{\alpha\sigma^2}{2} [(1 - \lambda_c)(\omega_i - \omega) + (1 - \lambda_d)(\omega_j - \omega)], \]

where we used Equations (A6) and (A7) to derive the last expression.

Hence, the average price in the customer market, i.e.,

\[ \overline{R}_c = \frac{1}{n_d(n - n_d)} \sum_{j=1}^{n_d} \sum_{i=n_d+1}^{n} R_{ij}, \]

is given by:

\[ \overline{R}_c - \mu = \alpha\sigma^2 \omega - \frac{1}{2} \alpha\sigma^2(\omega - \omega_d) \left[ (1 + \lambda_c)(1 - \lambda_d) - \frac{n_d}{n - n_d}(1 - \lambda_c) \right]. \]

> 0 if \( \frac{n_d}{n} < \frac{1}{2} \)

We can also write the average price in the customer market as a function of the average price in the dealer market as follows:

\[ \overline{R}_c = \overline{R}_d + \frac{1}{2} \alpha\sigma^2(1 - \lambda_c) \left[ 1 + (1 - \lambda_d) \frac{n - n_d}{n_d} \right] \frac{n_d}{n - n_d}(\omega - \omega_d) \]

A.2.3 Calibration

From Equation (12), we can compute \( \omega - \omega_d \) as a function of \( \omega_d \) and \( \lambda_d \):

\[ \omega - \omega_d = \frac{\omega_d}{\lambda_d}, \quad (A8) \]

Furthermore, we can write \( \lambda_d \) as follows:

\[ \lambda_d = \frac{\alpha\sigma^2\omega_d}{\alpha\sigma^2\omega_d + (\overline{R}_c - \overline{R}_d) 2 \left( 1 - \frac{n_d}{n} \right)}, \quad (A9) \]

by taking the difference between Equations (14) and (16) and solving for \( \lambda_d \).

The complete network benchmark price can be written as:

\[ \alpha\sigma^2 \omega = \overline{R}_d - \mu + \frac{1 - \lambda_d}{\lambda_d} \omega_d \alpha\sigma^2 = \overline{R}_d - \mu + (\overline{R}_c - \overline{R}_d) 2 \left( 1 - \frac{n_d}{n} \right), \]
where the first equality is derived by combining Equations (14) and (A8), and the second equality is obtained by substituting in Equation (A9).

We can rearrange Equation (24) to compute $\alpha$ as follows:

$$\alpha = \frac{1}{\sigma^2} \left[ \frac{1}{\lambda_d} \right]$$

and we can rearrange Equation (13) to compute $\phi$ as follows:

$$\phi = \frac{1}{2} n \sigma^2 \left[ \frac{1 - \lambda_d}{\alpha \sigma^2 \bar{z}_d} \right]$$

where $\lambda_d$ is computed from Equation (A9).

To compute the model-implied dealers’ pre-trade exposures, we can rearrange Equation (A6) as follows:

$$\omega - \omega_i = \frac{z_i}{\lambda_d} \quad \forall i = 1, \ldots, n,$$

and to compute customers’ pre-trade exposure we can rearrange Equation (A7) as well:

$$\omega - \omega_i = \frac{z_i}{\lambda_c} + (1 - \lambda_d)(\omega - \bar{x}) \quad \forall i = n_d + 1, \ldots, n.$$
and
\[ R_{ij} - \mu = A + B\alpha\sigma^2(z_i + \omega_i + z_j + \omega_j). \]

Hence, the first-order conditions imply:
\[
R_{ij} - \mu + \sum_s \gamma_{is} \frac{\partial}{\partial \gamma_{ij}} R_{ij} = \alpha\sigma^2(z_i + \omega_i) + \phi \gamma_{ij}
\]
\[
\implies R_{ij} - \mu = \alpha\sigma^2(z_i + \omega_i - Bz_i) + \phi \gamma_{ij}
\]

Under the no transaction cost assumption, i.e., \( R_{ij} = R_{ji} \), along with the bilateral clearing condition, i.e., \( \gamma_{ij} + \gamma_{ji} = 0 \), we can write equilibrium prices as follows:
\[
R_{ij} - \mu = \alpha\sigma^2 2(\omega_i + \omega_j + z_i + z_j)
\]

Applying the method of undetermined coefficients to our initial guess gives
\[ A = 0, \]
\[ B = C = \frac{1}{3}, \]
and
\[ D = E = \frac{1}{2}. \]

Hence, equilibrium prices are given by:
\[
R_{ij} - \mu = \alpha\sigma^2 \frac{1}{2}[(1 - B)z_i + \omega_i + (1 - B)z_j + \omega_j]
\]

and first-order condition can be written as:
\[
R_{ij} - \mu = \alpha\sigma^2 (\omega_i + \tilde{z}_i) + \phi \gamma_{ij}, \tag{A17}
\]

where \( \tilde{z}_i = \frac{2}{3}z_i \).

To derive equilibrium allocations, we can combined Equations (A16) and (A17), along with the fact that \( z_i = \sum_{j=1}^{n} \gamma_{ij} \):
\[
\tilde{z}_i + \omega_i = \left(1 - \tilde{\lambda}_i\right) \omega_i + \tilde{\lambda}_i \sum_{j=1}^{n} \tilde{g}_{ij} (\tilde{z}_j + \omega_j) \quad \forall i = 1, \ldots, n \tag{A18}
\]

where \( \tilde{z}_i = \frac{2}{3}z_i, \tilde{g}_{ij} = \frac{g_{ij}}{K_i}, K_i = \sum_{j=1}^{n} g_{ij}, \) and \( \tilde{\lambda}_i = \frac{K_i\alpha\sigma^2}{K_i\alpha\sigma^2 + 3\phi} \in (0, 1) \).

Notice that Equation (A18) is extremely similar to Equation (8), except that under price impact we have \( \tilde{z}_i \) and \( \tilde{\lambda}_i \) instead of \( z_i \) and \( \lambda_i \). As a result, the analyses discussed in the paper hold in a price impact environment as well.

**B Algorithm to Classify Market Participants as Dealers**

In this section, we describe a minimum-distance algorithm that we use to determine the size of the empirical core in the CDS market. The algorithm uses the fact that a pure core-periphery network requires that all dealers should be connected to each other and to every customer. Moreover, a pure core-periphery network stipulates that customers should be connected to all dealers and no one else. Based on these two observations, we select the number and identity of dealers and assign remaining agents to the periphery as follows:
1. Choose a threshold number of connections, \( m \), above which a counterparty will be classified as a dealer. If the number of connections is below this threshold, we label that agent as a customer. Define \( D_{i,t} \equiv \sum_j G_{i,j,t} \) as counterparty \( i \)'s degree on date \( t \). In words, \( D_{i,t} \) just counts the number of \( i \)'s trading partners. For a given threshold \( m \), agent \( i \) is a dealer if \( D_{i} \geq m \) and \( i \) is a customer otherwise.

2. For each threshold \( m \) and its implied definition of dealers and customers, we construct a counterfactual network that is perfectly core-periphery, that is, a network in which everyone is connected to all dealers but not to other customers. Let this counterfactual core-periphery network be \( G_{CP(m)} = (g_{CP(m)}^{ij})_{ij} \). Formally, \( g_{CP(m)}^{ii} = 1 \) for every \( i \), and for \( i \neq j \)

\[
g_{CP(m)}^{ij} = \begin{cases} 
1 & \text{if } D_{j,t} \geq m \\ 
0 & \text{otherwise} 
\end{cases}.
\]

3. We then compute the number of connections that should exist under a perfect core-periphery network but do not exist in the data, as well as the number of connections that do not exist in the data but should exist under a perfect core-periphery network. This is the number of elements of \( t \) that are not consistent with a core-periphery network. We then minimize over choices of \( m \) the average number of connections inconsistent with a core-periphery relative to the total number of connections under a perfect core-periphery network. Hence, the minimization problem is given by:

\[
\min_m \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \left| G_{i,j,t} - g_{CP(m)}^{ij} \right| \sum_{j=1}^{N} g_{CP(m)}^{ij},
\]

where \( N \) is the total number of counterparties.

Empirically, the algorithm generates a counterparty network with 14 dealers. Furthermore, in the Internet Appendix we show for robustness that our selection algorithm consistently identifies the same set of dealers even if we focus on subsamples of our data.