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OTC Intermediaries: Internet Appendix

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OTC Intermediaries*

Internet Appendix

(Not for Publication, Except Online)

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Abstract

In this appendix we present several pieces of supplementary analysis to support our work in the main text, including: (i) evidence that the CDS network has a core-periphery structure that is stable through time; and (ii) proof that the relationship between bilateral price concessions and concentration identifies the sign of in our model. We also provide additional details on how we construct the key variables used in our empirical analysis and develop further intuition for the baseline model. Finally, we explore the implications of different specifications for the preference to smooth out trades and develop several extensions of our baseline model (e.g., heterogenous beliefs about default risk).

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

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I.1 Supplementary Analysis

In this section, we supplement our work in the main text with the following analyses: (i) evidence that the CDS network has a stable, core-periphery structure; (ii) a proof that the regression of bilateral price concessions on concentration κ is a sharp test of whether $\quad > 0$ in the model, regardless of the shape of the network; (iii) robustness checks on the algorithm we use to define dealers; (iv) details on how we measure bilateral and net CDS exposures; and (v) robustness of the stress tests from the main text (e.g., customer removal).

I.1.1 The Persistence and Shape of the CDS Trading Network

I.1.1.1 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. We now 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:

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

where n is the total number of counterparties in the market.[1] $1\left(g_{i,j,t} = l\right)$ 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 $t+1$:

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

So, for instance, $N_{t+1}^{0,0}$ 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:

$$p_{t+1}^{l,m} = \frac{N_{t+1}^{l,m}}{N_t^l}, \quad l, m = 0, 1$$

[1]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.

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 I.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 network is incredibly persistent – new connections in the CDS market are rarely formed and existing connections are rarely broken.

Panel B of Table I.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:

$$c^e_{i,t} = \quad 1 \sum_{j \neq i} g_{i,j,t} \times c^e_{j,t}$$

Intuitively, counterparty i has a large eigenvector centrality if it is connected to other connected counterparties.[2]

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 I.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.

[2] Formally, it is the $(n \times 1)$ vector c^e_t that solves the system $G_t c^e_t = \ c^e_t$, where is the largest eigenvalue of G_t.

I.1.1.2 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 sample. This simplification is motivated by our preceding results showing that the CDS network is relatively static, meaning $G_t \approx G$.

Figure I.1 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 2.4 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 C, we provide details on a minimum-distance algorithm that we use 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.[3]

I.1.2 Testing $\quad > 0$ inside of the model

In this subsection, we show that, within the model framework, the coe cient from the price concession is negative if, and only if, $\quad > 0$. In the model, price concession and κ between agents i and j are defined as:

$$PriceConcession_{ij} = \begin{cases} R_i^{max} \quad R_{ij} & \text{if } \ _{ij} > 0 \\ R_{ij} \quad R_i^{min} & \text{if } \ _{ij} < 0 \end{cases}, \tag{I.1}$$

$$\kappa_{ij} = \frac{| \ _{ij}|}{\sum_{s=1}^{n} | \ _{is}|}, \tag{I.2}$$

where $R_i^{max} = \max_s R_{is}$ and $R_i^{min} = \min_s R_{is}$. We will restrict our analysis to parameterization in which κ_{ij} is well defined, that is $\sum_{s=1}^{n} | \ _{is}| > 0$ for every i.

[3]DTCC also classifies traders based on its list of registered dealer members. In single-name transaction data, 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. Throughout the paper and internet appendix, We provide robustness checks for our main results to DTCC dealer designation.

For $\quad_{ij} > 0$, that is, agent i sells protection to agent j, we can write the first-order condition as follows:

$$
\begin{aligned}
R_{ij} \quad \mu &= \alpha\sigma^2 (w_i + z_i) + \quad_{ij} \\
R_{ij} \quad \mu &= \alpha\sigma^2 (w_i + z_i) + \quad |\quad_{ij}| \\
R_{ij} &= \quad \mu \quad \alpha\sigma^2 (w_i + z_i) \qquad |\quad_{ij}| \, .
\end{aligned}
$$

By adding R_i^{max} on both sides, we have:

$$
\begin{aligned}
R_i^{max} \quad R_{ij} &= R_i^{max} \quad \mu \quad \alpha\sigma^2 (w_i + z_i) \qquad |\quad_{ij}| \\
R_i^{max} \quad R_{ij} &= R_i^{max} \quad \mu \quad \alpha\sigma^2 (w_i + z_i) \qquad \sum_{s=1}^{n} |\quad_{is}| \frac{|\quad_{ij}|}{\sum_{s=1}^{n} |\quad_{is}|} \\
R_i^{max} \quad R_{ij} &= a_i^s \quad b_i^s \kappa_{ij},
\end{aligned}
\tag{I.3}
$$

where $a_i^s = R_i^{max} \quad \mu \quad \alpha\sigma^2 (w_i + z_i)$ and $b_i^s = \quad \sum_{s=1}^{n} |\quad_{is}| \quad 0$.

For $\quad_{ij} < 0$, that is, agent i buys protection to agent j, we can write the first-order condition as follows:

$$
\begin{aligned}
R_{ij} \quad \mu &= \alpha\sigma^2 (w_i + z_i) + \quad_{ij} \\
R_{ij} &= \mu + \alpha\sigma^2 (w_i + z_i) \qquad |\quad_{ij}| \, .
\end{aligned}
$$

By subtracting R_i^{min} on both sides, we have:

$$
\begin{aligned}
R_{ij} \quad R_i^{min} &= \quad R_i^{min} + \mu + \alpha\sigma^2 (w_i + z_i) \qquad |\quad_{ij}| \\
R_{ij} \quad R_i^{min} &= \quad R_i^{min} + \mu + \alpha\sigma^2 (w_i + z_i) \qquad \sum_{s=1}^{n} |\quad_{is}| \frac{|\quad_{ij}|}{\sum_{s=1}^{n} |\quad_{is}|} \\
R_i^{max} \quad R_{ij} &= a_i^b \quad b_i^b \kappa_{ij},
\end{aligned}
\tag{I.4}
$$

where $a_i^b = \quad R_i^{min} + \mu + \alpha\sigma^2 (w_i + z_i)$ and $b_i^b = \quad \sum_{s=1}^{n} |\quad_{is}|$.

Notice that $b_i^s = b_i^b$. Let

$$
b_i = b_i^s = b_i^b = \quad \sum_{s=1}^{n} |\quad_{is}| \, . \tag{I.5}
$$

Also $b_i > 0$ whenever there trade in equilibrium and $\quad > 0$. We can write price concession as follows:

$$
PriceConcession_{ij} = \begin{cases} a_i^s \quad b_i \kappa_{ij} & \text{if } \quad_{ij} > 0 \\ a_i^b \quad b_i \kappa_{ij} & \text{if } \quad_{ij} < 0 \end{cases}, \tag{I.6}
$$

Next, we derive the coe cient of regressing $PriceConcession_{ij}$ on κ_{ij} with a fixed effect on agent i by whether agent i is seller or buyer of protection from agent j, that is, the coe cient on the following specification:

$$PriceConcession_{ij} = \;_i^{b/s} + \beta\kappa_{ij} + error_{ij}, \tag{I.7}$$

where $\;_i^{b/s}$ represents the fixed effects and $b/s \in \{s, b,\}$ specifies whether agent i sells of buy protection from agent j.

Let $\{\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3, \ldots, \mathcal{P}_{2n}\}$ be the partition of all (ij) pairs into fixed effects buckets. Formally, we define these set as follows. For $i = 1, \ldots, n$, $\mathcal{P}_i = \{(s, j) \in \mathbb{N}^2 : s = i \,\&\; _{ij} > 0\}$, which means that $\mathcal{P}_i$ is the group of pairs (s, j) such that s is fixed equal to i, and s sells protection to j. Analogously, for $i = n+1, \ldots, 2n$, $\mathcal{P}_i = \{(s, j) \in \mathbb{N}^2 : s = i \quad n \,\&\; _{ij} < 0\}$, which means that $\mathcal{P}_i$ is the group of pairs (s, j) such that s is fixed equal to $i \quad n$, and s buys protection from j.

To formally derive the regression coe cient, we start from Equation (I.6) and then demean within each fixed effect buckets:

$$\begin{aligned} PriceConcession_{ij} &= a_i^{b/s} \quad b_i\kappa_{ij} \\ PriceConcession_{ij} \quad \overline{PriceConcession}_{ij} &= \quad b_i\left(\kappa_{ij} \quad \overline{\kappa}_{ij}\right) \end{aligned} \tag{I.8}$$

where $b/s \in \{s, b,\}$, $\overline{PriceConcession}_{ij}$ is the average price concession within the group the pair (i, j) belongs to, and $\overline{\kappa}_{ij}$ is the average κ_{ij} within the group the pair (i, j) belongs to. Therefore, the model-equivalent regression coe cient from Equation (I.7) is given by:

$$\hat{\;}^{model} = \frac{\widehat{\text{Cov}} \;\; PriceConcession_{ij} \quad \overline{PriceConcession}_{ij}, \kappa_{ij} \quad \overline{\kappa}_{ij}}{\widehat{\text{Var}}\left(\kappa_{ij} \quad \overline{\kappa}_{ij}\right)} \tag{I.9}$$

Notice that the sign of the $\hat{\;}^{model}$ estimated is the same sign as the covariance term in denominator of the expression above.

We can write the covariance term as follows:

$$\widehat{\text{Cov}} \;\; PriceConcession_{ij} \quad \overline{PriceConcession}_{ij}, \kappa_{ij} \quad \overline{\kappa}_{ij}$$

using definition of covaraince:

$$\begin{aligned} = \frac{1}{\# \;\; \cup_{l=1}^{2n} \mathcal{P}_l} \sum_{(ij) \in \cup_{s=1}^{2n} \mathcal{P}_s} & PriceConcession_{ij} \quad \overline{PriceConcession}_{ij} \;\; \left(\kappa_{ij} \quad \overline{\kappa}_{ij}\right) \\ \frac{1}{\# \;\; \cup_{l=1}^{2n} \mathcal{P}_l} & \sum_{(ij) \in \cup_{s=1}^{2n} \mathcal{P}_s} PriceConcession_{ij} \quad \overline{PriceConcession}_{ij} \\ & \frac{1}{\# \;\; \cup_{l=1}^{2n} \mathcal{P}_l} \sum_{(ij) \in \cup_{s=1}^{2n} \mathcal{P}_s} \left(\kappa_{ij} \quad \overline{\kappa}_{ij}\right) \end{aligned}$$

applying law of iterated expectations:

$$
\begin{aligned}
&= \sum_{s=1}^{2n} \frac{\#\left(\mathcal{P}_s\right)}{\#\ \cup_{l=1}^{2n}\mathcal{P}_l} \frac{1}{\#\left(\mathcal{P}_s\right)} \sum_{(ij)\in\mathcal{P}_s} \left(PriceConcession_{ij} - \overline{PriceConcession}_{ij} \right) \left(\kappa_{ij} - \overline{\kappa}_{ij}\right) \\
&\quad \sum_{s=1}^{2n} \frac{\#\left(\mathcal{P}_s\right)}{\#\ \cup_{l=1}^{2n}\mathcal{P}_l} \frac{1}{\#\left(\mathcal{P}_s\right)} \underbrace{\sum_{(ij)\in\mathcal{P}_s} \left(PriceConcession_{ij} - \overline{PriceConcession}_{ij} \right)}_{=0} \\
&\quad \sum_{s=1}^{2n} \frac{\#\left(\mathcal{P}_s\right)}{\#\ \cup_{l=1}^{2n}\mathcal{P}_l} \frac{1}{\#\left(\mathcal{P}_s\right)} \underbrace{\sum_{(ij)\in\mathcal{P}_s} \left(\kappa_{ij} - \overline{\kappa}_{ij}\right)}_{=0} \\
&= \sum_{s=1}^{2n} \frac{\#\left(\mathcal{P}_s\right)}{\#\ \cup_{l=1}^{2n}\mathcal{P}_l} \frac{1}{\#\left(\mathcal{P}_s\right)} \sum_{(ij)\in\mathcal{P}_s} \left(PriceConcession_{ij} - \overline{PriceConcession}_{ij} \right) \left(\kappa_{ij} - \overline{\kappa}_{ij}\right)
\end{aligned}
$$

using Equation (I.8):

$$
= \sum_{s=1}^{2n} \frac{\#\left(\mathcal{P}_s\right)}{\#\ \cup_{l=1}^{2n}\mathcal{P}_l} \frac{1}{\#\left(\mathcal{P}_s\right)} \sum_{(ij)\in\mathcal{P}_s} b_i \left(\kappa_{ij} - \overline{\kappa}_{ij}\right)^2
$$

using Equation (I.5):

$$
= \underbrace{\sum_{s=1}^{2n} \left(\frac{\#\left(\mathcal{P}_s\right)}{\#\ \cup_{l=1}^{2n}\mathcal{P}_l} \frac{1}{\#\left(\mathcal{P}_s\right)} \sum_{(ij)\in\mathcal{P}_s} \left(\kappa_{ij} - \overline{\kappa}_{ij}\right)^2 \sum_{k=1}^{n} |\ {}_{ik}| \right)}_{>0}
$$

Therefore, under the assumptions of the model, we have that: > 0 if, and only if, $\hat{}^{model} < 0$.

I.1.3 Robustness of Dealer Selection Algorithm

To verify the robustness and consistency of our dealer selection algorithm from Appendix C, we perform the following exercise. We start with a full network matrix that includes all the existing counterparties, and compute who is a dealer based on the algorithm. In a second step, we sort all counterparties based on degree and then transaction volume. We then iteratively remove one counterparty at a time, based on the previous degree-volume sort. Every time we remove a counterparty, we rerun the algorithm for the remaining counterparties. In Figure I.2, we plot the number of dealers implied by our selection algorithm against the number of remaining agents in this interactive procedure. The main takeaway from this analysis is that the same 14 dealers survive this strict selection procedure for every network with more than 200 counterparties.

I.1.4 The Net Position of Dealers

In this section, we provide additional details and robustness checks on how we construct our measure of bilateral exposure between counterparties i and j. This metric is developed in Section 3.2.1 of the main text.

I.1.4.1 Estimating Betas

To keep this appendix self-contained, we repeat some details of our methodology that are presented in the main text. To start, 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. In addition, we match position p to Markit based on a number of other characteristics. These characteristics include Markit RED id (i.e. the underlying the firm), currency, capital structure tier, and documentation clause relating to the CDS default trigger. For instance, holding all other characteristics equal, Ford CDS quoted in USD and EUR would be matched to two different records in Markit. Similarly, Ford CDS on senior and junior debt, holding all other characteristics equal, would be matched to two different records in Markit.

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, as defined in Section 3.3.1 in the main text. 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.

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 $_{p,t}$ for every position and date in this disaggregated data.

I.1.4.2 Aggregation

Armed with 's for each position p, we then aggregate between two counterparties as follows:

$$\begin{aligned} E_{p,t} &\equiv \ _{p,t} \times Notional_{p,t} \\ \text{Net}_{i,j,t} &\equiv \sum_{p \in S_{i,j,t}} E_{p,t} \quad \sum_{p \in B_{i,j,t}} E_{p,t} \\ \text{Gross}_{i,j,t} &\equiv \sum_{p \in S_{i,j,t}} E_{p,t} + \sum_{p \in B_{i,j,t}} E_{p,t} \end{aligned} \tag{I.10}$$

where $S_{i,j,t}$ 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. Because these measures of bilateral exposure are weighted by $_{p,t}$, they provide a measure of net and gross bilateral exposure to our aggregate credit risk factor. And, 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.

To determine a given counterparty i's overall net exposure to aggregate credit risk, we can simply sum their net positions across all counterparties:

$$\text{Net}_{i,t} \equiv \sum_{j} \text{Net}_{i,j,t}$$

Our main measure of dealer exposure from Section 3.3.1 of the main text scales each dealer's net notional exposure by its market capitalization:

$$z_{i,t} \equiv \frac{\text{Net}_{i,t}}{MktCap_{i,t}}$$

Finally, the net exposure of the entire dealer sector, denoted $\bar{z}_{d,t}$, is simply the average $z_{i,t}$ across dealers.

I.1.4.3 Alternative Measure of Credit Risk Exposure

We now turn to an alternative way of computing $z_{i,t}$ for each dealer i and date t. As with our preferred measure of $z_{i,t}$, we start with the 's of each position (see Appendix I.1.4.1). After matching all DTCC positions to a , we then compute each position's "DV01". Analogous to an option delta, DV01 is the standard way that industry professionals quantify the dollar change of a position with respect to a move in the position's underlying credit spread. For example, suppose that a fictitious position on Xerox Corp. has a notional value of \$1. The DV01 tells how many dollars the seller in the swap would gain/lose if Xerox's credit spread falls by 1 basis point.[4]

We then use $DV01^{f}_{p,t}$ to denote position p's DV01 as of date t. The superscript f denotes that this DV01 is computed for a one basis point move *in firm f's CDS spread*. See Appendix I.1.4.4 for details on how we compute $DV01^{f}_{p,t}$. In all cases, we define $DV01^{f}_{p}$ from the perspective of the protection seller, meaning that it is always positive for sellers and is negative for buyers (e.g. a decrease in CDS spreads always helps the seller).

Once we compute $DV01^{f}_{p,t}$, it is easy to ask how much the seller would lose if there is a one-basis point fall in the aggregate credit risk factor:

$$DV01^{Agg}_{p,t} = DV01^{f}_{p,t} \times \quad _{p,t}$$

$DV01^{Agg}_{p,t}$ is useful because we can sum it across positions – its units are dollars per *one basis point fall in the aggregate credit risk factor*. Once we compute $DV01^{Agg}_{p,t}$ for all positions, we aggregate it bilaterally between counterparties i and j by setting $E_{p,t} = DV01^{Agg}_{p,t}$ in Equation (I.10). Computing net and gross exposures at the individual counterparty level and dealer sector then proceed as before. The gross exposure measure using DV01s in Equation (I.10) is further used as an input to computing bilateral concentration $\kappa_{i,j,t}$ in Section 3.3.2 in the main text.

Average Dealer Exposure Table I.2 presents some simple time-series averages of $\bar{z}_d$ for each of our construction methodologies. The biggest observation from the table is that all of the $\bar{z}_d$ are positive on average. Thus, regardless of how we measure exposure, dealers are on average sellers of credit protection during our sample. The DV01-based metric indicates that a 100 basis point increase in aggregate credit risk would cause the average dealer to lose 0.22 percent of their equity value.[5] Again, the larger point here is that dealers are exposed to the underlying credit risk of the economy during our sample. This basic fact is important in how we infer the structural parameters of our model based on the prices paid by dealers versus customers.

I.1.4.4 Computing Credit Sensitivities (DV01)

We define a position's credit portfolio sensitivity, $DV01^{f}_{p}$, as the sensitivity of the position to a change in the underlying reference entity's credit spread. We arrive at this measure by applying the ISDA Standard Model for pricing credit derivative contracts (CDS) and the implementation detailed in the Appendix of Paddrik, Rajan, and Young (2020). A CDS position p written on firm f can be expressed as the difference between premium leg $Prem^{s_f}$ and pay leg Pay^{s_f}, calibrated from market spread s_f (baseline). From the perspective of the seller, $Prem^{s_f}$ is the discounted present value of the buyer's incoming payments, while Pay^{s_f} is the present value of outgoing payouts

[4] Following with industry standard, we consider a one basis point decrease in the entire term structure of Xerox's CDS spread.

[5] In the table, we have scaled the DV01-based measure so that it corresponds to a 100 basis point move in the index.

contingent on default of f. Both components are functions of the underlying (risk-neutral) default risk of the firm, which is inferred from prevailing credit spreads s_f. (We suppress in our notation other characteristics which uniquely identify the market spread such as term, documentation clause, currency, and date of observation.) The position can be revalued under a differential shock to market spreads, $s'_f = s_f + ds_f$ (shock). Following industry practice, we adopt 1 basis point change. This permits us to express the $DV01_p^f$ from the protection seller's perspective as

$$DV01_p^f = (Prem^{s'_f} \quad Prem^{s_f}) \quad (Pay^{s'_f} \quad Pay^{s_f}) \cdot N_p$$

The $DV01$ expresses the difference between the baseline and a scenario in which credit spreads (e.g. default risk) rise. By this definition, it is therefore always negative from the perspective of the seller.

We rely on multiple data sources to identify contractual inputs for pricing positions. We use the underlying's reference entity's term structure of credit spreads, contract currency, floating risk-free rates, and capital structure of the CDS' underlying reference obligation. We source credit spreads from Markit, contract currency from DTCC, the term structure of risk-free rates for contract currencies from Haver Analytics, and reference entity capital structure from bond information provided by Bloomberg.

I.1.5 Customer Removal

We can also use the calibrated model from Section 3.4 to study the effects of a customer's removal. Table I.3 reports the effects of removing a customer as large as the largest-net-seller dealer. We conduct two distinct customer removal exercises. First, we remove a customer endowed with the same amount of pre-trade exposure as the largest-net-seller dealer. The effects of such removal are negligible and dealer market average spread barely changes, as reported in Column (2). According to Equation (14) in the main text, customer failure affects dealer average spread ($\overline{R}_d$) by changing the average pre-trade exposure in the economy ($\overline{\omega}$). Hence, the removal of a customer has limited impact on the dealer average spread as it almost does not change $\overline{\omega}$. A customer and a dealer endowed with the same pre-trade exposure are likely to hold different net positions in the CDS market because customers face fewer counterparties, which limits their risk-sharing ability.

In the second exercise, we remove a customer that holds a net selling position as large as the largest-net-seller dealer. To infer the customer's pre-trade exposure, we use Equation (A7) from the model's derivation detailed in the appendix. This implies a customer with an even lower pre-trade exposure to aggregate default. The removal of such customer has larger impact on equilibrium spreads as reported in Column (3), although it is significantly lower than the failure of a dealer providing the same amount of insurance to the economy. The average dealer market spread increases by less than 10 basis points, from 141 to 150.85 basis points.

I.1.6 Dealer Removal Robustness: $\overline{\omega}$ assumption, DTCC Dealers

For robustness, we confirm that our results do not rely on normalizing $\overline{\omega}$ to one. In Table I.4, we report the same set of results assuming $\overline{\omega} = 0.5$ and $\overline{\omega} = 3$ and our conclusions are the same. In Table I.5, we repeat the calibration and dealer removal exercise using DTCC's definition of dealers. We still find a large, yet lower, impact on credit spreads when a dealer fails. The effect is lower because there are more dealers under the DTCC's definition versus ours (26 vs. 14), so risk is more easily reallocated when a dealer fails.

I.2 Intuition for Baseline Model

In this section, we consider an example with three agents in order to provide intuition and to highlight key features of the model in Section 2. In Section I.2.2, we extend the three-agent model to have five agents, which lets us build intuition for the equilbrium when the network is core-periphery. Finally, we use the calibration from Section 3.4 to provide a sharper characterization of .

I.2.1 Three-agent example

We use an example with three agents to highlight three pieces of intuition that extend to the more general version of our baseline model. First, the three-agent model generates price dispersion and intermediation in equilibrium. Second, it generates what appears like bid-ask spreads with asymmetric prices. Lastly, the example can generate a counterintuitive trading pattern, in which an agent with higher pre-trade exposure sells protection to someone with lower pre-trade exposure to the underlying asset. The derivations of the three-agent example are in Appendix I.2.1.2.

I.2.1.1 Key Results

Start with the assumption that there are three agents in the economy. Agents 1 and 2 can trade with each other, and agents 1 and 3 can also trade with one another. However, agents 2 and 3 cannot trade with each other. Hence, agent 1 in this example acts like a central dealer to agents 2 and 3. Formally, the trading network is given by:

$$G = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}. \tag{I.11}$$

In this economy, agents 1, 2, and 3 have pre-trade exposures given by ω_1, ω_2, and ω_3, respectively. To keep the example more tractable, we set $\omega_1 = 0$. In equilibrium, based on Equation (8), agent 1's net position is:

$$z_1 = \frac{\alpha\sigma^2}{3\alpha\sigma^2 + 2}\left(\omega_2 + \omega_3\right). \tag{I.12}$$

Agent 1's net position, z_1, is a combination of the pre-trade exposures of agents 2 and 3. If agents 2 and 3 have pre-trade exposures greater than agent 1, i.e. $\omega_2 + \omega_3 > 0$, then agent 1 endogenously becomes a net seller of insurance with $z_1 > 0$ in equilibrium.

Using Equation (8) and agent 1's net position, agents 2 and 3 net positions are given by:

$$z_2 = \left(\frac{\alpha\sigma^2}{\alpha\sigma^2 + 2}\right)\left(\frac{\alpha\sigma^2}{3\alpha\sigma^2 + 2}\right)\left[\omega_3 - \omega_2\left(\frac{2\alpha\sigma^2 + 2}{\alpha\sigma^2}\right)\right]$$

and

$$z_3 = \left(\frac{\alpha\sigma^2}{\alpha\sigma^2 + 2}\right)\left(\frac{\alpha\sigma^2}{3\alpha\sigma^2 + 2}\right)\left[\omega_2 - \omega_3\left(\frac{2\alpha\sigma^2 + 2}{\alpha\sigma^2}\right)\right]$$

Next, we highlight the three aforementioned features of this example. First, notice that if $\omega_3 > 0$ and $\omega_2 = -\omega_3$, then $z_1 = 0$ in equilibrium from Equation (I.12). Also, in equilibrium, we would have $z_2 > 0$ and $z_3 < 0$. This example generates intermediation in equilibrium as agent 1 buys insurance from agent 2 and sells it to agent 3.

Second, this example generates what appears like bid-ask spreads. To see why, notice that the difference between the price at which agent 1 sells to agent 2 and the price at which agent 1 buys from agent 3 is positive and given by:

$$R_{13} - R_{12} = \left(\frac{\alpha\sigma^2}{\alpha\sigma^2 + 2}\right)(\omega_3 - \omega_2).$$

If $\omega_3 > \omega_2$, then such price difference is positive, i.e., $R_{13} - R_{12} > 0$.

Furthermore, prices are tilted towards larger pre-trade exposures, generating asymmetric bid-ask spreads. To show such asymmetry is generated, let R_{11} be the equilibrium price for agent 1 if it would trade with itself. Specifically, let $R_{11} - \mu = \alpha\sigma^2(z_1 + \omega_1) = \alpha\sigma^2 z_1$. Hence, we can show that:

$$R_{13} - R_{11} > R_{11} - R_{12} \Leftrightarrow \omega_3 > -\omega_2,$$

which means that the spread between agents 1 and 3 is greater than the spread between agent 1 and 2 if, and only if, agent 3's pre-trade exposure is sufficiently high. In this case, agent 3 has too much exposure relative to other market participants and pays a higher price in equilibrium to buy protection against the underlying default risk.

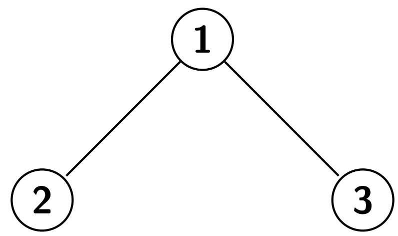
The third feature of this example is a counterintuitive trading pattern, in which an agent with higher pre-trade exposure sells protection to someone with lower pre-trade exposure to the underlying asset. Specifically, we have that

$$z_2 > 0 \Leftrightarrow \omega_3 > \frac{2\alpha\sigma^2 + 2}{\alpha\sigma^2}\omega_2.$$

This means that agent 2 sells insurance to agent 1, even if agent 2 is more exposed than agent 1 before trade, i.e., $\omega_2 > \omega_1 = 0$. This is true in equilibrium because agent 3 is significantly more exposed to the underlying default risk. In equilibrium, agent 3 demands more insurance from agent 1, who in order to supply such insurance, has to buy additional protection from agent 2. As a result, agent 1 buys insurance from agent 2 and sells to agent 3 in equilibrium.

I.2.1.2 Derivation

The following figure depicts the three-agent example:



which means that the trading network is given by:

$$G = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \tag{I.13}$$

Agents 1, 2, and 3 have pre-trade exposures given by ω_1, ω_2, and ω_3, respectively. Furthermore, we assume $\omega_1 = 0$.

Let us solve for agent 1's net position using Equation (8):

$$z_1 = \frac{1}{3}\left(\omega_2 + \omega_3 + z_1 + z_2 + z_3\right) = \frac{\alpha\sigma^2}{3\alpha\sigma^2 + 2}\left(\omega_2 + \omega_3\right).$$

The derivation above uses the fact that $\omega_1 = 0$, along with the clearing condition given by: $z_1 + z_2 + z_3 = 0$.

Using Equation (8) for agent 2, we have that agent 2's post-trade exposure, $z_2 + \omega_2$, is given by:

$$z_2 + \omega_2 = \frac{\alpha\sigma^2 z_1 + 2\phi\omega_2}{\alpha\sigma^2 + 2}$$

and, using z_1 from Equation (I.12), agent 2's net position, z_2, is given by:

$$z_2 = \left(\frac{\alpha\sigma^2}{\alpha\sigma^2 + 2}\right)\left(\frac{\alpha\sigma^2}{3\alpha\sigma^2 + 2}\right)\left[\omega_3 \quad \omega_2\left(\frac{2\alpha\sigma^2 + 2}{\alpha\sigma^2}\right)\right] \tag{I.14}$$

Similarly, agent 3's net position and post-trade exposure are given by:

$$z_3 + \omega_3 = \frac{\alpha\sigma^2 z_1 + 2\phi\omega_3}{\alpha\sigma^2 + 2},$$

and

$$z_3 = \left(\frac{\alpha\sigma^2}{\alpha\sigma^2+2}\right)\left(\frac{\alpha\sigma^2}{3\alpha\sigma^2+2}\right)\left[\omega_2 \quad \omega_3\left(\frac{2\alpha\sigma^2+2}{\alpha\sigma^2}\right)\right]$$

Equilibrium prices are be given by:

$$\begin{aligned} R_{12} \quad \mu &= \frac{1}{2}\alpha\sigma^2\left(z_1+\omega_1+z_2+\omega_2\right) \\ &= \frac{1}{2}\alpha\sigma^2 \times \frac{2\alpha\sigma^2 z_1 + 2\phi\omega_2 + 2 \quad z_1}{\alpha\sigma^2+2} \end{aligned}$$

and

$$R_{13} \quad \mu = \frac{1}{2}\alpha\sigma^2 \times \frac{2\alpha\sigma^2 z_1 + 2\phi\omega_3 + 2 \quad z_1}{\alpha\sigma^2+2}$$

Taking the difference, we have:

$$R_{13} \quad R_{12} = \frac{1}{2}\alpha\sigma^2\left(\frac{2}{\alpha\sigma^2+2}\right)(\omega_3 \quad \omega_2) > 0 \quad \Leftrightarrow \omega_3 > \omega_2.$$

The equilibrium price for agent 1 if she would trade with herself is given by:

$$\begin{aligned} R_{11} \quad \mu &= \alpha\sigma^2(z_1+\omega_1) \\ &= \alpha\sigma^2 z_1 \\ &= \alpha\sigma^2\frac{\alpha\sigma^2}{3\alpha\sigma^2+2}\left(\omega_2+\omega_3\right). \end{aligned}$$

Hence, we have:

$$\begin{aligned} R_{12} \quad \mu &= \frac{1}{2}\alpha\sigma^2\frac{2\alpha\sigma^2 z_1 + 2\phi\omega_2 + 2 \quad z_1}{\alpha\sigma^2+2}, \\ R_{13} \quad \mu &= \frac{1}{2}\alpha\sigma^2 \times \frac{2\alpha\sigma^2 z_1 + 2\phi\omega_3 + 2 \quad z_1}{\alpha\sigma^2+2}, \end{aligned}$$

and

$$\begin{aligned} R_{13}+R_{12} \quad 2R_{11} &= \alpha\sigma^2\frac{2\alpha\sigma^2 z_1 + \phi\omega_2 + \phi\omega_3 + 2 \quad z_1}{\alpha\sigma^2+2} \quad 2\alpha\sigma^2 z_1 \\ &= 2\alpha\sigma^2\frac{\alpha\sigma^2 z_1 + \quad \frac{1}{2}(\omega_2+\omega_3) + \quad z_1 \quad z_1(\alpha\sigma^2+2 \quad)}{\alpha\sigma^2+2} \\ &= \phi\alpha \quad {}^2\frac{(\omega_2+\omega_3) \quad 2z_1}{\alpha\sigma^2+2} \\ &= \phi\alpha \quad {}^2\underbrace{\frac{1 \quad \frac{2\alpha\sigma^2}{3\alpha\sigma^2+2}}{\alpha\sigma^2+2}}_{>0}\left(\omega_2+\omega_3\right). \end{aligned}$$

Thus:

$$R_{13} \quad R_{11} > R_{11} \quad R_{12} \Leftrightarrow \omega_3 > \quad \omega_2.$$

Based on Equation (I.14), notice that

$$z_2 > 0 \Leftrightarrow \omega_3 > \omega_2 \frac{2\alpha\sigma^2 + 2}{,}$$

which shows the third feature or the three-agent example.

I.2.2 Five-agent example

In this subsection, we consider a core-periphery network with two dealers and three customers. Agents 1 and 2 are dealers and agents 3, 4, and 5 are customers. Detailed derivations are provided in the Section I.2.2.2.

I.2.2.1 Key Results

Formally, the trading network in this example is given by:

$$G = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \end{bmatrix}. \tag{I.15}$$

The trading network is also represented in Figure I.3.

We can use Equation (8) in the main text and solve for dealers' positions in equilibrium. The post-trade exposures of dealers $i_d \in \{1, 2\}$ to the underlying default risk is given by:

$$z_{i_d} + \omega_{i_d} = \overline{\omega} \quad (1 \quad {}_d) [\overline{\omega} \quad \omega_{i_d}]$$

where ${}_d = \frac{5\alpha\sigma^2}{5\alpha\sigma^2+2}$. The derivation above uses the clearing condition given by $\sum_{i=1}^{5} z_i = 0$. If a dealer is less exposed to the underlying default risk than the average economy, i.e. $\overline{\omega} > \omega_{i_d}$, then such dealer will be also less exposed after trade, i.e. $\overline{\omega} > z_{i_d} + \omega_{i_d}$.

Post-trade exposures determine equilibrium prices, and the at which a CDS contract is traded in the dealer market, i.e., between agents 1 and 2, will be given by:

$$\overline{R}_d \equiv R_{12} = \mu + \alpha\sigma^2\overline{\omega} \quad \alpha\sigma^2 (1 \quad {}_d) [\overline{\omega} \quad \overline{\omega}_d], \tag{I.16}$$

where $\overline{\omega}_d = (\omega_1 + \omega_2)/2$ is the average pre-trade exposure among dealers. The dealer market price reflect dealers' post-trade exposure. Thus, if dealers are less exposed to default risk, then dealer market prices will be lower in equilibrium if compared against the complete network counterfactual. Formally, Equation (I.16) shows that $\overline{R}_d < \mu + \alpha\sigma^2\overline{\omega}$ if, and only if, $\overline{\omega} > \overline{\omega}_d$.

This example also features a customer market as customer and dealer trade with each other. We can again use Equation (8) and solve for customers' post-trade exposure in equilibrium:

$$z_{i_c} + \omega_{i_c} = \overline{\omega} + (1 \quad {}_c)\,(\omega_{i_c} \quad \overline{\omega}) \quad {}_c\,(1 \quad {}_d)\,(\overline{\omega} \quad \overline{\omega}_d), \quad i_c \in \{3,4,5\}.$$

where ${}_c = \frac{2\alpha\sigma^2}{2\alpha\sigma^2+2}$. The post-trade exposure of a customer depends not only on her pre-trade exposure but also on the average pre-trade exposure of dealers. If dealers are less exposed to default risk on average ($\overline{\omega} > \overline{\omega}_d$), then dealers take on credit risk in equilibrium lowering customers' post-trade exposures.

The price from a trade between dealer $i_d \in \{1,2\}$ and customer $i_c \in \{3,4,5\}$ is given by:

$$R_{i_d i_c} = \mu + \alpha\sigma^2 \frac{1}{2}\left(z_{i_c} + \omega_{i_c} + z_{i_d} + \omega_{i_d}\right),$$

and the average price in the customer market is defined as $\overline{R}_c \equiv \frac{1}{6}\sum_{i_d=1}^{2}\sum_{i_c=3}^{5} R_{i_d i_c}$. We can express the average price in the customer market as a function of the average price in the dealer market:

$$\overline{R}_c = \overline{R}_d + \frac{\alpha\sigma^2}{2}\,(\overline{\omega} \quad \overline{\omega}_d)\,(1 \quad {}_c)\left[\frac{2}{3} + (1 \quad {}_d)\right]. \tag{I.17}$$

Thus, we have that price are on average higher in the customer market than in the dealer market, whenever dealers are less exposed to default risk. Formally, $\overline{R}_c > \overline{R}_d$ if, and only if, $\overline{\omega} > \overline{\omega}_d$. This is a reflection of the customers' post-trade exposure being higher than dealers'. Prices represent the average post-trade exposure of the two counterparties trading, and, when dealers and customers trade, prices are higher than when dealers trade with each other because dealers' lower exposure to default risk.

We can express the average price in the customer market as follows:

$$\overline{R}_c = \mu + \alpha\sigma^2\overline{\omega} \quad \frac{\alpha\sigma^2}{2}\,(\overline{\omega} \quad \overline{\omega}_d)\left[\frac{4\alpha\sigma^2+2}{5\alpha\sigma^2+2} \quad \frac{2}{3}\right.$$

Notice that $\frac{4\alpha\sigma^2+2}{5\alpha\sigma^2+2} > \frac{4}{5}$ because both and $\alpha\sigma^2$ are positive. Thus, we have that $\overline{R}_c < \mu + \alpha\sigma^2\overline{\omega}$ if, and only if, $\overline{\omega} > \overline{\omega}_d$. Although dealers' post-trade exposure push prices up in the customer market relative to the dealer market, customers' pre-trade exposure being lower than dealers pushes prices down relative to customers' own shadow price of insurance. In equilibrium, the first effect dominates and prices in the customer market are lower than they would be under the complete network counterfactual, given that dealers are on average less exposed to aggregate default risk.

I.2.2.2 Detailed derivations of the five-agent example

Let us solve for the net position of dealers $i_d \in \{1, 2\}$ using Equation (8):

$$
\begin{aligned}
z_{i_d} + \omega_{i_d} &= (1 \quad {}_{d})\, \omega_{i_d} + \; {}_{d}\frac{1}{5} \quad \sum_{i=1}^{5} \omega_i + \sum_{i=1}^{5} z_i \Bigg) \\
z_{i_d} + \omega_{i_d} &= (1 \quad {}_{d})\, \omega_{i_d} + \; {}_{d}\overline{\omega} \\
z_{i_d} + \omega_{i_d} &= \overline{\omega} \quad (1 \quad {}_{d}) \left[\overline{\omega} \quad \omega_{i_d}\right] \\
z_{i_d} &= \; {}_{d} \left(\overline{\omega} \quad \omega_{i_d}\right),
\end{aligned}
$$

where ${}_{d} = \frac{5\alpha\sigma^2}{5\alpha\sigma^2+2}$. The derivation above uses the clearing condition given by: $\sum_{i=1}^{5} z_i = 0$. The price in the dealer market, i.e., between agents 1 and 2, will be given by:

$$
\overline{R}_d \equiv R_{12} = \mu + \alpha\sigma^2\overline{\omega} \quad \alpha\sigma^2 \left(1 \quad {}_{d}\right) \left[\overline{\omega} \quad \overline{\omega}_d\right],
$$

where $\overline{\omega}_d = (\omega_1 + \omega_2)/2$ is the average pre-trade exposure among dealers.

Based on Equation (8) in the main text, the net position of customer $i_c \in \{3, 4, 5\}$ is given by

$$
\begin{aligned}
z_{i_c} + \omega_{i_c} &= \left(1 \quad \frac{3\alpha\sigma^2}{3\alpha\sigma^2+2}\right) \Bigg(\omega_{i_c} + \frac{3\alpha\sigma^2}{3\alpha\sigma^2+2} \times \frac{1}{3} \left(\sum_{i_d=1}^{2} \left(\omega_{i_d} + z_{i_d}\right) + z_{i_c} + \omega_{i_c} \right) \Bigg(\\
z_{i_c} + \omega_{i_c} &= \left(1 \quad \frac{3\alpha\sigma^2}{3\alpha\sigma^2+2}\right) \omega_{i_c} + \frac{3\alpha\sigma^2}{3\alpha\sigma^2+2} \times \frac{1}{3} \left(2\left[(1 \quad {}_{d})\, \overline{\omega}_d + \; {}_{d}\overline{\omega}\right] + z_{i_c} + \omega_{i_c}\right) \\
z_{i_c} + \omega_{i_c} &= \left(1 \quad \frac{2\alpha\sigma^2}{3\alpha\sigma^2+2}\right) \omega_{i_c} + \frac{2\alpha\sigma^2}{3\alpha\sigma^2+2} \times \left[(1 \quad {}_{d})\, \overline{\omega}_d + \; {}_{d}\overline{\omega}\right] \\
z_{i_c} + \omega_{i_c} &= (1 \quad {}_{c})\, \omega_{i_c} + \; {}_{c}\left[(1 \quad {}_{d})\, \overline{\omega}_d + \; {}_{d}\overline{\omega}\right] \\
z_{i_c} + \omega_{i_c} &= (1 \quad {}_{c})\, \omega_{i_c} + \; {}_{c}\left[\overline{\omega} \quad (1 \quad {}_{d}) \left(\overline{\omega} \quad \overline{\omega}_d\right)\right] \\
z_{i_c} + \omega_{i_c} &= \overline{\omega} \quad (1 \quad {}_{c}) \left(\overline{\omega} \quad \omega_{i_c}\right) \quad {}_{c}(1 \quad {}_{d}) \left(\overline{\omega} \quad \overline{\omega}_d\right) \\
z_{i_c} &= \; {}_{c}\left[(1 \quad {}_{d})\, \overline{\omega}_d + \; {}_{d}\overline{\omega} \quad \omega_{i_c}\right],
\end{aligned}
$$

where ${}_{c} = \frac{2\alpha\sigma^2}{2\alpha\sigma^2+2}$.

The price from a trade between dealer $i_d \in \{1, 2\}$ and customer $i_c \in \{3, 4, 5\}$ is given by:

$$
\begin{aligned}
R_{i_d i_c} &= \mu + \alpha\sigma^2 \frac{1}{2} \left(z_{i_c} + \omega_{i_c} + z_{i_d} + \omega_{i_d}\right) \\
&= \mu + \alpha\sigma^2\overline{\omega} \quad \frac{1}{2} \; {}_{c}(1 \quad {}_{d}) \left(\overline{\omega} \quad \overline{\omega}_d\right) \quad \frac{1}{2}\alpha\sigma^2 \left[(1 \quad {}_{c}) \left(\overline{\omega} \quad \omega_{i_c}\right) + (1 \quad {}_{d}) \left(\overline{\omega} \quad \overline{\omega}_d\right)\right],
\end{aligned}
$$

and the average price in the customer market is given by:

$$
\overline{R}_c \equiv \frac{1}{6} \sum_{i_d=1}^{2} \sum_{i_c=3}^{5} R_{i_d i_c}
$$

$$= \mu + \alpha\sigma^2\overline{\omega} \quad \frac{\alpha\sigma^2}{2} \; {}_c\,(1 \quad {}_d)\,(\overline{\omega} \quad \overline{\omega}_d) \quad \frac{\alpha\sigma^2}{2}\left[(1 \quad {}_c)\,(\overline{\omega} \quad \overline{\omega}_c) + (1 \quad {}_d)\,(\overline{\omega} \quad \overline{\omega}_d)\right].$$

Notice that

$$\begin{aligned}
\overline{\omega} \quad \overline{\omega}_c &= \overline{\omega} \quad \frac{1}{3}\,(\omega_3 + \omega_4 + \omega_5) \\
&= \overline{\omega} \quad \frac{1}{3}\,(\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 \quad \omega_1 \quad \omega_2) \\
&= \overline{\omega} \quad \frac{1}{3}\,(5\overline{\omega} \quad 2\overline{\omega}_d) \\
&= \overline{\omega} \quad \frac{5}{3}\,(\overline{\omega} \quad \overline{\omega}_d) \quad \overline{\omega}_d \\
&= \quad \frac{2}{3}\,(\overline{\omega} \quad \overline{\omega}_d)\,,
\end{aligned}$$

hence we can simplify the average price in the customer market to:

$$\begin{aligned}
\overline{R}_c &= \mu + \alpha\sigma^2\overline{\omega} \quad \frac{\alpha\sigma^2}{2} \; {}_c\,(1 \quad {}_d)\,(\overline{\omega} \quad \overline{\omega}_d) \quad \frac{\alpha\sigma^2}{2}\left[\quad (1 \quad {}_c)\,\frac{2}{3}\,(\overline{\omega} \quad \overline{\omega}_d) + (1 \quad {}_d)\,(\overline{\omega} \quad \overline{\omega}_d)\right. \\
&= \mu + \alpha\sigma^2\overline{\omega} \quad \frac{\alpha\sigma^2}{2}\,(\overline{\omega} \quad \overline{\omega}_d)\left[\; {}_c\,(1 \quad {}_d) \quad (1 \quad {}_c)\,\frac{2}{3} + (1 \quad {}_d)\right. \\
&= \mu + \alpha\sigma^2\overline{\omega} \quad \frac{\alpha\sigma^2}{2}\,(\overline{\omega} \quad \overline{\omega}_d)\left[(1 \quad {}_d)\,(1 + \quad {}_c) \quad \frac{2}{3}\,(1 \quad {}_c)\right. \\
&= \mu + \alpha\sigma^2\overline{\omega} \quad \frac{\alpha\sigma^2}{2}\,(\overline{\omega} \quad \overline{\omega}_d)\,(1 \quad {}_c)\left[(1 \quad {}_d) \times \frac{1 + \quad {}_c}{1 \quad {}_c} \quad \frac{2}{3}\right. \\
&= \mu + \alpha\sigma^2\overline{\omega} \quad \frac{\alpha\sigma^2}{2}\,(\overline{\omega} \quad \overline{\omega}_d)\left[\left(\frac{2}{5\alpha\sigma^2 + 2} \times \frac{4\alpha\sigma^2 + 2}{2} \quad \frac{2}{3}\right.\right. \\
&= \mu + \alpha\sigma^2\overline{\omega} \quad \frac{\alpha\sigma^2}{2}\,(\overline{\omega} \quad \overline{\omega}_d)\left[\left(\frac{4\alpha\sigma^2 + 2}{5\alpha\sigma^2 + 2} \quad \frac{2}{3}\right.\right. \;.
\end{aligned}$$

Notice that $\frac{4\alpha\sigma^2+2}{5\alpha\sigma^2+2} > \frac{4}{5}$ because and $\alpha\sigma^2$ are both positive. Thus, we have that

$$\overline{R}_c < \mu + \alpha\sigma^2\overline{\omega}.$$

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

$$\begin{aligned}
\overline{R}_c &= \mu + \alpha\sigma^2\overline{\omega} \quad \frac{\alpha\sigma^2}{2} \; {}_c\,(1 \quad {}_d)\,(\overline{\omega} \quad \overline{\omega}_d) \quad \frac{\alpha\sigma^2}{2}\left[\quad (1 \quad {}_c)\,\frac{2}{3}\,(\overline{\omega} \quad \overline{\omega}_d) + (1 \quad {}_d)\,(\overline{\omega} \quad \overline{\omega}_d)\right. \\
&= \overline{R}_d \quad \frac{\alpha\sigma^2}{2} \; {}_c\,(1 \quad {}_d)\,(\overline{\omega} \quad \overline{\omega}_d) \quad \frac{\alpha\sigma^2}{2}\left[\quad (1 \quad {}_c)\,\frac{2}{3}\,(\overline{\omega} \quad \overline{\omega}_d) \quad (1 \quad {}_d)\,(\overline{\omega} \quad \overline{\omega}_d)\right. \\
&= \overline{R}_d + \frac{\alpha\sigma^2}{2}\,(\overline{\omega} \quad \overline{\omega}_d)\left[\quad {}_c\,(1 \quad {}_d) + (1 \quad {}_c)\,\frac{2}{3} + (1 \quad {}_d)\right. \\
&= \overline{R}_d + \frac{\alpha\sigma^2}{2}\,(\overline{\omega} \quad \overline{\omega}_d)\,(1 \quad {}_c)\left[\frac{2}{3} + (1 \quad {}_d)\right. \;.
\end{aligned}$$

Thus, we have that

$$\overline{R}_c > \overline{R}_d.$$

I.2.3 Interpretation of

To provide a sharper interpretation for the magnitude of , 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 position with j ($_{ij}$) and the shadow cost of insurance ($\hat{z}_i$). To contextualize the magnitude of the parameter , we can take Equation (5) and average across all of agent i's connected counterparties:

$$\overline{R}_i = \mu + \quad \frac{1}{K_i} z_i + \alpha \sigma^2 \left(z_i + \omega_i \right),$$

where $\overline{R}_i \equiv \frac{1}{K_i} \sum_{j:g_{ij}=1} R_{ij}$ is the average price faced by agent i. The term $\ \frac{1}{K_i} z_i$ is the average marginal cost of bilateral trading. If agent i is a net seller ($z_i > 0$), then the average marginal cost of bilateral trading 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 trading 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 trading is $\ \frac{1}{n} \overline{z}_d \approx 5$ 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 bilateral exposure and is therefore greater than the *average cost* associated with the holding of a position. We can measure average costs using agents' preferences. Specifically, the term $\frac{\ }{2} \sum_j \ {}^2_{ij}$ measures the total cost of trading with all the counterparties, and $\frac{\ }{2K_i} \sum_j \ {}^2_{ij}$ 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.[6] 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 the desire to smooth out trades is much smaller than average bid-ask spreads, which are on the order of one or two basis points.[7] Indeed, even if even we focus on the largest net seller dealer, its average total cost of holding concentration 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

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

[7] 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 (8)). As a result, the small per-trade cost induced by bilateral concentration aversion leads to sizable price dispersion in our model ($\bar{R}_c \quad \bar{R}_d = 5.12$ 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 ${}_d$=1. Table 5 shows that in the calibrated model, ${}_d$=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.

I.3 Model Extensions and Applications

I.3.1 Model with Alternative Preference for Smoothing Trades

In this section, we present a version of the model with an alternative quadratic trading cost function.

Agent i's optimization problem is given by:

$$\max_{\{\ {}_{ij}\}_{j=1,j\neq i}^{n}} \omega_i(1 \quad \mu) + \sum_{j=1}^{n} {}_{ij}(R_{ij} \quad \mu) \quad \frac{\alpha}{2}(w_i + z_i)^2 \ {}^2 \quad \frac{}{2} \sum_{j=1,j\neq i}^{n} g_{ij} \left({}_{ij} \quad \frac{z_i}{K_i \quad 1} \right)^2 \tag{I.18}$$

$$s.t. \qquad {}_{ij} = 0 \text{ if } g_{ij} = 0$$

$$z_i \quad \sum_{j=1}^{n} {}_{ij} = 0,$$

where $K_i = \sum_j g_{ij}$. Given that the market clearing conditions imply that ${}_{ii} = 0$, we assume ${}_{ii} = 0$ and that agent i chooses $\{\ {}_{ij}\}_{j=1,j\neq i}^{n}$ in its optimization problem.

The last term on objective function in Equation (I.18) captures represents a trading cost function where it is more costly to hold concentrated positions. Notice that $\frac{z_i}{K_i \quad 1}$ is agent i's average position across all its counterparties.[8] Hence, if agent i equally spreads its trading positions among all its counterparties, then the last term is always zero, regardless of the agent i's net position (z_i). Next, we solve agent i's optimization problem and also verify the second-order conditions.

The first-order condition for agent i with respect to trading with agent j ($g_{ij} = 1$) is given by:

$$\begin{aligned} R_{ij} \quad \mu &= \alpha\sigma^2(\omega_i + z_i) + \quad \left({}_{ij} \quad \frac{z_i}{K_i \quad 1} \right) \left(1 \quad \frac{1}{K_i \quad 1} \right) \quad \sum_{s\neq j,i} g_{is} \left({}_{is} \quad \frac{z_i}{K_i \quad 1} \right) \frac{1}{K_i \quad 1} \\ &= \alpha\sigma^2(\omega_i + z_i) + \quad \left({}_{ij} \quad \frac{z_i}{K_i \quad 1} \right) \quad \sum_{s\neq i} g_{is} \left({}_{is} \quad \frac{z_i}{K_i \quad 1} \right) \frac{1}{K_i \quad 1} \\ &= \alpha\sigma^2(\omega_i + z_i) + \quad \left({}_{ij} \quad \frac{z_i}{K_i \quad 1} \right) \quad \left(z_i \quad (K_i \quad 1) \frac{z_i}{K_i \quad 1} \right) \frac{1}{K_i \quad 1} \end{aligned}$$

[8]As in the benchmark, we assume $g_{ii} = 1$ for every i, hence $K_i \quad 1 = \sum_{j\neq i} g_{ij}$ is the number of trading counterparties of agent j.

$$= \alpha\sigma^2(\omega_i + z_i) + \quad \left(\quad _{ij} \quad \frac{z_i}{K_i \quad 1} \right)$$

where from the second to the third equality we used that fact that in equilibrium $\ _{ii} = 0$, which implies $z_i = \sum_j \ _{ij} = \sum_{j \neq i} \ _{ij}$.

Solving agent i's optimization problem, we have:

$$_{ij} = \begin{cases} \frac{z_i}{K_i \ 1} \ + \frac{1}{\ } \left[R_{ij} \quad \mu \quad \alpha(\omega_i + z_i) \ \ ^2 \right] & \text{if } g_{ij} = 1 \\ 0 & \text{if } g_{ij} = 0 \end{cases} \tag{I.19}$$

where

$$z_i = \sum_{j=1}^{n} \ _{ij} = \sum_{j \neq i} \ _{ij} = \frac{\frac{1}{K_i \ 1} \sum_{j \neq i} g_{ij}(R_{ij} \quad \mu)}{\alpha\sigma^2} \qquad w_i \tag{I.20}$$

The second-order condition is satisfied without additional assumptions. Let agent i's objective function be given by:

$$F_i = \omega_i(1 \quad \mu) + \sum_{j=1}^{n} \ _{ij}(R_{ij} \quad \mu) \quad \frac{\alpha}{2}(\omega_i + z_i)^2 \ \ ^2 \quad \frac{\ }{2} \sum_{j \neq i} g_{ij} \left(\ _{ij} \quad \frac{z_i}{K_i \quad 1} \right)^2$$

which implies that whenever $g_{ij} = 1$ we have:

$$\begin{aligned} \frac{\partial F_i}{\partial \gamma_{ij}} &= R_{ij} \quad \mu \quad \alpha(\omega_i + z_i) \ \ ^2 \quad \left(\ _{ij} \quad \frac{z_i}{K_i \quad 1} \right) \\ \frac{\partial^2 F_i}{\partial \gamma_{ij}^2} &= \quad \alpha\sigma^2 \quad \left(1 \quad \frac{1}{K_i \quad 1} \right) \\ \frac{\partial^2 F_i}{\partial \gamma_{ij} \partial \gamma_{is}} &= \quad \alpha\sigma^2 + \frac{1}{K_i \quad 1} \end{aligned}$$

To write in matrix notation, we can restrict the derivation to connections available to agent i, that is, every $j \neq i$ such that $g_{ij} = 1$. In Matrix notation, the Hessian becomes:

$$\begin{aligned} \nabla^2 F_i = & \quad I \left[\alpha\sigma^2 + \quad \left(1 \quad \frac{1}{K_i \quad 1} \right) \right] \quad \mathbf{1}\mathbf{1}' \quad I \quad \left(\alpha\sigma^2 \quad \frac{1}{K_i \quad 1} \right) \\ = & \quad \mathbf{1}\mathbf{1}'\alpha\sigma^2 \quad I \quad + \mathbf{1}\mathbf{1}' \ \frac{1}{K_i \quad 1} \end{aligned}$$

where $\mathbf{1}$ is a $K_i \quad 1$ by 1 column vector of ones and I is an identify matrix.

For any non-zero vector $x = (x_1, x_2, ..., x_{K_i \ \ 1})'$, we have that:

$$\begin{aligned} x'\nabla^2 F_i x = & \quad x'\mathbf{1}\mathbf{1}'x\alpha \ \ ^2 \quad x'x \quad + x'\mathbf{1}\mathbf{1}'x \ \frac{1}{K_i \quad 1} \\ = & \quad \alpha\sigma^2 \quad \left(\sum_s x_s \right)^2 \quad \sum_s x_s^2 + \frac{1}{K_i \quad 1} \quad \left(\sum_s x_s \right)^2 \end{aligned}$$

$$
\begin{aligned}
&= \quad \alpha\sigma^2 \quad \Big(\sum_s x_s\Big)^2 \quad \left[\sum_s \Big(x_s^2 \quad \frac{1}{K_i \quad 1} \quad \sum_s x_s\Big)^2\right] \\
&= \quad \alpha\sigma^2 \quad \Big(\sum_s x_s\Big)^2 \quad \sum_s \Big(x_s \quad \frac{1}{K_i \quad 1} \sum_s x_s\Big)^2 < 0
\end{aligned}
$$

Hence, $\nabla^2 F_i$ is negative definite and the second-order condition holds.

I.3.1.1 Equilibrium

As in the benchmark model, market clearing conditions are given by:

$$
{}_{ij} + \quad {}_{ji} = 0 \qquad \forall i, j = 1, \dots, n, \tag{I.21}
$$

and we assume no transaction costs:

$$
R_{ij} = R_{ji}.
$$

If agents i and j can trade (i.e., $g_{ij} = g_{ji} = 1$), we can use their optimality conditions from equation (I.19) and market clearing condition from equation (I.21) to solve for the equilibrium price of a contract between agents i and j:

$$
R_{ij} \quad \mu = \frac{\alpha\sigma^2(\omega_i + z_i) \qquad \frac{z_i}{K_i \quad 1} + \alpha\sigma^2(\omega_j + z_j) \qquad \frac{z_j}{K_j \quad 1}}{2} \tag{I.22}
$$

Notice that prices no longer represent only the average the counterparties shadow cost of insurance. Instead, prices also depend on how much each counterparty deviates from its average trade. For instance, if dealer i sells (buys) a lot more to (from) agent j than to (from) other agents, then R_{ij} will be higher (lower) to compensate dealers i for the concentrated trade.

The net positions, $\{z_i\}_i$, are determined in equilibrium. Starting from the first-order conditions, we have:

$$
R_{ij} \quad \mu = \Big(\quad {}_{ij} \quad \frac{z_i}{K_i \quad 1}\Big) + \alpha\sigma^2(\omega_i + z_i),
$$

which can be rearranged as follows by substituting prices from Equation (I.22):

$$
\begin{aligned}
\frac{\alpha\sigma^2(\omega_i + z_i) \qquad \frac{z_i}{K_i \quad 1} + \alpha\sigma^2(\omega_j + z_j) \qquad \frac{z_j}{K_j \quad 1}}{2} &= \Big(\quad {}_{ij} \quad \frac{z_i}{K_i \quad 1}\Big) + \alpha\sigma^2(\omega_i + z_i) \\
\alpha\sigma^2(\omega_i + z_i) \qquad \frac{z_i}{K_i \quad 1} + \alpha\sigma^2(\omega_j + z_j) \qquad \frac{z_j}{K_j \quad 1} &= 2 \Big(\quad {}_{ij} \quad \frac{z_i}{K_i \quad 1}\Big) + 2\alpha\sigma^2(\omega_i + z_i) \\
\alpha\sigma^2(\omega_i + z_i) \qquad \frac{z_i}{K_i \quad 1} + \alpha\sigma^2(\omega_j + z_j) \qquad \frac{z_j}{K_j \quad 1} &= 2 \Big(\quad {}_{ij} \quad \frac{z_i}{K_i \quad 1}\Big)
\end{aligned}
$$

If we sum over valid j's, i.e. $j \neq i$ such that $g_{ij} = 1$, than we have:

$$(K_i - 1)\,\alpha\sigma^2(\omega_i + z_i) - z_i + \alpha\sigma^2 \sum_{j\neq i} g_{ij}(\omega_j + z_j) - \sum_{j\neq i} g_{ij}\frac{z_j}{K_j - 1} = 0,$$

which we can rearrange as follows:

$$\omega_i + z_i = (1 - \vartheta_i)\,\omega_i + \vartheta_i \sum_j \left(\frac{g_{ij}}{K_i - 1}(\omega_j + z_j)\right) + \frac{1 - \vartheta_i}{2}\left(z_i - \sum_{j\neq i}\left(g_{ij}\frac{z_j}{K_j}\right)\right) \tag{I.23}$$

where $\vartheta_i = \frac{(K_i - 1)\alpha\sigma^2}{(K_i - 1)\alpha\sigma^2 + 2}$.

Equation (I.23) is intuitive. It is similar to Equation (8) in the paper, because agent i's post-trade exposure to aggregate default risk $(z_i + w_i)$ is a convex combination of her pre-trade exposure (w_i) and the average post-trade exposures of her trading counterparties. However, the last term in Equation (I.23) is new and it is a direct implication of the alternative trading cost function. The last term is positive if agent i is a larger net seller than the sum of the average net position of its neighbors, that is, $z_i > \sum_j \left(g_{ij}\frac{z_j}{K_j - 1}\right)$. Under the alternative trading cost function, a larger net seller is not penalized for holding large positions. Hence, it is less costly for agents to take on more credit risk. In equilibrium, large net seller are typically agents endowed with lower pre-trade exposure (i.e. low w_i). Under the alternative trading cost function, these agents are able to take on more credit risk and hold larger net selling positions, which leads to larger post-trade exposure. The last term in Equation (I.23) captures this additional channel through which agents with large net positions can diversify away aggregate credit risk without bearing large trading costs by holding less concentrated position across its counterparties.

I.3.1.2 Core-Periphery

Assuming a core-periphery network structure, we can derive an expression for dealers' pre-trade exposure as a function to parameters and their net positions. Under a core-periphery network, let us assume that, without loss of generality, agents $j = 1, \ldots, n_d$ are core agents (dealers) and agents $s = n_d + 1, \ldots, n$ are peripheral agents (customers) . That is, for a dealer $i \in \{1, \ldots, n_d\}$, we have $g_{ij} = 1$ for every $j \neq i$. For a customer $i \in \{n_d + 1, \ldots, n\}$, $g_{ij} = 1$ for every dealer $j = 1, \ldots, n_d$, and $g_{is} = 0$ for every customer $s = n_d + 1, \ldots, n$.

Under core-periphery network assumption, we can simplify Equation (I.23) for dealer i as follows:

$$\omega_i + z_i = (1 - \vartheta_d)\,\omega_i + \vartheta_d \sum_{j\neq i} \left(\frac{g_{ij}}{K_i - 1}(\omega_j + z_j)\right) + \frac{1 - \vartheta_d}{2}\left(z_i - \sum_{j\neq i}\left(g_{ij}\frac{z_j}{K_j}\right)\right)$$
$$\frac{1 + \vartheta_d}{2} z_i = -\vartheta_d\omega_i + \vartheta_d \sum_{j\neq i} \left(\frac{g_{ij}}{K_i - 1}(\omega_j + z_j)\right) - \frac{1 - \vartheta_d}{2}\sum_{j\neq i}\left(g_{ij}\frac{z_j}{K_j - 1}\right)$$

$$
\begin{aligned}
z_i &= -\frac{2\vartheta_d}{1+\vartheta_d}\omega_i + \frac{2\vartheta_d}{1+\vartheta_d}\sum_{j\neq i}\frac{g_{ij}}{K_i-1}\left(\omega_j + z_j\right) - \frac{1-\vartheta_d}{1+\vartheta_d}\sum_{j\neq i} g_{ij}\frac{z_j}{K_j-1} \\
z_i &= -\frac{2\vartheta_d}{1+\vartheta_d}\omega_i + \frac{2\vartheta_d}{1+\vartheta_d}\left(\frac{\overline{\omega}n-\omega_i}{n-1} - \frac{z_i}{n-1}\right) \\
&\quad - \frac{1-\vartheta_d}{1+\vartheta_d}\left[\frac{n_d}{n-1}\overline{z}_d - \frac{z_i}{n-1} + \frac{n-n_d}{n_d}\overline{z}_c\right] \\
\frac{2\vartheta_d}{1+\vartheta_d}\frac{n}{n-1}\omega_i &= -\left[1-\frac{1-3\vartheta_d}{(1+\vartheta_d)(n-1)}\right]z_i + \frac{2\vartheta_d}{1+\vartheta_d}\frac{n}{n-1}\overline{\omega} - \frac{1-\vartheta_d}{1+\vartheta_d}\left[\frac{n_d}{n-1}\overline{z}_d + \frac{n-n_d}{n_d}\overline{z}_c\right] \\
\frac{2\vartheta_d}{1+\vartheta_d}\frac{n}{n-1}\omega_i &= \frac{2\vartheta_d}{1+\vartheta_d}\frac{n}{n-1}\overline{\omega} - \left[1-\frac{1-3\vartheta_d}{(1+\vartheta_d)(n-1)}\right]z_i - \frac{1-\vartheta_d}{1+\vartheta_d}\left[\frac{n_d}{n-1} - 1\right]\overline{z}_d \\
\omega_i &= \overline{\omega} - \frac{(1+\vartheta_d)(n-1)}{2\vartheta_d n}\left[1-\frac{1-3\vartheta_d}{(1+\vartheta_d)(n-1)}\right]z_i \qquad \text{(I.24)} \\
&\quad - \frac{(1-\vartheta_d)(n-1)}{2\vartheta_d n}\left[\frac{n_d}{n-1} - 1\right]\overline{z}_d
\end{aligned}
$$

where $\overline{\omega}$ is the average pre-trade exposure of all agents, $\overline{z}_d$ is the average net position of dealers, $\overline{z}_c$ is the average net position of customers, $\vartheta_d = \frac{(n-1)\alpha\sigma^2}{(n-1)\alpha\sigma^2+2}$, and z_i is dealer i's net position. We can also rewrite Equation (I.24) to net positions as a function of parameters and pre-trade exposures:

$$
z_i = \frac{\frac{2\vartheta_d}{1+\vartheta_d}\frac{n}{n-1}\left(\overline{\omega}-\omega_i\right) - \frac{1-\vartheta_d}{1+\vartheta_d}\left[\frac{n_d}{n-1} - 1\right]\overline{z}_d}{1-\frac{1-3\vartheta_d}{(1+\vartheta_d)(n-1)}} \qquad \text{(I.25)}
$$

where the average net position of dealers is obtained by averaging Equation (I.26) across dealers,

$$
\overline{z}_d = \frac{\frac{2\vartheta_d}{1+\vartheta_d}\frac{n}{n-1}\left(\overline{\omega}-\overline{\omega}_d\right)}{1-\frac{1-3\vartheta_d}{(1+\vartheta_d)(n-1)} + \frac{1-\vartheta_d}{1+\vartheta_d}\left(\frac{n_d}{n-1}-1\right)}, \qquad \text{(I.26)}
$$

and $\overline{\omega}_d = \frac{1}{n_d}\sum_{i=1}^{n_d}\omega_i$.

Furthermore, we can write average prices among dealers as a function to parameters using Equation I.22, dealers' net positions and dealers' pre-trade exposures:

$$
\begin{aligned}
\overline{R}_d &\equiv \frac{1}{n_d(n_d-1)}\sum_{i=1}^{n_d}\sum_{j=1,j\neq i}^{n_d} R_{ij} \\
&= \mu + \frac{1}{n_d(n_d-1)}\sum_{i=1}^{n_d}\sum_{j=1,j\neq i}^{n_d}\frac{\alpha\sigma^2(\omega_i+z_i) - \frac{z_i}{n-1} + \alpha\sigma^2(\omega_j+z_j) - \frac{z_j}{n-1}}{2} \\
&= \mu + \frac{1}{n_d}\sum_{i=1}^{n_d}\frac{\alpha\sigma^2(\omega_i+z_i) - \frac{z_i}{n-1} + \alpha\sigma^2\frac{1}{n_d-1}\left(n_d\overline{\omega}_d + n_d\overline{z}_d - \omega_i - z_i\right) - \frac{1}{n-1}\frac{n_d\overline{z}_d - z_i}{n_d-1}}{2} \\
&= \mu + \frac{\alpha\sigma^2(\overline{\omega}_d+\overline{z}_d) - \frac{\overline{z}_d}{n-1} + \alpha\sigma^2\frac{1}{n_d-1}\left(n_d\overline{\omega}_d + n_d\overline{z}_d - \overline{\omega}_d - \overline{z}_d\right) - \frac{1}{n-1}\frac{n_d\overline{z}_d - \overline{z}_d}{n_d-1}}{2} \\
&= \mu + \frac{\alpha\sigma^2(\overline{\omega}_d+\overline{z}_d) - \frac{\overline{z}_d}{n-1} + \alpha\sigma^2\left(\overline{\omega}_d + \overline{z}_d\right) - \frac{1}{n-1}\overline{z}_d}{2}
\end{aligned}
$$

$$= \mu + \alpha\sigma^2 \left(\overline{\omega}_d + \overline{z}_d\right) \quad \frac{}{n \quad 1}\overline{z}_d. \tag{I.27}$$

Similarly, the average price in the customer-dealer market is given by:

$$\begin{aligned}
\overline{R}_c &\equiv \frac{1}{n_d(n \quad n_d)} \sum_{i=n_d+1}^{n} \sum_{j=1}^{n_d} R_{ij} \\
&= \mu + \frac{1}{n_d(n \quad n_d)} \sum_{i=n_d+1}^{n} \sum_{j=1}^{n_d} \left(\frac{\alpha\sigma^2(\omega_i + z_i) \quad \frac{z_i}{n_d} + \alpha\sigma^2(\omega_j + z_j) \quad \frac{z_j}{n \quad 1}}{2} \right. \\
&= \mu + \frac{1}{n \quad n_d} \sum_{i=n_d+1}^{n} \left(\frac{\alpha\sigma^2(\omega_i + z_i) \quad \frac{z_i}{n_d} + \alpha\sigma^2(\overline{\omega}_d + \overline{z}_d) \quad \frac{\overline{z}_d}{n \quad 1}}{2} \right. \\
&= \mu + \frac{\alpha\sigma^2(\overline{\omega}_c + \overline{z}_c) \quad \frac{\overline{z}_c}{n_d} + \alpha\sigma^2(\overline{\omega}_d + \overline{z}_d) \quad \frac{\overline{z}_d}{n \quad 1}}{2}
\end{aligned} \tag{I.28}$$

where $\overline{z}_c = \quad \frac{n_d}{n \quad 1}\overline{z}_d$ and $\overline{\omega}_c = \frac{\overline{\omega} \quad n_d\overline{\omega}_d}{n \quad n_d}$.

I.3.1.3 Calibration and Dealer Removal

To calibrate the model, we follow the same procedure as in the benchmark model. However, under this alternative specification, we do not have a closed-formed solutions for the moments we match. Hence, we rely on numerical solution. Formally, we use Equation (I.24) to get dealers' pre-trade exposure, and Equations (I.27) and (I.28) to compute average spreads in both dealer-dealer and dealer-customer markets. We choose , α to simultaneously match these average spreads. Table I.6 has the calibrated parameters.

Given the calibrated model, we conduct the dealer removal exercise by following the same steps as the dealer removal under the benchmark model. Given the calibrated parameters, we compute dealers' pre-trade exposures using Equation (I.24). The we remove the different dealers from the economy and solve for equilibrium prices and allocations. Table I.7 reports the effects of dealer removal on equilibrium spreads.

There are interesting similarities and differences between our benchmark model and the model under the alternative cost specification.

Perhaps the most important similarity is the quantitative impact of dealer exit, which we simulate exactly as we do in the main text (Section 4). In the model based on Equation (I.18), spreads in the dealer market increase from 133 bps to 165.8 bps after the largest net-selling dealer exits the market (column (2), Table I.7). This is very similar to the increase from 133 bps to 164.3 in dealer-dealer spreads reached after the dealer exits our benchmark model (Table 6 in the paper). These results suggest that our main conclusions are robust to modeling trading costs as a function of pure concentration, as opposed to the absolute size of bilateral positions.

Nonetheless, our benchmark framework and the one featuring this alternative cost function do have distinct implications for how spreads are influenced by the shape of the network. In particular, some parts of Proposition 1 in the paper break down when using Equation (I.18): when using the alternative cost function, dealer and customer markets are no longer below the level that obtains in a complete-network counterfactual. The key difference between the two models is that marginal trading costs are symmetric in our benchmark model but are not when using Equation (I.18). By symmetric, we simply mean that a given bilateral position $\ _{ij}$ has the same marginal utility cost for both counterparties in a trade. In equilibrium, this means that buyers and sellers of CDS will trade at a price that is exactly halfway between their respective shadow costs of insurance. Given dealers are on one side of every trade, spreads are heavily tilted towards their shadow cost of insurance. And, because dealers start with relatively low initial exposures empirically, spreads in both dealer and customer markets are therefore lower than what would prevail under a complete network counterfactual. This intuition is discussed in the main text after Proposition 1.

Under the alternative trading cost function in Equation (I.18), the marginal cost of trading is no longer symmetric. More concretely, suppose a customer is a net buyer of protection and equally spreads its trades across all its counterparties (i.e. all dealers). In this case, the customer's marginal trading cost is zero because its trades are equally distributed across all its counterparties. Consequently, the customer would not require any price concession due to trading costs and would be willing to buy protection at a price equal to its shadow cost of insurance. In turn, prices between this customer and any other dealer would be equal to the customers' shadow cost of insurance. In other words, under the trading cost function (I.18), prices will reflect how much counterparties deviate from their average position size. This means the average price in customer-dealer trades will not necessarily tilt towards dealers' lower-than-average shadow cost of insurance. Thus, unlike our benchmark model, dealer-dealer and customer-dealers average spreads are not necessarily lower than what would prevail under a complete network counterfactual.

I.3.1.4 Testing $\ > 0$

In this subsection, we show that, within the model framework with alternative preference for smoothing trade, the coe cient from the price concession is negative if, and only if, $\ > 0$. The model with alternative trading cost specification is detailed in Internet Appendix I.3.1. In the model, price concession and κ between agents i and j are defined as:

$$PriceConcession_{ij} = \begin{cases} R_i^{max} \quad R_{ij} & \text{if } \ _{ij} > 0 \\ R_{ij} \quad R_i^{min} & \text{if } \ _{ij} < 0 \end{cases}, \tag{I.29}$$

$$\kappa_{ij} = \frac{|\ _{ij}|}{\sum_{s=1}^{n} |\ _{is}|}, \tag{I.30}$$

where $R_i^{max} = \max_s R_{is}$ and $R_i^{min} = \min_s R_{is}$. We will restrict our analysis to parameterization in which κ_{ij} is well defined, that is $\sum_{s=1}^{n} |\ _{is}| > 0$ for every i.

For $\ _{ij} > 0$, that is, agent i sells protection to agent j, we can write the first-order condition as follows:

$$
\begin{aligned}
R_{ij} \quad \mu &= \alpha\sigma^2 (w_i + z_i) + \left(\quad _{ij} \quad \frac{z_i}{K_i \quad 1} \right) \Big(\\
R_{ij} \quad \mu &= \alpha\sigma^2 (w_i + z_i) + \quad _{ij} \quad \frac{z_i}{K_i \quad 1} \\
R_{ij} \quad \mu &= \alpha\sigma^2 (w_i + z_i) + \quad | \quad _{ij}| \quad \frac{z_i}{K_i \quad 1} \\
R_{ij} &= \quad \mu \quad \alpha\sigma^2 (w_i + z_i) + \frac{z_i}{K_i \quad 1} \quad | \quad _{ij}| .
\end{aligned}
$$

By adding R_i^{max} on both sides, we have:

$$
\begin{aligned}
R_i^{max} \quad R_{ij} &= R_i^{max} \quad \mu \quad \alpha\sigma^2 (w_i + z_i) + \frac{z_i}{K_i \quad 1} \quad | \quad _{ij}| \\
R_i^{max} \quad R_{ij} &= R_i^{max} \quad \mu \quad \alpha\sigma^2 (w_i + z_i) + \frac{z_i}{K_i \quad 1} \quad \sum_{s=1}^{n} \Big(\quad _{is}| \frac{| \quad _{ij}|}{\sum_{s=1}^{n} | \quad _{is}|} \\
R_i^{max} \quad R_{ij} &= \tilde{a}_i^s \quad \tilde{b}_i^s \kappa_{ij},
\end{aligned}
\tag{I.31}
$$

where $\tilde{a}_i^s = R_i^{max} \quad \mu \quad \alpha\sigma^2 (w_i + z_i) + \frac{z_i}{K_i \quad 1}$ and $\tilde{b}_i^s = \quad \sum_{s=1}^{n} \Big(| \quad _{is}| \quad 0$.

For $\quad _{ij} < 0$, that is, agent i buys protection to agent j, we can write the first-order condition as follows:

$$
\begin{aligned}
R_{ij} \quad \mu &= \alpha\sigma^2 (w_i + z_i) + \quad _{ij} \quad \frac{z_i}{K_i \quad 1} \\
R_{ij} &= \mu + \alpha\sigma^2 (w_i + z_i) \quad | \quad _{ij}| \quad \frac{z_i}{K_i \quad 1}.
\end{aligned}
$$

By subtracting R_i^{min} on both sides, we have:

$$
\begin{aligned}
R_{ij} \quad R_i^{min} &= \quad R_i^{min} + \mu + \alpha\sigma^2 (w_i + z_i) \quad \frac{z_i}{K_i \quad 1} \quad | \quad _{ij}| \\
R_{ij} \quad R_i^{min} &= \quad R_i^{min} + \mu + \alpha\sigma^2 (w_i + z_i) \quad \frac{z_i}{K_i \quad 1} \quad \sum_{s=1}^{n} | \quad _{is}| \frac{| \quad _{ij}|}{\sum_{s=1}^{n} | \quad _{is}|} \\
R_i^{max} \quad R_{ij} &= \tilde{a}_i^b \quad \tilde{b}_i^b \kappa_{ij},
\end{aligned}
\tag{I.32}
$$

where $\tilde{a}_i^b = \quad R_i^{min} + \mu + \alpha\sigma^2 (w_i + z_i) \quad \frac{z_i}{K_i \quad 1}$ and $\tilde{b}_i^b = \quad \sum_{s=1}^{n} | \quad _{is}|$. Notice that $\tilde{b}_i^s = \tilde{b}_i^b$.

The rest of the derivation is identical to the derivation in Internet Appendix I.1.2 from Equation (I.5) onward by using $\tilde{a}_i^s$, $\tilde{a}_i^b$, $\tilde{b}_i^s$, and $\tilde{b}_i^b$, instead of a_i^s, a_i^b, b_i^s, and b_i^b, respectively.

I.3.2 Price Impact

In this subsection, we derive an alternative version of the benchmark model in which agents internalize the effect of their own exposure to the underlying risk on equilibrium prices. In the benchmark model, equilibrium prices are given by Equation (7) in the main text, which means that when agent i sells insurance to agent j, then she receives R_{ij} as payment. Notice, however, this equilibrium price depends on both agents' post-trade exposures. Notice that agent i optimally chooses the total net exposure to the underlying default risk, i.e., z_i, but takes equilibrium prices as given. In this subsection, we derive equilibrium allocations and prices when agents take into account the effect of their net exposure to the underlying default risk on prices.

To solve this model, we guess and verify that the equilibrium price in a bilateral trade will be a linear combination of the counterparties' post-trade exposures. Specifically, we assume that:

$$R_{ij} - \mu = A + B\alpha\sigma^2 z_i + C\alpha\sigma^2 z_j + D\alpha\sigma^2\omega_i + E\alpha\sigma^2\omega_j,$$

where A, B, C, D, and E are coefficients to be determined. The assumption here is similar to a Cournot competition model in which firms take their competitors' quantities as given and equilibrium is pinned by the fixed point of best-responses. In our setting, agent i take j's exposure and all pre-trade exposures as given but internalize the effect of of i's exposure on equilibrium prices.

Formally, agent i solves the following optimization problem:

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

subject to

$$\gamma_{ij} = 0 \text{ if } g_{ij} = 0,$$
$$z_i = \sum_{j=1}^n \gamma_{ij},$$

and

$$R_{ij} - \mu = A + B\alpha\sigma^2(z_i+\omega_i+z_j+\omega_j).$$

Hence, the first-order conditions imply:

$$R_{ij} - \mu + \sum_s \gamma_{is}\frac{\partial}{\partial\gamma_{ij}}R_{ij} = \alpha\sigma^2(z_i+\omega_i) + \gamma_{ij}$$
$$\implies R_{ij} - \mu = \alpha\sigma^2(z_i+\omega_i-Bz_i) + \gamma_{ij}$$

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:

$$R_{ij} - \mu = \frac{\alpha\sigma^2}{2}[(1-B)z_i + \omega_i + (1-B)z_j + \omega_j]$$

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:

$$R_{ij} \quad \mu = \alpha\sigma^2 \frac{1}{2} \left[\omega_i + \omega_j + \tilde{z}_i + \tilde{z}_j\right], \tag{I.33}$$

and first-order condition can be written as:

$$R_{ij} \quad \mu = \alpha\sigma^2 \left(\omega_i + \tilde{z}_i\right) + \quad {}_{ij}, \tag{I.34}$$

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

To get derive equilibrium allocations, we can combined Equations (I.33) and (I.34), along with the fact that $z_i = \sum_{j=1}^{n} \;{}_{ij}$:

$$\tilde{z}_i + \omega_i = \left(1 \quad \tilde{}_i\right)\left(\omega_i + \tilde{}_i \sum_{j=1}^{n} \tilde{g}_{ij} \left(\tilde{z}_j + \omega_j\right)\right) \qquad \forall i = 1, \ldots, n \tag{I.35}$$

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 $\tilde{}_i = \frac{K_i \alpha\sigma^2}{K_i \alpha\sigma^2 + 3} \in (0, 1)$.

Notice that Equation (I.35) is extremely similar to Equation (8) in the main text, except that under price impact we have $\tilde{z}_i$ and $\tilde{}_i$ instead of z_i and ${}_i$. As a result, the analyses discussed in the paper hold in a price impact environment as well.

I.3.3 Model with Speculative Trading Motive

In this section, we consider a variation of the model in which agents disagree about expected default—they agree to disagree. Specifically, agent i beliefs expected default is $\mu_i = \mu + \nu_i$, where ν_i is independent across agent with mean zero. In this case, agents trade not only to share risk but also for speculative reasons. For instance, if agent k is more optimistic about the expected default than agent l, i.e. $\mu_k < \mu_l$, then agent k would be willing to sell insurance to agent l. In equilibrium, the total net positions of agent depends, of course, on the entire network structure and every agents' trades with other counterparties. Formally, in this variation of the model, agent i's optimization problem becomes:

$$\max_{\{\;{}_{ij}\}_{j=1}^{n}} w_i(1 \quad \mu_i) + \sum_{j=1}^{n} \;{}_{ij}(R_{ij} \quad \mu_i) \quad \frac{\alpha}{2} \left(w_i + z_i\right)^2 \;{}^2 \quad \frac{}{2} \sum_{j=1}^{n} \;{}_{ij}^2,$$

subject to ${}_{ij} = 0$ if $g_{ij} = 0$, and $z_i = \sum_{j=1}^{n} \;{}_{ij}$. Similar to the benchmark model, all bilateral markets clear, i.e. ${}_{ij} + \;{}_{ji} = 0$ for every i and j, and there are no transaction costs between counterparties, i.e. $R_{ij} = R_{ji}$ for every i and j.

Agent i's optimality conditions are given by:

$$R_{ij} \quad \mu_i \quad \alpha\left(w_i + z_i\right) \quad {}^2 \qquad {}_{ij} = 0 \qquad \forall j \text{ s.t. } g_{ij} = 1,$$

$$ {}_{ij} = 0 \qquad \forall j \text{ s.t. } g_{ij} = 0,$$

$$z_i \quad \sum_{j=1}^{n} \Big({}_{ij} = 0.$$

Next, we highlight two properties of the competitive equilibrium with heterogeneous beliefs about the expected default.

First, heterogeneity in beliefs (μ_i's) is isomorphic to heterogeneity in pre-trade exposures (ω_i's) in terms of equilibrium prices and quantities traded. Notice that the equilibrium allocation is the solution to the following system of equations:

$$R_{ij} \quad \mu_i \quad \alpha\left(w_i + z_i\right) \quad {}^2 \qquad {}_{ij} = 0 \qquad \forall j \text{ s.t. } g_{ij} = 1$$

$$ {}_{ij} = 0 \qquad \forall j \text{ s.t. } g_{ij} = 0$$

$$z_i \quad \sum_{j=1}^{n} \Big({}_{ij} = 0$$

$$ {}_{ij} + \quad {}_{ji} = 0$$

$$R_{ij} \quad R_{ji} = 0$$

Thus, any combination of μ_i and ω_i such that $\mu_i + \alpha\sigma^2 w_i$ remains constant delivers the same allocation and prices in equilibrium, i.e. 's and R's are exactly the same, and heterogeneity in beliefs is isomorphic to heterogeneity in pre-trade exposures. In other words, trading motives do not change equilibrium allocation whether these incentives are based on speculative or risk sharing motives. Therefore, our systemic risk analysis holds regardless of agents' motive for trade.

The intuition behind this result is that higher pre-trade exposure is allocationally equivalent to believing in a higher default probability, even though the reason for trade is very different. On one hand, an agent with higher pre-trade exposure is willing to buy more protection against aggregate default in order to protect herself against default risk. On the other hand, someone who beliefs that the default probability is higher is also willing to buy more insurance because the current exposure is perceived as riskier. Thus, higher ω_i and higher μ_i are equivalent in terms of demand for insurance.

Second, in terms of risk reallocation, heterogeneity in beliefs (μ_i's) is not isomorphic to heterogeneity in pre-trade exposures (ω_i's). Any combination of μ_i and ω_i such that $\mu_i + \alpha\sigma^2 w_i$ remains constant delivers the same allocation and prices in equilibrium, i.e. 's, z' and R's are exactly the same. For risk reallocation though, what matters is agents' post-trade exposures, which are given by $z_i + \omega_i$. These will vary with ω_i even if $\mu_i + \alpha\sigma^2 w_i$ remains constant. In equilibrium, an agent who beliefs in a higher (lower) expected default buys more (less) insurance against aggregate default risk, moving further away from an allocation with more risk-sharing.

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APPENDIX TABLES

Table I.1: Dynamics of the CDS Trading Network

Panel A: The Probability of Breaking and Forming Connections

	No Connection$_{t+1}$	Connection$_{t+1}$
No Connection$_t$	99.99%	0.01%
Connection$_t$	0.91%	99.09%

Panel B: Measuring the Persistence of the Network

	Degree Centrality		Eigenvector Centrality	
	AR-Coe cient	t-statistic	AR-Coe cient	t-statistic
p10	1.0*	-	1.0*	-
p20	0.80	19.67	0.80	19.47
p40	0.92	32.25	0.97	50.21
p60	0.92	33.85	0.90	30.18
p80	0.90	25.65	0.84	23.17
p90	0.92	35.47	0.98	72.30

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. $c_{p,t+1} = \eta_p + \ _p c_{p,t} + \varepsilon_{p,t+1}$. The table shows the estimated $\ _p$ 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 I.2: Average Dealer CDS Exposure

Method	$\bar{z}_d$
Notional, Beta-Weighted	0.045
DV01, Beta-Weighted (%)	0.22

Notes: This table presents some basic summary statistics about the average credit exposure of dealers to the aggregate credit risk index, denoted by $\bar{z}_d$. Our aggregate credit risk index on each date is the cross-sectional average of all 5-year U.S. CDS spreads in the Markit database. We define exposure to this index in two ways: (i) a beta-weighted average of the net notional sold across all CDS positions, with betas computed with respect to the aggregate credit risk index; and (ii) a beta-weighted average DV01 across all positions, which just measures how much the entire CDS portfolio would lose if there was a one hundred basis point move in the aggregate credit risk index. See Appendix I.1.4.3 for complete details. In all cases, positive values indicates that dealers are on average net sellers. For all metrics, we compute the exposure of dealers in our sample, then scale this exposure by their market capitalization. This is what we call a dealer-specific z_i. $\bar{z}_d$ in each week is the cross-sectional average of each z_i across dealers. The table reports average weekly $\bar{z}_d$ over the period January 2010 through December 2013. Source: Authors' analysis, which uses data provided to the OFR by the Depository Trust & Clearing Corporation.

Table I.3: Customer Removal

	Benchmark	Customer Removal	
	(1)	(2)	(3)
Number of dealers	14	14	14
Complete network $\overline{R}$ (bps)	143.04	143.74	172.76
$\overline{R}_d$ (bps):	133.00	133.22	142.48
$\overline{R}_c$ (bps):	138.12	138.58	157.92
$\overline{z}_d$	0.045	0.048	0.137

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 Appendix C. Column (1) reports our benchmark calibration. In Column (2) reports the results after removing a customer with the same pre-trade exposure as the largest net-seller dealer. Column (3) reports results after removing a customer with the same net positions as the largest net-seller dealer. Source: Authors' analysis, which uses data provided to the OFR by the Depository Trust & Clearing Corporation.

Table I.4: Dealer Removal Robustness: $\overline{\omega}$

	Benchmark (1)	Top (2)	90^{th} prc. (3)	Median (4)	Bottom (5)
Panel A: Assuming $\overline{\omega} = 0.5$					
Number of dealers	14	13	13	13	13
Complete network $\overline{R}$ (bps)	143.04	144.15	143.26	143.01	142.73
$\overline{R}_d$ (bps):	133.00	164.59	138.66	131.35	123.03
$\overline{R}_c$ (bps):	138.12	154.18	141.01	137.29	133.06
$\overline{z}_d$	0.045	0.092	0.021	0.053	0.089
Panel B: Assuming $\overline{\omega} = 3$					
Number of dealers	14	13	13	13	13
Complete network $\overline{R}$ (bps)	143.04	143.70	143.17	143.02	142.85
$\overline{R}_d$ (bps):	133.00	164.13	138.58	131.36	123.17
$\overline{R}_c$ (bps):	138.12	153.73	140.92	137.30	133.19
$\overline{z}_d$	0.045	0.092	0.021	0.053	0.089

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 I.1.1.2. In 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^{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. In Panel A, we report results assuming $\overline{\omega} = 0.5$, while in Panel B we report the results assuming $\overline{\omega} = 3$. In each Panel, given the assumed value for $\overline{\omega}$, we recalibrate the model following the procedure described in Section 3.4. Source: Authors' analysis, which uses data provided to the OFR by the Depository Trust & Clearing Corporation.

Table I.5: Dealer Removal Robustness: DTCC Dealers

	Benchmark	Top	90^{th} prc.	Median	Bottom
	(1)	(2)	(3)	(4)	(5)
Number of dealers	26	25	25	25	25
Complete network $\overline{R}$ (bps)	145.11	145.89	145.28	145.10	144.81
$\overline{R}_d$ (bps):	133.00	147.49	135.74	132.39	126.74
$\overline{R}_c$ (bps):	139.28	146.66	140.68	138.97	136.10
$\overline{z}_d$	0.062	0.008	0.049	0.065	0.093

Notes: This table uses the DTCC definition of dealers and recalibrates the model following the procedure described in Section 3.4. We report 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. In 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^{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.

Table I.6: Calibration under Alternative Trading Cost Function

Parameter	**Value**	**Source**
$\bar{z}_d$	0.045	DTCC Data 2010-2013
$\bar{R}_c \quad \bar{R}_d$ (bps)	5.12	DTCC Data 2010-2013
$\bar{R}_d$ (bps)	133.00	DTCC Data 2010-2013
n	723	DTCC Data 2010-2013
n_d	14	DTCC Data 2010-2013
$L =$ Loss-Given-Default	60.60%	Markit
$p =$ Probability of Default	0.65%	Moody's
$\alpha\sigma^2\overline{\omega} + \mu$	138.12	Model Implied
α	4.16	Model Implied
	7.98	Model Implied

Notes: This table shows parameters used to calibrate the model under the alternative trading cost specification. $\bar{z}_d$ 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 3.3.1 contains a full description of this procedure. Dealers are those identified by the algorithm described in Appendix C. $\bar{R}_c \quad \bar{R}_d$ 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 4 for complete details). $\bar{R}_d$ is the average transaction spread in the CDS market from Table 3. 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 $\bar{R}_c \quad \bar{R}_d$. See Table 4 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.

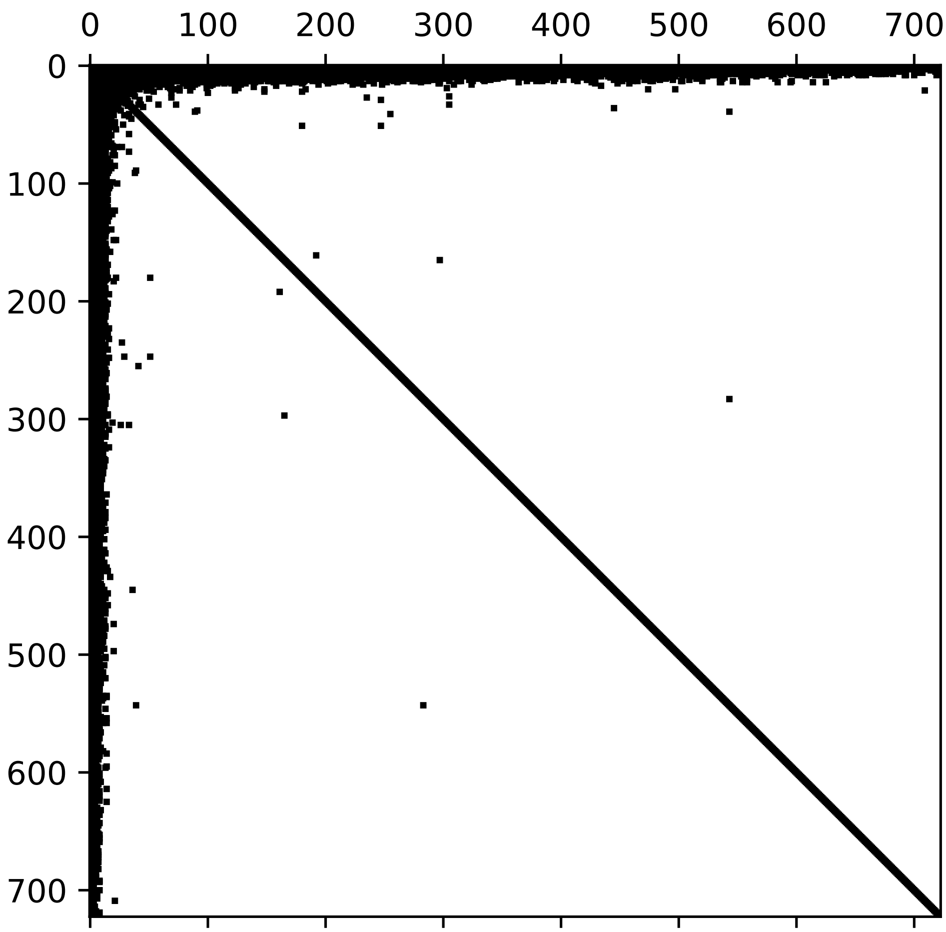
Table I.7: Dealer Removal under Alternative Trading Cost Function

	Benchmark	Top	90^{th} prc.	Median	Bottom
	(1)	(2)	(3)	(4)	(5)
Number of dealers	14	13	13	13	13
Complete network $\overline{R}$ (bps)	138.12	138.65	138.22	138.10	137.96
$\overline{R}_d$ (bps):	133.00	165.80	138.87	131.27	122.63
$\overline{R}_c$ (bps):	138.12	138.65	138.22	138.10	137.96
$\overline{z}_d$	0.045	0.241	0.006	0.061	0.136

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 use the alternative trading cost function described in Section I.3.1. 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^{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.

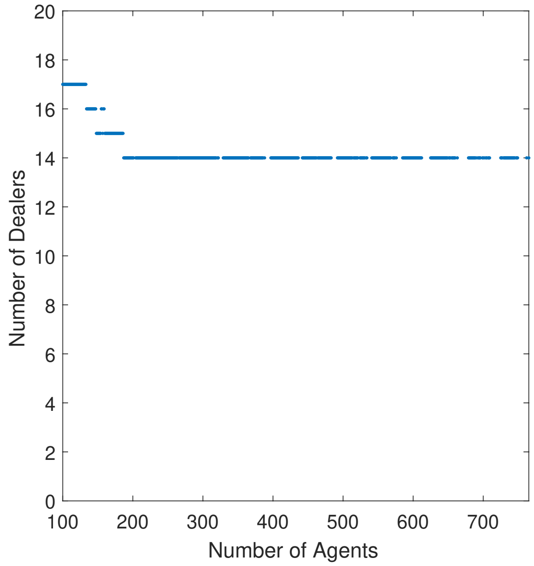
APPENDIX FIGURES

Figure I.1: The Empirical G Matrix



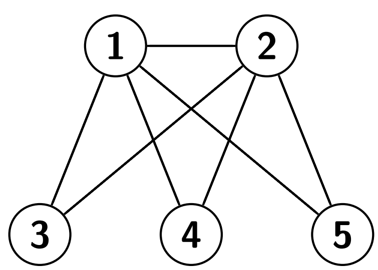
Notes: This figure plots the matrix G where element $G_{i,j}$ equals one if i and j have an open position with each other in our sample, for all counterparties with an open position in the investment grade index. If i and j do not have an open position, $G_{i,j}$ equals zero. Counterparties are ordered by their total number of connections, highest to lowest. Theoretically, a core-periphery network has a structure as in Definition 2.4, 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 I.2: Dealer Selection



Notes: In this figure, we report our selection algorithm outcome for different subsamples. We start with full network matrix that includes all the existing counterparties, compute who is a dealer based on the algorithm. In a second step, we sort all counterparties based on degree and then transaction volume. We then interactively remove one counterparty at a time, based on the previous degree-volume sort. Every time we remove a counterparty, we rerun the algorithm for the remaining counterparties. We plot the number of dealers implied by our selection algorithm against the number of remaining agents in this interactive procedure. Source: Authors' analysis, which uses data provided to the OFR by the Depository Trust & Clearing Corporation.

Figure I.3: Five-agent example



Notes:This figure represents an economy with five agents, in which agents 1 and 2 are connected to every agent and agent 3, 4, and 5 are not connected to each other. The network matrix in this example is given by Equation (I.15).