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Counterparty Choice, Bank Interconnectedness, and Systemic Risk

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Abstract

We provide evidence on how banks form network connections and endogenous risk-taking in their non-bank counterparty choices in the OTC derivative markets. We use confidential regulatory data from the Capital Assessment and Stress Testing reports that provide counterparty-level data across a wide range of OTC markets for the most systemically important U.S. banks. We show that banks are more likely to either establish or maintain a relationship, and increase their exposures within an existing relationship, with non-bank counterparties that are already heavily connected and exposed to other banks. Banks in such densely-connected networks are more likely to connect with riskier counterparties for their most material exposures. The effects are strongest in the case of (non-bank) financial counterparties. These findings suggest moral hazard behavior in counterparty choices. Finally, we demonstrate that these exposures are strongly linked to systemic risk. Overall, the results suggest a network formation process that amplifies risk propagation through non-bank linkages in opaque financial markets.

JEL Classification: G21, G22, D82

Keywords: Counterparty Risk, Financial Networks, Bank interconnectedness, Over-the-counter markets, Derivatives

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Counterparty Choice, Bank Interconnectedness, and Systemic Risk†

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This Draft: July 2021

Abstract

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1. Introduction

A broad literature studies how concentrations in linkages emerge in financial networks, and to what extent they contribute to systemic fragility.[1] In the seminal work by Allen and Gale (2000) and Freixas et al. (2000), densely connected networks tend to better withstand risks from contagion caused by exogenous shocks than those with fewer connections due to co-insurance. However, there are limits to the benefits of dense network connections, such that interconnectedness could propagate, rather than attenuate, shocks, resulting in a more fragile system (Acemoglu et al. (2015)). Recent studies have shifted attention to one important, hitherto largely ignored, direction: while most of the research in networks has concentrated on the spread of exogenous shocks, it has largely ignored the (endogenous) risk-taking behavior of banks within the network.

This question is central to our understanding of financial system resiliency to contagion because of at least two reasons: first, the impact of exogenous adverse shocks may be amplified for networks already weakened by riskier connections, and, second, a system may come under pressure from a network-intrinsic risk rather than an exogenous shock. Because network connections allow for the sharing of risks, it may also create moral hazard: a bank may connect to other banks to reduce its vulnerability to shocks through diversification, but it will also have the incentive to take on greater risks in other parts of its balance sheet (Brusco and Castiglionesi (2007), and Zawadowski (2013)). This behavior may extend to the choice of counterparties. Recent theoretical developments address precisely this point. Shu (2019) and Jackson and Pernoud (2020) investigate banks' incentives when choosing their risk exposure in financial networks, the former in the case of banks connected through cross-holdings of unsecured debts and the latter when banks are connected through debt and equity claims. In this environment, regulators should concern themselves not only with the contagion that may arise from an exogenous shock, but also about the endogenous risk taking by banks that may act as an amplifying mechanism in the case of an exogenous shock.[2] Empirical analysis has lagged behind these theoretical insights for various reasons.

This paper uses novel bank regulatory data, the Capital Assessments and Stress Testing reports (FR Y-14Q) over the period 2013-2020, that provide comprehensive, counterparty-level

[1] See, amongst others, Allen and Babus (2009), Cabrales, Gale, and Gottardi (2015), Glasserman and Young, (2016), and Summer (2013).
[2] See also Elliott et al. (2021) and Acharya (2009).

information in the OTC markets of systemically important U.S. banks to empirically investigate how banks choose (mostly) non-bank counterparties to link to. This allows us to examine how a counterparty's connections to other banks and its own risk affects the decision. Understanding these dynamics will not only provide insights into the fragility that common counterparty exposures may introduce, but also inform channels through which counterparty leverage can accumulate in opaque financial markets through derivative positions of non-bank counterparties. The granularity of the data allows us to directly address endogeneity issues that have limited prior analysis, enabling us to better isolate the effects of such interconnections from other counterparty characteristics. For the first time to our knowledge, we provide empirical evidence for the existence of endogenous risk-taking behavior of banks when choosing their counterparties. The moral hazard that is engendered by network connections, and the resulting risk-taking, is directly important for system-wide financial stability. Our results show that these linkages are associated with systemic effects.

Bank interconnectedness is multi-dimensional, on which we have very limited empirical evidence, and mostly focused on the inter-bank lending markets.[3] Bank interconnectedness does not emerge simply through inter-bank funding arrangements, but is a much richer concept. These funding arrangements provide us with *direct* bank connections, whereas a richer characterization of the interconnectedness has to consider *indirect* bank connections, i.e. banks getting connected through a common (non-bank) counterparty. Not considering these important indirect connections will underestimate the true impact of networks with clear impact on our understanding of contagion.[4]

Half of all bank counterparty arrangements in the over-the-counter (OTC) derivative markets are represented by non-bank counterparties with multiple bank dealers. Such interconnections in the financial network have been previously identified as an important source of systemic risk during the Great Financial Crisis (Basel Committee on Banking Supervision (2011), Financial Crisis Inquiry Commission (2012)), and remain an area of limited visibility for regulators and policymakers. Recent events, including the collapse of Archegos and Greensill

[3] See, for example, Upper and Worms (2004), Cocco et al. (2005), Furfine (2003), Degryse and Nguyen (2007), Brunetti et al. (2019)

[4] Financial institutions can become interconnected in many ways, including through their (a) investments, such as when asset similarities on their balance sheet emerge in an un-coordinated way, (b) their business of providing risk transfer from agents seeking to reduce risk to others willing to bear greater risk, or (c) in their business of helping corporations manage their exposures to risks (e.g. exchange rates, interest rates, and commodity prices) through derivatives and other contracts.

Capital, have reinforced concerns, as the prevalence of these forms of linkages often coincide with the build-up of synthetic leverage in the financial system.

One of the key aspects of the data concerns its coverage of 18 different over-the-counter (OTC) derivative markets. Bank interconnectedness through the OTC derivative markets was identified as an important factor that contributed to the severity of the Great Financial Crisis (FCIC (2011)), and remains an area of fragility of systemically important banks on which we have very limited understanding. The OTC derivatives trading is notoriously concentrated in the largest banks, which are also the ones for which we have data. One important feature is the substantial counterparty risk that banks face, in our context the most important counterparty risk is that faced by banks trading with non-bank entities.

We construct three measures of *indirect* bank interconnectedness associated with common counterparty exposures: (a) the number of banks with which a specific counterparty has a relationship with (i.e., the number of bank edges for a counterparty); (b) the network-wide dollar credit risk exposures of a specific counterparty across all banks, providing the amount of (dollar) credit risk exposure a bank connecting with the counterparty will get exposed to vis-à-vis other banks once a connection is established (i.e., the size of a counterparty node); and (c) the counterparty similarity in derivative portfolios between banks that are connected to a specific counterparty. Each measure captures different dimensions of the network structure and together will shed light on how risk can build in the network.

There are a number of empirical challenges that we need to address to precisely infer the impact of counterparty connections and risk on bank choices. Assortative bank-counterparty matching, arising from bank and counterparty characteristics and preferences unrelated to network choices, is one such challenge. Duffie et al. (2007) show how outcomes in OTC markets depend on investors' search abilities, bargaining power, risk aversion, and speed with which counterparties interact. Some of these characteristics are time-invariant, while some are time-varying. One effective way to control for them is the use of high-level fixed effects that absorb these characteristics and we use them in an approach reminiscent to the one used by Khwaja and Mian (2008). Specifically, we use counterparty-year-quarter and bank-year-quarter fixed effects that allow us to fully absorb all the relevant time-changing characteristics, as well as bank-counterparty fixed effects when appropriate and possible to account for other factors.

We start with our baseline model estimates to examine how the interconnectedness measures influence the bank's decision when it either establishes new, or continues with existing, relationships. We find that a systemically important bank has a higher propensity of establishing a new, or continuing in an existing, relationship the more existing bank connections the counterparty has. Specifically, we show that the interconnectedness measures have a strong and economically significant association with the bank's counterparty choice over the following quarter, both on the intensive and extensive margins. The results are strongest in the case of existing relationships. These results clearly imply that banks' actions lead towards a denser network, where banks become more connected with each other indirectly through common counterparties. Given that the resulting exposures represent synthetic liabilities of counterparties, the results also indicate that interconnectedness may be associated with higher counterparty leverage.

We further exploit an important feature of the data that provide us with information about the group of counterparties that banks, based on regulatory risk metrics, classify as material, which corresponds with the largest exposures for a given bank for a particular derivative market in each quarter. We find that interconnectedness have positive effects on the likelihood that the bank will select a counterparty associated with material exposures while the effects are mostly insignificant or negative for non-material counterparties.

A more densely connected network provides the benefit of co-insurance in the case of a shock but also the cost that banks will have the incentive to take on greater risk. Thus we should ask whether banks tend to balance over-connecting with limiting the moral hazard behavior by connecting with less risky counterparties. Answering this question is crucial to address the "connected-fragility" dimension studied by the literature (for example, Acemoglu et al. (2015), amongst others). We use the bank's estimate of the counterparty's probability of default (PD) to measure the riskiness of potential counterparties.

We find a number of important results. First, we find that counterparty risk amplifies the effects of interconnectedness for material exposures. For non-material exposures, counterparty risk has a negative or insignificant conditioning effect on the interconnectedness measures. In so far as material counterparties are more consequential from an economic standpoint, our findings suggest that banks maintain exposures to riskier counterparties, i.e. those that either can introduce risk in the network, or more likely to increase contagion in the event of an exogenous shock, in the case of the material counterparties. Our evidence is consistent with Acemoglu et al. (2015) who show that banks fail to internalize the negative externalities, in our case the counterparty's risk profile, on the other banks in the network. This suggests that moral hazard behavior is concentrated in counterparty exposures that are most consequential for banks.

Second, we examine the implications of an exogenous shock, stressing the network stability, to examine its effect on banks' counterparty choices. This exercise allows us to assess the resilience of interconnected linkages created during normal periods when they are stressed. The co-insurance view suggests that such linkages should be more resilient when the network is under stress, so as to stop potential contagion. To this end, we use the Covid-19 pandemic as an exogenous shock to the network, and evaluate differences in bank counterparty choice behavior before and after the onset of the pandemic. We find that material exposures for riskier counterparties that are more interconnected are more likely to be severed during the pandemic relative to those that are less interconnected.

Third, we investigate whether banks' counterparty choices differ across counterparties that use derivatives to meet different objectives. Non-bank financial counterparties may be relatively more likely to employ derivatives for investment or speculative purposes, beyond hedging activities, compared to non-financial corporate counterparties. After accounting for other counterparty characteristics, we expect bank risk incentives to be pronounced for counterparties that are more likely to use derivatives for investment purposes, and so expect the main results to be stronger for non-bank financial counterparties. We find that the main risk-taking effects are concentrated when banks link with non-bank financial counterparties and insignificant for non-financial corporate counterparties.

Finally, we investigate how interconnections between banks through common counterparties are related to systemic risk. We do so by constructing measures of pairwise exposures between banks based on credit exposures to counterparties that they share for each quarter. We conduct tests on whether there is a significant relationship between the pairwise exposures and the excess returns co-movement between the two banks. We document a significant and positive association for the joint exposures, and show that the effects are significantly larger during periods of market stress. While we do not find a significantly larger effect during the Covid-19 pandemic, we do find that the point estimates are substantially larger.

This paper makes a contribution to the growing literature that investigates the relationship between bank interconnectedness and financial system stability. The central question in this literature, addressed mostly through theoretical models, is whether a more densely-connected system leads to more or less stability when hit with a shock that can trigger higher risks (see Glasserman and Young (2016) for a survey of the literature). Broadly speaking, there are two schools of thought: first, the “stability-through-connections” view where a more densely connected network supplies higher liquidity insurance against exogenous shocks (Allen and Gale (2000), Freixas et al. (2000), Leitner (2005)), and second the “fragility-through-connections" view (Gai et al. (2011), Acemoglu et al. (2015), and Donaldson and Piacentino (2017)). These papers, however, do not take into consideration a bank’s risk-taking behavior when it decides on establishing or keeping existing counterparties given the status of network connections. We add to the literature by being the first to empirically investigate the role of counterparty risk when a bank decides on establishing a new link or keeping an existing one and find that banks tend to take on (counterparty) risk the more connected is the counterparty.

This evidence adds a new channel through which connections can lead to fragility, not through those established by the theoretical literature so far but rather through the risk taking externality behavior of banks. Our evidence is consistent with some very recent theoretical developments that analyze endogenous network formations. Acemoglu et al. (2015) investigate lending and its impact on third parties through network externalities and find that banks do internalize counterparty risks through charging a higher interest rate but do not take into consideration the externalities that such risky lending have on the network participants. Closer to the spirit of our paper, Shu (2019) theoretically shows how risk-taking externalities within networks can develop. While we cannot empirically resolve the question whether connections lead to less or more fragility, we identify one ignored dimension of the network literature, i.e. the moral hazard arising from the network’s co-insurance, and which requires further investigation.

Our paper also makes a contribution to another literature that investigates the role of the financial system architecture as an amplification mechanism. The literature so far has looked at the banking system as a network of interlinked balance sheets where leverage plays a central role (Shin, 2008, 2009), and how asset commonalities across banks determines the likelihood of systemic crises (Allen et al., 2012). The theoretical literature and the empirical literature using interbank lending focus exclusively on direct linkages. Yet we know that banks are connected not only through direct links but also, subtly and perhaps more importantly, through indirect links. Our paper extends this literature by bringing in those indirect connections through common counterparties. Our evidence could pave the way toward a more comprehensive understanding, both at the theory and the empirical levels, of the endogenous network formation, its impact on bank-level outcomes and impact on systemic risk.

The rest of the paper is organized as follows. Section 2 describes the data sources and provides descriptive statistics and visualizations of the counterparty-level data. Section 3 motivates and outlines the empirical design. Section 4 presents the main results for the counterparty-level tests. Section 5 examines how the main results differ for non-bank financial and non-financial corporate counterparties. Section 6 describes the systemic risk tests, and presents the results. Section 7 concludes.

2. Data, Institutional Details, and Variable Construction

The paper uses data from confidential regulatory filings associated with the Capital Assessments and Stress Testing reports from 2013:Q3 to 2020:Q4. Specifically, we use data from Schedule L of FR Y-14Q, which contains detailed and confidential information on counterparties that spans 18 OTC derivative markets for which the bank has counterparty risk exposures through their trading operations.[5] The data are used to support supervisory stress testing and monitoring efforts. It spans counterparties for all uncleared derivatives and other forms of bilateral agreements in the trading book, including interest rate swaps, credit default swaps, foreign exchange, equity, commodities, and other material exposures.[6]

Bank holding companies that are required to report the schedule include large and complex banks, defined as those with total assets above $250 billion, average total nonbank assets above $75 billion, and have been designated as a U.S. global systemically important bank holding company. The schedule focuses specifically on counterparty credit risk, allowing bank supervisors to quantify such exposures, and provides information on net receivable positions, or agreements for which counterparties have liabilities. This is in contrast to credit risks that the bank may hold in the form of wholesale loans or securities holdings.

[5] For the purpose of the analysis, we specifically use the Schedule L.1.a data.
[6] For the banks in our sample, 90% of the gross credit exposure and 69% of the net credit exposure are un-cleared. Because the data only cover uncleared positions, central counterparties are not included.

As part of the reporting requirements, banks provide the identities and other information regarding their counterparties. Counterparties for each bank are ranked based on their exposure, specifically based on the Credit Valuation Adjustment (CVA), and the counterparties that comprise the top 95 percent of the bank's total CVA are included in the data. We only include banks that began reporting in 2013, and doing so accounts for the vast majority of the overall number of counterparties and overall exposures in the raw data. This provides us with confidence that our sample is representative of trading between systemically important banks and their counterparties. As of the 2019:Q4, the average number of counterparties reported per bank in the sample is 1,844, and the total notional amount for the reported counterparties is almost $100 trillion. To place these values in the correct context, it should be noted that the Bank of International Settlements estimated the total notional in the derivative markets globally to stand at $640 trillion as of mid-June 2019. This suggests that the banks in our sample are not only important for U.S. markets, but also account for a significant share in international markets.

We manually review the counterparty information to form a consistent set of identifiers allowing us to track the same counterparty across banks and over time.[7] With the bank and counterparty identities, we construct a quarterly panel of bank-counterparty network mappings. We are able to observe when new bank-counterparty links are formed and when existing links are destroyed. We can also detect changes in exposures between banks and counterparties. Most relevant to this study, this information allow us to precisely quantify interconnections between banks through common counterparties.

The data include the counterparty-level, asset-side credit valuation adjustment (CVA), which is calculated by each bank for every counterparty with which it is linked.[8] The data also report other forms of bank counterparty exposures, such as gross and net credit exposures. While gross and net credit exposures are common measures used in the literature, CVA is also used extensively by industry and regulators. The CVA is an adjustment applied to the market or fair value of derivatives positions to account for the counterparty's credit risk. Specifically, the counterparty's CVA takes into consideration not only the traditional measure of default probabilities but also the bank's expected losses arising from the exposure to a specific

[7] Specifically, we examine by hand the counterparties and match them across banks based on their name, internal counterparty identifiers, and legal entity identifiers when available.
[8] The CVA calculations are not to be conditioned on the survival of the bank.

counterparty. Perhaps for similar reasons, regulatory capital charges are based on CVA rather than other measures of exposures.[9]

2.2 Network Description

An important aspect of the data for our analysis is that it allows us to comprehensively map the financial network based on counterparty linkages of the most systemically important U.S. banks. Critically, the data enables us to study changes in the financial network. To motivate, we next describe the network based on the data and how network density has changed over the sample period.

Figure 1 displays a snapshot of bank counterparty network just prior to the Covid-19 pandemic (as of December 31, 2019). The nodes represent banks counterparties with at least one relationship with the sample banks. The size of each node corresponds with a logarithmic mapping of the total bank exposures, based on CVA, contributed by the counterparty. The color of each node corresponds with the number of banks linkages, where dark red shades correspond with a multiple bank linkages, and dark blue shares correspond with single-bank linkages.

The mapping resembles a core-periphery network structure, similar to what has been previously shown for other financial markets. The clusters connected to many nodes correspond with the reporting banks. Given that the underlying data span a large range of markets, the figure indicates that core-periphery network structures likely characterize trading in a broad set of markets. The figure also shows a large number of nodes that have multiple edges, i.e., counterparties with linkages to more than one bank. These counterparties represent indirect interconnections between banks, and is the focus of the analysis.

[Insert Figure 1]

Figure 2 displays how the network structure changed over calendar year 2020 compared to 2019. Such changes provide a visual idea of how the network changed as the Covid-19 pandemic caused market stress across different asset classes. The color of each node corresponds

[9] The CVA, along with counterparty default risk, is an important component of the Basel III counterparty credit risk framework. While counterparty default risk was already a part of Basel I and II, Basel III introduced a new capital charge based on CVA that was intended to capture potential mark-to-market losses due to counterparty credit deterioration.

to the number of bank linkages and whether the number of bank linkages have changed since December 31, 2019 for the counterparty. The light red nodes correspond with counterparties with multiple bank linkages where the number of bank counterparties have not changed since 2019, dark red nodes correspond with counterparties where the number of bank counterparties have increased since 2019, light blue nodes correspond with counterparties with single bank linkages where the number of bank counterparties have not changed since 2019, and dark blue nodes correspond with counterparties where the number of bank counterparties have decreased since 2019. The figure shows that, for a majority of the counterparties, the number of bank linkages did not change throughout the course of the pandemic. There are quite of few counterparties that experienced an increase or decrease in the number of bank linkages, though they do not cluster in a specific areas of the network and vary in node size.

[Insert Figure 2]

Figure 3 shows how the prevalence of counterparties with multiple bank connections evolve over the full sample period. The number of counterparty pairs (edges in the network), associated with counterparties with at least two (common), or one (unique) bank connection are displayed in the two area series. The share of overall bank exposures associated with counterparties with at least two bank linkages (i.e. indirect non-bank connections) and bank-to-bank linkages (i.e. direct bank connections) are displayed in the line series. The figure shows that the overall number of edges in the network declined from 2016 through 2018 before increasing again, most notably during the Covid-19 pandemic. The pattern is similar to the aggregate changes in the overall size of the derivatives markets. Interestingly, the number of connections associated with counterparties with multiple bank connections have been gradually increasing during this period, increasing by 18.2% up until the pandemic. This increase may have also corresponded with considerable churning of counterparties that transition in and out of this group that is masked by the aggregates. In contrast, the fraction of total exposures associated with multiple bank counterparties experienced a large increase from 2013 to 2017, and has oscillated around 50% thereafter. For comparison, the fraction of total exposures associated with bank-to-bank connections are small and have decreased over the sample period.

[Insert Figure 3]

2.3 Interconnectedness Measures

The first task to investigate our research question is the construction of various bank-counterparties interconnectedness measures. To that end, we use three measures of indirect bank interconnectedness. Rather than capturing interconnections for the aggregate network, these measures focus on local interconnections based on bank-counterparty-level linkages. The granularity of the data allows us to use interconnections at the bank-counterparty level which will allow for a more precise estimates of how counterparty risk affects banks' decisions. Our first two measures are based on the network's edge counts and edge size. The third measure incorporates richer information regarding the individual counterparty's connections to other banks.

The first interconnected measure, $CP\ Bank\ Link_{j,t}$ is defined as the natural log of one plus the total number of banks for which counterparty j has a relationship at quarter *t*. Higher values of $CP\ Bank\ Link_{j,t}$ imply a larger number of indirect connections to other banks introduced if a bank were to enter into an agreement with the specific counterparty.

The second interconnected measure, $Total\ CR\ Exposure_{j,t}$ is defined as the natural log of one plus the total net credit exposures across banks of counterparty j at quarter *t*. Higher values of $Total\ CR\ Exposure_{j,t}$ implies larger, network-wide bank exposures that would be generated if a bank were to enter into an agreement with the counterparty.

These two measures capture different aspects of counterparty interconnectedness. **Figure 4** provides a visual explanation for how the measures are constructed, and how differences in the measures can arise.

[Insert Figure 4]

The figure is based on an example considering three different banks and a large number of non-bank counterparties. The dotted lines are the edges that are associated with direct bank-to-bank connections while the solid lines are edges that denote bank connections to non-bank counterparties. The thickness of the lines corresponds with the size of the exposures between banks and counterparties, and range from thin, regular and thick for small, intermediate and large exposure size, respectively. In this example, $CR\ Bank\ Links_{j,t}$ is the number of edges connected to the bank nodes, so that counterparty j_1 receives a value of three; counterparties j_2 and j_3 receives a value of two each; and all other counterparties receive a value of one.

In contrast, $Total\ CR\ Exposure_{j,t}$ correspond with the edge sizes, i.e., the dollar exposure that each counterparty has rather than a count of links. Suppose thin, normal, and thick edges were associated with net credit exposure units of one, two and, three, respectively. In this case, counterparty j_2 has the largest value of six units, followed by four units for counterparty j_3, and two units for counterparty j_1. All the other counterparties have values ranging between one and three units. With respect to contagion risks, $Total\ CR\ Exposure_{j,t}$ may be more informative than $CR\ Bank\ Links_{j,t}$ as the propagation of shocks to a counterparty are more likely in the case of large exposures.

As the figure shows, both measures only capture common exposures based on information associated with adjacent nodes, as opposed to information related to the broader network. The extant literature argues that network fragility is also determined by higher order exposures. One important dimension is the similarity in overall exposures between banks connected to the same counterparty, as it relates directly to the transmission of shocks from one bank to other banks in the network through common counterparty linkages. While $Total\ CR\ Exposure_{j,t}$ and $CR\ Bank\ Links_{j,t}$ may also capture this to some extent, they do so narrowly through individual counterparty exposures. In our context, this means we need to measure the overlap in derivative exposures to the same counterparties between banks across the entire network. This is conceptually similar to other measures of portfolio similarity used in other contexts (Sias et al. (2016); Cai et al. (2018); Girardi et al. (2021)). For example, Cai et al. (2018) construct overlap measures that captures common borrower exposures across the loan portfolios of financial institutions. In the same spirit, we propose a measure that focuses on common counterparty exposures in bank derivative portfolios.

To this end, to capture broader network information related to common counterparty exposures, we construct a third measure, $Bank\ CP\ Overlap_{i,j,t}$, that measures the overlap between banks across all their counterparties, for bank i when connecting to counterparty j at quarter t. In other words, the measure captures the contribution of a particular counterparty to the similarity in the overall exposures between banks.

$$Bank\ CP\ Overlap_{i,j,t} = \sum_{m \neq i} \left(\underbrace{\frac{NetCE_{m,j,t}}{\sum_{m \neq i} NetCE_{m,j,t}}}_{\substack{\text{Counterparty } j \text{ exposure} \\ \text{weight for bank } m}} \underbrace{\sum_{\ell} \mathrm{I}(\ell \in \mathrm{C}_{m,t}) \times NetCEShare_{i,\ell,t}}_{\substack{\text{\% counterparty exposure for bank} \\ i \text{ that overlap with bank } m}} \right) \quad (1)$$

Define $\{\mathrm{C}_{m,t}\}$ as the complete set of counterparties associated with bank $m \neq i$ at quarter *t*; $NetCE_{m,j,t}$ as the net credit exposure associated with counterparty *j* for bank *m* at quarter *t*; and $NetCEShare_{i,\ell,t}$ as the fraction of bank *i*'s total net credit exposure that is associated with counterparty ℓ.[10] Equation (1) can be decomposed into two components. The first component is the weights based on the proportion of system-wide exposures to counterparty *j* across all banks m excluding bank i. The second component is the pairwise counterparty overlap between two banks, or the fraction of bank *i*'s total net credit exposure for counterparties also connected to bank m. Combined, the two components give us a measure that is the weighted-average of the fraction of overall counterparty overlap between bank i and other banks connected to counterparty *j*. Note that, unlike the first two measures, values of $Bank\ CP\ Overlap_{i,j,t}$ can differ across banks for the same counterparty *j* and this feature will help us use more granular fixed effects in our model specifications.

While all three measures capture different dimensions of interconnectedness, it is plausible that banks may not have the required information to compute these measures as data on bank-counterparty relationships are not publicly available. Recall that we are both interested in the establishing of new relationships and the maintaining of existing ones. We expect the measures to be closer to banks' own assessments for bank-counterparty pairs for which there is an existing relationship, as banks are more likely to have at least approximate these measures due to soft information that the bank gathers throughout the course of the relationship. Of the three measures, $Bank\ CP\ Overlap_{i,j,t}$ may be the most difficult to compute for banks, as it requires information on not only the counterparty but also all the other counterparties of connected banks. On a separate note, the data we use are directly observable to regulators and thus can be used by the latter when observing bank-level risk taking.

[10] The results are not sensitive to basing the measure on CVA rather than net credit exposure.

3. Research Design

A key challenge for the analysis is distinguishing decisions made by banks when establishing or maintaining relationships arising from the type of linkages they want to establish within the network, from other bank and counterparty characteristics that may also influence counterparty choice in the OTC market. The bank-counterparty linkage is the outcome of an assortative match between the two parties and, ideally, the identification strategy isolates the network decision from other bank-level or counterparty-level dimensions that may correlate with that decision. For example, balance sheet and regulatory constraints may limit the ability of banks to offer services or restrict exposures to some firms. Counterparty hedging and investment demand as well as counterparty quality can also affect counterparty choice. Outcomes in OTC markets may also depend on investors' search abilities, bargaining power, risk aversion, and speed with which counterparties interact (Duffie et al. 2007).

Our aim is to directly examine whether, and how, banks consider the network structure itself, or the degree of interconnectedness that is introduced once a link is establish, when choosing to form new or extend existing relationships. The granularity of our data allows us to make an important contribution on this front. In order to distinguish the effects of network factors on counterparty choice, we construct tests that exploit differences based on existing counterparty relationship and employ bank-year-quarter, counterparty-year-quarter, and bank-counterparty fixed effects that purge the effects of any form of time-varying bank and counterparty heterogeneity unrelated to the network structure itself. That is, because of the double interactive fixed effects, we can address the challenge of unobserved heterogeneity not only at the time-invariant level (e.g., if a bank has certain preferences that are unchanged) but also at the time-varying level as well (e.g., if a bank alters counterparty choice in response to changes in aggregate conditions). Importantly, the bank-counterparty fixed effects will absorb all time-invariant factors related to the assortative matching described above.

Banks may consider trade-offs between risk-sharing benefits and the risk of contagion exposures associated with counterparties with greater linkages to other banks. Linkages to these types of counterparties may promote risk-sharing due to diversification. However, these linkages represent common exposures to shocks to the counterparty, and so may increase contagion risks. A number of papers have examined network formation models that incorporate these forms of trade-offs (Elliott et al., 2014; Acemoglu et al., 2015; Glasserman and Young, 2015; Babus, 2016; Cabrales et al., 2017). For example, Babus (2016) examines a model where banks consider these trade-offs when choosing other banks through bilateral agreements. The model suggests that banks generally form networks that are resilient to contagion risks. Other studies yield more nuanced predictions. Cabrales et al. (2017) point out that bank stress testing often focuses on severe but limited sets of shocks. Their paper, as well as others, observes that the entire shock distribution is necessary to understand the trade-offs, and not doing so may yield incorrect conclusions.

Accounting for existing bank counterparty relationships is also important, as not doing so may understate the effects we wish to study. Banks do not have complete information on network structure, as complete information on new counterparties, i.e., counterparties of other banks and with which a bank is determining whether to establish a new relationship, is not typically available to banks. That is, while the regulatory data allows us an unfettered view into the financial network mapping and so precisely measure the interconnectedness measures, banks may not have the same information. This may lead to attenuation in our estimates as the data may not necessarily correspond with the bank's information set. The case of existing relationships is quite different. Banks may be able to produce such information over the course of the relationship for existing counterparties. In standard search models, firms may solicit bids from many dealers and so do not maintain finite network structures (Duffie, Garleanu, and Pedersen, 2005; Lagos and Rocheteau, 2007; Gavazza, 2016). However, relationships in OTC markets are generally sticky and most firms only enter agreements with one or a few dealers (Afonso et al. (2014), Du et al. (2019), Henderschott et al. (2020)), allowing banks to glean information through the counterparty's trading and non-trading activities. Studies examining bank lending relationships find similar patterns. In those studies, banks produce soft information through the course of the relationship, including information about other lenders, and is particularly beneficial when hard information is scarce (Liberti and Pedersen, 2018). As such, the effects of network structure on counterparty choice is likely to be stronger when dealers determine whether to maintain an existing relationship rather than establish a new one.

Our model specifications will draw on the existing theoretical models and applying it to the data from the Capital Assessment and Stress Testing reports.

3.1. Sample Construction and Baseline Model Specification

In our baseline models, we estimate the relationship between the three measures of interconnectedness on bank counterparty choice outcomes. One of our objectives is to investigate whether different bank behavior is observed when (a) establishing a new relationship with a new counterparty, and (b) maintaining an existing relationship, as we expect it to differ for reasons mentioned in the previous section.

To that end, we construct an augmented panel of existing bank-counterparty pairings as well as ones that do not currently exist. We do so because the data only provides information on existing relationships at each point in time. For each time period, we consider all possible bank-counterparty pairings given the set of counterparties with at least one bank in our sample. Specifically, at quarter *t*, for counterparty *j* that has an existing relationship with at least one of the sample banks, we reshape the dataset to include all possible pairings between counterparty *j* and the sample banks for whom a relationship does or does not exist. We only consider the creation and destruction of linkages from quarters *t* to *t+1* for this set of bank-counterparty pairings. Given the reporting criteria for the data, this approach will likely exclude counterparties that are extremely small.

We compare the effects of establishing versus maintaining a relationship by separately performing analysis on subsamples based on whether a relationship exists, as well as pooled estimators that explicitly test for differences. The specification controls for interactive fixed effects to account for time-varying bank and counterparty heterogeneity, other assortative matching factors by using bank-counterparty fixed effects, and control variables to account for various counterparty characteristics. The baseline regression model for bank *i* and counterparty *j* at quarter *t* is as follows:

$$Y_{i,j,t+1} = \beta_1 \times IC_{i,j,t} + \beta_2 \times Relationship_{i,j,t} + \beta_3 \times Relationship_{i,j,t} \times IC_{i,j,t} + \boldsymbol{\beta} \times \boldsymbol{X_{i,j,t}} + \boldsymbol{\gamma_{j\times t}} + \boldsymbol{\gamma_{i\times t}} + \boldsymbol{\gamma_{i\times j}} + \xi_{i,j,t+1} \quad (2)$$

For the dependent variables ($Y_{i,j,t+1}$), we consider three measures to assess the impact of the interconnectedness measures on the extensive and intensive margins. They include (a) $Link_{\mathrm{i,j,t+1}}$ is a dummy taking value one if bank *i* and counterparty *j* have a relationship at quarter *t+1,* and zero otherwise; (b) $\Delta GrossCE_{\mathrm{i,j,t+1}}$ is the change in the natural log of one plus the gross credit exposure for bank i to counterparty j between quarters t and $t+1$; (c) $\Delta NetCE_{\text{i,j,t+1}}$ is the change in the natural log of one plus the net credit exposure for bank i to counterparty j between quarters t and $t+1$; and (d) $\Delta CVA_{\text{i,j,t+1}}$ is the change in the natural log of one plus the CVA for bank i to counterparty j between quarters t and $t+1$. While the $Link_{\text{i,j,t+1}}$ dummy will establish the simple action of establishing/maintaining a relationship, irrespective of the size of the exposure involved in the relationship, i.e. the extensive margin of the relationship, the other dependent variables will capture the exposure's intensity, i.e. the intensive margin of the relationship. Finally, in addition to being a measure of exposure intensity, $\Delta CVA_{\text{i,j,t+1}}$ also takes into consideration the riskiness involved with the exposure.

The key explanatory variables ($IC_{i,j,t}$) are the three measures of interconnectedness discussed in Section 2. The uninteracted $IC_{i,j,t}$ terms are dropped from the model in specifications where the measure is only available on the counterparty-level due to collinearity, namely for *CP Bank Link,* and *Total CR Exposure*. $Relationship_{i,j,t}$ is a bank-level dummy variable to indicate whether a bank i was in an existing relationship with counterparty j at quarter t, and zero otherwise. The interaction term between $IC_{i,j,t}$ and $Relationship_{i,j,t}$ captures the differential effect of $IC_{i,j,t}$ on the outcomes variables between existing and non-existing relationships, and is the focus of the analysis.

We include control variables ($\boldsymbol{X_{i,j,t}}$) related to existing network properties and counterparty characteristics. These include the natural log of the counterparty's CVA for bank i at quarter t, the natural log of one plus the counterparty's net credit exposures for bank i at quarter t, and the default probability for counterparty j at quarter t. For non-existing relationships, the CVA and net credit exposure measures are set at zero. The counterparty default probability is defined as the average mapping between the firm's risk ratings to default probability densities based on the regulatory reports. The specification also includes bank-year-quarter ($\boldsymbol{\gamma_{i\times t}}$), counterparty-year-quarter ($\boldsymbol{\gamma_{j\times t}}$), and bank-counterparty ($\boldsymbol{\gamma_{i\times j}}$) fixed effects. In all the specifications, we calculate robust standard errors for the point estimates that are double clustered on the bank-year-quarter and counterparty-year-quarter levels.

3.2. Counterparty Risk

We next develop tests for endogenous risk-taking in the counterparty choice of each single bank within the network that it belongs to. Specifically, we examine the effects of interconnectedness on a bank's choice of material exposures and how it is conditioned by counterparty default risk.

We use the difference between material and non-material relationships, as defined by regulatory reporting requirements, to better investigate the risk-taking behavior in counterparty choice. Material exposures, or exposures associated with concentrated positions that are relatively large for a particular activity, are likely to be a source of vulnerability for contagion and counterparty risks. Regulators require banks to identify the material counterparties precisely to better identify such vulnerabilities. The data provide information about material exposures for specific markets starting in 2017. Specifically, the respondent banks are required to list the top ten counterparties based on counterparty CVA sensitivities for each market where the bank has an active participation. The CVA sensitivities relate to changes in CVA given some shock to the contract's underlying – e.g., a large decline in stock returns – for each instrument class – e.g., total return swaps. We use this information to decompose *Link* into material and non-material exposures. The decomposition allows us to assess whether the effects we found in the previous section plausibly have the potential to be destabilizing, as material positions are large by definition and may be more difficult to diversify. Unfortunately, we do not have analogous measures for the other outcome variables, and so the tests in section focus only on extensive margin.

Critically, we augment the baseline regression model to assess the role of counterparty risk in shaping the bank's decision when, and how, relationships are formed. Thus we ask whether banks tend to balance the creation of more indirect bank connections with connections to less risky counterparties (i.e., co-insurance) or to riskier counterparties (i.e., moral hazard). Answering this question helps us better address the "connected-fragility" dimension addressed by the literature. To do so, we use the counterparty probability of default (PD) to measure the riskiness of potential counterparties.

We use the following regression model to investigate the effect of counterparty risk on banks' counterparty choices:

$$Link_{i,k,t+1}^{Material} = \theta_1 \times IC_{i,j,t} + \theta_2 \times Relationship_{i,j,t} + \theta_3 \times Relationship_{i,j,t} \times IC_{i,j,t} + \theta_4 \times IC_{i,j,t} \times PD_{j,t} + \theta_5 \times Relationship_{i,j,t} \times PD_{j,t} + \theta_6 \times Relationship_{i,j,t} \times IC_{i,j,t} \times PD_{j,t} + \boldsymbol{\theta} \times \boldsymbol{X_{i,k,t}} + \boldsymbol{\gamma_{k\times t}} + \boldsymbol{\gamma_{i\times t}} + \varepsilon_{i,k,t+1} \quad (3)$$

The dependent variable, $Link_{i,k,t+1}^{Material}$, is a dummy that takes value one if counterparty k is considered by bank *i* as a material exposure at quarter *t+1*, and zero otherwise. For comparison, we also examine an analogous measure based on non-material exposures. In the tests, we focus on the triple interaction term coefficient, or θ_6. A positive sign would be consistent with the endogenous risk-taking channel. In words, it would suggest that the effect of the interconnectedness measures on material exposures is stronger for riskier counterparties. Given that risks associated with linkages to material counterparties are difficult to mitigate due to their size, they would be magnified when the counterparty is riskier.

In these specifications, we further differentiate the effects between the pre-pandemic and pandemic periods in order to better understand bank behavior during normal and stress periods. This allows us to evaluate the resilience of links that were created during normal periods when they are stressed. Such linkages are expected to remain resilient when the network is stressed under the co-insurance view, but deteriorate when formed due to moral hazard behavior.

3.3. Descriptive Statistics

Table 1 displays summary statistics of the variables used in the analysis on the augmented panel data. All variables are winsorized at the 1% and 99% sample percentiles to mitigate the influence of outliers.

[Insert Table 1]

Panel A displays the full sample, while Panel displays the subset of existing relationships. A vast majority of counterparty linkages are to a single bank, as is suggested in **Figure 4**. The sample mean of *CP Bank Link* is 1.302 banks of the full sample and 1.732 banks in the existing relationship subsample, as expected. The second row displays statistics on a dummy variable associated with counterparties with at least two banks. The table indicates that around 18.5% of counterparty connections are with at least two banks in the full sample, but doubles to 37.5%

when we consider the existing relationship subsample. The sample mean for *Total CR Exposure* is $758.2 million for the full sample, but $1,369.0 million for the existing relationship subsample. Both are significantly larger than their median, indicating substantial positive skewness. Natural log transformations are applied to one plus *Total CR Exposure*, as with *CP Bank Link*, to account for this in the analysis. When compared to *Net CE*, *Total CR Exposure* is substantially larger based on the sample means, but less so when using medians. Again, this is to some extent due to the presence of large counterparty exposures across banks. In contrast to the other two interconnectedness measures, the sample mean for *Bank CP Overlap* is larger in the full sample, or 0.162 for the full sample and 0.085 for the existing relationship subsample. Finally, the average exposures for the existing relationship subsample is $50.2, $21.0 and $1.0 million based on gross credit exposure, net credit exposures, and CVA, respectively.

The correlations between the three interconnectedness measures are not uniformly high. As would be expected, *CP Bank Link* and *Total CR Exposure* have a large and positive correlations, or 46.4%. However, *Bank CP Overlap* have low correlations with the other two measures: 4.2% with *CP Bank Link* and 1.2% with *Total CR Exposure*. This is due in part to the measure's scaling.

4. Bank Counterparty Choice Results

4.1 Baseline Results

The estimates from the baseline regression models show a strong, positive association between the bank interconnectedness measures with counterparty choice over the following quarter. We also find that the bank interconnectedness measures are positively related to growth in counterparty exposures. We conclude by discussing alternative explanations and presenting robustness checks.

Table 2 displays the results for the tests on the extensive margin. The dependent variable in the regression models is *Link*, and the three interconnectedness measure specifications (denoted in the table as *IC*): *CP Bank Link* (Panels A), *Total CR Exposure* (Panel B), and *Bank CP Overlap* (Panel C). Columns (1) through (3) do not include any of the control variables or fixed effects. Columns (4) through (8) iteratively includes the control variables and the fixed effects terms.

[Insert Table 2]

Across all the specifications, the interconnectedness measures have a positive and statistically significant association with bank counterparty choice. We begin by describing the results using *CP Bank Link* in Panel A. Columns (1) and (2) are estimated on subsamples of the data based on whether the bank does not have an existing relationship – i.e., the creation of new links – and has an existing relationship – i.e., maintaining existing linkages – with the counterparty, respectively. The *IC* coefficient in the non-existing relationship subsample (estimate = 0.041, *t*-value = 9.74) is much smaller in magnitude than the coefficient in the existing relationship subsample (estimate = 0.126, *t*-value = 13.21). For the pooled specification in Column (3), the magnitudes are comparable, where both the uninteracted and interacted *IC* coefficients are both positive and statistically significant at the 1% level.

With the inclusion of the control variables, the *IC* interaction term coefficient attenuates but remains significant. The inclusion of bank-year-quarter and counterparty-year quarter fixed effects does not affect the estimates meaningfully, suggesting that other bank and counterparty factors not captured by the control variables do not influence the results. Finally, the results remain significant after the inclusion of the bank-counterparty fixed effects in Column (8), though the *IC* interaction term coefficient increases almost three-fold. The specification in Column (8) focuses on intra-pair variation, and mitigates the influence of pairs where a counterparty always has or does not have a relationship with a bank over the entire sample period. The results suggest that assortative matching factors not captured by the control variables and other fixed effects are understating the effects. Finally, the effects are also economically significant. The marginal effect of adding an additional bank linkage from the mean translates to a 7.29 percentage point increase in *Link*, which is meaningful compared to the sample mean of 0.162.

The results are similar when using *Total CR Exposure* (Panel B) and *Bank CP Overlap* (Panel C). Across all the specifications, the effect of interconnectedness is much larger for existing relationships, and have a positive association with bank counterparty choice. A one standard deviation increase from the sample mean for *Total CR Exposure* (*Bank CP Overlap*) translates to an increase in *Link* of 8.70 (2.36) percentage points. As with the results for *CP Bank Link*, the inclusion of fixed effects that account for time-varying bank and counterparty heterogeneity do not influence the estimates after including the control variables, alleviating omitted variable bias concerns. Likewise, inclusion of the bank-counterparty fixed effects leads to larger point estimates, albeit less so for the *Total CR Exposure* specifications. The consistency and significance of the results across the three different interconnectedness measures strongly suggest a meaningful effect on the extensive margin.

We next turn our attention to the tests on the extensive margin. **Table 3** presents the results when using *ΔGrossCE* (Columns (1) through (3)), *ΔNetCE* (Columns (4) through (6)), and *ΔCVA* (Columns (7) through (9)) as the dependent variables. Columns (1), (4), and (7) use *CP Bank Link* for the interconnectedness measure. Columns (2), (5), and (8) use *CR Total Exposure* for the interconnectedness measure. Columns (3), (6), and (9) use *Bank CP Overlap* for the interconnectedness measure. All the models use the full specification used in Column (8) of **Table 2**.

[Insert Table 3]

Across all the specifications, the *IC* interaction term coefficient is positive and statistically significant. The results show that existing bank interconnections is associated with increasing bank exposures, and the significance of the differential effects of counterparties with existing versus non-existing relationships indicate that the effects are not driven by new linkages. As with the extensive margin tests, the economic effects are large. For example, the models imply that an additional bank linkage relative to the sample mean increases exposures by 0.154 for *ΔGrossCE*, 0.180 for *ΔNetCE*, and 0.051 for *ΔCVA,* which are sizable compared to the sample standard deviation of the exposure measures.

The results indicate that the interconnectedness measures have a both statistically and economically significant predictive effect on the formation of new linkages and retention of existing ones over the following quarter, as well as to growth in exposures. These exposures represent synthetic liabilities of the counterparties, i.e., counterparty leverage through their derivative positions, and the results suggest a link between interconnectedness and higher counterparty leverage.

We conclude by discussing robustness checks to address other potential explanations for the results not already accounted for by the baseline model specification. First, given that *Total*

CR Exposure only captures net exposures, there may be concerns that the results will differ when using other forms of exposures. To address this concern, we reconstruct *Total CR Exposure* based on total gross credit exposures or total gross credit valuations rather than total net credit exposures. We find qualitatively similar results when using these alternative measures (**Table A.1**). Second, both *CP Bank Link* and *Total CR Exposure* are calculated inclusive of information related to a bank *i*'s existing relationship and exposure with counterparty *j*.

Second, there may be concerns that so-called reflection problems could influence the results. These and other issues that are common in peer effect research in other contexts are analogous to the assertive matching issues that the models are designed to mitigate. The potential omitted variable biases that could be related to these issues should be correlated with counterparty and bank characteristics, which are addressed by the inclusion of counterparty-year-quarter and bank-counterparty fixed effects. An alternative approach common to that literature that partially addresses the issue is to employ leave-out mean versions of the interconnectedness measures, namely for *CP Bank Link* and *Total CP Exposure*. The approach is not applicable to *Bank CP Overlap* as it *already* excludes bank *i* from the calculations. In untabulated results, we find that the main results are not sensitive to this alternative specification.

Third, we show in untabulated results that the estimates from the exposure tests are not sensitive to alternative specifications of the exposure variables that focus on non-linearity in the changes. Namely, we show similar results when using dummy variables associated with large increases and decreases in exposures.

4.2. Material Exposures

We next examine material and non-material exposure prior to the pandemic. That is, we estimate a version of Equation (3) that omits the *PD* terms. The results are displayed in **Table 4**. Odd-numbered models present the results for *Link* based on material exposures, while the even-numbered models are based on non-material exposures. The results are displayed based on which *IC* specification is used: *CP Bank Link* (Columns (1) and (2)), *Total CR Exposure* (Columns (3) and (4)), and *Bank CP Overlap* (Columns (5) and (6)). Given that the material counterparty exposure data is only available for a much more limited sample period, we do not include bank-counterparty fixed effects in these specifications, as doing so would dramatically decrease the power of the tests. All specifications in the table include the control variables, bank-year-quarter fixed effects, and counterparty-year-quarter fixed effects.

[Insert Table 4]

The estimates show that the *IC* interaction term coefficients across the *IC* specifications are all positive and significant for material exposure linkages. However, the results are mixed though mostly negative for the non-material exposures. For example, for the *CP Bank Link* specifications, the *IC* interaction term coefficient in Column (1) is positive and statistically significant at the 1% level, or 0.061 (*t*-value = 5.22). However, in Column (2), the *IC* interaction term coefficient is negative and statistically significant at the 1% level, or -0.059 (*t*-value = -3.54). These results suggest that the baseline regressions models are likely to be driven by material exposures. They are also consistent with the idea that these connections are likely to be a source of fragility.

4.3. Counterparty Risk

Before proceeding to the results for full model, we start by examining a simpler version of the main specifications using sample splits to facilitate interpretability for the effects of counterparty risk. Namely, we examine how the effects of bank interconnectedness are conditioned by counterparty risk in each of the non-existing and existing counterparty relationship subsamples without the control variables and the fixed effects. **Table 5** presents the results of these tests prior to the pandemic. Panels A, B, and C display the results using *CP Bank Link, Total CR Exposure,* and *Bank CP Overlap* for the *IC* specification, respectively.

[Insert Table 5]

Across all the specifications, the interaction term has a positive and statistically significant effect on material exposure linkages based on the existing relationship subsample. The coefficients are also much larger in absolute magnitude than those for the material exposure models based on the non-existing relationship subsample. Across these specifications, the uninteracted *IC* coefficient is positive and statistically significant for both subsamples, though again are larger using the existing relationship subsample. The *PD* coefficients are insignificant in half of the specifications, though interestingly are positive and statistically significant in the others. These results indicate that at least some of the explanatory power of bank interconnectedness is due to riskier counterparties. In contrast, the interaction term has a negative effect on non-material exposures based on the existing relationship subsample, and is statistically significant for two of the three *IC* specifications. The coefficients are similarly larger in absolute magnitude than those for non-material exposures based on the non-existing relationship subsample. The patterns shown here are consistent with the results from the full model, which is presented next.

Table 6 presents the full model for the pre-pandemic period. The *IC* specifications used for Columns (1) and (2) are *CP Bank Link*, Columns (3) and (4) are *Total CR Exposure*, and Columns (5) and (6) are *Bank CP Overlap*. The odd-numbered models present the results for material exposures, while the even-numbered ones present those for non-material exposures.

[Insert Table 6]

We focus on the triple interaction term between *IC*, *Relationship*, and *PD*. Across the specifications, the coefficient on the triple interaction term is positive and statistically significant for material exposures. In other words, the effect we document in Table 4 of interconnectedness on the choice of material counterparties increases in counterparty risk. We find effects in the opposite direction for non-material positions. The triple interaction term coefficient is negative and statistically significant for all the non-material exposure models. That is, bank avoid riskier counterparties that with higher interconnections for their non-material exposures. The results on the interaction term between *IC* and *Relationship* is similar to those of Table 4 across the specifications for material exposures, though are stronger once accounting for counterparty risk. Similarly, effect of the interaction term between *Relationship* and *PD* has a stronger effects here for material exposures compared to Table 4, and the coefficients are positive and statistically significant.

4.4. Counterparty Choice During Stress Periods

We next repeat the analyses in Tables 4 and 6 but include the pandemic period. To differentiate the effects during the pandemic, we use a dummy taking value one if the sample period is associated with 2020:Q1 and thereafter, and zero otherwise. This variable, referred to as *Pandemic* in the tables, are interacted with all the terms in Equation (3).

Table 7 presents the results without the *PD* terms. The table is formatted similarly to Table 4. In all the specifications, the interaction term between *IC*, *Relationship*, and Pandemic are negative for material exposures, and are statistically significant in two of the three specifications. This indicates that the effects documented in Table 4 at least attenuates during the crisis. The sum of the *IC* × *Relationship* and *IC* × *Relationship* × *Pandemic* interaction term coefficients remain positive for the *CP Bank Link* and *Total CR Exposure* specifications, and close to zero for the *Bank CP Overlap* specification. The coefficient for the interaction term *Relationship* × *Pandemic* is negative and statistically significant in these specifications, suggesting an unconditional, negative effect on the retention of existing relationships during this period. These coefficients are at least comparable but mostly larger to the *Relationship* coefficient, suggesting that banks were no more likely to retain to keep existing material exposures than create new ones with different counterparties during the pandemic. These results stand in contrast to the non-material exposure results. The triple interaction term coefficient is statistically insignificant for all the specifications. Moreover, the *Relationship* × *Pandemic* interaction term coefficient is positive and statistically significant.

[Insert Table 7]

Table 8 presents the results from the full model with the *Pandemic* terms. The coefficient for the interaction term *IC* × *Relationship* × *PD* × *Pandemic* is negative and statistically significant for all the material exposure specifications. This is consistent with risk mitigation efforts likely undertaken by banks during this period. The absolute magnitudes of the coefficients are comparable to the pre-pandemic effects associated with the interaction term *IC* × *Relationship* × *PD*, such that the sum of the two is close to zero. The results also indicate that the pandemic has a strong negative effect on the retention of existing material exposures, though moreso for riskier counterparties. Overall, these results suggest that banks built up material exposures to riskier counterparties prior to the pandemic, though quickly reduced them during the pandemic.

[Insert Table 8]

For non-material exposures, the quadruple interaction term is mostly insignificant. Interestingly, the interaction term *Relationship* × *PD* × *Pandemic* has a positive coefficient across the specifications and are statistically significant. This suggests that banks were not only more likely to retain these counterparties, but the effect was stronger for riskier counterparties during the pandemic irrespective of their interconnectedness.

5. Non-bank Financial and Non-financial Corporate Counterparties

Different types of counterparties make use of derivatives for different reasons and we examine to what extent this dimension of each counterparty may influence banks' choices. We can classify counterparties in two broad groups: non-bank financial institutions and non-financial corporations.[11] Non-bank financial institutions are more likely to use derivatives for investment or speculation purposes, while non-financial corporations are relatively less likely to use them for speculation purposes. After accounting for other counterparty characteristics, such as counterparty credit risk and other factors relevant for the coinsurance channel, we should not expect any differences in the results unless if bank risk incentives across the two counterparty groups.

5.1. Composition Trends

Compositional breakdowns between bank, non-bank financial and non-financial corporate counterparties in OTC derivative markets has dramatically changed since the financial crisis. Publicly available data indicate that the share of financial firms in aggregate bank exposures has decreased while the share of non-financial corporations has increased, as shown in **Figure 6**, which displays the share of OTC derivative net credit exposures for non-bank financial

[11] For the analysis, we do not use other industry groupings, such as banks and sovereigns, and counterparties for which industry classifiers are missing. These cases account for a much smaller fraction of the sample.

and non-financial corporate firms from June 30, 2009 to September 30, 2020.[12,13] Though not shown, aggregate net bank exposures before the pandemic exhibits similar patterns. Overall, the share of bank exposures to financial firms has declined by 43.5% while the share to non-financial firms has declined by 0.7%.

[Insert Figure 6]

There are a number of factors that can explain declining bank exposures during this period. Some are related to the expansion of central clearing in certain OTC derivative markets. Figure 6 also displays the proportion of notional amount of OTC derivative contracts that are cleared through a central counterparty.[14] The data is only available from December 31, 2012. The data indicates that 53% of bank OTC derivative contracts are cleared as of September 2020, one-quarter larger than the clearing rate in December 2012, or 43%. Even with this increase, a substantial proportion of bank counterparty exposures are uncleared. This is in part due to the fact that clearing is still not as prevalent or feasible for certain types of derivative instruments.

What is unclear from Figure 6 is to what extent banks, non-bank financial, and non-financial corporate counterparties account for large exposures, and public regulatory filings do not provide information in this regard. However, there is one data point that comes from documents released by the Financial Crisis Inquiry Commission. **Figure 7** displays the information on Goldman Sachs' top OTC derivative counterparties by instrument class based on notional exposures as of June 2008. Given that the information is based on notional exposures, it is not surprising that interest rate products account for the lion's share of overall exposures. However, even when examining top counterparties within each instrument class, the largest exposures are concentrated in bank or other financial counterparties. It is worth emphasizing, however, that the information is from prior to the market and regulatory changes that took place in the post-crisis period, and is only based on one, albeit important, example. Nonetheless, it is still useful for highlighting differences in the composition of the counterparty groupings.

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[12] The data are from Schedule HC-L of FR Y-9C.

[13] Specifically, the data series shown is the net current credit exposures, or the fair value of the derivative contract when it is positive. These figures include derivative contracts covered and not covered by risk-based capital standards.

[14] The clearing data are from FR Y-15.

[Insert Figure 7]

We next turn to the confidential Y-14 data to focus on counterparty composition related to uncleared bank exposures.[15] In these figures, in addition to the number of bank linkages, we measure exposures based on CVA. **Figure 8** displays shares based on the number of bank linkages (**Panel A**) and exposures (**Panel B**) for banks, non-bank financial institutions, and non-financial corporates from June 30, 2013 through December 31, 2020.

[Insert Figure 8]

Panel A shows that the majority of bank linkages is accounted for by non-financial corporations for every quarter in the sample period. The share of bank linkages associated with non-bank financial is on average higher than that of banks, with the share declining for banks over the sample period. **Panel B** displays the estimates related to exposures. During the pre-pandemic period, the share of exposures steadily increased for both non-bank financials and non-financial corporates through 2018. After that point, the share continued to increase for non-financial corporates but began to wane somewhat for non-financial counterparties. The share of bank exposures consistently declined throughout the same period.

One explanation for the rapidly increasing share of non-financial corporate counterparties during this period is the decline in bank exposures to other counterparties not listed in the figure, which include sovereigns. The migration towards central clearing for these counterparties, particularly in interest rate swap contracts, contributed to aggregate declines in bank exposures, and so the share of exposures accounted for by other counterparties. Just prior to the pandemic, non-financial corporate counterparties accounted for 50% of the aggregate exposures, compared to 20% for non-bank financial and 9% for other bank counterparties. During the pandemic, the share dramatically increased for non-financial corporates, and has remained at its highest levels over the entire sample period. Bank exposures to non-financial corporate counterparties increased by 21.7% from December 2019 to December 2020. The share for non-bank financials

[15] We also examine the composition of domestic versus foreign counterparties. We find that the plurality of exposures is to U.S. domiciled firms. However, the data does include large, concentrated exposures to foreign firms as well, possibly through foreign subsidiaries.

continued its decline during the pandemic, even though exposures to these counterparties increased by 9.7%.

5.2. Summary Statistics

Non-bank financial and non-financial corporate counterparties have several notable differences in their network characteristics. **Table 9** presents summary statistics by subsamples for the variables used in the analysis. The last column displays the differences in the sample means.

[Insert Table 9]

A slightly smaller fraction of non-bank financials are material exposures in the sample, though a similar proportion of counterparties have existing relationships with non-bank financials as non-financial corporates. In terms of the number of bank linkages, non-bank financial have a greater number of bank linkages (1.32), on average, compared to non-financial corporate counterparties (1.24), and the difference is statistically significant at the 1% level. Additionally, a larger proportion of non-bank financials have at least two bank linkages (18.9% versus 15.7%). However, non-financial corporates are associated with higher values for *TotalCRExposure* and *Bank CP Overlap* than non-bank financials, on average. In other words, while the sample differences are statistically significant, the direction of the differences in sample means between the subsamples vary depending on the interconnectedness measure. Non-bank financial have greater gross credit exposures, but lower net credit exposures, attributable in part to differences in purposes non-bank financials may have for their derivative positions. While the differences in CVA are statistically significant, they are relatively small. Finally, changes in exposures are on average more negative for non-bank financials, though the differences are also relatively small.

5.3. Non-bank Financial versus Non-financial Corporate Counterparty Choice

We next examine how the results from Section 4 differ for the two counterparty groupings based on sample splits. **Table 10** displays the results. The table organization is based on the different specifications for the three IC measures: *CP Bank Link* (Panels A), *Total CR Exposure* (Panel B), and *Bank CP Overlap* (Panel C). Columns (1) and (2) display the results for non-bank financials while Columns (3) and (4) display the results for non-financial corporates. Models (1) and (3) are associated with the material exposure specifications, while Columns (2) and (4) are for the non-material exposure specifications. The key explanatory variables, control variables and fixed effects are identical to those used in Table 8.

[Insert Table 10]

For the *CP Bank Link* specifications in Panel A, we find that most of the effects documented in Table 8 are concentrated in non-bank financials. Across the material and non-material counterparty specifications, the quadruple interaction term is negative and significant for only material exposures of non-bank financial counterparties. Prior to the pandemic, the interaction between counterparty risk and interconnectedness is positive for these counterparties, though is statistically insignificant in the other specifications, including for material exposures of non-financial corporate counterparties. The coefficient is of similar size in absolute magnitude to that of the *IC* × *Relationship* × *PD* coefficient, and the sum of the two coefficients are insignificant from zero. Likewise, the *IC* × *Relationship* × *PD* coefficient for non-material exposures in the non-bank financial counterparty subsample is negative and statistically significant. In contrast, the interaction term coefficients are statistically insignificant in the non-material counterparty subsample for both material and non-material exposures.

The results differ somewhat when using *Total CR Exposure* though consistent when using *Bank CP Overlap*. Panel B presents the results for *Total CR Exposure*. In the pre-pandemic period, the *IC* × *Relationship* × *PD* coefficient is positive and statistically significant of material exposures in both subsamples. The quadruple interaction term is statistically insignificant in those two models. Panel C presents the results for *Bank CP Overlap*. Similar to the results for the *CP Bank Link* specification, the quadruple interaction term coefficient is negative and statistically significant for material exposures in the non-bank financial counterparty subsample. The *IC* × *Relationship* × *PD* coefficient is also positive and statistically significant in the same specification. That is, irrespective of the *IC* specification, the effects for the pre-pandemic period are significant for non-bank financials, though the pandemic periods results are sensitive to the *IC* specification. In contrast, the effects on material exposures for the non-financial corporate subsample are mostly insignificant and the estimates generally smaller in absolute magnitude compared to those for non-bank financials.

Given that the counterparty grouping tests only provide information about the extensive margin related to material exposures, we re-estimate the baseline specifications for each subsample. **Table A.2** presents the results for the non-bank financial subsample. As with the results from the baseline specifications, the IC interaction term coefficients are positive and statistically significant. **Table A.3** presents the results for the non-financial corporate subsample. Again, the results are positive and statistically significant across all the specifications. Comparing the results, there are instances where the coefficients are larger in one subsample versus the other. However, these tests do not distinguish between material versus non-material exposures, and the patterns are sensitive to which *IC* specification is used.

6. Bank Interconnectedness and Systemic Risk

In this section, we investigate to what extent this behavior propagates systemic effects in the financial system. In order to do so, we construct tests that exploit the counterparty-level data to construct measures of bilateral exposures between banks due to common counterparties, and assess to what extent it correlates with systemic risk. To conclude, we discuss and provide evidence for the plausibility of our approach.

We address two key challenges that are common in the literature in order to analyze the effect of interconnectedness on systemic risks. First, direct measures of interconnectedness are difficult to obtain and are often derived indirectly. We address this issue by using the counterparty-level data to construct bilateral measures of OTC derivative market interconnections on the bank pair-level. Second, bank interconnections may be endogenous to prevailing market conditions and other fundamental factors. Our empirical strategy utilizes granular fixed effects that purge variation associated with these common factors allowing us to precisely identify the effects of interconnectedness. Specifically, we include two-way fixed effects that include bank-year-quarter fixed effects for banks i_1 and i_2 associated with each bank pair. In other words, the tests focus on differing degrees of interconnectedness for bank i_1 across other bank i_2 within each quarter.

We derive pairwise measures of systemic risk and examine to what extent the bilateral exposures relate to them. Specifically, we examine how pair-wise bank interconnections affect the excess returns co-movement between each bank pair. Intuitively, excess returns co-movement between two banks should reflect their joint exposures independent of systematic risks. Excess returns co-movement, or ρ^{IdRet}, is calculated for each quarter as the correlation between the idiosyncratic daily returns between banks for each bank pair. Idiosyncratic returns are calculated as the residual from the three-factor model from Fama and French (1994) augmented with the Carhart (1997) factor, estimated separately for each quarter. This approach is similar in spirit to the CoVaR approach from Adrian and Brunnemeier (2011), though with a narrower focus on potentially systemic effects between bank pairs. Unlike the CoVaR approach, excess returns co-movement may not necessarily correspond with non-linear tail dependence, and it is difficult to adapt their methodology for our purposes. To help address this shortcoming, we also examine excess volatility co-movement, which may better corresponds with tail dependence. We define excess volatility co-movement, or $\rho^{|IdRet|}$, as the correlation between the absolute value of the idiosyncratic daily returns between banks for a given pair. Significant associations between the interconnectedness and systemic risk measures would strongly suggest that the fragility implied by the counterparty choice results documented in the previous section contributes to systemic risks.

We begin by constructing a panel dataset of all possible bank pairs, where bank $i_1 \neq i_2$, for each year-quarter in the sample. For each bank pair, we calculate the fraction of bank i_1's total exposures, specifically CVA, that are associated with counterparties that are also connected to bank i_2. We refer to this bank interconnectedness measure as *%CommonPairExposure*. Given the results in Table 10, we also assess whether the effects of common counterparty exposures differ between non-bank financial and non-financial corporate counterparties. To do so, we decompose *%CommonPairExposure* based on the counterparty groupings from the previous section: *%CommonPairExposure*$^{Non\text{-}Bank\ Financial}$ and *%CommonPairExposure*$^{Non\text{-}Financial\ Corporate}$ captures common counterparty exposures to non-bank financials and non-financial corporates, respectively. We consider the effects of all three interconnectedness measures in each of the tests. The standard errors used in these tests are triple-clustered on the bank i_1-year-quarter, bank i_2-year-quarter, and the bank pair group levels.

Table 11 displays the results for excess returns comovement tests. Column (1) presents the univariate regression model results. The *%CommonPairExposure* coefficient is positive and is statistically significant at the 1% level. Column (2) adds date fixed effects to the specification, and the *%CommonPairExposure* coefficient remains similar and statistically significant. Column (3) includes the time-varying bank fixed effects. The coefficient attenuates by one-third though remains statistically significant at the 1% level. Columns (4) and (5) display the results when using the *%CommonPairExposure* measures based on counterparty groupings. For both forms, the coefficients are positive and statistically significant, though is slightly larger for *%CommonPairExposure*$^{Non\text{-}Bank\ Financial}$. Column (6) includes both versions in the same model, and the coefficients remain quite similar to the estimates in Columns (4) and (5).

[Insert Table 11]

Table 12 presents the results for the excess volatility tests. The table is formatted similarly to Table 11. The *%CommonPairExposure* coefficients are positive and statistically significant, even with the inclusion of the fixed effects. For the counterparty grouping versions of *%CommonPairExposure*, the results are also similar. The coefficient associated with non-bank financials are also somewhat larger in magnitude. Overall, these results demonstrate a strong association between the bank interconnectedness measures related to common counterparty exposures and the systemic risk measures.

[Insert Table 12]

We next consider the effects of these interconnections during market stress events. To identify such events, we use the quarterly average of the end-of-day daily VIX. **Table 13** presents the results. Panels A and B display the results for excess returns and volatility comovement, respectively. Column (1) of Panel A displays the results for *%CommonPairExposure* and its interaction with the VIX. While the interaction term coefficient is positive, it is not statistically significant at the 10% level. Columns (2) and (3) display the results for the counterparty grouping versions of *%CommonPairExposure*. The interaction term in Column (2) is positive and statistically significant while the same in Column (3) is statistically insignificant. In all three specifications, the uninteracted *%CommonPairExposure* coefficient is positive and statistically significant. Finally, Column (4) includes both sets of interaction terms for the counterparty grouping measures, and yields consistent results. The results in Panel B are qualitatively similar. Overall, the tests indicate that the effects of bank interconnections are magnified during market stress events for non-bank financial counterparties, but not for non-financial corporate or other counterparties.

[Insert Table 13]

Finally, we repeat the analysis for the pandemic period. *Pandemic* is a dummy taking value one if quarter *t* takes place from 2020:Q1, and is zero otherwise. **Table 14** presents the results, and is formatted similar to Table 13. Across all the specifications, the *Pandemic* interaction terms are statistically insignificant in almost all the specifications, including most that focus on non-bank financials. However, the size of the coefficients are generally large, and is almost double in the non-bank financial specifications. These results suggest that the effects from Table 13 are not simply driven by the pandemic period. In untabulated results, we repeat the tests excluding the pandemic period, and find that the results remain significant.

[Insert Table 14]

Finally, we consider a potential channel through which the effect we document are likely to manifest. The results are likely to be related to bank trading operation outcomes, given the measures are based on bank OTC market activities. Additionally, one important identifying assumption underlying these tests is that market participants are able to either directly or indirectly infer bilateral counterparty exposures. While it is quite implausible that a direct inference is made, it is possible that market participants may infer the linkages indirectly. In particular, while individual bank counterparty data may be unavailable, market participants may be able to observe trading desk outcomes which may be correlated with bank interconnectedness.

To address these issues, we examine the relationship between the interconnectedness measure and total trading desk volume, total trading desk revenues, and the frequency of loss days incurred by bank trading operations. In these tests, we aggregate the counterparty-level data to the bank-level, such that the pair-level data is ignored. Specifically, *%CommonExposure* is the fraction of bank *i*'s total CVA that is associated with counterparties that are common to any of the other banks in the sample. In this regard, these tests are more susceptible to omitted variable biases that are accounted for in the bank pair tests. To alleviate concerns, we include control variables – the natural log of the ratio of total gross CVA-to-total number of counterparties, the natural log of the total number of counterparties, and the natural log of the trading assets – as well as date fixed effects. We only focus on the pre-pandemic period in these tests given that data on daily trading profits and losses for some of the sample banks is unavailable during the pandemic period. **Table A.4** presents the results. Across all the specifications, the *%CommonExposure* is positive and statistically significant, suggesting that bank interconnections are generally more profitable, but they are also associated with greater frequency of daily losses.

7. Conclusion

This paper is, to our knowledge, the first to empirically investigate the endogenous risk-taking behavior of banks arising from the moral hazard of interacting within a network. We provide direct empirical evidence on how banks choose counterparties and to what extent network structure plays in that decision. Namely, we show that banks prefer to establish and maintain relationships with non-bank counterparties that have a larger set of connections with other banks, leading to a more densely connected network. These effects are isolated in riskier counterparties that represent material exposures to the bank. We demonstrate that these exposures can manifest systemic effects, particularly during stress periods.

A more densely connected network provides the benefit of co-insurance in the case of a shock but also the cost that banks will have the incentive to take on greater risk. In this paper we ask whether banks tend to balance over-connecting with limiting the moral hazard behavior by connecting with less risky counterparties. We find that, in the case of material counterparties, banks tend to connect, or keep their relationship, with riskier counterparties. In so far as material counterparties are more consequential from a regulatory and economic standpoint, our findings suggest that banks maintain exposures to counterparties that are more likely to increase contagion risks while managing exposures to those that are less likely to represent significant risks. Our empirical results are consistent with Acemoglu et al. (2015) who show that banks fail to internalize the negative externalities, in our case, the counterparty's risk profile, on the other banks in the network.

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Figure 1
Bank Counterparty Linkages as of 2019

The figure displays a graphical illustration of bank linkages to counterparties as of December 31, 2019. The nodes represent firms or institutions that have at least one link with banks in the sample. The size of each node corresponds to a mapping of the total gross credit valuation adjustment contributed to all banks in the sample by the counterparty. The color of each node corresponds to the number of banks linkages, where the dark red nodes correspond with multiple bank linkages and dark blue nodes correspond with single bank linkages.

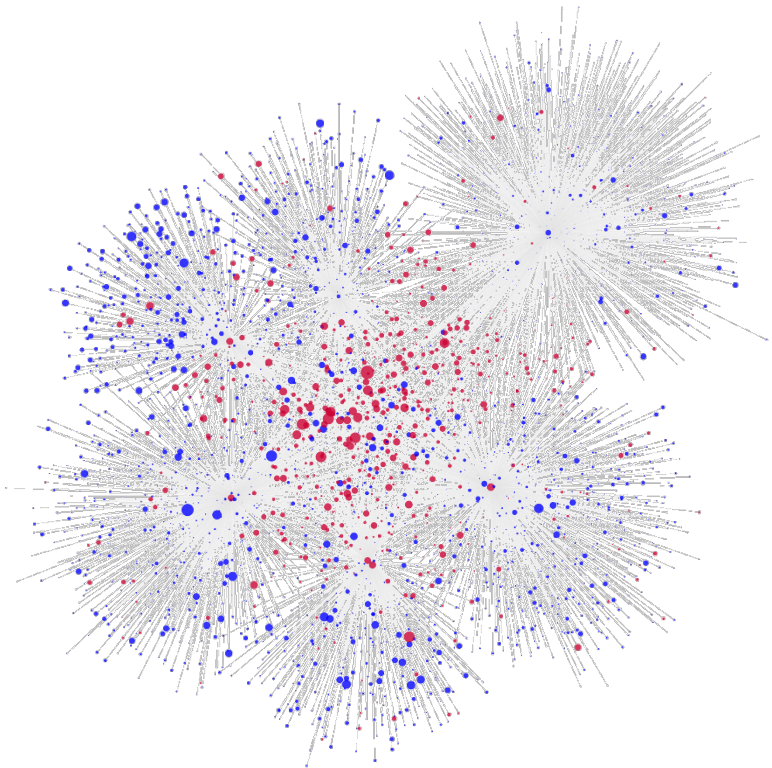


Figure 2
Changes in Bank Counterparty Linkages over 2020

The figure displays a graphical illustration of changes in bank linkages to counterparties as of December 31, 2020. The nodes represent firms or institutions that have at least one link with banks in the sample. The size of each node corresponds to a logarithmic mapping of the total gross credit valuation adjustment contributed to all banks in the sample by the counterparty. The color of each node corresponds to the number of banks linkages, where the light red nodes correspond with counterparties with multiple bank linkages where the number of bank counterparties have not changed since 2019:Q4, dark red nodes correspond with counterparties where the number of bank counterparties have increased since 2019:Q4, light blue nodes correspond with counterparties with single bank linkages where the number of bank counterparties have not changed since 2019:Q4, and dark blue nodes correspond with counterparties where the number of bank counterparties have decreased since 2019:Q4.

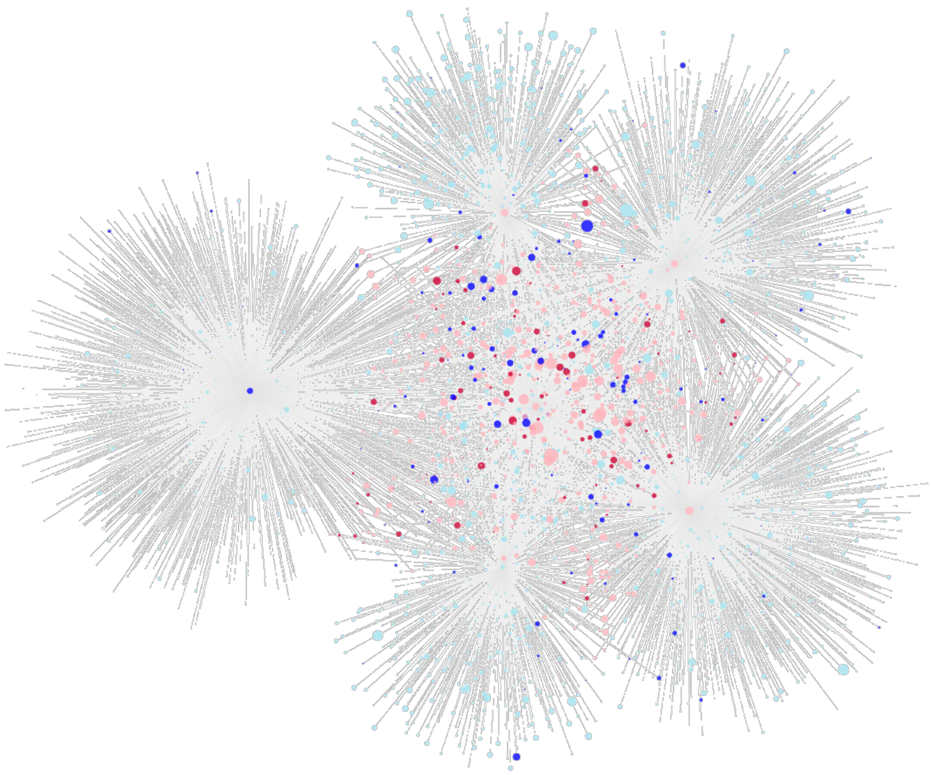


Figure 3
Bank Interconnectedness over Time

The figure displays a graphical illustration of bank interconnectedness from 2013:Q2 to 2020:Q4. The number of unique counterparty pairs are displayed in the area series for counterparties with connections to more than one bank (dark blue) or to one bank (light blue). The *% Indirect Non-Bank Common Exposures* (yellow) and *% Direct Bank Exposures* (green) line series are calculated as the proportion of total credit valuation adjustment associated with non-bank counterparties with more than one bank connection and bank counterparties, respectively.

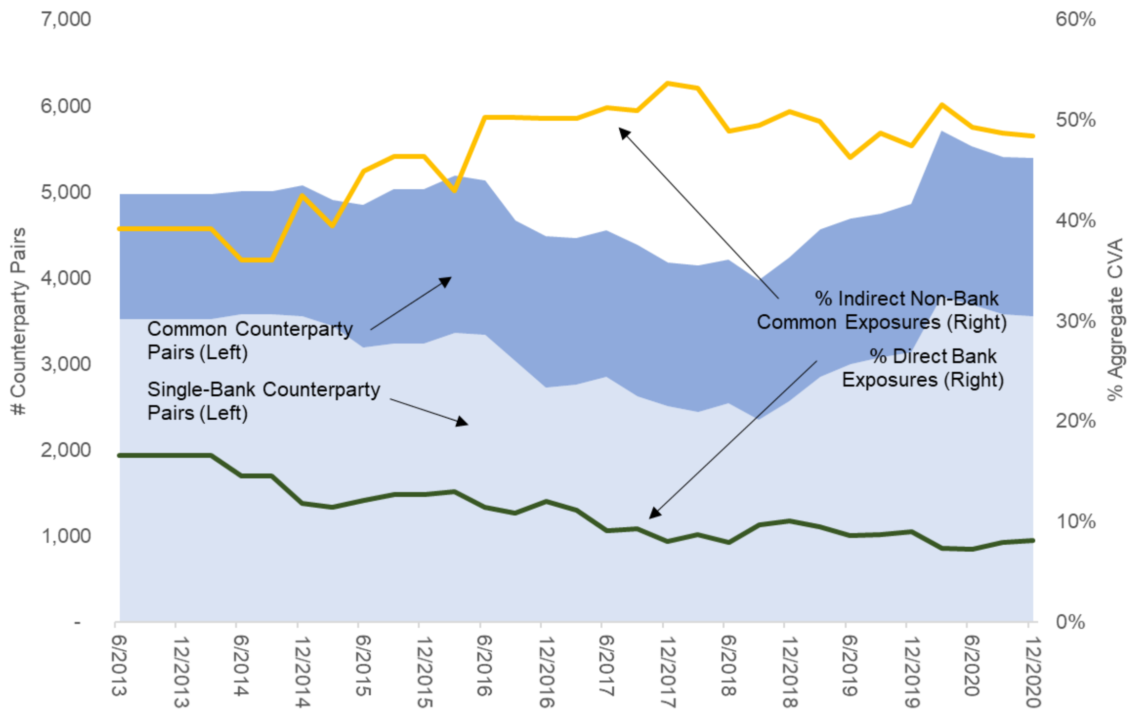


Figure 4
Illustration of *CP Bank Links* and *Total CR Exposure* Measures

The figure displays an example of three different banks (i) and a large number of non-bank counterparties (j). The dotted edges are associated with direct bank-to-bank connections while the solid edges denote bank connections to non-bank counterparties. The thickness of the edges corresponds with the size of the exposures between banks and counterparties, and range from thin, regular and thick for small, intermediate and large exposure size, respectively.

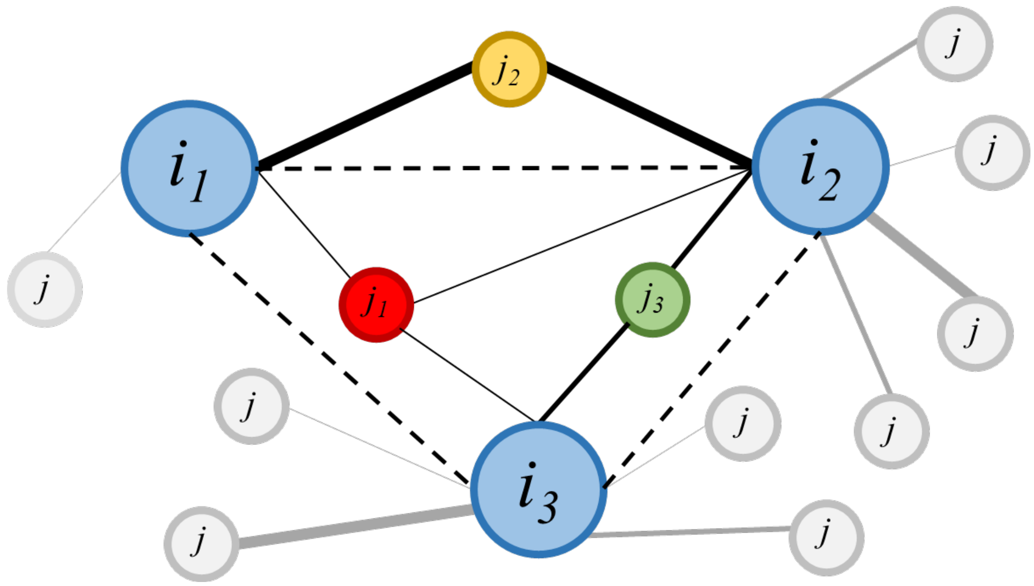


Figure 5
Net OTC Derivative Credit Exposures over Time

The figure displays the net OTC derivative credit exposures of bank holding companies for bank and non-bank financial counterparties as well as non-financial corporate counterparties from 2009:Q2 to 2020:Q4 and the proportion of cleared derivative positions from 2012:Q4 to 2020:Q4.

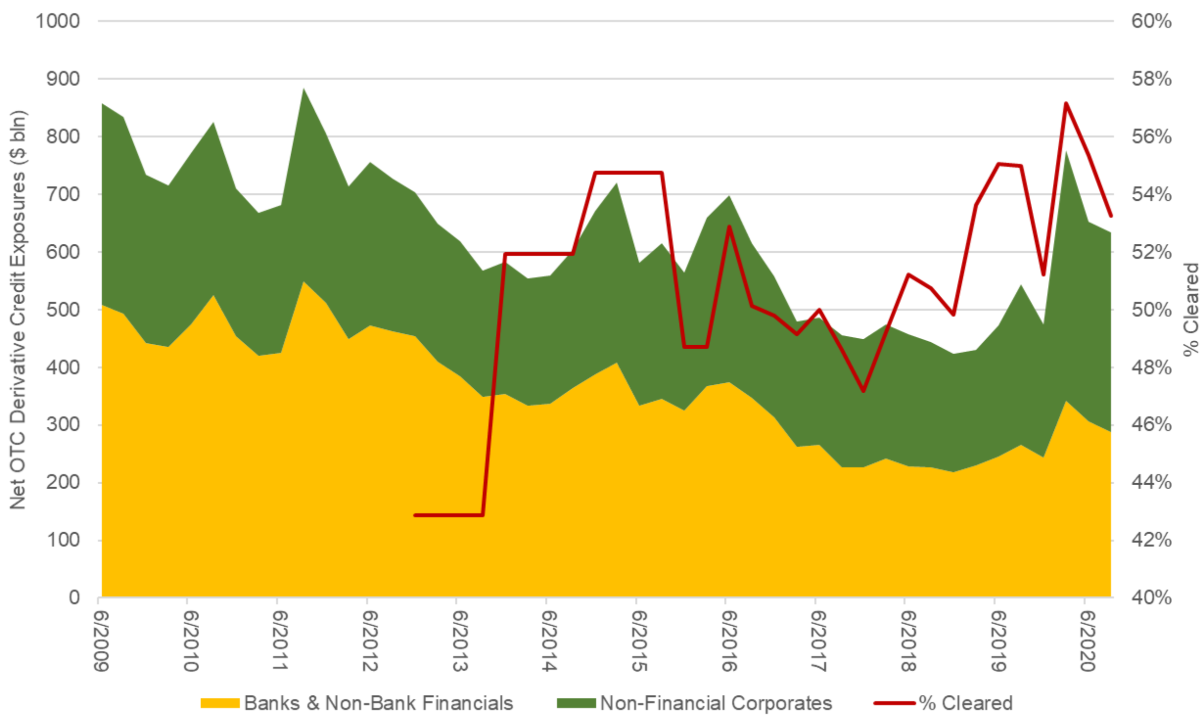


Figure 6
Goldman Sachs Top Derivative Counterparties in June 2008

The figure is a illustration collected by the Financial Crisis Inquiry Commission of Goldman Sachs' top derivative counterparties as of June 2008.

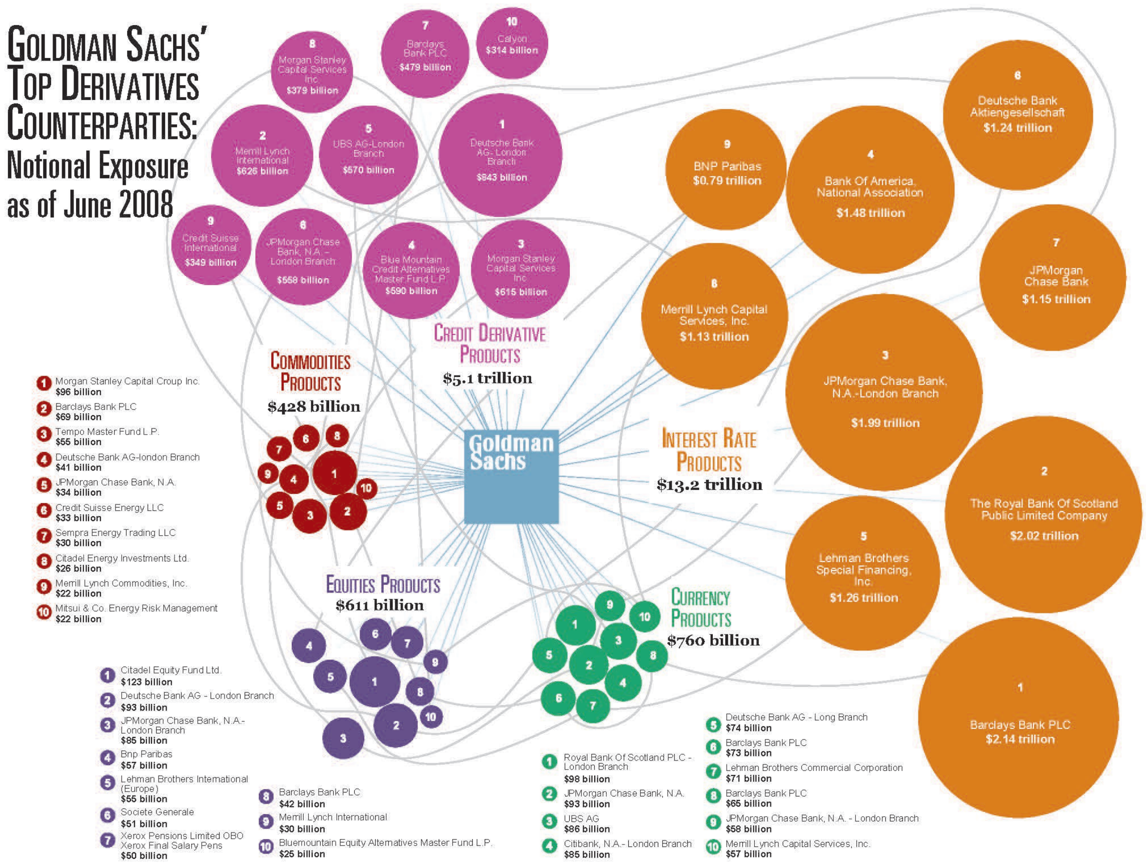
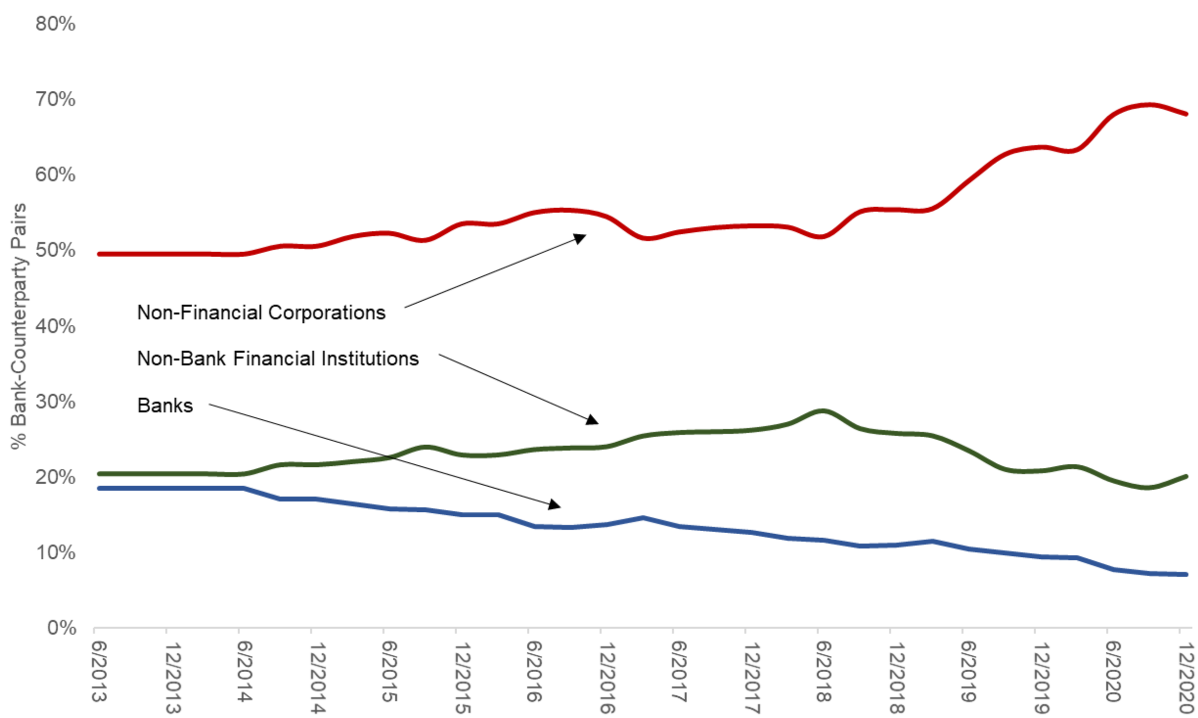


Figure 7
Non-bank Financial versus Non-financial Corporate Counterparty Composition over Time

The figure displays the breakdown of the share of the total number of bank-counterparty pairs (Panel A) and aggregate gross credit valuation adjustments (Panel B) across the sample banks attributable to banks, non-bank financial institutions and non-financial corporations for all uncleared derivative positions from 2013:Q2 to 2020:Q4.

Panel A: Bank-Counterparty Pairs



Panel B: Bank Exposures

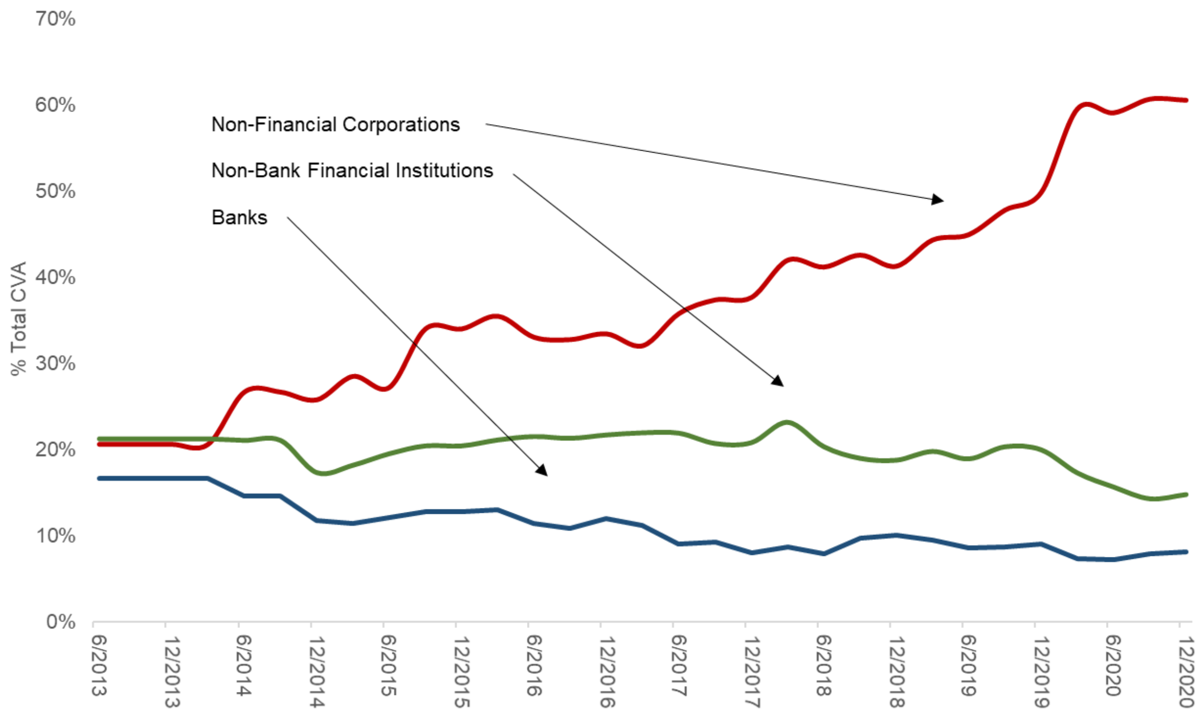


Table 1
Summary Statistics

The table displays summary statistics for the variables used in the analysis. Panel A is based on the full sample, and Panel B is based on the existing relationship subsample. The existing relationship subsample includes only bank-counterparty pairs that exist as of quarter *t*. The variables included in the table are as follows, and are not logged unless indicated otherwise for interpretability. *Relationship* is a dummy that takes value one if bank *i* has a relationship with counterparty j during quarter *t*. *Material* is a dummy that takes value one if counterparty *j* is in the list of top CVA sensitivities for any risk factor for bank *i* during quarter *t*. *CP Bank Link* is the total number of unique bank linkages to counterparty *j* during quarter *t*. *Multiple Bank* is a dummy that takes value one if the number of unique bank linkages to counterparty *j* during quarter *t* is greater than one, and zero otherwise. *Total CR Exposure* is the total gross net credit exposure of counterparty *j* across all banks during quarter *t*. *Bank CP Overlap* is the average fraction of bank *i*'s total net credit exposures of counterparties that are in common with other banks that are also connected to counterparty *j* during quarter *t*. *Gross CE* is the gross credit exposure for bank *i* of counterparty *j* during quarter *t*. *Net CE* is the net credit exposure for bank *i* of counterparty *j* during quarter *t*. *CVA* is the gross credit valuation adjustment for bank *i* of counterparty *j* during quarter *t*. *PD* is the default probability of counterparty *j* during quarter *t*. *ΔGrossCE* is the change in *GrossCE* between quarters *t* and *t+1*. *ΔNetCE* is the change in *NetCE* between quarters *t* and *t+1*. *ΔCVA* is the change in *CVA* between quarters *t* and *t+1*.

Panel A: Full Sample

	N	Mean	Standard Deviation	Q1	Median	Q3
Relationship	526,695	0.218	0.413	0.000	0.000	0.000
Material	526,695	0.029	0.168	0.000	0.000	0.000
CP Bank Link (not logged)	526,695	1.302	0.745	1.000	1.000	1.000
Multiple Bank	526,695	0.185	0.388	0.000	0.000	0.000
Total CR Exposure	526,695	758.2	1959.2	14.2	96.4	0.0
Bank CP Overlap	526,695	0.162	0.145	0.000	0.151	0.249
Gross CE	526,695	10.9	50.8	0.0	0.0	0.0
Net CE	526,695	4.6	18.7	0.0	0.0	0.0
CVA	526,695	0.208	0.797	0.000	0.000	0.000
PD	526,695	0.009	0.053	0.000	0.000	0.003
ΔGrossCE	526,695	-0.034	0.502	0.000	0.000	0.000
ΔNetCE	526,695	-0.026	0.486	0.000	0.000	0.000
ΔCVA	526,695	-0.005	0.149	0.000	0.000	0.000

Panel B: Existing Relationship						
	N	Mean	Standard Deviation	Q1	Median	Q3
Relationship	114,713	1.000	0.000	1.000	1.000	1.000
Material	114,713	0.122	0.328	0.000	0.000	0.000
CP Bank Link (not logged)	114,713	1.732	1.143	1.000	1.000	2.000
Multiple Bank	114,713	0.375	0.484	0.000	0.000	1.000
Total CR Exposure	114,713	1369.0	2826.7	24.6	194.9	1089.2
Bank CP Overlap	114,713	0.085	0.136	0.000	0.000	0.182
Gross CE	114,713	50.2	99.3	0.8	8.4	41.2
Net CE	114,713	21.0	35.4	0.4	4.8	23.1
CVA	114,713	0.957	1.483	0.118	0.336	0.993
PD	114,713	0.011	0.059	0.000	0.000	0.003
ΔGrossCE	114,713	-0.191	1.038	-0.549	0.000	0.323
ΔNetCE	114,713	-0.153	1.005	-0.566	0.000	0.343
ΔCVA	114,713	-0.029	0.312	-0.135	-0.012	0.074

Table 2
Extensive Margin

The table displays regression model results where the dependent variable is *Link* and is based on whether bank *i* is connected to counterparty *j* measured over quarter *t+1*. Columns (1) and (2) are based on the subsamples of counterparties without and with a bank relationship as of quarter *t*, respectively. All other columns are based on the full sample. The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link* (Panel A), *Total CR Exposure* (Panel B), and *Bank CP Overlap* (Panel C) measured at quarter *t*. *Relationship* is a dummy taking value one if the bank has a relationship with the counterparty at quarter *t*. Fixed effects on the bank-year-quarter, counterparty-year-quarter and bank-counterparty levels are included where indicated, but are not reported. The control variables measured at quarter *t* included in all the models are *CVA*, *CE*, and *PD*, though are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: *CP Bank Link* Interconnectedness Measure

Interconnectedness (IC) Specification:	CP Bank Link	CP Bank Link	CP Bank Link	CP Bank Link	CP Bank Link	CP Bank Link	CP Bank Link	CP Bank Link
Relationship Subsample:	None	Existing	All	All	All	All	All	All
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IC_{j,t}$	0.041***	0.126***	0.041***	0.041***	0.041***			
	(0.004)	(0.010)	(0.004)	(0.004)	(0.005)			
$Relationship_{i,j,t}$			0.819***	0.761***	0.762***	0.757***	0.761***	0.497***
			(0.016)	(0.028)	(0.021)	(0.024)	(0.018)	(0.023)
$IC_{j,t}$ × $Relationship_{i,j,t}$			0.085***	0.036***	0.035***	0.035***	0.039***	0.128***
			(0.009)	(0.013)	(0.010)	(0.013)	(0.010)	(0.021)
Control Variables	NO	NO	NO	YES	YES	YES	YES	YES
Bank × Year × Quarter FEs	NO	NO	NO	NO	YES	NO	YES	YES
Counterparty × Year × Quarter FEs	NO	NO	NO	NO	NO	YES	YES	YES
Bank × Counterparty FEs	NO	NO	NO	NO	NO	NO	NO	YES
N	411,982	114,713	526,695	524,973	524,973	524,973	524,973	508,371
R^2	0.7%	1.5%	77.7%	78.1%	79.2%	82.1%	82.9%	87.5%

Panel B: *Total CR Exposure* Interconnectedness Measure								
Interconnectedness (IC) Specification:	Total CR Exposure	Total CR Exposure	Total CR Exposure	Total CR Exposure	Total CR Exposure	Total CR Exposure	Total CR Exposure	Total CR Exposure
Relationship Subsample:	None	Existing	All	All	All	All	All	All
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IC_{j,t}$	0.003***	0.037***	0.003***	0.003***	0.003***			
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)			
$Relationship_{i,j,t}$			0.815***	0.821***	0.820***	0.812***	0.815***	0.489***
			(0.016)	(0.029)	(0.022)	(0.026)	(0.019)	(0.041)
$IC_{j,t} \times Relationship_{i,j,t}$			0.035***	0.036***	0.036***	0.035***	0.036***	0.037***
			(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
Control Variables	NO	NO	NO	YES	YES	YES	YES	YES
Bank × Year × Quarter FEs	NO	NO	NO	NO	YES	NO	YES	YES
Counterparty × Year × Quarter FEs	NO	NO	NO	NO	NO	YES	YES	YES
Bank × Counterparty FEs	NO	NO	NO	NO	NO	NO	NO	YES
N	411,982	114,713	526,695	524,973	524,973	524,973	524,973	508,371
R^2	0.5%	6.7%	78.6%	78.7%	79.8%	82.5%	83.3%	87.6%

Panel C: *Bank CP Overlap* Interconnectedness Measure								
Interconnectedness (IC) Specification:	Bank CP Overlap	Bank CP Overlap	Bank CP Overlap	Bank CP Overlap	Bank CP Overlap	Bank CP Overlap	Bank CP Overlap	Bank CP Overlap
Relationship Subsample:	None	Existing	All	All	All	All	All	All
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IC_{i,j,t}$	0.007***	0.290***	0.007***	0.008***	-0.002	-0.006	-0.024	-0.018
	(0.003)	(0.035)	(0.003)	(0.003)	(0.008)	(0.026)	(0.020)	(0.019)
$Relationship_{i,j,t}$			0.861***	0.785***	0.783***	0.767***	0.770***	0.532***
			(0.012)	(0.028)	(0.021)	(0.023)	(0.018)	(0.025)
$IC_{i,j,t} \times Relationship_{i,j,t}$			0.283***	0.154***	0.154***	0.081***	0.089***	0.163***
			(0.035)	(0.026)	(0.026)	(0.030)	(0.029)	(0.049)
Control Variables	NO	NO	NO	YES	YES	YES	YES	YES
Bank × Year × Quarter FEs	NO	NO	NO	NO	YES	NO	YES	YES
Counterparty × Year × Quarter FEs	NO	NO	NO	NO	NO	YES	YES	YES
Bank × Counterparty FEs	NO	NO	NO	NO	NO	NO	NO	YES
N	411,982	114,713	526,695	524,973	524,973	524,973	524,973	508,371
R^2	0.0%	1.2%	77.6%	78.0%	79.2%	82.1%	82.9%	87.5%

Table 3
Intensive Margin

The table displays regression model results where the dependent variable is *ΔGrossCE*, *ΔNetCE*, and *ΔCVA* measured over quarter *t+1*. The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link*, *Total CR Exposure*, and *Bank CP Overlap* measured at quarter *t*. *Relationship* is a dummy taking value one if the bank has a relationship with the counterparty at quarter *t*. Fixed effects on the bank-year-quarter, counterparty-year-quarter and bank-counterparty levels are included in all the models, but are not reported. The control variables measured at quarter *t* included in all the models are *CVA*, *CE*, and *PD*, though are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Interconnectedness (IC) Specification:	CP Bank Link	Total CR Exposure	Bank CP Overlap	CP Bank Link	Total CR Exposure	Bank CP Overlap	CP Bank Link	Total CR Exposure	Bank CP Overlap
Dependent Variable:	$\Delta GrossCE_{i,j,t+1}$			$\Delta NetCE_{i,j,t+1}$			$\Delta CVA_{i,j,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IC_{i,j,t}$			-0.002			0.069			-0.029
			(0.077)			(0.073)			(0.028)
$Relationship_{i,j,t}$	-0.099*	-0.141***	-0.022***	0.286***	0.231***	0.381***	0.080***	0.072***	0.106***
	(0.056)	(0.021)	(0.008)	(0.029)	(0.029)	(0.008)	(0.008)	(0.007)	(0.000)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$	0.271***	0.105***	0.342**	0.315***	0.127***	0.456***	0.089***	0.029***	0.131**
	(0.047)	(0.012)	(0.138)	(0.040)	(0.015)	(0.124)	(0.018)	(0.004)	(0.051)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Counterparty × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Counterparty FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	508,371	508,371	508,371	508,371	508,371	508,371	508,367	508,367	508,367
R^2	38.8%	39.1%	38.8%	45.2%	45.6%	45.2%	48.0%	48.2%	47.9%

Table 4
Material Exposures before the Pandemic

The table displays regression model results where the dependent variable is *Link* based on if the exposures are material or not material, excluding the pandemic period. An exposure is categorized as material if the counterparty is listed as a top 10 counterparty for at least one of the risk factors in terms of CVA sensitivity as reported in the data, and is otherwise categorized as non-material. The first row indicates the IC specification. Row two indicates whether *Link* is based on material or non-material exposures. The control variables are identical to those used in Table 2. Fixed effects on the bank-year-quarter and counterparty-year-quarter levels are included in all the models, but are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Interconnectedness (IC) Specification:	*CP Bank Link*		*Total CR Exposure*		*Bank CP Overlap*	
Material Exposure:	Yes	No	Yes	No	Yes	No
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$IC_{i,j,t}$					0.028***	-0.039**
					(0.009)	(0.017)
$Relationship_{i,j,t}$	0.026***	0.732***	0.039***	0.757***	0.042***	0.722***
	(0.004)	(0.035)	(0.005)	(0.034)	(0.007)	(0.033)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$	0.061***	-0.059***	0.011***	0.021***	0.102***	-0.048
	(0.012)	(0.017)	(0.001)	(0.003)	(0.029)	(0.035)
Control Variables	YES	YES	YES	YES	YES	YES
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
Counterparty × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
N	225,310	225,310	225,310	225,310	225,310	225,310
R^2	40.8%	69.7%	40.8%	69.8%	40.8%	69.7%

Table 5
Relationship Sample Splits for Material Exposures and Counterparty Risk before the Pandemic

The table displays regression model results where the dependent variable is *Link* based on if the exposures are material or not material, excluding the pandemic period. Columns (1) and (3) are based on the subsample of counterparties without a relationship as of quarter *t*, while Columns (2) and (4) are based on the subsample of counterparties with a relationship as of quarter *t*. The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link* (Panel A), *Total CR Exposure* (Panel B), and *Bank CP Overlap* (Panel C) measured at quarter *t*. The first row indicates the IC specification. Row two indicates whether *Link* is based on material or non-material exposures. Row three indicates the relationship subsample used. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: *CP Bank Link* Interconnectedness Measure

Interconnectedness (IC) Specification:	*CP Bank Link*		*CP Bank Link*	
Material Exposure:	Yes		No	
Relationship Subsample:	None	Existing	None	Existing
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)
$IC_{j,t}$	0.028***	0.205***	0.029***	-0.081***
	(0.003)	(0.013)	(0.005)	(0.023)
$PD_{j,t}$	0.000	-0.001	-0.001	-0.005
	(0.000)	(0.003)	(0.001)	(0.008)
$IC_{j,t} \times PD_{j,t}$	0.001	0.053***	-0.006	-0.042***
	(0.002)	(0.011)	(0.005)	(0.014)
N	174,642	49,858	174,642	49,858
R^2	0.6%	3.8%	0.4%	0.4%

Panel B: *Total CR Exposure* Interconnectedness Measure

Interconnectedness (IC) Specification:	*Total CR Exposure*		*Total CR Exposure*	
Material Exposure:	Yes		No	
Relationship Subsample:	None	Existing	None	Existing
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)
$IC_{j,t}$	0.002***	0.039***	0.002***	0.002
	(0.000)	(0.001)	(0.000)	(0.008)
$PD_{j,t}$	0.000***	-0.002	0.000	-0.006
	(0.000)	(0.002)	(0.000)	(0.009)
$IC_{j,t} \times PD_{j,t}$	0.000***	0.004***	0.000	-0.005**
	(0.000)	(0.001)	(0.000)	(0.002)
N	174,642	49,858	174,642	49,858
R^2	0.3%	6.6%	0.2%	0.1%

Panel C: *Bank CP Overlap* Interconnectedness Measure

Interconnectedness (IC) Specification:	*Bank CP Overlap*		*Bank CP Overlap*	
Material Exposure:	Yes		No	
Relationship Subsample:	None	Existing	None	Existing
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)
$IC_{i,j,t}$	0.013***	0.430***	0.002	-0.110
	(0.002)	(0.038)	(0.006)	(0.079)
$PD_{j,t}$	0.000***	0.013**	0.000	-0.014**
	(0.000)	(0.005)	(0.000)	(0.007)
$IC_{i,j,t} \times PD_{j,t}$	0.003**	0.098***	0.003*	-0.067
	(0.001)	(0.033)	(0.002)	(0.041)
N	174,642	49,858	174,642	49,858
R^2	0.1%	2.5%	0.0%	0.1%

Table 6
Bank Interconnectedness and Counterparty Risk before the Pandemic

The table displays regression model results where the dependent variable is *Link* based on if the exposures are material or not material, excluding the pandemic period. The first row indicates the IC specification. Row two indicates whether *Link* is based on material or non-material exposures. The control variables are identical to those used in Table 2. Fixed effects on the bank-year-quarter and counterparty-year-quarter levels are included in all the models, but are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Interconnectedness (IC) Specification:	*CP Bank Link*		*Total CR Exposure*		*Bank CP Overlap*	
Material Exposure:	Yes	No	Yes	No	Yes	No
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$IC_{i,j,t}$					0.020**	-0.024
					(0.010)	(0.017)
$Relationship_{i,j,t}$	0.028***	0.731***	0.040***	0.756***	0.043***	0.721***
	(0.005)	(0.036)	(0.005)	(0.035)	(0.007)	(0.033)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$	0.064***	-0.062***	0.012***	0.020***	0.112***	-0.061*
	(0.012)	(0.017)	(0.001)	(0.003)	(0.030)	(0.036)
$Relationship_{i,j,t}$ × $PD_{j,t}$	0.006***	-0.005	0.005**	-0.006	0.112***	-0.061*
	(0.002)	(0.004)	(0.002)	(0.004)	(0.030)	(0.036)
$IC_{i,j,t}$ × $PD_{j,t}$					-0.014**	0.028***
					(0.006)	(0.008)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $PD_{j,t}$	0.031***	-0.031**	0.003***	-0.004**	0.074***	-0.069**
	(0.011)	(0.013)	(0.001)	(0.002)	(0.022)	(0.031)
Control Variables	YES	YES	YES	YES	YES	YES
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
Counterparty × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
N	224,500	224,500	224,500	224,500	224,500	224,500
R^2	40.8%	69.7%	40.9%	69.8%	40.8%	69.7%

Table 7
Stressed Material Exposures

The table displays regression model results where the dependent variable is *Link* based on if the exposures are material or not material, including the pandemic period. The first row indicates the IC specification. Row two indicates whether *Link* is based on material or non-material exposures. The control variables are identical to those used in Table 2. Fixed effects on the bank-year-quarter and counterparty-year-quarter levels are included in all the models, but are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Interconnectedness (IC) Specification:	*CP Bank Link*		*Total CR Exposure*		*Bank CP Overlap*	
Material Exposure:	Yes	No	Yes	No	Yes	No
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$IC_{i,j,t}$					0.020**	-0.035**
					(0.009)	(0.017)
$Relationship_{i,j,t}$	0.039***	0.726***	0.053***	0.746***	0.056***	0.715***
	(0.005)	(0.029)	(0.006)	(0.029)	(0.007)	(0.026)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$	0.071***	-0.064***	0.015***	0.018***	0.126***	-0.060
	(0.012)	(0.017)	(0.001)	(0.003)	(0.029)	(0.041)
$Relationship_{i,j,t}$ × $Pandemic_t$	-0.060***	0.066***	-0.052***	0.081***	-0.070***	0.064***
	(0.011)	(0.019)	(0.011)	(0.020)	(0.014)	(0.017)
$IC_{i,j,t}$ × $Pandemic_t$					0.036**	0.014
					(0.017)	(0.030)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $Pandemic_t$	-0.006	-0.047	-0.007***	-0.003	-0.128***	-0.040
	(0.024)	(0.033)	(0.002)	(0.007)	(0.048)	(0.081)
Control Variables	YES	YES	YES	YES	YES	YES
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
Counterparty × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
N	327,269	327,269	327,269	327,269	327,269	327,269
R^2	40.1%	71.3%	40.2%	71.3%	40.1%	71.2%

Table 8
Bank Interconnectedness and Counterparty Risk under Stress

The table displays regression model results where the dependent variable is *Link* based on if the exposures are material or not material, including the pandemic period. The first row indicates the IC specification. Row two indicates whether *Link* is based on material or non-material exposures. The control variables are identical to those used in Table 2. Fixed effects on the bank-year-quarter and counterparty-year-quarter levels are included in all the models, but are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Interconnectedness (IC) Specification:	*CP Bank Link*		*Total CR Exposure*		*Bank CP Overlap*	
Material Exposure:	Yes	No	Yes	No	Yes	No
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$IC_{i,j,t}$					0.012***	-0.021***
					(0.005)	(0.000)
$Relationship_{i,j,t}$	0.041***	0.725***	0.053***	0.745***	0.058***	0.715***
	(0.005)	(0.030)	(0.006)	(0.030)	(0.007)	(0.028)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$	0.074***	-0.067	0.015	0.017	0.136***	-0.071
	(0.001)	(0.099)	(0.930)	(0.563)	(0.030)	(0.047)
$Relationship_{i,j,t}$ × $PD_{j,t}$	0.006***	-0.005	0.004**	-0.006	0.013***	-0.009*
	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.005)
$IC_{i,j,t}$ × $PD_{j,t}$					-0.014**	0.028***
					(0.006)	(0.008)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $PD_{j,t}$	0.033***	-0.032**	0.003***	-0.004**	0.076***	-0.069**
	(0.011)	(0.013)	(0.001)	(0.002)	(0.022)	(0.031)
$IC_{i,j,t}$ × $Pandemic_t$					0.041***	-0.012
					(0.016)	(0.035)
$Relationship_{i,j,t}$ × $Pandemic_t$	-0.056***	0.035*	-0.049***	0.050*	-0.066***	0.031**
	(0.011)	(0.021)	(0.011)	(0.028)	(0.016)	(0.015)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $Pandemic_t$	-0.005	-0.059	-0.007***	0.004	-0.133**	-0.032
	(0.031)	(0.061)	(0.003)	(0.011)	(0.054)	(0.110)
$Relationship_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$	-0.012*	0.040***	-0.009	0.043***	-0.018**	0.043***
	(0.007)	(0.010)	(0.006)	(0.012)	(0.009)	(0.008)
$IC_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$					0.020*	-0.016
					(0.010)	(0.016)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$	-0.035*	0.036	-0.003***	-0.003	-0.080**	0.056
	(0.018)	(0.030)	(0.001)	(0.005)	(0.034)	(0.066)
Control Variables	YES	YES	YES	YES	YES	YES
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
Counterparty × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
N	326,459	326,459	326,459	326,459	326,459	326,459
R^2	40.2%	71.3%	40.3%	71.4%	40.1%	71.3%

Table 9
Summary Statistics on Non-bank Financial and Non-financial Corporate Counterparties

The table displays summary statistics for the variables used in the analysis by two counterparty groupings: non-bank financials (Column (1)) and non-financial corporates (Column (2)). All variables are described in Table 1. The last column displays the differences in sample means between the subsamples. The asterisks next to the differences denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Counterparty Industry:	(1) Non-Bank Financial		(2) Non-Financial Corporate		(1) - (2)
	Mean	Standard Deviation	Mean	Standard Deviation	Difference
Relationship	0.222	(0.416)	0.207	(0.405)	0.015
Material	0.028	(0.165)	0.030	(0.172)	-0.002**
CP Bank Link (not logged)	1.320	(0.773)	1.238	(0.642)	0.082***
Multiple Bank	0.189	(0.392)	0.157	(0.364)	0.032***
Total CR Exposure	598.8	(1929.5)	680.8	(1697.1)	-82.0***
Bank CP Overlap	0.146	(0.152)	0.167	(0.143)	-0.021***
Gross CE	11.2	(52.8)	6.2	(31.5)	5.0***
Net CE	3.4	(16.5)	4.4	(17.8)	-0.9***
CVA	0.198	(0.765)	0.186	(0.741)	0.013*
PD	0.008	(0.054)	0.010	(0.056)	-0.002
ΔGrossCE	-0.042	(0.539)	-0.019	(0.450)	-0.024***
ΔNetCE	-0.025	(0.504)	-0.015	(0.440)	-0.011*
ΔCVA	-0.006	(0.150)	-0.001	(0.144)	-0.005**

Table 10
Bank and Non-bank Financial Counterparty Interconnectedness

The table displays regression model results where the dependent variable is *Link* based on if the exposures are material or not material, including the pandemic period, for the subsamples based on whether the counterparty is a non-bank financial (Columns (1) and (2)) or a non-financial corporate (Columns (3) and (4)). The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link* (Panel A), *Total CR Exposure* (Panel B), and *Bank CP Overlap* (Panel C) measured at quarter *t*. The first row indicates the counterparty grouping subsample. Row two indicates the IC specification. Row three indicates whether *Link* is based on material or non-material exposures. The control variables are identical to those used in Table 2. Fixed effects on the bank-year-quarter and counterparty-year-quarter levels are included in all the models, but are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: *CP Bank Link* Interconnectedness Measure				
Counterparty Industry:	Non-Bank Financial		Non-Financial Corporate	
Interconnectedness (IC) Specification:	*CP Bank Link*		*CP Bank Link*	
Material Exposure:	Yes	No	Yes	No
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)
$Relationship_{i,j,t}$	0.007	0.711***	0.077***	0.705***
	(0.006)	(0.034)	(0.006)	(0.028)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$	0.034**	0.013	0.123***	-0.141***
	(0.015)	(0.019)	(0.017)	(0.023)
$Relationship_{i,j,t}$ × $PD_{j,t}$	0.008**	0.000	0.001	-0.003
	(0.003)	(0.006)	(0.003)	(0.004)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $PD_{j,t}$	0.061***	-0.072***	0.002	0.010
	(0.017)	(0.019)	(0.016)	(0.019)
$Relationship_{i,j,t}$ × $Pandemic_t$	-0.059***	0.018	-0.061***	0.045**
	(0.012)	(0.023)	(0.011)	(0.019)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $Pandemic_t$	-0.071	0.033	-0.011	-0.050
	(0.047)	(0.050)	(0.034)	(0.040)
$Relationship_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$	-0.006	0.053***	-0.006	0.029***
	(0.006)	(0.008)	(0.008)	(0.009)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$	-0.057**	0.037	-0.003	0.012
	(0.027)	(0.030)	(0.023)	(0.027)
Control Variables	YES	YES	YES	YES
Bank × Year × Quarter FEs	YES	YES	YES	YES
Counterparty × Year × Quarter FEs	YES	YES	YES	YES
N	77,372	77,372	202,753	202,753
R^2	39.3%	69.4%	40.7%	72.4%

Panel B: *Total CR Exposure* Interconnectedness Measure				
Counterparty Industry:	Non-Bank Financial		Non-Financial Corporate	
Interconnectedness (IC) Specification:	*Total CR Exposure*		*Total CR Exposure*	
Material Exposure:	Yes	No	Yes	No
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)
$Relationship_{i,j,t}$	0.019***	0.773***	0.088***	0.719***
	(0.006)	(0.031)	(0.007)	(0.030)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$	0.010***	0.033***	0.017***	0.012***
	(0.002)	(0.004)	(0.002)	(0.005)
$Relationship_{i,j,t}$ × $PD_{j,t}$	0.006*	-0.004	0.002	-0.008*
	(0.003)	(0.005)	(0.002)	(0.005)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $PD_{j,t}$	0.003***	-0.004*	0.002*	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)
$Relationship_{i,j,t}$ × $Pandemic_t$	-0.061***	0.043**	-0.052***	0.063***
	(0.013)	(0.020)	(0.011)	(0.021)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $Pandemic_t$	-0.011***	0.015**	-0.005	0.003
	(0.003)	(0.006)	(0.003)	(0.009)
$Relationship_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$	-0.005	0.052***	-0.006	0.035***
	(0.006)	(0.008)	(0.007)	(0.010)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$	-0.002	-0.011***	-0.002	-0.003
	(0.002)	(0.003)	(0.002)	(0.005)
Control Variables	YES	YES	YES	YES
Bank × Year × Quarter FEs	YES	YES	YES	YES
Counterparty × Year × Quarter FEs	YES	YES	YES	YES
N	77,372	77,372	202,753	202,753
R^2	39.4%	70.0%	40.7%	72.3%

Panel C: *Bank CP Overlap* Interconnectedness Measure				
Counterparty Industry:	Non-Bank Financial		Non-Financial Corporate	
Interconnectedness (IC) Specification:	*Bank CP Overlap*		*Bank CP Overlap*	
Material Exposure:	Yes	No	Yes	No
Dependent Variable:	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$	$Link_{i,j,t+1}$
	(1)	(2)	(3)	(4)
$IC_{i,j,t}$	0.024*	-0.024	0.015	-0.017
	(0.014)	(0.025)	(0.010)	(0.023)
$Relationship_{i,j,t}$	0.018**	0.719***	0.099***	0.685***
	(0.007)	(0.031)	(0.007)	(0.026)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$	0.076**	0.070	0.181***	-0.167***
	(0.032)	(0.048)	(0.040)	(0.053)
$Relationship_{i,j,t}$ × $PD_{j,t}$	0.015**	-0.007	0.005	-0.003
	(0.007)	(0.009)	(0.006)	(0.006)
$IC_{i,j,t}$ × $PD_{j,t}$	-0.009	0.023*	-0.020***	0.028***
	(0.009)	(0.013)	(0.007)	(0.009)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $PD_{j,t}$	0.088**	-0.103**	0.052	-0.024
	(0.038)	(0.047)	(0.035)	(0.042)
$IC_{i,j,t}$ × $Pandemic_t$	0.062**	-0.038	0.029*	-0.007
	(0.024)	(0.050)	(0.016)	(0.030)
$Relationship_{i,j,t}$ × $Pandemic_t$	-0.069***	0.021	-0.077***	0.050***
	(0.015)	(0.020)	(0.015)	(0.016)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $Pandemic_t$	-0.154**	0.080	-0.162**	0.015
	(0.076)	(0.112)	(0.064)	(0.085)
$Relationship_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$	-0.015	0.053***	-0.009	0.031***
	(0.009)	(0.011)	(0.010)	(0.010)
$IC_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$	0.012	0.005	0.025**	-0.030*
	(0.016)	(0.022)	(0.012)	(0.016)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$ × $PD_{j,t}$ × $Pandemic_t$	-0.091*	-0.003	-0.050	0.044
	(0.054)	(0.071)	(0.048)	(0.061)
Control Variables	YES	YES	YES	YES
Bank × Year × Quarter FEs	YES	YES	YES	YES
Counterparty × Year × Quarter FEs	YES	YES	YES	YES
N	77,372	77,372	202,753	202,753
R^2	39.4%	69.4%	40.6%	72.3%

Table 11
Interbank Counterparty Exposures and Excess Returns Comovement

The table displays regression model results where the dependent variable is the correlation in daily idiosyncratic returns between banks i_1 and i_2, or ρ^{IdRet}, measured during quarter $t+1$. The dataset used is based on bank i_1 and i_2 pairs for each quarter t. *%CommonPairExposure* is the fraction of the total gross credit valuation adjustment for bank i_1 that is associated with counterparties that are common between banks i_1 and i_2 during quarter t. *%CommonPairExposure*$^{Non\text{-}Bank\ Financial}$ and *%CommonPairExposure*$^{Non\text{-}Financial\ Corporate}$ are calculated in a similar manner, though based on common non-bank financial and non-financial corporate counterparties, respectively. Fixed effects on the year-quarter, bank i_1-year-quarter and bank i_2-year-quarter levels are included where indicated, but not reported. Robust standard errors clustered on the bank i_1-year-quarter, bank i_2-year-quarter and bank pair grouping-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
%CommonPairExposure$_{i1,i2,t}$	0.946***	1.093***	0.709***			
	(0.120)	(0.086)	(0.114)			
%CommonPairExposure$_{i1,i2,t}^{Non\text{-}Bank\ Financial}$				0.778***		0.738***
				(0.156)		(0.153)
%CommonPairExposure$_{i1,i2,t}^{Non\text{-}Financial\ Corporate}$					0.674***	0.617***
					(0.205)	(0.203)
Date FEs	NO	YES	NO	NO	NO	NO
Bank i_1 × Year × Quarter FEs	NO	NO	YES	YES	YES	YES
Bank i_2 × Year × Quarter FEs	NO	NO	YES	YES	YES	YES
N	840	840	840	840	840	840
R^2	14.3%	44.4%	78.8%	78.2%	77.8%	78.7%

Table 12
Interbank Counterparty Exposures and Excess Volatility Comovement

The table displays regression model results where the dependent variable is the correlation in the absolute value of daily idiosyncratic returns between banks i_1 and i_2, or $\rho^{|IdRet|}$, measured during quarter *t+1*. The dataset used is based on bank i_1 and i_2 pairs for each quarter *t*. *%CommonPairExposure* is the fraction of the total gross credit valuation adjustment for bank i_1 that is associated with counterparties that are common between banks i_1 and i_2 during quarter *t*. *%CommonPairExposure*$^{Non\text{-}Bank\ Financial}$ and *%CommonPairExposure*$^{Non\text{-}Financial\ Corporate}$ are calculated in a similar manner, though based on common non-bank financial and non-financial corporate counterparties, respectively. Fixed effects on the year-quarter, bank i_1-year-quarter and bank i_2-year-quarter levels are included where indicated, but not reported. Robust standard errors clustered on the bank i_1-year-quarter, bank i_2-year-quarter and bank pair grouping-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	$\rho^{\|IdRet\|}_{i1,i2,t+1}$	$\rho^{\|IdRet\|}_{i1,i2,t+1}$	$\rho^{\|IdRet\|}_{i1,i2,t+1}$	$\rho^{\|IdRet\|}_{i1,i2,t+1}$	$\rho^{\|IdRet\|}_{i1,i2,t+1}$	$\rho^{\|IdRet\|}_{i1,i2,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\%CommonPairExposure_{i1,i2,t}$	0.705***	0.741***	0.498***			
	(0.111)	(0.085)	(0.129)			
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Bank\ Financial}$				0.619***		0.588***
				(0.183)		(0.179)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Financial\ Corporate}$					0.523***	0.478**
					(0.194)	(0.192)
Date FEs	NO	YES	NO	NO	NO	NO
Bank i_1 × Year × Quarter FEs	NO	NO	YES	YES	YES	YES
Bank i_2 × Year × Quarter FEs	NO	NO	YES	YES	YES	YES
N	840	840	840	840	840	840
R^2	9.3%	38.2%	68.2%	68.0%	67.7%	68.3%

Table 13
Interbank Counterparty Exposures, Systemic Risk and Market Stress

The table displays regression model results where the dependent variables are ρ^{IdRet} and $\rho^{|IdRet|}$ measured during quarter *t+1*. The dataset used is based on bank i_1 and i_2 pairs for each quarter *t*. *%CommonPairExposure* is the fraction of the total gross credit valuation adjustment for bank i_1 that is associated with counterparties that are common between banks i_1 and i_2 during quarter *t*. *%CommonPairExposure*$^{Non\text{-}Bank\ Financial}$ and *%CommonPairExposure*$^{Non\text{-}Financial\ Corporate}$ are calculated in a similar manner, though based on common non-bank financial and non-financial corporate counterparties, respectively. *VIX* is the average VIX level during quarter *t*. Fixed effects on the bank i_1-year-quarter and bank i_2-year-quarter levels are included in all the models, but not reported. Robust standard errors clustered on the bank i_1-year-quarter, bank i_2-year-quarter and bank pair grouping-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Idiosyncratic Returns Comovement

Dependent Variable:	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$
	(1)	(2)	(3)	(4)
$\%CommonPairExposure_{i1,i2,t}$	0.710***			
	(0.114)			
$\%CommonPairExposure_{i1,i2,t} \times VIX_t$	0.017			
	(0.027)			
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Bank\ Financial}$		0.910***		0.861***
		(0.153)		(0.153)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Bank\ Financial} \times VIX_t$		0.098***		0.090***
		(0.033)		(0.032)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Financial\ Corporate}$			0.670***	0.597***
			(0.191)	(0.191)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Financial\ Corporate} \times VIX_t$			0.002	-0.002
			(0.031)	(0.031)
Bank i_1 × Year × Quarter FEs	YES	YES	YES	YES
Bank i_2 × Year × Quarter FEs	YES	YES	YES	YES
N	840	840	840	840
R^2	78.9%	78.4%	77.8%	78.9%

Panel B: Idiosyncratic Volatility Comovement				
Dependent Variable:	$\rho^{\lvert IdRet \rvert}_{i1,i2,t+1}$	$\rho^{\lvert IdRet \rvert}_{i1,i2,t+1}$	$\rho^{\lvert IdRet \rvert}_{i1,i2,t+1}$	$\rho^{\lvert IdRet \rvert}_{i1,i2,t+1}$
	(1)	(2)	(3)	(4)
$\%CommonPairExposure_{i1,i2,t}$	0.498***			
	(0.129)			
$\%CommonPairExposure_{i1,i2,t} \times VIX_t$	0.004			
	(0.025)			
$\%CommonPairExposure_{i1,i2,t}^{\text{Non-Bank Financial}}$		0.724***		0.691***
		(0.185)		(0.184)
$\%CommonPairExposure_{i1,i2,t}^{\text{Non-Bank Financial}} \times VIX_t$		0.079**		0.075**
		(0.033)		(0.033)
$\%CommonPairExposure_{i1,i2,t}^{\text{Non-Financial Corporate}}$			0.561***	0.502**
			(0.200)	(0.199)
$\%CommonPairExposure_{i1,i2,t}^{\text{Non-Financial Corporate}} \times VIX_t$			-0.019	-0.022
			(0.028)	(0.026)
Bank i_1 × Year × Quarter FEs	YES	YES	YES	YES
Bank i_2 × Year × Quarter FEs	YES	YES	YES	YES
N	840	840	840	840
R^2	68.2%	68.1%	67.7%	68.5%

Table 14
Interbank Counterparty Exposures, Systemic Risk, and the Pandemic

The table displays regression model results where the dependent variables are ρ^{IdRet} and $\rho^{|IdRet|}$ measured during quarter *t+1*. The dataset used is based on bank i_1 and i_2 pairs for each quarter *t*. *%CommonPairExposure* is the fraction of the total gross credit valuation adjustment for bank i_1 that is associated with counterparties that are common between banks i_1 and i_2 during quarter *t*. *%CommonPairExposure*$^{Non\text{-}Bank\ Financial}$ and *%CommonPairExposure*$^{Non\text{-}Financial\ Corporate}$ are calculated in a similar manner, though based on common non-bank financial and non-financial corporate counterparties, respectively. *Pandemic* is a dummy taking value one if quarter t is associated with the pandemic period, and zero otherwise. Fixed effects on the bank i_1-year-quarter and bank i_2-year-quarter levels are included in all the models, but not reported. Robust standard errors clustered on the bank i_1-year-quarter, bank i_2-year-quarter and bank pair grouping-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Idiosyncratic Returns Comovement				
Dependent Variable:	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$	$\rho^{IdRet}_{i1,i2,t+1}$
	(1)	(2)	(3)	(4)
$\%CommonPairExposure_{i1,i2,t}$	0.636***			
	(0.111)			
$\%CommonPairExposure_{i1,i2,t} \times Pandemic_t$	0.507			
	(0.442)			
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Bank\ Financial}$		0.698***		0.674***
		(0.157)		(0.157)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Bank\ Financial} \times Pandemic_t$		1.298*		1.040
		(0.733)		(0.688)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Financial\ Corporate}$			0.529***	0.478**
			(0.201)	(0.201)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Financial\ Corporate} \times Pandemic_t$			0.536	0.445
			(0.543)	(0.545)
Bank i_1 × Year × Quarter FEs	YES	YES	YES	YES
Bank i_2 × Year × Quarter FEs	YES	YES	YES	YES
N	840	840	840	840
R^2	78.9%	78.3%	77.9%	78.8%

Panel B: Idiosyncratic Volatility Comovement				
Dependent Variable:	$\rho^{\lvert IdRet \rvert}_{i1,i2,t+1}$	$\rho^{\lvert IdRet \rvert}_{i1,i2,t+1}$	$\rho^{\lvert IdRet \rvert}_{i1,i2,t+1}$	$\rho^{\lvert IdRet \rvert}_{i1,i2,t+1}$
	(1)	(2)	(3)	(4)
$\%CommonPairExposure_{i1,i2,t}$	0.484***			
	(0.140)			
$\%CommonPairExposure_{i1,i2,t} \times Pandemic_t$	0.091			
	(0.368)			
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Bank\ Financial}$		0.585***		0.561***
		(0.192)		(0.189)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Bank\ Financial} \times Pandemic_t$		0.544		0.437
		(0.534)		(0.494)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Financial\ Corporate}$			0.528**	0.485**
			(0.223)	(0.222)
$\%CommonPairExposure_{i1,i2,t}^{Non\text{-}Financial\ Corporate} \times Pandemic_t$			-0.017	-0.057
			(0.451)	(0.433)
Bank i_1 × Year × Quarter FEs	YES	YES	YES	YES
Bank i_2 × Year × Quarter FEs	YES	YES	YES	YES
N	840	840	840	840
R^2	68.2%	68.0%	67.7%	68.3%

Table A.1
Alternative *Total CR Exposure* Specifications

The table displays regression model results where the dependent variable is *Link*, *ΔGrossCE*, *ΔNetCE*, and *ΔCVA* measured over quarter *t+1*. The bank interconnectedness measures (IC) used for the analysis are alternative specifications for *Total CR Exposure* measured at quarter *t* based on gross credit exposures and gross credit valuation adjustments. The first row displays the IC specification. *Relationship* is a dummy taking value one if the bank has a relationship with the counterparty at quarter *t*. Fixed effects on the bank-year-quarter, counterparty-year-quarter and bank-counterparty levels are included in all the models, but are not reported. The control variables measured at quarter *t* included in all the models are *CVA*, *CE*, and *PD*, though are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Interconnectedness (IC) Specification:	TotalCRExposure (Gross CE)				TotalCRExposure (CVA)			
Dependent Variable:	$Link_{i,j,t+1}$	$\Delta GrossCE_{i,j,t+1}$	$\Delta NetCE_{i,j,t+1}$	$\Delta CVA_{i,j,t+1}$	$Link_{i,j,t+1}$	$\Delta GrossCE_{i,j,t+1}$	$\Delta NetCE_{i,j,t+1}$	$\Delta CVA_{i,j,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Relationship_{i,j,t}$	0.475***	-0.106***	0.230***	0.064***	0.481***	-0.160***	0.239***	0.056***
	(0.017)	(0.027)	(0.013)	(0.007)	(0.014)	(0.025)	(0.033)	(0.007)
$IC_{i,j,t}$ × $Relationship_{i,j,t}$	0.035***	0.047***	0.087***	0.025***	0.060***	0.164***	0.158***	0.059***
	(0.004)	(0.012)	(0.009)	(0.003)	(0.007)	(0.017)	(0.014)	(0.007)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	NO	NO	NO	NO	NO	NO	NO	NO
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES
Counterparty × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Counterparty FEs	YES	YES	YES	YES	YES	YES	YES	YES
N	508,371	508,371	508,371	508,367	508,371	508,367	508,371	508,367
R^2	87.6%	38.8%	45.3%	48.1%	39.1%	48.0%	38.8%	48.2%

Table A.2
Alternative Specifications for Non-Bank Financial Counterparties

The table displays regression model results where the dependent variable is *Link, ΔGrossCE*, *ΔNetCE*, and *ΔCVA* measured over quarter *t+1* on the subsample of non-bank financial counterparties. The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link*, *Total CR Exposure*, and *Bank CP Overlap* measured at quarter *t*. The first row displays the IC specification. *Relationship* is a dummy taking value one if the bank has a relationship with the counterparty at quarter *t*. Fixed effects on the bank-year-quarter, counterparty-year-quarter and bank-counterparty levels are included where indicated, but are not reported. The control variables measured at quarter *t* included in all the models are *CVA*, *CE*, and *PD*, though are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Interconnectedness (IC) Specification:	CP Bank Link	Total CR Exposure	Bank CP Overlap	CP Bank Link	Total CR Exposure	Bank CP Overlap	CP Bank Link	Total CR Exposure	Bank CP Overlap	CP Bank Link	Total CR Exposure	Bank CP Overlap
Dependent Variable:	$Link_{i,j,t+1}$			$\Delta GrossCE_{i,j,t+1}$			$\Delta NetCE_{i,j,t+1}$			$\Delta CVA_{i,j,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$IC_{i,j,t}$			-0.023			0.018			0.145**			-0.022
			(0.018)			(0.075)			(0.064)			(0.025)
$Relationship_{i,j,t}$	0.466***	0.495***	0.514***	-0.282***	-0.243***	-0.213***	0.265***	0.303***	0.350***	0.068***	0.082***	0.093***
	(0.008)	(0.038)	(0.042)	(0.036)	(0.029)	(0.004)	(0.023)	(0.020)	(0.015)	(0.009)	(0.008)	(0.002)
$IC_{i,j,t} \times Relationship_{i,j,t}$	0.154***	0.037***	0.240***	0.219***	0.066***	0.374***	0.237***	0.129***	0.460***	0.076***	0.027***	0.161***
	(0.024)	(0.005)	(0.047)	(0.060)	(0.016)	(0.121)	(0.053)	(0.017)	(0.115)	(0.022)	(0.004)	(0.044)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Counterparty × Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Counterparty FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	109,210	109,210	109,210	109,210	109,210	109,210	109,210	109,210	109,210	109,206	109,206	109,206
R^2	86.0%	86.1%	86.0%	36.2%	36.4%	36.2%	48.5%	49.2%	48.6%	49.7%	50.0%	49.7%

Table A.3
Alternative Specifications for Non-Financial Corporate Counterparties

The table displays regression model results where the dependent variable is *Link, ΔGrossCE*, *ΔNetCE*, and *ΔCVA* measured over quarter *t+1* on the subsample of non-financial corporate counterparties. The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link*, *Total CR Exposure*, and *Bank CP Overlap* measured at quarter *t*. The first row displays the IC specification. *Relationship* is a dummy taking value one if the bank has a relationship with the counterparty at quarter *t*. Fixed effects on the bank-year-quarter, counterparty-year-quarter and bank-counterparty levels are included where indicated, but are not reported. The control variables measured at quarter *t* included in all the models are *CVA*, *CE*, and *PD*, though are not reported. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Interconnectedness (IC) Specification:	CP Bank Link	Total CR Exposure	Bank CP Overlap	CP Bank Link	Total CR Exposure	Bank CP Overlap	CP Bank Link	Total CR Exposure	Bank CP Overlap	CP Bank Link	Total CR Exposure	Bank CP Overlap
Dependent Variable:	$Link_{i,j,t+1}$			$\Delta GrossCE_{i,j,t+1}$			$\Delta NetCE_{i,j,t+1}$			$\Delta CVA_{i,j,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$IC_{i,j,t}$			-0.015			-0.015			0.001			-0.045
			(0.018)			(0.018)			(0.084)			(0.031)
$Relationship_{i,j,t}$	0.487***	0.466***	0.513***	0.487***	0.466***	0.513***	0.211***	0.123***	0.296***	0.086***	0.069***	0.111***
	(0.022)	(0.046)	(0.013)	(0.022)	(0.046)	(0.013)	(0.028)	(0.040)	(0.057)	(0.009)	(0.014)	(0.004)
$IC_{i,j,t} \times Relationship_{i,j,t}$	0.102***	0.032***	0.129**	0.102***	0.032***	0.129**	0.313***	0.117***	0.423***	0.094***	0.028***	0.154***
	(0.028)	(0.006)	(0.053)	(0.028)	(0.006)	(0.053)	(0.053)	(0.014)	(0.151)	(0.019)	(0.004)	(0.057)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Counterparty × Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Counterparty FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	287,821	287,821	287,821	287,821	287,821	287,821	287,821	287,821	287,821	287,821	287,821	287,821
R^2	88.8%	88.8%	88.8%	88.8%	88.8%	88.8%	42.1%	42.4%	42.1%	45.9%	46.0%	45.9%

Table A.4
Bank-level Trading Desk Outcomes

The table displays the results of the regression models where the dependent variables are the natural log of one plus the trading volume-to-trading asset ratio (*Trade Volume*), the natural log of one plus the net trading revenue-to-trading asset ratio (*Trade Revenue*), and the natural log of one plus the proportion of days in which the trading desk experienced a net loss (*Loss Days*) over quarter *t+1*. The main explanatory variable is *%CommonExposure*, which is the fraction of total gross credit valuation adjustment associated with counterparties with more than two bank counterparties for bank *i* at quarter *t*. The control variables are measured over quarter *t*, and include, but are not reported: the natural log of the ratio of total gross CVA-to-total number of counterparties for bank *i*, the natural log of the total number of counterparties for bank *i*, and the natural log of the trading assets for bank *i*. Fixed effects on the year-quarter level is included in all the models, but are not reported. Robust standard errors are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Trade $Volume_{i,t+1}$	Trade $Volume_{i,t+1}$	Trade $Revenue_{i,t+1}$	Trade $Revenue_{i,t+1}$	Loss $Days_{i,t+1}$	Loss $Days_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\%CommonExposure_{i,t}$	1.301***	2.902***	0.244***	0.195***	0.311***	1.896***
	(0.400)	(0.698)	(0.048)	(0.050)	(0.100)	(0.205)
Control Variables	NO	YES	NO	YES	NO	YES
Year-Quarter FEs	YES	YES	YES	YES	YES	YES
N	135	133	135	133	135	133
R^2	4.3%	42.0%	14.2%	79.5%	2.6%	64.7%