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Counterparty Choice, Interconnectedness, and Bank Risk-taking

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Abstract

We investigate whether banks' counterparty choices in OTC derivative markets contribute to network fragility. We use novel confidential regulatory data and show that banks are more likely to choose densely connected non-bank counterparties and do not hedge such exposures. Banks are also more likely to connect with riskier counterparties for their most material exposures, suggesting the existence of moral hazard behavior in network formation. Finally, we show that these exposures are correlated with systemic risk measures despite greater regulatory oversight after the crisis. Overall, the results provide evidence of risk propagation in bank networks through non-bank linkages in opaque markets. *JEL* codes: G21, G22, D82

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1. Introduction

Half of all bilateral 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 were previously identified as important sources of systemic risk during the Great Financial Crisis.[1] A broad body of literature studies how concentrations in linkages between banks emerge in financial networks, and to what extent they contribute to systemic fragility.[2] In seminal works 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. Theoretical work points to limits to the benefits of dense network connections, because high interconnectedness could propagate, rather than attenuate, shocks, resulting in a more fragile system (Acemoglu et al. (2015)). In this paper we depart from the existing literature and look at a largely overlooked direction: investigating the risk-taking behavior of banks within the network through the choice of their non-bank counterparties. Banks become more interconnected as they share more common non-bank counterparties. We examine how network density and counterparty risk affect the choices made by banks, and the resulting impact of these decisions on financial fragility.

This question about counterparty choice is central to our understanding of the financial system's resilience 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; second, a system may come under pressure from a network-intrinsic risk rather than an exogenous shock and counterparty risk is one mechanism.

Because network connections allow for the sharing of risks, it may also create moral hazard. While a bank may connect to other banks to reduce its vulnerability to shocks through diversification, it will then 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-

[1] See BCBS (2011), FCIC (2012), and Borio et al. (2020).

[2] See Allen and Babus (2009), Cabrales, Gale, and Gottardi (2015), Glasserman and Young, (2016), and Summer (2013).

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 exogenous shocks, but also the endogenous risk-taking by banks, manifested through their choice of counterparties, that may act as an amplifying mechanism in the case of an exogenous shock.[3]

Network connections and choice of counterparties is especially important for the derivative markets, where banks have both very large exposures and highly dense interconnections with other banks through common non-bank counterparties. Despite post-crisis regulatory reforms aimed at addressing these issues, there is still debate on their effectiveness.[4] A significant gray area is that the current U.S. regulatory framework focuses primarily on direct (i.e., bank to bank) counterparty exposures rather than indirect ones, where banks get connected through common non-bank counterparties. The indirect connections can also be an important source of contagion on which there is very limited empirical evidence within the derivatives markets. Data limitations and identification challenges are two explanations for this dearth of empirical evidence and we plan to overcome each of these challenges in our paper because of the granularity of the datasets.

We are the first to provide empirical evidence in the OTC derivative markets that suggests the existence of endogenous risk-taking behavior by banks related to network formation.[5] We do so by using novel bank regulatory data, the Capital Assessments and Stress Testing reports (FR Y-14Q) from the period 2013-2020, providing comprehensive, counterparty-level information on the uncleared OTC derivative markets of systemically important U.S. banks to empirically investigate how banks choose to link to (mostly) non-bank counterparties.[6]

Our analysis focuses on the uncleared derivatives markets. Despite stricter requirements for uncleared derivative activities and mandatory clearing, uncleared derivatives currently account for approximately half of all derivative activities by banks, and therefore represent a significant

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[3] See also Elliott et al. (2021) and Acharya (2009).
[4] For example, see Glasserman and Ghamami (2017), Cont (2018), Paddrik and Zhang (2022). Clancy (2022) describes some of the ways in which banks have circumvented post-crisis regulations related to the bilateral derivatives markets.
[5] There is an existing empirical literature that mostly focuses on the inter-bank lending markets (Upper and Worms (2004); Cocco et al. (2005); Degryse and Nguyen (2007); and Brunetti et al. (2019)). However, bank interconnectedness does not emerge simply through inter-bank funding arrangements and, as a result, is a much richer concept. These funding arrangements provide us with direct bank connections, whereas a richer characterization of the interconnectedness must consider indirect bank connections, i.e., banks getting connected through a common (non-bank) counterparty. Failure to consider these important indirect connections will underestimate the true impact of networks on our understanding of contagion.
[6] Specifically, the data covers 18 different over-the-counter (OTC) derivative markets.

fraction of their trading operations overall. Of these activities, a significant fraction consists of non-bank counterparties with multiple bank relationships. The existence of such dense linkages may be in part due to counterparty demand factors, such as improved execution.[7] However, several recent studies suggest that supply factors are important as well.[8] Uncleared derivative activities also lack the same level of transparency as cleared derivatives, making it difficult to account for system-wide exposures when evaluating counterparty risks and set margins to properly mitigate potential losses. Opaqueness, in turn, may provide banks with incentives to circumvent regulatory oversight and creates opportunities for leakage.[9] Losses on uncleared derivatives are fully borne by the bank, whereas those for cleared derivatives are mutualized across member firms of the clearinghouse. As such, bank exposures to uncleared derivatives are more economically meaningful and relevant for our research question. The data allow us to examine how a counterparty's uncleared connections to other banks affect the bank counterparty choices, providing insights into the fragility that common counterparty exposures may introduce without them being detected by regulators. Our analysis also informs channels through which synthetic leverage can accumulate in opaque financial markets through derivative positions of non-bank counterparties.

The granular data and our empirical strategy help us disentangle the network effects in the counterparty choice from other alternative channels that may confound our results. One empirical challenge is the assortative bank-counterparty matching arising from bank and counterparty characteristics and preferences unrelated to network choices. Both banks' and counterparties' business models are examples of time-invariant forces that may lead to an assortative match, unrelated to any risk-taking motives stemming from network considerations. Assortative matching may change across time as banks' business models change, also in response to market-wide changes. Regulatory reforms over the past decade, including mandatory clearing, uncleared margin rules, and Basel III bank reforms, are also likely to have affected both demand and other supply factors influencing the bank-counterparty matching process.[10] We address these issues by

[7] For example, Hendershott et al. (2019) study the counterparty's choice of trading networks in the OTC corporate bond markets.
[8] See, for example, Siriwardane (2019), Paddrik & Tompaidis (2021), Colliard et al. (2021), and Eisfeldt et al. (Forthcoming).
[9] Clancy (2022) provides anecdotal evidence related to the collapse of Archegos Capital Management.
[10] For example, increased margin requirements may have reduced demand for riskier counterparties, who were affected more by the uncleared margin rules. These counterparties tend to be smaller in size and have fewer existing

using high-level fixed effects that absorb these characteristics within an empirical strategy reminiscent of Khwaja and Mian (2008). By using counterparty-year-quarter and bank-year-quarter fixed effects we fully absorb all the relevant time-changing characteristics, in addition to bank-counterparty characteristics, including collateral and hedging behavior, to account for other non-network dimensions that may influence assortative matching.

We show that systemically important banks have a greater propensity of choosing counterparties with a higher degree of existing connections to other systemically important banks. In our baseline regression models, we find that various measures of interconnectedness have a strong, economically significant association with the bank's counterparty choice over the following quarter, both on the intensive and extensive margins. These results imply that banks prefer a denser network, in which they become more connected with each other indirectly through common counterparties. Furthermore, we exploit a regulatory-mandated classification of counterparties that provides us with information about the group of counterparties that banks declare as material, which corresponds with the largest exposures for a given bank for a particular derivative market in each quarter. Material counterparties are riskier by definition due to the large concentrations in exposures that they represent, carry greater weight in regulatory capital requirements, and may be more likely to be undercollateralized (Cont (2018)). The results are pronounced in material counterparties while the effects are mostly insignificant or negative for non-material counterparties. The findings also provide strong corroborating evidence that the network outcomes we document are being driven by banks' network preferences rather than any choices or preferences of counterparties. The potential influence of unobservable counterparty demand on the interconnectedness measures should be similar for material and non-material counterparties and thus the differences in outcomes between the two different types of relationships should be accounted by bank-level preferences.

Banks may hedge their credit risk exposures to interconnected counterparties, mitigating the potential impact if these counterparties were to fail. While our counterparty choice tests control for counterparty hedges, we further examine associations between interconnectedness with bank hedging activities. First, for more than three-quarters of material counterparties, there is no single-name CDS available for banks to directly hedge counterparty credit risks, limiting the ability of

connections to banks, and so may generate spurious associations between measures of interconnectedness and changes in network linkages due to time-varying counterparty demand rather than bank choice.

banks to ever hedge these exposures. Second, counterparty interconnectedness has a strong, negative association with net hedge positions, especially for material counterparties. Third, we find a strong positive association between interconnectedness and CDS protection sales. In other words, in addition to documenting large bilateral exposures to interconnected counterparties in the counterparty choice tests, we show that banks *increase* credit risk exposures to those same counterparties through arrangements with other counterparties in their CDS activities. Overall, these results suggest the existence of endogenous risk-taking associated with network formation in the OTC derivative markets.

Next we examine how counterparty risk influences the impact of interconnectedness when banks establish or maintain relationships with counterparties. A more densely connected network provides banks with the benefit of co-insurance in the case of a shock, but also the incentive to take on greater risk. Thus, we should ask whether banks tend to balance over-connecting with limiting moral hazard behavior by connecting with less risky counterparties. Answering this question is crucial to address the "connected-fragility" dimension studied by the literature (Acemoglu et al. (2015)). Our results show that counterparty risk amplifies the effects of interconnectedness on bank choice for material 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 suggest that moral hazard behavior is concentrated in counterparty exposures that are most consequential for banks. This evidence is consistent with the arguments made by Acemoglu et al. (2015) and applied to our set-up: banks seem to fail to internalize the negative externalities arising from counterparty risk on the other banks in the network.

Finally, we investigate whether bank interconnectedness has systemic effects in the post-crisis period. Even if these interconnections contribute to fragility in the financial network, reforms in the post-crisis derivative markets may have ameliorated their systemic effects. Using bank-level data, we show that common counterparty exposure has a positive and significant association with various systemic risk and trading desk performance measures. We then exploit the granularity of the data to examine systemic effects using pairwise bank exposures. These tests use high-dimensional fixed effects to account for time-varying bank heterogeneity that limit the bank-level tests. We find a positive association between pairwise bank exposures and joint bank tail risks. These results confirm, at least at the correlation level, a connection between the level of bank interconnectedness through common counterparties and measures of systemic risk, suggesting limitations to regulatory reforms in the OTC derivative markets in recent years.

This paper contributes 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, Parigi, and Rochet (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 are 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 more (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. 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 has 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 of 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, which requires further investigation.

Our paper also contributes to another literature that investigates the role of the architecture of the financial system 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 determine the likelihood of systemic crises (Allen et al., 2012). Existing literature focuses 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 endogenous network formation and its impact on bank-level outcomes as well as its 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 studies the conditioning effects of counterparty risk on bank choice. Section 6 describes the systemic risk tests and presents the results. Section 7 concludes with policy implications.

2. Data and Variable Construction

This paper uses data from confidential regulatory filings associated with the Capital Assessments and Stress Testing reports from 2013:Q3 to 2020:Q4. 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.[11] 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.

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 contrasts with credit risks that the bank may hold in the form of wholesale loans or securities holdings.

[11] For the purpose of the analysis, we use the Schedule L.1.a data.

As part of their reporting requirements, banks provide 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. 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 counterparty.

We only include banks that began reporting in 2013, representing the vast majority of the overall number of counterparties and overall exposures in the raw data. This ensures that we have a stable number of banks in the analysis, mitigating potential concerns due to the addition of banks to the dataset throughout the sample period. As of 2019, the average number of counterparties reported per bank in our 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 of 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.[12] With the bank and counterparty identities, we construct a quarterly panel of bank-counterparty network mappings. We can observe when new bank-counterparty links are formed and when existing links are terminated. We can also detect changes in exposures between banks and counterparties. Most relevant to this study, this information allows us to precisely quantify interconnections between banks through common counterparties.

The data include the counterparty-level, asset-side CVA, which is calculated by each bank for every counterparty with which it is linked. 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

[12] We manually match counterparties across banks based on their name, internal counterparty identifiers, and legal entity identifiers when available.

and regulators. It should be noted that regulatory capital charges are based on CVA rather than other measures of exposures.[13]

The data also provide other information pertinent to the bank's exposures to each counterparty. For each date, this includes hedging activities, or the net hedge position based on outstanding single-name CDS positions the bank holds where the counterparty is the reference entity; collateral associated with the positions; and the weighted-average maturity across all the outstanding positions with the counterparty. While our analysis focuses on uncleared positions, the data also provide information on cleared positions, although at a relatively aggregated level. Namely, we have information about net exposures associated with cleared and uncleared positions for counterparties by internal risk rating groups over time. These variables will be used as control variables in the empirical design.

2.1 Network Description

An important aspect of our data is that we can comprehensively map the financial network based on counterparty linkages of the most systemically important U.S. banks based on uncleared positions. Thus, we can study changes in the financial network. Next, we describe the network based on the data and how network density has changed over the sample period.

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

[Insert Figure 1]

[13] 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.

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 to 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 many nodes that have multiple edges, i.e., counterparties with linkages to more than one bank. These counterparties represent indirect interconnections between banks and are the focus of the analysis.

Figure 2 displays how the network structure changed over calendar year 2020 compared to 2019 and is the background for our analysis of the effects caused by a market dislocation event (the Covid-19 pandemic) to network connections. 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 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 to counterparties with multiple bank linkages where the number of bank counterparties have not changed since 2019; dark red nodes correspond to counterparties where the number of bank counterparties have increased since 2019,; light blue nodes correspond to counterparties with single bank linkages where the number of bank counterparties have not changed since 2019; and dark blue nodes correspond to counterparties where the number of bank counterparties have decreased since 2019. The figure shows that, for most of the counterparties, the number of bank linkages did not change throughout the course of the market stress period. There are quite a few counterparties that experienced either an increase or a decrease in the number of bank linkages, though the corresponding nodes do not cluster in any specific area of the network and vary in node size.

[Insert Figure 2]

Figure 3 shows how the prevalence of counterparties with multiple bank connections evolved 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 that have at least two bank linkages (indirect non-bank connections) and bank-to-bank linkages (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 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 gradually increased during this period. This increase may be related to the 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 oscillated around 50% thereafter. For comparison, the fraction of total exposures associated with bank-to-bank connections are small and decreased over the sample period.

[Insert Figure 3]

Critically for our analysis, the data allow us to identify nodes, or counterparties, associated with greater density and construct measures based on several different dimensions of interconnectedness. Next, we describe these measures.

2.2 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. The granularity of the data allows us to use interconnections at the bank-counterparty level, thus providing us with 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. Rather than capturing interconnections for the aggregate network, these measures focus on local interconnections based on bank-counterparty-level linkages. 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 that counterparty j has a relationship with 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 establish a relationship with the 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 many 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 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, $Total\ CR\ Exposure_{j,t}$ corresponds to the edge sizes, i.e., the dollar exposure that each counterparty has, rather than a simple 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 with 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. 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 capture 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, $Bank\ CP\ Overlap_{i,j,t}$, to calculate 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 counterparty to the similarity in the overall exposures between banks.

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

Define $\{C_{m,t}\}$ 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.[14] 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

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

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.

3. Research Design

A challenge to our analysis is distinguishing decisions made by banks when establishing or maintaining relationships arising from network considerations, from (a) other bank- and counterparty-level characteristics, and (b) assortative matching that may also influence counterparty choice. For us to be able to answer the research question, our identification strategy needs to isolate the network decision from other bank-level or counterparty-level dimensions that may correlate with that decision.

Time-invariant factors at the bank- or counterparty-levels may influence the counterparty choices and the assortative matching driving the establishment and maintaining of relationships. For example, larger counterparties may be able to better afford the fixed costs of multiple dealer relationships and may lead to associations with interconnectedness measures and counterparty choice due to counterparty demand. Safer counterparties may not need to post as much collateral to enter into bilateral agreements, which may also affect their ability to establish relationships with multiple dealers. Banks are subject to regulatory charges based on total uncleared derivative exposures, which may be particularly costly for those with relatively lower capital. Larger banks may have different trading businesses, and so they may face different regulations that limit the ability of banks to offer services or restrict exposures to certain counterparties. These banks may also be better able to hedge counterparty risks, as they may already have broad participation in the credit default swap markets.

The impacts of these bank- and counterparty-level effects may have changed over our sample period due to changes in the many regulatory reforms that created structural shifts in the derivatives markets. These changes have plausibly induced time-variation in both demand and supply factors that affect counterparty choice, potentially confounding associations between measures of interconnectedness and bank's choices of counterparties if not accounted for.[15] These

[15] See Gandre et al. (2020) for discussion.

changes should have plausibly produced heterogenous effects across different banks and counterparties. Tighter margin requirements for uncleared derivatives may have magnified costs for riskier counterparties to enter into such agreements, potentially decreasing demand and resulting in a lower number of bank linkages for these counterparties.[16] Mandatory clearing may have diminished counterparty demand for a bank's supply of non-standard or other agreements where central clearing is not readily available.[17,18]

Our empirical design will account for these potentially confounding issues. The granularity of our data allows us to map the relationships of each counterparty with different banks. This structure will allow us to use high level fixed effects of three types: (a) bank-year-quarter, (b) counterparty-year-quarter, and (c) in some specifications, bank-counterparty fixed effects. The first two types of fixed effects will absorb the effects of any form of bank- and counterparty-level heterogeneity and its time-varying dimension that could influence network outcomes unrelated to our research question. For example, the counterparty-year-quarter fixed effects absorb time variation in counterparty demand (e.g., due to the introduction of minimum margin requirements and mandatory clearing) as well as time-invariant factors at the counterparty-level (e.g., associated with counterparty size and risk). Likewise, the bank-year-quarter fixed effects absorb time variation in bank-level risk management practices, including hedging, due to changes in capital requirements directly associated with these reforms.

One limitation to the interpretation of our results arises from the lack of transparency in the uncleared derivatives markets. The opaqueness of the OTC derivative markets is such that banks may not have full information about the entire financial network. This said, there is evidence suggesting that banks are well informed about other banks connected to their existing clients. FCIC (2012) indicates that many large banks were at least aware of other institutions that entered

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[16] However, some sutides have argued that margin requirements may not necessarily lead to lower counterparty demand. For example, Duffie et al. (2015) show that while aggregate collateral, or margin, demand increases with initial margin requirements, mandatory central clearing could have a counteracting effect due to multilateral netting and exposures diversification. Moreover, it is unclear when banks began imposing minimum collateral requirements on uncleared derivatives, and anecdotal evidence suggests that at least some did so long before these requirements became effective.

[17] Central clearing carries certain netting and operational benefits that bilateral contracts do not. For instance, multilateral netting allows a CCP to potentially reduce the number and notional amount of bilateral positions, which can be beneficial to counterparties and influence demand. Likewise, netting can also lower capital requirements. However, such benefits may weaken in the presence of multiple CCPs where netting across CCPs is difficult, as noted in Duffie and Zhu (2011), Heller and Vause (2012), and Cont and Kokholm (2014).

[18] See Heller and Vause (2012) and Sidanius and Zikes (2012) for earlier work on the effects of mandatory central clearing.

into bilateral derivative agreements with their material counterparties during the financial crisis. There are similar accounts for banks that were exposed to the Archegos event (e.g., Aliaj et al. (2021)).

We address this point by investigating both the establishment of new relationships as well as the continuation (or termination) of existing relationships. It is very plausible that such an asymmetry is present when it comes to the establishment of new relationships and less so (or even non-existent) in the case of existing relationships. For new relationships, banks may not have complete information on the connections of the prospective counterparty because they would never have transacted with the counterparty before. 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, particularly when hard information is scarce (Liberti and Petersen (2019)), such as is the case in OTC markets. Other studies have documented that trading relationships in OTC markets are generally sticky (Afonso et al. (2014), Du et al. (2019), Henderschott et al. (2020)), potentially allowing banks to glean information through the counterparty's trading and non-trading activities.[19] Accordingly, the effects of network structure on counterparty choice are likely to be stronger when banks determine whether to maintain an existing relationship rather than establish a new one, which is validated in our analysis.

3.1. Baseline Model Specification

In our baseline models, we estimate sensitivities between the three measures of interconnectedness on bank counterparty choice outcomes. 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 provide 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 each of the banks in the sample for whom a relationship does or does not exist. We only consider the establishment and destruction of linkages from quarters t to $t+1$ for this set of bank-counterparty pairings.

[19] This is in contrast with standard search models, where firms may solicit bids from many dealers and so do not maintain finite network structures (Duffie et al., 2005; Lagos and Rocheteau, 2007; Gavazza, 2016).

We estimate the effects of maintaining existing relationships versus establishing a new relationship by interacting the interconnectedness measures with an indicator associated with existing bank relationships. The specification controls for interactive fixed effects to account for time-varying bank and counterparty heterogeneity, 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:

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

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. First, $Link_{\mathrm{i,j,t+1}}$ is a dummy taking value one if bank *i* and counterparty *j* have a relationship at quarter *t+1,* and zero otherwise. $Link_{\mathrm{i,j,t+1}}$ allows us to examine 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.

We consider three additional dependent variables to capture the exposure's intensity, i.e., the intensive margin of the relationship. $\Delta GrossCE_{\mathrm{i,j,t+1}}$ 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*. $\Delta NetCE_{\mathrm{i,j,t+1}}$ 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*. $\Delta CVA_{\mathrm{i,j,t+1}}$ is the change in the natural log of one plus the CVA for bank *i* to counterparty *j* between quarters *t* and *t+1*. In addition to being a measure of exposure intensity, $\Delta CVA_{\mathrm{i,j,t+1}}$ also takes into consideration the riskiness involved with the exposure, as it corresponds with the discounted expected losses due to default of the counterparty to the bank.

The key explanatory variables ($IC_{i,j,t}$) are the three measures of interconnectedness discussed in Section 2. The non-interacted $IC_{i,j,t}$ 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 outcome variables between existing and non-existing relationships and is the focus of the analysis.

To account for time-varying unobservable heterogeneity related to demand and other supply factors, we use various specifications that include 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. We include control variables ($\boldsymbol{X_{i,j,t}}$) related to bank-and counterparty-level characteristics to account for other assortative match factors. We control for the bank's current exposures to the counterparty, as measured by the natural log of the counterparty's CVA for bank *i* at quarter *t* and the natural log of one plus the counterparty's net credit exposures for bank *i* at quarter *t*. To account for existing collateral and hedging associated with the position, we control for the amount of collateral posted relative to counterparty's gross exposures for bank *i* at quarter *t* and the amount of hedging relative to gross the counterparty's exposures for bank *i* at quarter *t*. To control for counterparties with longer-term arrangements, we include the natural log of the weighted average maturity for bank *i* at quarter *t*. To account for differences in bank activities in cleared versus uncleared derivatives, we include the fraction of activities associated with CCP for bank *i* and the counterparty's risk rating category at quarter *t*. For cases where a counterparty does not have a relationship with a bank, these variables are set at zero. Though not on the bank-counterparty-level, we also include in some of the specifications the counterparty default probability, defined as the average mapping between the firm's risk ratings to default probability densities based on regulatory reports. The standard errors are clustered at the bank-year-quarter and counterparty-year-quarter levels.

3.2. Material Counterparties

Material exposures, or exposures associated with positions that are concentrated or relatively large for a particular activity, are likely to be a source of vulnerability for contagion and counterparty risks. They are not only riskier given their high concentration but are also more likely to be undercollateralized (Cont (2018)). Regulators require banks to identify these types of exposures in the data. In our analysis, we decompose $Link_{\mathrm{i,j,t+1}}$ based on whether the linkage is to a material counterparty, or counterparties associated with material exposures, or not. This decomposition allows us to assess whether the associations we study in the baseline model plausibly have the potential to be destabilizing, as material positions are generally large and may be more difficult to diversify. We do not have analogous measures for the other outcome variables, and so the tests based on this decomposition use the extensive margin only.

The data provide information about material exposures for specific markets starting in 2017. As such, the analysis on material counterparties uses data from 2017 through 2020. 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 total return swaps – e.g., a large decline in stock returns – for each instrument class. We use this information to decompose *Link* into material and non-material exposures.

An additional benefit of distinguishing between material and non-material counterparties is that it allows us to further assess the validity of our empirical strategy in its ability to distinguish between banks' network preferences vis-à-vis other unobserved factors, even at the counterparty level. Note that counterparties that are material for one bank may be non-material for other banks. This consideration implies that if we were to find differences between material and non-material relationships, such differences are more likely to be driven by bank-level preferences rather than a specific counterparty's preferences. In other words, potential unobservable heterogeneity related to the counterparty's choice of banks should influence the interconnectedness measures similarly for material and non-material counterparties.

3.3. Hedging Behavior

Banks have incentives to hedge their uncleared derivative exposures as it allows them to offset regulatory capital charges. However, these offsets focus narrowly on single-name CDS positions and depend on CDS availability. Single-name CDSs are generally available only for a limited number of counterparties and are unavailable for a vast majority of counterparties represented in the data.[20]

When single-name CDSs are available for a particular counterparty, regulators examine the net hedging position of the bank overall, rather than individual contracts, as the bank could have large protection sale positions that would increase, rather than decrease, counterparty risk.

[20] Outside of credit risk hedges for individual positions, banks could choose to employ index CDS for portfolio hedges. However, these forms of hedges are already accounted for in the analysis through the use of bank-year-quarter fixed effects.

These cases are not uncommon. For material exposures, 23.9% are associated with net protection sales positions, and a majority are not associated with any CDS position, presumably due to CDS availability. Interestingly, the proportion of counterparties with net protection sales positions for non-material exposures is lower, or 6.9%, though this is likely to be due to CDS availability.

The analysis examines bank counterparty hedging behavior and examines to what extent it is associated with the interconnectedness measures. For the regression models, shown below, we are particularly interested in how these associations differ for material exposures.

$$\%NetHedge_{i,j,t} = \delta_1 IC_{i,j,t} + \delta_2 Material_{i,j,t} + \delta_3 Material_{i,j,t} \times IC_{i,j,t} + \boldsymbol{\delta W_{i,j,t}} + \boldsymbol{\gamma_{i \times t}} + \varsigma_{i,j,t+1} \quad (3)$$

The regression models use $\%NetHedge_{i,j,t}$ for bank i, counterparty j during quarter t as the dependent variable. The variable is based on CDS activities across the bank's trading operations, not specific to any individual account, per requirements associated with the accounting treatment of the regulatory offsets. $Material_{i,j,t}$ is a dummy associated with whether counterparty j currently has material exposures with bank i. The tests focus on the $IC_{i,j,t}$ term coefficients. If banks hedge exposures to interconnected counterparties, we expected a positive association, or $\delta_1 > 0$. It is possible that banks may primarily hedge their material exposures, in which case the interaction term coefficient should be positive, or $\delta_3 > 0$. Such associations would be inconsistent with the endogenous risk-taking hypothesis.

The model is estimated on the subsample of bank-counterparty pairings with an existing relationship or material exposure. As such, we only include bank-year-quarter fixed effects. This allows us to capture time-varying bank factors that may drive bank hedging behavior and portfolio hedges. We do not include counterparty-year-quarter fixed effects as we are primarily interested in the direct association between the interconnectedness measures and hedging behavior.

The control variables allow us to account for observable counterparty factors associated with demand. We include the counterparty's total net credit exposure to the bank, the total credit valuation adjustment represented by the counterparty to the bank, the counterparty's default probability, the amount of collateral posted relative to counterparty's gross exposures, the weighted average maturity of the counterparty's positions with the bank, the fraction of activities associated with CCPs, and the total amount of net CDS positions across banks where the CDS reference entity is the counterparty. Because the variable is influenced in part by other counterparties in the CDS markets, the total amount of net CDS positions is included to account for demand in the single-name CDS markets. It also allows us to account for counterparties without single-name CDS. The results are virtually identical when including a dummy associated with counterparties for which none of the banks have CDS positions where the counterparty is the reference entity.

3.4. Descriptive Statistics

Table 1 displays summary statistics of the variables used in the analysis on the augmented panel data. Descriptions of each variable can be found in Table A.1. 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 in 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 are \$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 large and positive correlations, or 46.4%. However, *Bank CP Overlap* has 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

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* (Panel A), *Total CR Exposure* (Panel B), and *Bank CP Overlap* (Panel C).

[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. In Column (1), the magnitude of the *IC* coefficients have both high statistical and economic significance. With the inclusion of the control variables in Column (2), the magnitude of 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 in a meaningful way. Finally, the results remain significant after the inclusion of the bank-counterparty fixed effects in Column (6), though the *IC* interaction term coefficient increases almost three-fold. This specification 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. Based on the estimates from Column (6), the marginal effect of adding an additional bank linkage from the mean translates to a 3.10 percentage point increase in *Link*, which is meaningful compared to the sample mean of 0.218.

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 has a positive association with bank counterparty choice. 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 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 intensive margins. Table 3 presents the results when using *ΔGrossCE* (Columns (1), (4), and (7)), *ΔNetCE* (Columns (2), (5), and (8)), and *ΔCVA* (Columns (3), (6), and (9)) as the dependent variables. Columns (1) through (3) use *CP Bank Link* for the interconnectedness measure. Columns (4) through (6) use *CR Total Exposure* for the interconnectedness measure. Columns (7) through (9) use *Bank CP Overlap* for the interconnectedness measure. All models use the full specification used in Column (6) 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 are 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 0.178 for *ΔGrossCE*, 0.153 for *ΔNetCE*, and 0.052 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 the 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 measures 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 (results shown in Table A.2).

Second, in un-tabulated results we show that the estimates from the exposure tests are not sensitive to alternative specifications of the dependent variables in Table 3 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.

Third, the length of maturity of contracts could induce a mechanical relationship in the case of the choice to continue the link with an existing counterparty. To this end, we need to account for counterparties with contracts that are unlikely to expire within the next quarter. We include, as a control, a dummy variable that takes the value of 1 in the case of counterparties with contracts that have a weighted average maturity exceeding one quarter with the bank and zero otherwise. In un-tabulated results, we find that the estimates are almost identical with the inclusion of this control.

4.2. Material Exposures

Next, we examine material and non-material counterparty exposures. 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 significantly 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]

We want to examine the importance of existing relationships for material and non-material exposures during normal market conditions and how they may differ during market stress periods, using the market dislocation of 2020 as a measure of stress. *Stress* is defined as a dummy variable taking value 1 if date *t* occurs during 2020, and zero otherwise. We start by investigating the impact of existing relationships on counterparty choice during normal times. The main coefficients of interest are found in the third row: all *IC* interaction term coefficients across the different specifications (found in columns (1), (3) and (5)) are all positive and significant for material exposure linkages. The coefficient estimates for the non-material exposures (found in columns (2), (4), and (6)) are very mixed: two out of three specifications show a negative or a non-statistically significant coefficient. 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. However, in Column (2), the *IC* interaction term coefficient is negative and statistically significant at the 1% level. These results suggest that the baseline regressions models are likely to be driven by material exposures. As explained above, the results cannot be explained by counterparty size, which may be correlated with material exposures, or other regulatory factors given the fixed effects that we include.

What is the impact of market stress on these relationships? Do banks reign in the level of links they have established as market dislocation puts pressure on their balance sheets? To investigate this behavior, we use an interaction term between *IC*, *Relationship*, and *Stress*. The coefficients, found in the sixth row, are negative for material exposures, and are statistically significant in two of the three specifications, indicating that the effects documented in Table 2 at least attenuated during the crisis. The sum of the *IC* × *Relationship* and *IC* × *Relationship* × *Stress* 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* × *Stress* is negative and statistically significant in all the specifications, suggesting a relatively weaker effect on the retention of existing relationships during this period.

4.3. Hedging Behavior

The results so far indicate that banks prefer interconnected counterparties. While the tests directly control for a number of factors associated with risk mitigation, such as hedging, we want to further investigate any association between the interconnectedness measures and credit risk hedging behavior by banks. The dependent variable used in the specifications, *%NetHedge*, is the hedging positions entered into by bank *i* against counterparty *j* relative to the bank's gross exposures in each quarter. Table 5 displays the results.

[Insert Table 5]

Columns (1), (3), (4), (6), and (7) are based on the sample of existing relationships, while Columns (2), (5), and (8) are based on the subsample of existing material exposures. In most specifications (six out of eight), the un-interacted interconnectedness coefficients are negative and statistically significant. This result indicates that, for more interconnected counterparties, banks are not more engaged in hedging these exposures. The results, rather surprisingly, show the opposite: banks are less likely to hedge these exposures. These patterns are pronounced for material counterparties, whose positions are generally riskier for the bank. That is, even though banks possess greater incentives to hedge material counterparties, we find evidence that this is not the case.

One possible interpretation of the results shown in Table 5 is that banks, rather than hedging their exposures to more interconnected counterparties, are actually selling insurance against them. We thus ask the question whether banks increase counterparty credit risk exposures through their CDS trading operations. The counterparty choice tests focus on exposures related to direct arrangements with the counterparty. In these tests, we study indirect exposures where the counterparty is the reference entity. We estimate a similar model to the one tested in the specifications shown in Table 5 but replace the dependent variable: we use a dummy variable, *ProtectionSeller*, which takes the value of 1 if bank *i* has an overall net protection sales position where the reference entity is counterparty *j,* and zero otherwise.

[Insert Table 6]

Table 6 presents the results using the same structure as the one we used in table 5. Across all the specifications, the interconnectedness coefficients, shown in the first row, are positive and statistically significant. This means that counterparty interconnectedness is positively associated with net sales positions taken by the bank against the counterparty. The effects are pronounced for material exposures. Overall, the results in Tables 5 and 6 rule out the possibility that banks may counterbalance the effects from a densely interconnected counterparty through hedging against the counterparty and, if anything, banks are likely to sell, rather than buy, protection against them.

Together, the results suggest that banks not only prefer interconnected counterparties but may also increase credit risk exposures to those counterparties through their CDS activities. Our results are reminiscent of Elliott et al. (2021). Using German data, the authors provide evidence that banks with greater interconnections through common obligors in their loan portfolios are more likely to also lend to each other in the interbank lending markets, consistent with the bank risk-taking predictions from their theoretical model. Our results compliment these findings because we find banks taking on correlated risks across their trading operations, but they do so in the more opaque and regulatory-challenging environment of the OTC derivatives markets where exposures are based on implicitly leverage positions due to the payoff structure associated with these contracts.

5. Counterparty Risk

The results thus far suggest network fragility arising from bank counterparty choice and hedging behavior, consistent with risk-taking by banks in network formation. While the empirical design accounts for alternative explanations associated with regulatory shocks, counterparty demand, and other supply factors, it is difficult to pin down causal relationships as the tests do not use any exogenous variation in the network structure in the analysis. As such, we develop additional tests based on counterparty credit risk in order to further assess to what extent our findings are related to risk-taking behavior.

We augment the baseline regression model to assess the role of counterparty credit risk in shaping the bank's decision when, and how, relationships are formed. We ask whether banks tend to balance the creation of more indirect bank connections with connections to safer or riskier counterparties. On the one hand, it is conceivable that interconnected counterparties are generally safer, so that linkages to these counterparties may enhance stability. On the other hand, linkages to interconnected counterparties with higher credit risk may be destabilizing, particularly if they are associated with material exposures. Such connections may increase the vector for contagion risks, given that they represent interactions between systemic and credit risks. Answering this question helps us better address the "connected-fragility" dimension addressed by the literature (for example, Acemoglu et al. (2015), amongst others) compared to the baseline model. In order to do so, we use the counterparty probability of default (PD) to measure the riskiness of potential counterparties.

We test the following regression model:

$$Link_{i,j,t+1}^{Material} = \theta_1 IC_{i,j,t} + \theta_2 Relationship_{i,j,t} + \theta_3 Relationship_{i,j,t} \times IC_{i,j,t} +$$
$$\theta_4 IC_{i,j,t} \times PD_{j,t} + \theta_5 Relationship_{i,j,t} \times PD_{j,t} + \theta_6 Relationship_{i,j,t} \times IC_{i,j,t} \times PD_{j,t} +$$
$$\boldsymbol{\theta X_{i,j,t}} + \boldsymbol{\gamma_{j\times t}} + \boldsymbol{\gamma_{i\times t}} + \varepsilon_{i,j,t+1} \tag{4}$$

The dependent variable, $Link_{i,j,t+1}^{Material}$, is a dummy that takes value one if counterparty *j* 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 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 further amplified due to counterparty risk.

As with the previous section, we differentiate the effects between normal market conditions and market stress periods in order to better understand banks' risk-taking behavior. 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 if they were formed due to risk-sharing motives but deteriorate when formed due to moral hazard behavior.

Before proceeding to the results for the full model, we start by presenting results from univariate tests to facilitate interpretability for the effects of bank interconnectedness and how they are conditioned by counterparty risk. Specifically, we divide the data into subsamples based on whether the counterparty is in the top or bottom quartile in terms of interconnectedness and probability of default. Only observations that are in either the top or bottom quartile for each variable are used. Sample means for the counterparty choice variables are presented for these groupings, less the sample means of the observations not included in these groupings. We focus on comparisons between the high and low interconnectedness groups for counterparties with high and low default probabilities to assess how the effects of interconnectedness differ based on counterparty risk. We perform this exercise for counterparties with and without existing relationships separately. Table 7 presents the results. Throughout these specifications, we use *CP Bank Link* as the measure of interconnectedness. Results do not differ using the other measures.

[Insert Table 7]

The results in Table 7 show that the effects of interconnectedness increase in counterparty risk for material exposures but decrease for non-material exposures. These effects are isolated in the existing relationship subsample. Across all counterparty risk groups, interconnectedness has a positive association with material counterparty exposures. For existing relationships, however, the association is larger in magnitude for the high counterparty risk group. For counterparties without existing relationships, the magnitude is similar, and the difference is statistically insignificant. Interestingly, the association between interconnectedness and non-material exposures is negative and decreases in magnitude for riskier counterparties. These results indicate that counterparty risk amplifies the effects of interconnectedness for material exposures but has an attenuating and negative effect for non-material exposures. We will next show that these patterns hold even when including control variables and fixed effects that address endogeneity issues discussed above.

Table 8 presents the full model. 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 8]

We focus on the triple interaction term between *IC*, *Relationship*, and *PD*, which captures the effects during normal market conditions. 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, banks avoid riskier counterparties with higher interconnections for their non-material exposures. The results on the interaction term between *IC* and *Relationship* is like those of Table 4 across the specifications for material exposures, though they are stronger when accounting for counterparty risk. Similarly, the effect of the interaction term between *Relationship* and *PD* is stronger for material exposures compared to Table 4, and the coefficients are positive and statistically significant.

Next, we discuss the results associated with the *Stress* terms. The coefficient for the interaction term *IC* × *Relationship* × *PD* × *Stress* 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 more so 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.

For non-material exposures, the quadruple interaction term is mostly insignificant. Interestingly, the interaction term *Relationship* × *PD* × *Stress* has a positive coefficient across the specifications and is 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.

As a robustness check, we examine heterogeneity in counterparty types to further investigate whether the results are related to bank risk-taking behavior. Specifically, we consider whether the effects differ for counterparties that are more likely to utilize synthetic leverage for investment purposes. These counterparties are generally riskier as they may have positions across banks that are generally more difficult to unwind. Towards this end, we perform the tests separately for non-bank financial counterparties—who are more likely to use synthetic leverage and enter into derivative positions for investment or speculation purposes—and non-financial corporate counterparties—who are relatively less likely to do so.[21] Table A.3 displays the results. We find that most of the effects documented in Table 8 are concentrated in non-bank financials.

We also re-estimate the specifications from Tables 2 and 3 for the non-bank financial and non-financial corporate sub-samples. Table A.4 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.5 presents the results for the non-financial corporate subsample. The results are positive and statistically significant across all the specifications.

6. Bank Interconnectedness and Systemic Risk

In the previous sections, we provide evidence consistent with the existence of risk-taking behavior in bank counterparty choices. However, even if a bank's choices contribute to fragility in the financial network, it is unclear whether they necessarily produce systemic effects. Another reason is regulation: the post-crisis period has witnessed significant regulatory reforms of the derivative markets. In this section, we investigate to what extent the potential fragility from networks through common counterparties propagates systemic effects in the financial system in the post-crisis period.

6.1. Systemic Risk and Trading Desk Outcomes

We begin the analysis by testing whether bank-level common counterparty exposures are associated with systemic risk measures and trading desk outcomes. In these tests, we examine two common measures of systemic risk: SRISK (Brownless and Engle, 2017) and Marginal Expected Shortfall, or MES (Acharya et al., 2017). Our findings in the previous sections are likely to be related to bank trading operation outcomes, given the measures are based on bank OTC market activities. As such, we also examine bank trading desk volumes and revenues. For the main explanatory variable, we aggregate the bank-counterparty-level data to the bank-level. Specifically, we measure the variable *%CommonExposure* which 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. One potential limitation of the analysis is data aggregation which is coarser than what we used

[21] 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.

earlier. These tests are more susceptible to omitted variable bias and thus our evidence can only be interpreted as suggestive of any systemic effects. To mitigate these concerns to some extent, 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 two-way bank and date fixed effects. Robust standard errors are reported in parentheses.

[Insert Table 9]

Table 9 presents the results. In Columns (1) and (2), the *%CommonExposure* is positive and statistically significant, suggesting that bank interconnectedness is associated with SRISK and MES, respectively, in the following quarter. These results provide evidence that common counterparty exposures are linked to higher levels of systemic risk. Columns (3) and (4) present the results on bank trading desk volumes and revenues, respectively. The coefficients are also positive and statistically significant, suggesting that banks with higher degrees of interconnectedness have greater trading activities and profitability. These results suggest that common counterparty exposures significantly contribute to systemic risk even in the post-period time frame.

6.2. Bank Pairwise Exposures

One limitation of the tests of Table 9 is that bank interconnectedness may be correlated with unobservable time-varying bank factors that are not properly accounted for in the models. For example, differences in trading operations across banks may influence their ability to cater to counterparties with higher demand. Some banks may be associated with higher systemic risk due to institutional reasons rather than common counterparty exposures.

To overcome these challenges, we employ an empirical strategy that allows us to address these endogeneity issues. We develop tests that exploit the counterparty-level data to construct measures of pairwise exposures between banks related to common counterparties. That is, for each pairing of banks i_1 and i_2, we can precisely calculate the degree of counterparty overlap between the two banks. We then assess the extent to which these measures correlate with bank risk while accounting for time-varying unobservable bank heterogeneity through the inclusion of high-dimensional fixed effects. 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.

The measures of systemic risk used in Table 9 are at the bank-level, and it is difficult to construct analogous measures at the bank pair-level. To address this issue, we examine a related measure based on joint bank tail risks. When carrying out these tests, we are interested in answering the following question: if bank i_1 experiences a shock, captured by a sharp decline in stock price, to what extent does bank i_2 experience a similar outcome if they have shared versus unrelated counterparty exposures? To answer this question, we measure the co-movement of idiosyncratic returns volatility between each bank pair. Intuitively, co-movement in idiosyncratic returns volatility between two banks should capture joint tail risks that are independent of other systematic factors. Idiosyncratic returns volatility co-movement, or ρ^{IdVol}, is calculated for each quarter as the correlation between the idiosyncratic daily returns squared for each bank pair in the sample. Idiosyncratic returns are calculated as the residual from the three-factor model from Fama and French (1993) augmented with the Carhart (1997) factor, estimated separately for each quarter.

We begin by constructing a panel dataset of all possible bank pairs for each year-quarter in the sample. For each bank pair, we calculate the fraction of bank i_1's total exposures 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 the previous section, we also assess whether the effects of common counterparty exposures differ for non-bank financial counterparties, who are more likely to use derivatives for synthetic leverage purposes, relative to 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. 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.

[Insert Table 10]

Table 10 displays the results. They show a positive and statistically significant association between the banks' pairwise exposures and joint bank tail risks. The results remain significant even after with the inclusion of the high dimensional fixed effects terms, suggesting that the results of Table 9 are unlikely to be driven by omitted factors. The results are similar when considering pairwise exposures related to non-bank financial and non-financial corporate counterparties, separately.

[Insert Table 11]

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 11 presents the results. Column (1) 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 un-interacted *%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. Overall, the results indicate that the effects of bank interconnections are magnified during market stress events primarily for non-bank financial counterparties. In other words, they suggest that bank tail events during stress periods are to some extent related to common non-bank financial counterparty exposures across banks.

As a robustness check, we repeat the analysis for the market stress associated with the pandemic period. Table A.6 presents the results, following the same structure as Table 11. Across all the specifications, the *Stress* interaction terms are statistically insignificant in almost all the specifications, including most that focus on non-bank financials. However, the size of the coefficients is generally large, and is almost double in the non-bank financial specifications. These results suggest that the effects from Table 12 are not simply driven by the pandemic period.

7. Conclusions and Policy Implications

This paper is, to our knowledge, the first to provide evidence of the risk-taking behavior of banks in the choice of their non-bank counterparties through which they amplify their connections with other banks. We directly examine how banks choose counterparties and to what extent network structure plays in that decision. We find that banks prefer to establish and maintain relationships with non-bank counterparties that have a larger set of connections with other banks, particularly for their riskiest exposures, leading to a more densely connected network. We then show that banks not only hedge these counterparties relatively less but are also more likely to increase credit risk exposures to them through their CDS activities. Moreover, the effects on counterparty choice are amplified by counterparty credit risk. Finally, we demonstrate a link between common counterparty exposures and bank tail risks, 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. Overall, 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.

Our findings have a number of potentially important policy implications. First, bank regulators primarily focus on direct counterparty exposures to calculate regulatory capital charges, overlooking broader network information related to how counterparties may be connected to other banks. As our analysis suggests, this may provide opportunities for leakage, as banks may be able to increase indirect interconnections without the same degree of regulatory scrutiny. Our paper demonstrates that it is possible to monitor these types of interconnections using existing regulatory data.

Second, the results are consistent with predictions of theoretical models that bank risk-taking behavior can exacerbate fragility in dense network structures. One potential criticism of these models is that banks were quite resilient during the significant shocks to the financial system in March 2020. It also casts doubt on the validity of skepticism of post-crisis reforms designed to mitigate systemic risks. At the same time, the very meaningful regulatory interventions that were implemented throughout 2020 suggest that there are deficiencies in the post-crisis regulatory framework that should be addressed, and the network connections documented in this paper can be an area requiring regulatory attention.

Finally, our analysis focuses on the uncleared derivatives markets. The mechanisms we study are not mutually exclusive to these markets and could exist in the cleared markets as well. One implication is that risks to CCPs may be understated based on most conventional metrics. However, what helps allay concerns to some extent is that certain types of derivative instruments used by counterparties to increase risk through their derivative positions cannot be readily cleared, including total return swaps. Regardless, further research could provide insights into this issue area.

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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.

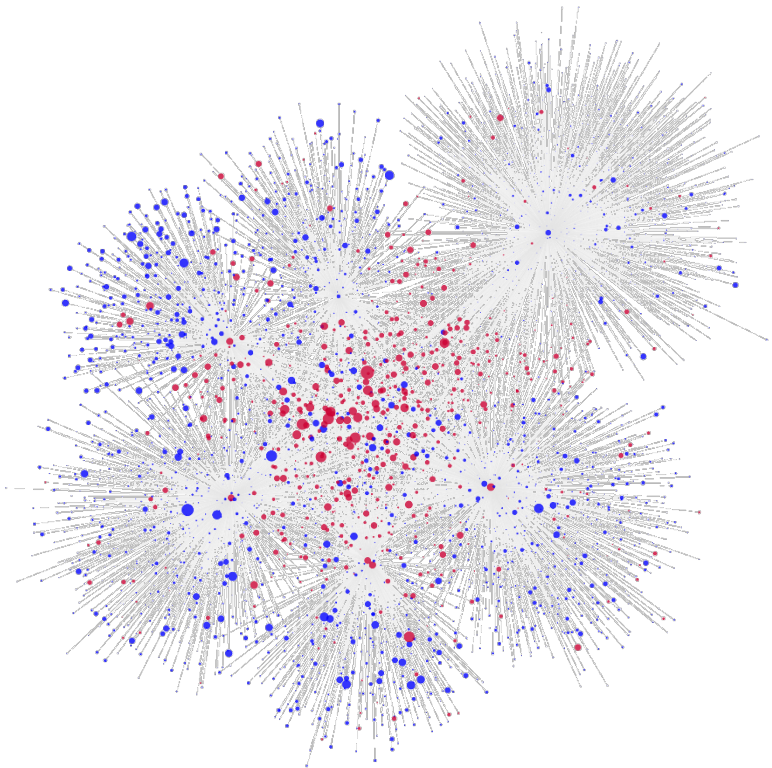

Figure 2
Changes in Bank Counterparty Linkages over 2020

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.

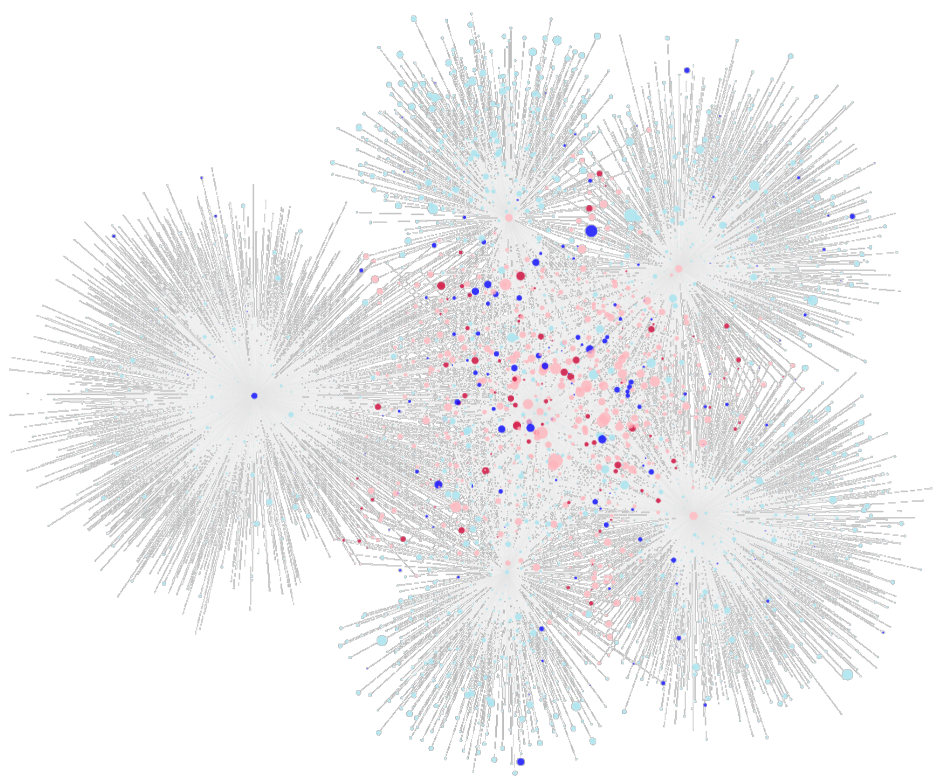

Figure 3
Bank Interconnectedness over Time

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.

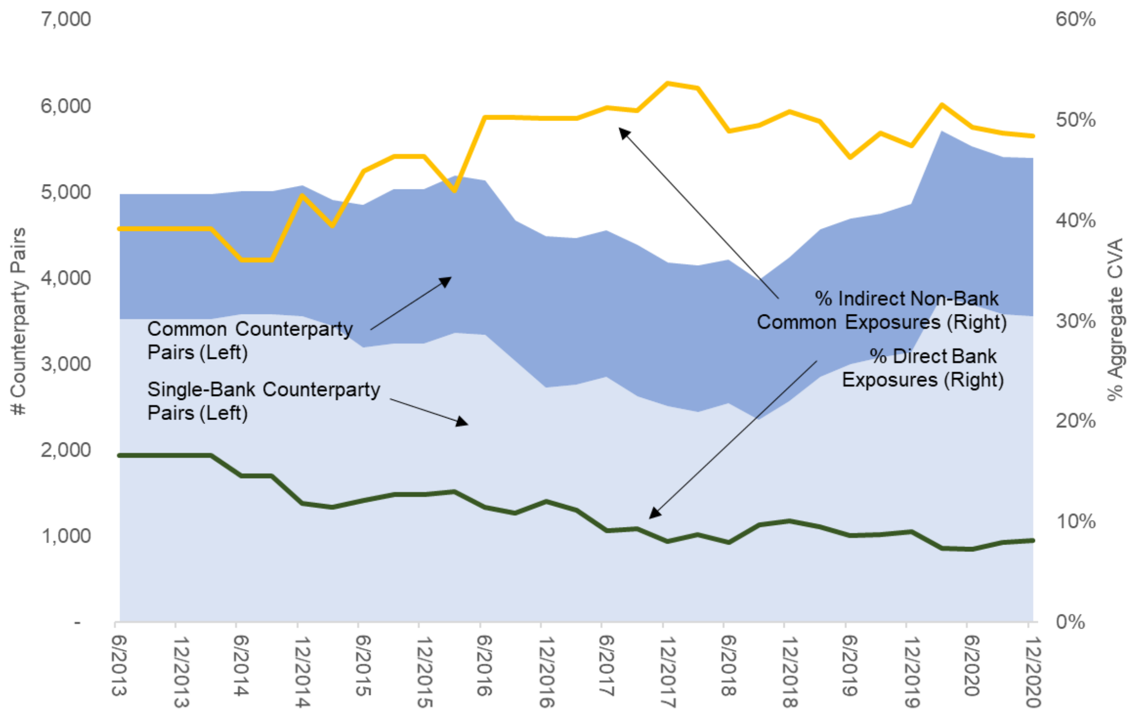

Figure 4
Illustration of *CP Bank Links* and *Total CR Exposure* Measures

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

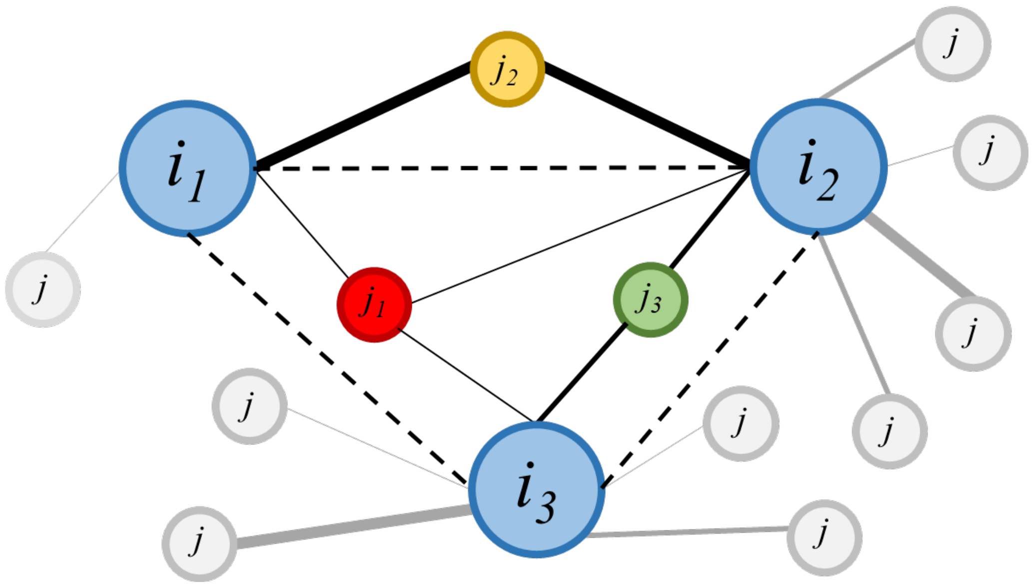

Table 1
Summary Statistics

The table displays summary statistics for the variables used in the analysis. Panel A shows the statistics for the full sample, and Panel B shows the statistics for the sample of existing relationship, i.e. it includes only bank-counterparty pairs that exist as of quarter *t*. Table A.1 provides descriptions of the variables.

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
Collateral	526,695	0.011	0.098	0.000	0.000	0.000
%NetHedge	526,695	-0.006	0.055	0.000	0.000	0.000
WAM	526,695	0.690	2.657	0.000	0.000	0.000
%CCP	526,695	0.033	0.095	0.000	0.000	0.000
ΔGross	526,695	-0.034	0.502	0.000	0.000	0.000
ΔNet	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 Relationships						
	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
Collateral	114,713	1.094	12.426	0.000	0.000	0.000
%NetHedge	114,713	-0.111	0.710	0.000	0.000	0.000
WAM	114,713	3.351	5.528	0.000	0.000	4.618
%CCP	114,713	0.153	0.160	0.008	0.099	0.257
ΔGross	114,713	-0.191	1.038	-0.549	0.000	0.323
ΔNet	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: Bank-Counterparty Connections: Extensive Margin

The table displays regression model results where the dependent variable is *Link,* which measures whether bank *i* is connected to counterparty *j* in quarter *t+1*. 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 the value of one if the bank has a relationship with the counterparty at quarter *t* and zero otherwise. Fixed effects on the bank-year-quarter, counterparty-year-quarter and bank-counterparty levels are included as specified in each column. The control variables measured at quarter *t* included in all the specifications are *CVA*, *NetCE*, *PD*, *Collateral, %NetHedge, WAM,* and *%CCP*, and are described in Table A.1. 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: Interconnectedness (IC) Measure - *CPBankLink*

	(1)	(2)	(3)	(4)	(5)	(6)
IC	0.041***	0.041***	0.040***			
	(0.004)	(0.004)	(0.005)			
Relationship	0.819***	0.712***	0.713***	0.703***	0.708***	0.487***
	(0.016)	(0.038)	(0.028)	(0.034)	(0.025)	(0.040)
IC × Relationship	0.085***	0.031**	0.035***	0.031**	0.040***	0.125***
	(0.009)	(0.014)	(0.010)	(0.015)	(0.010)	(0.017)
Bank × Year × Quarter FEs	NO	NO	YES	NO	YES	YES
CP × Year × Quarter FEs	NO	NO	NO	YES	YES	YES
Bank × CP FEs	NO	NO	NO	NO	NO	YES
Control Variables	NO	YES	YES	YES	YES	YES
N	526,695	526,695	526,695	526,695	526,695	510,069
R^2	77.7%	78.4%	79.5%	82.4%	83.1%	87.5%

Panel B: Interconnectedness (IC) Measure - *TotalCPExposure*						
	(1)	(2)	(3)	(4)	(5)	(6)
IC	0.003***	0.003***	0.003***			
	(0.000)	(0.000)	(0.000)			
Relationship	0.815***	0.781***	0.782***	0.765***	0.772***	0.484***
	(0.016)	(0.044)	(0.031)	(0.039)	(0.028)	(0.036)
IC × Relationship	0.035***	0.035***	0.035***	0.033***	0.034***	0.036***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Bank × Year × Quarter FEs	NO	NO	YES	NO	YES	YES
CP × Year × Quarter FEs	NO	NO	NO	YES	YES	YES
Bank × CP FEs	NO	NO	NO	NO	NO	YES
Control Variables	NO	YES	YES	YES	YES	YES
N	526,695	526,695	526,695	526,695	526,695	510,069
R^2	78.6%	78.9%	80.0%	82.8%	83.5%	87.6%

Panel C: Interconnectedness (IC) Measure - *BankCPOverlap*						
	(1)	(2)	(3)	(4)	(5)	(6)
IC	0.007***	0.007***	0.004			
	(0.003)	(0.003)	(0.006)			
Relationship	0.861***	0.732***	0.733***	0.711***	0.716***	0.522***
	(0.012)	(0.039)	(0.028)	(0.034)	(0.024)	(0.036)
IC × Relationship	0.283***	0.133***	0.137***	0.055*	0.068**	0.157***
	(0.035)	(0.025)	(0.024)	(0.032)	(0.027)	(0.043)
Bank × Year × Quarter FEs	NO	NO	YES	NO	YES	YES
CP × Year × Quarter FEs	NO	NO	NO	YES	YES	YES
Bank × CP FEs	NO	NO	NO	NO	NO	YES
Control Variables	NO	YES	YES	YES	YES	YES
N	526,695	526,695	526,695	526,695	526,695	510,069
R^2	77.6%	78.4%	79.4%	82.4%	83.1%	87.5%

Table 3: Bank-Counterparty Connections: Intensive Margins

The table displays regression model results where the dependent variable is *ΔGrossCE (in columns (1), (4), and (7))*, *ΔNetCE (in columns (2), (5), and (8))*, and *ΔCVA (in columns (3), (6), and (9))* measured over quarter *t+1*. The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link (specifications shown in columns (1)-(3))*, *Total CR Exposure (specifications shown in columns (4)-(6))*, and *Bank CP Overlap (specifications shown in columns (7)-(9))* measured at quarter *t*. *Relationship* is a dummy taking the value of one if the bank has a relationship with the counterparty at quarter *t* and zero otherwise. Fixed effects on the bank-year-quarter, counterparty-year-quarter and bank-counterparty levels are included in all the specifications. The control variables measured at quarter *t* included in all the models are *CVA*, *NetCE*, *PD*, *Collateral, %NetHedge, WAM,* and *%CCP*, and are described in Table A.1. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IC Measure:	*CPBankLink*			*TotalCPExposure*			*BankCPOverlap*		
Dependent Variable:	*ΔGross*	*ΔNet*	*ΔCVA*	*ΔGross*	*ΔNet*	*ΔCVA*	*ΔGross*	*ΔNet*	*ΔCVA*
IC							0.075	-0.008	-0.025
							(0.073)	(0.077)	(0.028)
Relationship	0.252***	-0.118**	0.082***	0.213***	-0.149***	0.076***	0.347***	-0.041	0.108***
	(0.038)	(0.048)	(0.017)	(0.021)	(0.036)	(0.009)	(0.012)	(0.071)	(0.017)
IC × Relationship	0.312***	0.270***	0.091***	0.125***	0.105***	0.030***	0.452***	0.348***	0.134***
	(0.037)	(0.044)	(0.017)	(0.016)	(0.014)	(0.004)	(0.118)	(0.132)	(0.051)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
CP × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × CP FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	510,069	510,069	510,069	510,069	510,069	510,069	510,069	510,069	510,069
R^2	45.3%	39.1%	48.1%	45.8%	39.4%	48.3%	45.3%	39.0%	48.1%

Table 4: Bank-Counterparty Connections: Material and Non-material Exposures

The table displays regression model results where the dependent variable is *Link* which measures whether bank *i* is connected to counterparty *j* in quarter *t*+1. Each link is classified as either material or not material depending on the regulatory-mandated classification of counterparties. Banks are required to declare as material those counterparties with the largest exposures for a given bank for a particular derivative market in each quarter. Results for material exposures are shown in columns (1), (3) and (5), while those for non-material exposures are shown in columns (2), (4) and (6). The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link (specifications shown in columns (1)-(2))*, *Total CR Exposure (specifications shown in columns (3)-(4))*, and *Bank CP Overlap (specifications shown in columns (5)-(6))* measured at quarter *t*. *Relationship* is a dummy taking the value of one if the bank has a relationship with the counterparty at quarter *t* and zero otherwise. *Stress* is a variable that measures an event that caused market dislocation, the Covid-19 pandemic, and is a dummy variable that takes the value for observations in 2020 and zero otherwise. The control variables measured at quarter *t* included in all the models are *CVA*, *NetCE*, *PD*, *Collateral, %NetHedge, WAM,* and *%CCP*, and are described in Table A.1. Fixed effects on the bank-year-quarter and counterparty-year-quarter levels are included in all the specifications. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
IC Measure:	*CPBankLink*		*TotalCPExposure*		*BankCPOverlap*	
Link Material Exposure:	Yes	No	Yes	No	Yes	No
IC					0.016	-0.025
					(0.010)	(0.018)
Relationship	0.078***	0.611***	0.096***	0.637***	0.092***	0.604***
	(0.010)	(0.044)	(0.009)	(0.047)	(0.010)	(0.042)
IC × Relationship	0.050***	-0.035**	0.014***	0.017***	0.109***	-0.037
	(0.010)	(0.016)	(0.001)	(0.003)	(0.026)	(0.035)
Relationship × Stress	-0.049***	0.033*	-0.040***	0.041**	-0.056***	0.028
	(0.012)	(0.019)	(0.011)	(0.020)	(0.014)	(0.018)
IC × Stress					0.034*	0.014
					(0.018)	(0.030)
IC × Relationship × Stress	0.001	-0.057*	-0.006***	-0.004	-0.119***	-0.050
	(0.024)	(0.033)	(0.002)	(0.007)	(0.046)	(0.078)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
CP × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES
N	327,269	327,269	327,269	327,269	327,269	327,269
R^2	40.9%	72.1%	41.0%	72.2%	40.9%	72.1%

Table 5: Bank's Hedging of Counterparty Exposure

The table displays regression model results where the dependent variable is *%NetHedge*, defined as a bank's counterparty hedging relative to gross exposures measured at quarter *t*. The specifications are for the sample of existing relationship and for exposures classified as material. The sample of existing relationships is formed by bank-counterparty pairs that exist as of quarter *t*, and are shown in columns (1), (3), (4), (6), (7) an (9). The sample of material exposures are bank-counterparty pairs that banks declare as material, being counterparties with the largest exposures for a given bank for a particular derivative market in each quarter. Results for material exposures are shown in columns (2), (5) and (8). The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link (shown in columns (1)-(3))*, *Total CR Exposure (shown in columns (4)-(6))*, and *Bank CP Overlap (shown in columns (7)-(9))* measured at quarter *t*. *Material* is a dummy that takes the value of one if counterparty *j* is in the list of top credit valuation adjustment (CVA) sensitivities for any risk factor for bank *i* during quarter *t* and zero otherwise. The control variables included are *NetCE, CVA, PD, Collateral, WAM, %CCP, and CDSVolume*, and are described in Table A.1. Fixed effects on the bank-year-quarter are included in all the models. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relationship Subsample:	Existing	Material	Existing	Existing	Material	Existing	Existing	Material	Existing
IC Measure:	*CPBankLink*			*TotalCPExposure*			*BankCPOverlap*		
IC	-0.026***	-0.055***	-0.008*	-0.001**	-0.006***	0.001	-0.022***	-0.060***	0.004
	(0.004)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.006)	(0.010)	(0.006)
Material			-0.005***			0.001			-0.027***
			(0.002)			(0.002)			(0.002)
IC × Material			-0.064***			-0.013***			-0.110***
			(0.004)			(0.001)			(0.012)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	71,550	12,843	71,550	71,550	12,843	71,550	71,550	12,843	71,550
R^2	40.8%	44.0%	41.6%	40.4%	43.1%	41.5%	40.4%	43.0%	41.0%

Table 6
Bank Counterparty Net Protection Sellers

The table displays regression model results where the dependent variable is *ProtectionSeller*, which is a dummy variable that takes the value of one if the bank is a net protection seller for the counterparty *j* in quarter *t* and zero otherwise. The specifications are for the sample of existing relationship and for exposures classified as material. The sample of existing relationships is formed by bank-counterparty pairs that exist as of quarter *t*, and are shown in columns (1), (3), (4), (6), (7) an (9). The sample of material exposures are bank-counterparty pairs that banks declare as material, being counterparties with the largest exposures for a given bank for a particular derivative market in each quarter. Results for material exposures are shown in columns (2), (5) and (8). The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link (shown in columns (1)-(3))*, *Total CR Exposure (shown in columns (4)-(6))*, and *Bank CP Overlap (shown in columns (7)-(9))* measured at quarter *t*. *Material* is a dummy that takes the value of one if counterparty *j* is in the list of top credit valuation adjustment (CVA) sensitivities for any risk factor for bank *i* during quarter *t* and zero otherwise. The control variables included are *NetCE, CVA, PD, Collateral, WAM, %CCP, and CDSVolume,* and area described in Table A.1. Fixed effects on the bank-year-quarter are included in all the specifications. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relationship Subsample:	Existing	Material	Existing	Existing	Material	Existing	Existing	Material	Existing
IC Measure:	*CPBankLink*			*TotalCPExposure*			*BankCPOverlap*		
IC	0.098***	0.187***	0.053***	0.012***	0.024***	0.007***	0.126***	0.272***	0.052***
	(0.011)	(0.012)	(0.011)	(0.002)	(0.002)	(0.002)	(0.017)	(0.029)	(0.016)
Material			0.017***			0.002			0.075***
			(0.005)			(0.004)			(0.006)
IC × Material			0.163***			0.034***			0.321***
			(0.009)			(0.002)			(0.030)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	71,550	12,843	71,550	71,550	12,843	71,550	71,550	12,843	71,550
R^2	39.7%	41.0%	40.7%	39.2%	39.3%	40.5%	39.0%	39.1%	39.8%

Table 7: Interconnectedness and Counterparty Risk: Univariate Tests

The table shows univariate test results for the intersection of the measure of *Link,* which measures whether bank *i* is connected to counterparty *j* in quarter *t+1,* and the riskiness of the counterparty measured by its probability of default (PD). The statistics are for different samples grouped based on whether the counterparty interconnectedness measures (IC) and probability of default (PD) are high (low) based on whether the observation is in the top (bottom) sample quartile. The statistics reported are sample means for each grouping less the sample mean of the excluded observations. We report the statistics for the sample of exposures in the case of existing relationships (i.e. continuation of relationships) and non-existing relationships (i.e. establishment of new relationships), and for material and non-material counterparties. The separation into material and non-material counterparties is obtained using data provided by banks which are required to declare as material those counterparties with the largest exposures for a given bank for a particular derivative market in each quarter. Robust standard errors clustered on the bank-year-quarter and counterparty-year-quarter levels are used to calculate test statistics for the differences. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Material Exposures, Existing Relationship			
	Low IC	High IC	High - Low IC
Low PD	-0.045	0.060	0.105***
High PD	-0.069	0.115	0.184***
Diff High - Low PD:			0.079***

Panel B: Material Exposures, Non-existing Relationship			
	Low IC	High IC	High - Low IC
Low PD	-0.003	0.026	0.028***
High PD	-0.002	0.026	0.028***
Diff High - Low PD:			0.000

Panel C: Non-material Exposures, Existing Relationship			
	Low IC	High IC	High - Low IC
Low PD	0.049	0.017	-0.032***
High PD	0.116	-0.007	-0.123
Diff High - Low PD:			-0.091***

Panel D: Non-material Exposures, Non-existing Relationship			
	Low IC	High IC	High - Low IC
Low PD	-0.003	0.018	0.021***
High PD	-0.007	0.011	0.017***
Diff High - Low PD:			-0.004

Table 8: Bank Interconnectedness and Counterparty Risk

The table displays results from various regression model specifications where the dependent variable is *Link,* which measures whether bank *i* is connected to counterparty *j* in quarter *t+1*. The specifications are for the sample of counterparties that are classified as material and non-material. The separation into material and non-material counterparties is obtained using data provided by banks which are required to declare as material those counterparties with the largest exposures for a given bank for a particular derivative market in each quarter. Results for material counterparties are shown in columns (1), (3) and (5), and those for non-material counterparties are shown in columns (2), (4) and (6). The bank interconnectedness measures (IC) used for the analysis are *CP Bank Link (shown in columns (1)-(2))*, *Total CR Exposure (shown in columns (3)-(4))*, and *Bank CP Overlap (shown in columns (5)-(6))* measured at quarter *t*. *Relationship* is a dummy taking the value of one if the bank has a relationship with the counterparty at quarter *t* and zero otherwise. *PD* is the probability of default for counterparty *j* during quarter *t*. *Stress* is a variable that measures an event that caused market dislocation, the Covid-19 pandemic, and is a dummy variable that takes the value for observations in 2020 and zero otherwise. All other variables are described in Table A.1. The control variables measured at quarter *t* included in all the specifications are *CVA*, *NetCE*, *Collateral, %NetHedge, WAM,* and *%CCP*. Fixed effects on the bank-year-quarter and counterparty-year-quarter levels are included in all the models. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
IC Measure:	*CPBankLink*		*TotalCPExposure*		*BankCPOverlap*	
Link Material Exposure:	Yes	No	Yes	No	Yes	No
Relationship	0.079***	0.611***	0.096***	0.637***	0.093***	0.605***
	(0.010)	(0.044)	(0.010)	(0.069)	(0.010)	(0.043)
IC					0.009***	-0.014**
					(0.001)	(0.007)
IC × Relationship	0.052	-0.036***	0.015	0.017	0.117***	-0.045
	(0.048)	(0.004)	(0.126)	(0.846)	(0.027)	(0.037)
Relationship × PD	0.006**	-0.005	0.004	-0.006	0.013***	-0.008
	(0.002)	(0.004)	(0.002)	(0.013)	(0.004)	(0.005)
IC × PD					-0.012**	0.024***
					(0.006)	(0.008)
IC × Relationship × PD	0.032***	-0.029**	0.003***	-0.004*	0.073***	-0.060**
	(0.010)	(0.012)	(0.001)	(0.002)	(0.020)	(0.029)
Relationship × Stress	-0.046***	0.005	-0.038***	0.012	-0.055***	0.000
	(0.012)	(0.019)	(0.011)	(0.453)	(0.015)	(0.016)
IC × Stress	0.000	0.000	-0.038***	0.012	0.037**	-0.008
	(0.000)	(0.000)	(0.011)	(0.453)	(0.016)	(0.034)
IC × Relationship × Stress	-0.004	-0.053	-0.006**	0.004	-0.130***	-0.022
	(0.030)	(0.064)	(0.003)	(0.207)	(0.050)	(0.103)
Relationship × PD × Stress	-0.011	0.037***	-0.007	0.042	-0.016*	0.038***
	(0.006)	(0.008)	(0.006)	(0.139)	(0.008)	(0.008)
IC × PD × Stress					0.017*	-0.013
					(0.010)	(0.015)
IC × Relationship × PD × Stress	-0.029*	0.019	-0.003**	-0.004	-0.070**	0.025
	(0.017)	(0.030)	(0.001)	(0.061)	(0.031)	(0.061)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
CP × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES
N	327,269	327,269	327,269	327,269	327,269	327,269
R^2	40.9%	72.2%	41.1%	72.3%	41.0%	72.2%

Table 9

Systemic Risk and Trading Desk Outcomes

The table displays the results of the regression models where the dependent variables are: the SRISK-to-trading assets ratio (*SRISK*), the marginal expected shortfall *(*MES), the natural log of one plus the trading volume-to-trading asset ratio (*Trading Volume*), and the natural log of one plus the net trading revenue-to-trading asset ratio (*Trading Revenue*) over quarter *t+1*. SRISK and MES are based on methodologies described in Brownlees and Engle (2017) and Acharya et al. (2010), respectively, and are obtained from NYU Stern V-Lab. The main explanatory variable is *%CommonExposure*, which is the fraction of total gross credit valuation adjustment (CVA) associated with counterparties with more than two bank counterparties for bank *i* at quarter *t*. The control variables are measured over quarter *t*, and are 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 bank and year-quarter levels are included in all the models. Robust standard errors are reported in parentheses. The asterisks denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variables:	SRISK	MES	Trading Volume	Trading Revenue
%CommonExposure	0.134***	0.024**	0.013***	0.003**
	(0.029)	(0.011)	(0.002)	(0.001)
Control Variables	YES	YES	YES	YES
Bank FEs	YES	YES	YES	YES
Year-Quarter FEs	YES	YES	YES	YES
N	204	204	188	204
R^2	65.09%	87.70%	90.34%	82.18%

Table 10
Interbank Counterparty Exposures and Excess Volatility Co-movement

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.

	(1)	(2)	(3)	(4)	(5)	(6)
%CommonPairExposure	0.705***	0.741***	0.498***			
	(0.111)	(0.085)	(0.129)			
%CommonPairExposure$^{Non\text{-}Bank\ Financial}$				0.619***		0.588***
				(0.183)		(0.179)
%CommonPairExposure$^{Non\text{-}Financial\ Corporate}$					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 11
Interbank Counterparty Exposures, Systemic Risk and Market Stress

The table displays regression model results where the dependent variable is $\rho^{|IdRet|}$ 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.

	(1)	(2)	(3)	(4)
%CommonPairExposure	0.498***			
	(0.129)			
%CommonPairExposure × VIX	0.004			
	(0.025)			
%CommonPairExposure$^{Non\text{-}Bank\ Financial}$		0.724***		0.691***
		(0.185)		(0.184)
%CommonPairExposure$^{Non\text{-}Bank\ Financial}$ × VIX		0.079**		0.075**
		(0.033)		(0.033)
%CommonPairExposure$^{Non\text{-}Financial\ Corporate}$			0.561***	0.502**
			(0.200)	(0.199)
%CommonPairExposure$^{Non\text{-}Financial\ Corporate}$ × VIX			-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 A.1
Variable Names and Descriptions

This table displays the names and descriptions of variables used in the analysis.

Variable Name	Variable Description
Relationship	A dummy that takes the value of one if bank *i* has a relationship with counterparty j during quarter *t* and zero otherwise.
Material	A dummy that takes the value of one if counterparty *j* is in the list of top credit valuation adjustment (CVA) sensitivities for any risk factor for bank *i* during quarter *t* and zero otherwise.
CP Bank Link (not logged)	The total number of unique bank linkages to counterparty *j* during quarter *t* and zero otherwise.
Multiple Bank	A dummy that takes the value of one if the number of unique bank linkages to counterparty *j* during quarter *t* is greater than one, and zero otherwise.
Total CR Exposure	The total gross net credit exposure of counterparty *j* across all banks during quarter *t*.
Bank CP Overlap	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	The gross credit exposure for bank *i* of counterparty *j* during quarter *t*.
Net CE	The net credit exposure for bank *i* of counterparty *j* during quarter *t*.
CVA	The gross credit valuation adjustment for bank *i* of counterparty *j* during quarter *t*.
PD	The default probability of counterparty *j* during quarter *t*.
Collateral	The natural log of the collateral divided by gross notional across all contracts between counterparty *j* and bank *i* during quarter *t*.
%NetHedge	The hedging quantity divided by gross notional for counterparty *j* and bank *i* during quarter *t*.
WAM	The natural log of the weighted average maturity across all contracts between counterparty *j* and bank *i* during quarter *t*.
%CCP	The ratio of net credit exposure of CCP positions relative to total positions for counterparties of the same internal rating at bank *i* during quarter *t*.
ΔGross	The change in *Gross CE* between quarters *t* and *t+1*.
ΔNet	The change in *Net CE* between quarters *t* and *t+1*.
ΔCVA	The change in *CVA* between quarters *t* and *t+1*.

Table A.2
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*, *NetCE*, *PD*, *Collateral, %NetHedge, WAM,* and *%CCP*, and are described in Table A.1. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TotalCPExposure IC Specification:	Gross CE				CVA			
Dependent Variable:	*Link*	*ΔGross*	*ΔNet*	*ΔCVA*	*Link*	*ΔGross*	*ΔNet*	*ΔCVA*
Relationship	0.471***	0.207***	-0.125***	0.069***	0.476***	0.219***	-0.166***	0.063***
	(0.037)	(0.042)	(0.039)	(0.009)	(0.036)	(0.042)	(0.037)	(0.010)
IC × Relationship	0.034***	0.087***	0.051***	0.025***	0.059***	0.154***	0.163***	0.059***
	(0.003)	(0.010)	(0.014)	(0.003)	(0.005)	(0.015)	(0.019)	(0.007)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES
CP × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES
Bank × CP FEs	YES	YES	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
N	510,069	510,069	510,069	510,069	510,069	510,069	510,069	510,069
R^2	87.6%	45.5%	39.1%	48.3%	87.6%	45.6%	39.4%	48.6%

Table A.3
Interconnectedness and Non-bank Financial and Non-financial Corporate Counterparties

The table displays regression model results by counterparty type where the dependent variable is *Link* which measures whether bank *i* is connected to counterparty *j* in quarter *t*+1. Each link is classified as either material or not material depending on the regulatory-mandated classification of counterparties. Banks are required to declare as material those counterparties with the largest exposures for a given bank for a particular derivative market in each quarter. 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 measured at quarter *t* included in all the models are *CVA*, *NetCE*, *PD*, *Collateral, %NetHedge, WAM,* and *%CCP*, and are described in Table A.1. 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: Non-Bank Financial Counterparties						
	(1)	(2)	(3)	(4)	(5)	(6)
IC Measure:	*CPBankLink*		*TotalCPExposure*		*BankCPOverlap*	
Link Material Exposure:	Yes	No	Yes	No	Yes	No
Relationship	0.020**	0.619***	0.033***	0.693***	0.028***	0.631***
	(0.009)	(0.055)	(0.009)	(0.057)	(0.010)	(0.054)
IC					0.021	-0.017***
					(1.006)	(0.006)
IC × Relationship	0.022***	0.034***	0.009	0.033	0.062*	0.083*
	(0.007)	(0.005)	(0.217)	(0.339)	(0.032)	(0.044)
Relationship × PD	0.008**	0.000	0.006*	-0.005	0.015**	-0.006
	(0.003)	(0.007)	(0.003)	(0.006)	(0.007)	(0.009)
IC × PD					-0.009	0.023*
					(0.009)	(0.013)
IC × Relationship × PD	0.061***	-0.071***	0.003***	-0.004	0.089**	-0.091*
	(0.016)	(0.020)	(0.001)	(0.002)	(0.038)	(0.049)
Relationship × Stress	-0.053***	-0.001	-0.055***	0.019	-0.062***	-0.002
	(0.012)	(0.023)	(0.013)	(0.020)	(0.014)	(0.021)
IC × Stress	0.000	0.000	-0.055***	0.019	0.061**	-0.035
	(0.000)	(0.000)	(0.013)	(0.020)	(0.024)	(0.048)
IC × Relationship × Stress	-0.069	0.019	-0.011***	0.014**	-0.144*	0.046
	(0.045)	(0.052)	(0.003)	(0.006)	(0.074)	(0.108)
Relationship × PD × Stress	-0.006	0.051***	-0.004	0.050***	-0.014	0.047***
	(0.006)	(0.009)	(0.006)	(0.008)	(0.009)	(0.012)
IC × PD × Stress					0.013	0.001
					(0.016)	(0.023)
IC × Relationship × PD × Stress	-0.056**	0.030	-0.002	-0.012***	-0.091*	-0.016
	(0.027)	(0.031)	(0.002)	(0.003)	(0.052)	(0.072)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
CP × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES
N	77,486	77,486	77,486	77,486	77,486	77,486
R^2	39.6%	69.8%	39.7%	70.3%	39.6%	69.8%

Panel B: Non-Financial Corporate Counterparties						
	(1)	(2)	(3)	(4)	(5)	(6)
IC Measure:	*CPBankLink*$_{j,t}$		*TotalCPExposure*$_{j,t}$		*BankCPOverlap*$_{i,j,t}$	
Link Material Exposure:	Yes	No	Yes	No	Yes	No
Relationship	0.123***	0.580***	0.139***	0.595***	0.141***	0.564***
	(0.044)	(0.197)	(0.034)	(0.209)	(0.037)	(0.178)
IC					0.013	-0.006
					(0.043)	(0.220)
IC × Relationship	0.095	-0.105	0.017	0.011	0.154	-0.135
	(0.085)	(0.195)	(0.042)	(0.041)	(0.171)	(0.482)
Relationship × PD	0.002	-0.005	0.002	-0.008	0.007	-0.006
	(0.005)	(0.025)	(0.005)	(0.038)	(0.008)	(0.008)
IC × PD					-0.015	0.022
					(0.020)	(0.058)
IC × Relationship × PD	0.001	0.009	0.003	-0.002	0.050	-0.025
	(0.017)	(0.082)	(0.005)	(0.014)	(0.081)	(0.247)
Relationship × Stress	-0.044	0.007	-0.034	0.014	-0.059	0.011
	(0.125)	(0.239)	(0.119)	(0.271)	(0.152)	(0.193)
IC × Stress	0.000	0.000	-0.034	0.014	0.025	-0.007
	(0.000)	(0.000)	(0.119)	(0.271)	(0.141)	(0.265)
IC × Relationship × Stress	-0.015	-0.028	-0.005	0.006	-0.165	0.045
	(0.334)	(0.317)	(0.033)	(0.041)	(0.497)	(0.695)
Relationship × PD × Stress	-0.007	0.030	-0.006	0.035	-0.009	0.030
	(0.060)	(0.139)	(0.053)	(0.150)	(0.074)	(0.123)
IC × PD × Stress					0.019	-0.020
					(0.012)	(0.085)
IC × Relationship × PD × Stress	0.005	-0.003	-0.002	-0.003	-0.037	0.015
	(0.129)	(0.117)	(0.016)	(0.030)	(0.155)	(0.299)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
CP × Year × Quarter FEs	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES
N	203,419	203,419	203,419	203,419	203,419	203,419
R^2	41.6%	73.4%	41.7%	73.4%	41.6%	73.4%

Table A.4
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*, *NetCE*, *PD*, *Collateral, %NetHedge, WAM,* and *%CCP*, and are described in Table A.1. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IC Measure:	*CPBankLink*				*TotalCPExposure*				*BankCPOverlap*			
Dependent Variable:	*Link*	*ΔGross*	*ΔNet*	*ΔCVA*	*Link*	*ΔGross*	*ΔNet*	*ΔCVA*	*Link*	*ΔGross*	*ΔNet*	*ΔCVA*
IC									-0.026	0.139**	-0.115*	-0.034
									(0.018)	(0.066)	(0.069)	(0.025)
Relationship	0.459***	0.215***	-0.285***	0.071***	0.494***	0.270***	-0.239***	0.089***	0.506***	0.298***	-0.221***	0.097***
	(0.026)	(0.030)	(0.080)	(0.016)	(0.016)	(0.022)	(0.013)	(0.010)	(0.042)	(0.016)	(0.009)	(0.006)
IC × Relationship	0.147***	0.227***	0.194***	0.078***	0.044***	0.119***	0.078***	0.027***	0.229***	0.450***	0.379***	0.163***
	(0.023)	(0.052)	(0.056)	(0.021)	(0.005)	(0.016)	(0.013)	(0.004)	(0.044)	(0.114)	(0.119)	(0.044)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
CP × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × CP FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	109,396	109,396	109,396	109,396	109,396	109,396	109,396	109,396	109,396	109,396	109,396	109,396
R^2	86.1%	48.6%	36.5%	49.7%	86.2%	49.3%	36.8%	50.0%	86.0%	48.7%	36.5%	49.7%

Table A.5
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*, *NetCE*, *PD*, *Collateral, %NetHedge, WAM,* and *%CCP*, and are described in Table A.1. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IC Measure:	*CPBankLink*				*TotalCPExposure*				*BankCPOverlap*			
Dependent Variable:	*Link*	*ΔGross*	*ΔNet*	*ΔCVA*	*Link*	*ΔGross*	*ΔNet*	*ΔCVA*	*Link*	*ΔGross*	*ΔNet*	*ΔCVA*
IC									-0.013	0.019	-0.010	-0.040
									(0.018)	(0.083)	(0.085)	(0.031)
Relationship	0.479***	0.183***	0.076*	0.087***	0.461***	0.104***	0.004	0.071***	0.504***	0.264***	0.155**	0.111***
	(0.038)	(0.035)	(0.044)	(0.012)	(0.036)	(0.032)	(0.036)	(0.016)	(0.013)	(0.002)	(0.072)	(0.008)
IC × Relationship	0.099***	0.299***	0.298***	0.092***	0.031***	0.114***	0.109***	0.028***	0.124***	0.404***	0.395***	0.152***
	(0.024)	(0.049)	(0.051)	(0.018)	(0.005)	(0.016)	(0.015)	(0.004)	(0.047)	(0.143)	(0.151)	(0.056)
Bank × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
CP × Year × Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × CP FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	289,279	289,279	289,279	289,279	289,279	289,279	289,279	289,279	289,279	289,279	289,279	289,279
R^2	88.8%	42.4%	40.9%	46.3%	88.8%	42.7%	41.1%	46.4%	88.8%	42.4%	40.9%	46.3%

Table A.6
Interbank Counterparty Exposures, Systemic Risk, and Market Stress

The table displays regression model results where the dependent variable is $\rho^{|IdRet|}$ 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. *Stress* 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.

	(1)	(2)	(3)	(4)
%CommonPairExposure	0.484***			
	(0.140)			
%CommonPairExposure × Pandemic	0.091			
	(0.368)			
%CommonPairExposure$^{Non\text{-}Bank\ Financial}$		0.585***		0.561***
		(0.192)		(0.189)
%CommonPairExposure$^{Non\text{-}Bank\ Financial}$ × Pandemic		0.544		0.437
		(0.534)		(0.494)
%CommonPairExposure$^{Non\text{-}Financial\ Corporate}$			0.528**	0.485**
			(0.223)	(0.222)
%CommonPairExposure$^{Non\text{-}Financial\ Corporate}$ × Pandemic			-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%