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# Credit risk interconnectedness: What does the market really know?☆

Puriya Abbassi[a,*], Christian Brownlees[b], Christina Hans[b], Natalia Podlich[a]

[a] Deutsche Bundesbank, Wilhelm-Epstein-Str. 14, D-60431 Frankfurt am Main, Germany
[b] Department of Economics and Business, Universitat Pompeu Fabra and Barcelona GSE, Ramon Trias Fargas 25-27, E-08005 Barcelona, Spain

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ABSTRACT

We analyze the relation between market-based credit risk interconnectedness among banks during the crisis and the associated balance sheet linkages via funding and securities holdings. For identification, we use a proprietary dataset that has the funding positions of banks at the bank-to-bank level for 2006–2013 in conjunction with investments of banks at the security level and the credit register from Germany. We find asymmetries both cross-sectionally and over time: when banks face difficulties to raise funding, the interbank lending affects market-based bank interconnectedness. Moreover, banks with investments in securities related to troubled classes have a higher credit risk interconnectedness. Overall, our results suggest that market-based measures of interdependence can serve well as risk monitoring tools in the absence of disaggregated high-frequency bank fundamental data.



## 1. Introduction

The recent financial and sovereign debt crises in Europe have forcefully shown the importance of bank interconnectedness for the stability of the financial system. In order to measure bank interconnectedness empirically, a number of authors have recently put forward network estimation techniques based on market information.[1] There is, however, a challenge in the identification of the propagation channels of financial shocks, as well as the quantification of their relevance. Market-based measures do not allow for disentangling between the transmission of idiosyncratic shocks through the financial system (contagion) and endogenous shocks initiated by excessive risk-taking, rational revisions, or pure panics (Freixas et al., 2015). Any identification of the propagation channels requires granular datasets at disaggregated levels that are not always available, even to supervisors and regulators. Thus, overall it is still unclear if these market information-based measures capture actual bank balance sheet linkages and risks, and, if yes, to which extent. The objective of this study is to shed light onto this question by studying the relationship between market- based measures of credit risk interconnectedness and actual common exposures of banks through their funding and securities holdings (liability-asset structure).

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* Corresponding author.
*E-mail addresses:* puriya.abbassi@bundesbank.de (P. Abbassi), christian.brownlees@upf.edu (C. Brownlees), christina.hans@upf.edu (C. Hans), natalia.podlich@ecb.europa.eu (N. Podlich).

[1] Contributions in this area include the work of Diebold and Yilmaz (2015), Billio et al. (2015), Zhang et al. (2014), Betz et al. (2016), Brownlees et al. (2016).

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On the theoretical front, there is a growing literature that analyzes how balance sheet channels such as interbank lending, loan syndication or asset commonality induce interconnectedness among banks and propagate distress (*inter alia*, research by Freixas et al., 2000; Iyer and Peydró, 2005; Gai et al., 2011; Greenwood et al., 2015; Caballero and Simsek, 2013; Duarte and Eisenbach, 2015; Hale et al., 2016; Suhua et al., 2013). On the empirical side, there is a large literature which focuses on measuring credit risk interconnectedness from market data (Kritzman et al., 2011; Zhang et al., 2014; Barigozzi and Brownlees, 2013; Podlich and Wedow, 2014; Betz et al., 2016). However, it seems unclear why high frequency market data should reflect bank fundamentals (actual balance sheet information), that - at best - are only available annually. To the best of our knowledge, ours is the first study to document that market-based measures of bank interconnectedness reflect actual balance sheet information.

Despite the importance of this link both for policy and macro-finance, its quantification has so far been elusive. This is due to the lack of exploitation of comprehensive balance sheet data, such as detailed wholesale funding relations and individual portfolio compositions. In this work we overcome this hurdle and analyze this question by taking advantage of a unique proprietary dataset of the German banking sector for 2006–2013, which contains data on banks' funding and asset allocations. Our study investigates the link between market-based measurement of bank credit risk interconnectedness stemming from CDS data and underlying balance sheet channels. In particular, our methodology allows us to assess empirically the relevance of the balance sheet channels as drivers of credit risk interdependence. The contribution of this study is two-fold. First, it sheds light on the relative quantitative importance of both direct and indirect channels of interconnectedness for the market's perception of bank credit risk interdependence. Second, by assessing to what extent market- based measures of interconnectedness reflect balance sheet exposures, we evaluate the use of such measures of interdependence as risk monitoring tools in the absence of granular data.

The literature has established a number of direct and indirect channels which can induce interdependence in bank credit risk. In the recent crises, the propagation of distress can be traced back to the way banks managed their liquidity on both sides of the balance sheet. Banks relied heavily on the short-term interbank money market and thus became highly exposed to funding risk, which particularly unraveled in the aftermath of Lehman's failure. But also, the misjudgment of the quality of asset-backed securities and the bias towards fixed-income products issued by periphery euro-area member states made banks particularly vulnerable to the deteriorating market liquidity of the underlying asset. Both the funding and market liquidity risk triggered a liquidity spiral (Brunnermeier, 2009; Brunnermeier and Pedersen, 2009) with self-enforcing dynamics for a given bank and the banking sector as a whole. This motivates us to construct indices that focus on capturing these channels. The funding side of banks' balance sheets is identified through bilateral exposures in the wholesale funding market, which has become an increasing source of funding risk with banks' increased reliance on short-term funds. Asset allocations are decomposed into banks' securities investments and loans granted to the real economy. Note that interbank exposures are an example of a direct channel, whereas the latter two are indirect balance sheet channels of interconnectedness.

We measure market-based interconnectedness between banks using idiosyncratic partial correlations, which are a natural choice for our analysis. The idiosyncratic partial correlation between two banks is defined as their correlation after netting out the influence of (i) common systematic factors and (ii) all remaining entities in the panel. While simple correlation between two banks might be spurious and could be driven by common dependence with a third party, partial correlation does not suffer from this drawback as it nets out the influence of all remaining entities. In order to focus on credit risk dependence, we construct our partial correlation index based on banks' idiosyncratic default intensities implied by CDS prices, building upon (Ang and Longstaff, 2013; Brownlees et al., 2016). For simplicity, we call our market–based measure of bank interconnectedness based on idiosyncratic partial correlations simply as realized interconnectedness.

Two main results emerge from the analysis. First, we find that realized interconnectedness strongly reflects both direct (wholesale funding market) and indirect channels (securities management and credit supply) and is influenced by banks' liquidity management on both sides of the balance sheet. On the funding side, we find that bank pairs in the case of which both counterparties have higher Tier 1 capital-weighted interbank exposure show higher realized interconnectedness. On the asset allocation side, we document that both banks' exposure to the real economy and their securities investments, have an impact on realized network connections. Bank pairs with more similar lending practices to the real economy show up as more interconnected. Moreover, we find higher realized interconnections among bank pairs with higher exposures to risky securities.

Second, we show that the relation between realized interconnectedness and the balance sheet positions exhibits asymmetries both cross-sectionally and over time. We find that interbank lending is a relevant driver of realized interconnectedness during crisis times. On the asset allocation side, we show that banks' securities investments have asymmetric effects in the cross-section: bank pairs with higher exposures to the troubled security classes show up as more interconnected. On the contrary, commonality in securities investments related to crisis-unaffected security classes does not induce higher dependency.

This work relates mainly to two different strands in the literature. First, it is related to literature on balance sheet channels of bank interconnectedness. Important examples on direct channels such as interbank lending include (Iyer and Peydró, 2005; Dasgupta, 2004; Freixas et al., 2000; Fourel et al., 2013; Memmel and Sachs, 2013; Ippolito et al., 2015). On the relevance of indirect sources of interconnectedness, Allen et al. (2012) as well as Duarte and Eisenbach (2015) are recent examples. Furthermore, Nier et al. (2010) relate bank interconnectedness to bank-specific balance sheet information. Secondly, it is related to empirical papers estimating systemic risk and bank interconnectedness from market data. Contributions in this area include the work of Adrian and Brunnermeier (2016), Acharya et al. (2016), Diebold and Yilmaz (2016, 2015), Zhang et al. (2014), Billio et al. (2015), Betz et al. (2016), Brownlees et al. (2016), Cetina et al. (2016), Constantina et al. (2016).

The remainder of the paper is organized as follows. Section 2 introduces the dataset and variable definitions. Section 3 explains the model and estimation methodology. Section 4 presents empirical results and Section 5 concludes. A detailed description of the network estimation technique we use can be found in Appendix A.

## 2. Data

The sample consists of 78 bilateral bank connections stemming from a database of 13 large German banks between January 2006 and December 2013. The sample of banks included in the analysis is the one of large German banks for which reliable CDS data is available over the entire sample period. Overall, our sample covers nearly 60% of assets of the German banking sector.

We combine different data sources to construct the dataset used in this paper: Markit pricing data on CDS contracts as well as the Deutsche Bundesbank credit register, borrowers statistics, security holdings statistics and banking statistics. From Markit pricing data we obtain daily mid-market spreads for one-year, two-year, three-year, five-year, seven-year and ten-year senior CDS contracts. The sample consists of quotes contributed by more than 30 dealers for all trading days. Markit CDS spread quotes are one of the most widely used sources of CDS data in the literature (Mayordomo et al., 2014).

The Deutsche Bundesbank credit register contains data on large exposures of banks to individual borrowers. The institutions are required to report if their exposures to an individual borrower or the sum of exposures to borrowers belonging to one borrower unit exceeds the threshold of 1.5 million euro. In our analysis, we use interbank loans. The credit register applies a broad definition of loan including traditional loans, bonds, off-balance sheet positions and exposures from derivative positions (excluding trading book positions). The quarterly reporting is pair-wise, such that for each observation we are able to uniquely identify both the borrower and the lender.[2]

The Deutsche Bundesbank borrowers statistics are used to extract banks' domestic lending practices to the German real economy. This is a database to which banks report outstanding loan amounts to all German borrowers itemized across 23 industries on a quarterly basis.

We gather data on bank portfolios from the Deutsche Bundesbank securities holdings statistics, which contain detailed quarterly information on all securities holdings of German banks in terms of volume (i.e. euro total) excluding derivatives. This data is very fine-grained so that we can identify securities at the ISIN level. For the purpose of our analysis, we eliminate those observations from the sample where a bank holds securities for its customers and those observations where the holder is equivalent to the issuer. A major portion of banks' portfolios consists of different types of bonds including floating rate notes, Pfandbriefe (covered bonds), government bonds and other bonds.

Lastly, we collect data on banks' Core Tier 1 ratio, equity, leverage ratio (calculated as total assets over Core Tier 1 capital) and risk-weighted assets from the Deutsche Bundesbank banking statistics.

In carrying out the analysis, we convert all variables to weekly frequency. One of the challenges we are facing is the mixed frequency in the original data: the banking network is computed at daily frequency, while all explanatory variables are only available quarterly. Therefore, we decide to run regressions on a basis of weekly data. For converting the bank credit risk network to weekly frequency, we take the average of the values for all trading days within a week obtained through the rolling analysis, and date them to the respective Friday. In order to increase the frequency of the explanatory variables to weekly, we perform one-dimensional linear interpolation separately for each bank pair.

We carry out the analysis both in a baseline specification over the full sample period and an extended specification with subsample-specific coefficients. For the extended specification we consider four subperiods in line with important macroeconomic and financial events. We define a pre-crisis period to run from the beginning of our sample until July 31st, 2008. This period length is chosen such that it ends roughly six weeks before the failure of investment bank Lehman Brothers, in order to take out any anticipation effects from the sample. The banking crisis period is defined to run from August 1st, 2008 until March 31st, 2010, so that it ends with the Greek claim to a sovereign bailout scheme by the IMF on April 10th, 2010. The sovereign debt crisis period runs accordingly from April 1st, 2010 until August 31st, 2012. Its end is assumed to be the announcement of Outright Monetary Transactions by the ECB on September 6th, 2012. The last period, which we carefully dub "post-crisis" then runs from September 1st, 2012 until the end of our sample.

[2] Since a typical interbank loan is relatively large, we think that the threshold of 1.5 million euro does not cause a bias.

**Table 1**
Summary statistics of bank CDS spreads.

| | Mean | Std. dev. | Min. | Median | Max. |
|---|---|---|---|---|---|
| Bank A | 66.77 | 42.42 | 5.93 | 69.27 | 192.08 |
| Bank B | 100.81 | 72.15 | 5.62 | 103.5 | 346.07 |
| Bank C | 104.84 | 84.5 | 7.97 | 84.54 | 364.12 |
| Bank D | 89.36 | 59.55 | 8.92 | 92.51 | 317.8 |
| Bank E | 89.91 | 49.04 | 10.25 | 103.31 | 189.63 |
| Bank F | 69.97 | 41.72 | 7.92 | 69.9 | 155.8 |
| Bank G | 154.29 | 104.35 | 7 | 167.16 | 445.19 |
| Bank H | 102.79 | 64.47 | 7.29 | 119.19 | 259.97 |
| Bank I | 120.65 | 87.98 | 5.69 | 112.95 | 361.54 |
| Bank J | 101.39 | 71.38 | 5.91 | 113.06 | 355.33 |
| Bank K | 103.21 | 69.45 | 5.95 | 116.33 | 302.56 |
| Bank L | 48.55 | 26.04 | 5.63 | 50.93 | 125.64 |
| Bank M | 99.38 | 68.91 | 5.77 | 109.97 | 334.66 |

This table shows summary statistics for daily mid-market CDS spreads with 5-year maturity for all banks in the sample. Spreads are denoted in basis points.

### 2.1. Variable definitions

#### 2.1.1. Realized bank interconnectedness

In this work we define interconnectedness among banks on the basis of standard reduced form credit risk models used in the finance literature. More precisely, we draw upon the Ang and Longstaff (2013) credit risk model. In this model the default intensity of a financial entity is decomposed into a common systematic factor and an entity-specific idiosyncratic component. We associate interconnectedness between banks with the partial correlation among those idiosyncratic intensity components. In this context, partial correlation measures linear dependence between two banks conditional on all other institutions in the panel, and thus captures pair-wise relations and is not affected by spurious effects.

We make use of CDS data to back out partial correlations implied by market prices. We provide a detailed description of the estimation approach in Appendix A and summarize here the main steps here. First, we identify the systematic default intensity as that of the German sovereign. Making use of the full term structure of CDS prices and corresponding risk-neutral rates, we apply a standard bootstrapping algorithm to obtain instantaneous default intensity for all banks in the sample as well as the German sovereign, which we denote respectively as $\lambda_{it}$ and $\lambda_{ft}$. We obtain idiosyncratic default intensities for each bank as the residuals of the regression of the bank default intensity $\lambda_{it}$ on the systematic default intensity $\lambda_{ft}$ (in first differences). Finally, we estimate partial correlation among the idiosyncratic intensities as the residuals of the first step. We call this realized interconnectedness and denote it $\rho_{ij}$.

Partial correlations are estimated daily on a rolling basis. The window length used throughout the paper amounts to 500 trading days, roughly equaling 2 years of data. The partial correlation obtained from the rolling procedures are denoted by $\rho_{ijt}$.

Table 1 summarizes CDS spreads for all banks in the sample, from which we back out individual instantaneous default intensities. Fig. 1 shows the term structure of sovereign CDS spreads for Germany, which we use to identify the systematic default intensity. Fig. 2 shows the risk-neutral default intensity for the German sovereign resulting from the bootstrapping procedure.

#### 2.1.2. Interbank exposure

We construct an interbank exposure index using interbank lending data from the Deutsche Bundesbank credit register. As

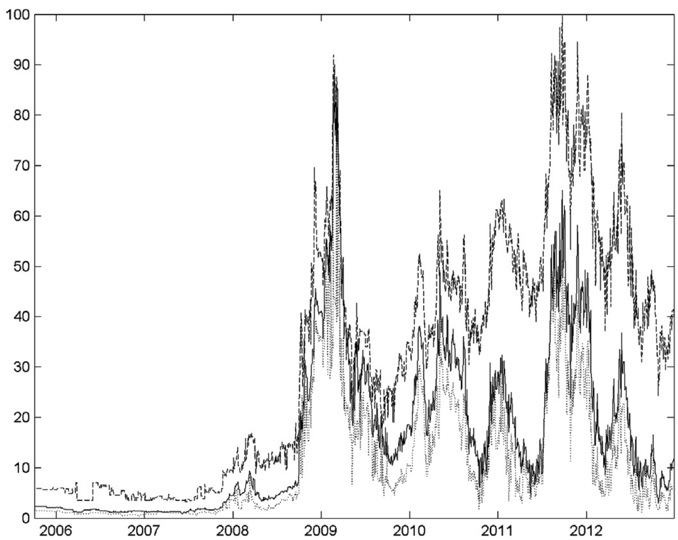


**Fig. 1.** Term structure of 1-year, 5-year and 10-year CDS spreads for German sovereign. This figure shows term structure for daily mid-market CDS spreads with 1-year *(dotted lines)*, 5-year *(solid lines)* and 10 -year *(dashed lines)* maturity for German sovereign. Spreads are denoted in basis points.

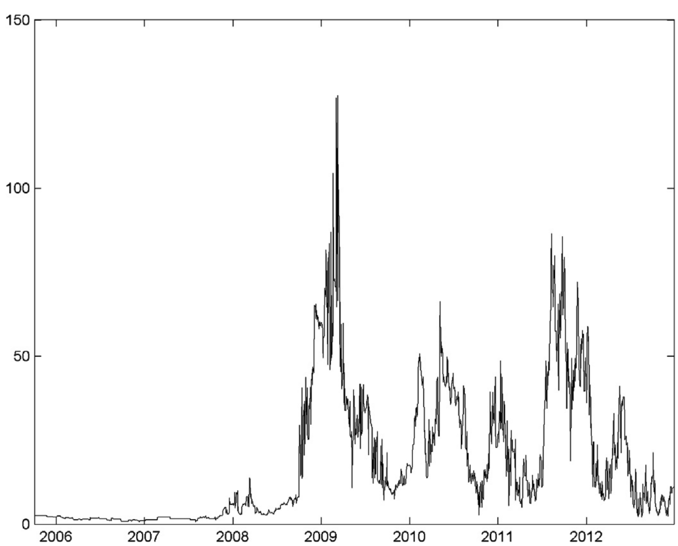


**Fig. 2.** CDS-implied default intensity of German sovereign. This figure shows the default intensity for German sovereign bootstrapped from 1-year, 3-year, 5-year, 7-year and 10-year CDS spreads and corresponding risk- neutral rates. The intensity is denoted in basis points.

suggested in, for example, e.g. Upper (2011) we calculate interbank lending over capital as

$$IB_{ijt} = \frac{1}{2}\left(\frac{IBL_{i\to jt}}{CT1cap_{it}} + \frac{IBL_{j\to it}}{CT1cap_{jt}}\right)$$

where $IBL_{i\to jt}$ denotes the amount of interbank lending from bank $i$ to bank $j$ at time $t$ and $CT1cap_{it}$ is the Core Tier 1 capital of bank $i$ at time $t$. We take the average of both interbank positions weighted by capital since, in case of a default on interbank positions, both sides are affected, for the lender the position constitutes a credit risk which can potentially wipe out part of his capital in case of default. For the borrower, however, this constitutes a funding risk: in case of default the corresponding position has to be substituted by another interbank relation.

### 2.1.3. Similarity in lending practice

The second channel assessed in this paper is similarity in lending practices of two banks. For obtaining a measure of pair-wise distance, we rely on the methodology proposed in Cai et al. (2016). Their measure is constructed in such a way that a lower distance between two banks implies greater similarity in terms of their lending portfolios. Categories in the lending register are defined along two dimensions: borrower type and loan type. We compute portfolio weights for each bank according to the defined categories.[3] Denote by $w_{ilt}$ the relative portfolio weight of bank $i$ in loan category $l$ at time $t$. Let $L$ be the total number of loan categories defined, and notice that for bank $i$ we have that $\sum_{l=1}^{L} w_{ilt} = 1$ at each time $t$. Then the distance between two banks $i$ and $j$ at time $t$ is defined as

$$LD_{ijt} = \sqrt{\sum_{l=1}^{L} (w_{ilt} - w_{jlt})^2}$$

For interpretation purposes, we standardize the distance variable to be between 0 and 1, where 0 refers to the lowest distance between two banks in our sample.

### 2.1.4. Commonality in securities investments

Next we construct an index measuring commonality in securities investments on the basis of the Deutsche Bundesbank securities holdings register. We decompose commonality into "safe" and "troubled" security classes. We consider securities issued in Germany as safe and, because of the time period of this analysis, securities issued in Greece, Ireland, Italy, Portugal and Spain as troubled. We define safe exposures for the $(i, j)$th pair at time $t$ as

$$SE_{ijt} = \log(D_{it})\log(D_{jt}).$$

where $D_{it}$ denotes the total monetary value of bank $i$'s exposures to securities issued in Germany at time $t$, and analogously troubled exposures as

$$TE_{ijt} = \log(GIIPS_{it})\log(GIIPS_{jt}).$$

where $GIIPS_{ijt}$ is the sum of bank $i$'s exposures to Greece, Ireland, Italy, Portugal and Spain at time $t$. In the case that at least one of the counterparties does not have any exposures to said securities, this value is replaced by zero. This specification allows us to relate the impact of commonality in securities investments to specific security classes over different time periods for each bank pair.

## 3. Methodology

We use a regression framework to analyze the relation between realized interconnectedness and the balance sheet channels. In particular, we regress partial correlations on indices capturing the various balance sheet channels, together with a set of controls and fixed effects. The peculiarity of our regression exercise is that the data has a paired structure. This type of regression often appears in social network or trade flows analysis and is commonly referred to as "dyadic regression" (cf Krackhardt, 1988). Inference on the dyadic regression model parameters is carried out here by standard OLS while computation of the robust standard errors requires

[3] Examples of borrower types distinguished in the database are enterprises and self-employed private individuals or salaried individuals and other private individuals. Loans granted to the enterprises and self-employed individuals category are then further distinguished into industries such as agriculture, forestry, fishery and aquaculture or wholesale, retail trade and repair of motor vehicles and motorcycles. Loan types include, e.g. acceptance credit and credit for housing construction.

**Table 2**
Summary statistics of bank balance sheet data.

| | Mean | Std. dev. | 10% quantile | Median | 90% quantile |
|---|---|---|---|---|---|
| Core Tier 1 Capital Ratio | 9.54 | 2.57 | 6.28 | 9.19 | 12.94 |
| Core Tier 1 Capital | 12005.19 | 2313.97 | 8614.27 | 13448.45 | 14914.86 |
| Equity | 16256.97 | 2100.42 | 13519.12 | 17045.22 | 19006.38 |
| Risk-weighted Assets | 127140.59 | 23959.46 | 97678.19 | 135479.37 | 158233.81 |
| Leverage Ratio | 36.51 | 5.75 | 29.46 | 37.05 | 44.42 |

This table shows summary statistics for variables used as controls in different regression equations: Core Tier 1 Capital Ratio, Core Tier 1 Capital, Equity, Risk-weighted Assets and Leverage Ratio (calculated as total assets over Core Tier 1 capital). Core Tier 1 Capital Ratio is denoted in percent, whereas Core Tier 1 Capital, Equity and Risk-Weighted Assets are denoted in million Euros.

appropriate clustering that takes into account the special correlation structure of the model.

More precisely, we consider the dyadic regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 IB_{ijt} + \beta_2 LD_{ijt} + \beta_3 TE_{ijt} + \beta_4 SE_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}, \quad (1)$$

where $IB_{ijt}$ denotes the interbank exposure, $LD_{ijt}$ is the measure of distance in lending practice, and $TE_{ijt}$ and $SE_{ijt}$ correspond to pairwise security class exposures, respectively. To account for time and cross-sectional heterogeneity, we include both bank-fixed effects $\alpha_i$, $\alpha_j$ and time-fixed effects $\alpha_t$. The vector $z_{ij,t-1}$ contains control variables. Controls are constructed as the pairwise product of a set of bank characteristics: (log) banks' equity, (log) risk-weighted assets, Core Tier 1 capital ratio and the leverage ratio total book equity over total book assets plus off-balance sheet exposures. In the analysis, control variables are lagged by one period. Table 2 contains summary statistics of the variables used to construct the controls. Because of the dyadic structure of the panel in our model, the error term is correlated across observations that have an element in common. More specifically, the error term is assumed to be zero mean, uncorrelated with the explanatory variables, and have nonzero correlation only with the errors which either have $i$ and $j$ in common, that is,

$$\mathrm{E}(\epsilon_{ijt}\epsilon_{klt}|x_{ijt}, x_{klt}) = 0 \quad \text{unless} \quad i = k \text{ or } i = l \text{ or } j = k \text{ or } j = l,$$

where $x_{ijt}$ denotes a vector containing the regressors of Eq. (1). In order to take into account the correlation pattern of the dyadic regression, standard errors are clustered along both dimensions of the pair.

In order to capture sub-sample-specific effects, we also consider a variation of the baseline model in (1) in which we interact the channels with indicator variables for the different subsample periods. This specification allows the various balance sheet channels to have different impacts in each phase of the crisis. For instance, for the interbank lending channel we consider the specification

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 IB_{ijt}\mathbf{1}_{pre} + \beta_2 IB_{ijt}\mathbf{1}_{ban} + \beta_3 IB_{ijt}\mathbf{1}_{sov} + \beta_4 IB_{ijt}\mathbf{1}_{post} + \gamma' z_{ij,t-1} + \epsilon_{ijt}, \quad (2)$$

where $\mathbf{1}_{pre}$, $\mathbf{1}_{ban}$, $\mathbf{1}_{sov}$ and $\mathbf{1}_{post}$ are dummy variables equal to 1 if the observation lies within the defined subsample period, and 0 otherwise. We define analogously the interacted specifications for $LD_{ijt}$, $SE_{ijt}$ and $TE_{ijt}$.

## 4. Empirical results

### 4.1. Baseline specification

We begin by estimating the baseline dyadic regression model of Eq. (1) introduced in the previous section. We consider different variants of the specification. Table 3 contains the regression results.

The first channel we investigate are bilateral exposures in the interbank market. We hypothesize that interbank lending between two banks can lead to higher realized interconnectedness in credit risk if and only if the exposure is large relative to the lender's Core Tier 1 capital. Quantile statistics for interbank lending over Core Tier 1 capital are shown in Table 4. In our sample, the average interbank loan between two banks amounts to 0.19% of the lender's Core Tier 1 capital.

Table 3 shows the result for the baseline regression model. We find that higher amounts of interbank exposure between two banks are related to higher realized interconnectedness, given that we include both time and bank-fixed effects. In the first specification which does not control for time, we do not find any significant effect. The magnitude of the coefficient changes only slightly for different variants: with both time- and bank-fixed effects and including a set of control variables, we find that an increase of interbank lending weighted by Core Tier 1 capital by one percentage point is related to a 4.518 percentage point increase in partial correlations.

In order to detect non-linear effects of different magnitudes of interbank lending, we divide the variable into four regions: the 1st region contains values of bilateral interbank lending lower than 0.1% of the lender's Core Tier 1 Capital, which captures approx. the lower 40% of the distribution. The second region contains all values that lie between 0.1 and 0.3% of the lender's Core Tier 1 capital, which captures another 40% of the distribution. The two highest regions divide the remaining 20%, such that region 3 contains all values between 0.3 and 0.4% of the lender's Core Tier 1 capital, and the fourth region contains all values above.[4] Results for the effects of the four different regions of interbank exposures are displayed in Table 5. The specification again includes both time- and bank-fixed effects and the set of control variables.

Table 5 shows that the positive relation between interbank exposures and realized interconnectedness is highly significant in all four regions. In terms of magnitude of the coefficients, the effect is strongest in the lowest region: a percentage point increase in interbank lending weighted by Core Tier 1 capital leads to relatively higher interconnectedness when interbank exposures between the counterparties are initially low.

The second channel we investigate is similarity in lending practice. We hypothesize that two banks with more similar lending practices have a higher common exposure to specific risk factors and should therefore be perceived as more interconnected by the market. Quantile statistics for the distance variable are depicted in Table 4.

Recall that the distance measure is constructed such that a higher value per dyad indicates less similar lending practices to the real economy, hence we expect the coefficient to have a negative sign. Table 3 confirms this hypothesis: two banks with less similar lending practices show lower realized interconnectedness, and the coefficient is significant at the 5% level. An increase of 1 percentage point in lending distance is associated with a decrease in partial correlations of 0.06 percentage points. The magnitude remains largely

[4] Our results are robust to changes in the way we define the regions.

**Table 3**
Variants of baseline regression.

| VARIABLES | (1) | (2) | (3) | (4) | **(5)** | (6) | (7) | (8) | (9) | **(10)** | (11) | (12) | (13) | (14) | **(15)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\boldsymbol{\rho}$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\boldsymbol{\rho}$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\boldsymbol{\rho}$ |
| IB Lending | 3.388 | | | | **3.756**$^{+}$ | 4.161$^{*}$ | | | | **4.759**$^{**}$ | 4.006$^{*}$ | | | | **4.518**$^{**}$ |
| | (2.066) | | | | (1.669) | (2.120) | | | | (1.575) | (2.202) | | | | (1.643) |
| Lend. Distance | | −0.0615$^{*}$ | | | **−0.0626**$^{*}$ | | −0.0631$^{*}$ | | | **−0.0644**$^{*}$ | | −0.0677$^{*}$ | | | **−0.0694**$^{*}$ |
| | | (0.0288) | | | (0.0290) | | (0.0308) | | | (0.0320) | | (0.0283) | | | (0.0290) |
| Troubled Exp. | | | 0.00471$^{***}$ | | **0.00444**$^{+}$ | | | 0.00588$^{***}$ | | **0.00600**$^{***}$ | | | 0.00705$^{***}$ | | **0.00708**$^{***}$ |
| | | | (0.00122) | | (0.00144) | | | (0.00156) | | (0.00166) | | | (0.00125) | | (0.00106) |
| Safe Exp. | | | | −0.00106 | **−0.000315** | | | | −0.00146 | **−0.00136** | | | | −0.00108 | **−0.00112** |
| | | | | (0.00411) | (0.00396) | | | | (0.00406) | (0.00383) | | | | (0.00377) | (0.00325) |
| Number of Banks | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 |
| Observations | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 |
| Adj. $R$-squared | 0.141 | 0.145 | 0.141 | 0.137 | 0.153 | 0.148 | 0.151 | 0.149 | 0.143 | 0.164 | 0.154 | 0.158 | 0.156 | 0.149 | 0.171 |
| Control Variables | No | No | No | No | No | No | No | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | No | No | No | No | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Two-way cluster robust standard errors in parenthesis.
This table shows coefficient estimates and standard errors for different variants of the baseline regression model

$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 IB_{ijt} + \beta_2 LD_{ijt} + \beta_3 TE_{ijt} + \beta_4 SE_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$

Rho denotes the idiosyncratic partial correlation between two banks implied by CDS prices. Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. Troubled Exposures and Safe Exposures refer to the product of two banks' log exposures to assets issued in GIIPS countries and Germany, respectively. Standard errors are based on two-dimensional clustering along both banks contained in the dyad.

$^{+}$ $p$<0.10.
$^{*}$ $p$<0.05.
$^{**}$ $p$<0.01.
$^{***}$ $p$<0.001.

unchanged and significance increases when enhancing the specification with both bank fixed effects and control variables.

For detecting non-linear effects in the cross-section, we again divide the variable into four different regions. Since there is no intuitive interpretation of specific values, we make use of quartiles for determining cutoff points. Results are depicted in Table 6.

The negative relation between distance in lending practice and realized interconnectedness is highly significant at any value of the distance variable. The magnitude of the coefficient varies strongly in the cross-section and is highest when the distance between two banks is very small: within the lowest quartile, a percentage point decrease in the lending distance between two banks is associated with a 0.4 percentage point increase in partial correlations.

The third channel we investigate are common exposures to similar securities. Recall that, as explained in section 2.1.4, we decompose pair-wise common securities holdings into two different categories: "troubled exposures" proxied by securities issued in one of the GIIPS countries, and "safe exposures" proxied by securities issued in Germany. We hypothesize that two banks with higher common exposures should have higher credit risk interconnectedness. Disentangling the "troubled" and the "safe" securities allows us to additionally investigate whether those have different effects on realized interconnectedness. Quantile statistics for exposures to Germany and the GIIPS countries are shown in Table 4.

Again, results for the relation between commonality in securities investments and results interconnectedness are depicted in Table 3. Results confirm our hypothesis: two banks with higher exposures to securities issued in one of the GIIPS countries are perceived as more interconnected by the market, and this effect is significant at the 1% level. Note that the commonality variable is calculated as a pair-wise log: a percentage increase in exposures to the GIIPS countries for one of the banks is associated with a 0.444 percentage point increase in partial correlations in the first variant, keeping exposures of the counterparty stable. This coefficient increases slightly in magnitude when adding control variables and time fixed effects and significance increases. We do not find any significant effect for exposures to securities issues in Germany. We conclude that the market perceives stronger links between banks with higher common holdings given that these are related to troubled exposures.

Last, we divide exposures to securities issued in one of the GIIPS countries into four different regions again defined by quartiles, and let coefficients vary among those. Results are shown in Table 7.

The relation between pair-wise holdings of troubled exposures and realized interconnectedness is significant only in the highest quartile: two banks are perceived as more interconnected if and only if their common exposures to troubled security classes are large. Note that the value of zero in the first quartile stems from pairs where at least one bank does not have any exposures to securities issued in one of the GIIPS countries. An increase in securities holdings of GIIPS countries of one of the counterparties by 1 percent is associated with a 0.96 percentage point increase in partial correlation.

While two-way clustering along both dimensions in the pair is a natural approach to the peculiar correlation structure of our model, we acknowledge that the small number of clusters ($K$ = 13) might lead to an over-rejection of the null hypothesis in some cases. Thus, we run the third variant of the baseline regression with both bank- and time fixed effects as well as a set of control variables with two different kinds of standard errors: Huber–White standard errors and cluster-robust standard errors with clusters at the pair level. For comparison purposes, we report again the results of this regression with standard errors clustered along both dimensions of the dyad. Results for these specifications are displayed in Table 8.

We can see that Hubert–White standard errors are considerably smaller for all variables, whereas standard errors increase slightly

**Table 4**
Quantiles statistics.

| Quantile | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Interbank Lending | 0.0499% | 0.0710% | 0.0889% | 0.1077% | 0.1432% | 0.1612% | 0.2039% | 0.2596% | 0.3949% |
| Lending Distance | 0.051 | 0.095 | 0.144 | 0.194 | 0.247 | 0.312 | 0.379 | 0.445 | 0.552 |
| Security Holdings Germany | 0 | 0 | 0 | 0 | 3.157 | 3.769 | 4.201 | 4.471 | 4.998 |
| Security Holdings GIIPS | 0 | 0 | 0 | 0 | 2.268 | 2.847 | 3.324 | 3.663 | 4.279 |

This table shows quantiles statistics for confidential explanatory variables: Interbank Lending, Lending Distance, Troubled Exposures and Safe Exposures. The value of 0 for the lower quantiles of pair-wise exposures refers to cases in which at least one of the counterparties does not have any exposures to the respective securities.

**Table 5**
Differential effects for regions of Interbank Lending.

| VARIABLES | $\rho$ |
|---|---|
| IB Lending 1st Region | 39.83* |
| | (16.92) |
| IB Lending 2nd Region | 18.16* |
| | (7.942) |
| IB Lending 3rd Region | 20.76*** |
| | (5.701) |
| IB Lending 4th Region | 5.033* |
| | (2.073) |
| Number of Banks | 13 |
| Observations | 20779 |
| Adj. *R*-squared | 0.173 |
| Control Variables | Yes |
| Bank Fixed Effects | Yes |
| Time Fixed Effects | Yes |

Two-way cluster robust standard errors in parenthesis.
This table reports coefficient estimates and standard errors for the regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 IB_{ijt}\mathbf{1}_{IB1} + \beta_2 IB_{ijt}\mathbf{1}_{IB2} + \beta_3 IB_{ijt}\mathbf{1}_{IB3} + \beta_4 IB_{ijt}\mathbf{1}_{IB4} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. The binary variable $\mathbf{1}_{IB1}$ is equal to one if the observation lies in the first region of Interbank Lending as defined in Section 4. $\mathbf{1}_{IB2}$, $\mathbf{1}_{IB3}$ and $\mathbf{1}_{IB4}$ are defined analogously.
+ $p<0.10$.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

**Table 6**
Differential effects for quartiles of Distance in Lending Practice.

| VARIABLES | $\rho$ |
|---|---|
| Lend. Distance 1st Quartile | −0.452*** |
| | (0.136) |
| Lend. Distance 2nd Quartile | −0.219** |
| | (0.0753) |
| Lend. Distance 3rd Quartile | −0.165*** |
| | (0.0379) |
| Lend. Distance 4th Quartile | −0.0991** |
| | (0.0324) |
| Number of Banks | 13 |
| Observations | 20779 |
| Adj. *R*-squared | 0.160 |
| Control Variables | Yes |
| Bank Fixed Effects | Yes |
| Time Fixed Effects | Yes |

Two-way cluster robust standard errors in parenthesis.
This table reports coefficient estimates and standard errors for the regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 LD_{ijt}\mathbf{1}_{LD1} + \beta_2 LD_{ijt}\mathbf{1}_{LD2} + \beta_3 LD_{ijt}\mathbf{1}_{LD3} + \beta_4 LD_{ijt}\mathbf{1}_{LD4} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. The binary variable $\mathbf{1}_{LD1}$ is equal to one if the observation lies in the first quartile of the Lending Distance variable. $\mathbf{1}_{LD2}$, $\mathbf{1}_{LD3}$ and $\mathbf{1}_{LD4}$ are defined analogously.
+ $p<0.10$.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

when clustering at the pair level. Using simple Hubert–White standard errors should lead to overly small standard errors and narrow confidence intervals and hence overestimate the significance of the coefficients. On the other hand, clustering at the pair level underestimates the correlation structure of the model, since we do not allow for standard errors to be correlated across pairs containing common elements. The standard errors, and thus significance levels, of the coefficients we obtain with our default approach are in the middle of these two cases. The significance of interbank lending varies substantially with the choice of standard errors. The variable has a highly significant effect using Hubert–White standard errors, while significance vanishes when clustering standard errors at the pair level. For similarity in lending practices and exposures to troubled securities we find significant effects irrespective of the clustering of standard errors.

In a second robustness check of our results we run another variant of the baseline specification with both time and pair fixed effects for ruling out omitted variable bias at the pair level. Results are displayed in Table 9.

Note that this variant controls for all observable and unobservable characteristics of within-bank relationships. The coefficient thus picks up only the time-varying part of variation at the pair-level within the same pair and measures whether, controlling for the average pairwise level of realized interconnectedness, we find differential effects associated to our set of explanatory variables. Similarity in lending practice between two banks remains significant at the 5% level with a slight increase in magnitude of the coefficient: controlling for all within-pair characteristics, an increase in the distance between two banks by one percentage point is associated with a decrease in partial correlations by 0.077 percentage points. Pair-wise exposures to securities issued in the GIIPS countries are related to an increase in realized interconnectedness, and this effect is significant at the 1% level. Note that, also here, the coefficient changes only slightly in magnitude. In contrast, we do not find any significant result for interbank lending once we take out all within-pair variation. This result is due to the stable nature of interbank lending, where the relation comes at the individual pair level without much variation over time.

Focusing on the time-varying part of variation within the same pair, we find a significant positive effect for pairwise exposures to securities issued in Germany: two banks with higher pairwise exposures are perceived as less interconnected by the market. This assigns a stabilizing role of common exposures to non-troubled securities: two banks which have safer security portfolios individually are also perceived as less interconnected in terms of credit risk. This is in line with the results of Brownlees et al. (2016) who find that perceived interconnectedness increases with the extent of "troubledness" of individual banks, and is thus lower for safer individuals.

To shed light on the robustness of results to using different standard errors, we again run the specification with Hubert–White

**Table 7**
Differential effects for quartiles for Troubled Exposures.

| VARIABLES | $\rho$ |
|---|---|
| Troubled Exp. 1st Quartile | 0 |
| | (0) |
| Troubled Exp. 2nd Quartile | 0.00757 |
| | (0.00894) |
| Troubled Exp. 3rd Quartile | 0.00171 |
| | (0.00305) |
| Troubled Exp. 4th Quartile | 0.00958*** |
| | (0.00186) |
| Number of Banks | 13 |
| Observations | 20779 |
| Adj. $R$-squared | 0.158 |
| Control Variables | Yes |
| Bank Fixed Effects | Yes |
| Time Fixed Effects | Yes |

Two-way cluster robust standard errors in parenthesis.
This table reports coefficient estimates and standard errors for the regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 TE_{ijt}\mathbf{1}_{TE1} + \beta_2 TE_{ijt}\mathbf{1}_{TE2} + \beta_3 TE_{ijt}\mathbf{1}_{TE3} + \beta_4 TE_{ijt}\mathbf{1}_{TE4} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Troubled Exposures are defined as the product of two banks' log exposures to assets issued in GIIPS countries. The binary variable $\mathbf{1}_{TE1}$ is equal to one if the observation lies in the first quartile of the Troubled Exposures variable. $\mathbf{1}_{TE2}$, $\mathbf{1}_{TE3}$ and $\mathbf{1}_{TE4}$ are defined analogously.
+$p$<0.10.
* $p$<0.05.
** $p$<0.01.
*** $p$<0.001.

standard errors and standard errors clustered at the pair level in addition. Results for three variants are displayed in Table 10.

Similarly to previous results, significance levels we obtain with two-way clustering along both dimensions of the pair lie in between the ones resulting from Hubert–White standard errors and clustering on the pair level.

### 4.2. Extended specification: subsample specific effects

In order to capture subsample-specific effects, we consider an extension of the baseline specification stated in Eq. (2). We expect channels to have different impacts depending on the subperiod. Results for the analysis are shown in Table 11.

Interbank lending is strongly related to market-perceived interconnectedness starting with the banking crisis period: a percentage point increase of interbank exposure weighted by capital is associated with a 5.956 percentage point increase in partial correlation between two entities, and this effect is significant at the 1% level. The coefficient on interbank lending remains largely stable in the two following periods, as already indicated by the results in Table 9. Results are intuitive: starting with the banking crisis period, options for banks to obtain outside funding were largely limited, with higher information asymmetry, lower confidence in the financial system and deteriorating financing conditions. As shown in, for example, Bolton et al. (2016), Braeuning and Fecht (2016), interbank positions, which are typically long-term relationships, become an important source of funding for banks in troublesome times thanks to informational advantages. Furthermore, when banks are financially constrained, bilateral interbank positions become harder to substitute in case of a default on the obligation. This positive effect of interbank lending on realized interconnectedness continues to hold good for the remainder of the sample period.

The time pattern greatly differs for similarity in lending practices to the real economy. Both in the pre- crisis and in the banking

**Table 8**
Variant of baseline regression with different standard errors.

| | (1) | (2) | (3) | (4) | **(5)** | (6) | (7) | (8) | (9) | **(10)** | (11) | (12) | (13) | (14) | **(15)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ |
| IB Lending | 4.006*** | | | | **4.518***** | 4.006 | | | | **4.518**+ | 4.006+ | | | | **4.518**** |
| | (0.269) | | | | (0.264) | (2.447) | | | | (2.344) | (2.202) | | | | (1.643) |
| Lend. Distance | | −0.0677*** | | | − **0.0694***** | | −0.0677* | | | − **0.0694*** | | −0.0677* | | | − **0.0694*** |
| | | (0.00344) | | | (0.00344) | | (0.0301) | | | (0.0298) | | (0.0283) | | | (0.0290) |
| Troubled Exp. | | | 0.00705*** | | **0.00708***** | | | 0.00705** | | **0.00708**** | | | 0.00705*** | | **0.00708***** |
| | | | (0.000367) | | (0.000362) | | | (0.00230) | | (0.00228) | | | (0.00125) | | (0.00106) |
| Safe Exp. | | | | −0.00108* | − **0.00112*** | | | | −0.00108 | − **0.00112** | | | | −0.00108 | − **0.00112** |
| | | | | (0.000498) | (0.000483) | | | | (0.00481) | (0.00446) | | | | (0.00377) | (0.00325) |
| Number of Banks | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 |
| Observations | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 |
| Adj. $R$-squared | 0.154 | 0.158 | 0.156 | 0.149 | 0.171 | 0.154 | 0.158 | 0.156 | 0.149 | 0.171 | 0.154 | 0.158 | 0.156 | 0.149 | 0.171 |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Respective standard errors in parenthesis.
This table shows coefficient estimates and standard errors for a variant of the baseline regression model $\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 IB_{ijt} + \beta_2 LD_{ijt} + \beta_3 TE_{ijt} + \beta_4 SE_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$ Rho denotes the idiosyncratic partial correlation between two banks implied by CDS prices. Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. Troubled Exposures and Safe Exposures refer to the product of two banks' log exposures to assets issued in GIIPS countries and Germany, respectively. Standard errors differ across three specifications: Columns 1–5 show heteroskedasticity robust standard errors, columns 6–10 show standard errors clustered at the pair level and columns 11–15 standard errors clustered along both dimensions in the dyad.
+ $p$<0.10.
* $p$<0.05.
** $p$<0.01.
*** $p$<0.001.

**Table 9**
Baseline regression with pair fixed effects.

| VARIABLES | (1) $\rho$ | (2) $\rho$ | (3) $\rho$ | (4) $\rho$ | (5) $\rho$ | (6) $\rho$ | (7) $\rho$ | (8) $\rho$ | (9) $\rho$ | (10) $\rho$ |
|---|---|---|---|---|---|---|---|---|---|---|
| IB Lending | −2.914 | | | | − **1.237** | −0.755 | | | | − **0.568** |
| | (6.589) | | | | (1.032) | (7.236) | | | | (6.492) |
| Lend. Distance | | −0.0723$^{+}$ | | | − **0.0693**$^{+}$ | | −0.0715$^{+}$ | | | − **0.0667**$^{+}$ |
| | | (0.0393) | | | (0.0362) | | (0.0425) | | | (0.0396) |
| Troubled Exp. | | | 0.00412$^{**}$ | | **0.00369**$^{**}$ | | | 0.00511$^{*}$ | | **0.00474**$^{*}$ |
| | | | (0.00134) | | (0.00131) | | | (0.00189) | | (0.00200) |
| Safe Exp. | | | | −0.00613$^{*}$ | − **0.00704**$^{***}$ | | | | −0.00598 | − **0.00767**$^{*}$ |
| | | | | (0.00252) | (0.000817) | | | | (0.00500) | (0.00346) |
| Number of Banks | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 |
| Observations | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 |
| Adj. $R$-squared | 0.507 | 0.510 | 0.510 | 0.508 | 0.514 | 0.508 | 0.511 | 0.511 | 0.509 | 0.533 |
| Control Variables | No | No | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pair Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Two-way cluster robust standard errors in parenthesis.
This table shows coefficient estimates and standard errors for a variant of the baseline regression model with pair-fixed effects

$$\rho_{ijt} = \alpha_{ij} + \alpha_t + \beta_0 + \beta_1 IB_{ijt} + \beta_2 LD_{ijt} + \beta_3 TE_{ijt} + \beta_4 SE_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Rho denotes the idiosyncratic partial correlation between two banks implied by CDS prices. Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. Troubled Exposures and Safe Exposures refer to the product of two banks' log exposures to assets issued in GIIPS countries and Germany, respectively. Standard errors are based on two-dimensional clustering along both banks contained in the dyad.

$^{+}$ $p$<0.10.
$^{*}$ $p$<0.05.
$^{**}$ $p$<0.01.
$^{***}$ $p$<0.001.

**Table 10**
Baseline regression with pair fixed effects and different standard errors.

| VARIABLES | (1) $\rho$ | (2) $\rho$ | (3) $\rho$ | (4) $\rho$ | (5) $\rho$ | (6) $\rho$ | (7) $\rho$ | (8) $\rho$ | (9) $\rho$ | (10) $\rho$ | (11) $\rho$ | (12) $\rho$ | (13) $\rho$ | (14) $\rho$ | (15) $\rho$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| IB Lending | −0.755 | | | | − **0.568** | −0.755 | | | | − **0.568** | −0.755 | | | | − **0.568** |
| | (0.675) | | | | (0.663) | (4.508) | | | | (3.965) | (7.236) | | | | (6.492) |
| Lend. Distance | | −0.0715$^{***}$ | | | − **0.0667**$^{***}$ | | −0.0715$^{*}$ | | | − **0.0667**$^{+}$ | | −0.0715$^{+}$ | | | − **0.0667**$^{+}$ |
| | | (0.00455) | | | (0.00456) | | (0.0325) | | | (0.0338) | | (0.0425) | | | (0.0396) |
| Troubled Exp. | | | 0.00511$^{***}$ | | **0.00474**$^{***}$ | | | 0.00511$^{**}$ | | **0.00474**$^{*}$ | | | 0.00511$^{*}$ | | **0.00474**$^{*}$ |
| | | | (0.000310) | | (0.000308) | | | (0.00195) | | (0.00195) | | | (0.00205) | | (0.00200) |
| Safe Exp. | | | | −0.00598$^{***}$ | − **0.00767**$^{***}$ | | | | −0.00598 | − **0.00767**$^{+}$ | | | | −0.00598 | − **0.00767**$^{*}$ |
| | | | | (0.000636) | (0.000603) | | | | (0.00432) | (0.00414) | | | | (0.00500) | (0.00346) |
| Number of Banks | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 |
| Observations | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 | 20779 |
| Adj. $R$-squared | 0.508 | 0.511 | 0.511 | 0.509 | 0.533 | 0.508 | 0.511 | 0.511 | 0.509 | 0.533 | 0.508 | 0.511 | 0.511 | 0.509 | 0.533 |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pair Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Respective standard errors in parenthesis.
This table shows coefficient estimates and standard errors for a variant of the baseline regression model with pair-fixed effects and different standard errors

$$\rho_{ijt} = \alpha_{ij} + \alpha_t + \beta_0 + \beta_1 IB_{ijt} + \beta_2 LD_{ijt} + \beta_3 TE_{ijt} + \beta_4 SE_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Rho denotes the idiosyncratic partial correlation between two banks implied by CDS prices. Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. Troubled Exposures and Safe Exposures refer to the product of two banks' log exposures to assets issued in GIIPS countries and Germany, respectively. Standard errors differ across three specifications: Columns 1–5 show heteroskedasticity robust standard errors, columns 6–10 show standard errors clustered at the pair level and columns 11–15 standard errors clustered along both dimensions in the dyad.

$^{+}$ $p$<0.10.
$^{*}$ $p$<0.05.
$^{**}$ $p$<0.01.
$^{***}$ $p$<0.001.

**Table 11**
Differential effects in subsample periods.

| VARIABLES | (1) $\rho$ | (2) $\rho$ | (3) $\rho$ | (4) $\rho$ | (5) $\rho$ |
|---|---|---|---|---|---|
| IBpre | −0.213 | | | | 2.110 |
| | (2.047) | | | | (1.425) |
| IBban | 5.956* | | | | 6.760*** |
| | (2.402) | | | | (1.304) |
| IBsov | 5.111** | | | | 5.288** |
| | (1.927) | | | | (1.614) |
| IBpost | 7.318** | | | | 8.154*** |
| | (2.800) | | | | (1.511) |
| LDpre | | −0.136*** | | | −0.137** |
| | | (0.0294) | | | (0.0419) |
| LDban | | −0.0845** | | | −0.0818* |
| | | (0.0279) | | | (0.0334) |
| LDsov | | −0.0407 | | | −0.0465 |
| | | (0.0354) | | | (0.0413) |
| LDpost | | −0.0116 | | | −0.0270 |
| | | (0.0526) | | | (0.0563) |
| TEpre | | | 0.00566*** | | 0.00888*** |
| | | | (0.00138) | | (0.00217) |
| TEban | | | 0.00502* | | 0.00609* |
| | | | (0.00255) | | (0.00269) |
| TEsov | | | 0.00911*** | | 0.00500* |
| | | | (0.00225) | | (0.00211) |
| TEpost | | | 0.00453+ | | −0.000689 |
| | | | (0.00270) | | (0.00500) |
| SEpre | | | | −0.00996** | −0.00871+ |
| | | | | (0.00308) | (0.00443) |
| SEban | | | | −0.00403 | −0.00303 |
| | | | | (0.00577) | (0.00599) |
| SEsov | | | | 0.00410 | 0.00479 |
| | | | | (0.00356) | (0.00585) |
| SEpost | | | | 0.000842 | 0.00425 |
| | | | | (0.00309) | (0.00305) |
| Number of Banks | 13 | 13 | 13 | 13 | 13 |
| Observations | 20779 | 20779 | 20779 | 20779 | 20779 |
| Adj. $R$-squared | 0.157 | 0.162 | 0.157 | 0.161 | 0.188 |
| Control Variables | Yes | Yes | Yes | Yes | Yes |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes |

Two-way cluster robust standard errors in parenthesis.
This table shows coefficient estimates and standard errors for a variant of the baseline regression model with sub-sample specific effects. For the example of Interbank Lending,

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 IB_{ijt}\mathbf{1}_{pre} + \beta_2 IB_{ijt}\mathbf{1}_{ban} + \beta_3 IB_{ijt}\mathbf{1}_{sov} + \beta_4 IB_{ijt}\mathbf{1}_{post} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

The binary variables $\mathbf{1}_{pre}$, $\mathbf{1}_{ban}$, $\mathbf{1}_{sov}$, $\mathbf{1}_{post}$ indicate whether the observation lies in the specific subsample period pre-crisis, banking crisis, sovereign debt crisis or post crisis. The regression model is specified for Lending Distance, Troubled Exposures and Safe Exposures analogously. Standard errors are based on two-dimensional clustering along both banks contained in the dyad.
+ $p<0.10$.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

crisis period, we find a negative effect: two banks with less similar lending practices are perceived as less interconnected by the market, and this is significant at the 1% level. In the pre-crisis period, during calm times, a percentage point increase in the distance between two banks is associated with a 13.6 percentage point drop in partial correlation. In the banking crisis period the magnitude of the coefficient approximately halves. With the beginning of the sovereign debt crisis period, significance of the effect vanishes. We conclude that, as overall turmoil in financial system increases, other factors such as interbank lending and commonality in securities investments become more important in the view of market participants and dominate the effect of similar lending practices to the real economy.

Last, we investigate the effect of commonality in securities investments related to troubled and safe securities. In the pre-crisis period, we find opposing significant coefficients for both security classes: higher pair-wise exposures to troubled securities are related to higher realized interconnectedness, whereas higher exposures to safe security classes are associated with lower realized interconnectedness. This points towards market participants perceiving troubled securities as a potential source of contagion, whereas safe securities should induce stability in financial markets and hence lead to lower interconnectedness in credit risk.

For safe security classes, this effect vanishes with the start of the banking crisis. We conclude that, during turmoil in financial markets, the definition of safe security classes becomes unclear, and market participants do not perceive any type of common holdings as inducing stability. Note that these results are in line with Table 11 where we find a significant negative effect for exposures to non-troubled securities when focusing on the time-varying part of variation within the same pair.

For troubled securities, we see a second, quantitatively stronger effect emerging during the sovereign debt crisis: following the Greek filing for sovereign bailout, market participants perceive a strong relation between exposures to securities issued in any of the GIIPS countries and realized interconnectedness: an increase in said holdings by one of the counterparties by 1% is associated with a 0.9 percentage point increase in partial correlations, and this effect is significant at the 0.1% level. We conclude that this strong effect is related to the greater riskiness which was induced by holdings of securities issued in the GIIPS countries specifically during this period when these securities were most troubled.

## 5. Conclusion

The identification and quantification of the systemic component of financial risk requires an in-depth understanding of the channels through which shocks can spread and amplify, thereby jeopardizing the stability of a financial system. Our understanding of these links as a whole is, however, hampered by the absent comprehension of the key determinants of financial institutions' interconnections. This has been due to the lack of comprehensive datasets that are sufficient for analyses of this kind. The contribution of this paper is to study the relationship between market information-based credit risk interconnectedness and *actual* common exposures of banks through their actual funding and securities holding (liability-asset structure). We measure empirical bank interconnectedness of a partial correlation measure that relies solely on market- based information proposed in Brownlees et al. (2016).

Two main results emerge from our analysis. First, we find that realized interconnectedness strongly reflects both bank exposure vis-a-vis the wholesale funding market and assets associated with securities investments and credit supply. We find that bank pairs where both counterparties have higher Core Tier 1 capital-weighted interbank exposure show higher realized interconnectedness. On the asset allocation side, we document that both banks' exposure to the real economy and their securities investments have an impact on realized network connections. Bank pairs with more similar lending practices to the real economy show up as more interconnected. Moreover, we find higher realized interconnections among bank pairs with higher exposures to risky securities.

Second, we show that the relation between realized interconnectedness and the balance sheet positions exhibits asymmetries both cross-sectionally and over time. We find that interbank lending is a relevant driver of realized interconnectedness during crisis times as other sources of financing become hard to obtain. On the asset allocation side, we show that banks' securities investments have asymmetric effects in the cross-section: bank pairs with higher exposures to the troubled security classes show up as more interconnected. On the contrary, commonality in securities investments related to crisis-unaffected security classes does not induce higher dependency.

These results show that banks' wholesale funding exposure, securities investment and credit supply affect the interdependency in bank credit risk. Moreover, they show that market information-based measures of interdependence can serve well as risk monitoring tools in the absence of disaggregated high-frequency bank fundamental data.

## Appendix A. Estimating the bank credit risk network

We follow Ang and Longstaff (2013) in modelling credit events as jumps of a Poisson process with stochastic intensity, and consider two different types of credit events which can trigger default.

The first event is a systematic shock which affects all entities in the economy, modelled as the jump of a Poisson process $M(t)$ with stochastic intensity $\lambda$ that follows a standard square root process,

$$d\lambda(t) = a(m-\lambda(t))dt + b\sqrt{\lambda(t)}dW(t)$$

where $W(t)$ denotes a Brownian motion. Following a systematic shock, entity $i$ will default with conditional probability $\gamma_i$,

$$\gamma_i = \text{Prob}(\text{default}_i|\text{systematicdefault}),$$

The second event is an idiosyncratic triggering default of entity $i$ with certainty, modelled accordingly as the first jump of a Poisson process $N_i(t)$ with stochastic intensity $\xi_i$ that follows a standard square root process,

$$d\xi_i(t) = \alpha_i(\mu_i - \xi_i(t))dt + \sqrt{\xi_i(t)}dB_i(t) \,\text{with}\, i = 1, \ldots, n,$$

where again $B_i(t)$ denotes an entity specific Brownian motion with $B_i \perp W_i \,\forall i$.

For entities $1, \ldots, n$, the Brownian motions $(B_1(t), \ldots, B_n(t))'$ are assumed to be correlated with covariance matrix $\Sigma t$. Following a well established result by (), the conditional independence network can be fully characterized by the sparsity structure of $K_t$, the inverse of $\Sigma_t$: two entities $i$ and $j$ are conditionally independent if and only if the $i-j-th$ entry $k_{ij} = 0$.

The probability that an entity has not defaulted by time $t$ is

$$P(\text{nodefault}_i\,\text{occursbytimet}) = \exp\left(-\int_0^t (\gamma_i\lambda(s) + \xi_i(s))ds\right)$$

We refer to $\lambda_i(s) = \gamma_i\lambda(s) + \xi_i(s)$ as the marginal default intensity of entity i. We can now use the standard framework for valuing credit derivatives as established in Duffie and Singleton (1999) setting the default probability equal to the marginal default intensity for each entity. Following this, we can express the protection leg of a CDS contract as

$$CDS_i^{pro} = E^Q\left(\int_0^T \exp\left[-\int_0^t (r(s) + \gamma_i\lambda(s) + \xi_i(s))(1-\omega)ds\right] dt\right)$$

and its premium leg as

$$CDS_i^{pre} = E^Q\left(s_i\int_0^T \exp\left[-\int_0^t (r(s) + \gamma_i\lambda(s) + \xi_i(s))ds\right] dt\right)$$

where $s_i$ is the CDS spread and $1-\omega$ is the recovery fraction. For no arbitrage, those two must be equal, and we get

$$s_i = \frac{\omega E^Q\left(\int_0^T D(t)(\gamma_i\lambda(t) + \xi_i(t))\exp\left[-\int_0^t(\gamma_i\lambda(s) + \xi_i(s))ds\right] dt\right)}{E^Q\left(\int_0^T D(t)\exp\left[-\int_0^t(\gamma_i\lambda(s) + \xi_i(s))ds\right] dt\right)}$$

where $D(t) = E^Q\left(\exp - \int_0^t r(s)ds\right)$

The estimation then proceeds as follows: For each institution $i$, we identify the systematic intensity as the default intensity of Germany. Applying a bootstrapping algorithm to make use of the full term structure of CDS spreads, we back out systematic default intensity $\lambda$ and $n$ marginal default intensities $\lambda_i$. In order to filter out the systematic component, idiosyncratic intensity differences are estimated as the residual of the regression of marginal intensity differences $\Delta\hat{\lambda}_i$ on systematic intensity differences $\Delta\hat{\lambda}$. The interconnectedness measured used in this work is the partial correlation among banks obtained from the residuals of this regression.

## References


Acharya, V., Pedersen, L., Philippon, T., Richardson, M., 2016. Measuring systemic risk. Rev. Financ. Stud. 30 (1), 2–47.
Adrian, T., Brunnermeier, M., 2016. CoVar. Am. Econ. Rev. 106 (7), 1705–1741.
Allen, F., Babus, A., Carletti, E., 2012. Financial Connections and Systemic Risk. Market Institutions and Financial Market Risk, Carey, Kashyap, Rajan, and Stulz.
Ang, A., Longstaff, F., 2013. Systemic sovereign credit risk: lessons from the U.S. and Europe. J. Monet. Econ. 60, 493–510.
Barigozzi, M., Brownlees, C., 2013. NETS: Network Estimation for Time Series. Barcelona Graduate School of Economics Working Papers, 723.
Betz, F., Hautsch, N., Peltonen, T., Schienle, M., 2016. Systemic risk spillovers in the European banking and sovereign network. J. Financ. Stab. 25 (C), 206–224.
Billio, M., Gray, D., Lo, A., Merton, R., Pelizzon, L., 2015. Sovereign, Bank, and Insurance Credit Spreads: Connectedness and System Networks. Working Paper.
Bolton, P., Freixas, X., Gambacorta, L., Mistrulli, P., 2016. Relationship and transaction lending in a crisis. Rev. Financ. Stud. 29 (10), 2643–2676.
Braeuning, F., Fecht, F., 2016. Relationship lending in the interbank market and the price of liquidity. Rev. Financ. (forthcoming).
Brownlees, C., Hans, C., Nualart, E. (2016). Bank Credit Risk Networks: Evidence from the Eurozone. Working Paper.
Brunnermeier, M., 2009. Deciphering the liquidity and credit crunch 2007–2008. The Journal of Economic Perspectives 23 (1), 77–100.
Brunnermeier, M., Pedersen, L., 2009. Market liquidity and funding liquidity. Rev. Financ. Stud. 22 (6), 2201–2238.
Caballero, R., Simsek, A., 2013. Fire sales in a model of complexity. J. Financ. 68, 2549–2587.
Cai, J., Saunders, A., Steffen, S., 2016. Syndication, Interconnectedness and Systemic Risk. Working Paper.
Cetina, J., Paddrik, M., Rajan, S., 2016. Stressed to the core: counterparty concentrations and systemic losses in CDS markets. J. Financ. Stab. (forthcoming).
Constantina, A., Peltonen, T., Sarlin, P., 2016. Network linkages to predict bank distress. J. Financ. Stab. (forthcoming).
Dasgupta, A., 2004. Financial contagion through capital connections: a model of the origin and spread of bank panics. J. Eur. Econ. Assoc. 2 (6), 1084–2019.
Diebold, F., Yilmaz, K., 2015. Financial and Macroeconomic Connectedness. Oxford University Press.
Diebold, F.X., Yilmaz, K., 2016. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econ. 128, 119–134.
Duarte, F., Eisenbach, T., 2015. Fire-Sale Spillovers and Systemic Risk. Federal Reserve Bank of New York Staff Reports No 645.
Duffie, D., Singleton, K., 1999. Modeling term structures of defaultable bonds. Rev. Financ. Stud. 12 (4), 687–720.
Fourel, V., Héam, J.-C., Salakhova, D., Tavolaro, S., 2013. Domino effects when banks hoard liquidity: the French network. In: Banque de France Working Paper No. 432.
Freixas, J., Laeven, L., Peydro, J., 2015. Systemic Risk, Crises, and Macroprudential Regulation. MIT Press.
Freixas, X., Parigi, B.M., Rochet, J.-C., 2000. Systemic risk, interbank relations and liquidity provision by the central bank. J. Money Credit Bank. 32 (3), 611–638.
Gai, P., Haldane, A., Kapadia, S., 2011. Complexity, concentration and contagion. J. Monet. Econ. 58, 453–470.
Greenwood, R., Landier, A., Thesmar, D., 2015. Vulnerable banks. J. Financ. Econ. 115, 471–485.
Hale, G., Kapan, T., Minoiu, C., 2016. Crisis transmission in the global banking network. In: Federal Reserve Bank of San Francisco Working Paper.
Ippolito, F., Peydró, J.-L., Polo, A., Sette, E., 2015. Double bank runs and liquidity risk management. J. Financ. Econ. (forthcoming).
Iyer, R., Peydró, J.-L., 2005. How does a shock propagate? A model of contagion in the interbank market due to financial linkages. In: Proceedings of the European Finance Association Annual Meetings.
Krackhardt, D., 1988. Predicting with networks: nonparameric multiple regression analysis of dyadic data. Soc. Netw. 10 (4), 359–381.
Kritzman, M., Yuanzhen, L., Page, S., Rigobon, R., 2011. Principal components as a measure of systemic risk. J. Portfol. Manage. 37 (4), 112–126.
Mayordomo, S., Peña, J., Schwartz, E., 2014. Are all credit default swap databases equal? Eur. Financ. Manage. 20 (4).
Memmel, C., Sachs, A., 2013. Contagion in the interbank market and its determinants. J. Financ. Stab. 9, 46–54.
Nier, E.W., Yang, J., Yorulmazer, T., Alentorn, A., 2010. Network models and financial stability. J. Econ. Dyn. Control 31 (6), 2033–2060, Bank of England Working Paper No. 346.
Podlich, N., Wedow, M., 2014. Crossborder financial contagion to Germany: how important are OTC dealers? Int. Rev. Financ. Anal., 33.
Suhua, T., Yunhong, Y., Gaiyan, Z., 2013. Bank capital, interbank contagion and bailout policy. J. Bank. Financ. 37, 2765–2778.
Upper, C., 2011. Simulation methods to assess the danger of contagion in interbank markets. J. Financ. Stab. 7 (3), 111–125.
Zhang, X., Schwaab, B., Lucas, A., 2014. Conditional euro area sovereign default risk. J. Bus. Econ. Stat. 32 (2).