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Contagion in the Banking Industry: a Robust-to-Endogeneity Analysis

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Abstract

What drives financial contagion? The empirical literature aimed at modeling financial risk spillovers in crisis periods and documenting the role of contagion channels is subject to an endogeneity issue, as the channel itself can respond to a change in the level of risk. We tackle this issue by using a novel spatial econometric estimation procedure based on a control function approach and offer "robust-to-endogeneity " evidence on the role of *indirect financial contagion channels* in the banking industry. Our estimations, based on on 28 large US banks during the financial crisis (2007Q3-2013Q2), confirm that several channels are endogeneous. Accounting for endogeneity is proved to be important for recovering reliable estimates of transmission mechanisms. Banks' *common exposure* as well

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as *similarity in fundamentals* and *similarity in investment strategy* appear as significant drivers of contagion. Based on these estimates, we can derive a simple systemic risk indicators called the "Interaction-Based Centrality " index, that can be used by regulatory authorities and policy makers to track vulnerable institutions.

Key words: banking; common asset exposures; contagion; endogeneity; Katz centrality; market-price channel; information channel; spatial econometrics; spillover effects

JEL classifications: G21, G10, C33

The key ingredient in 2007 was indirect contagion, which occurs when a firm's actions generate externalities that affect other firms through non-contractual channels. (Clerc et al., 2016, p.3)

1 Introduction

Contagion cascades in the banking industry build on the premise that banks' losses in a crisis period can be transmitted from one institution to another through their interconnectedness, meaning that a small segment of the market can destabilize the whole industry. In the case of the global banking crisis that broke out in 2007 multiple channels of contagion were potentially at play, including cross-lending in interbank markets, fire-sale externalities and characteristics-based similarities (information channels) to cite a few (see Clerc et al., 2016). Growing consensus on the importance of financial sector interconnectedness has spread rapidly in both the research and policy worlds. In the latter, policymakers have pressed forcefully for the introduction of insights from financial interconnectedness and network theory on stress testing (Espinosa-Vega and Sole, 2014) and identification of Globally Systemically Important Banks (GSIBs). On the other side, the research community has been implicitly entrusted to guide policy decisions by documenting theoretically and empirically the contagion channels as well as the associated transmission mechanisms.

What drives financial contagion? We argue in this paper that the empirical literature aimed at documenting the channels of contagion is subject to an endogeneity issue, which means that careful treatment of the data is required to retrieve reliable evidence. The problem stems from the response of the transmission channel itself to the distress of a financial institution or a country, depending on the context. Ignoring this form of endogeneity yields inconsistent and biased parameters estimates, as acknowledged in recent studies on spillover effects (see Kelejian and Piras, 2014; Qu and Lee, 2015). Relying on a "robust-to-endogeneity" framework recently developed by Shi and Lee (2018), this paper provides new evidence about the drivers of financial contagion in the banking industry, which was at core of the US financial crisis in the late 2000s. In a nutshell, our results – based on a sample of 28 large US institutions over the 2007Q3-2013Q2 period[1] – unambiguously confirm the endogeneity of several transmission channels discussed in the literature, show the importance of controlling for it in the estimation procedure and confirm the role of common portfolio exposure, along with both investment-based similarity and fundamental-based similarity, as channels of contagion.

While the theoretical or simulation-based literature is vast, econometric studies on interconnectedness and spillover effects in the banking industry are scarcer (see, for an overview of contagion in financial networks, Glasserman and Young, 2016).[2] Among the causes explaining this asymmetry of treatment stand two historical caveats. First, the applied literature has suffered from limited access to data on banks' physical inter-

[1] As often in the literature (Billio et al., 2012; Balla et al., 2014), we consider the problems of Bear Stearns' hedge funds in Q3 2007 as a starting period to define the crisis period. The end of the period corresponds with the first announcement by the Federal Reserve on May 2013 on tapering back the large-scale operations in the bond market. We also test the robustness of our conclusions to slight alterations of the definition of the end of crisis period.

[2] Notable empirical contributions aiming to estimate financial interconnectedness include, for instance, Billio et al. (2012), Blasques et al. (2016), Demirer et al. (2018) and Betz et al. (2016) and, more recently, Wang et al. (2019).

connectedness. Second, estimating a contagion model requires applying an econometric approach that deals with cross-sectional dependence in the data. In recent years, however, remarkable progress has been made on both fronts. Data have been made increasingly available to researchers, even though relevant information such as cross-lending is still difficult to obtain by most researchers outside central banks.[3] Meanwhile, new classes of "system-wide" econometric models have emerged in applied works on macroeconomic or financial contagion, accommodating cross-sectional correlation in the data. Among these models, some remain "agnostic" on the nature of interconnections, such as large VAR models (Diebold and Yilmaz, 2009). Others pertaining to Global Vector Auto-Regression (GVAR) or spatial econometrics models explicitly specify in their reduced form equation the links governing the spillover effects process (see, among others Favero, 2013 for GVAR and Blasques et al., 2016 and Debarsy et al., 2018 for spatial econometric models). Spatial econometric models in particular display several attractive features in relation to model contagion. This class of models builds on the premise that a specific individual (here a bank characterized by its stock returns' volatility) is affected by her neighborhood. The closer the neighbors, the stronger their influence. Whether other entities populating the system are distant or close is governed by an interaction scheme (matrix) imposed by the researcher. Modelling propagation of financial turbulence, Jing et al. (2018) use, for instance, trade and capital flows as interaction matrices. Importantly, the statistical inference regarding the relevance of each interaction scheme can be performed. Compared to "agnostic" models such as large VAR models that do not impose economically-based interaction schemes, these models

[3] Data on cross-lending for instance are made available on a discretionary basis to central banks (see regulation introduced by the ECB, 2012, and set of data available here) .

enable isolating the contribution of specific channels of spillover (i.e. specific matrices). They also allow comparison of their respective importance (see Debarsy et al., 2018; Elhorst et al., 2018 for further discussions on these two classes of models), making them of utmost interest for policymakers.

When it comes to estimating these models, however, one central assumption was often overlooked. It pertains to the exogeneity of the interaction matrix.[4] We argue that this assumption might be violated in a number of cases, be it in the banking industry or, in many other instances in economics and finance more generally. In our context, for instance, the exogeneity assumption implies that interaction matrices (i.e. transmission channels) such as those constructed from cross-lending or characteristics-based similarities (e.g. similarity in size or portfolio composition) do not respond to a change in the financial conditions of an institution. In practice, though, it is likely that the distress of a bank, for instance, will soon affect its lending relationship or the composition of its portfolio, changing its interaction scheme with the rest of the industry. Wang et al. (2019) acknowledge the problem in a contribution, closely related to ours, documenting the role of the information contagion channel with a spatial econometric model. Quoting their study, they emphasize that " [t]he data-generating process assumes that information contagion happens for given perceptions of the bank similarities. However, if the underlying similarities can change as a result of information spillovers, then simultaneity will lead to biased estimates of the network effects." Eventually, they try

[4] Some studies try to mitigate the problem by taking lagged values of the interaction matrix. However, this approach is subject to the same well-known criticisms as traditional endogenous regressors. An alternative consists in using a fixed interaction matrix that disregards their actual dynamics through time.

to mitigate the problem by playing with the data frequency. We add to their contribution by addressing the problem in full, proposing a "robust" approach to contagion. Robust, in our context, means that we test contagion effects in the banking industry while relaxing the exogeneity assumption on the channel of transmission. Specifically, we proceed in two steps. First, we test for the presence of endogeneity. Second, we interpret the results for the most suited model – that is, with a correction for the presence of endogeneity should the matrix be endogenous or without otherwise.

To do so, we rely on the spatial panel data model with time-varying interaction matrices recently developed by Shi and Lee (2018). This paper develops a control function approach that accommodates endogenous interaction matrices. It also displays two additional interesting features for modelling the contagion phenomenon. First, it does not require identifying external instruments, which is often a difficult task and a subject of debate. Second, it enables including in a single model both spillover effects and " systematic " effects through the inclusion of common factors. The effects of common risk factors can thus be easily separated from purely cascading mechanisms when the risk is transmitted from one institution to another. To our knowledge, we are the first to use this flexible econometric framework in the field of finance.[5] In line with recent contributions focusing on risk transmission in the banking industry (see, for instance, Balla et al., 2014; Korobilis and Yilmaz, 2018; Patro et al., 2013), we apply our model to a set of 28 large US depository institutions (hereafter, banks), over the period 2007Q3-

[5]Balla et al. (2014) display several similarities with our analysis as they assess the link between interconnectedness and the systemic risk of US banks. A notable difference lies in the role of the transmission channel. Balla et al. (2014) remain agnostic about the transmission channel, while our econometric set-up allows identification of the channels through which the transmission operates.

2013Q2. The risk of each institution is measured by its stock market volatility, as often in the literature (see, for instance, Korobilis and Yilmaz, 2018).[6] Most bank-level characteristics are extracted from Bloomberg and the Center for research in Security Prices (CRSP). Full information on portfolio holdings is retrieved for each bank at a quarterly frequency from Form 13F for to the Securities and Exchange Commission (SEC). Our baseline model includes standard bank-specific characteristics along with common factors. The model with spillover effects adds to the baseline equation an interaction component, which is constructed as the weighted sum of the risks of all surrounding institutions. The weights are given by a specific interaction matrix in each model. We concentrate on *indirect financial contagion* channels. Unlike with *direct financial contagion*, negative externalities occur without contractual obligation (Kiyotaki and Moore, 2002) such as cross-lending. Typical causes for indirect financial contagion are common asset exposure and fire sales of assets – *market price channel* – or when disclosure of financial trouble by one bank leads market participants to make inferences about problems of other banks viewed as similar – *information channel* – spreading the stress from one institution to others. As expressed in the opening quote from Clerc et al. (2016), this source of contagion is often cited as critical in explaining the financial crisis that followed the collapse of the US housing market. Documenting empirically the role of the different sub-channels that could have been at play is therefore of utmost importance. Within this framework, we consider in total 15 alternative interaction schemes belong-

[6] Volatility is standard as a measure of risk in finance. In the banking literature, alternatives such as the z-score are also often used. However, the z-score is only available at a low frequency, typically yearly, while asset returns volatility is commonly computed at higher frequencies such as monthly, weekly or daily. Volatility appears therefore better suited to analyze fast-changing financial phenomena such as contagion.

ing to three broad categories: (i) common asset exposures (market price channel), (ii) fundamental-based similarity (information channel), (iii) investment-based similarity, which includes both sector-based similarity and diversification-based similarity (information channel), and cover as a result a wide array of potential contagion channels. The contribution of each channel is tested separately. Eventually, we can use the estimations from the spatial model to compute the Katz centrality measures, for which the value of the attenuation factor is estimated from the data. Equipped with this centrality measure, we can build an interconnectedness indicator, named "Interaction-Based Centrality "(IBC). To illustrate how vulnerable institutions can be compared and tracked over time with this indicator, we select a subset of matrices and represent the associated networks where the nodes are scaled by our IBC indicator.

Overall, several important outcomes emerge from our analysis. First, our estimation procedure supports the presence of endogeneity in several transmission channels. This finding confirms the need to apply robust-to-endogeneity methods to analyze financial contagion. Looking at the magnitude of the problem created by the endogeneity of the interaction matrix, we show that applying the control approach procedure proposed by Shi and Lee (2018), when needed, may change the value of the coefficients attached to the spillover term by a factor up to four. Second, our framework identifies several active channels of indirect financial contagion in the banking industry. Common exposure emerges as a driver of financial contagion, whereby two banks that have invested in the same assets are more exposed to contagion. Likewise, the similarity in sectoral investments appears as a significant channel of risk spillovers. We also find significant spillovers when we consider similarities in fundamentals such as dividend yield and market value to total asset ratio. Third, we can observe from our network representation of the system time variations in the vulnerability of institutions across time.

The remainder of the paper is as follows. Section 2 introduces the data along with the empirical estimation strategy. Section 3 discusses the empirical results. Section 4 concludes.

2 Data and methodology

We study risk spillovers in 28 US large banks.[7] We consider the period of 2007Q3-2013Q2 as the crisis period for our baseline model and test other alternatives for the robustness check.[8] Table 1 summarizes the full list of banks considered.

[7]Our sample of institutions is comparable in size and bank's profiles to other studies on interconnectedness and spillover effects in the banking industry. Balla et al. (2014) investigate the extreme loss tail dependence between the stock returns of 27 large US depository institutions. Korobilis and Yilmaz (2018) analyze banking interconnectedness by estimating a large Bayesian time-varying parameter vector autoregressive (TVP-VAR) model on 35 US and European financial institutions. Patro et al. (2013) explore the link between the 22 largest bank holding companies and investment banks.

[8]Selecting the sample period to characterize the chain reaction or domino effects among banks is not trivial. On the one hand, the model needs enough chronological data to identify regular patterns across time periods. On the other hand, we must be as close as possible to the crisis period to estimate the effects when these mechanisms operate more forcefully. For these reasons, we consider 2007Q3, marked by the problems of two Bear Stearns' hedge funds, as a starting date. This choice is consistent with a large part of the literature (see for instance Balla et al., 2014; Acharya et al., 2017; Billio et al., 2012). For an end date, we select the statement made by Ben Bernanke before the Congress on May 22, 2013, announcing that the Fed would likely start "tapering" the pace of its bond purchases. The end date also corresponds with the period when the S&P500 resumed to its level of 2007Q3.

Table 1: Banks considered

Label	Firm	Label	Firm
BAC	Bank of America	UMBF	UMB Financial
JPM	JPMorgan Chase	HBHC	Hancock Holding Co
PNC	PNC financial Services	TRMK	Trustmark Corp
STI	Suntrust Banks	FMBI	First Midwest Bancorp
BBT	BB&T Corporation	PRK	Park National Corp
RF	Regions Financial	FCF	First Commonwealth Bank
CMA	Comerica	NBTB	NBT Bancorp Inc
HBAN	Huntington Bank NA	WSBC	Wesbanco Inc
SNV	Synovus Financial	SRCE	1st Source Bank
ASB	Associated Banc-Corp	TMP	Tompkins Financial Corp
CYN	City National Bank	WASH	Washington Trust Bank
CBSH	Commerce Bank NA	UVSP	Univest Bank
CFR	Cullen Frost Bankers	SYBT	Stock Yards Bank
BXS	Bancorpsouth Inc	PGC	Peapack Gladstone Financial Corp

This section presents our main variable of interest and the methodology to assess the role of alternative transmission channels.

2.1 Risk measure

Our dependent variable is the level of risk of a banking institution. We take as a risk measure stock market volatility which has been widely used in the literature to assess the risk of either a stock, portfolio or company. For instance, Korobilis and Yilmaz (2018), in a study closely related to ours, reconstruct the bank contagion network by modelling stock-market volatility with the Time Varying VAR model (see also Diebold and Yilmaz, 2015; Sarin and Summers, 2016).

For each institution, we compute within-quarter historical volatility (standard deviation) from the daily returns collected on the CRSP database. Figure 1 displays the evolution of the median value of banks' historical stock market volatility over the period

2005Q1-2013Q4. The shaded area represents the inter-quartile range. Unsurprisingly, it can be seen that the banks' risk increases sharply in 2007 at the beginning of the crisis, reaches a peak in early 2009 and slowly decreases until it reaches the pre-crisis period level in 2013Q2.

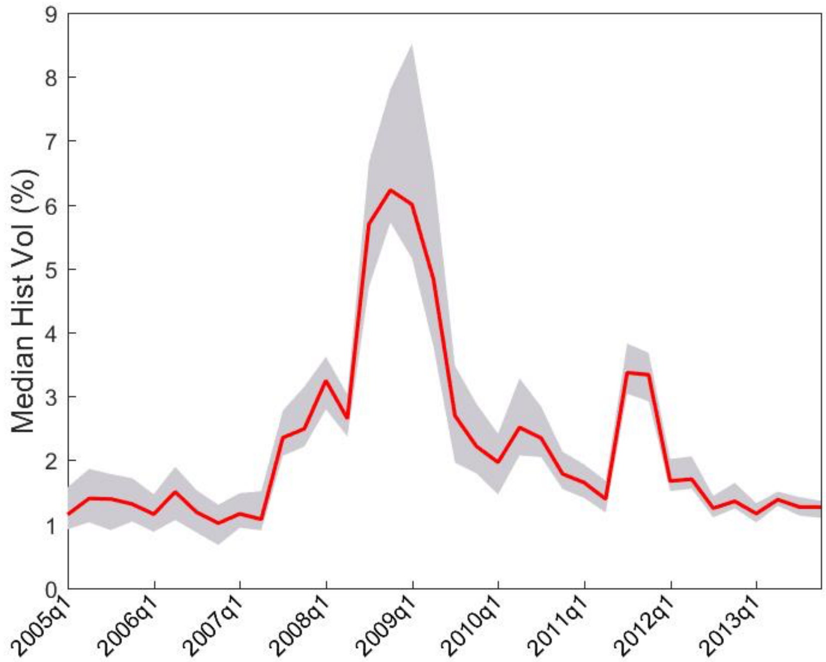

Figure 1: Quarterly stock market historical volatility based on daily data (shaded area represents the interquartile range).

2.2 Baseline econometric model

To assess the role of alternative channels in the transmission of risk across banks, we posit the following econometric model:

$$y_t = X_{yt}\beta_y + \Gamma_y f_{yt} + \lambda W_t y_t + V_t, \tag{1}$$

where for a given time t, y_t is a $n \times 1$ vector of risk measures for all the considered banks. X_{yt} is a $n \times K$ matrix of banks' specific characteristics with the associated $K \times 1$ vector of parameters β_y.[9] In this study, we consider three types of bank characteristics: business model, liquidity measure and credit risk variables (see Tables 2 and 3 respectively for a definition of the variables and descriptive statistics).

Table 2: Definition of variables

Variable	Definition	Source
Dependent variable		
Volatility	Quarterly stock market historical volatility based on daily data	CRSP
Control variables		
Loan_Dep	Ratio of customer loans to customer deposits	Bloomberg
Leverage	Financial Leverage	Bloomberg
Loss_Iinc	Loan Loss Provisions to Interest Income	CRSP

W_t is an $n \times n$ matrix modeling time-varying interdependences between banks and represents a specific transmission channel.[10] The spatial lag $W_t y_t$ captures interactions between banks' volatility and its intensity is quantified through the cross-sectional de-

[9] In spatial econometrics models, observations form triangular arrays (see Kelejian and Prucha, 2010). All variables should therefore be indexed by n, the number of banks considered. However, we omit this notation for the sake of readability.

[10] We delay further details about the specification of the interaction matrix to section 2.3.

Table 3: Descriptive statistics

	Nobs	Mean	STD	Min	P25	Median	P75	Max
Volat	672	2.894	1.963	0.689	1.570	2.299	3.427	15.630
Loan_Dep	672	85.516	14.206	45.001	77.432	87.776	94.577	126.931
Leverage	672	10.459	1.893	6.976	9.141	10.187	11.338	18.085
Loss_Iinc	672	18.268	21.544	-6.042	5.587	11.418	21.631	171.491

pendence parameter λ that needs to be estimated. When λ is statistically different from 0, one faces evidence of spillover effects through the transmission channel characterized by W_t. This way of testing for contagion effects in finance is derived from the wide class of spatial econometric models (see Anselin and Bera, 1998; LeSage and Pace, 2009) and was applied in early studies such as Blocher (2016); Tonzer (2015); Cohen-Cole et al. (2011); Liedorp et al. (2010), among others.

However, we depart from these studies in two main directions. First, we include in model (1) unobserved common factors (labeled "interactive effects" in the literature) $\Gamma_y f_{yt}$, where f_{yt} is a $R_y \times 1$ vector of unobserved factors and Γ_y is a $n \times R_y$ matrix of factor loadings. The interactive effects capture the fact that bank risk can be influenced by common global factors that can have different impacts on individual banks. It is important to account for these effects in the econometric model so as to clean the cross-sectional dependence parameter from their influence. Our specification thus allows for a flexible yet parsimonious way to model common shocks and account for their heterogeneous effect on banks. Following Bai (2009), we treat Γ_y and f_{yt} as fixed effects parameters to be estimated. Second, the interaction matrix, W_t, is time-varying and possibly endogenous. A common and key feature of econometric models in applied research on economic spillovers (Dell'Erba et al., 2013; Blasques et al., 2016; Debarsy et al., 2018) and financial spillovers (Eder and Keiler, 2015; Tonzer, 2015; Wang et al., 2019) is to assume the interaction scheme between individuals to be time-invariant or at least exogenous. These assumptions are the centerpiece of classical spatial econometrics models for which several estimation methods have been proposed.[11] However in some circumstances this assumption can be too strong, especially when the interaction structure is constructed from economic or financial variables (see for example Eder and Keiler, 2015 and Caporin and Paruolo, 2015).[12] A novel generation of models have been very recently introduced (Kelejian and Piras, 2014; Qu and Lee, 2015; Qu et al., 2016; Han and Lee, 2016; Qu et al., 2017; Shi and Lee, 2018) accommodating a time-varying and endogenous interaction scheme. As further discussed when presenting the estimation procedure developed by Shi and Lee (2018) we build on these developments to document the role of indirect contagion in the banking industry. Finally, V_t is a $n \times 1$ vector of independent and normally distributed error terms with mean 0 and variance $\sigma_v^2 I_n$.

2.3 Characterization of indirect financial contagion channels

A key feature of the spatial econometrics model is the specification of the interaction matrix. The matrix models the channel through which the transmission operates. We rely on the literature to select the set of channels to be tested. More specifically, we focus on indirect contagion. Within this framework, we consider the two main

[11] Ord (1975); Lee (2004) developed the quasi-maximum likelihood estimator while Kelejian and Prucha (1998, 1999); Lee (2007); Lee and Liu (2010) and Lin and Lee (2010) derived the two stage least square and generalized method of moments estimators. Finally, Lesage (1997) and LeSage and Pace (2009) developed the Markov Chain Monte Carlo methods.

[12] This exogeneity limit was acknowledged in Tonzer (2015) and Blasques et al. (2016).

families of channels: (i) market-price channels and (ii) information channels. According to the theoretical literature (Duarte and Eisenbach, 2015; Greenwood et al., 2015; Cont and Schaanning, 2017), the market-price channel is a key contributor to financial contagion. The transmission mechanism operates through common asset exposure and fire sales of assets. If a large bank experiences distress and is forced to liquidate its assets with a haircut, the asset price will spiral down, forcing banks holding similar assets in their portfolio to get rid of them under fire-sale conditions. Such a response contributes to reinforcing as well as diffusing the initial shock. This mechanism is studied in Greenwood et al. (2015), who propose a theoretical model to analyze the effect of fire sales when a bank has a regulatory leverage constraint. The theoretical foundation of spillovers through information channels can be traced back to the seminal work of Diamond and Dybvig (1983). The transmission mechanism at work in this case suggests that investors use signals or information about one bank in distress to infer the likelihood of distress in another bank that shares similar characteristics. By adjusting their positions accordingly, investors contribute to spreading of the distress. In their paper, Clerc et al. (2016) stress the critical role of this channel, arguing that runs are rarely driven by pure hysteria but tend to be related to fundamental changes in information, such as bad news about the health of a bank.

An interesting source of data is the quarterly US data on institutional portfolio holdings as reported through the Form 13F to the Securities and Exchange Commission (SEC).[13] According to rule 13(f)-1 of the Security Exchange Act of 1934, any institutional investment manager who exercises investment discretion over 100 million

[13] See details on http://www.sec.gov/answers/form13f.htm. Information valid on October 13, 2020

USD or more in securities of a class specified by the SEC has to report its holdings through Form 13F. This form provides information about the issuer of the asset, and the type and value of the asset held, among others. Holdings are reported by a wide range of institutional investors including banks, insurance companies, investment advisors, mutual and pension funds, etc. and data are available since 1980. It is worth noting that only long positions are included in the reports and the assets are mostly equities. These portfolio holdings data have been used in several studies: for instance, Gompers and Metrick (2001); Cai and Zheng (2004); Phalippou (2007); Koijen and Yogo (2015); Guo et al. (2016). Our data are retrieved primarily from Bloomberg and CRSP and we use the official Form 13F filed by institutions and available on the SEC's website to control for missing values and outliers.

Equipped with these data, we can construct our connectivity matrices. For the information channel, the underlying mechanism builds on the existence of imperfect information in financial markets. It further supposes that market participants can use the characteristics attached to one financial institution for extracting a signal on those judged as similar. The similarity of two institutions as perceived by the market is the cornerstone of the mechanisms. We consider two criteria here: (i) similarity of investments and (ii) similarity of fundamentals. The components of our similarity-based interaction matrices take the following generic form:

$$w_{ij,t}^{s} = \frac{1}{1 + |z_{i,t}^{s} - z_{j,t}^{s}|}, \tag{2}$$

where $z_{i,t}^{s}$ depends on specific characteristics. For the similarity of investment, we

Table 4: Construction of the interaction matrices

Category	Variable	Definition	Source
Common exposure (market price channel)	Common exposure	Share of the set of assets held in all portfolios in the portfolio of each bank	Bloomberg
Fundamental-based similarity (informational channel)	Div_Yld	Dividend yield	Bloomberg
	Debt_ass	Ratio of total debt to total assets (in percentage)	Bloomberg
	Mkt_Ass.	Total current market value of all of a company's outstanding shares stated in USD over total asset (in percentage)	Bloomberg
Investment-based similarity (informational channel)	Portfolio holdings by sectors	Value (in USD) of holdings by sector over total asset	Bloomberg
	Port. Div.	Index of portfolio diversification computed at sector level and accounting for market volatility. For a given portfolio i at time t, it is computed as $div\_idx_{i,t} = \frac{P'_{i,t}\Sigma_t}{\sqrt{P'_{i,t}V_t P_{i,t}}}$, where $P_{i,t} = (P_{i,1,t}, ;P_{i,S,t})$ is a vector of investment shares (that sum to 1) at sector level, Σ_t is a vector of volatility measures and V_t the associated covariance matrice. Σ_t and V_t are computed over a rolling window of four quarters using the daily returns on the S&P500 sector indices.	Bloomberg

consider the level of industry concentration (i.e. sector-based similarity matrices), which has been shown to be a critical feature of investment strategy by financial institutions (see Kacperczyk et al., 2005). Hence, $z^s_{i,t}$ is the ratio between the total amount of assets held by bank i in sector s and its balance sheet total asset at time t, $s = 1, \ldots, S$, where S is the number of sectors (in our case S=10; see Table 5 for the detailed list).[14] Another measure of investment similarity, *Portfolio Diversification index* - feature the level of diversification of the portfolio (see Table 4 for further details).

For fundamental-based measures of similarity, we consider three standard characteristics of banks: the *dividend yield* ratio, the *debt to total assets* ratio and the *market capitalization to total assets* ratio.

We go on to construct a measure of common exposure based on granular data on portfolio holdings. As further explained in Section 2.4, we need to impose some restrictions on the measure to be used in our econometric setting. In particular, the

[14]Assets are categorized following the Global Industry Classification Standard (GICS).

Table 5: List of sectors in the portfolio holding data

Label	Sector
CD	Consumer Discretionary
EN	Energy
HC	Health care
IT	Information Technology
MA	Materials
TS	Telecommunication Services
CS	Consumer Staples
FI	Financial
IN	Industrial
UT	Utilities

matrix should be constructed as a combination of bank i and bank j characteristics. For this purpose, we first identify the set of assets held in all portfolios. Next, we compute the share invested in this category of "common assets" for each institution. It gives z_i and z_j for banks i and j. Then, elements of the connectivity matrix $w_{ij,t}$ are constructed using the same formula as equation (2).

The resulting $w^s_{ij,t}$ defines the constituents of our different transmission channels, W_t. In total, we count 15 matrices. We finally standardize these interaction matrices by the maximum eigenvalue to ensure comparability of the cross-sectional dependence parameter (λ) across specifications.

2.4 Econometric approach to the endogeneity of transmission channels

Traditional estimation methods in spatial econometrics rely on the assumption that the interaction matrix is exogenous. When the interaction structure is constructed from economic or financial variables and hence contains economic interpretation (see, for example, the interaction structures in Eder and Keiler, 2015 and Caporin and Paruolo, 2015), this exogeneity assumption might be too strong. Ignoring this endogeneity yields inconsistent and biased parameters estimates. We tackle this issue by harnessing the emerging literature on endogenous interaction matrices in spatial econometrics (see Kelejian and Piras, 2014; Qu and Lee, 2015; Han and Lee, 2016; Qu et al., 2016, 2017; Shi and Lee, 2018) and specifically exploit the approach recently developed by Shi and Lee (2018). In that framework, the elements of the interaction matrix W_t are constructed from a variable z_{it}.[15]

The variable Z_t is modeled as follows:

$$Z_t = X'_{zt}\beta_z + \Gamma_z f_{zt} + \epsilon_t, \tag{3}$$

where X_{tz} are $k_z \times 1$ regressors with corresponding coefficient vector β_{zl}, f_{zt} which consists of $R_z \times 1$ time factors with loading Γ_z and ϵ_t, an idiosyncratic error. Finally, Assumption 2 from Shi and Lee (2018), reproduced below, models the source of endogeneity of the interaction matrix.

> *The error terms (v_{it}, ϵ_{it}) are independently and identically distributed across i and over t, and have a joint distribution $(v_{it}, \epsilon_{it})' \sim (0, \Sigma_{v\epsilon})$, where $\Sigma_{v\epsilon} = \begin{pmatrix} \sigma_v^2 & \sigma_{v\epsilon} \\ \sigma_{v\epsilon} & \sigma_\epsilon^2 \end{pmatrix}$ is positive definite, σ_v^2 is the variance of v_{it}, $\sigma_{v\epsilon}$ is the covariance between v_{it} and ϵ_{it} and σ_ϵ^2 is the variance of ϵ_{it}. Furthermore*

[15] For instance $w_{ij,t} = \frac{1}{(z_{it}-z_{jt})}$. In their paper, Shi and Lee (2018) allow $w_{ij,t}$ to be constructed from multivariate vector of p variables Z_t. However, in this contribution, we consider an univariate Z_t.

$\sup_{n,T}\sup_{i,T}\mathbb{E}\,|v_{it}|^{4+\delta_\epsilon}$ and $\sup_{n,T}\sup_{i,T}\mathbb{E}\,|\epsilon_{it}|^{4+\delta_\epsilon}$ exist for $\delta_\epsilon > 0$. Denote $\mathbb{E}(v_{it}|\epsilon_{it}) = \epsilon_{it}\delta$ and define $\xi_{it} = v_{it} - \epsilon_{it}\delta$, assuming that $\mathbb{E}(\xi_{it}^2|\epsilon_{it}) = \mathbb{E}(\xi_{it}^2) = \sigma_\xi^2$, $\mathbb{E}(\xi_{it}^3|\epsilon_{it}) = \mathbb{E}(\xi_{it}^3)$ and $\mathbb{E}(\xi_{it}^4|\epsilon_{it}) = \mathbb{E}(\xi_{it}^4)$.

When $\sigma_{v\epsilon} \neq 0$, the error terms v_{it} and ϵ_{it} are correlated and the interaction matrix W_t becomes endogenous. Under this assumption, $V_t = \xi_t + \epsilon_t\delta$. Substituting this expression in equation (1) yields:

$$y_t = \lambda W_t y_t + X_{yt}\beta_y + \Gamma_y f_{yt} + \epsilon_t\delta + \xi_t, \tag{4}$$

where the $(n \times 1)$ vector of error terms ξ_t are i.i.d across i and t. We also have $\mathbb{E}(\xi_t|\epsilon_t) = 0$, $Var(\xi_t|\epsilon_t) = \sigma_\xi^2 I_n$ and ξ_t uncorrelated with the regressors.
Identifying appropriate instrumental variables, X_{zt}, in empirical applications is often a difficult task. For the problem at hand, the economic theory provides us with limited guidance. Due to the highly nonlinear relation between W_t and the exogenous X_{yt} variables, we do not necessarily need to rely on external exogenous variables to instrument Z_t.[16] Thus, X_{zt} and X_{yt} can share common components (see Shi and Lee, 2018, p.3). Further, as often done in empirical studies in a similar situation, we use the first order lag of the endogenous variable, Z_{t-1} as instrument (see Reed, 2015).

Shi and Lee (2018) develop and study the asymptotic properties of the quasi-maximum likelihood estimator of model (4). Denoting $\theta = (\beta_z^{'}, \beta_y^{'}, \lambda, \sigma_\xi, \sigma_\epsilon^2, \delta)'$ and treating the unobserved heterogeneity components $(\Gamma_y, \Gamma_z, F_y, F_z)$, with $F_y = (f_{y1}, \cdots, f_{yT})'$

[16] There are two sources of nonlinearity in the relation between W_t and X_{yt} : 1) W_t is a nonlinear function of Z_t and 2), the reduced form of model (1) shows a nonlinear relation between W_t and X_{yt}.

and $F_z = (f_{z1}, \cdots, f_{zT})'$, as fixed-effects parameters to be estimated, the sample average log-likelihood function of the model is:

$$\begin{aligned}\frac{1}{nT}\log L_{nT}\left(\theta, \Gamma_y, F_{Ty}\right) = &-\log\left(2\pi\right) - \frac{1}{2}\log\sigma_\xi^2 - \frac{1}{2}\log|\sigma_\epsilon^2| + \frac{1}{nT}\sum_{t=1}^{T}\log|S_t(\lambda)| \\ &- \frac{1}{2nT\sigma_\xi^2\sigma_\epsilon^2}\sum_{t=1}^{T} e_t' e_t \\ &- \frac{1}{2\sigma_\xi^2 nT}\sum_{t=1}^{T}\left[S_t(\lambda)y_t - X_t\beta_y - \left(\delta' \otimes I_n\right)e_t - \Gamma_y f_{yt}\right]' \\ &\times \left[S_t(\lambda)y_t - X_t\beta_y - \left(\delta' \otimes I_n\right)e_t - \Gamma_y f_{yt}\right],\end{aligned}$$

where $S_t = (I_n - \lambda W_t)$ and $e_t = Z_t - X_{zt}\beta_z - \Gamma_z f_{zt}$.

In the estimation strategy they propose, time factors as well as loading parameters are concentrated out of the above log-likelihood function so that only the parameter vector θ needs to be estimated. Further, even though we can recover the value of the time factors and loading parameters, they are not uniquely defined (even though the value of the other parameters is not affected).[17]

When dealing with unobserved common factors, an important question is the number of factors to consider in the empirical estimation. Indeed, we need to make sure to include enough factors to avoid an omitted variable bias. In this contribution, we rely on the Ahn and Alex (2013) growth ratio, as proposed by Shi and Lee (2018), to find the optimal number of time factors to consider.

[17]By imposing stricter restrictions on the factors and the matrix of loading parameters, one could uniquely identify them (see among others, Bai, 2009). However, Shi and Lee (2018) do not wish to impose these constraints, leading to non-uniquely identified time factors and loading parameters.

2.5 An Interaction-Based Centrality indicator

We propose to derive a metric from our spatial econometrics framework assessing how much a bank is exposed to the rest of the system. We call this metrics " Interaction-Based Centrality" (IBC). It consists of the Katz centrality measure (Katz, 1953) where the attenuation factor is estimated from the data. The original Katz centrality measure for observation i, denoted c_i, is given by expression (6),

$$IBC_{i,t} = (I_n - \lambda W_t)^{-1}_{i.} \iota_n \tag{5}$$

$$c_i = \kappa \sum_{j \neq i}^{n} w_{ij} c_j + \delta \tag{6}$$

where n is the number of observations (banks here), κ a parameter whose value is less than the largest eigenvalue of the adjacency matrix W and δ a scalar parameter. This equation can be rewritten into matrix form as follows:

$$c = \delta (I - \kappa W)^{-1} \iota \tag{7}$$

with c, the n-dimensional column vector of Katz centralities and ι an n-dimensional vector of one. Each element of c indicates how important a bank is in the sense that it is linked to other important banks. The advantage with our spatial econometrics modelling is that, instead of having to set κ, the so-called "attenuation parameter" (the equivalent for λ in our spatial setting) to a predefined value as done usually in the network literature, we can let the data speak and provide rigorous statistical inference about it. In other words, the value of κ is estimated rather than chosen on an ad-hoc basis. However, for convenience, $\delta = 1$ (see Newman, 2010, p.173).

We then visually illustrate how our indicator can be used for monitoring purposes by representing time-varying networks of vulnerable institutions. In the reported figures, the size of the nodes represents the IBC measure and the line width of edges between two nodes corresponds to interaction's intensity between them, given by the selected matrix.[18]

3 Estimation results

The baseline results are provided in Tables 6 to 9. which report estimates for time-varying interaction matrices. Each column represents a specific channel of transmission. Tables 6 to 8 are based on the Shi and Lee (2018) approach and include the control function parameter, δ, to test and control for the presence of endogeneity in the interaction matrix. In Tables 7 and 9, the model is estimated by the same approach but imposing the exogeneity of the matrix.

Before going further, it is worth clarifying which results should be considered in the case of conflicting outcomes, and when. Recall that the Shi and Lee (2018) approach including the correction provides unbiased and consistent estimators regardless of the nature of W_t (exogenous or endogenous). In the absence of endogeneity, the estimator is, however, inefficient. In large samples, estimating the model either with or without controlling for the endogeneity should not matter much if W_t is exogenous. In small

[18]More precisely, for the sake of visibility, we truncate the matrices and only consider the 40% largest interactions between banks.

Table 6: Estimations for investment-based similarity matrices (sector-based and diversification-based matrices) using the subsample Q3 2007–Q2 2013 (T=24)

Parameters	Port. Div	CD	MA	EN	HC	IT	TS	CS	FI	IN	UT
	Estimation results of the main SAR model (eq. 4)										
Loan_Dep	0.003	0.007	0.007	0.008	0.008	0.009	0.008	0.008	0.008	0.009	0.008
	(1.700)	(3.910)	(3.777)	(4.349)	(4.222)	(4.551)	(3.910)	(4.302)	(4.646)	(4.581)	(4.107)
Lev	-0.000	0.071	0.069	0.076	0.081	0.079	0.078	0.067	0.065	0.075	0.069
	(-0.041)	(4.935)	(4.892)	(5.587)	(5.176)	(5.593)	(5.416)	(5.428)	(4.835)	(5.629)	(5.423)
Loss_Iinc	0.009	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
	(5.510)	(5.445)	(5.474)	(5.420)	(5.375)	(5.408)	(5.353)	(5.650)	(5.402)	(5.429)	(5.573)
WY	0.728	0.189	0.182	0.092	0.088	0.045	0.094	0.161	0.144	0.046	0.118
	(16.051)	(2.029)	(1.966)	(1.124)	(0.928)	(0.501)	(0.918)	(2.424)	(1.894)	(0.541)	(1.377)
δ	0.721	-0.431	-0.600	-0.246	-0.403	-0.295	-1.646	-0.097	-0.066	-0.221	-0.268
	(6.415)	(-2.787)	(-2.255)	(-2.421)	(-3.516)	(-2.631)	(-3.499)	(-0.690)	(-0.981)	(-1.801)	(-0.989)
Log-lik	-90362.748	-79159.774	-81460.460	-78683.762	-69220.544	-73454.804	-87428.413	-73742.035	-70333.785	-84981.096	-82653.537
Number of factors in y	1	1	1	1	1	1	1	1	1	1	1
n	28	28	28	28	28	28	28	28	28	28	28
T	24	24	24	24	24	24	24	24	24	24	24
	Estimation results of the reduced form model for W (eq. 3)										
Loan_Dep	0.001	0.001	0.000	-0.000	0.000	0.001	0.000	-0.000	0.001	-0.000	-0.000
	(3.955)	(1.789)	(1.636)	(-0.195)	(0.904)	(1.104)	(0.093)	(-1.172)	(1.063)	(-0.861)	(-2.242)
Lev	0.002	-0.005	-0.004	-0.001	-0.002	-0.005	0.000	0.003	-0.006	0.002	0.002
	(1.647)	(-1.682)	(-2.132)	(-0.151)	(-0.730)	(-1.299)	(0.399)	(1.073)	(-0.985)	(0.510)	(2.084)
Loss_Iinc	-0.000	-0.000	0.000	0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000	0.000
	(-0.191)	(-0.040)	(1.282)	(0.369)	(-0.866)	(0.573)	(-0.245)	(-0.840)	(-0.158)	(1.062)	(0.523)
Z_{t-1}	0.684	0.777	0.850	0.842	0.655	0.841	0.823	1.052	0.847	0.881	0.990
	(235.315)	(57.001)	(62.680)	(112.479)	(42.233)	(82.321)	(57.714)	(133.426)	(85.292)	(116.508)	(91.202)
Number of factors in Z	1	1	1	1	2	1	1	1	1	1	1

T-stats between brackets.

Table 7: Estimations for investment-based similarity matrices (sector-based and diversification-based matrices) using the subsample Q3 2007–Q2 2013 (T=24) using time-varying but exogenous matrices

Parameters	Port. Div	CD	MA	EN	HC	IT	TS	CS	FI	IN	UT
	Estimation results of the main SAR model (eq. 4)										
Loan_Dep	0.002	0.005	0.004	0.008	0.007	0.008	0.004	0.008	0.008	0.009	0.008
	(1.510)	(3.149)	(2.719)	(4.340)	(4.086)	(4.501)	(2.858)	(4.333)	(4.747)	(4.655)	(4.100)
Lev	0.013	0.009	0.006	0.071	0.065	0.071	-0.005	0.067	0.066	0.073	0.069
	(1.021)	(0.783)	(0.511)	(5.858)	(5.334)	(5.785)	(-0.446)	(5.413)	(5.179)	(5.908)	(5.421)
Loss_Iinc	0.009	0.003	0.005	0.010	0.010	0.010	0.004	0.010	0.010	0.010	0.010
	(5.090)	(1.925)	(3.018)	(5.568)	(5.459)	(5.585)	(2.733)	(5.660)	(5.396)	(5.529)	(5.608)
WY	0.746	0.867	0.858	0.130	0.201	0.100	0.877	0.161	0.136	0.061	0.125
	(15.567)	(33.102)	(34.878)	(1.929)	(2.980)	(1.337)	(39.652)	(2.425)	(1.970)	(0.828)	(1.500)
Log-lik	-629.134	-629.685	-624.253	-636.928	-636.200	-637.042	-619.555	-636.513	-636.890	-636.974	-637.312
Number of factors in y	1	1	1	1	1	1	1	1	1	1	1
n	28	28		28 28	28	28	28	28	28	28	28
T	24	24		24 24	24	24	24	24	24	24	24

T-stats between brackets

samples, conversely, marked differences could emerge between the two approaches. In this case, estimating the model under the correct assumption for the interaction matrix should be preferred. We thus propose to proceed in two steps. First, we estimate the model by including the correction term. After testing for the presence of endogeneity, we are left with two options. If δ is statistically significant, we interpret all the remaining coefficients (Tables 6 and 8). If δ is not significant, we consider the model without correction – that is, the one supposing an exogenous time-varying matrix (Tables 7 and 9). We go on to compare, in Tables 10 and 11, our baseline results with the case where one treats the channels as exogenous and time-invariant. In that setting, we use the data in 2007Q3 (initial period) to construct the interaction matrices.

Our controls in Tables 6 to 9 all exhibit the expected signs. In particular, the loan-to-deposit ratio, the level of leverage, as well as the loan loss provisions to interest income ratio, are all positive and significant, with the exception of two models over 30.[19]

We now turn to our main parameter of interest at this stage – the one controlling for the presence of endogeneity in the model, namely δ. We start our analysis with the sector-based similarity matrices. Table 6 shows that δ is statistically significant for 6 sectors over 10. Consumer Staples, Financial, Industrial and Utilities are the sectors for which W_t can be assumed as exogenous. Further, the exogeneity of the channel constructed

[19]To rigorously interpret the impact of a change in an exogenous determinant on the risk variable, we should compute the reduced form of the model, then calculate matrices of partial derivatives of the dependent variable wrt. the relevant determinant and finally compute direct, indirect and total effects, as shown in LeSage and Pace (2009). However, this is not the main objective of this contribution. We can nevertheless say that the direct impact of an increase in whatever measure of indebtedness of the bank will be an increase in its risk, measured by the volatility.

from Portfolio Diversification index is also rejected. Consistently with the above discussion, we proceed by considering the most suited approach for each channel. Table 6 shows that for the 7 endogenous matrices the cross-sectional dependence parameter λ is statistically significant for three of them: Portfolio Diversification, Consumer Discretionary and Materials. We cannot reject the null of no contagion effects for the others. Turning to the exogenous matrices, two models out of four, Consumer Staples and Financial, display significant cross-sectional dependence. This first set of results confirms the existence of positive and significant externalities stemming from sector-based similarity, which implies that a stress in a bank tends to spread out to other institutions sharing similar sectoral investment strategies. Looking more carefully at the different sectors, we observe that the results are quite stable over the 4 significant sector-based transmission channels (Consumer Discretionary, Financial, Consumer Staples, Materials) with coefficient estimates for λ ranging from 0.189 (Consumer Discretionary) to 0.136 (Financial). However, the interaction intensity is much higher for the Portfolio Diversification channels, with $\lambda = 0.728$.

To assess the influence of the correction, we examine the consequences of wrongly assuming W_t as exogenous. To do so, we compare the significance along with size of the coefficients with the two approaches for the seven endogenous matrices (Tables 6 and 7). Both approaches reach similar conclusions in four instances. For the Information Technology sector, we cannot find cross-sectional correlation. For three matrices –Portfolio Diversification, Consumer Discretionary and Materials – contagion effects are detected with and without corrections (even though results with the correction are relatively less striking). In three cases (Energy, Health Care, Telecommunication Services), we observe conflicting results; that is we reach a wrong conclusion by not correcting for the presence of endogeneity. In each case, we can reject the null of no contagion without correction, but not with the robust approach. Turning to the size of the coefficients, we consider the three endogenous matrices for which the cross-sectional coefficient is significant: Portfolio Diversification, Consumer Discretionary, and Materials. While the estimated values of λ for the first channel are quite similar (0.728 and 0.746), the situation is quite different for the last two. The estimated values are equal to 0.19 (Consumer Discretionary) and 0.18 (Materials) when applying Shi and Lee (2018) with the correction, compared to 0.86 and 0.85 without. These figures show that failing to control for endogeneity may, in our context, to inflate the magnitude of contagion effects up to a factor of four.

We now consider the models with transmission channels related to common exposure and fundamental-based similarity matrices (Tables 8 and 9).

Here, we cannot reject the null hypothesis of exogeneity in any case. If we consider the estimators of λ consistent with the test, the cross-sectional dependence parameter appears always highly significant (except for the channel constructed from debt over asset ratios). This suggests that those characteristics – Dividend yield (DIV_YLD) and Market value to total asset ratio (MKT_ASS) – are relevant in explaining risk spillovers across banks, although with different intensities. Finally, the last column of Table 8 reports the results for the market price channel. The testing procedure does not allow the rejection of the null of exogeneity for this interaction matrix. Here also,

Table 8: Estimations for fundamental-based and common exposure matrices using the subsample Q3 2007–Q2 2013 (T=24)

Parameters	DEB_ASS	DIV_YLD	MKT_ASS	COM_EXPO
	Estimation results of the main SAR model (eq. 4)			
Loan_Dep	0.009	0.009	0.007	0.009
	(5.122)	(5.289)	(3.506)	(5.153)
Lev	0.074	0.051	0.067	0.059
	(5.892)	(3.845)	(4.963)	(4.760)
Loss_Iinc	0.010	0.010	0.010	0.009
	(5.420)	(5.676)	(5.572)	(4.999)
WY	0.006	0.227	0.220	0.278
	(0.106)	(3.871)	(3.360)	(3.880)
δ	0.003	-0.007	-0.005	-0.384
	(0.171)	(-0.299)	(-0.341)	(-0.357)
Log-lik	-71870.177	-67753.082	-60850.679	-52200.508
Number of factors in y	1	1	1	1
n	28	28	28	28
T	24	24	24	24
	Estimation results of the reduced form model for W (eq. 3)			
Loan_Dep	0.002	0.005	-0.022	0.000
	(0.862)	(3.683)	(-3.430)	(0.205)
Lev	0.000	0.003	-0.180	0.001
	(0.002)	(0.301)	(-4.539)	(1.610)
Loss_Iinc	-0.002	-0.008	-0.008	-0.000
	(-0.814)	(-6.130)	(-2.418)	§§(-2.373)
Z_{t-1}	0.967	0.873	0.668	0.716
	(100.402)	(75.706)	(34.976)	(67.111)
Number of factors in Z	1	2	1	2

T-stats between brackets.

Table 9: Estimations for fundamental-based and common exposure matrices using the subsample Q3 2007–Q2 2013 (T=24) using time-varying but exogenous matrices

Parameters	DEB_ASS	DIV_YLD	MKT_ASS	COM_EXPO
	Estimation results of the main SAR model (eq. 4)			
Loan_Dep	0.009	0.009	0.007	0.008
	(5.117)	(5.297)	(3.868)	(4.913)
Lev	0.074	0.051	0.065	0.062
	(5.923)	(3.862)	(5.338)	(4.902)
Loss_Iinc	0.010	0.010	0.010	0.009
	(5.474)	(5.671)	(5.582)	(5.049)
WY	0.004	0.227	0.221	0.159
	(0.067)	(3.912)	(3.385)	(2.860)
Log-lik	-636.310	-634.408	-633.989	-634.765
Number of factors in y	1	1	1	1
n	28	28	28	28
T	24	24	24	24

T-stats between brackets.

the λ is strongly significant. The sign is positive, meaning that two banking institutions investing in the same assets are prone to contagious effects.

The bottom panels of Tables 6 and 8 finally report the relevant number of considered common factors in the main equation (number of factors in y) and in the control function equation (number of factors in Z). The results show that considering one unobserved factor is sufficient in the main equation, while a second factor is sometimes needed for the control function equation (when Z_t is built on Health Care, Dividend Yield and Common Exposure).

As a matter of comparison, we report in Tables 10 and 11 the estimation results when transmission channels are treated as time-invariant. We observe several differences with time-varying matrices. Notably, the Common Exposure, Portfolio Diversification and Dividend Yields transmission channels are no longer identified as transmitting risk among banking institutions. In contrast, the channel constructed from the ratio of debt over assets becomes statistically significant. Further, transmission channels based on similarity of investment in the Health Care, Industry and Telecommunication Services sectors become significant when assuming constant and exogenous connectivity matrices. These discrepancies illustrate that relying on time-invariant transmission channels may lead to inaccurate conclusions.

To close the discussion on the estimation part, we check the robustness of our results to the sample period. Tables 12 to 15 display the main coefficients of interest for our

Table 10: Estimations for investment-based similarity matrices (sector-based and diversification-based matrices) using the subsample Q3 2007–Q2 2013 (T=24) using constant (2007Q3) and exogenous matrices

Parameters	Port. Div.	CD	MA	EN	HC	IT	TS	CS	FI	IN	UT
	Estimation results of the main SAR model (eq. 4)										
Loan_Dep	0.008	0.007	0.004	0.008	0.008	0.009	0.003	0.008	0.008	0.008	0.010
	(3.850)	(3.774)	(2.658)	(4.214)	(4.065)	(4.638)	(2.413)	(4.278)	(4.261)	(4.458)	(4.492)
Lev	0.072	0.052	-0.005	0.073	0.065	0.071	-0.005	0.060	0.067	0.069	0.082
	(4.977)	(4.127)	(-0.413)	(6.007)	(5.222)	(5.538)	(-0.444)	(4.629)	(5.302)	(5.626)	(5.855)
Loss_Iinc	0.010	0.010	0.006	0.010	0.010	0.010	0.006	0.010	0.010	0.010	0.010
	(5.526)	(5.528)	(3.443)	(5.567)	(5.612)	(5.559)	(3.819)	(5.683)	(5.517)	(5.557)	(5.447)
WY	0.061	0.306	0.816	0.088	0.172	0.063	0.841	0.194	0.137	0.121	-0.087
	(0.534)	(4.593)	(31.783)	(1.318)	(2.402)	(0.859)	(37.050)	(2.841)	(2.041)	(1.910)	(-0.757)
Log-lik	-636.833	-634.973	-634.323	-637.042	-636.946	-636.938	-617.019	-636.440	-636.894	-636.875	-635.018
Number of factors in y	1	1	1	1	1	1	1	1	1	1	1
n	28	28	28	28	28	28	28	28	28	28	28
T	24	24	24	24	24	24	24	24	24	24	24

T-stats between brackets

Table 11: Estimations for fundamental-based and common exposure matrices using the subsample Q3 2007–Q2 2013 (T=24) using constant (2007Q3) and exogenous matrices

Parameters	DEB_ASS	DIV_YLD	MKT_ASS	COM_EXPO
	Estimation results of the main SAR model (eq. 4)			
Loan_Dep	0.007	0.009	0.007	0.010
	(3.763)	(4.095)	(3.602)	(5.377)
Lev	0.059	0.071	0.073	0.079
	(4.512)	(5.395)	(5.997)	(6.198)
Loss_Iinc	0.010	0.010	0.010	0.010
	(5.481)	(5.568)	(5.640)	(5.401)
WY	0.214	0.053	0.124	-0.054
	(3.094)	(0.656)	(1.940)	(-0.972)
Log-lik	-636.024	-636.803	-636.732	-634.942
Number of factors in y	1	1	1	1
n	28	28	28	28
T	24	24	24	24

T-stats between brackets.

two main cases: time-varying matrices with and without exogeneity of the transmission channel. In each case, we slightly alter the reference period. Overall, the results are robust. We note, however, a slight loss of significance for the cross-sectional coefficient of sector-based matrices as the time span to estimate the model shrinks.

Equipped with estimated values for the strength of the various channels, we construct an Interaction-Based Centrality index, derived from our spatial model. This index measures the overall exposure of a bank vis-à-vis the whole system, according to equation (5). We then proceed to plot in Figures 2 to 5 the network of institutions at different time periods (2007Q3, 2009Q3 and 2013Q2). The size of the node represents the vulnerability of each institution as measured by the IBC index. The widths of lines to draw the edges are constructed from the intensity of links in the relevant matrix. For the sake of parsimony, we restrict our illustration to best-in-class channels – that is, those with a significant λ displaying the maximum value of the log-likelihood function within their class. The selected matrices are therefore the investments in the Consumer Staples sector, Portfolio Diversification and Market value to total asset ratio for, respectively, the strategy-based and fundamental-based information channels along with our measure of Common Exposure. Also, to ease the visualization, we trim the links to keep only the strongest 40%.[20]

Three main remarks can be drawn from these figures. First, we notice that the IBC index is much higher for the market capitalization over assets similarity matrix than for the three others. This may be explained by higher similarities between banks with

[20]The matrices being full, a representation showing all the links would not be readable.

Table 12: Analysis of Robustness for alternative time periods, investment-based similarity matrices (sector-based and diversification-based matrices). Results accounting for the possible endogeneity of matrices

		Port. Div	CD	MA	EN	HC	IT	TS	CS	FI	IN	UT
Q3 2007-Q2 2013	**WY**	0.728	0.189	0.182	0.092	0.088	0.045	0.094	0.161	0.144	0.046	0.118
		(16.051)	(2.029)	(1.966)	(1.124)	(0.928)	(0.501)	(0.918)	(2.424)	(1.894)	(0.541)	(1.377)
	δ	0.721	-0.431	-0.600	-0.246	-0.403	-0.295	-1.646	-0.097	-0.066	-0.221	-0.26
		(6.415)	(-2.787)	(-2.255)	(-2.421)	(-3.516)	(-2.631)	(-3.499)	(-0.690)	(-0.981)	(-1.801)	(-0.989)
Q3 2007-Q1 2013	**WY**	0.728	0.174	0.164	0.088	0.095	0.042	0.065	0.162	0.138	0.046	0.01
		(15.714)	(1.816)	(1.684)	(1.036)	(1.065)	(0.453)	(0.602)	(2.369)	(1.767)	(0.512)	(0.087)
	δ	0.705	-0.483	-0.701	-0.263	-0.590	-0.307	-2.014	-0.105	-0.067	-0.239	-0.564
		(6.166)	(-2.950)	(-2.516)	(-2.437)	(-3.417)	(-2.641)	(-3.726)	(-0.658)	(-0.946)	(-1.853)	(-3.194)
Q3 2007-Q4 2012	**WY**	0.712	0.161	0.158	0.082	0.090	0.013	0.068	0.156	0.127	0.050	0.013
		(14.476)	(1.641)	(1.593)	(0.948)	(1.005)	(0.126)	(0.632)	(2.248)	(1.576)	(0.558)	(0.119)
	δ	0.707	-0.491	-0.702	-0.261	-0.596	-0.223	-1.941	-0.138	-0.060	-0.223	-0.517
		(5.987)	(-2.934)	(-2.512)	(-2.424)	(-3.303)	(-2.912)	(-3.497)	(-0.821)	(-0.829)	(-1.680)	(-2.984)
Q3 2007-Q2 2012	**WY**	0.706	0.173	0.183	0.084	0.092	0.070	0.099	0.031	0.117	0.065	0.087
		(13.596)	(1.828)	(1.888)	(0.950)	(1.034)	(0.823)	(0.945)	(0.320)	(1.446)	(0.654)	(0.877)
	δ	0.647	-0.570	-0.737	-0.263	-0.630	-0.309	-2.015	-0.677	-0.044	-0.141	-0.941
		(5.099)	(-2.773)	(-2.450)	(-2.518)	(-3.247)	(-2.275)	(-3.499)	(-3.766)	(-0.538)	(-2.003)	(-2.056)
Q3 2007-Q4 2011	**WY**	0.688	0.143	0.145	0.062	0.081	0.045	0.069	0.006	0.094	0.054	0.026
		(11.902)	(1.412)	(1.399)	(0.661)	(0.884)	(0.490)	(0.616)	(0.054)	(1.098)	(0.574)	(0.236)
	δ	0.674	-0.612	-0.751	-0.261	-0.616	-0.295	-1.980	-0.677	-0.026	-0.215	-0.695
		(5.027)	(-2.672)	(-2.365)	(-2.509)	(-2.911)	(-2.121)	(-3.142)	(-3.631)	(-0.309)	(-1.510)	(-2.243)

T-stats between brackets.

Table 13: Analysis of Robustness for alternative time periods, investment-based similarity matrices (sector-based and diversification-based matrices). Results assuming time-varying but exogenous matrices

		Port. Div	CD	MA	EN	HC	IT	TS	CS	FI	IN	UT
Q3 2007-Q2 2013	**WY**	0.746	0.867	0.858	0.130	0.201	0.100	0.877	0.161	0.136	0.061	0.125
		(15.567)	(33.102)	(34.878)	(1.929)	(2.980)	(1.337)	(39.652)	(2.425)	(1.970)	(0.828)	(1.500)
Q3 2007-Q1 2013	**WY**	0.740	0.867	0.857	0.128	0.199	0.100	0.877	0.162	0.130	0.062	0.115
		(14.908)	(32.295)	(33.969)	(1.862)	(2.870)	(1.311)	(38.678)	(2.372)	(1.824)	(0.814)	(1.345)
Q3 2007-Q4 2012	**WY**	0.710	0.241	0.850	0.125	0.192	0.100	0.872	0.159	0.115	0.062	0.111
		(12.995)	(3.042)	(31.965)	(1.807)	(2.735)	(1.295)	(36.562)	(2.314)	(1.578)	(0.809)	(1.271)
Q3 2007-Q2 2012	**WY**	0.656	0.845	0.253	0.136	0.194	0.116	0.865	0.175	0.101	0.084	0.13
		(10.387)	(27.052)	(3.018)	(2.039)	(2.811)	(1.543)	(32.858)	(2.583)	(1.366)	(1.133)	(1.495)
Q3 2007-Q4 2011	**WY**	0.623	0.215	0.214	0.123	0.172	0.093	0.862	0.155	0.072	0.064	0.089
		(8.685)	(2.608)	(2.365)	(1.764)	(2.362)	(1.184)	(30.336)	(2.165)	(0.918)	(0.835)	(0.95)

T-stats between brackets.

Table 14: Analysis of Robustness for alternative time periods, fundamental-based and common exposure matrices. Results accounting for the possible endogeneity of matrices

		DEB_ASS	DIV_YLD	MKT_ASS	COM_EXPO
Q3 2007-Q2 2013	**WY**	0.006	0.227	0.220	0.278
		(0.106)	(3.871)	(3.360)	(3.880)
	δ	0.003	-0.007	-0.005	-0.384
		(0.171)	(-0.299)	(-0.341)	(-0.357)
Q3 2007-Q1 2013	**WY**	-0.000	0.230	0.210	0.276
		(-0.007)	(3.827)	(3.326)	(3.760)
	δ	0.003	-0.008	-0.005	-0.426
		(0.177)	(-0.314)	(-0.326)	(-0.385)
Q3 2007-Q4 2012	**WY**	-0.001	0.226	0.206	0.28
		(-0.012)	(3.697)	(3.276)	(3.699)
	δ	0.003	-0.009	-0.004	-0.493
		(0.214)	(-0.369)	(-0.251)	(-0.433)
Q3 2007-Q2 2012	**WY**	0.009	0.247	0.202	0.17
		(0.158)	(3.922)	(3.379)	(2.528)
	δ	-0.000	-0.002	-0.002	0.052
		(-0.005)	(-0.076)	(-0.127)	(0.039)
Q3 2007-Q4 2011	**WY**	0.004	0.252	0.219	0.22
		(0.069)	(3.778)	(3.469)	(3.027)
	δ	0.000	0.000	0.001	-0.432
		(0.026)	(0.003)	(0.041)	(-0.317)

T-stats between brackets.

Table 15: Analysis of Robustness for alternative time periods, fundamental-based and common exposure matrices. Results assuming time-varying but exogenous matrices

		DEB_ASS	DIV_YLD	MKT_ASS	COM_EXPO
Q3 2007-Q2 2013	**WY**	0.004 (0.067)	0.227 (3.912)	0.221 (3.385)	0.159 (2.860)
Q3 2007-Q1 2013	**WY**	-0.002 (-0.045)	0.230 (3.875)	0.211 (3.355)	0.153 (2.685)
Q3 2007-Q4 2012	**WY**	-0.003 (-0.050)	0.228 (3.761)	0.207 (3.304)	0.144 (2.483)
Q3 2007-Q2 2012	**WY**	0.008 (0.146)	0.244 (3.917)	0.201 (3.402)	0.137 (2.336)
Q3 2007-Q4 2011	**WY**	0.003 (0.056)	0.248 (3.757)	0.216 (3.482)	0.162 (2.680)

T-stats between brackets.

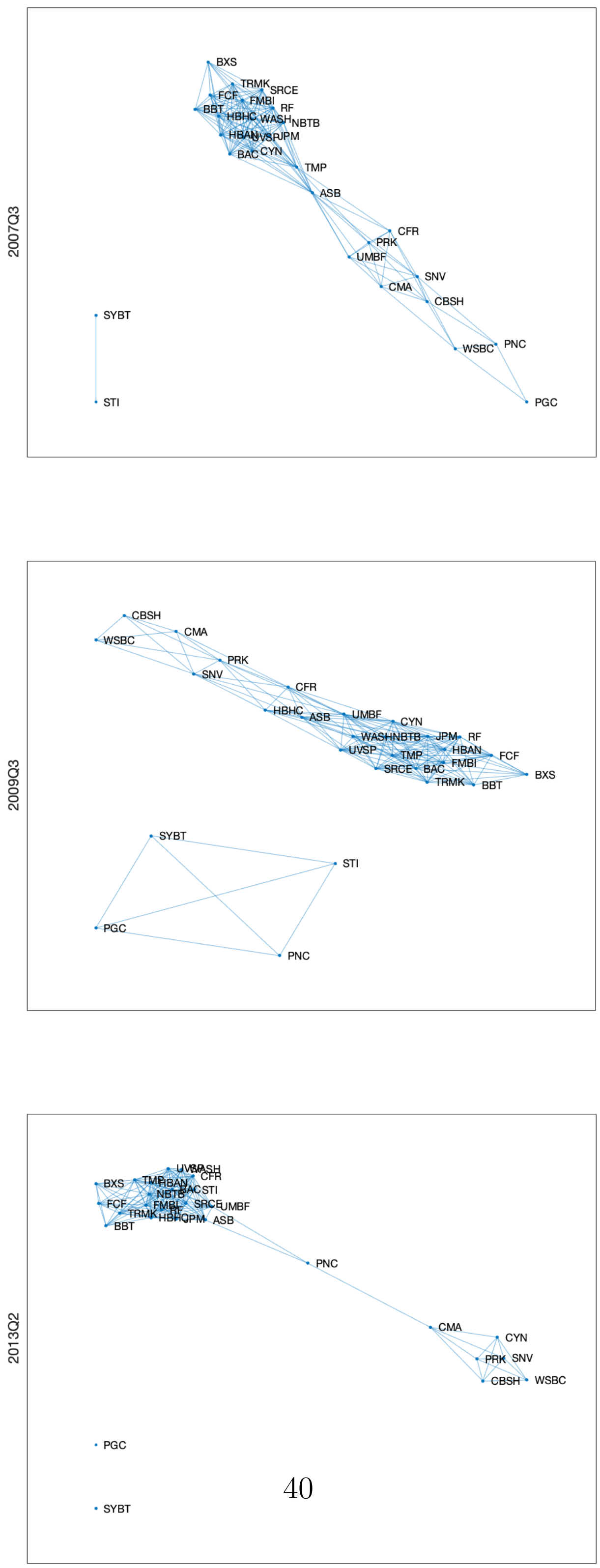

Figure 2: Network representation of Consumer Staples connectivity matrix for 3 periods

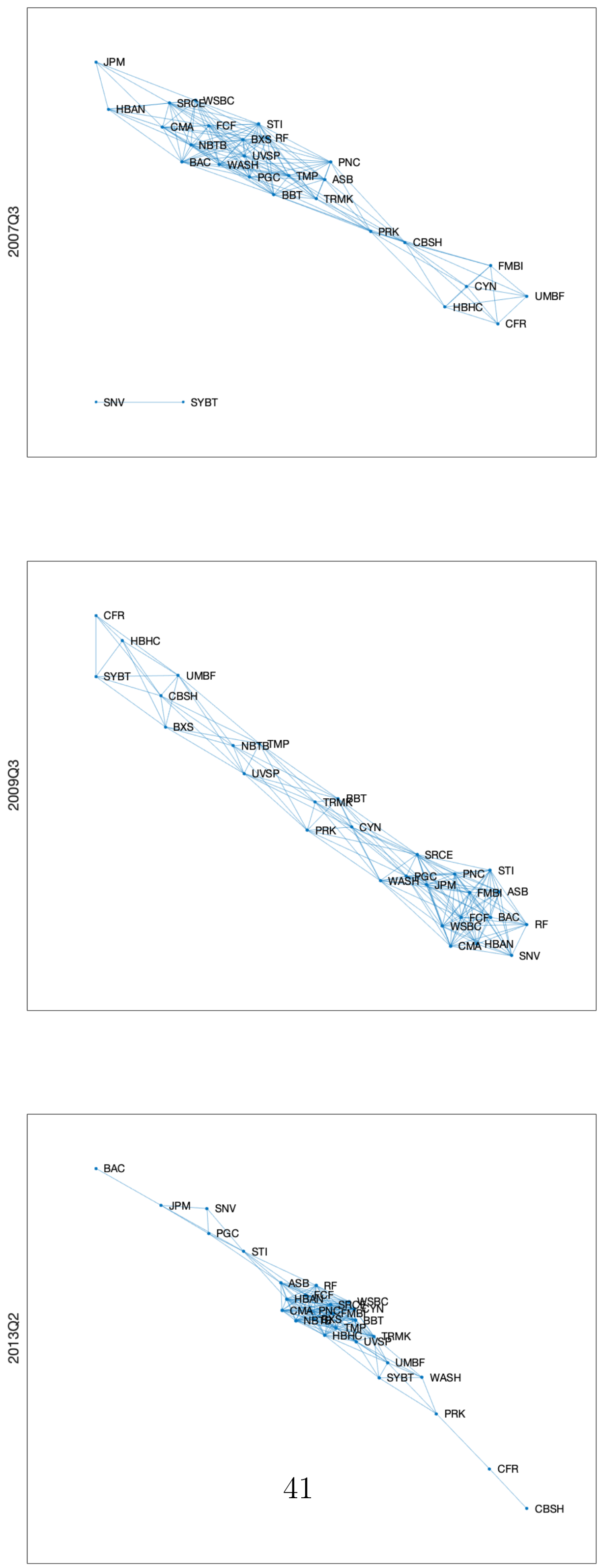

Figure 3: Network representation of Portfolio Diversification connectivity matrix for 3 periods

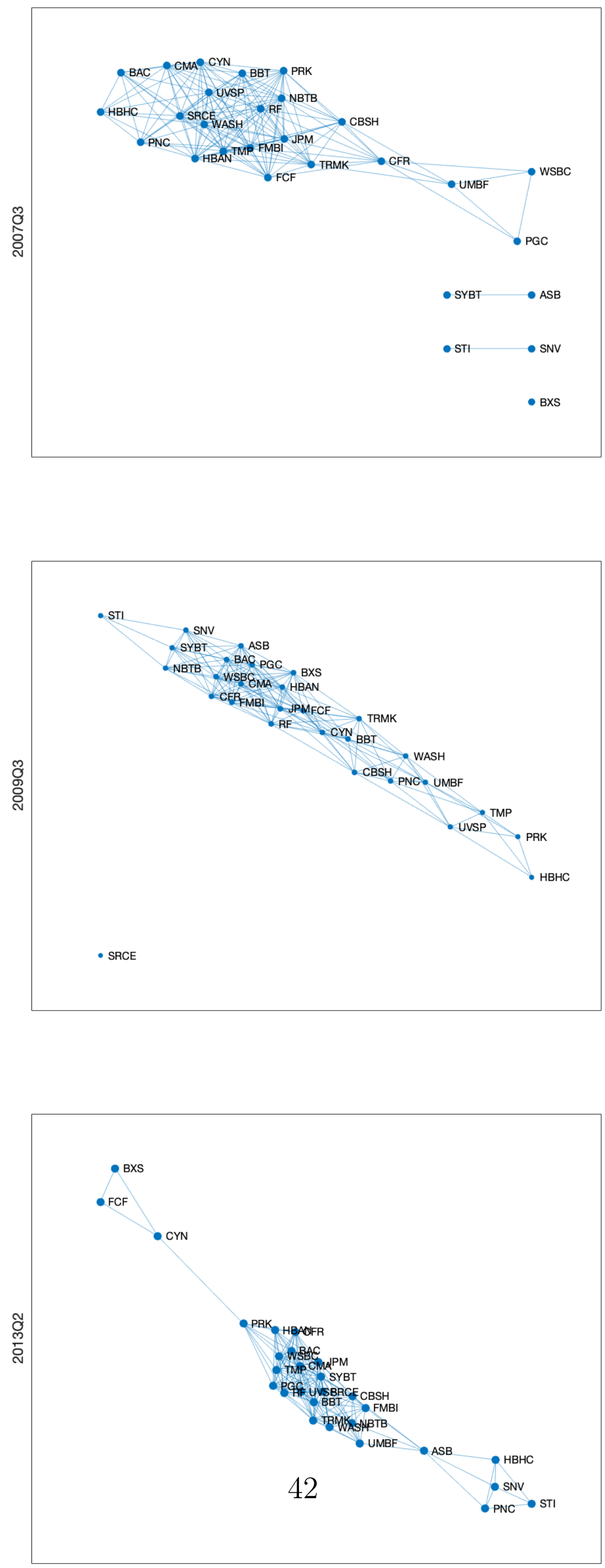

Figure 4: Network representation of Market Capitalization over assets Ratio connectivity matrix for 3 periods

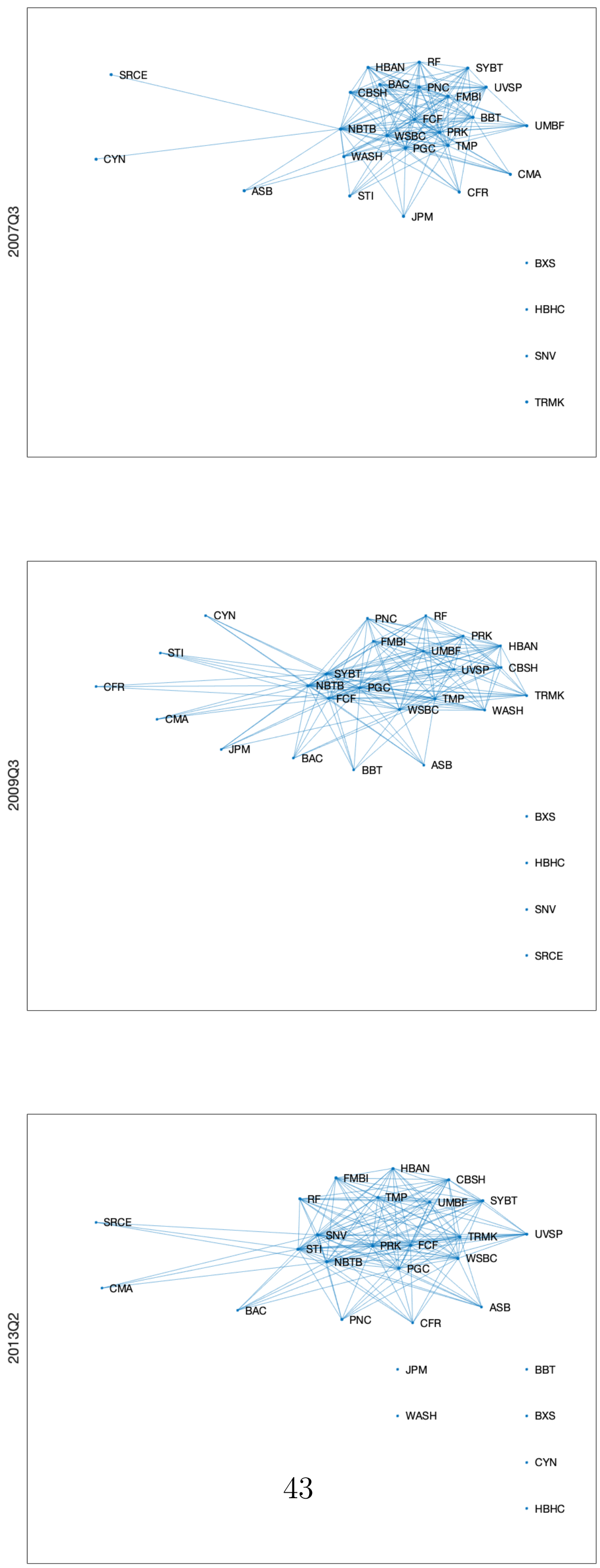

Figure 5: Network representation of Common Exposure channel for 3 periods

respect to this dimension compared to the others. Second, the evolution of the networks varies across the matrices. Specifically, matrices based on consumer staples, market capitalization over assets and as well as portfolio diversification display substantial changes over time. Third, we finally observe that the distribution of links is also channel-dependent. As such, for the common exposure matrix, the 40% most important links are distributed roughly equally among the connected banks, with a subgroup not connected. For other channels, the distribution of links is more heterogeneous and time-varying. For instance, the fundamental-based channel constructed from the market capitalization over assets ratio similarity matrix exhibits a homogeneous distribution of links among a subgroup of banks at the beginning of the period (2007Q3). In the next graph, this subgroup of well-connected institutions widens with only one bank disconnected. The third graph, which corresponds to the 2013 Q2 period, displays some changes in the distribution of links, with a subgroup of banks heavily connected and surrounded by two less connected subgroups. A similar pattern can be observed for the Portfolio Diversification similarity matrix.

4 Conclusion

What drives financial contagion? We empirically document in this paper the role of indirect contagion channels during the financial crisis of the late 2000s. Indirect contagion has been argued to be a "key ingredient in 2007", to quote Clerc et al. (2016). But its driving factors can be diverse. The transmission of risk from one institution to another in a crisis period can be due to common exposure (i.e. market price channel), for example, or to similarity in size, diversification, industrial concentration strategy (i.e. information channels), etc. Providing sound empirical evidence about the contribution of each specific channel is not trivial, however. As discussed in the paper (see also Wang et al., 2019), standard econometric approaches may be ill-suited to do so because of the endogenous response of certain transmission channels to the risk of a financial institution. This paper addresses this endogeneity issue in order to document the role of 15 indirect channels. To do so, we use a newly-developed spatial econometrics model "robust" to endogeneity in the time-varying interaction matrix (i.e. transmission channel). Within this framework, we are in addition able to decompose bank risk into systematic risk and spillover risk components while controlling for common factors. Overall, our results confirm that endogeneity characterizes part of our data and can affect the statistical significance along with the magnitude of the results compared to a situation in which the interaction matrix is wrongly assumed to be exogenous. Endogeneity in the transmission channel is therefore a critical feature that needs to be properly taken into account in empirical studies on contagion. Our findings also reveal positive and significant spillover effects through market price (i.e. common asset exposures) and information channels. Two banks that have invested in the same assets, for instance, are more exposed to contagion. Likewise, the similarity in sectoral investments strategy appears as a significant channel of risk spillovers. We also find significant spillovers when we consider similarities in fundamentals such as dividend yield or similarity in diversification strategy. Building on the estimations of the spatial model, we are able to construct an "Interaction-Based Centrality" index, which can be used by regulatory authorities and policymakers to track vulnerable institutions.

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