Instability spillovers in the banking sector: A spatial econometrics approach

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ABSTRACT

In the study, we employ a dynamic spatial panel model to identify factors that are the sources of instability spillover in the banking sector. Using a sample of publicly listed banks, we document that the stability of a bank depends not only on its own characteristics and the macroeconomic conditions of its home country, but also on the stability of other banks in the same and other countries. We find weak evidence that the spillover effects are greater from domestic banks than from foreign ones. This study has significant implications for market regulators in terms of the role of country interdependence as a spillover mechanism during times of financial turbulence.

1. Introduction

Although the issue of contagion in the banking sector has attracted much attention in scientific research over the past decades, the global financial crisis (GFC) of 2007–2008 has led to renewed debate about banks' asset interdependencies across countries. Moreover, it has initiated discussions about how these interlinkages influence banks' stability, and whether these influences differ in times of financial crisis compared to times of prosperity. This seems to be general agreement that the banking sector has become highly complex and integrated with cross-border linkages; however, the identification of complex asset spillovers is a challenging issue for economists and econometricians.

In terms of methodological developments, a number of measures to capture instability spillovers have been developed, including the conditional value-at-risk (Adams, Füss, & Gropp, 2014; Adrian & Brunnermeier, 2016; Ghulam & Doering, 2018). Bernal, Gnabo, & Guilmin (2014) expanded the ΔCoVaR methodology to find the contributions of banking and other financial services sectors to systemic risk. Additionally, there are examples of systemic risk measuring based on extreme value analyses: Acharya, Pedersen, Philippon, & Richardson (2017) used Systemic Expected Shortfall (SES) to measure the contribution of each single institution to the financial system; Brownlees & Engle (2017) developed ways to estimate systemic risk using Marginal Expected Shortfall (MES) and GARCH and Dynamic Conditional Correlation; Segoviano & Goodhart (2009) use the Consistent Information Multivariate Density Optimizing Methodology to find the multivariate density of portfolio tail. They define the financial sector as a portfolio of individual financial institutions and show that density provides some measures of systemic risk.

The global financial crisis in 2007–2008 documented the important role of domestic and cross-border transmissions of bank

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instability. While the time-series methods mentioned above can model the contagion effects in general, they are usually limited to several units (countries or institutions). The spatial econometrics offers a much broader perspective, as its tools are tailored for measuring interrelations between many objects. In this paper, we follow Barro & Basso (2010), Tonzer (2015), Fernandes & Artes (2016), and Zhu (2018), among others, and use a spatial panel data model to study spillovers of instability between banks from all over the world. What distinguish our study from most papers mentioned above is that we focus on individual banks instead of the whole countries. This allows us to disentangle the stability spillovers from domestic and foreign institutions and considerably increases the sample size, which improves the reliability of the inference.

Our study contributes to the banking literature in two more ways. First, our study investigates the risk measured by Z-score – insolvency risk indicator in commercial banks globally and determines how the bank's risk depends on individual bank-specific factors and external variables. The literature on spillover mechanisms has identified bank risk-taking interdependence channels, however mostly in individual country, or region (Asgharian, Hess, & Liu, 2013; Choudhry & Jayasekera, 2014; Gernát, Košťálová, & Lyócsa, 2020; Ghulam & Doering, 2018; Wong & Fong, 2011). Understanding the dependence structure of banking risk transmission between different countries in a global scale can help reduce the impact on neighboring economies and diffuse the systemic risk.

Our second contribution is in the detection of the transmission of banking asset shock associated with the global financial crisis (GFC) of 2007–2008. Early literature provides some evidence of negative shocks to bank balance sheets (Ahrend & Goujard, 2015; Van Rijckeghem & Weder, 2003) and the transmission of the crisis internationally (De Haas & Van Horen, 2013; Jiménez, Ongena, Peydró, & Saurina, 2012). However, not much is known about the common characteristics of the GFC and which banking and country-specific factors can mitigate insolvency and international crisis transmission. An important question is how interaction effects within the banking sector between different countries vary across bearish and bullish markets. Thus, we contribute to the growing body of literature that examines the role of banks in the transmission of the financial crisis of 2007–2009.

These are important considerations for policymakers because the propagation of shocks affects the stability of the banking sector and the effectiveness of monetary policy. Our approach may be useful for further development of new methods to measure systemic risk and analyze the channels through which shocks may generate global financial crises.

The remainder of this paper is structured as follows. Section 2 reviews some theoretical foundations for contagion and presents our testable hypotheses. Section 3 describes the data, presents summary statistics, and outlines our estimation approach. Section 4 presents our research results, followed by robustness checks in Section 5. Finally, Section 6 concludes our findings and discusses how our results may influence regulation and policy.

2. Literature review and hypotheses

One of the fundamental frameworks for examining spillover effects on banking stability is Markowitz's diversification theory (Goldstein & Pauzner, 2004; Yildirim & Efthyvoulou, 2018). According to this theory, diversification opportunities are a driving force for investors. Therefore, the demand for an asset depends on the correlation between that asset's returns and the returns of other assets in the same portfolio. To hedge risk through global diversification, financial investors need to understand the interconnectedness of financial markets and the sensitivity of markets to financial external shocks. Therefore, it is necessary to study the linkages that are important for the transmission of market-specific shocks to other markets (Arreola Hernandez, Kang, Shahzad & Yoon, 2020). From the standpoint of global investors such as banks, they should consider the problem of increasing the integration of the financial markets, which reduces the positive effects of portfolio diversification and strengthens the phenomenon known as spillover.

A major potential cause of systemic problems caused by financial instability in the banking system is the potential for spillover interaction between the various participants. This interaction can have many channels, such as direct counterparty effects when one party fails or credit cuts causing economic depression and leading to failures elsewhere. These interactions can occur directly between banks through interbank linkages or between banks and other participants in the economy through credit and lending markets. The spillover in the banking sector is a central issue of its financial instability. The interactions that arise between different economic actors in different markets due to their instability generate systemic risk. The European Central Bank (ECB, 2010, p. 147) proposes a definition of systemic risk as the risk of a systemic event occurring, which is broadly defined as the result of financial instability that spillsover so widely that the financial intermediation process is disrupted and economic growth is adversely affected in a significant way.

The factors leading to the spread of instability spillovers can be divided into two basic groups: i) those that are endogenous to the banking sector, such as asset quality, credit and liquidity risk, profitability, and capital ratio; and ii) those that are exogenous, reflecting the fragility of the banking system due to asset price and collateral imbalances, or decline in debt repayment capacity caused by domestic or international macroeconomic disturbances (Bardsen, Lindquist, & Tsomocos, 2006). Much of the academic literature in this field has focused on analyzing the co-movement across banking sectors in neighboring regions, but not on a global scale. For example, Maghyereh & Awartani (2012) investigate the integration of the banking sector in the Gulf Cooperation Council using bootstrap measures and show convergence effects during the transition period 2003–2009. Jokipii & Lucey (2007) found a contagion effect in the Central and Eastern European banking sector. Using GARCH models, Alexandrou, Koulakiotis, & Dasilas (2011) emphasize that the enlargement of the European Union has strengthened the integration of the European banking industry.

The strongest growth in research on the spillover effect occurred after the foreign exchange crisis in East Asian countries and Latin America in the early 1990s (Calvo & Mendoza, 1996; Frankel & Schmukler, 1997). For example, several studies (Batuo, Mlambo, & Asongu, 2018; Dornbusch, Park, & Claessens, 2000; Kleinow, Moreira, Strobl, & Vahamaa, 2017) pointed to three transmission channels of financial market instability: commercial, business cycle, and behavioral inconsistency of monetary policy. According to this concept, the disorder usually moves within a group of countries with similar levels of economic development. This type of

contagion may arise when economies have strong macroeconomic integration through trade (Glick & Rose, 1998) and financial linkages (Neaime, 2012). Research on the determinants of bank instability has usually analyzed the extent to which bank characteristics such as efficiency, leverage, and liquidity are affected by those factors in a single country (Athanasoglou, Brissimis, & Delis, 2008; Dietrich & Wanzenried, 2011), or in country groups, for example the EU (Abreu, Kimura, & Sobreiro, 2019; Amaral, Abreu, & Mendes, 2014; Demirgüç-Kunt & Huizinga, 2010; Goddard, Molyneux, & Wilson, 2004). Some articles focus on the influence of regulatory and institutional variables as explanatory of bank efficiency (Arnold & Soederhuizen, 2018; Barth, Caprio, & Levine, 2013). Our study emphasizes the impact on neighboring economies in diffusing systemic risk. Therefore, we propose Hypothesis 1 as follows: *Banking instability depends not only on specific banks or macroeconomic factors, but also on the (in)stability of other banks from the same or neighboring countries.*

In the ongoing debates on financial crises, three issues are of growing interest. The first is the nature of geographical space, considering that most financial crises in recent years have come from one country and spread to several others (Richards, Acharya, & Kagan, 2008; Vitali & Battiston, 2011; Yildirim & Efthyvoulou, 2018). The second question concerns the direction in which the crisis spreads: from developing to developed countries or vice versa (Chang & Majnoni, 2001; Rivera-Castro, Ugolini, & Arismendi Zambrano, 2018; Yu, Li, & Huang, 2017; Yun & Moon, 2014). The third challenge is the role of "network spillover" in the spread of financial turbulence, both among financial institutions within one country and internationally (Allen & Gale, 2000; Horst, 2007; Vitali, Battiston, & Gallegati, 2016). Most of the existing research focuses on financial networks among banks. The presence of a balance between the potential for diversification and the risk of transmission as interbank connections increase has already been confirmed by interbank network models (Stiglitz, 2010; Wagner, 2011). However, the discussion is still open, and each model employs a more or less explicit mechanism to find a trade-off. Our contribution is to examine the banking sector and provide an analytical explanation for its instability within and between countries. Intuition suggests that as long as countries are economically isolated, companies and financial institutions are not in a position to use the potential of access to other markets; thus, they are only affected by local financial instability and remain protected from global crises. In the event that entities have access to counterparties from different regions, both companies and banks use diversification to limit their exposure to individual risk; however, they are also affected by systemic risk. While Petersen & Rajan (2002) provide a proof that geographic space between financial lenders and borrowers is less significant than developments in information transfer techniques, Amaral, Abreu, & Mendes (2014) stresses the existence of geographical interdependence between the financial sectors, providing that contagion effects may result either from the commerce relationship between institutions of varied countries or from institutional homogeneity between banking sector structures. Regardless of this controversy, there are few empirical studies on the function of geography as a driver of instability spillover in the banking sector. Thus, our next Hypothesis 2 is as follows: *Relationships between banking instability levels are stronger within countries than between them.*

Strong financial spillovers were the main aspect of the 2007–09 period, when the financial crisis in the US banking sector spread rapidly worldwide (Bekaert, Ehrmann, Fratzscher, & Mehl, 2014). In previous research, the authors identified that banking crises are overwhelmingly associated with the presence of systematic and idiosyncratic contagion (Dungey & Gajurel, 2015) and studied the link between stability and the business cycle (Albertazzi & Gambacorta, 2009; Cetorelli & Goldberg, 2011; Vives, 2019; Wang, Chen, & Xiong, 2019). Tsoumas (2017) focuses on the impact of a bank failure on neighbouring banks, which spreads through disrupted local economic activity in areas where the failed bank operated through its divisions. This impact is driven by a decline in capital, an expansion of non-performing loans, and a rapid increase in profit fluctuations. Similarly, in a sample of 146 developed and emerging economies from 1984 to 2011, Ahrend & Goujard (2015) investigated whether shocks to creditors of cross-border banks increase the risk of financial turmoil in debtor banks' countries. Their findings emphasize that local banking sector vulnerabilities, such as an unexpected decrease in the deposit to asset ratio and a high level of illiquid assets, increase contagion risk and can lead to crisis. On the contrary, the high global liquidity of multinational banks' assets reduces the spread of crisis to borrower countries. Acemoglu, Ozdaglar, & Tahbaz-Salehi (2015) note that financial contagion exhibits different phases of intensity. The results of their study demonstrate that as long as the magnitude of negative shocks affecting banks is small enough, a more closely connected financial network enhances financial stability. This supports the theory of more diversified interbank liabilities. However, beyond a critical point, dense interconnectedness induces shock propagation, generating instability. Therefore, the study highlights that the same factors that contribute to resilience under some conditions can generate significant sources of systemic risk under others. Using a Markov-switching Factor Augmented VAR model, Dungey, Flavin, & Lagoa-Varela (2020) study the contagion of shocks between global and domestic banking in Eurozone countries during the crisis timeframe. They find that contagion played a role in the expansion of global banking shocks to the banking sectors of smaller countries, intensifying the crisis in these countries. In conclusion, the literature shows that spillover mechanisms may change in the face of a financial crisis. Therefore, our research identifies the interdependence structure of banking risk transmission on a global scale after the 2007–2008 turbulence. To incorporate these considerations, we propose Hypothesis 3: *Instability-causing dependencies between banks increased after the recent financial crisis.*

In terms of methods, our study is similar to the work of Tonzer (2015), who uses country-level data from 15 advanced economies to document considerable instability spillover to the cross-border interbank network. She also employs spatial econometrics, although estimates a static model. The weighting matrix is formed using similar BIS data. In this study, we use a much larger bank-level sample, which allows us to distinguish the instability effects of domestic and foreign banks. We also consider a dynamic version of the spatial autoregressive model.

3. Data

Our database consists of an international sample of commercial banks observed during the period 2003–2015. To standardize activity and risk management, we selected 248 banks listed on stock exchanges. Bank-related measures are collected from the Thomson

Table 1
Compositions of the samples.

Country	Number of banks	Fraction of banks	Developed	Country	Number of banks	Fraction of banks	Developed
United States	31	12,5%	1	Canada	5	2,0%	1
Japan	28	11,3%	1	South Africa	5	2,0%	0
Switzerland	16	6,5%	1	Austria	4	1,6%	1
Italy	15	6,0%	1	Germany	4	1,6%	1
France	11	4,4%	1	Pakistan	4	1,6%	0
Indonesia	11	4,4%	0	Spain	4	1,6%	1
Norway	9	3,6%	1	Thailand	4	1,6%	0
China	8	3,2%	0	Israel	3	1,2%	1
Hong Kong	8	3,2%	0	Singapore	3	1,2%	1
India	8	3,2%	0	Sweden	3	1,2%	1
Philippines	8	3,2%	0	Turkey	3	1,2%	0
Denmark	7	2,8%	1	Belgium	2	0,8%	1
Taiwan	7	2,8%	1	Portugal	2	0,8%	1
United Kingdom	7	2,8%	1	Czech Republic	1	0,4%	1
Australia	6	2,4%	1	Hungary	1	0,4%	0
Malaysia	6	2,4%	0	Ireland	1	0,4%	1
Poland	6	2,4%	0	Mexico	1	0,4%	0
Brazil	5	2,0%	0	Russian Federation	1	0,4%	0
				Total	248	100%	

The column "Developed" indicates developed countries according to the IMF classification for 2010.

Reuters Datastream database, while the World Bank database is the source of country-specific indicators. The selection of the research sample is primarily determined by the availability of long time series of balance sheet data on credit risk, in particular, the share of NPLs in total loans. To increase the number of banks in the sample, we included banks with no more than two missing values per series that were subsequently imputed using either simple interpolation or regression against other banks from the same country. The only exceptions were the United States and Japan. Due to overrepresentation, only banks with no missing data were taken for these countries.

The composition of the sample is shown in Table 1. The dataset is dominated by banks from the United States and Japan, the shares of which exceed 10%. Nonetheless, the sample appears to be geographically balanced, including considerable shares of banks from Europe and other Asian countries. The balanced share of the sample between developed and developing countries, with no clear dominance of either group, will verify earlier hypotheses that the source of the crisis may originate in emerging markets and mature market economies.

We use a Z-score measure to assess banking stability. This proxy captures the probability of default of a bank. Another word Z-score compares the buffer of a bank's stability (capitalization and returns) with the volatility of its returns. In general, the measure is calculated as follows:

$$Z_{it} = \frac{car_{it} + \mu_{roa,it}}{\sigma_{roa,it}} \tag{1}$$

where car is the bank's capital-asset ratio, while $\mu_{roa,it}$ and $\sigma_{roa,it}$ represent estimates of the expected value and the standard deviation of the bank's return on assets, respectively. Thus, the Z-score is the number of standard deviations by which a bank's return on assets has to fall for the bank to become insolvent.

In the literature, we find four groups of systemic risk measures: (1) the codependence risk (Co-Risk) proposed by Chan-Lau, Espinosa, Giesecke, & Sole (2009), (2) the delta conditional value at risk (ΔCoVaR) of Adrian & Brunnermeier (2016), (3) the marginal expected shortfall (MES) developed by Acharya, Engle, & Richardson (2012), and (4) the lower tail dependence (LTD) proposed by Weiß, Neumann, & Bostandzic (2014). Empirical findings demonstrate that the four market-based measurement approaches produce very different estimates of systemic risk. On the other hand, approaches to measuring systemic risk can be broadly divided into measures based on financial market variables (market-based), interbank data (risk positions and cash flows), and on balance sheet variables (accounting-based). Despite efforts dedicated to measuring systemic risk after the 2007–2008 crisis, our knowledge about the effectiveness of the different measurement methods is limited. The search for ever-newer solutions that will bring us closer to the ideal estimation is still being explored. In order not to distort the results of the spatial method-based of our study, we limited the measurement of systemic risk to a single approach of the Z-score. Additionally, we decided to use the Z-score method because of the accounting nature of the data and the spatial autoregression model for which we used the data of consolidated positions of residents of countries taken from the Bank of International Settlements database. In this case, using the method based on the capital market data would not be appropriate, due to the differences that the bank balance sheet variables have with their stock market valuation.

Furthermore, due to the regulation implemented by the supervision in the banking sector to strengthen the implementation of Basel II and III regulations, we use the Z-score measure including both the bank's profitability and its leverage. The choice of this indicator is confirmed in the literature. Finally, the advantage of Z-scores measure is making our results more comparable to other studies. In particular, Calmès & Théoret (2013) emphasise that banks focused on investment activities are oriented towards high profitability at

Table 2

Descriptive statistics of the variables.

Symbol	Description	N	Mean	St. dev.	Min	Max	Skewness
Dependent variables							
Z3	logarithm of Z-scores (ver. 3)	3224	3.33	0.89	−5.00	6.03	−1.49
Z5	logarithm of Z-scores (ver. 5)	3224	3.34	0.87	−5.00	6.03	−1.13
Bank-specific controls							
dep_to_loa	total deposits to total loans	3224	1.03	0.42	0.05	6.89	2.65
cap_to_ce	ratio of market capitalization to common equity	3224	1.45	0.90	0.1	8.57	1.77
nonp_loa	ratio of non-performing loans to total loans	3224	0.03	0.04	0	0.51	4.05
assets	logarithm of total assets	3224	19.23	2.57	12.46	27.53	0.29
loa_to_ass	ratio of total loans to total assets	3224	0.66	0.15	0.09	0.97	−0.54
Country-specific controls							
gdp_growth	GDP growth rates	3224	2.78	3.11	−7.82	26.28	0.42
log_gdp	logarithm of GDP per capita	3224	10.03	1.20	6.75	11.43	−1.20
rir	real interest rate	3224	3.66	5.25	−12.28	46.45	4.72
unemployment	unemployment rate	3224	6.70	3.92	0.19	27.14	2.65

an equally high leverage risk. The Z-score value is an expression of the number of standard deviations by which the ROA must decrease relative to the expected value so that the capital is considered depleted and the bank faces insolvency.

Following Lepetit & Strobel (2013), we consider two different versions of the Z-score using different estimates of the return on assets:

Z3 – where we approximate $\mu_{roa,it}$ by the current period value of *roa* and calculate $\sigma_{roa,it} = \sigma_{roa,i}$ over the full sample (Hesse & Cihak, 2007);

Z5 – where we approximate $\mu_{roa,it} = \mu_{roa,i}$ and $\sigma_{roa,it} = \sigma_{roa,i}$ by their estimates calculated from a full available sample.

In both cases, we employ the current period value of the common equity to the total asset indicator from Datastream as a proxy for the car_{it} variable. According to Lepetit & Strobel (2013), these two versions of the Z-score should be preferred over alternatives (denoted Z1, Z2, and Z4). The minimum value for the logarithm of the Z-scores is set at −5. A few outliers where Z-score is equal to 0 are replaced by the minimum value.

As regressors, we use several bank-specific variables as well as country-specific variables. The former group includes the ratios of deposits to loans, market capitalization to common equity, non-performing loans, to total loans, and loans to assets. We also consider the bank size as measured by total assets. Country-specific controls consist of the real GDP growth rates, GDP per capita, the real interest rate, and unemployment rate.

The sample is balanced and the missing values were either interpolated or imputed on linear regression with the appropriate variable from the other similar bank as the benchmark. In particular, this approach was used in the case of missing *roa* values. All variables are annual because balanced bank financial data are available at this frequency. However, it should be noted that higher frequency data would have provided the opportunity to see more variability in the explanatory variable. Table 2 contains descriptive statistics of the variables used in the study.

4. Methods

4.1. General model

To investigate the relationship between the stability of different banks, we utilize spatial models. More specifically, we estimate the parameters of the fixed effect dynamic spatial autoregression model of the following form (Elhorst, 2014):

$$Y_t = \rho Y_{t-1} + \lambda W Y_t + \sum_{j=1}^{k} \beta_j X_{jt-1} + \mu + \epsilon_t, \tag{2}$$

where:

Y_t– vector of observed values of the dependent variable in period *t*,
X_{jt}– vector of observed values of the *j*-th regressor in period *t*,
W– weight matrix,
ϵ_t– error term,
ρ, λ – time and spatial autoregression parameters,
β_j– structural coefficients,
μ– vector of bank-specific means.

The model captures the observed persistence of the stability measures ρY_{t-1} as well as the impact of the set of regressors $(\sum_{j=1}^{k} \beta_j X_{jt-1})$. It should be noted that all the regressors are lagged by one year to deal with the endogeneity issue. Interbank dependencies are represented by the term $\lambda W Y_t$, where the weight matrix W captures the strength of connections between the banks and λ measures the impact of the connections on banking stability. Our specification that includes the time autocorrelation coefficient is rather conservative compared to Tonzer (2015) because this term partially offsets the role of the spatial spillover. Accounting for the time autocorrelation of the stability measures seems to be important yet, as it protects us from finding spurious correlations because of the existence of common trends.

The parameters of the model are estimated with a bias-corrected quasi maximum likelihood method (Yu, de Jong, & Lee, 2008) using a Stata's function *xsmle* (Belotti, Hughes, & Piano Mortari, 2017). Robust standard errors are reported. In the case of short panels, the method can be inconsistent and seriously biased if incorrect assumptions on the initial values are made. Therefore, the results are also checked using a unified M-estimation approach developed by (Yang, 2018). However, this approach cannot be treated as more reliable because it can also suffer from some drawbacks, as recently shown by Li & Yang (2020).

4.2. Direct, indirect, and total effects

The spatial autoregression term represents the effects of the spillover and feedback loop in banking stability measures. A positive reaction of the Z-score to changes in a regressor value for one bank also affects the stability of the other connected banks. The rise in the stability of these banks increases, in turn, the stability of the bank where the initial change occurred. These feedback loops were further amplified by the temporal persistence of the Z-score measures. To assess the quantitative consequences of the spillovers, the so-called short-term direct, indirect, and total effects are calculated (see Belotti, Hughes, & Piano Mortari, 2017; Elhorst, 2014, p. 105).

The short-term direct effect measures the immediate impact of a unit change in a lagged (because we have X_{jt-1} in (2)) regressor value for a certain bank on the Z-score of this bank, taking into account the spatial feedback loops. In other words, it measures to what extent a change in the regressor affects next-period-stability of the bank taking into account its impact on stability of the banking system as a whole. The short-term indirect effect represents the same impact of a unit change in a regressor from other banks on the stability of a certain bank. These effects are bank-specific and are summarized by averaging across all banks in the sample. The total short-run effects are the sum of both, direct and indirect effects and the share of the indirect short-run to total effects approximately equals the spatial autocorrelation coefficient λ.

The amplification resulting from the persistence of the Z-score measures is captured by long-term effects; these show changes in Z-scores due to the permanent one-unit rise in regressor values. The persistence of the result primarily reinforces the impact of indirect factors. The share of indirect to total effects is $(1 - \rho)^{-1}$-times higher than for the short-run effects.

We calculate the effects using the formulas from Belotti, Hughes, & Piano Mortari (2017). The confidence intervals are based on Monte Carlo simulations. Denoting the estimated vector of structural parameters by $\widehat{\boldsymbol{\theta}} = \begin{bmatrix} \widehat{\rho} & \widehat{\lambda} & \widehat{\boldsymbol{\beta}} \end{bmatrix}$ and its covariance matrix by $\widehat{\Sigma}(\widehat{\boldsymbol{\theta}})$, we draw a large sample of coefficients from $N(\widehat{\boldsymbol{\theta}}, \widehat{\Sigma}(\widehat{\boldsymbol{\theta}}))$. For each of the sample sets of parameters, we calculate the direct, indirect, and total effects in the short- and long-run. The confidence intervals are defined by the appropriate percentiles of the simulated distributions.

The spillover measures are crucially dependent on the stationarity of the estimated model (2). According to Elhorst (2014, p. 97; see also Lee & Yu, 2010), the model is stationary if all characteristic roots of a matrix $\rho(\boldsymbol{I_n} - \lambda \boldsymbol{W})^{-1}$ lie within a unit circle, where $\boldsymbol{I_n}$ denotes a unit matrix of order n. The trajectories of nonstationary models may be explosive and calculating the long-term effects is impossible. Although all but two estimated models in the study are stationary, non-stationarity may arise during Monte Carlo simulations of the confidence intervals for the effects, especially when $\widehat{\rho} + \widehat{\lambda}$ is close to one. Therefore, the nonstationary draws are discarded, and the confidence intervals for the effects are calculated assuming the stationarity of the models.

4.3. Weight matrices

The weight matrix $\boldsymbol{W}$ is a square matrix where the number of rows and columns is equal to the number of banks. Its main diagonal elements are zeros, and rows are normalized and identical for banks from the same country. Its nondiagonal elements represent the strength of the relationships between the banks considered.

Banks that operate in more than one country may be better diversified, but they are also more vulnerable to shocks. Different responses to a foreign shock should be expected from banks that operate only in the domestic economy and those that are international. Unfortunately, there are no data that directly show the interdependencies of the banks in our sample that could be used to set the off-diagonal values of the weight matrix. Instead, we employ the aggregated bank dependency data at the national level. More specifically, we use data from the consolidated positions of residents of countries taken from the Bank of International Settlements database (Table B4 from Consolidated Banking Statistics), which provides a comprehensive view of international cross-country banking links. These data capture exposures of reporting banks in a given location and are useful for measuring financial integration between countries. This approach is used in empirical research on contagion effects in the financial market. For example, Brutti & Sauré (2015) measure bilateral financial linkages with Greece using bilateral cross-border bank exposures from the BIS Consolidated Banking Statistics of the BIS. On the other hand, Dungey, Flavin, & Lagoa-Varela (2020) use the BIS consolidated banking statistics to construct a regional breakdown of foreign claims of the banking sector in countries in the Eurozone. We consider the total claims from the Consolidated Banking Statistics, on an ultimate risk basis, that banks in a given country hold on banks in counterparty countries. The

data were taken at the end of 2012.

The list of reporting countries in the database covers all countries in the sample, but some reported country data is missing. To complete the missing data, we focus primarily on matching the share of the claims held by other banks in the same country, which generally dominates the structure of banking claims. (For the available countries, the weighted mean share is equal to 64%, and the minimum and maximum values are equal to 4.7% and 89.2%, respectively.).

The missing data is of two types:

1. Data on claims that banks in a given country have on banks in the same country at the end of 2012 are unavailable.
2. The data on claims that a bank has a bank in a counterparty country that is not covered in the database.

The first type of missing data affects Australia, Austria, Belgium, Canada, Spain, Italy, Switzerland, Taiwan, and the United States. To calculate the missing amount of internal claims, we use the share of domestic claims from the nearest available period, which in most cases is the end of 2013.

The second type of missing data is related to the developing economies of Brazil, China, the Czech Republic, Denmark, Hong Kong, Hungary, India, Indonesia, Israel, Malaysia, Mexico, Norway, Pakistan, Philippines, Poland, Russian Federation, Singapore, South Africa, Thailand and Turkey. Because these countries have a relatively low share of banking claims, we replace these missing values with zeros, excepting only the share of claims to banks from the same country, which we replace with the mean value for the sample of 64%. As a robustness check, we also consider the matrices, denoted by W_2 and W_3, where these shares correspond to the first and the third quartile of the sample equal to 13.6% (W_2) and 70.5% (W_3), respectively.

Given the values of the country-level interbank claims, c_{lq}, the elements of the weight matrix are calculated as follows:

$$w_{jl,pq} = \begin{cases} \dfrac{c_{lq}}{\sum\limits_{q} n_q \cdot c_{lq}} & \text{if} \quad j \neq p \text{ or } l \neq q \\ 0 & \text{if} \quad j = p \text{ and } l = q, \end{cases}$$

where:

$w_{jl,pq}$– weight measure between bank j in country l and bank p in country q,
c_{lq}– aggregate claims of banks from country l on banks from country q,
n_q– number of banks from country q in sample,
j – reporting bank index,
l – reporting country index,
p – counterparty bank index,
q – counterparty country index.

In other words, the entries in a row indexed as jl approximate the shares of banking claims that a bank j from country l holds on the other banks (indexed by p and q) in the sample.

To separate the spillover effects from domestic and foreign banks, we also utilize two alternative weight matrices. The first one, which captures the impact of domestic bank stability on the other banks from the same country, is a nearest neighbor matrix $W^{(d)}$ where banks from the same country are considered as neighbors. Formally:

$$w_{jl,pq}^{(d)} = \begin{cases} \dfrac{1}{n_q - 1} & \text{if} \quad j \neq p \text{ and } l = q \\ 0 & \text{if} \quad j = p \text{ or } l \neq q. \end{cases}$$

The second matrix $W^{(f)}$ represents the impact of foreign banks on domestic bank stability. Therefore, it is a row-normalized version of the matrix W, where the entries for other banks from the same country are equal to 0:

$$w_{jl,pq}^{(f)} = \begin{cases} \dfrac{c_{lq}}{\sum\limits_{q \neq l} n_q \cdot c_{lq}} & \text{if} \quad l \neq q \\ 0 & \text{if} \quad l = q. \end{cases}$$

5. Empirical results

In the following, we present and discuss the estimation results aimed at verifying the research hypotheses stated in Section 2. Calculations are performed separately for the two versions of the Z-score stability measure.

Table 3

Baseline estimation results for Z3 indicator.

Variables	Coeffs. & st. err.	Short run total effects	Long run total effects
ρ (time autocorr.)	**0.611*** (0.092)**		
λ (space autocorr.)	**0.254*** (0.044)**		
dep_to_loa	0.012 (0.021)	0.016 [−0.032; 0.061]	0.088 [−0.171; 0.805]
cap_to_ce	0.012 (0.010)	0.015 [−0.004; 0.038]	0.085 [−0.036; 0.346]
nonp_loa	0.122 (0.481)	0.164 [−0.874; 1.004]	0.904 [−3.110; 17.995]
assets	−0.068** (0.028)	−0.092 [−0.152; −0.029]	**−0.505 [−2.650; −0.133]**
loa_to_ass	0.090 (0.170)	0.121 [−0.265; 0.515]	0.666 [−2.274; 5.179]
gdp_growth	−0.001 (0.002)	−0.001 [−0.007; 0.004]	−0.008 [−0.069; 0.033]
log_gdp	**0.418*** (0.128)**	**0.560 [0.306; 0.840]**	**3.084 [1.382; 13.554]**
rir	0.003 (0.003)	0.004 [−0.003; 0.011]	0.022 [−0.021; 0.142]
unemployment	0.006 (0.006)	0.008 [−0.003; 0.020]	0.046 [−0.020; 0.210]
Indirect share		0.251	0.640
Non-stat. probab.	0.115		
R^2 overall	0.527		
R^2 within	0.276		
N	2976		
n banks	248		

All the regressors are lagged by one year. Robust standard errors of the estimates are shown in parentheses. Brackets contain 90% Monte Carlo confidence intervals for the effects based on 2000 random draws. The estimates significant at 0.01 (***), 0.05 (**), or 0.1 (*) are denoted by stars and bolded. Indirect share shows the share of indirect to total effects (same for all variables). Non-stat. probab. represents the Monte Carlo estimated probability that the data generating process is non-stationary.

Table 4

Baseline estimation results for Z5 indicator.

Variables	Coeffs. & st. err.	Short run total effects	Long run total effects
ρ (time autocorr.)	**0.699*** (0.041)**		
λ (space autocorr.)	**0.187*** (0.057)**		
dep_to_loa	0.014 (0.020)	0.017 [−0.022; 0.057]	0.123 [−0.178; 0.861]
cap_to_ce	0.007 (0.009)	0.009 [−0.008; 0.026]	0.062 [−0.072; 0.332]
nonp_loa	−0.412 (0.591)	−0.507 [−1.648; 0.706]	−3.613 [−15.881; 9.820]
assets	−0.021 (0.030)	−0.026 [−0.091; 0.035]	−0.188 [−1.451; 0.268]
loa_to_ass	−0.049 (0.228)	−0.061 [−0.523; 0.427]	−0.434 [−4.913; 4.995]
gdp_growth	0.001 (0.003)	0.001 [−0.005; 0.006]	0.007 [−0.055; 0.063]
log_gdp	**0.216** (0.106)**	**0.266 [0.054; 0.494]**	**1.894 [0.354; 9.832]**
rir	0.004 (0.004)	0.005 [−0.002; 0.012]	0.037 [−0.019; 0.156]
unemployment	0.005 (0.005)	0.006 [−0.004; 0.017]	0.044 [−0.043; 0.222]
Indirect share		0.185	0.610
Non-stat. probab.	0.041		
R^2 overall	0.782		
R^2 within	0.378		
N	2976		
n banks	248		

All the regressors are lagged by one year. Robust standard errors of the estimates are shown in parentheses. Brackets contain 90% Monte Carlo confidence intervals for the effects based on 2000 random draws. The estimates significant at 0.01 (***), 0.05 (**), or 0.1 (*) are denoted by stars and bolded. Indirect share shows the share of indirect to total effects (same for all variables). Non-stat. probab. represents the Monte Carlo estimated probability that the data generating process is non-stationary.

5.1. Baseline results

Tables 3 and 4 contain the baseline results of our study. They show that spatial spillovers are rather low but statistically significant at the 0.01 confidence level ($\widehat{\lambda} = 0.254$ for Z3 and $\widehat{\lambda} = 0.187$ for Z5). The time-persistence of the stability measures is much higher reaching 0.611 and 0.699, respectively. Given the uncertainty of the estimation, it is possible that the whole system is nonstationary. The simulated probabilities of non-stationarity are equal to 11.5% (Z3) and 4.1% (Z5).

For Z3, the short-run total effects exceed the point estimates approximately by 30%, of which 25% are due to indirect spillovers from other banks. In the case of the Z5 indicator, these numbers are 26% and 18.5%, respectively. The long-run total effects, which additionally account for the high estimates of the time series persistence $\widehat{\rho}$, are of almost one order of magnitude higher than the point estimates. Most of these effects result from indirect spillovers.

Our estimates of the spatial autoregressive terms are about two times lower than the estimates reported by Tonzer (2015). However, it should be noted that she operates on the country-level only with a smaller group of countries, and the standard errors of

Table 5
Estimation results for within and between countries spatial effects.

Variables	Z3		Z5	
	Within country	Between countries	Within country	Between countries
ρ (time autocorr.)	**0.604*** (0.092)**	**0.616*** (0.093)**	**0.693*** (0.041)**	**0.699*** (0.040)**
λ (space autocorr.)	**0.168*** (0.031)**	**0.185* (0.108)**	**0.147*** (0.038)**	−0.109 (0.131)
dep_to_loa	0.010 (0.021)	0.015 (0.020)	0.012 (0.020)	0.012 (0.020)
cap_to_ce	0.011 (0.010)	0.014 (0.011)	0.005 (0.009)	0.010 (0.008)
nonp_loa	0.070 (0.474)	0.023 (0.485)	−0.439 (0.587)	−0.554 (0.580)
assets	**−0.073*** (0.028)**	**−0.067** (0.029)**	−0.025 (0.031)	−0.026 (0.029)
loa_to_ass	0.092 (0.171)	0.069 (0.171)	−0.045 (0.229)	−0.055 (0.227)
gdp_growth	−0.001 (0.002)	0.000 (0.002)	0.001 (0.003)	0.002 (0.003)
log_gdp	**0.402*** (0.127)**	**0.484*** (0.127)**	**0.194* (0.108)**	**0.262** (0.105)**
rir	0.003 (0.003)	0.004 (0.003)	0.004 (0.004)	0.005 (0.003)
unemployment	0.006 (0.006)	0.008 (0.006)	0.005 (0.005)	0.006 (0.005)
Indirect share short	0.161	0.185	0.141	−0.109
Indirect share long	0.393	0.481	0.441	−0.363
Non-stat. probab.	0.008	0.142	0.002	0.077
R^2 overall	0.503	0.528	0.768	0.775
R^2 within	0.277	0.278	0.378	0.380
N	2976	2976	2976	2976
n banks	248	248	248	248

All the regressors are lagged by one year. Robust standard errors of the estimates are shown in parentheses. The estimates significant at 0.01 (***), 0.05 (**), or 0.1 (*) are denoted by stars and bolded. Indirect shares show the shares of indirect to total effects (same for all variables). Non-stat. probab. represents the Monte Carlo estimated probability that the data generating process is non-stationary.

her estimates are relatively high, usually exceeding 0.1. Moreover, our specification includes the time autoregression, which offsets the spatial effects to some extent.

The results presented in this subsection strongly support Hypothesis 1 that the stability of a bank depends not only on its own characteristics and macroeconomic conditions, but also on the stability of other banks from the same or neighboring countries.

In terms of bank-specific control variables are concerned, the bank stability is negatively associated with bank size and the Z3 indicator only. Therefore, this study emphasizes that large banks exacerbate the instability and cannot hold abundant stable funding as a buffer to respond to the crisis. Among the country-level indicators, the GDP level has a positive impact on stability, which suggests that banks from the richer countries are generally more stable than those from the poorer countries.

5.2. Robustness checks

The results of the robustness checks presented in Appendix A also confirm our baseline results. First, in Table A1, we consider the alternative estimation method. Although the results do not differ considerably from those presented in Tables 3 and 4, they do imply considerably stronger spillover effects probabilities, especially in the long run as the estimates of both autoregressive coefficients are higher. As a consequence, the simulated non-stationarity probabilities are much higher than in the baseline case, reaching approximately 37% for both measures.

In Table A2, the results for the alternative weighting matrices are presented. The differences for all estimates are negligible. The spatial autoregressive term is the only exception here, that is considerably higher ($\hat{\lambda} = 0.413$ for Z3 and $\hat{\lambda} = 0.268$ for Z5) for W_2 matrix and slightly lower ($\hat{\lambda} = 0.230$ for Z3 and $\hat{\lambda} = 0.171$ for Z5) in the case of W_3 matrix. All these results suggest that our baseline estimates of the spatial spillover effects are rather conservative.

5.3. Dependencies within and between countries

In this subsection, we separately study the spillover effects from other domestic and foreign banks. In the first, within-country case, model (2) is estimated using $W^{(d)}$ weight matrix. In the case of between-country dependencies, $W^{(f)}$ matrix is employed. The point estimates for these two cases are compared in Table 5. The spillover effects of other domestic banks are clearly higher than the effects from the foreign banks only for the Z5 measure ($\hat{\lambda} = 0.147$ under $W^{(d)}$ and $\hat{\lambda} = -0.109$ under $W^{(f)}$). For Z3, the point estimates are virtually the same. These results only weakly support Hypothesis 2 that the spillover effects are stronger from domestic banks than from foreign banks.

5.4. Impact of the financial crisis on banks' stability interdependencies

In this subsection, we check whether the spillover strength changed after the financial crisis. We divide the sample into pre- (2003–2008) and post-crisis (2009–2015) subsamples and estimate the parameters of model (2). The point estimates are presented in Table 6. This table also contains the results of the statistical test comparing the spatial autocorrelations in the two subsamples. Both,

Table 6
Estimation results for within and between countries spatial effects.

Variables	Z3		Z5	
	Pre 2009	Post 2009	Pre 2009	Post 2009
ρ (time autocorr.)	**0.321** (0.138)**	**0.908*** (0.059)**	**0.331*** (0.108)**	**0.948*** (0.040)**
λ (space autocorr.)	**0.172*** (0.062)**	**0.196** (0.084)**	**0.240*** (0.076)**	**0.179** (0.075)**
dep_to_loa	−0.111 (0.176)	**0.032** (0.013)**	−0.069 (0.138)	**0.036*** (0.012)**
cap_to_ce	**0.048** (0.019)**	**0.042** (0.019)**	0.026 (0.016)	**0.042** (0.018)**
nonp_loa	−0.022 (0.763)	0.214 (1.487)	−0.104 (0.487)	−0.452 (1.300)
assets	−0.170 (0.136)	0.042 (0.061)	−0.031 (0.077)	0.057 (0.056)
loa_to_ass	0.176 (0.481)	0.169 (0.308)	0.046 (0.387)	0.110 (0.285)
gdp_growth	0.032 (0.025)	−0.002 (0.003)	0.009 (0.011)	−0.001 (0.002)
log_gdp	0.417 (0.385)	−0.147 (0.188)	0.196 (0.278)	−0.120 (0.173)
rir	0.008 (0.016)	0.004 (0.008)	0.008 (0.009)	0.003 (0.008)
unemployment	**0.036* (0.019)**	0.010 (0.013)	0.028 (0.018)	0.010 (0.011)
space diff. test – Z	0.230		0.571	
space diff. test – pv	0.818		0.568	
Indirect share short	0.171	0.194	0.237	0.178
Indirect share long	0.251	0.653	0.354	2.344
Non-stat. probab.	0.003	0.952	0.000	0.976
R^2 overall	0.291	0.841	0.574	0.860
R^2 within	0.012	0.361	0.030	0.405
N	1240	1736	1240	1736
n banks	248	248	248	248

All the regressors are lagged by one year. Robust standard errors of the estimates are shown in parentheses. The estimates significant at 0.01 (***), 0.05 (**), or 0.1 (*) are denoted by stars and bolded. Space diff. test contain test statistics and the two-sided p values for the test of equality of the space autocorrelation parameters λ. Indirect shares show the shares of indirect to total effects (same for all variables). Non-stat. probab. represents the Monte Carlo estimated probability that the data generating process is non-stationary.

the point estimates and the statistical test, clearly show that no significant change in spillover effects is observed after the financial crisis. Therefore, Hypothesis 3 is not supported by the results. However, it is worth noting the considerable differences in the time autoregressive estimates and the goodness of fit. Both characteristics are definitely higher in the post-crisis period.

6. Conclusions

The recent global financial crisis highlighted the importance of stability in the banking sector. In response, financial regulators took action to improve macroprudential practices in the banking system to reduce the banking risk that led to many bankruptcies. Our research continues to explore the theory of systemic risk and the discussion of the influence on bank instability. We proposed a dynamic spatial panel data model of an international sample of commercial banks observed during the period 2003–2015. To standardize activity and risk management, we selected 248 banks that are listed on the stock exchange to examine the effects of cross-sectional dependence in the banking sector. The term "spatial autoregression" represents spillover and feedback loop effects in measures of bank stability. A positive reaction of a bank's insolvency ratio, measured by the Z-score, to changes in a regressor value for one bank also affects the stability of other connected banks. The rise in stability of these banks increases in turn stability of the bank where the initial change occurred. These feedback loops were further amplified by the temporal persistence of the Z-score measures.

In conclusion, this study offers several contributions to the literature. First, it provides robust evidence of the presence of spillover effects in the instability of banks around the world. Second, our research expands the spatial autocorrelation model into an empirical study of banking instability. To the best of our knowledge, there are only a few studies using a similar research method to measure the links between banks from the same or different countries. Therefore, the results of our study should be helpful for academics and regulators who estimate the risk of insolvency in the financial sector. Third, we confirm the robust evidence that systemic risk occurs not only due to internal banking decisions about risk-taking, but also external conditions and links to other banks. Fourth, we emphasize that spillovers are higher from domestic banks than from foreign ones, which provides a next step that offers an explanation for the inconclusive results of previous studies. Thus, our results are in line with Chen & Lee (2020), who find evidence of liquidity spillover through varying spatial dependence based on geographical and economic closeness within banks.

The estimation results show that statistically significant spillover effects on banking stability are observed. These spillover effects considerably increase the impact of changes in factors affecting stability, especially in the long run, when they are amplified by the temporal persistence of the stability measures. We also find some evidence that the spillover effects of domestic banks are stronger than those from foreign banks. Finally, we did not observe any changes in spatial spillover strength after the recent 2007–2008 financial crisis.

More specifically, our results find evidence supporting the hypothesis that the stability of a bank depends not only on its own characteristics and macroeconomic conditions but also on the stability of other banks from the same or other countries. However, we

Table A1

The comparison of the baseline estimates obtained from the baseline QML and the unified M-estimation methods.

Variables	Z3		Z5	
	QML	M-estimation	QML	M-estimation
ρ (time autocorr.)	**0.611*** (0.092)**	**0.654*** (0.137)**	**0.699*** (0.041)**	**0.746*** (0.064)**
λ (space autocorr.)	**0.254*** (0.044)**	**0.281*** (0.093)**	**0.187*** (0.057)**	**0.212* (0.120)**
dep_to_loa	0.012 (0.021)	0.019 (0.021)	0.014 (0.020)	0.021 (0.014)
cap_to_ce	0.012 (0.010)	0.012 (0.010)	0.007 (0.009)	0.008 (0.008)
nonp_loa	0.122 (0.481)	0.323 (0.753)	−0.412 (0.591)	−0.232 (0.293)
assets	**−0.068*** (0.028)**	**−0.064*** (0.022)**	−0.021 (0.030)	−0.018 (0.023)
loa_to_ass	0.090 (0.170)	0.103 (0.116)	−0.049 (0.228)	−0.050 (0.206)
gdp_growth	−0.001 (0.002)	−0.002 (0.002)	0.001 (0.003)	0.000 (0.003)
log_gdp	**0.418*** (0.128)**	**0.386*** (0.136)**	**0.216** (0.106)**	**0.190** (0.085)**
rir	0.003 (0.003)	0.003 (0.003)	0.004 (0.004)	0.004 (0.004)
unemployment	0.006 (0.006)	0.005 (0.006)	0.005 (0.005)	0.004 (0.004)
Nonstat. probab.	0.115	0.369	0.041	0.377

All the regressors are lagged by one year. Robust standard errors of the estimates are shown in parentheses. The estimates significant at 0.01 (***), 0.05 (**), or 0.1 (*) are denoted by stars and bolded. Nonstat. probab. contains the Monte Carlo estimated probability that the data generating process is nonstationary.

Table A2

Estimation results for alternative weighting matrices.

Variables	Z3		Z5	
	W2	W3	W2	W3
ρ (time autocorr.)	**0.615*** (0.092)**	**0.611*** (0.092)**	**0.701*** (0.041)**	**0.699*** (0.041)**
λ (space autocorr.)	**0.413*** (0.068)**	**0.230*** (0.041)**	**0.268** (0.109)**	**0.171*** (0.052)**
dep_to_loa	0.014 (0.021)	0.012 (0.021)	0.015 (0.020)	0.014 (0.020)
cap_to_ce	0.012 (0.010)	0.012 (0.010)	0.009 (0.008)	0.007 (0.009)
nonp_loa	0.156 (0.487)	0.112 (0.480)	−0.409 (0.602)	−0.417 (0.588)
assets	**−0.060** (0.027)**	**−0.069** (0.028)**	−0.019 (0.030)	−0.022 (0.030)
loa_to_ass	0.104 (0.170)	0.088 (0.170)	−0.043 (0.230)	−0.050 (0.228)
gdp_growth	−0.001 (0.002)	−0.001 (0.002)	0.001 (0.003)	0.001 (0.003)
log_gdp	**0.444*** (0.126)**	**0.417*** (0.128)**	**0.244** (0.106)**	**0.214** (0.106)**
rir	0.005 (0.003)	0.003 (0.003)	0.005 (0.003)	0.004 (0.004)
unemployment	0.007 (0.006)	0.006 (0.006)	0.006 (0.005)	0.005 (0.005)
Indirect share short	0.409	0.228	0.266	0.170
Indirect share long	1.076	0.580	0.887	0.557
Non-stat. probab.	0.589	0.069	0.391	0.013
R^2 overall	0.540	0.526	0.778	0.783
R^2 within	0.273	0.276	0.379	0.378
N	2976	2976	2976	2976
n banks	248	248	248	248

All the regressors are lagged by one year. Robust standard errors of the estimates are shown in parentheses. The estimates significant at 0.01 (***), 0.05 (**), or 0.1 (*) are denoted by stars and bolded. Indirect shares show the shares of indirect to total effects (same for all variables). Non-stat. probab. represents the Monte Carlo estimated probability that the data generating process is non-stationary.

did not confirm the hypothesis that the dependencies between banks' instability changed after the recent financial crisis and the spillover effect was exacerbated after crisis disturbances. Previous studies often emphasize the importance of dependencies between banks as crucial factors for systemic risk. Strong financial spillovers were the main aspect of the 2007–09 period, when the financial crisis in the U.S. banking sector rapidly spread into a global crisis. Although the dangers of spillover effects are widely acknowledged, there is no agreement on the primary channels through which financial instability propagates between countries. Therefore, our spatial approach can be useful for measuring systemic risk because it represents one of the channels through which shocks can generate global financial crises. The study indicates an important role for spatial model in macroprudential regulation for studying instability spillovers between banks from all over the world. Furthermore, this information is useful for policymakers because the propagation of shocks affects the effectiveness of monetary policy and the stability of the financial system.

The solvency interdependencies between banks from different countries that we find here should promote a deeper understanding of bank behavior under stressful situations. We hope that our study contributes to the understanding of the spillover effect in the banking sector and motivates further research to protect financial stability and design macroprudential reforms. Further studies could focus on this aspect to justify the value of spatial analysis in particular traditional and non-traditional banking activities.

One of the main limitations of this study is the accessibility of the data. First, we would like to have cross-border information for all

financial sectors in the system, but data constraints make this impossible. However, we maintain that we have obtained a significant proportion of cross-border links due to the fact that the banking sector is the main driver of cross-border exposures because of the traditionally strong links. Second, detailed data on interbank claims is necessary to measure the distance between banks more accurately. Although the available data are also limited in this area, we believe that it is rich enough to create a reasonable approximation to interbank connections.

CRediT authorship contribution statement

Acedański Jan: Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Karkowska Renata:** Conceptualization, Investigation, Data curation, Writing – original draft, Writing – review & editing.

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Appendix

This Appendix contains further robustness-checks results for the baseline estimates.

References

De Abreu, E. S., Kimura, H., & Sobreiro, V. A. (2019). What is going on with studies on banking efficiency? *Research in International Business and Finance, 47*(2018), 195–219. https://doi.org/10.1016/j.ribaf.2018.07.010

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic Risk and Stability in Financial Networks. *American Economic Review, 105*(2), 564–608. https://doi.org/10.1257/AER.20130456

Acharya, V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review, 102*(3), 59–64. https://doi.org/10.1257/AER.102.3.59

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *Review of Financial Studies, 30*(1), 2–47. https://doi.org/10.1093/rfs/hhw088

Adams, Z., Füss, R., & Gropp, R. (2014). Spillover effects among financial institutions: A state-dependent sensitivity value-at-risk approach. *Journal of Financial and Quantitative Analysis, 49*, 575–598. https://doi.org/10.1017/S0022109014000325

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review, 106*(7), 1705–1741. https://doi.org/10.1257/aer.20120555

Ahrend, R., & Goujard, A. (2015). Global banking, global crises? The role of the bank balance-sheet channel for the transmission of financial crises. *European Economic Review, 80*, 253–279. https://doi.org/10.1016/j.euroecorev.2015.10.003

Albertazzi, U., & Gambacorta, L. (2009). Bank profitability and the business cycle. *Journal of Financial Stability, 5*(4), 393–409. https://doi.org/10.1016/J.JFS.2008.10.002

Alexandrou, G., Koulakiotis, A., & Dasilas, A. (2011). GARCH modelling of banking integration in the Eurozone. *Research in International Business and Finance, 25*(1), 1–10. https://doi.org/10.1016/j.ribaf.2010.05.001

Allen, F., & Gale, D. (2000). Financial contagion. *Journal of Political Economy, 108*(1), 1–33. https://doi.org/10.1086/262109

Amaral, A., Abreu, M., & Mendes, V. (2014). The spatial Probit model - An application to the study of banking crises at the end of the 1990's. *Physica A: Statistical Mechanics and Its Applications, 415*(1), 251–260. https://doi.org/10.1016/j.physa.2014.07.044

Arnold, I. J. M., & Soederhuizen, B. (2018). Bank stability and refinancing operations during the crisis: Which way causality? *Research in International Business and Finance, 43*(2017), 79–89. https://doi.org/10.1016/j.ribaf.2017.07.122

Arreola Hernandez, J., Kang, S. H., Shahzad, S. J. H., & Yoon, S. M. (2020). Spillovers and diversification potential of bank equity returns from developed and emerging America. *North American Journal of Economics and Finance, 54*(May), 101219. https://doi.org/10.1016/j.najef.2020.101219

Asgharian, H., Hess, W., & Liu, L. (2013). A spatial analysis of international stock market linkages. *Journal of Banking and Finance, 37*(12), 4738–4754. https://doi.org/10.1016/j.jbankfin.2013.08.015

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions and Money, 18*(2), 121–136. https://doi.org/10.1016/j.intfin.2006.07.001

Barro, D., & Basso, A. (2010). Credit contagion in a network of firms with spatial interaction. *European Journal of Operational Research, 205*(2), 459–468. https://doi.org/10.1016/j.ejor.2010.01.017

Barth, J. R., Caprio, G., & Levine, R. (2013). Bank regulation and supervision in 180 countries from 1999 to 2011. *Journal of Financial Economic Policy, 5*(2), 111–219. https://doi.org/10.1108/17576381311329661

Batuo, M., Mlambo, K., & Asongu, S. (2018). Linkages between financial development, financial instability, financial liberalisation and economic growth in Africa. *Research in International Business and Finance, 45*(2016), 168–179. https://doi.org/10.1016/j.ribaf.2017.07.148

Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2014). The global crisis and equity market contagion. *The Journal of Finance, 69*(6), 2597–2649. https://doi.org/10.1111/JOFI.12203

Belotti, F., Hughes, G., & Piano Mortari, A. (2017). Spatial panel-data models using Stata. *The Stata Journal, 17*(1), 139–180. https://doi.org/10.1177/1536867X1701700109

Bernal, O., Gnabo, J. Y., & Guilmin, G. (2014). Assessing the contribution of banks, insurance and other financial services to systemic risk. *Journal of Banking and Finance, 47*, 270–287. https://doi.org/10.1016/j.jbankfin.2014.05.030

Brownlees, C. T., & Engle, R. (2017). SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies, 30*(1), 48–79. https://doi.org/10.1093/rfs/hhw060

Brutti, F., & Sauré, P. (2015). Transmission of sovereign risk in the Euro crisis. *Journal of International Economics, 97*(2), 231–248. https://doi.org/10.1016/j.jinteco.2015.03.009

Calmès, C., & Théoret, R. (2013). Market-oriented banking, financial stability and macro-prudential indicators of leverage. *Journal of International Financial Markets, Institutions and Money, 27*(1), 13–34. https://doi.org/10.1016/j.intfin.2013.07.004

Calvo, G. A., & Mendoza, E. G. (1996). Mexico's balance-of-payments crisis: A chronicle of a death foretold. *Journal of International Economics, 41*(3–4), 235–264. https://doi.org/10.1016/S0022-1996(96)01436-5

Cetorelli, N., & Goldberg, L. S. (2011). Global banks and international shock transmission: Evidence from the crisis. *IMF Economic Review, 59*(1), 41–76. https://doi.org/10.1057/imfer.2010.9

Chan-Lau, J. A., Espinosa, M., Giesecke, K., Sole, J. A. (2009). Assessing the Systemic Implications of Financial Linkages. In *IMF Global Financial Stability Report April 2009. Vol. 2*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1417920.

Chang, R., & Majnoni, G. (2001). International contagion - implications for policy. In: Claessens, S. & Forbes K.J. (eds) International Financial Contagion. Springer, Boston, MA. 10.1007/978-1-4757-3314-3_15.

Chen, T. H., & Lee, C. C. (2020). Spatial analysis of liquidity risk in China. *North American Journal of Economics and Finance, 54*(2019). https://doi.org/10.1016/j.najef.2019.101047

Choudhry, T., & Jayasekera, R. (2014). Returns and volatility spillover in the European banking industry during global financial crisis: Flight to perceived quality or contagion? *International Review of Financial Analysis, 36*(C), 36–45. https://doi.org/10.1016/j.irfa.2014.05.003

De Haas, R., & Van Horen, N. (2013). Running for the exit? International bank lending during a financial crisis. *Review of Financial Studies, 26*(1), 244–285. https://doi.org/10.1093/rfs/hhs113

Demirgüç-Kunt, A., & Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns. *Journal of Financial Economics, 98*(3), 626–650. https://doi.org/10.1016/J.JFINECO.2010.06.004

Dietrich, A., & Wanzenried, G. (2011). Determinants of bank profitability before and during the crisis: Evidence from Switzerland. *Journal of International Financial Markets, Institutions and Money, 21*(3), 307–327. https://doi.org/10.1016/j.intfin.2010.11.002

Dornbusch, R., Park, Y. C., & Claessens, S. (2000). Contagion: Understanding how it spreads. *The World Bank Research Observer, 15*(2), 177–197. https://doi.org/10.1093/wbro/15.2.177

Dungey, M., Flavin, T. J., & Lagoa-Varela, D. (2020). Are banking shocks contagious? Evidence from the eurozone. *Journal of Banking & Finance, 112*, 105386. https://doi.org/10.1016/J.JBANKFIN.2018.07.010

Dungey, M., & Gajurel, D. (2015). Contagion and banking crisis - International evidence for 2007–2009. *Journal of Banking and Finance, 60*, 271–283. https://doi.org/10.1016/j.jbankfin.2015.08.007

ECB. (2010). *Financial Stability Review*. Retrieved from http://www.ecb.europa.eu.

Elhorst, J. P. (2014). Spatial Econometrics. From Cross-Sectional Data to Spatial Panels. Berlin, Springer. 10.1007/978-3-642-40340-8.

Fernandes, G. B., & Artes, R. (2016). Spatial dependence in credit risk and its improvement in credit scoring. *European Journal of Operational Research, 249*(2), 517–524. https://doi.org/10.1016/j.ejor.2015.07.013

Frankel, J. A., & Schmukler, S. L. (1997). Crisis, contagion, and country funds: Effects on East Asia and Latin America. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.9516

Gernát, P., Košťálová, Z., & Lyócsa, Š. (2020). What drives U.S. financial sector volatility? A Bayesian model averaging perspective. *Research in International Business and Finance, 51*(2019), 101095. https://doi.org/10.1016/j.ribaf.2019.101095

Ghulam, Y., & Doering, J. (2018). Spillover effects among financial institutions within Germany and the United Kingdom. *Research in International Business and Finance, 44*(March), 49–63. https://doi.org/10.1016/j.ribaf.2017.03.004

Glick, R., & Rose, A. K. (1998). How do currency crises spread? *FRBSF Economic Letter*. Retrieved from https://ideas.repec.org/a/fip/fedfel/y1998iaug28n98-25.html.

Goddard, J. A., Molyneux, P., & Wilson, J. O. S. (2004). Dynamics of growth and profitability in banking. *Journal of Money, Credit, and Banking, 36*(6), 1069–1090. https://doi.org/10.1353/mcb.2005.0015

Goldstein, I., & Pauzner, A. (2004). Contagion of self-fulfilling financial crises due to diversification of investment portfolios. *Journal of Economic Theory, 119*(1), 151–183. https://doi.org/10.1016/J.JET.2004.03.004

Bardsen, G., Lindquist, K. G., & Tsomocos, D. P. (2006). Evaluation of macroeconomic models for financial stability analysis. Working Paper No. 2006/1. Norges Bank.

Hesse, H., & Cihak, M. (2007). Cooperative banks and financial stability. IMF Working Paper 07/02. https://doi.org/10.5089/9781451865660.001.

Horst, U. (2007). Stochastic cascades, credit contagion, and large portfolio losses. *Journal of Economic Behavior & Organization, 63*(1), 25–54. https://doi.org/10.1016/J.JEBO.2005.02.005

Jiménez, G., Ongena, S., Peydró, J.-L., & Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review, 102*(5), 2301–2326. https://doi.org/10.1257/aer.102.5.2301

Jokipii, T., & Lucey, B. (2007). Contagion and interdependence: Measuring CEE banking sector co-movements. *Economic Systems, 31*(1), 71–96. https://doi.org/10.1016/j.ecosys.2006.05.001

Kleinow, J., Moreira, F., Strobl, S., & Vahamaa, S. (2017). Measuring systemic risk: A comparison of alternative market-based approaches. *Finance Research Letters, 21*, 40–46. https://doi.org/10.1016/j.frl.2017.01.003

Lee, Lung-Fei & Yu, Jihai (2010). Some recent developments in spatial panel data models. *Regional Science and Urban Economics, 40*(5), 255–271. https://doi.org/10.1016/j.regsciurbeco.2009.09.002

Lepetit, L., & Strobel, F. (2013). Bank insolvency and time-varying Z-score measures. *Journal of International Financial Markets, Institutions and Money, 25*, 73–87. https://doi.org/10.1016/j.intfin.2013.01.004

Li, L., & Yang, Z. (2020). Estimation of fixed effects spatial dynamic panel data models with small T and unknown heteroskedasticity. *Regional Science and Urban Economics, 81*, 103520. https://doi.org/10.1016/j.regsciurbeco.2020.103520

Maghyereh, A. I., & Awartani, B. (2012). Financial integration of GCC banking markets: A non-parametric bootstrap DEA estimation approach. *Research in International Business and Finance, 26*(2), 181–195. https://doi.org/10.1016/j.ribaf.2011.10.001

Neaime, S. (2012). The global financial crisis, financial linkages and correlations in returns and volatilities in emerging MENA stock markets. *Emerging Markets Review, 13*(3), 268–282. https://doi.org/10.1016/J.EMEMAR.2012.01.006

Petersen M., & Rajan, R. (2002). Does Distance Still Matter? The Information Revolution in Small Business Lending. NBER Working Paper 7685.

Richards, T. J., Acharya, R. N., & Kagan, A. (2008). Spatial competition and market power in banking. *Journal of Economics and Business, 60*(5). https://doi.org/10.1016/j.jeconbus.2007.06.002

Rivera-Castro, M. A., Ugolini, A., & Arismendi Zambrano, J. (2018). Tail systemic risk and contagion: Evidence from the Brazilian and Latin America banking network. *Emerging Markets Review, 35*. https://doi.org/10.1016/j.ememar.2018.02.004

Segoviano, M. A., & Goodhart, C. (2009). *Banking Stability Measures*. IMF Working Paper No. WP/09/4.

Stiglitz, J. E. (2010). Risk and global economic architecture: Why full financial integration may be undesirable. *American Economic Review, 100*(2), 388–392. https://doi.org/10.1257/aer.100.2.388

Tonzer, L. (2015). Cross-border interbank networks, banking risk and contagion. *Journal of Financial Stability, 18*, 19–32. https://doi.org/10.1016/j.jfs.2015.02.002

Tsoumas, C. (2017). Bank defaults and spillover effects in US local banking markets. *Journal of Economic Asymmetries, 16*(March), 1–11. https://doi.org/10.1016/j.jeca.2017.04.001

Van Rijckeghem, C., & Weder, B. (2003). Spillovers through banking centers: A panel data analysis of bank flows. *Journal of International Money and Finance, 22*(4), 483–509. https://doi.org/10.1016/S0261-5606(03)00017-2

Vitali, S., & Battiston, S. (2011). Geography versus topology in the European Ownership Network. *New Journal of Physics, 13*(6), 063021. https://doi.org/10.1088/1367-2630/13/6/063021

Vitali, S., Battiston, S., & Gallegati, M. (2016). Financial fragility and distress propagation in a network of regions. *Journal of Economic Dynamics and Control, 62*, 56–75. https://doi.org/10.1016/j.jedc.2015.10.003

Vives, X. (2019). Competition and stability in modern banking: A post-crisis perspective. *International Journal of Industrial Organization, 64*, 55–69. https://doi.org/10.1016/j.ijindorg.2018.08.011

Wagner, W. (2011). Systemic liquidation risk and the diversity-diversification trade-off. *The Journal of Finance, 66*(4), 1141–1175. https://doi.org/10.1111/j.1540-6261.2011.01666.x

Wang, S., Chen, L., & Xiong, X. (2019). Asset bubbles, banking stability and economic growth. *Economic Modelling, 78*, 108–117. https://doi.org/10.1016/j.econmod.2018.08.014

Weiß, G. N. F., Neumann, S., & Bostandzic, D. (2014). Systemic risk and bank consolidation: International evidence. *Journal of Banking and Finance, 40*(1), 165–181. https://doi.org/10.1016/j.jbankfin.2013.11.032

Wong, A. Y. T., & Fong, T. P. W. (2011). Analysing interconnectivity among economies. *Emerging Markets Review, 12*(4), 432–442. https://doi.org/10.1016/j.ememar.2011.06.004

Yang, Z. (2018). Unified M-estimation of fixed-effects spatial dynamic models with short panels. *Journal of Econometrics, 205*(2), 423–447. https://doi.org/10.1016/j.jeconom.2017.08.019

Yildirim, C., & Efthyvoulou, G. (2018). Bank value and geographic diversification: Regional vs global. *Journal of Financial Stability, 36*, 225–245. https://doi.org/10.1016/j.jfs.2018.04.003

Yu, J., de Jong, R., & Lee, L. F. (2008). Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both N and T are large. *Journal of Econometrics, 146*(1), 118–134. https://doi.org/10.1016/j.jeconom.2008.08.002

Yu, X., Li, M., & Huang, S. (2017). Financial functions and financial development in China: A spatial effect analysis. *Emerging Markets Finance and Trade, 53*(9), 2052–2062. https://doi.org/10.1080/1540496X.2017.1286588

Yun, J., & Moon, H. (2014). Measuring systemic risk in the Korean banking sector via dynamic conditional correlation models. *Pacific Basin Finance Journal, 27*(1), 94–114. https://doi.org/10.1016/j.pacfin.2014.02.005

Zhu, B. (2018). The multi-country transmission of sovereign and banking risk: A spatial vector autoregressive approach. *Spatial Economic Analysis, 13*(4), 422–441. https://doi.org/10.1080/17421772.2018.1473890