Cultural similarity and bank interconnectedness

Abstract

We analyze the impact of cultural similarity on bank interconnectedness across thirty-seven OCED countries. The bank interconnectedness is measured using both correlation network measured by Granger causality of bank returns and physical network based on interbank common asset holdings. Cultural similarity impact shows a trade-off between safety and growth exhibiting a non-monotonic relation to the bank interconnectedness. When cultural similarity is low, banks show safety focused culture by reducing return synchronicity and physical interconnectedness. However, when cultural similarity is high, banks show growth focused culture with increased correlation and physical networks which in turn increases systemic risk.

Key Words: Cultural similarity; Correlation network; Physical network; Banks

JEL Classification: G4, G15, G21, G41

1. Introduction

Bank interconnectedness is a matter of significant interest and concern to the financial markets and regulators. Although closer connections allow banks to expand business and diversify risk, research has shown that they increase financial contagion risk. Acemoglu et al. (2015) argue that even though a more densely connected financial network enhances financial stability, beyond a certain point these interconnections serve as a mechanism for the propagation of shocks, leading to a more fragile financial system. Further, interconnectedness leads to more complex and less transparent network of banks, thereby worsening information asymmetry (Caballero and Simsek, 2013). Thus, high interconnectedness among banks may adversely affect financial stability and do more harm than good.

Although bank interconnectedness is one of the key systemic risk factors (Drehmann and Tarashev, 2013), research on the drivers of interconnectedness has gathered momentum since the 2007-2008 Global Financial Crisis (GFC). Cai et al. (2018) argue that interconnectedness is driven mainly by bank diversification which is positively correlated with different bank-level systemic risk. Eisert and Eufinger (2019) find that banks protected by government guarantees increase the degree of interconnectedness with longer intermediation chains that attract other banks. Brunetti et al. (2019) investigate how European bank interconnectedness evolved during the GFC. They show that during the crisis, whilst the physical network connectedness declined, there was a significant increase in the correlation network. They suggest that a significant decline in physical interconnectedness reflects hoarding behavior among banks which adversely affects interbank market liquidity. On the contrary, increased interconnectedness in the correlation network reflects greater comovements among equity returns during the crisis.

Despite the systemic importance of bank interconnectedness, the literature has not considered the role of cultural similarity.[1] In this paper, after controlling for bank characteristics as well as economic and financial market factors, we investigate how cultural similarity affects bank interconnectedness. We argue that culture may affect bank interconnectedness primarily for two reasons. First, culture being "the collective programming of the mind" (Hofstede and Bond, 1988)

[1] Nguyen et al. (2019) suggest bank culture lies at the heart of risk-taking behavior potentially undermining financial stability. Also both the President and Chief Executive Officer of the Federal Reserve Bank have repeatedly emphasized the need for improving the culture of banks (De Nederlandsche Bank report, 2015).

guides the decisions and behavior of economic agents. Several studies show that culture influences bank capital structure decisions (Haq, et al., 2018), trade credit provisions (Ghoul et al., 2016), and bank level failures (Berger et al., 2021). Second, corporate culture prevailing in banks has a significant role in many decisions. For example, using a large dataset of international syndicated bank loans, Gianetti and Yafeh (2012) find that culturally distant banks offer smaller loans at higher costs and cultural differences not only affect borrower relations but also hinder risk sharing among banks. Nguyen et al. (2019) contend that the corporate culture of banks is a root cause of excessive risk-taking behavior and plays a key role in influencing financial stability. Song and Thakor (2019) suggest that bank culture is an important issue in the context of bank risk and financial stability. They view bank culture as a choice between growth and safety and argue that a strong safety culture can moderate competition induced excessive focus on growth.

Since cultural similarity is associated with shared social signals and provides an emotional bond for people sharing similar cultural backgrounds, it will have a significant influence on the bank's resource allocation to growth and safety which in turn will influence bank interconnectedness. On one hand, banks could use cultural similarity for peer monitoring enabling them to reduce interconnectedness risks. On the other hand, cultural similarity may enable banks to enhance growth by doing more business with peers thus increasing the risks arising from greater interconnections.

There are several reasons for studying the drivers of bank interconnectedness. First, high bank interconnectedness could rapidly spread financial stress of one bank to another and across the financial system. Second, though critical for facilitating funding and transferring risk, bank interconnectedness increases likelihood of financial contagion and a reduction in the aggregate provision of financial services. This can lead to reduced lending and liquidity amplifying the adverse effects of macroeconomic downturns. In a financial system with long and complex chains of intermediation, failure of a highly interconnected banks could cause major disruptions and a series of bank failures.[2] Third, bank interconnectedness is considered as one of the key factors in assessing the systemic risk of the financial system by the International Monetary Fund (IMF), Bank for

[2] This was evident during the 2008 financial crisis when many banks ran into financial problems following the demise of Lehman Brothers.

International Settlements (BIS) and Financial Stability Board (FSB) because of its significant implications for cross-border supervision and resolution

Although cultural and ethical issues are not unique to the finance industry, banks are different from other firms in important ways. First, the financial sector plays a key role in allocating scarce capital and exerting market discipline. A vibrant and sound financial sector is therefore critical for achieving long-term growth. Second, unlike other industry, banks perform a critical public function of providing access to finance, create liquidity, and transfer risk. Hence public trust in the financial sector is critical for banks to function effectively (Dudley, 2014). Notwithstanding the cultural impact on country- and firm-level outcomes, cultural similarity could be a key determinant of bank interconnectedness which in turn may have significant implications for systemic risk.

Motivated by these reasons, we examine the influence of cultural similarity on bank interconnectedness. Using data from thirty-seven OCED countries we find the impact of cultural similarity on bank interconnectedness is non-monotonic. We show that at low level of cultural similarity, banks seem to prioritize safety over growth indicating lower synchronicity. However, when the cultural similarity level is high, banks seem to display a growth focus with increased stock return correlations and the physical interconnectedness. Although, on average, both correlation and physical networks show higher sensitivities to financial crises, their sensitivities to cultural similarity differ during financial crises depending on the financial characteristics of banks. The crises seem to have greater impact on the correlation network of large banks with high capital adequacy ratio. On the other hand, the impact of on the physical network is higher for small banks. Finally, we find banks with higher capital adequacy ratio as required by the financial regulation show reduced interconnectedness during crises periods.

We make three distinct contributions to the current literature. First, as far as we are aware, this is the first paper which offers evidence of the impact of cultural similarity on bank interconnectedness. Second, unlike many previous studies, we use data from thirty-seven OCED countries and provide a comprehensive analysis drawing on the growth and safety culture ideas proposed by Song and Thakor

(2019). Third, we show that moderate level of cultural similarity with other banks may be helpful in achieving optimal balance between safety and growth.

Rest of the paper is organized as follows. Section 2 provides a discussion of the literature. Section 3 explains our research motivation and provides discussion of culture and bank interconnectedness. Section 4 outlines methodology and the empirical approach. Section 5 describes the data. Section 6 presents empirical results and section 7 concludes.

2. Literature review

2.1 Bank Interconnectedness

Extant research has mainly focused on interconnectedness amongst financial institutions (e.g., Allen and Gale, 2000; Elliott et al., 2014; Cabrales et al., 2017) caused by overlapping portfolios of bank loans (Cai et al., 2018), government guarantees (Eisert and Eufinger, 2019), correlations in financial assets (Brunetti et al., 2019), and leverage overlaps defined as a ratio of overlapping volume with the peer bank and the banks' capital (Roncoroni et al., 2019) among other factors. De Vries (2005) argues that by holding similar portfolios, banks are exposed to the same market risks causing equity returns to be asymptotically dependent. Similarly, Acharya and Yorulmazer (2008) suggest interdependence in bank equity returns are caused by holding stakes in same firms. Other papers have used balance sheet channels, long term interbank loans, loan syndication, credit risk interconnectedness, and funding and securities holdings (e.g., Hale et al., 2016; Abbassi et al., 2017) as potential channels through which systemic risk may be transmitted.

Another stream of research has examined the consequences of interconnectedness. Gai et al. (2011) examine the impact of financial networks' degree of concentration and complexity on systemic risk. They argue that network interconnectedness and complexity increase systemic risk even though strict liquidity policies and macro-prudential regulations can enhance a network's ability to guard against potential risk. Acemoglu et al. (2015) show that when shocks are small, a closely interconnected network is beneficial for the stability of the system. However, when a shock is relatively large, interconnectedness makes it easier for risk to contaminate the stability of the system. On the contrary, Allen and Gale (2000) argue that banks with densely connected networks tend to better withstand risks from contagion caused by exogenous shocks due to co-insurance than those with fewer connections. However, there are limits to the benefits of dense network connections and interconnectedness could propagate, rather than attenuate shocks, resulting in a more fragile system (Acemoglu et al., 2015).

2.2 Bank and culture

Over 92% of senior executives of 1,348 North American firms believe that improvements in prevailing culture will increase their company's value (Graham et al., 2017). While the literature has established a number of direct and indirect channels which can induce interconnectedness amongst banks, there is little or no research on how cultural similarity affects bank interconnectedness. Similarities in cultural values across countries where banks are domiciled can play a significant part in understanding their role in inducing both financial and physical bank interconnectedness.

Although there is extensive literature on corporate culture (e.g., Quinn and Rohrbaugh, 1983; Cartwright and Cooper, 1993; Cameron and Quinn, 2011; Cameron et al., 2014), research on role of culture in banks is limited. Zaal et al. (2019) use a survey to measure ethical culture in one of the leading wholesale banks in Europe and find that it significantly affects the bank's behavior towards its customers. Nguyen et al. (2019) explain how the culture of pursuing either growth or safety leads to differing levels of bank risk-taking. Using textual analysis of 10-K reports, they examine how culture influences banks' lending terms and pricing decisions. Agarwal et al. (2019) also use textual analysis to quantify culture of banks and report how risk impacts bank reputation, employee characteristics and strategy. Haq et al. (2018) employ individualism, power distance, long-term orientation and indulgence cultural measures of Hofstede (2001) to explain their impact on bank leverage. They find that banks in countries with high individualism are more leveraged while those in countries with high power distance, long-term orientation and indulgence are less leveraged. Boubakri et al. (2023) investigate the relationship between national culture and cross-country variations in bank liquidity. They argue that individualistic societies facilitate bank liquidity creation owing to risk-taking and overconfidence bias and better access to soft information. On the contrary, they find that uncertainty avoidance and power distance are related to lower liquidity creation. Berger et al. (2021) report that individualism and masculinity cultural characteristics increase bank failures across 92 countries between 2010 and 2014. They argue that individualism heightens portfolio risks while masculinity reduces liquidity and bailouts.

2.3 Cultural similarity

Hofstede's (1980, 2001) measures of national culture (i.e., power distance, uncertainty avoidance, masculinity-femininity, and individualism-collectivism) have been widely used in the literature. Gelfand et al. (2011) show that loose culture fosters innovation and creative ideas and, on the contrary, tight culture demands strict adherence to rules. In this study, we build a cultural similarity index using the tightness/looseness, individualism/collectivism, trust and uncertainty avoidance/risk-taking dimensions.

Tightness/looseness is defined by the strength of punishment for the deviant behavior and degree of latitude/permissiveness. In contrast to loose cultures where social norms are informal and flexible, tight cultures show high social stability, low drug and alcohol use, lower rates of homelessness, and lower social disorganization. However, tight culture increases incarceration rates, discrimination and inequality as well as lowers creativity, and happiness (Harrington and Gelfand, 2014; Gelfand et al., 2006). We argue that banks located in countries with tight culture are likely to herd towards the prevalent business practices. Furthermore, banks in tight cultures may also be subjected to stricter financial regulations and monitoring since financial stability may be considered more important than profitability. This could be particularly relevant in case of Systematically Important Financial Institutions (SIFIs) which make up a major proportion of the banking sector. Besides forcing banks to adhere to global practices and norms, banks in tight cultures are more likely to be compliant to the capital reserve requirements and increase their interbank lending. Consequently, banks in tight cultures are likely to show higher level of correlation and physical interconnectedness.

Previous studies have shown that those from individualistic cultures exhibit analytical thinking (Choi and Nisbett, 2000; Nisbett et al., 2001), overconfidence, self-attribution bias and less herding behavior (Chui et al., 2010). In contrast, those from collectivistic culture show greater herding behavior. Consequently, banks in individualistic cultures are likely to be more customer focused than those in collectivist cultures are expected to operate with a holistic approach (Choi and Nisbett, 2000; Nisbett et al., 2001; Eun et al., 2015).

Trust reflects willingness to rely on others in circumstances which can make one vulnerable to the other party (Doney et al., 1998). Trust can lower transaction costs in uncertain environments (Dore, 1983; Noordewier et al., 1990), facilitate long-term relationship between firms (Ganesan, 1994; Ring and Van de Ven, 1992), bring success to strategic alliances (Browning et al., 1995; Gulati, 1995), help improve strategy and managerial coordination (McAllister, 1995), and effective teamwork (Lawler, 1992). Trust is a critical factor in corporate culture because it improves communication, commitment, team work and productivity. Therefore, banks in strong trusting cultures may show higher loan approval rates and greater interbank asset holdings.

Uncertainty avoidance shows the degree of comfort in unfamiliar situations and the extent to which 'a society tries to control the uncontrollable' (Hofstede, 2001). Muzaffarjon and Hove (2020) find that trust in banks is lower in countries that score high on Hofstede's uncertainty avoidance index. Thus, in high uncertainty avoidance cultures, banks may be less willing to accept risks (Litvin et al., 2004) and more concerned with maintaining financial stability.

We create a cultural similarity index by using these four cultural dimensions and examine how it affects bank interconnectedness. Cultural similarity increases information sharing through easier communication and promoting greater cooperation between businesses who share similar beliefs (Rogers and Bhowmik, 1970; Giannetti and Yafeh, 2012). Thus, cultural similarity can help better negotiations and reduce contracting costs as culturally similar banks would have superior information about each other and impose less restrictive contract terms. On the contrary, banks from dis-similar cultures may impose higher costs arising from risk hedging due to lack of information and familiarity. Lack of cultural similarity may encourage banks to restrict loan size and demand higher interest and third-party guarantees. Thus, we argue that superior information available in culturally similar countries may influence their willingness to take greater risks in pursuit of higher profits.

We expect growth focused motive to be stronger for culturally similar banks. However, when banks don't have access to enough information due to low cultural similarities, they become safety focused and increase peer monitoring. Consequently, we expect a non-monotonic impact of cultural similarity on bank interconnectedness caused by a trade-off between growth and safety.

4. Methodology

4.1. Cultural similarity

We quantify cultural similarity (*Cul_Sim*) using Jaffe's (1986) distance measure which is a pair-wise function to calculate the proximity between two subjects using the angular separation or correlation between them. The cultural similarity of banks between countries *i* and *j* is derived as:

$$Cul\_Sim_{\,i,j} = \frac{X_i X_j'}{(X_i X_i')^{0.5} (X_j X_j')^{0.5}} \tag{1}$$

where, $X_{i,} = (X_{i,Tight}, X_{i,Indiv}, X_{i,Trust}, X_{i,Riskav})$ is a vector of cultural values in each cultural subcategory $X_{i,k,t}$ (where k = *Tight* (Tightness), *Indiv* (Individualism), *Trust* (Trust), *Riskav* (Uncertainty Avoidance)) of country *i*. Cultural similarity accounts for the missing cultural values by automatically canceling out the distance calculation if at least one side of the vector multiplication belonging to the same cultural subcategory has missing value set to zero. For instance, if cultural value for *Trust* in country *i* is 30 ($X_{i,Trust}$ = 30) while such value of country *j* is missing ($X'_{j,Trust}$= 0) then their multiplication becomes zero thus ($X_{i,Trust}X'_{j,Trust} = 0$) nullifying their distance calculation.[3]

Each cultural value has a different scale as shown in appendix I. Thus, we use the min-max normalization method where values for cultural dimensions vary between zero and one as inputs into equation (1). For instance, if $x_{i,k,t}$ is the cultural value of subcategory *k* for country *i* at time *t*, the min-max normalized cultural value for this subcategory is calculated as $x_{i,k,t} = \frac{x_{i,k,t} - min\,(x_{i,k,t})}{max\,(x_{i,k,t}) - min\,(x_{i,k,t})}$. This normalization process can also produce zero values if the corresponding cultural value within the same cultural dimension category is missing. We extend equation (1) by using the average cultural similarity values from country *i* against the rest of the sample countries. We then weight this by w_i, the number of

[3] This contrasts the widely used Euclidian distance and other similar measures (e.g., Giannetti and Yafeh, 2012; Siegel et al., 2011) which cannot produce distances between subjects with missing values.

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banks in country *i*, denoted as N_i , compared to total number of banks across all *c* number of countries in our sample as shown in equation (2).

$$Cul\_Sim_i = w_i E\left[\frac{X_i X_j'}{\left(X_i X_i'\right)^{0.5}\left(X_j X_j'\right)^{0.5}} \mid i \neq j\right] \tag{2}$$

where

$$w_i = \frac{N_i}{\sum_{i=1}^{c} N_i}$$

Equation (2) is thus weighted average cultural similarity value (*Cul_Sim*) for country *i* against all possible pairs within our sample countries. We scale this weighted average cultural similarity value in equation (2) to vary between zero and one by using the min-max normalization to produce a scaled index value for comparable interpretations across countries.

4.2. Bank interconnectedness

Following Brunetti et al. (2019), we consider two interconnectedness measures: correlation network and physical networks. Correlation networks are inferred from the granger causalities among stock returns of banks. If the stock return of bank *n* Granger-causes the stock return of bank *m* at time *t* at the 5% significance level, we denote it as one ($a_{n,m,t}$ = 1) and zero ($a_{n,m,t}$ = 0) otherwise. We do not regard Granger-causality of returns within the same bank ($n \neq m$). The pairwise Granger causality $Corr\_net_{n,t}$ is computed by counting the number of Granger-causalities of bank *n* to all $N_t(N_t - 1)$ pairs among N_t number of banks at time *t* using a 36-months rolling windows following. Following Billio et al. (2012), we proxy correlation network by the degree of Granger Causality in equation (3).

$$Corr\_net_{n,t} = \binom{N_t}{2}^{-1} \sum_{n=1,}^{N_t} \sum_{m=1}^{N_t} a_{n,m,t} \tag{3}$$

where

$$(n \rightarrow m) = \begin{cases} a_{n,m,t} = 1 & \text{if } n \text{ Granger causes } m \text{ time } t \\ a_{n,m,t} = 0 & \text{otherwise} \end{cases}, \quad (n \rightarrow n) \equiv 0$$

Thus, the correlation (*Corr_net*) network is measured by the granger causality in stock returns in the 36-month rolling window. The normalized correlation network ($N\_corr\_net_{n,i,t}$) for bank n in country i at time t is scaled as follows.

$$N\_corr\_net_{n,i,t} = \frac{Corr\_net_{n,i,t} - min\,(Corr\_net_{n,i,t})}{max\left(Corr\_net_{n,i,t}\right) - min\,(Corr\_net_{n,i,t})} \tag{4}$$

Physical networks are measured by the relative amount of interbank common asset holdings. Similar to Brunetti et al. (2019), we use the interbank asset holding to represent the interbank lending network and capture funding liquidity between banks.

The impact of interbank asset exposure would differ according to their size (i.e., total assets). Therefore, we compute the interbank asset holding weighted by total assets of bank n relative to all possible $N_t\,(N_t - 1)$ pairs among our N_t number of banks at time t.[4] Similar to correlation network, we measure the degree of Granger Causality for physical networks in equation (5) following Billio et al. (2012).

$$Phy\_net_{n,t} = \binom{N_t}{2}^{-1} \sum_{n=1,}^{N_t} \sum_{m=1}^{N_t} b_{n,m,t} \tag{5}$$

where

$$b_{n,m,t} = \frac{\sum_{m=1}^{N_t} \frac{Interbank\_assets_{n,m,t}}{Total\_assets_{n,m,t}}}{\sum_{n=1}^{N_t} \sum_{m=1}^{N_t} \frac{Interbank\_assets_{n,m,t}}{Total\_assets_{n,m,t}}}\,,\ (n \rightarrow n) \equiv 0$$

$Interbank\_assets_{n,t}$ = Short-term interest-earning loans to banks except the central bank$_{n,t}$ + Call loans, receivables from other banks$_{n,t}$ + Federal funds sold and securities purchased under agreements to resell$_{n,t}$ + Federal funds sold and repurchase agreements$_{n,t}$ + Deposits at interest with other banks$_{n,t}$ (6)

[4] The interbank asset definition follows the Bloomberg data source definition. Therefore, the interbank total asset amount of bank *n* may cover more than our *N* number of sample banks. However, since this same situation applies to all banks simultaneously, we use the interbank asset data from Bloomberg as a proxy for physical networks among our sample banks which already comprise the major banks listed in stock indices across countries.

We then calculate the normalized physical network ($N\_phy\_net_{n,i,t}$) for bank n in country i at time t as we have done for our correlation networks to have comparable interpretation.

$$N\_phy\_net_{n,i,t} = \frac{Phy\_net_{n,i,t} - min\,(Phy\_net_{n,i,t})}{max\left(Phy\_net_{n,i,t}\right) - min\,(Phy\_net_{n,i,t})} \qquad (7)$$

4.3. Empirical model

We use the dynamic panel regression model (equation 8) based on Kilian and Vega (2011) to measure the impact of cultural similarity on banks interconnectedness in the presence of economic shocks.

$$Y_{n,i,t} = \alpha + \beta_1 Cul\_Sim_i + \beta_2 Cul\_Sim^2_i + \beta_3 Stock\_R_{n,i,t-1} + \beta_4 Stock\_V_{n,i,t-1} + \beta_5 FRB_{t-1} + \beta_6 \Delta EPU_{t-1} + \beta_7 \Delta MSCI_{t-1} + \beta_8 Crises_{i,t-1} + \beta_9 Y_{n,i,t-1} + \varepsilon_{n,i,t} \qquad (8)$$

where, $Y_{n,i,t}$ denotes interconnectedness, either correlation ($N\_corr\_net_{n,i,t}$) or physical ($N\_phy\_net_{n,i,t}$) network, of banks. Cul_Sim_i is the weighted cultural similarity derived from equation (2). We also use $Cul\_Sim^2_i$ to capture any non-monotonic relationship between culture and bank interconnectedness.[5] We include log returns ($Stock\_R_{n,i,t}$) and log scaled stock trading volumes ($Stock\_V_{n,i,t}$) of banks along with the log returns of MSCI world index ($\Delta MSCI$) to capture global stock market developments together. $Crises_{i,t-1}$ is a summation of five crises dummies: Asian crisis, the Dotcom crisis, the Global Financial Crisis, the European Sovereign Debt Crisis, and the Covid-19 pandemic. Further, we control for global macro-economic shocks by using the Federal Reserve Bank's (FRB_t) monetary policy announcement counts per quarter (Ammer et al., 2010), and the Economic Policy Uncertainty index (ΔEPU_t). The subscripts n, i, and t denote bank, country, and time (in quarters), respectively. α is the intercept and $\varepsilon_{n,i,t}$ is the error term. The control variables are lagged by one quarter to avoid hindsight bias.

The systemic risk arising from the interconnectedness of banks has been one the major concerns of the Basel Committee on Banking Supervision. The Basel III has introduced higher capital requirements for banks to help address systemic risk and interconnectedness arising from their inter-

[5] The literature considers culture to change very slowly over the centuries or millennia (e.g., Williamson, 2000; Hofstede, 2001; Licht et al., 2005). Therefore, culture variable can be considered as non-time varying.

financial sector exposures, trading and derivative activities, complex securitizations, off-balance sheet exposures, and so on (Basel Committee on Banking Supervision, 2010). Therefore, we use the Capital Adequacy Ratio (*CAR*) of banks in our sample as a proxy to capture the impact of financial regulation. We compare the impact for high and low *CAR* banks relative to the sample median *CAR*. Using a Difference in Differences (DiD) model, we consider, the high *CAR* banks as the treatment group and the low *CAR* banks as the control group. We extend model (8) by including a binary variable $CAR\_High_{n,i,t-1}$ which is equal to one if *CAR* is higher than the sample median and zero otherwise (model (9)). We interact this with the *Crises* variable to study its impact during the crises. Both $Crises_{i,t-1}$ and $CAR\_High_{n,i,t-1}$ are lagged by one quarter to avoid hindsight bias.

$$Y_{n,i,t} = \alpha + \beta_1 Cul\_Sim_i + \beta_2 Cul\_Sim^2_i + \beta_3\, CAR\_High_{n,i,t-1} + \beta_4\, CAR\_High_{n,i,t-1} \times Crises_{i,t-1} + \beta_5\, Crises_{i,t-1}$$
$$+ \beta_6 Stock\_R_{n,i,t-1} + \beta_7 Stock\_V_{n,i,t-1} + \beta_8 FRB_{t-1} + \beta_9 \Delta EPU_{t-1} + \beta_{10} \Delta MSCI_{t-1} + \beta_{11} Y_{n,i,t-1} + \varepsilon_{n,i,t} \qquad (9)$$

5. Data

We collect quarterly data of live banks in the OECD countries which have not been delisted in any of the quarters from March 1995 to March 2021. This leads to an initial sample of 4403 unique banks.[6] We collect data on total assets (*TA*), interbank asset to total asset ratios (*Interbank_Asset/TA*), stock returns (*Stock_R*), trading volumes (*Stock_V*), and capital adequacy ratio (*CAR*) in quarterly frequencies.[7] Although we collect our sample from March 1995, our analysis starts from March 1998 as we require 36-trailing months of stock price information to calculate the correlation networks using equation (3) in section 4.2.

We count the number of announcements in the Federal Open Market Committee (FOMC) minutes and policy statements each quarter and use them as our *FRB* variable. We collect Economic Policy Uncertainty Index (*EPU*) data from the Economic Policy Uncertainty database (https://www.policyuncertainty.com/) and calculate percentage change in the EPU (ΔEPU) adjusted by

[6] We remove banks from Luxembourg as we do not have cultural data.
[7] We firstly collect the monthly stock returns (*Stock_R*) of banks to calculate their correlation networks (*N_corr_net*) using equation (3). We then use only the quarterly values of *N_corr_net* for our analyses.

purchasing power parity (PPP) as a proxy for the global economic policy uncertainty.[8] We collect data on the Morgan Stanley Capital International world index to capture the global stock market performance of large and mid-cap companies across 23 developed countries[9] (MSCI, 2022). Financial data are transformed to US dollars.

Crises is a dummy variable representing the Asian crisis (July 1997 − December 1998)[10], the Dotcom crisis (March 2000 − Oct 2002)[11], the Global Financial Crisis (August 2007 − June 2009)[12], the European Sovereign Debt Crisis (October 2008 − July 2012)[13], and the Covid-19 pandemic (2020 onwards) showing one if the quarter belongs to any of these crises and zero otherwise. The Covid-19 period differs for each country. Therefore, we use the *Our World in Data* (https://ourworldindata.org/coronavirus) to collect the exact Covid-19 pandemic periods for each country which is based on the dates when the infections started to emerge. We winsorize data at the 1st and 99th percentiles and replace any missing values by the corresponding quarterly median values. This leads to a final sample of 2589 banks (see Appendix III).

Summary statistics in Table 1 show that the average of the total assets of banks in our sample is $536,038 million. The average quarterly stock return and trading volume are -0.52% and 17 million shares, respectively. Stock returns (*Stock_R*) show high clustering with a left-skewed distribution which indicates that though most banks have positive stock returns, there are small number of banks showing large negative returns.

The median value of *FRB* is 3 indicating that on average, each quarter there were three monetary policy announcements by the Federal Reserve Bank. The average change in economic uncertainty

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[8] Since the EPU database does not cover all OECD countries in our sample, we use the global index for the economic policy uncertainty measure for our analysis.
[9] 23 countries include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK and the US (MSCI, 2022).
[10] See Carson and Clark (2013).
[11] Nasdaq companies lost around $5 trillion after the market bottomed on October 2002 (Geier, 2015; Levy,2022)
[12] The GFC lasted until June 2009 (Rich, 2013). There are slightly different views on how long the Global Financial Crisis has lasted which overlaps with the European Sovereign Debt crisis period. Our Crises dummy has the flexibility to encompass this variability.
[13] We consider start of the European Sovereign Debt crisis with the collapse of Iceland banking system in October 2008 (Fraser, 2022). We regard this crisis to have lasted until July 2012 when high sovereign bond yields began to dissipate after the ECB president Mario Draghi promised to do "whatever it takes preserve the euro." (Samarakoon, 2017).

(*ΔEPU*) is 5.51% with a standard deviation of 30.74% indicating there has been some highly disruptive economic events throughout our sample period. The *Crises* variable shows an average value of 0.499 indicating around 49.9% of our sample has been subjected to one of the crises. We find the average *CAR* (15.04%) of our sample banks is much higher than the minimum 8% set by the Basel committee. The average interbank asset ratio (*Interbank_Asset/TA*) is 4.05%. The normalized bank interconnectedness measures, correlation (*N_corr_net*) and physical (*N_phy_net*) networks, have higher average than median which suggests a positively skewed distribution. This suggests that a small number of banks demonstrate high interconnectedness compared to rest of the banks. The *Cul_Sim* weighted by the number of banks for each country shows a mean value of 0.730 which suggests that there is relatively high level of cultural similarity across OECD countries' listed banks.

We convert panel data into time series by calculating their annual average values and using min-max normalization method. Figure 1 shows the time-varying correlation and physical networks We find that except for the Dotcom crisis, the correlation of stocks returns tend to rise leading up to and during the crises. Physical interconnectedness too shows a similar pattern. This evidence is consistent with Brunetti et al (2019) who report heightened correlations during the GFC.

[Insert Figure 1 here]

We use four cultural variables, i.e., *Tight*, *Indiv*, *Trust* and *Riskav* to build a cultural similarity index. *Tight* culture is proxied by country-specific tightness-looseness score from Gelfand et al.'s (2011) data set. A tight (loose) culture characterizes a country with strong (weak) social norms and low (high) tolerance for deviant behavior (Gelfand et al., 2011). *Indiv* is the country-specific individualism-collectivism score obtained from the Hofstede's (2001). It is based on the extent to which people are integrated into groups and focuses on their internal attributes used for differentiating from others (Hofstede, 1980, 2001; Eun et al., 2015). *Trust* is collected from the World Values Survey (WVS) using the proportion of respondents to the question whether "Most people can be trusted" across five consecutive waves of WVS.[14] *Riskav* is the degree of risk-aversion measure from Hofstede's (2001). The raw cultural indices are shown in Appendix I.

A comparison of cultural variable pairs for countries in our sample in panels A and B in appendix II, shows tighter cultures tend to be less individualistic. This implies that tighter (looser) cultures are likely to promote collective (individualistic) attributes. Similarly, higher (lower) trusting cultures tend to demonstrate lower (higher) risk aversion. Intuitively, more (less) trusting culture tend to be high risk-taking (risk-aversion).

[Insert Table 1 here]

6. Analysis and Results

6.1. Cultural similarity and bank interconnectedness

Following Song and Thakor (2019), we consider a bank's culture as a trade-off between growth and safety. Since familiarity with culture would be expected to reduce contracting and information gathering costs (see for example, Giannetti and Yafeh, 2012), we argue when cultural similarity is high, banks tend to focus more on growth. Similarly, when cultural similarity is low, banks tend to be safety focused.

We show the relationship between cultural similarity and correlation and physical networks in Figure 2. We find the relationship consistent with our expectations. When cultural similarity is low (left hand side of the inflection point of the curve), banks tend to be safety focused with a reduction in the correlation network. On the contrary, when the cultural similarity is high (right hand side of the inflection point of the curve in Figure 2), banks tend to be growth focused and their stock returns show higher comovements. We also find the cultural similarity has an analogous non-monotonic impact on the physical networks. Like the correlation network, banks tend to focus on safety when not enough information is available because of low cultural similarity. They are incentivized to reduce their physical interconnectedness by peer monitoring their interbank lending activities. On the contrary, when the

[14] This question asks *"Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?"*. The five waves of WVS were wave 3 (1995−1998), wave 4 (1999−2004), wave 5 (2005−2009), wave 6 (2010−2014), and wave 7 (2017−2020).

cultural similarity is high, banks tend to focus on growth since they benefit from easier business negotiations and reduced contracting costs leading to more interbank lending (Giannetti and Yafeh, 2012). However, this increases their physical networks and vulnerability to contagion.

Table 2 shows that cultural similarity shows non-monotonic impact on correlation and physical networks. We also find the bank interconnectedness is more strongly related to the downside risks of stock returns. In terms of the impact of economic shocks, results show that the monetary policy shocks (*FRB*) generally increase both correlation and physical interconnectedness. However, both macroeconomic shocks (ΔEPU) and global stock market performance ($\Delta MSCI$) are significantly negatively correlated with the correlation network but show no significant impact on the physical network. Consistent with findings reported by Brunetti et al. (2019), we find evidence of increased correlation network during the crises. However, the physical trading networks is significantly negatively affected during the crisis. Finally, we find consistently significant and positive impact of the lagged correlation (*N_corr_net*) and physical (*N_phy_net*) networks.[15]

[Insert Table 2 here]

[Insert Figure 2 here]

6.2. Crises, cultural similarity, and interconnectedness

We further investigate the moderating effect of crises on cultural similarity's impact on bank interconnectedness using equation (8). Although figure 3 shows similar the non-monotonic impact of cultural similarity on bank interconnectedness with and without crises, sensitivity to cultural similarity is higher for banks which are exposed to the crises. The convex shapes of cultural similarity impact on both correlation and physical networks are steeper during crises periods. Both correlation (Figure 3.1) and physical (figure 3.2) networks show higher sensitivity to cultural similarity confirming potential for higher contagion risks during crises.

[Insert Figure 3 here]

6.3. Bank characteristics, cultural similarity, and interconnectedness

[15] We find no multicollinearity in our data. Generalized Variance Inflation factor (GVIF) tests show all values are close to one (see appendix IV).

Next, we examine how bank characteristics affect cultural similarity's impact on correlation (figure 4) and physical (figure 5) interconnectedness. We compare the cultural similarity's impact on for large versus small size (*TA*) (figures 4.1 and 5.1), and high versus low capital adequacy ratio (*CAR*) (figures 4.2 and 5.2) banks using their corresponding sample median values.

Following the Global Financial Crisis, there have been calls for limiting bank size to reduce systemic risks. Both past and present chiefs of Federal Reserve Bank and Bank of England [16] have expressed their concerns about the dangers of 'too big to fail' (TBTF) banks. There are several studies which argue that bank size influences systemic risk (e.g., Vallascas and Keasey, 2012; Drehmann and Tarashev, 2013; Laeven et al., 2016; Gofman, 2017).

Consistent with above concerns, we find in figure 4.1 that correlation network of large banks shows a convex reaction to cultural similarity. However, small banks show lack of sensitivity to differing levels of cultural similarity. In contrast, figure 5.1 demonstrates that compared to large banks, small banks show higher physical network sensitivities. This could be because smaller banks rely more on relationships to overcome their relatively limited access to interbank market liquidity (Cocco et al., 2009). Thus, the size of banks has a significant moderating effect on the relationship between cultural similarity and interconnectedness.

The capital adequacy ratio (*CAR*) represents the amount of risk-based capital (i.e., tier 1 + tier 2 capital) held by the banks relative to their risk-weighted assets. Although it protects banks from unexpected losses and effectively reduce interconnectedness risks (Chen, 2022), the risk-based capital is highly costly for banks to hold and reduces their profitability (Tran et al., 2016).

In figures 4.2 and 5.2, we find both the correlation and physical networks of high *CAR* banks show slightly greater sensitivity to cultural similarity than those of low *CAR* banks. It is plausible that better capitalized banks might be willing to take greater risks in pursuit of more profits consequently increasing their correlation and physical networks in presence of high cultural similarity.

[Insert Figure 4 here]

[16] These include Paul Volcker (Federal Reserve Chairman), Richard Fisher (Federal Reserve Bank of Dallas), Thomas Hoenig (Federal Reserve Bank of Kansas), James Bullard (Federal Reserve Bank of St. Louis), Bank of England (Mervyn King), among others.

[Insert Figure 5 here]

6.4. Robustness tests

There is potential endogeneity arising from reverse causality in our empirical framework despite the fact that culture has a long history and changes very slowly over time (e.g., Williamson, 2000; Hofstede, 2001; Licht et al., 2005). Prior literature including Ahern et al. (2015), Bryan et al. (2015), Eun et al. (2015), El Ghoul and Zheng (2016), Gorodnichenko and Roland (2011a, 2011b, 2017), Griffin et al. (2018), and Nash and Patel (2019) have confirmed *Fst* distance as a valid instrument for culture. *Fst* distance is a country specific value calculated by using the genetic distance with the US where higher *Fst* indicates larger genetic distance. We use the genetic distance (*Fst*) to be our Instrumental Variable (IV) for cultural similarity (*Cul_Sim*).

Additionally, we consider second and third lags of correlation ($N\_corr\_net_{n,i,t-2}$, $N\_corr\_net_{n,i,t-3}$) and physical ($N\_phy\_net_{n,i,t-2}$, $N\_ phy\ \_net_{n,i,t-3}$) networks as instruments for their first lags of correlation ($N\_corr\_net_{n,i,t-1}$) and physical ($N\_phy\_net_{n,i,t-1}$) networks, respectively. In table 3, columns 2, 3 & 4 in panels A and B show the first stage IV analyses for correlation and physical networks, respectively. In both panels A and B, we find significant and consistent negative and positive impact of our instrument *Fst* and its squared term Fst^2 on cultural similarity (*Cul_Sim*) and its squared term (Cul_Sim^2). This suggests that higher genetic distance *Fst* reduces cultural similarity while its squared term Fst^2 nullifies the opposite impact between genetic 'distance' and cultural 'similarity. We find that the second and third lags of correlation ($N\_corr\_net_{n,i,t-2}$, $N\_corr\_net_{n,i,t-3}$) and physical ($N\_phy\_net_{n,i,t-2}$, $N\_ phy\ \_net_{n,i,t-3}$) networks are positively related to first lags of correlation ($N\_corr\_net_{n,i,t-2}$) (column 4 in panels A & B).

We present our IV second stage analyses in column 5 for both correlation (panel A) and physical (panel B) networks. The findings confirm that the cultural similarity shows non-monotonic impact (significantly positive and negative coefficients for Cul_Sim^2 and *Cul_Sim*, respectively) on both correlation and physical networks. We perform Wald weak instrument tests to assess the suitability of our instruments. We find that the instruments are significant at 1% level. We also run the Sargan overidentification test to investigate whether the instruments and error term are uncorrelated and find insignificant results which confirms that the instrument is not correlated with the error terms and therefore reliable.

[Insert Table 3 here]

6.5. Crises, capital adequacy ratio, and cultural similarity impact on interconnectedness

In this section, we examine the moderating role of bank capital. As suggested by Chen (2022), bank capital plays a critical role in ensuring financial stability and banks do adjust capital levels according to the degree to which they are connected with other banks. For example, when a bank hedges risk by buying derivatives from other banks, it reduces its risk as well as the level of required risk capital. However, doing so gives rise to interconnectedness with the bank selling the hedge. Thus, the role of bank capital may be useful in gaining insights on the relation between cultural similarity and bank interconnectedness.

A relatively limited studies have investigated the role of bank capital in interconnectedness. Niera et al. (2007) construct banking systems that are connected by interbank linkages and find better capitalized banks are more resilient against contagious risk. Glasserman and Young (2015) measure the impact of interconnectedness of banks on expected losses and defaults in the presence of shocks. However, they use capital to measure credit quality, one of the consequences rather than a source of bank interconnectedness. Chen (2022) analyzes the relation between bank capital and interconnectedness and reports that bank interconnectedness is more harmful when the economy turns abruptly from boom to recession.

We analyze the moderating effect of capital adequacy ratio on the relation between cultural similarity and bank interconnectedness during crises using a difference-in-differences model (9). We examine whether being more regulatory compliant helps banks reduce their interconnectedness risks during crises. We define our treatment group as banks with high capital adequacy ratio (*CAR_High*) compared to the sample median *CAR*. Our control group comprises banks with low capital adequacy ratio (*CAR_Low*). *CAR_High* and *CAR_Low* are mutually exclusive binary variables showing value of one if the bank shows higher and lower *CAR* than the sample median *CAR*, respectively, and zero otherwise.

In table 4, our results remain consistent about the non-monotonic relation between cultural similarity and the correlation and physical networks. The interaction terms for high *CAR* banks with *Crises* (*CAR_High* × *Crises* in model (4)), are significantly negative. This suggest that banks with higher *CARs* are less impacted during the crises. However, during the periods without crises, the high *CAR* banks (*CAR_High*) show less correlation interconnectedness but the impact on the physical networks is positive. The *Crises* coefficients remain significantly positive for correlation networks and negative for physical networks.

[Insert Table 4 here]

7. Conclusion

The paper examines how cultural similarity based on tightness-looseness, individualism-collectivism, trust and uncertainty avoidance variables impacts the interconnectedness across the OECD banks. To the best of our knowledge, this is the first study that offers evidence of how culture impacts bank interconnectedness. We use both correlation and physical network as measures of bank interconnectedness following Brunetti et al. (2019). We use Jaffe's (1986) distance method weighted by the number of banks as a measure of cultural similarity.

Our paper shows that the impact of cultural similarity on bank interconnectedness is non-monotonic for both correlation and physical networks. Banks with cultural similarities below the inflection point (which appears to be around 50% (0.5) of our normalized cultural similarity values) tend to prioritize safety. When banks focus on safety, cultural similarity seems to reduce business and stock price synchronicity. We attribute these findings to greater peer monitoring.

Above the inflection point, banks tend to focus on growth by exploiting cultural similarity. Growth focused banks tend to follow business practices of large banks which may be a contributing factor for the greater stock return comovements. With greater cultural similarity, banks benefit from easier business negotiations and lower transaction costs for interbank lending reflected by an increase in the physical network. Our findings are robust to an alternative specification of culture similarity. Finally, we use the difference-in-differences method to analyze the impact on interconnectedness for high *CAR* banks during crises periods. Our analysis shows that in the presence of cultural similarity, banks with high *CAR* effectively reduce their interconnectedness during crises periods.

Our paper documents the importance of culture which has been thus far ignored in the bank interconnectedness literature. Our findings imply that a moderate level of cultural similarity may be helpful for banks to achieve optimal balance between safety and growth with minimal interconnectedness risks.

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Table 1. Summary statistics

The following table shows the summary statistics of our data. *Tight*, *Indiv*, *Trust*, and *Riskav* are our four cultural factors we use in their normalized forms to create our *Cul_Sim* (weighted cultural similarity) according to equation (2). *Tight* (tightness) is the extent to which a country has strong norms and low tolerance of deviant behavior collected from Gelfand et al. (2011). *Indiv* (individualism) is the Hofstede's (2001) measure showing the degree that people focus on their own internal attributes to differentiate themselves from others. *Trust* is the measure of willingness to rely on others despite of the possible vulnerability by doing so (Doney et al., 1998) which we collect from the respondents across five consecutive waves of World Valued Survey (WVS) between 1995 and 2020. *Riskav* is the uncertainty avoidance collected from Hofstede (2001) showing the degree of comfort in unfamiliar situations and how much a society is trying to control the uncontrollable. *TA* (total asset), *Stock_R* (log stock return) and *Stock_V* (log stock trading volume) are banks' financial characteristics. *FRB* is the Federal Reserve Bank's monetary policy announcement counts per quarter. Δ*EPU* is the percentage change in the Economic Policy Uncertainty Index collected from the Economic Policy Uncertainty database. Δ*MSCI* is the percentage change in Morgan Stanley Capital International world index. *Crises* is a dummy variable representing the Asian crisis, the Dotcom crisis, the Global Financial Crisis, the European Sovereign Debt Crisis, and the Covid-19 pandemic showing one if the quarter belongs any of these crises and zero otherwise. *CAR* is the capital adequacy ratio, which is the ratio of total risk-based capital to risk-weighted assets for each bank. *Interbank_Asset/TA* is the ratio of interbank asset to total asset collected to calculate the *N_phy_net* (normalized physical network). *Fst* is the fixation index representing the genetic distance collected from Cavalli-Sforza et al. (1994). *N_corr_net* and *N_phy_net* are the normalized correlation and physical networks, respectively, we use for our bank interconnectedness measures. The units are shown within brackets next to each variable as percentage (%), million US dollars ($M) and million shares (M). We winsorize variables at the 25th and 75th percentiles. We report the Mean, Median, Std. (standard deviation), 25th Per (25th percentile), 75th Per (75th percentile) and *N* (number of observations) of each variable in our sample.

Panel A. Summary statistics						
	Mean	Median	Std.	25th Per	75th Per	*N*
Cul_Sim	0.730	1.000	0.435	0.083	1.000	109,474
Tight	0.412	0.338	0.167	0.338	0.378	109,474
Indiv	0.883	0.997	0.219	0.808	0.997	109,474
Trust	0.437	0.452	0.122	0.452	0.452	109,474
Riskav	0.339	0.258	0.185	0.258	0.258	109,474
TA ($M)	536,038	1,255	2,525,050	407	10,319	109,474
Stock_R (%)	-0.52%	0.00%	8.70%	-1.99%	1.93%	109,474
Stock_V (M)	17,358,570	109,414	79,872,660	15,950	1,287,293	109,474
FRB	2.935	3.000	0.995	2.000	4.000	109,474
Δ*EPU* (%)	5.51%	-3.13%	30.74%	-12.40%	20.18%	109,474
Δ*MSCI* (%)	1.04%	2.04%	9.04%	-2.48%	6.37%	109,474
Crises	0.499	0.000	0.500	0.000	1.000	109,474
CAR (%)	15.04%	14.15%	4.69%	12.58%	15.73%	109,474
Interbank_Asset/TA (%)	4.05	2.21	5.12	0.49	5.54	109,474
Fst	0.018	0.000	0.036	0.000	0.032	109,474
N_corr_net	0.234	0.185	0.177	0.127	0.284	109,474
N_phy_net	0.149	0.083	0.184	0.032	0.190	109,474

Table 2. Cultural similarity impact on the bank interconnectedness

The following table analyzes the cultural similarity impact on the correlation ((1) and (2)) and physical ((3) and (4)) networks in banks based on model (8) in section 4.3. We present the standard errors in parentheses. We provide adjusted R^2 (*Adj* R^2) and *F*-statistics (*F-stats*) as for our goodness-of-fit measures. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$N\_corr\_net_{n,I,t}$ (1)	$N\_corr\_net_{n,i,t}$ (2)	$N\_phy\_net_{n,i,t}$ (3)	$N\_phy\_net_{n,i,t}$ (4)
Intercept	0.042***		0.039***	
	(0.002)		(0.002)	
Cul_Sim_i	-0.105***		-0.336***	
	(0.021)		(0.018)	
$Cul\_Sim^2_i$	0.105***		0.316***	
	(0.021)		(0.018)	
$Stock\_R_{n,i,t-1}$	-0.028***	-0.028***	-0.015***	-0.015***
	(0.004)	(0.004)	(0.003)	(0.003)
$Stock\_V_{n,i,t-1}$	-0.001***	0.0004*	-0.0003***	0.001***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
FRB_{t-1}	0.003***	0.004***	0.001***	-0.0006**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
ΔEPU_{t-1}	-0.006***	-0.008***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta MSCI_{t-1}$	-0.084***	-0.088***	-0.005	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)
$Crises_{i,t-1}$	0.012***	0.017***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
$N\_corr\_net_{n,i,t-1}$	0.79***	0.75***		
	(0.002)	(0.002)		
$N\_phy\_net_{n,i,t-1}$			0.87***	0.714***
			(0.001)	(0.002)
Firm fixed	No	Yes	No	Yes
Country fixed	No	Yes	No	Yes
No. of obs	109,473	109,473	109,473	109,473
Banks	2,589	2,589	2,589	2,589
Countries	37	37	37	37
Adj R^2	0.66	0.60	0.78	0.53
F-stats	23491.5***	23830***	42792.8***	18138.4***

Table 3. Cultural similarity impact on the bank interconnectedness - instrumental variable (IV) analysis

The following table reports estimates from IV regression estimates for analyzing the effects of cultural similarity on bank interconnectedness, correlation (panel A) and physical (panel B) networks. The instruments for cultural similarity (*Cul_Sim*) and its squared term (Cul_Sim^2) are the genetic distance (*Fst*) and its squared term (Fst^2), respectively. The lagged correlation ($N\_corr\_net_{n,i,t\text{-}2}$ and $N\_corr\_net_{n,i,t\text{-}3}$) and physical ($N\_phy\_net_{n,i,t\text{-}2}$ and $N\_phy\_net_{n,i,t\text{-}3}$) networks are instruments for their first lagged correlation ($N\_corr\_net_{n,i,t\text{-}1}$) and physical ($N\_phy\_net_{n,i,t\text{-}1}$) networks, respectively. We report the weak Wald instrument and Sargan overidentification tests to check the relevance and validity of our instruments. We present the standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Correlation Network				
	IV First Stage Cul_Sim_i (1)	IV First Stage $Cul\_Sim^2_i$ (2)	IV First Stage $N\_corr\_net_{n,i,t\text{-}1}$ (3)	IV Second Stage (4)
Intercept	0.972*** (0.001)	0.968*** (0.001)	0.029*** (0.002)	0.042*** (0.002)
Cul_Sim_i				-0.124*** (0.02)
$Cul\_Sim^2_i$				0.124*** (0.02)
Fst_i	-33.272*** (0.02)	-33.387*** (0.021)	-0.04 (0.03)	
Fst^2_i	205.733*** (0.161)	202.579*** (0.175)	-0.254 (0.244)	
$Stock\_R_{n,i,t\text{-}1}$	0.005* (0.002)	0.005** (0.003)	-0.095*** (0.004)	-0.028*** (0.004)
$Stock\_V_{n,i,t\text{-}1}$	0.002*** (0.0001)	0.002*** (0.0001)	-0.0002** (0.0001)	-0.001*** (0.0001)
$FRB_{t\text{-}1}$	-0.0004* (0.0002)	-0.0004* (0.0002)	0.006*** (0.0003)	0.003*** (0.0003)
$\Delta EPU_{t\text{-}1}$	-0.0004 (0.001)	-0.0004 (0.001)	-0.016*** (0.001)	-0.006*** (0.001)
$\Delta MSCI_{t\text{-}1}$	0.001 (0.003)	0.001 (0.003)	-0.145*** (0.004)	-0.084*** (0.005)
$Crises_{i,t\text{-}1}$	0.002*** (0.0004)	0.002*** (0.0005)	0.014*** (0.001)	0.012*** (0.001)
$N\_corr\_net_{n,i,t\text{-}1}$				0.795*** (0.004)
$N\_corr\_net_{n,i,t\text{-}2}$	-0.002 (0.002)	-0.002 (0.002)	0.786*** (0.003)	
$N\_corr\_net_{n,i,t\text{-}3}$	-0.002 (0.002)	-0.002 (0.002)	0.005* (0.003)	
No. of obs	109,473	109,473	109,473	109,473
Banks	2,589	2,589	2,589	2,589
Countries	37	37	37	37
Wald weak instrument test for Cul_Sim_i				278700***

Wald weak instrument test for $Cul\_Sim^2_i$				242400***
Wald weak instrument test for $N\_corr\_net_{n,i,t-1}$				15690***
Sargan overidentification test				2.544

Panel B. Physical Network	IV First Stage Cul_Sim_i (1)	IV First Stage $Cul\_Sim^2_i$ (2)	IV First Stage $N\_phy\_net_{n,i,t-1}$ (3)	IV Second Stage (4)
Intercept	0.974***	0.970***	0.025***	0.02***
	(0.001)	(0.001)	(0.001)	(0.002)
Cul_Sim_i				-0.239***
				(0.018)
$Cul\_Sim^2_i$				0.227***
				(0.017)
Fst_i	-33.215***	-33.330***	0.537***	
	(0.021)	(0.022)	(0.026)	
Fst^2_i	205.265***	202.117***	-4.481***	
	(0.169)	(0.184)	(0.213)	
$Stock\_R_{n,i,t-1}$	0.004*	0.005*	-0.006*	-0.013***
	(0.002)	(0.003)	(0.003)	(0.003)
$Stock\_V_{n,i,t-1}$	0.002***	0.002***	-0.0002***	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
FRB_{t-1}	-0.001***	-0.001***	-0.002***	0.002***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
ΔEPU_{t-1}	-0.0003	-0.0003	0.0001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta MSCI_{t-1}$	0.0004	0.0003	-0.021***	-0.005
	(0.003)	(0.003)	(0.004)	(0.004)
$Crises_{i,t-1}$	0.002***	0.002***	-0.004***	-0.005***
	(0.0004)	(0.0005)	(0.001)	(0.001)
$N\_phy\_net_{n,i,t-1}$				0.923***
				(0.003)
$N\_phy\_net_{n,i,t-2}$	-0.005**	-0.005**	0.706***	
	(0.002)	(0.003)	(0.003)	
$N\_phy\_net_{n,i,t-3}$	-0.006**	-0.006**	0.188***	
	(0.002)	(0.003)	(0.003)	
No. of obs	109,473	109,473	109,473	109,473
Banks	2,589	2,589	2,589	2,589
Countries	37	37	37	37
Wald weak instrument test for Cul_Sim_i				282031***
Wald weak instrument test for $Cul\_Sim^2_i$				245938***
Wald weak instrument test for $N\_phy\_net_{n,i,t-1}$				25675***
Sargan overidentification test				2.53

Table 4. Bank interconnectedness responses to crises, capital adequacy ratio, and cultural similarity of banks.

The table presents the model (9) results of bank interconnectedness responses to crises between high and low capitalized banks. The high capitalized banks are our treatment group defined as banks with high capital adequacy ratio (*CAR_High*) compared to their sample median and vice-versa for the rest of the banks, our control group. We present the standard errors in parentheses. We provide adjusted R^2 (*Adj* R^2) and *F*-statistics (*F-stats*) as for our goodness-of-fit measures. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$N\_corr\_net_{n,i,t}$ (1)	$N\_corr\_net_{n,i,t}$ (2)	$N\_phy\_net_{n,i,t}$ (3)	$N\_phy\_net_{n,i,t}$ (4)
Intercept	0.049***		0.036***	
	(0.002)		(0.002)	
Cul_Sim_i	-0.105***		-0.347***	
	(0.021)		(0.018)	
$Cul\_Sim^2_i$	0.106***		0.327***	
	(0.021)		(0.018)	
$CAR\_High_{n,i,t-1}$	-0.005***	-0.008***	0.006***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
$CAR\_High_{n,i,t-1} \times Crises_{i,t-1}$	-0.01***	-0.011***	-0.007***	-0.01***
	(0.001)	(0.001)	(0.001)	(0.001)
$Crises_{i,t-1}$	0.013***	0.018***	-0.005***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
$Stock\_R_{n,i,t-1}$	-0.028***	-0.028***	-0.015***	-0.015***
	(0.004)	(0.004)	(0.003)	(0.003)
$Stock\_V_{n,i,t-1}$	-0.001***	0.001**	-0.0002*	0.001***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
FRB_{t-1}	0.003***	0.004	0.001***	-0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
ΔEPU_{t-1}	-0.006***	-0.007***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta MSCI_{t-1}$	-0.08***	-0.083***	-0.006	-0.006*
	(0.004)	(0.004)	(0.004)	(0.004)
$N\_corr\_net_{n,i,t-1}$	0.789***	0.748***		
	(0.002)	(0.002)		
$N\_phy\_net_{n,i,t-1}$			0.868***	0.71***
			(0.002)	(0.002)
Firm fixed	No	Yes	No	Yes
Country fixed	No	Yes	No	Yes
No. of obs	109,473	109,473	109,473	109,473
Banks	2,589	2,589	2,589	2,589
Countries	37	37	37	37
Adj R^2	0.66	0.60	0.78	0.53
F-stats	19251.2***	18581.6***	35077.5 ***	14174.5***

Figure 1. Time series of banks' interconnectedness

The following figure presents the banks' interconnectedness in time series. We use the quarterly average correlation and physical networks and use mix-max normalization to make comparable values varying between zero and one.

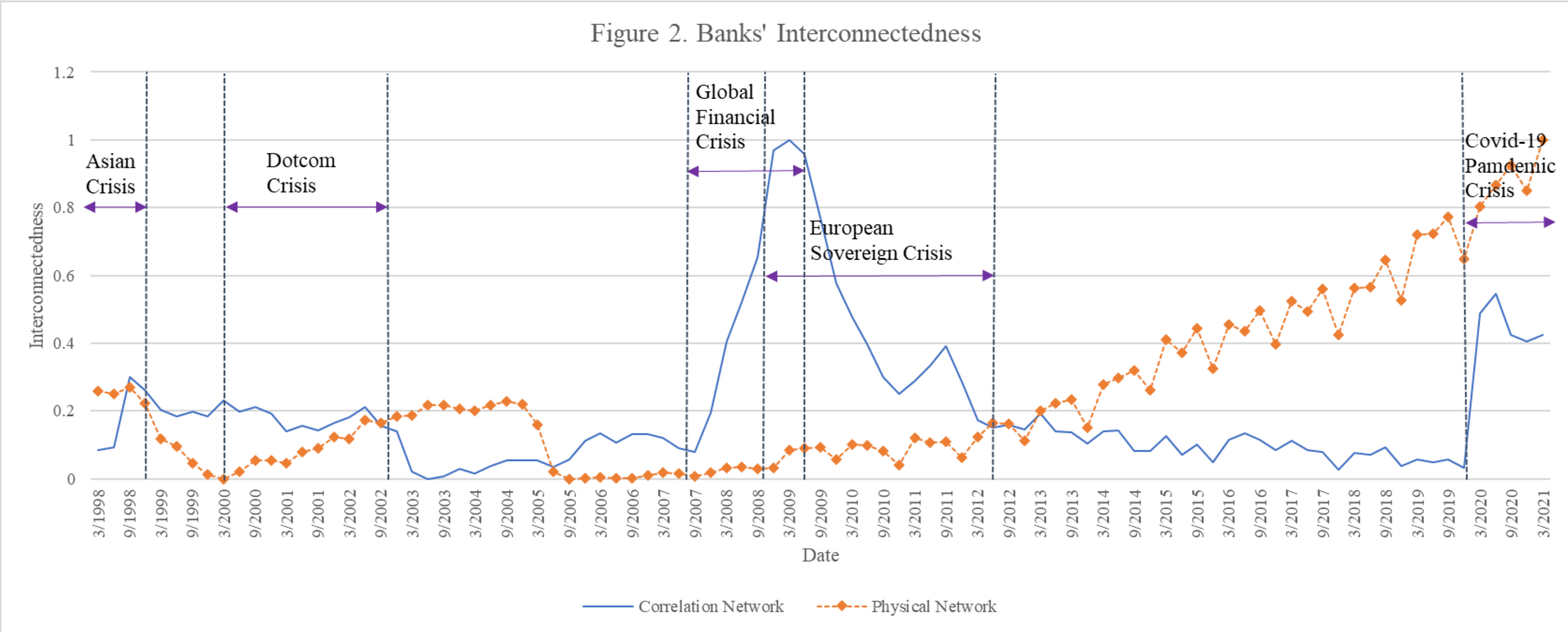


Figure 2. Non-monotonic cultural similarity impact on the bank interconnectedness
The following figure presents the non-monotonic impact of cultural similarity on bank interconnectedness measured by correlation and physical networks based on dynamic panel regressions in table 2. The left- and right-hand side of the curve's inflection point indicate the safety and growth focused behaviors of banks, respectively, depending on the degree of cultural similarities they have.

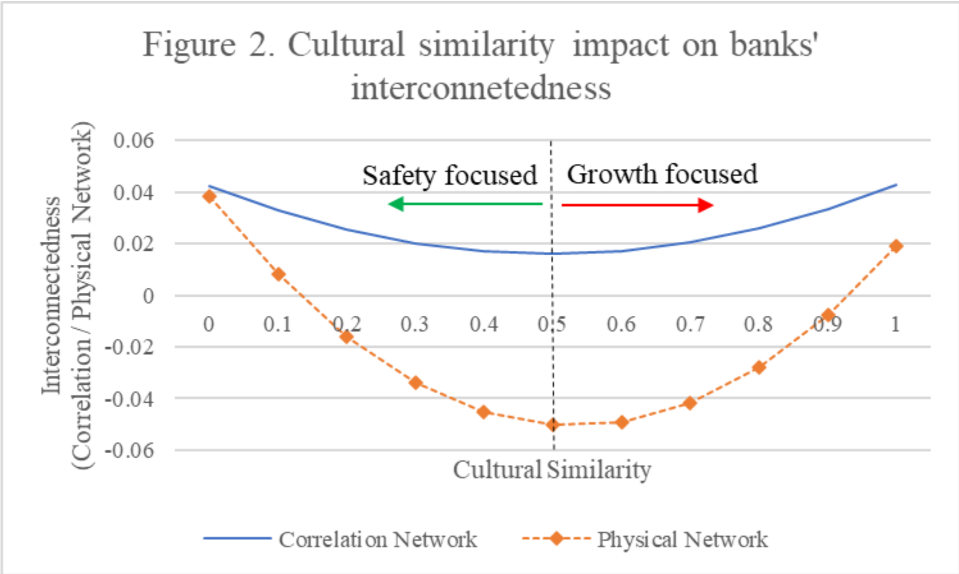
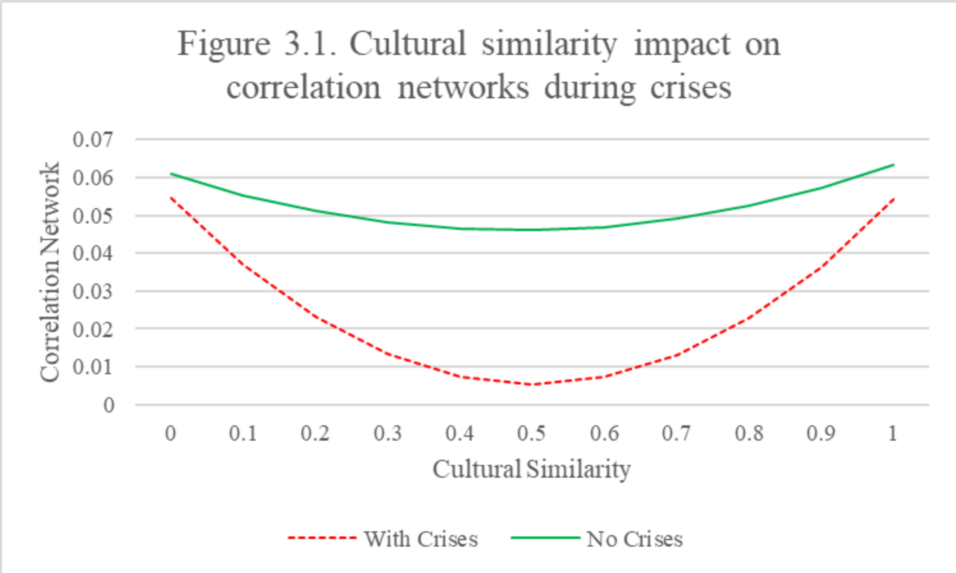


Figure 3. Cultural similarity impact on bank interconnectedness with crises

The following figures show the non-monotonic cultural similarity impact on banks' correlation (figure 3.1) and physical (figure 3.2) networks with and without crises periods based on dynamic panel regressions in table 3.



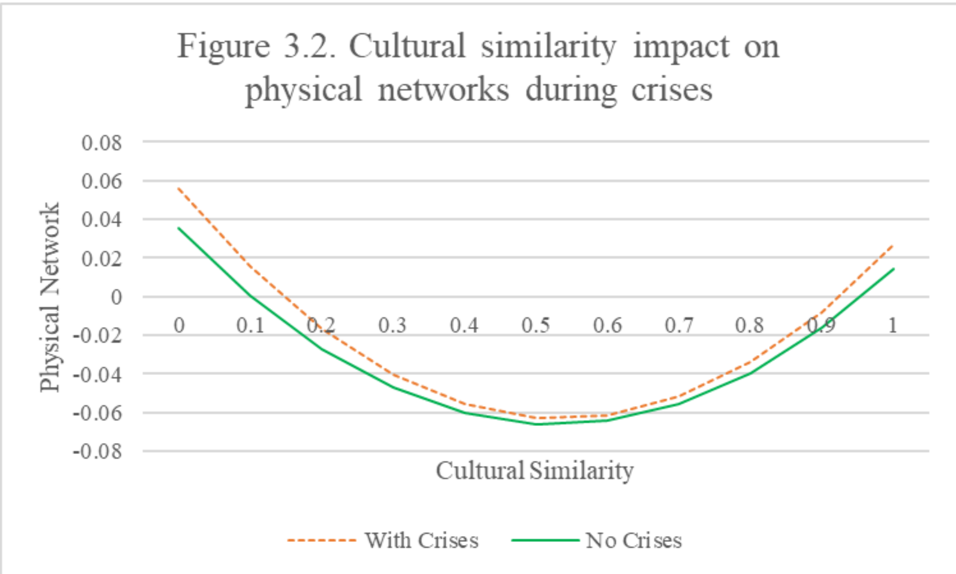
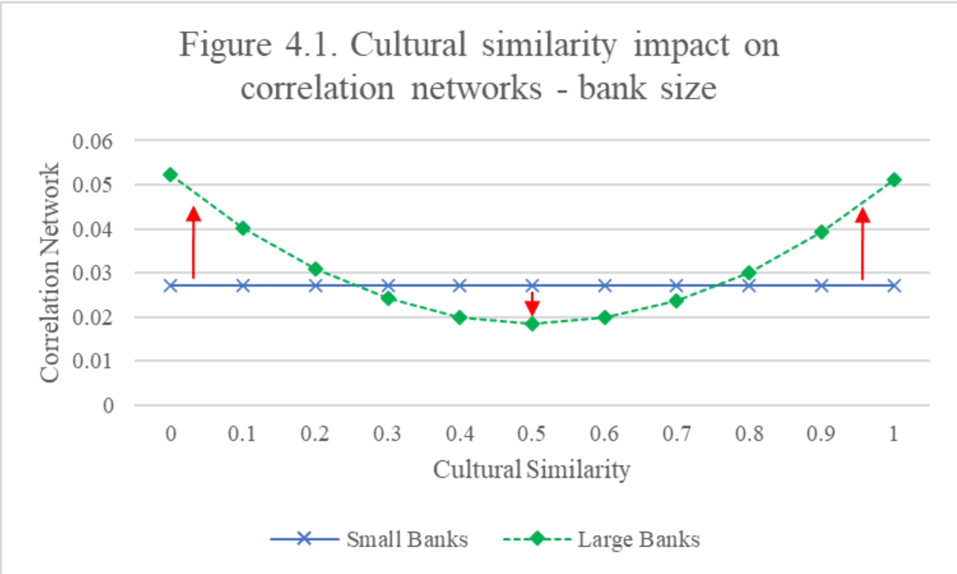


Figure 4. Cultural similarity impact on the correlation network – bank's characteristics
The following figures present the non-monotonic impact of cultural similarity on banks' correlation networks related to their financial characteristics in relation to size (figure 4.1) and capital adequacy ratio (*CAR*) (figure 4.2). We present the different correlation networks' dynamics in banks depending on large versus small size (figure 4.1) and high *CAR* versus low *CAR* (figure 4.2) of banks compared to their sample median values.



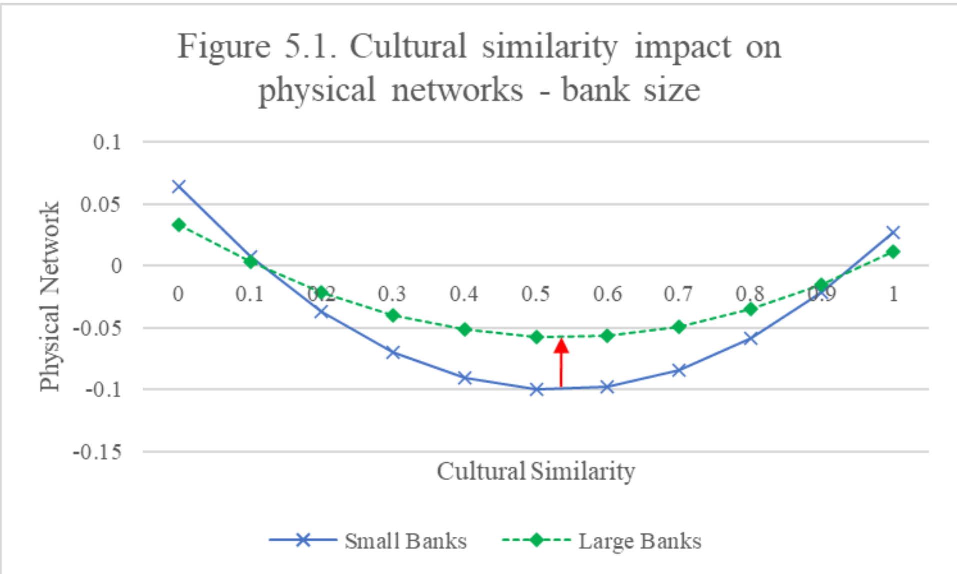
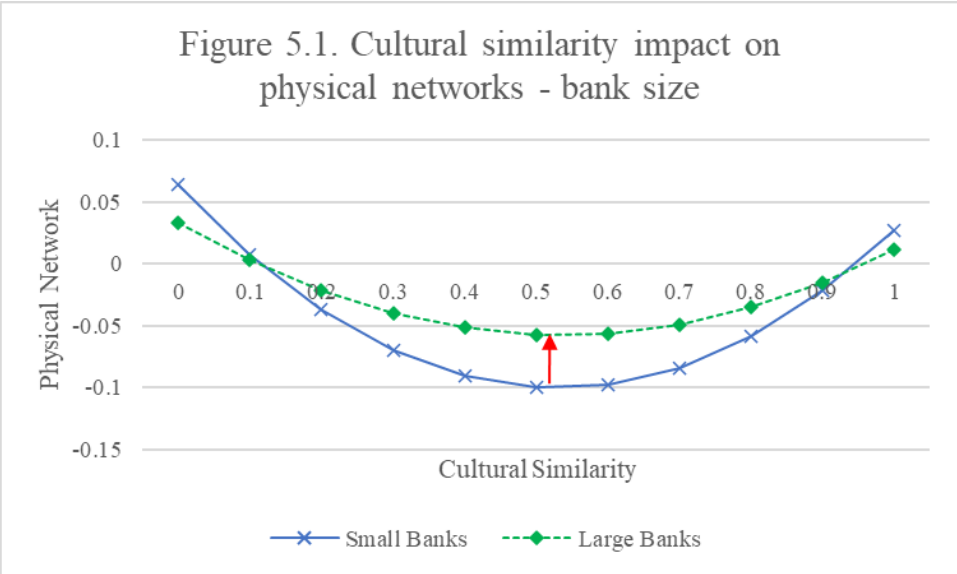
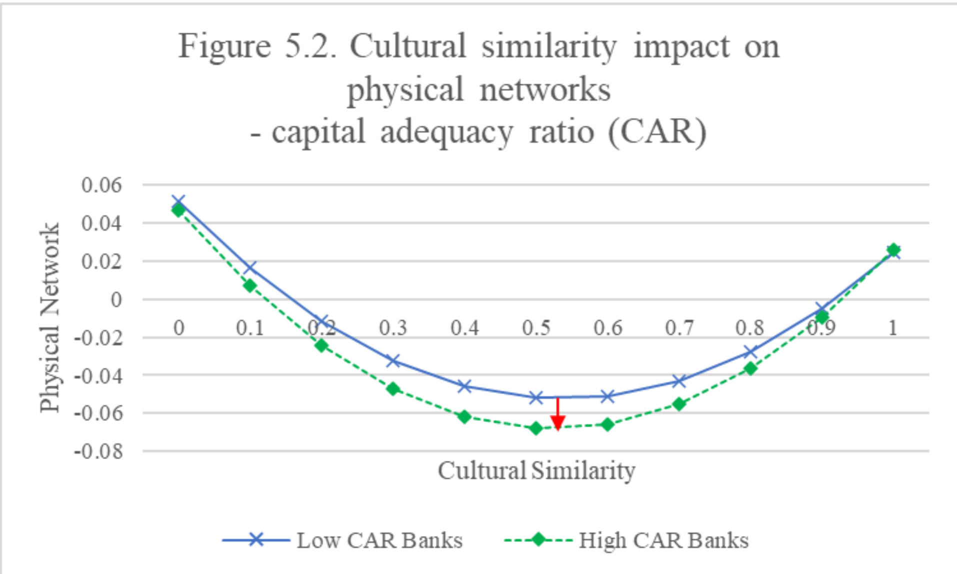


Figure 5. Cultural similarity impact on the physical network – bank's characteristics
The following figures present the non-monotonic impact of cultural similarity on banks' physical networks related to their financial characteristics in relation to size (figure 5.1) and capital adequacy ratio (*CAR*) (figure 5.2). We present the different physical networks' dynamics in banks depending on large versus small size (figure 5.1) and high *CAR* versus low *CAR* (figure 5.2) of banks compared to their sample median values.





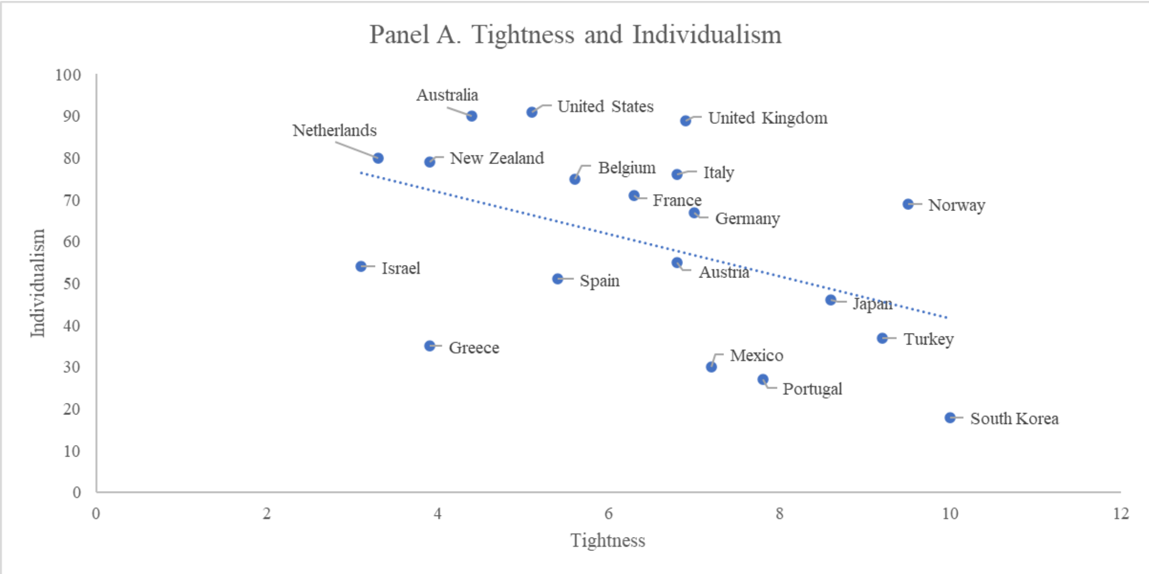
Appendix I. Cultural values for each country

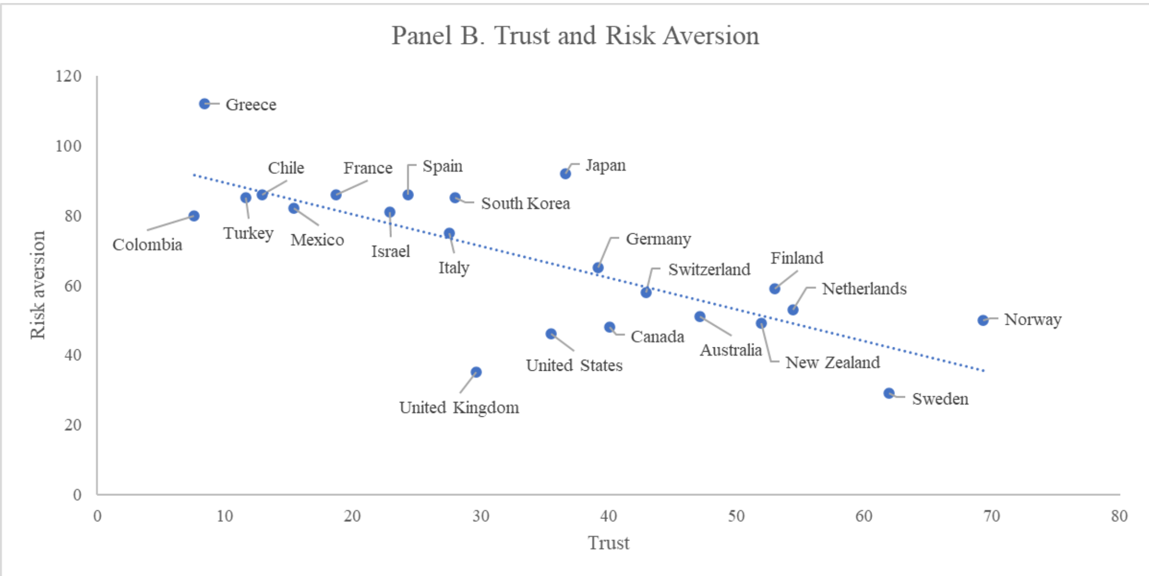
Tightness is the extent to which a country has strong norms and low tolerance of deviant behavior collected from Gelfand et al. (2011). Individualism is the Hofstede's (2001) measure showing the degree that people focus on their own internal attributes to differentiate themselves from others. Trust is the measure of willingness to rely on others despite of the possible vulnerability by doing so (Doney et al., 1998) which we collect from the respondents across five consecutive waves of World Valued Survey (WVS) between 1995 and 2020. Uncertainty avoidance is collected from Hofstede (2001) showing the degree of comfort in unfamiliar situations and how much a society is trying to control the uncontrollable.

Country	Tightness	Individualism	Trust	Uncertainty Avoidance
Australia	4.4	90	47.1	51
Austria	6.8	55		70
Belgium	5.6	75		94
Canada		80	40.1	48
Chile		23	12.9	86
Colombia		13	7.6	80
Costa Rica		15		86
Czech			27.2	
Denmark		74		23
Estonia	2.6		30.1	
Finland		63	53	59
France	6.3	71	18.7	86
Germany	7	67	39.2	65
Greece	3.9	35	8.4	112
Hungary	2.9		25.6	
Iceland	6.4			
Ireland		70		35
Israel	3.1	54	22.9	81
Italy	6.8	76	27.5	75
Japan	8.6	46	36.6	92
Latvia			23.9	
Lithuania			21.3	
Mexico	7.2	30	15.4	82
Netherlands	3.3	80	54.4	53
New Zealand	3.9	79	51.9	49
Norway	9.5	69	69.3	50
Poland	6		18.1	
Portugal	7.8	27		104
Slovakia			25.8	
Slovenia			17.5	
South Korea	10	18	28	85
Spain	5.4	51	24.3	86
Sweden		71	61.9	29
Switzerland		68	42.9	58
Turkey	9.2	37	11.6	85
United Kingdom	6.9	89	29.6	35
United States	5.1	91	35.5	46

Appendix II. Tightness versus Individualism, and Trust versus Risk Aversion

The following figure plots the tightness versus individualism (panel A) and trust versus risk aversion (panel B) scores available for our sample countries with simultaneously available raw cultural values in appendix I.





Appendix III. Country list and number of banks

The following table shows the number of unique banks used for each country within our sample period between March 1998 and March 2021.

Country	Number of banks
Australia	10
Austria	15
Belgium	8
Canada	10
Chile	9
Colombia	8
Costa Rica	1
Czech	4
Denmark	51
Estonia	7
Finland	8
France	36
Germany	22
Greece	21
Hungary	4
Iceland	4
Ireland	5
Israel	14
Italy	68
Japan	154
Latvia	3
Lithuania	8
Mexico	4
Netherlands	4
New Zealand	1
Norway	51
Poland	23
Portugal	11
Slovakia	5
Slovenia	8
South Korea	26
Spain	32
Sweden	8
Switzerland	46
Turkey	22
United Kingdom	22
United States	1875

Appendix IV. Generalized variance inflation factor (GVIF) test

The following table shows the generalized variance inflation factor (GVIF) test to check multicollinearity in our models (8) and (9). GVIF test showing values close to one indicates no multicollinearity problem.

Panel A. GVIF test for regression model (8)			
Endogenous variables	*Degrees of freedom*	$N\_corr\_net_{n,i\ t}$	$N\_phy\_net_{n,i,t}$
Cul_Sim_i	2	1.021	1.042
$Stock\_R_{n,i,t-1}$	1	1.020	1.019
$Stock\_V_{n,i,t-1}$	1	1.039	1.040
FRB_{t-1}	1	1.056	1.047
ΔEPU_{t-1}	1	1.218	1.217
$\Delta MSCI_{t-1}$	1	1.272	1.272
$Crises_{i,t-1}$	1	1.056	1.031
$N\_corr\_net_{n,i\ t-1}$	1	1.051	
$N\_phy\_net_{n,i,t-1}$	1		1.048

Panel B. GVIF test for regression model (9)			
Endogenous variables	*Degrees of freedom*	$N\_corr\_net_{n,i\ t}$	$N\_phy\_net_{n,i,t}$
Cul_Sim_i	2	1.022	1.044
$CAR\_High_{n,i,t-1}$	1	1.009	1.015
$CAR\_High_{n,i,t-1} \times Crises_{i,t-1}$	1	1.010	1.010
$Crises_{i,t-1}$	1	1.057	1.032
$Stock\_R_{n,i,t-1}$	1	1.020	1.019
$Stock\_V_{n,i,t-1}$	1	1.044	1.045
FRB_{t-1}	1	1.058	1.049
ΔEPU_{t-1}	1	1.219	1.218
$\Delta MSCI_{t-1}$	1	1.277	1.277
$N\_corr\_net_{n,i\ t-1}$	1	1.052	
$N\_phy\_net_{n,i,t-1}$	1		1.056