Cultural Similarity, Bank Interconnectedness, and Risk-Taking

Abstract

We analyze the impact of cultural similarity on bank interconnectedness across sixty major developed and developing countries. The bank interconnectedness is measured using both correlation and physical networks. We use bank-level culture based on directors' nationalities and calculate their pair-wise cultural similarities with other banks. We find cultural similarity increases both return synchronicity (correlation network) and interbank lending (physical network). Our results suggest that cultural similarity could be an important contributor to the potential contagion risk arising from high bank interconnectedness. We also investigate the influence of bank interconnectedness on risk-taking and find evidence that is consistent with the theoretical framework of Altinoglu and Stiglitz (2023) who propose that both reinforce each other.

Key Words: Cultural similarity; Correlation network; Physical network; Banks; Risk-taking behavior

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 enable 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 a 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.

Another closely related issue, which holds significant implications for regulators and policymakers, is the risk-taking behavior of banks. A commonly discussed paradigm is that increased competition leads to higher risk-taking by banks which could in turn endanger the financial solvency as well as the overall stability of the banking system. The argument rests on the premise that increased bank risk-taking motivates banks to take on more credit risk in their loan portfolio and/or reduce the level of risk capital. On the contrary, less competition encourages banks to pursue safer policies, thus contributing to the banking sector's stability. Since it is known that banks are a major source of contagion risk (Acharya et al., 2014), interconnectedness could be both a source of as well as the consequence of bank risk-taking. In this paper, we investigate the impact of bank culture on both bank interconnectedness and bank risk-taking.

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 risks. 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 the 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 indicates greater comovements among equity returns during the crisis.

Altinoglu and Stiglitz (2023) argue that in developed economies, few large financial institutions are highly interconnected with many smaller ones that could be a potential source of systemic instability. The concentration of resources in systemically important financial institutions is considered an important contributing factor to systemic instability and crises. They develop a theoretical model and demonstrate that interconnectedness and excessive risk-taking reinforce one another. This implies that bank interconnectedness and risk-taking need to be studied together to obtain useful insights for the prevention of systemic risk. Extant literature has largely focused on factors for bank risk-taking from the perspectives of both bank-level characteristics and macro conditions. For example, Saunders et al. (1990) consider the impact of ownership structure on bank risk-taking while Laeven and Levine (2009) emphasize the relevance of governance on bank risk-taking. Berger et al. (2009) and Beck et al. (2013) examine the influence of bank competition on risk-taking. However, there is sparse research analyzing the impact of bank interconnectedness on bank risk-taking. Furthermore, 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 and economic and financial market factors, we investigate how cultural similarity affects bank interconnectedness and how this in turn affects bank risk-taking.

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) guides the behaviors and decisions of economic agents. Several studies show that culture influences bank capital structure decisions (Haq et al., 2018), trade credit provisions (El Ghoul et al., 2016), and bank-level failures (Berger et al.,

[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 in banks (De Nederlandsche Bank report, 2015).

2021). Second, the culture prevailing in banks has a significant role in many decisions. For example, using a large dataset of international syndicated bank loans, Giannetti 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.

There are several reasons for studying the drivers of bank interconnectedness and its effects on risk-taking. First, high bank interconnectedness could rapidly spread financial stress from one bank to another and across the financial system. Second, though critical for facilitating funding and transferring risk, bank interconnectedness increases the likelihood of financial contagion which, in turn, can reduce inter-bank lending and liquidity. In a financial system with long and complex chains of intermediation, failure of highly interconnected banks could cause major disruptions and a series of bank failures.[2] Third, bank interconnectedness is considered one of the key factors in assessing the systemic risk of the financial system by the International Monetary Fund (IMF), Bank for 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

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

exerting market discipline. A vibrant and sound financial sector is therefore critical for achieving long-term growth. Second, unlike other industries, banks perform critical public functions of providing access to finance, creating liquidity, and transferring 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, and understanding its effect may be crucial for managing systemic risk.

Motivated by these reasons, we examine the influence of cultural similarity on bank interconnectedness and risk-taking. Using data from sixty major developed and developing countries, we find cultural similarity increases the correlation and physical interconnectedness between banks. We then analyze how bank interconnectedness interacts with risk-taking behavior. Consistent with Altinoglu and Stiglitz (2023), we find bank interconnectedness and risk-taking behavior reinforce each other. We find that post Basel III the risk-taking behavior of too-big-to-fail (TBTF) banks has not changed. The result implies that higher and stricter risk capital requirements have not succeeded in curbing risk-taking by systemically important banks.

We make three distinct contributions to the current literature. First, as far as we are aware, this is the first paper that offers comprehensive evidence of the impact of cultural similarity on bank interconnectedness. Second, we empirically show that bank interconnectedness and risk-taking behavior reinforce each other supporting the theoretical arguments of Altinoglu and Stiglitz (2023). Third, we provide evidence of the efficacy of Basel III. Our findings imply that regulation alone is not enough to restrict bank risk-taking, given the moral hazard incentives, particularly in the case of TBTF banks.

The rest of the paper is organized as follows. Section 2 discusses relevant literature and hypotheses. Section 3 outlines the methodology and the empirical approach. Section 4 describes the data. Section 5 presents empirical results and section 6 concludes.

2. Literature Review and Hypotheses Development

2.1 Bank Interconnectedness

Extant research has mainly focused on interconnectedness among 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) contends that by holding similar portfolios, banks are exposed to the same market risks causing equity returns to be asymptotically dependent. Acharya and Yorulmazer (2008) argue that to minimize the impact of information contagion on profits, banks alter their ex-ante investment choices. They show when loan returns have a common systematic factor, banks have an incentive to herd and mitigate the adverse effects on their cost of borrowing by undertaking correlated investments. Drehmann and Tarashev (2013) assert that the measured systemic importance of individual banks can differ substantially, especially when banks are interconnected. 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 the potential channels through which systemic risk may be transmitted. Bostandzic and Weiß (2018) find that European banks demonstrate a relatively higher interconnectedness with the global financial system compared to US banks. Calomiris et al. (2022) demonstrate that contractual connections among banks significantly influence liquidity risk. Chen (2022) claims that banks need sufficient incentives to reduce their interconnectedness if the consequent systemic risk becomes a serious concern for the regulators.

Another stream of research has examined the consequences of interconnectedness. Gai et al. (2011) examine how the degree of concentration and complexity of financial networks impact 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). 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 the 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 the 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 increased bank failures across 92 countries between 2010 and 2014. They claim that individualism heightens portfolio risks while masculinity reduces liquidity and bailouts.

While the literature has established several direct and indirect channels that can induce interconnectedness among banks, there is little or no research on how cultural similarity affects bank interconnectedness. Similarities in bank-level culture can play a significant part in understanding their role in inducing both financial and physical bank interconnectedness.

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 the 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, low rates of homelessness, and low 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 a tight culture will likely motivate banks to herd towards the prevalent business practices. Furthermore, banks in tight cultures may also be subject to stricter financial regulations and monitoring since financial stability may be considered more important than profitability. This could be particularly relevant in the case of Systematically Important Financial Institutions (SIFIs). Besides forcing banks to adhere to global practices and norms, banks with tight cultures are more likely to be compliant with the capital reserve requirements and increase their interbank lending. Consequently, banks in tight cultures are likely to show higher levels of 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). Consequently, banks in individualistic cultures are likely to be more customer-focused than those in collectivist cultures where they are expected to operate with a holistic approach (Choi and Nisbett, 2000; Nisbett et al., 2001; Eun et al., 2015). In contrast, those from collectivistic cultures show greater herding behavior which may lead to higher bank interconnectedness.

Trust reflects the willingness to rely on others in circumstances that 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 relationships 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 promote effective teamwork (Lawler, 1992). Trust is a critical factor in corporate culture because it improves communication, commitment, teamwork, and productivity. Therefore, banks in strong trusting cultures may show higher loan approval rates and greater interbank asset holdings, resulting in higher interconnectedness.

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 highly 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 show greater concern with maintaining financial stability to affect their interconnectedness.

Overall, there may be significant implications of cultural similarity for bank interconnectedness. Cultural similarity increases information sharing through easier communication and greater cooperation between businesses that share similar beliefs (Rogers and Bhowmik, 1970; Giannetti and Yafeh, 2012). Consequently, cultural similarity can help improve negotiations and reduce contracting costs as culturally similar banks would have adequate information about each other and may impose less restrictive contract terms. On the contrary, banks from dis-similar cultures may impose higher costs arising from risk hedging due to a lack of information and familiarity. A lack of cultural similarity may encourage banks to restrict loan size and demand higher interest and third-party guarantees. Accetturo et al. (2023) find that firms are more likely to seek loans from culturally proximate banks, highlighting the role of cultural similarity in mitigating information asymmetry in firm-bank relationships in the South Tyrol region of Northern Italy. Thus, we argue that better information sharing among culturally similar banks will encourage them to interconnect more:

H_1: Culturally similar banks will be more interconnected.

2.4 Bank Risk-Taking Behavior and Interconnectedness

There is relatively less research relating bank interconnectedness with risk-taking. It is worth asking how interconnectedness affects banks' risk-taking. On one hand, interconnectedness may increase bank risk-taking as the multi-disciplinary nature of their business may provide them a way to evade regulation and increase credit risk. On the other hand, increased financial networks may reduce bank risk due to improved resource complementarity and information. Brusco and Castiglionesi (2007) argue that banks may be financially linked through interbank deposits for liquidity coinsurance and take excessive risk when they are in regions protected by limited liability. Zawadowski (2013) and Ellul and Kim (2022) analyze the bank risk-taking behavior related to network formation through the over-the-counter (OTC) derivative markets. They contend that network connections facilitate the sharing of risks. A bank may connect to other banks to diversify its vulnerability to shocks which could create an incentive to take greater risks in other parts of its balance sheet (Brusco and Castiglionesi, 2007; Zawadowski, 2013).

Altinoglu and Stiglitz (2023) provide a theoretical perspective to explain how financial structure alters the risk-taking incentives. They argue that by issuing interbank claims, risky financial institutions endogenously become large and interconnected. While the interconnectedness enables financial institutions to share the systemic risk, it leads to excessive risk-taking even by secondary institutions. They show that interconnectedness and excessive risk-taking reinforce one another, which leads to our second hypothesis:

H_2: Bank risk-taking behavior and interconnectedness reinforce each other.

3. Methodology

3.1 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. To start with, we calculate the vector of bank-level culture in four dimensions $X_{n,t,k}$= ($X_{n,t,Tight}$, $X_{n,t,Indiv}$, $X_{n,t,Trust}$, $X_{n,t,Riskav}$) for bank *n* by taking the average cultural values of each dimension i.e., *Tight*, *Indiv*, *Trust*, and *Riskav* across 88 different nationalities (Appendix I) within bank *n*'s directors at time *t*.[3] We then calculate cultural similarity between banks *n* and *m* at time *t*:

$$Cul\_Sim_{n,m,t} = \frac{X_{n,t}X'_{m,t}}{(X_{n,t}X'_{n,t})^{0.5}(X_{m,t}X'_{m,t})^{0.5}} \quad (1)$$

where, $X_{n,t,k}$ = ($X_{n,t,Tight}$, $X_{n,t,Indiv}$, $X_{n,t,Trust}$, $X_{n,t,Riskav}$) is a vector of cultural values in each cultural subcategory $X_{n,t,k}$ (where, k = *Tight* (Tightness), *Indiv* (Individualism), *Trust* (Trust), *Riskav* (Uncertainty Avoidance)) of bank *n* at time *t*.

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 Hofstede (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 Valued Survey (WVS) using the proportion of

[3] The majority of directors have the same nationality as the national orgin of the bank.

respondents to the question of whether "Most people can be trusted" across four consecutive waves of WVS.[4] *Riskav* is the degree of risk-aversion measure from Hofstede's (2001). The raw cultural values are shown in Appendix I.

The cultural similarity score is set to zero in cases where there are missing values. For instance, if the cultural value for *Trust* in bank *n* is 30 ($X_{n,t,Trust} = 30$) while such value for bank *m* is missing ($X^{'}_{m,t,Trust} = 0$) at time *t*, then their multiplication results in zero thus ($X_{n,t,Trust}X^{'}_{m,t,Trust} = 0$) nullifying their distance calculation.[5]

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 $x_{n,t,k}$ is the cultural value of subcategory *k* for bank *n* at time *t*, the min-max normalized cultural value for this subcategory is calculated as $x_{n,t,k} = \frac{x_{n,t,k} - min(x_{n,t,k})}{max\ (x_{n,t,k}) - min(x_{n,t,k})}$. We then use the average cultural similarity for bank *n* against the rest of the sample banks at time *t* as follows.

$$Cul\_Sim_{n,t} = E[\frac{X_{n,t}X^{'}_{m,t}}{\left(X_{n,t}X^{'}_{n,t}\right)^{0.5}\left(X_{m,t}X^{'}_{m,t}\right)^{0.5}}|n \neq m] \quad (2)$$

Equation (2) is the average cultural similarity value (*Cul_Sim*) for bank *n* against other banks at time *t*. Our average cultural similarity value in equation (2) varies between zero and one. We use the min-max normalization (equation (3)) to produce a scaled index value for comparable interpretations across banks.

$$Cul\_Sim_{n,i,t} = \frac{Cul\_Sim_{i,t} - \max(Cul\_Sim_{i,t})}{\min(Cul\_Sim_{i,t}) - \max(Cul\_Sim_{i,t})} \quad (3)$$

[4] The 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 four waves of WVS are wave 4 (1999−2004), wave 5 (2005−2009), wave 6 (2010−2014), and wave 7 (2017−2022).

[5] This contrasts the widely used Euclidian distance and other similar measures (e.g., Giannetti and Yafeh, 2012; Siegel et al., 2011) which ignore the impact of missing values.

$Cul\_Sim_{n,i,t}$ is the scaled cultural similarity of bank *n* in country *i* at time *t* we use for our analysis. $Cul\_Sim_{n,i,t}$ is the bank director-level average cultural similarity using the director's nationality as a measure of culture using four dimensions, *Tight*, *Indiv*, *Trust*, and *Riskav* as discussed before.

We use Kogut and Singh's (1988) cultural distance (*Cul_Dist*) as an alternative cultural proximity measure for our robustness test. *Cul_Dist* is also min-max scaled using the bank director-level average cultural distance in four dimensions (*Tight*, *Indiv*, *Trust*, and *Riskav*) based on the directors' nationalities.

3.2 Bank Interconnectedness

We estimate the correlation network and physical network following Brunetti et al. (2019). 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 assign a value of one ($a_{n,m,t} = 1$) and, zero ($a_{n,m,t} = 0$) otherwise. The pairwise Granger causality $Corr\_net_{n,t}$ is computed by counting the number of Granger-causalities of bank *n* to all $N(N-1)$ pairs among N number of banks using a 36-month rolling window. Following Billio et al. (2012), we proxy the correlation network by the degree of Granger Causality in equation (4).

$$Corr\_net_{n,t} = \binom{N}{2}^{-1} \sum_{n=1,}^{N} \sum_{m=1}^{N} a_{n,m,t} \tag{4}$$

where,

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

The normalized correlation network ($Corr\_net_{n,i,t}$) for bank *n* in country *i* at time *t* is scaled as follows.

$$Corr\_net_{n,i,t} = \frac{Corr\_net_{n,i,t} - min(Corr\_net_{n,i,t})}{max\left(Corr\_net_{n,i,t}\right) - min(Corr\_net_{n,i,t})} \tag{5}$$

We estimate the physical network using interbank loans and long-term bank deposits. We compute the interbank asset holding of bank *n* relative to all possible $N(N-1)$ pairs among our N number of banks which are scaled by their corresponding total assets. [6] Similar to the correlation network, we measure the degree of Granger Causality for physical networks in equation (6) following Billio et al. (2012).

$$Phy\_net_{n,t} = \binom{N}{2}^{-1} \sum_{n=1,}^{N} \sum_{m=1}^{N} b_{n,m,t} \tag{6}$$

where,

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

Similar to the correlation network to ensure comparable interpretation, we calculate the normalized physical network ($Phy\_net_{n,i,t}$) for bank n in country i at time t as follows:[7]

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

3.3 Empirical Model

Bank interconnectedness, correlation, and physical networks reflect economic conditions in the banking sector. Brunetti et al. (2019) find that they respond to monetary and macroeconomic shocks differently in the European banking sector as physical networks show quicker adjustments to new information announcements to manage their liquidity, while correlation networks so not react as much to these announcements. On a global level, we analyze how cultural similarity impacts bank interconnectedness as its fundamental driver while controlling for monetary and macroeconomic shocks in our baseline model (8).

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[6] The interbank asset definition follows the Refinitiv data source definition. Therefore, the interbank total asset amount of bank n may cover more than N number of banks in our sample. However, since the same applies to all banks simultaneously, we use the interbank asset data from Refinitiv.

[7] The min-max normalization has the advantage of preserving the relationships among the original values, but this may also keep some outliers as well (Han et al., 2012). To mitigate the outlier concerns, we winsorize our data at the 1st and 99th percentiles.

$$Y_{n,i,t} = \alpha + \beta_1 Cul\_Sim_{n,i,t} + \beta_2 FRB_{t-1} + \beta_3 \Delta EPU_{t-1} + \beta_4 \Delta MSCI_{t-1} + \varepsilon_{n,i,t} \quad (8)$$

where, $Y_{n,i,t}$ denotes interconnectedness, correlation ($Corr\_net_{n,i,t}$) or physical ($Phy\_net_{n,i,t}$) network. $Cul\_Sim_{n,i,t}$ is the bank-level cultural similarity derived from equation (3). We include the log returns of the MSCI (Morgan Stanley Capital International) world index ($\Delta MSCI_{t-1}$) to capture the global stock market shock of large and mid-cap companies across 23 major countries[8] (MSCI, 2022). Further, we control for global macro-economic shocks by using the Federal Reserve Bank's (FRB_{t-1}) which counts the number of announcements in the Federal Open Market Committee (FOMC) minutes and policy statements each quarter (Ammer et al., 2010), and the economic uncertainty using the percentage change in Economic Policy Uncertainty index (ΔEPU_{t-1}) adjusted by purchasing power parity (PPP) on the global level collected from the Economic Policy Uncertainty database (https://www.policyuncertainty.com/). 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. We extend our baseline model (8) by including revenue growth rate ($\Delta REV_{n,i,t-1}$), bank competition ($COMP_{n,i.t-1}$) (the sum of squares of the market share (deposits) size of each bank in each country), and natural log scaled stock price ($ln(Stock\_P)_{n,i.t-1}$) as additional variables:

$$Y_{n,i,t} = \alpha + \beta_1 Cul\_Sim_{n,i,t} + \beta_2 FRB_{t-1} + \beta_3 \Delta EPU_{t-1} + \beta_4 \Delta MSCI_{t-1} + \beta_5 \Delta REV_{n,i,t-1} + \beta_6 COMP_{n,i.t-1}$$
$$+ \beta_7 ln(Stock\_P)_{n,i.t-1} + \varepsilon_{n,i,t} \quad (9)$$

Next, we analyze how bank interconnectedness affects risk-taking. We extend Kanagaretnam et al.'s (2019) baseline model as specified in equations (10) and (11). Following previous literature (e.g., Kanagaretnam et al., 2019; Houston et al., 2010; Laeven and Levine, 2009), we measure bank risk-taking using Z-score ($Z\_Score_{n,i,t}$). It is computed as $(-1) \times ln((CAR+ROA)/\sigma(ROA))$ where CAR, ROA, and $\sigma(ROA)$ are the capital over asset ratio, return on assets, and standard deviation of return on assets,

[8] 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).

respectively.[9] We control for bank-related characteristics and other control variables as done in prior studies (e.g., Houston et al., 2010; Kanagaretnam et al., 2014, 2015, 2019; Laeven and Levine, 2009) in the model (10). $SOE_{n,i,t}$ is an indicator variable for state-owned enterprises. $TOO\_BIG_{n,i,t}$ is an indicator variable for TBTF banks with deposits comprising more than 10% of a country's total deposits within a fiscal quarter. For the financial characteristics, we collect $\Delta REV_{n,i,t-1}$ (revenue growth), $COMP_{n,i,t-1}$ (bank competition which is the sum of squares of the market share (deposits) of each bank in each country), $Stock\_R_{n,i,t-1}$ (natural log return of stock price), $ln(Stock\_V)_{n,i,t-1}$ (natural log of stock trading volume), and $Loan/TA_{n,i,t-1}$ (total loan over total asset).

$$Z\_Score_{n,i,t}=\alpha+\beta_1 Y_{n,i,t}+\beta_2 SOE_{n,i,t}+\beta_3 TOO\_BIG_{n,i,t}+\beta_4\Delta REV_{n,i,t-1}+\beta_5 COMP_{n,i,t-1}+\beta_6 FRB_{t-1}+\beta_7\Delta EPU_{t-1} +\beta_8\Delta MSCI_{t-1}+\beta_9 Stock\_R_{n,i,t-1}+\beta_{10} ln(Stock\_V)_{n,i,t-1}+\beta_{11} Loan/TA_{n,i,t-1}+\varepsilon_{n,i,t} \quad (10)$$

We note that $Z\_Score_{n,i,t}$ may affect bank interconnectedness $Y_{n,i,t}$ since bank interconnectedness and risk-taking behavior may affect each other (Altinoglu and Stiglitz, 2023). Hence we use an alternative specification of model (10) below:

$$Y_{n,i,t}=\alpha+\beta_1 Z\_Score_{n,i,t}+\beta_2 SOE_{n,i,t}+\beta_3 TOO\_BIG_{n,i,t}+\beta_4\Delta REV_{n,i,t-1}+\beta_5 COMP_{n,i,t-1}+\beta_6 FRB_{t-1}+\beta_7\Delta EPU_{t-1} +\beta_8\Delta MSCI_{t-1}+\beta_9 Stock\_R_{n,i,t-1}+\beta_{10} ln(Stock\_V)_{n,i,t-1}+\beta_{11} Loan/TA_{n,i,t-1}+\varepsilon_{n,i,t} \quad (11)$$

4. Data

We first collect the ISIN (International Securities Identification Number) codes for all major listed banks available across North America (including the United States and Canada), the United Kingdom, Europe, and the rest of the world between March 2000 and June 2023 from Boardex. This enables us to form a sample of listed banks around the world where we have director nationality data. We then match these ISIN codes with Refinitiv. This leads us to quarterly data of 519 unique listed banks (Appendix II) comprising 88 different director nationalities (Appendix I) across 60 major developed and developing

[9] We use natural log values of The *Z_Score* to ensure its higher value represents higher bank risk-taking (Kanagaretnam et al., 2019).

countries. We match the four cultural dimensions (*Tight*, *Indiv*, *Trust*, *Riskav* in Appendix I) to each director's nationality and take the average across directors within each bank to construct bank-level cultural similarity based on the method in section 3.1.

The four cultural variables (i.e., *Tight*, *Indiv*, *Trust*, and *Riskav*) used to produce our cultural similarity (*Cul_Sim*) measure are collected from Hofstede (2001), Gelfand et al. (2011), and WVS databases which we use to build cultural similarity indices from 88 different nationalities of our bank directors. We use stock prices and interbank assets (i.e., interbank loans and long-term deposits with other banks) from Refinitiv to calculate correlation (*Corr_net*) and physical (*Phy_net*) networks, respectively, following our methods explained in section 3.2. We also collect bank control variables used in models (9), (10), and (11) from Refinitiv in quarterly frequencies. Financial data are transformed into US dollars. We winsorize our data at the 1st and 99th percentiles.[10]

5. Analysis and Results

Summary statistics in Table 1 show that *Cul_Sim* has a mean value of 0.784 indicating that the bank-level cultural similarity is generally high. *Cul_Dist* is an alternative proxy (Kogut and Singh's, 1988) that uses average cultural distance with other banks based on four cultural dimensions *Tight*, *Indiv*, *Trust*, and *Riskav* has a mean value of 0.152.

The bank interconnectedness measures (*Corr_net* and *Phy_net*) show a lower median value than the average indicating a right-skewed distribution. This suggests that a small number of banks demonstrate high interconnectedness compared to the rest of the banks. The bank risk-taking measure *Z_Score* shows a mean value of -3.222 which is generally aligned with prior literature (e.g., Kanagaretnam et al.,2014, 2019; Laeven and Levine, 2009). We find that only 5.3% of banks are state-owned enterprises (SOEs), indicating that the majority of banks in our sample are non-state-owned. Additionally, 24.8% of banks are TBTF banks

[10] We find no multicollinearity issue in the reported correlation matrices in Appendix III.

(*TOO_BIG*). The data show that in each quarter there are three monetary policy announcements by the Federal Reserve Bank (*FRB*).

[Insert Table 1 here]

In Figure 1, we show the bank interconnectedness over time using the annual averaged values of correlation and physical networks. As expected, we observe increased correlation during the Global Financial Crisis (August 2007 − June 2009)[11], the European Sovereign Debt Crisis (November 2009 − July 2012)[12], and the Covid-19 pandemic (January 2020 – May 2023)[13]. The correlation of stock returns tends to rise leading up to the crises. On the other hand, physical interconnectedness drops relatively soon after the crises occur. This evidence is consistent with Brunetti et al (2019) who report heightened stock price correlations (correlation network) and breakdown in connectivity in the interbank market (physical network) during the global financial crisis.

[Insert Figure 1 here]

5.1 Cultural Similarity and Bank Interconnectedness

We analyze how bank-level cultural similarity impacts the correlation and physical networks based on panel regressions (equations 8 and 9). Consistent with our expectations in the first hypothesis, we find banks with high cultural similarity demonstrate increased interconnectedness. In other words, an increase in cultural similarity is positively related to an increase in both correlation and physical networks. In the last columns of Tables 2 and 3, we use an alternative measure of cultural similarity based on Kogut and

[11] The GFC lasted until June 2009 (Rich, 2013). There are slightly different views on how long the Global Financial Crisis had lasted which overlaps with the European Sovereign Debt crisis period.

[12] We consider the start of the European Sovereign Debt crisis after Greece announced large budget deficits in November 2009. 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 to preserve the euro." (Samarakoon, 2017).

[13] We use the WHO (World Health Organization) public health emergency declaration date of January 30, 2020 (since still far east countries like China suffered from December 2019) and the pandemic declaration end date May 5, 2023 as for our start and end dates, respectively, of Covid-19 crisis period (https://www.who.int/europe/emergencies/situations/covid-19).

Singh's (1988) cultural distance measure (*Cul_Dist*). Our finding of the significant impact of cultural similarity on bank interconnectedness (both correlation and physical) remains robust.

We find banks with small stock prices (*ln*(*Stock_P*)) tend to follow the stock prices of other banks. Similar to the results reported by Brunetti et al. (2019), we find physical networks show stronger responses while correlation networks demonstrate relatively muted responses to economic and monetary policy shocks. The downside risk of global stock market shock (Δ*MSCI*) tends to increase the physical networks. Banks with higher monopoly power (*COMP*) and stock prices (*ln*(*Stock_P*)) show more physical interconnectedness.

[Insert Table 2 here]

[Insert Table 3 here]

5.2 Robustness Tests on the Cultural Similarity Relation to Bank Interconnectedness

Even though culture has a long history and changes very slowly over time (e.g., Williamson, 2000; Hofstede, 2001; Licht et al., 2005), there may be endogeneity arising from reverse causality in our empirical framework. We therefore use the genetic distance (*Fst*) as an Instrumental Variable (IV) for cultural similarity (*Cul_Sim*). Previous studies[14] show *Fst* distance as a valid instrument for culture. *Fst* is a country-specific fixation index collected from Cavalli-Sforza et al. (1994) and the online Appendix of Spolaore and Wacziarg (2009). It measures the average genetic distance of one nationality to other nationalities for each bank against other banks where higher *Fst* indicates a larger genetic distance. We use the min-max scaled *Fst* measure to make it comparable with the cultural similarity variable. In Tables 4 and 5, we use the genetic distance (*Fst*) as our main instrument for cultural similarity (*Cul_Sim*). Additionally, we consider the total loan over total asset ($Loan/TA_{n,i,t-1}$) as an instrument for correlation networks (Table 4). We also use the volatility of the bank's core business performance (standard deviation of net interest margin

[14] These include 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).

($\sigma(NIM)_{n,i,t-1}$), following (Jin et al, 2013), as an additional instrument for the physical network in Table 5. In both Tables 4 and 5, we find that *Fst* shows a significant and negative relation to cultural similarity (*Cul_Sim*). This suggests that higher genetic distance (*Fst*) reduces cultural similarity. The findings are consistent with previously reported findings (e.g., Bryan et al., 2015) that greater genetic distance indicates less cultural similarity.

We present the second stage IV using model (2) in the last columns of Tables 4 and 5. The results confirm a positive impact of cultural similarity (*Cul_Sim*) on bank correlation (Table 4) and physical (Table 5) networks. Since IV regression requires the instruments to be exogenous to be valid (Stock and Yogo, 2002), we perform the Wald weak instrument test to assess the relevance and suitability of our instruments. We find that the instruments are significant at the 1% level rejecting the null hypothesis that the coefficient estimates of these variables are equal to zero. Therefore, our instruments appear to be both relevant and valid. The Wu-Hausman test accepts the null hypothesis that the endogeneity problem does not exist in our model. Finally, we run Wooldridge's (1995) overidentification test, which is identical to Sargan's (1958) test with classical standard errors, to investigate whether the instruments and error terms are uncorrelated. The results confirm that the instruments are not correlated with the error terms and therefore reliable.

[Insert Table 4 here]

[Insert Table 5 here]

5.3 Bank Interconnectedness and Risk-Taking Behavior.

Altinoglu and Stiglitz (2023) have theoretically shown that bank interconnectedness and risk-taking reinforce each other. We empirically test this theory by analyzing how bank interconnectedness affects risk-taking (Table 6) and vice-versa (Table 7). In Table 6, we find both correlation and physical networks increase bank risk-taking. We find that TBTF (*TOO_BIG*) banks tend to take more risks. Banks also show high risk-taking with more competition (*COMP*), large economic (ΔEPU and $\Delta MSCI$) and monetary shocks (*FRB*), and high loan debt ratios (*Loan/TA*).

[Insert Table 6 here]

Results in Table 7 show that bank risk-taking increases bank interconnectedness. Therefore, our results in both Tables 6 and 7 are consistent with Altinoglu and Stiglitz's (2023) theoretical arguments. State-owned banks (*SOE*) have public policy objectives and are the main transmitters of the government's monetary policy (Ornelas et al., 2022). Consequently, *SOE* banks tend to be more active in interbank lending. The results in Table 7 show that *SOE* banks' risk-taking is positively related to physical bank interconnectedness. We find that macroeconomic shocks negatively affect correlation and physical networks albeit they are mostly statistically significant only in the case of physical networks.

[Insert Table 7 here]

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 [15] have expressed their concerns about the dangers of TBTF banks. Several studies argue that bank size influences systemic risk (e.g., Vallascas and Keasey, 2012; Drehmann and Tarashev, 2013; Laeven et al., 2016; Gofman, 2017). We use *Basel_III* as an exogenous variable that takes the value of one if the data belongs to the period starting from the first quarter of 2013, and zero otherwise.

In Table 8, we use the difference-in-differences (DID) method (equations 12 and 13) to analyze the risk-taking behavior and interconnectedness of TBTF banks after the implementation of Basel III in early 2013.

$$
\begin{aligned}
Z\_Score_{n,i,t} = {} & \alpha + \beta_1 Y_{n,i,t} + \beta_2 SOE_{n,i,t} + \beta_3 TOO\_BIG_{n,i,t} + \beta_4 TOO\_BIG_{n,i,t} \times Basel\_III_t + \beta_5 Basel\_III_t \\
& + \beta_6 \Delta REV_{n,i,t-1} + \beta_7 COMP_{n,i,t-1} + \beta_8 FRB_{t-1} + \beta_9 \Delta EPU_{t-1} + \beta_{10} \Delta MSCI_{t-1} + \beta_{11} Stock\_R_{n,i,t-1} \\
& + \beta_{12} ln(Stock\_V)_{n,i,t-1} + \beta_{13} Loan/TA_{n,i,t-1} + \varepsilon_{n,i,t} \qquad (12)
\end{aligned}
$$

$$
\begin{aligned}
Y_{n,i,t} = {} & \alpha + \beta_1 Z\_Score_{n,i,t} + \beta_2 SOE_{n,i,t} + \beta_3 TOO\_BIG_{n,i,t} + \beta_4 TOO\_BIG_{n,i,t} \times Basel\_III_t + \beta_5 Basel\_III_t \\
& + \beta_6 \Delta REV_{n,i,t-1} + \beta_7 COMP_{n,i,t-1} + \beta_8 FRB_{t-1} + \beta_9 \Delta EPU_{t-1} + \beta_{10} \Delta MSCI_{t-1} + \beta_{11} Stock\_R_{n,i,t-1}
\end{aligned}
$$

[15] 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.

$+\beta_{12} ln(Stock\_V)_{n,i,t-1}+\beta_{13} Loan/TA_{n,i,t-1}+\varepsilon_{n,i,t}$ (13)

As in our earlier models, $Y_{n,i,t}$ is the bank interconnectedness, correlation ($Corr\_net_{n,i,t}$) or physical ($Phy\_net_{n,i,t}$) network. We find that Basel III has not been effective in mitigating the risk-taking behavior of TBTF banks ($TOO\_BIG \times Basel\_III$ in models 1 and 2). The results suggest that regulatory policies will need to continually evolve in managing the risk-taking incentives for TBTF banks. The impact of Basel III on correlation and physical interconnectedness is also mixed. This implies that increased risk capital requirements alone may not be enough to reduce bank risk-taking behavior. Previous studies recommend that a tax system in the form of capital surcharge may be more effective compared to regulation like Basel III (Acharya et al., 2017; Chen, 2022).

[Insert Table 8 here]

6. Conclusion

The extant research argues that though bank interconnectedness facilitates funding and transferring of risk, highly interconnected banks pose significant systemic risk. There is little research on how cultural similarity affects bank interconnectedness. This paper fills an important gap in the literature by providing evidence of how bank-level cultural similarity impacts their interconnectedness using a large sample of listed banks across 60 developed and developing countries. We use both correlation and physical networks as measures of bank interconnectedness similar to Brunetti et al. (2019) and Jaffe's (1986) distance method as a measure of cultural similarity. Furthermore, we empirically test how bank interconnectedness and risk-taking reinforce each other.

Our results show that high cultural similarity increases both correlation and physical interconnectedness. This highlights the relevance of considering culture in bank interconnectedness studies. Our findings imply that cultural similarity plays a critical role in bringing banks closer. We also find that bank interconnectedness exacerbates bank risk-taking which suggests that increased connection may be a possible channel of higher risk-taking. Our findings support the theoretical prediction of Altinoglu and

Stiglitz (2023) who argue that interconnectedness and risk-taking reinforce one another. We investigate the impact of Basel III regulation and find that this has not had much of an impact on bank risk-taking behavior. Contrary to expectations, our results show an increase in risk-taking by TBTF banks post-Basel III. Our results are robust after controlling for the possible influence of several endogenous and exogenous variables.

Our findings have important policy implications. First, regulators should monitor the interactivity between banks as the strengthening of financial and physical networks may intensify bank risk-taking. The results also suggest that this problem could be particularly serious in TBTF banks which share a complex business network that often allows them to operate under the radar of regulatory authorities. Therefore, stronger networks may aggravate systemic risks. Regulators may be able to monitor these risks by developing a risk control system that would enable them to regulate the operational risks.

However, our research study considers interconnectedness only between banks and excludes other financial institutions like pension funds, insurance companies, etc. Future studies could consider developing appropriate measures of interconnectedness among all major financial institutions.

Declarations of interest: none

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Table 1. Summary Statistics

The following table shows the summary statistics of our data. *Cul_Sim* is the cultural similarity calculated based on section 3.1's method. *Cul_Dist* is the cultural distance measure based on Kogut and Singh (1988). Both *Cul_Sim* and *Cul_Dist* use our bank director-level cultural factors of *Tight*, *Indiv*, *Trust*, and *Riskav* as shown in Appendix I. *Corr_net* and *Phy_net* are the normalized correlation and physical networks, respectively. *Z_Score* measures the bank risk-taking (Kanagaretnam et al., 2019) computed as $(-1) \times ln((CAR+ROA)/\sigma(ROA))$ where *CAR*, *ROA,* and $\sigma(ROA)$ are the capital over asset ratio, return on assets, and standard deviation of return on assets, respectively. *SOE* is the state ownership dummy showing one if the bank is owned by the state, and zero otherwise. *TOO_BIG* is a dummy variable showing one if the bank's deposits comprise more than 10% of the country's total deposits within a quarter, and zero otherwise. ΔREV (revenue growth rate), *COMP* (bank competition measured as the sum of the squares of the market share (deposits) of each bank in each country), *Stock_R* (natural log stock return), *ln*(*Stock_P*) (natural log of stock price), *ln*(*Stock_V*) (natural log of stock trading volume), and *Loan*/*TA* (total loan over total asset) are banks' financial controls. *FRB* is the Federal Reserve Bank's monetary policy announcement counts per quarter. *EPU* is the Economic Policy Uncertainty Index collected from the Economic Policy Uncertainty database. *MSCI* is the Morgan Stanley Capital International world index. $\sigma(NIM)$ is the standard deviation of the net interest margins. *Basel_III* is a binary variable showing one if the period belongs to the Basel III financial regulation which has happened since the first quarter of 2013. We report the Mean, Median, Std. (standard deviation), 25^{th} Per (25^{th} percentile), 75^{th} Per (75^{th} percentile), and *N* (number of observations) of each variable in our sample.

	Mean	Median	Std.	25^{th} Per	75^{th} Per	*N*
Cul_Sim	0.784	0.848	0.183	0.774	0.876	12,774
Cul_Dist	0.152	0.019	0.227	0.016	0.225	12,774
Corr_net	0.232	0.182	0.181	0.115	0.288	12,775
Phy_net	0.076	0.033	0.140	0.008	0.084	9,028
Z_Score	-3.222	-3.210	1.147	-3.944	-2.534	6,826
SOE	0.053	0.000	0.223	0.000	0.000	12,775
TOO_BIG	0.248	0.000	0.432	0.000	0.000	11,572
ΔREV	0.007	0.002	0.044	-0.011	0.019	10,185
COMP	0.158	0.088	0.160	0.067	0.175	12,775
FRB	3.067	3.000	1.160	2.000	4.000	12,775
EPU	179.1	160.0	73.4	128.0	207.6	12,775
MSCI	1,795.8	1,698.4	576.6	1,311.5	2,184.0	12,775
Stock_R	0.024	0.034	0.174	-0.058	0.124	12,572
ln(*Stock_P*)	3.409	3.143	1.687	2.462	3.949	12,580
ln(*Stock_V*)	12.13	11.98	3.15	9.89	14.67	9,059
Loan/TA	0.672	0.684	0.175	0.591	0.764	11,080
Basel_III	0.641	1.000	0.480	0.000	1.000	12,775

Table 2. Cultural Similarity's Impact on the Bank Interconnectedness – Correlation Networks
The following table analyzes the cultural similarity impact on the correlation ($Corr\_net_{n,i,t}$) in banks based on model (8) in section 3.3. We present the standard errors in parentheses. We provide the adjusted R^2 ($Adj\text{-}R^2$) and F-statistics (F-stats) for our goodness-of-fit measures. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Corr\_net_{n,i,t}$ (1)	$Corr\_net_{n,i,t}$ (2)	$Corr\_net_{n,i,t}$ (3)	$Corr\_net_{n,i,t}$ (4)
$Cul\_Sim_{n,i,t}$		0.07***	0.084***	
		(0.024)	(0.03)	
$Cul\_Dist_{n,i,t}$				-0.067***
				(0.018)
FRB_{t-1}	0.0001	0.00003	-0.002	-0.002
	(0.006)	(0.006)	(0.006)	(0.006)
ΔEPU_{t-1}	0.002	0.004	-0.011	-0.012
	(0.015)	(0.015)	(0.016)	(0.016)
$\Delta MSCI_{t-1}$	0.061	0.06	0.017	0.021
	(0.05)	(0.05)	(0.051)	(0.051)
$\Delta REV_{n,i,t-1}$			-0.025	-0.028
			(0.039)	(0.039)
$COMP_{n,i,t-1}$			-0.026	-0.017
			(0.029)	(0.029)
$ln(Stock\_P)_{n,i,t-1}$			-0.023***	-0.021***
			(0.003)	(0.003)
Intercept	0.285***	0.23***	0.33***	0.402***
	(0.03)	(0.035)	(0.041)	(0.033)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	12,775	12,774	10,098	10,098
$Adj\text{-}R^2$	0.165	0.165	0.186	0.187
F-stats	5.66***	5.67***	5.65***	5.66***

Table 3. Cultural Similarity's Impact on the Bank Interconnectedness – Physical Networks
The following table analyzes the cultural similarity impact on the physical networks ($Phy\_net_{n,i,t}$) in banks based on model (8) in section 3.3. We present the standard errors in parentheses. We provide the adjusted R^2 (Adj-R^2) and F-statistics (F-stats) for our goodness-of-fit measures. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Phy\_net_{n,i,t}$ (1)	$Phy\_net_{n,i,t}$ (2)	$Phy\_net_{n,i,t}$ (3)	$Phy\_net_{n,i,t}$ (4)
$Cul\_Sim_{n,i,t}$		0.025^{**}	0.066^{***}	
		(0.011)	(0.015)	
$Cul\_Dist_{n,i,t}$				-0.024^{**}
				(0.01)
FRB_{t-1}	-0.0002	-0.0004	-0.006	-0.006
	(0.003)	(0.003)	(0.004)	(0.004)
ΔEPU_{t-1}	-0.104^{***}	-0.103^{***}	-0.113^{***}	-0.114^{***}
	(0.01)	(0.01)	(0.011)	(0.011)
$\Delta MSCI_{t-1}$	-0.097^{***}	-0.098^{***}	-0.214^{***}	-0.212^{***}
	(0.033)	(0.033)	(0.037)	(0.037)
$\Delta REV_{n,i,t-1}$			-0.01	-0.014
			(0.022)	(0.022)
$COMP_{n,i,t-1}$			0.09^{***}	0.092^{***}
			(0.019)	(0.019)
$ln(Stock\_P)_{n,i,t-1}$			0.004^{***}	0.005^{***}
			(0.002)	(0.002)
Intercept	0.055^{***}	0.036^{**}	-0.026	0.029^{*}
	(0.014)	(0.016)	(0.021)	(0.017)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	9,028	9,028	7,293	7,293
Adj-R^2	0.733	0.733	0.739	0.739
F-stats	56.84^{***}	56.75^{***}	51.75^{***}	51.63^{***}

Table 4. Cultural Similarity's Impact on the Correlation Networks - Instrumental Variable (IV)
The following table reports estimates from IV regression estimates for analyzing the effects of cultural similarity on the correlation networks. The instrument for cultural similarity ($Cul\_Sim_{n,i,t}$) is the genetic distance ($Fst_{n,i,t}$). We also use the total loan over total asset ($Loan/TA_{n,i,t-1}$) as an additional instrument for the correlation network ($Corr\_net_{n,i,t}$). We report the weak Wald instrument, Wu-Hausman test, and Wooldridge's (1995) overidentification tests to check the relevance, endogeneity, and validity of our instruments, respectively. We present the standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	IV First Stage $Cul\_Sim_{n,i,t}$ (1)	IV Second Stage $Corr\_net_{n,i,t}$ (2)
$Cul\_Sim_{n,i,t}$		0.147^{***}
		(0.048)
$Fst_{n,i,t}$	-0.199^{***}	
	(0.008)	
$Loan/TA_{n,i,t-1}$	-0.02^{**}	
	(0.009)	
FRB_{t-1}	0.008^{***}	0.003
	(0.002)	(0.002)
ΔEPU_{t-1}	0.009	0.016^{***}
	(0.008)	(0.008)
$\Delta MSCI_{t-1}$	0.001	-0.006
	(0.028)	(0.032)
$\Delta REV_{n,i,t-1}$	-0.127^{***}	-0.009
	(0.038)	(0.046)
$COMP_{n,i,t-1}$	-0.484^{***}	0.121^{***}
	(0.014)	(0.026)
$ln(Stock\_P)_{n,i,t-1}$	-0.012^{***}	-0.002
	(0.001)	(0.001)
Intercept	0.937^{***}	0.094^{***}
	(0.01)	(0.044)
Observations	8,912	8,912
Wald weak instrument test for $Cul\_Sim_{i,t}$		128.24^{***}
Wu-Hausman Test (*p-value*)		0.113
Overidentification test (*p-value*)		0.115

Table 5. Cultural Similarity's Impact on the Physical Networks - Instrumental Variable (IV)
The following table reports estimates from IV regression estimates for analyzing the effects of cultural similarity on the physical networks. The instrument for cultural similarity ($Cul\_Sim_{n,i,t}$) is the genetic distance ($Fst_{n,i,t}$). We also use the standard deviation of net interest margin ($\sigma(NIM)_{n,i,t-1}$) as an additional instrument for the physical network ($Phy\_net_{n,i,t}$). We report the weak Wald instrument, Wu-Hausman test, and Wooldridge's (1995) overidentification tests to check the relevance, endogeneity, and validity of our instruments, respectively. We present the standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	IV First Stage $Cul\_Sim_{n,i,t}$ (1)	IV Second Stage $Phy\_net_{n,i,t}$ (2)
$Cul\_Sim_{n,i,t}$		0.105^{***}
		(0.014)
$Fst_{n,i,t}$	-0.318^{***}	
	(0.009)	
$\sigma(NIM)_{n,i,t-1}$	-0.129^{***}	
	(0.008)	
FRB_{t-1}	0.004	0.008^{***}
	(0.003)	(0.003)
ΔEPU_{t-1}	-0.032^{***}	-0.003
	(0.01)	(0.011)
$\Delta MSCI_{t-1}$	-0.117^{***}	0.033
	(0.045)	(0.062)
$\Delta REV_{n,i,t-1}$	-0.117^{**}	-0.037
	(0.053)	(0.038)
$COMP_{n,i,t-1}$	-0.161^{***}	0.147^{***}
	(0.015)	(0.03)
$ln(Stock\_P)_{n,i,t-1}$	-0.006^{***}	0.008^{***}
	(0.001)	(0.001)
Intercept	0.898^{***}	-0.116^{***}
	(0.008)	(0.017)
Observations	6,549	4,933
Wald weak instrument test for $Cul\_Sim_{i,t}$		425.88^{***}
Wu-Hausman Test (*p-value*)		0.218
Overidentification test (*p-value*)		0.985

Table 6. Bank Interconnectedness' Impact on the Bank Risk–Taking

The following table shows the bank interconnectedness' impact on the bank risk-taking behavior based on the model (10). We present the standard errors in parentheses. We provide the adjusted R^2 ($Adj\text{-}R^2$) and F-statistics (F-stats) for our goodness-of-fit measures. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Z\_Score_{n,i,t}$ (1)	$Z\_Score_{n,i,t}$ (2)	$Z\_Score_{n,i,t}$ (3)
$Corr\_net_{n,i,t}$		0.318^{***}	
		(0.098)	
$Phy\_net_{n,i,t}$			1.318^{**}
			(0.555)
$SOE_{n,i,t}$	-0.547	-0.504	-0.328
	(0.684)	(0.683)	(0.718)
$TOO\_BIG_{n,i,t}$	0.152	0.151	0.445^{**}
	(0.122)	(0.121)	(0.174)
$\Delta REV_{n,i,t-1}$	-0.454	-0.449	-0.033
	(0.454)	(0.453)	(0.542)
$COMP_{n,i,t-1}$	-1.067^{**}	-1.009^{**}	-1.139^{*}
	(0.489)	(0.489)	(0.617)
FRB_{t-1}	0.173^{***}	0.172^{***}	0.076
	(0.06)	(0.06)	(0.09)
ΔEPU_{t-1}	1.216^{***}	1.24^{***}	1.317^{***}
	(0.168)	(0.168)	(0.297)
$\Delta MSCI_{t-1}$	1.917^{***}	1.898^{***}	1.288
	(0.496)	(0.495)	(1.069)
$Stock\_R_{n,i,t-1}$	0.235^{*}	0.238^{**}	0.48^{***}
	(0.12)	(0.12)	(0.144)
$ln(Stock\_V)_{n,i,t-1}$	0.066^{***}	0.064^{***}	0.068^{***}
	(0.022)	(0.022)	(0.026)
$Loan/TA_{n,i,t-1}$	0.397^{***}	0.405^{***}	0.337^{*}
	(0.148)	(0.148)	(0.175)
Intercept	-4.266^{***}	-4.386^{***}	-4.62^{***}
	(0.479)	(0.48)	(0.617)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	4,182	4,182	3,170
$Adj\text{-}R^2$	0.447	0.448	0.454
F-stats	9.63^{***}	9.66^{***}	8.9^{***}

Table 7. Bank Risk-Taking's Impact on Bank Interconnectedness
The following table shows the bank risk-taking behavior's impact on the bank interconnectedness based on the model (11). We present the standard errors in parentheses. We provide the adjusted R^2 (*Adj-*R^2) and F-statistics (*F*-stats) for our goodness-of-fit measures. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

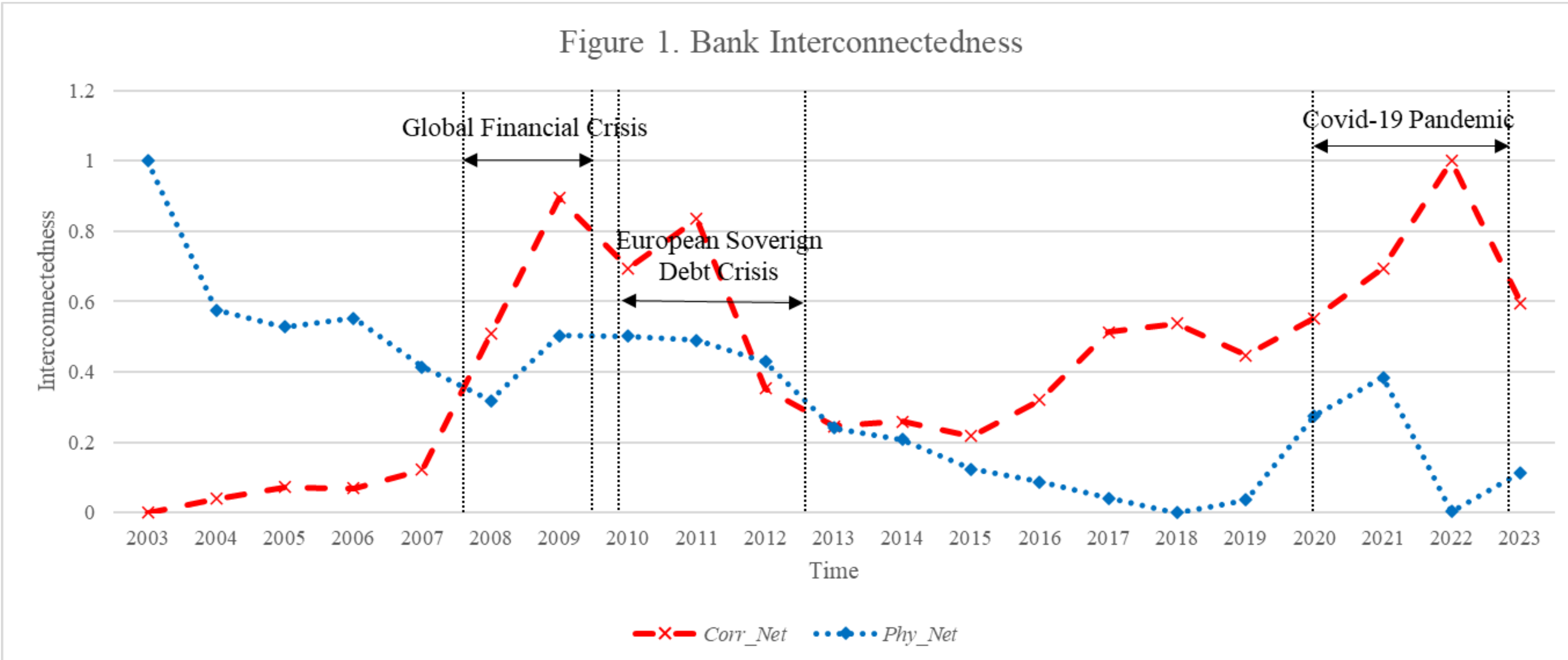
	$Corr\_net_{n,i,t}$ (1)	$Corr\_net_{n,i,t}$ (2)	$Phy\_net_{n,i,t}$ (3)	$Phy\_net_{n,i,t}$ (4)
$Z\_Score_{n,i,t}$		0.009***		0.002**
		(0.003)		(0.001)
$SOE_{n,i,t}$	-0.112*	-0.13	0.101***	0.052**
	(0.058)	(0.113)	(0.017)	(0.024)
$TOO\_BIG_{n,i,t}$	-0.037**	0.002	-0.004	-0.003
	(0.016)	(0.02)	(0.006)	(0.006)
$\Delta REV_{n,i,t-1}$	0.057	-0.011	0.035*	0.006
	(0.056)	(0.075)	(0.018)	(0.018)
$COMP_{n,i,t-1}$	-0.031	-0.173**	-0.004	0.037*
	(0.055)	(0.081)	(0.019)	(0.021)
FRB_{t-1}	0.002	-0.0004	-0.034***	-0.035***
	(0.009)	(0.01)	(0.003)	(0.003)
ΔEPU_{t-1}	-0.038	-0.085***	-0.172***	-0.034***
	(0.024)	(0.028)	(0.011)	(0.01)
$\Delta MSCI_{t-1}$	0.057	0.043	-0.549***	-0.299***
	(0.073)	(0.082)	(0.039)	(0.036)
$Stock\_R_{n,i,t-1}$	-0.043***	-0.011	0.012**	-0.025***
	(0.015)	(0.02)	(0.005)	(0.005)
$ln(Stock\_V)_{n,i,t-1}$	0.006**	0.006*	0.00003	-0.0003
	(0.002)	(0.004)	(0.001)	(0.001)
$Loan/TA_{n,i,t-1}$	-0.013	-0.029	-0.055***	-0.022***
	(0.019)	(0.025)	(0.006)	(0.006)
Intercept	0.305***	0.412***	0.155***	0.099***
	(0.053)	(0.08)	(0.018)	(0.021)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	6,064	4,182	4,651	3,170
Adj-R^2	0.26	0.281	0.848	0.907
F-stats	5.86***	5.17***	68.94***	93.96***

Table 8. Risk-Taking Behaviors and Interconnectedness of Too-Big-To-Fail Banks after Basel III
The following table shows the too-big-to-fail banks' risk-taking behaviors and interconnectedness after the Basel III regulation. We present the standard errors in parentheses. We provide the adjusted R^2 (*Adj-R^2*) and *F*-statistics (*F*-stats) for our goodness-of-fit measures. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Z\_Score_{n,i,t}$ (1)	$Z\_Score_{n,i,t}$ (2)	$Corr\_net_{n,i,t}$ (3)	$Phy\_net_{n,i,t}$ (4)
$TOO\_BIG_{n,i,t}$	-0.342**	-0.159	-0.016	0.002
	(0.135)	(0.187)	(0.023)	(0.006)
$TOO\_BIG_{n,i,t} \times Basel\_III_t$	0.735***	0.933***	0.026*	-0.008**
	(0.091)	(0.113)	(0.015)	(0.004)
$Basel\_III_t$	0.061	0.608	-0.156**	-0.736***
	(0.418)	(1.004)	(0.07)	(0.031)
$Corr\_net_{n,i,t-1}$	0.291***			
	(0.097)			
$Phy\_net_{n,i,t-1}$		1.457***		
		(0.549)		
$Z\_Score_{n,i,t}$			0.008***	0.002***
			(0.003)	(0.001)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	4,182	3,170	4,182	3,170
Adj-R^2	0.457	0.467	0.282	0.908
F-stats	9.96***	9.29***	5.17***	93.79***

Figure 1. Bank Interconnectedness

The following figure presents the banks' interconnectedness in time series for our correlation (*N_corr_net*) and physical (*N_phy_net*) networks. The interconnectedness measures are averaged across our sample banks for each year.



Appendix I.

The following tables show the raw cultural values we collected for tightness-looseness, individualism-collectivism, uncertainty avoidance (panel A), and trusting (panel B) cultures comprised of 50 different nationalities of the bank directors from Boardex. Tightness-looseness (*Tight*) is the extent to which a country has strong norms and low tolerance for deviant behavior collected from Gelfand et al. (2011). Individualism-collectivism (*Indiv*) is Hofstede's (2001) measure showing the degree to which people focus on their internal attributes to differentiate themselves from others. Uncertainty avoidance (*Riskav*) is collected from Hofstede (2001) showing the degree of comfort in unfamiliar situations and how much a society is trying to control the uncontrollable. Trusting (*Trust*) culture is the measure of willingness to rely on others despite the possible vulnerability by doing so (Doney et al., 1998) which we collected from the respondents across four consecutive waves of the World Valued Survey (WVS) between 2000 and 2022.

Panel A. Tightness-looseness (*Tight*), individualism-collectivism (*Indiv*), and uncertainty avoidance (*Riskav*) cultures

Nationality of directors	*Tight*	*Indiv*	*Riskav*
American	5.1	91	46
Argentine		46	86
Australian	4.4	90	51
Austrian	6.8	55	70
Belgian	5.6	75	94
Brazilian	3.5	38	75
British	6.9	89	35
Canadian		80	48
Chilean		23	86
Chinese	7.9		
Taiwanese		17	69
Colombian		13	80
Danish		74	23
Dutch	3.3	80	53
Estonian	2.6		
Filipino		32	44
Finnish		63	59
French	6.3	71	86
German	7	67	65
Greek	3.9	35	112
Guatemalan		6	101
Hungarian	2.9		
Icelander	6.4		
Indian	11	48	40
Indonesian		14	48
Iranian		41	59
Irish		70	35
Israeli	3.1	54	81
Italian	6.8	76	75
Jamaican		39	13
Japanese	8.6	46	92
Malaysian	11.8	26	36
Mexican	7.2	30	82

New Zealander	3.9	79	49
Norwegian	9.5	69	50
Pakistani	12.3	14	70
Panamanian		11	86
Peruvian		16	87
Polish	6		
Portuguese	7.8	27	104
Saudi		38	68
Singaporean	10.4	20	8
South African		65	49
South Korean	10	18	
Spanish	5.4	51	86
Swedish		71	29
Swiss		68	58
Thai		20	64
Turkish	9.2	37	85
Ukrainian	1.6		

Panel B. Trusting (*Trust*) culture

Nationality of directors	*Trust*			
	2000-2004	2005-2009	2010-2014	2017-2022
American	35.5	39.1	34.8	37
Argentine	15	17.4	19.2	19.2
Australian		45.6	51.4	48.5
Austrian				49.8
Azerbaijani			14.8	26.3
Bangladeshi	23.3			12.9
Bosnian	15.6			9.6
Brazilian		9.2	7.1	6.5
British		30		
Bulgarian		19.6		17.1
Canadian	38.4	41.8		46.7
Chilean	22.2	12.4	12.4	12.9
Chinese	52.5	49.3	60.3	63.5
Colombian		14.3	4.1	4.5
Croatian				13.6
Cypriot		9.7	7.5	6.6
Czech				27.3
Danish				73.9
Dutch		42.6	66.1	57
Egyptian	37.5	18.5	21.5	7.3
Estonian			39	33.9
Ethiopian		21.4		11.9
Filipino	8.3		3.2	5.3
Finnish		58		68.4
French		18.7		26.3
Georgian		17.6	8.8	9

German		33.8	44.6	41.6
Ghanaian		8.5	5	
Greek				8.4
Guatemalan		14.9		18
Hungarian		28.7		27.2
Icelander				62.3
Indian	38.9	20.7	16.7	
Indonesian	45.7	37.5		4.6
Iranian	49.6	10.5		14.8
Iraqi	46.1	38.6	30	11
Israeli	22.9			
Italian		27.5		26.6
Japanese	39.6	36.6	35.9	33.7
Jordanian	27.1	30.7	13.2	15.9
Kazakhstani			38.3	22.8
Kenyan				9.5
Kuwaiti			28.5	
Kyrgyzstani	16.6		36.3	12.8
Lebanese			9.8	9.9
Libyan			10	9.1
Lithuanian				31.7
Malaysian		8.8	8.5	19.6
Mexican	20.8	15.4	12.4	10.5
Mongolian				26
Montenegrin	32.9			21.7
Moroccan	23	12.8	12.3	16.5
New Zealander		48.5	55.3	56.6
Nigerian	25.3		15	13
Norwegian		73.7		72.1
Pakistani	28.1		22.2	23.3
Peruvian	10.6	6.2	8.4	4.2
Polish		18.1	22.2	24.1
Portuguese				16.9
Puerto Rican	22.4			17.7
Qatari			21.4	
Romanian		19.3	7.7	12.1
Russian		24.6	27.8	22.9
Saudi	50.5			
Serbian	18.3	13.6		16.3
Singaporean	16.7		37.3	34.4
Slovak				21.6
Slovene		17.5	19.9	25.3
South African	11.5		23.3	
South Korean	27.3	28	26.5	32.9
Spanish	32.7	19.8	19	41
Swedish	63.7	65.2	60.1	62.8
Swiss		51.2		57.1
Thai		41.3	32.1	28.9
Trinidadian/Tobagonian		3.8	3.2	

Tunisian			15.5	13.8
Turkish	18.6	4.8	11.6	14
Ugandan	7.6			
Ukrainian		24.5	23.1	28.4
Vietnamese	38.7	50.9		27.7
Yemeni			38.5	
Zambian		10.8		
Zimbabwean	11.7		8.3	2.1

Appendix II.
The following table shows the headquarters' country locations of our sample banks and their numbers in each country.

Headquarters locations of the banks	Number of banks
Argentina	2
Australia	6
Austria	2
Belgium	2
Brazil	2
Canada	5
Chile	3
China	14
Colombia	2
Cyprus	2
Czech Republic	1
Denmark	6
Egypt	2
Faroe Islands	1
Finland	3
France	4
Germany	7
Greece	4
Hong Kong	4
Hungary	1
Iceland	4
India	19
Indonesia	10
Ireland	2
Israel	3
Italy	13
Japan	13
Jordan	2
South Korea	1
Kuwait	2
Liechtenstein	2
Malaysia	7
Mexico	3
Morocco	4
Netherlands	2
Nigeria	1
Norway	6
Oman	3
Pakistan	3
Panama	1
Peru	4
Philippines	5
Poland	7

Portugal	3
Puerto Rico	3
Qatar	2
Romania	2
Russia	2
Saudi Arabia	10
Singapore	2
South Africa	4
Spain	8
Sweden	2
Switzerland	10
Taiwan	9
Turkey	7
United Arab Emirates	4
United Kingdom	12
United States of America	248
Vietnam	1

Appendix III. Correlation Matrix

The following tables show the Pearson's correlation matrices for models used for our analyses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Correlation matrix for section 5.1							
	Cul_Sim	*FRB*	Δ*EPU*	Δ*MSCI*	Δ*REV*	*COMP*	*ln*(*Stock_P*)
Cul_Sim	1^{***}						
FRB	0.07^{***}	1^{***}					
Δ*EPU*	0.05^{***}	0.38^{***}	1^{***}				
Δ*MSCI*	-0.02^{*}	-0.14^{***}	-0.67^{***}	1^{***}			
Δ*REV*	-0.03^{***}	0	-0.03^{***}	0.07^{***}	1^{***}		
COMP	-0.21^{***}	-0.03^{***}	-0.03^{***}	0	0.03	1^{***}	
ln(*Stock_P*)	-0.21^{***}	-0.02^{***}	-0.03^{***}	0.02^{**}	0.04	0.09^{***}	1^{***}

Panel B. Correlation matrix for section 5.1							
	Cul_Dist	*FRB*	Δ*EPU*	Δ*MSCI*	Δ*REV*	*COMP*	*ln*(*Stock_P*)
Cul_Dist	1^{***}						
FRB	0	1^{***}					
Δ*EPU*	-0.01	0.38^{***}	1^{***}				
Δ*MSCI*	0	-0.14^{***}	-0.67^{***}	1^{***}			
Δ*REV*	0.02^{**}	0	-0.03^{***}	0.07^{***}	1^{***}		
COMP	0.39^{***}	-0.03^{***}	-0.03^{***}	0	0.03	1^{***}	
ln(*Stock_P*)	0.18^{***}	-0.02^{***}	-0.03^{***}	0.02^{**}	0.04	0.09^{***}	1^{***}

Panel C. Correlation matrix for section 5.3

	Corr_net	*SOE*	*TOO_BIG*	*ΔREV*	*COMP*	*FRB*	*ΔEPU*	*MSCI*	*Stock_R*	*ln*(*Stock_V*)	*Loan/TA*
Corr_net	1***										
SOE	-0.03***	1***									
TOO_BIG	-0.03***	0.14***	1***								
ΔREV	-0.01	0.01	-0.01	1***							
COMP	0	0.05***	0.59***	0.03***	1***						
FRB	0.03***	0.03***	0	0	-0.03***	1***					
ΔEPU	0.04***	-0.02***	-0.02*	-0.03***	-0.03***	0.38***	1***				
ΔMSCI	-0.01	0.01	-0.01	0.07***	0	-0.14***	-0.67***	1***			
Stock_R	-0.06***	-0.05***	-0.05***	0.11***	-0.03***	-0.15***	-0.32***	0.15***	1***		
ln(*Stock_V*)	-0.09***	0.22***	0.43***	0.05***	0.23***	0	-0.04***	0.03***	-0.05***	1***	
Loan/TA	-0.01	-0.06***	-0.2***	0	-0.13***	0.01	0.03***	0	-0.01	-0.24***	1***

Panel D. Correlation matrix for section 5.3

	Phy_net	*SOE*	*TOO_BIG*	*ΔREV*	*COMP*	*FRB*	*ΔEPU*	*MSCI*	*Stock_R*	*ln*(*Stock_V*)	*Loan/TA*
Phy_net	1***										
SOE	0.04***	1***									
TOO_BIG	0.23***	0.14***	1***								
ΔREV	-0.01	0.01	-0.01	1***							
COMP	0.28***	0.05***	0.59***	0.03***	1***						
FRB	0.03***	0.03***	0	0	-0.03***	1***					
ΔEPU	-0.04***	-0.02***	-0.02*	-0.03***	-0.03***	0.38***	1***				
ΔMSCI	-0.01	0.01	-0.01	0.07***	0	-0.14***	-0.67***	1***			
Stock_R	-0.06***	-0.05***	-0.05***	0.11***	-0.03***	-0.15***	-0.32***	0.15***	1***		
ln(*Stock_V*)	0.15***	0.22***	0.43***	0.05***	0.23***	0	-0.04***	0.03***	-0.05***	1***	
Loan/TA	-0.06***	-0.06***	-0.2***	0	-0.13***	0.01	0.03***	0	-0.01	-0.24***	1***

Panel E. Correlation matrix for section 5.4											
	Z_Score	*SOE*	*TOO_BIG*	Δ*REV*	*COMP*	*FRB*	Δ*EPU*	*MSCI*	*Stock_R*	*ln*(*Stock_V*)	*Loan/TA*
Z_Score	1***										
SOE	0.14***	1***									
TOO_BIG	0.26***	0.14***	1***								
Δ*REV*	0.05***	0.01	-0.01	1***							
COMP	0.22***	0.05***	0.59***	0.03***	1***						
FRB	-0.05***	0.03***	0	0	-0.03***	1***					
Δ*EPU*	-0.04***	-0.02***	-0.02*	-0.03***	-0.03***	0.38***	1***				
Δ*MSCI*	0.05***	0.01	-0.01	0.07***	0	-0.14***	-0.67***	1***			
Stock_R	0.02*	-0.05***	-0.05***	0.11***	-0.03***	-0.15***	-0.32***	0.15***	1***		
ln(*Stock_V*)	0.36***	0.22***	0.43***	0.05***	0.23***	0	-0.04***	0.03***	-0.05***	1***	
Loan/TA	-0.17***	-0.06***	-0.2***	0	-0.13***	0.01	0.03***	0	-0.01	-0.24***	1***