Banks Interconnectivity and Leverage*

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Abstract

In the period that preceded the 2008 crisis, US financial intermediaries have become more leveraged (measured as the ratio of assets over equity) and interconnected (measured as the share of liabilities held by other financial intermediaries). This upward trend in leverage and interconnectivity sharply reversed after the crisis. To understand the factors that could have caused this dynamic, we develop a model where banks make risky investments in the non-financial sector and sell part of their investments to other banks (diversification). The model predicts a positive correlation between leverage and interconnectivity which we explore empirically using balance sheet data for over 14,000 financial intermediaries in 32 OECD countries. We enrich the theoretical model by allowing for Bayesian learning about the likelihood of a bank crisis (aggregate risk) and show that the model can capture the dynamics of leverage and interconnectivity observed in the data.

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1 Introduction

During the last three decades we have witnessed a significant expansion of the financial sector. As shown in Figure 1, the assets of US financial businesses have more than doubled as a fraction of the country GDP. This trend has been associated with two additional trends within the financial sector. First, in the period that preceded the 2008 crisis, financial intermediaries have increased the issuance of liabilities held by other financial intermediaries. Second, financial firms have become more leveraged.

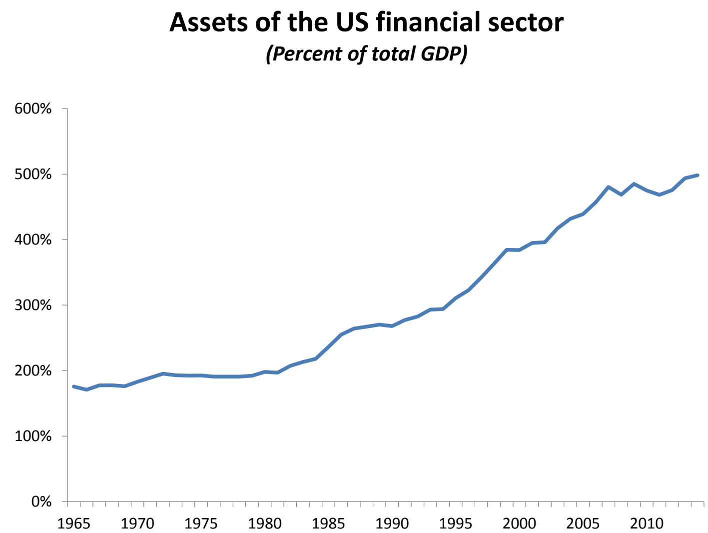

Figure 1: The growth of the financial sector.

To illustrate these two trends, the first panel of Figure 2 plots the ratio of non-core liabilities over total assets for the US banking sector using data from Bankscope over the period 1999-2014. A more detailed description of the data will be provided later in the empirical section of the paper but an important difference between core and non-core liabilities is that the former are mostly held by the nonfinancial sector (like the typical bank deposits of households and nonfinancial businesses) while the latter are mostly held by financial intermediaries (banks and other financial institutions).

Even though a significant fraction of non-core liabilities issued by banks are held by other financial institutions that are different from banks, we these non-core liabilities as a 'proxy' for bank liabilities held by other banks. Thus, we interpret the ratio displayed in the first panel of Figure 2 as an index of financial interconnectivity among financial institutions since the holding of liabilities issued by other banks creates a 'direct' balance sheet linkage between them. As can be seen from the figure, this ratio has increased significantly prior to the 2008 financial crisis and then drastically declined during and after the financial crisis.

Figure 2: The expansion and decline of banks connectivity (first panel) and leverage (second panel) in the United States.

The second panel of Figure 2 plots the ratio of assets over equity for the US banking sector. This is our primary measure of leverage. As can be seen from the figure, this ratio has increased during the same period in which banks interconnectivity has increased, that is, prior to the 2008 crisis. We can also see that the subsequent decline after the crisis tracks quite closely the decline in interconnectivity.

To further illustrate the co-movement between interconnectivity and leverage, Figure 3 plots the indices of interconnectivity and leverage for each year in which data is available. The figure shows that there is a very strong positive correlation between these two indices. In the empirical section we will shows that these empirical patterns are not limited to the United States but, with few exceptions, they are also observed in other countries.

Motivated by these empirical observations, this paper addresses two questions. First, how is interconnectivity and leverage related at the bank level? Second, what are the forces that have induced banks to become more interconnected and leveraged before the crisis and

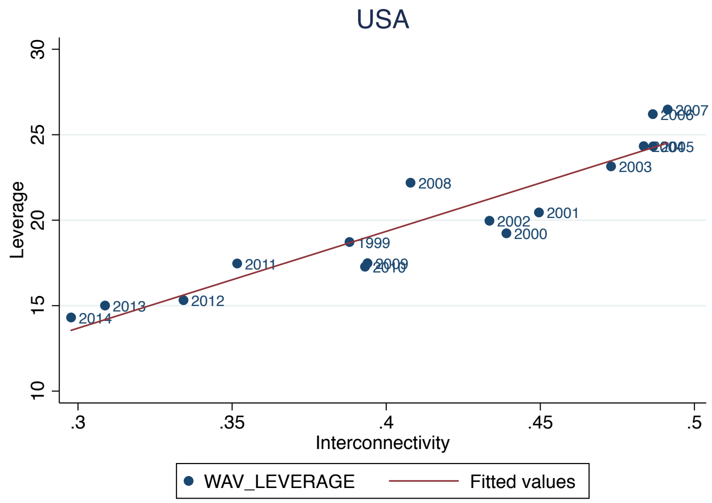

Figure 3: Interconnectivity and Leverage in the United States.

caused the reversal after the crisis?

To address the first question we develop a dynamic model without aggregate uncertainty where banks make risky investments in the nonfinancial sector funded with equity and debt. Higher leverage implies higher risk and to reduce the risk banks sell some of the investments to other banks. However, the sales of investments to other banks implies an agency cost that increases with the degree of diversification. Because of this cost, in equilibrium banks are only partially diversified.

An important implication of the model is that, when banks become more leveraged, they face higher risk and, therefore, they have higher incentives to diversify. In the model, greater diversification is achieved by selling some of the risky investments to other banks and, in this way, banks become more interconnected. At the same time, when banks are more interconnected, they face lower risk, which increases the incentive to leverage.

We use data from Bankscope to explore the empirical significance of these properties along three dimensions: across banks, across time and across countries. The empirical analysis shows that there is a strong association between banks interconnectivity and leverage, as predicted by the model. In particular, banks that are more financially interconnected are more leveraged; when an individual bank is more connected to other banks, it is also more leveraged; countries in which the banking sector is more connected tend to have more leveraged banks. Although these empirical relations do not test the specific mechanism that in the model generates the positive association between connectivity and leverage, they are consistent with it.

After showing that in the data there is a strong association between interconnectivity and leverage, we turn to the second question addressed in this paper: why interconnectivity and leverage increased before the crisis and drastically reversed after the crisis. In general, the simultaneous increase in leverage and interconnectivity could be caused by two forces: higher incentive for banks to leverage and/or more favorable conditions for diversification. We explore one particular mechanism which is based on the Bayesian updating about the likelihood of a crisis.

We first extend the model by adding an aggregate shock to the whole banking sector. A negative realization of this shock takes the form of a fall in the investment return of all banks, which we interpret as an economy-wide banking crisis. Furthermore, we assume that the probability distribution of the aggregate shock is unknown and banks make their portfolios decisions based on the 'belief' about the probability of a crisis. The belief is then updated over time through Bayesian learning.

Bayesian learning implies that when a crisis (negative aggregate shock) does not materialize, banks lower the assessed risk of a crisis. But a lower assessed risk implies that it is optimal for banks to leverage more and become more interconnected. The first time a crisis materializes, however, the probability of a crisis is revised upward. Importantly, if a crisis is a low probability event, the observation of a crisis induces a large upward revision of the assessed risk. This causes a drastic reduction in leverage and interconnectivity. In this way, the model with Bayesian learning can generate the dynamics of interconnectivity and leverage observed in data, which is characterized by a gradual upward trend before the crisis and a drastic reversal after the crisis. We also contrast the learning mechanism with two alternative mechanisms: the increase in return differential between bank investments and liabilities (which encourages leverage) and the decline in the cost of interbank diversification as a result of financial innovations (which facilitates interbank connectivity).

The model also provides some predictions about the investment sensitivity of heterogeneous banks to the aggregate shock. In particular, it predicts that the investment growth of more interconnected banks falls more than less interconnected banks in response to a negative aggregate shock. We test this property empirically and find that after the crisis the fall in lending growth was in fact more pronounced for banks that were more interconnected.

The paper is organized as follows. Section 1.1 provides a brief review of the most related studies. Section 2 describes the basic model and characterizes its properties. Section 3 investigate empirically the relation between interconnectivity and leverage predicted by the model. Section 4 extends the model by adding aggregate shocks and Bayesian learning about the distribution of these shocks. Section 5 studies the investment sensitivity of heterogenous banks to aggregate shocks. Section 6 concludes.

1.1 Related literature

The paper is related to several strands of literature. The first is the literature on interconnectedness. There are many theoretical contributions starting with Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000). They provided the first formal treatments of how interconnectedness within the financial sector can be a source of propagation of shocks. These two papers led to the development of a large literature. More recently, David and Lear (2011) proposed a model in which large interconnection facilitates mutual private sector bailouts as opposed to government bailouts. Allen, Babus, and Carletti (2012) proposed a model where asset commonalities between different banks affect the likelihood of systemic crises. Eiser and Eufinger (2014) showed that banks could have an incentive to become interconnected to exploit their implicit government guarantee. Finally, Acemoglu at el. (2015) proposed a model where a more densely connected financial network enhances financial stability for small realization of shocks. However, beyond a certain point, dense interconnection serves as a mechanism for the amplification of large shocks, leading to a more fragile financial system.

On the empirical side, Billio et al.(2012) proposed some measures of systemic risk based on principal components analysis and Granger-causality tests. Cai, Saunders and Steffen (2014) presented evidence that banks who are more interconnected are characterized by higher measures of systemic risk.[1] Moreover, Hale et al. (2016) studied the transmission of financial crises via interbank exposures based on deal-level data on interbank syndicated loans. They distinguished direct exposure (first degree) and indirect exposure (second degree) and found that direct exposure reduces bank profitability.[2] Peltonen et al. (2015) analyzed the role of interconnectedness of the banking system as a source of vulnerability to crises.

The second strand of literature related to this paper is on bank leverage. In a series of papers, Adrian and Shin (2010, 2011, 2014) documented that leverage is pro-cyclical and there is a strong positive relationship between leverage and balance sheet size. They also showed that, at the aggregate level, changes in balance sheets impact asset prices via changes in risk appetite.[3] Nuno and Thomas (2012) documented the presence of a bank leverage cycle in the post-war US data. They showed that leverage is more volatile than GDP, and it is pro-cyclical both with respect to total assets and GDP. Devereux and Yetman (2010) showed that leverage constraints can also affect the nature of cross-countries business cycle co-movements.

The third strand of literature includes empirical studies that use bank-level data. Gropp and Heider (2010) analyzed the determinants of capital structure for the largest American and European listed banks and concluded that bank fixed effects are the most important determinants of leverage. Kalemli-Ozcan et al (2012) documented a rise in leverage in many developed and developing countries using micro data from ORBIS. Bremus et al (2014) used our same data to illustrate the granularity nature of banking industry in many countries and its implication for macroeconomic outcomes.

Our work is also related to the literature on learning. Pastor and Veronesi (2009) provided an overview of the use of learning in the finance literature. Closer to our learning mecha-

[1]See also Drehmann and Tarashev (2013) for an empirical analysis of banks interconnectedness and systemic risk, as well as Cetorelli and Goldberg (2012) and Barattieri et. al (2015) for an application of financial interconnectedness to the monetary policy transmission.

[2]See also Liu et al., 2015 for an analysis of different sources of interconnectedness in the banking sector.

[3]Geanakopulos (2010) and Simsek (2013) proposed some explanations for the pro-ciclicality of leverage.

nism is Boz and Mendoza (2014) who proposed a model where Bayesian learning about the financial risk can generate credit booms and busts.

Finally, the last part of our paper is related to the literature that studies the impact of the Great Recession on bank lending. We find that more interconnected banks experienced larger contractions in lending growth, which is consistent with the findings of Ivashina and Scharfstein (2010) and Abbassi et al (2015). Our paper provides a theoretical framework that rationalizes these empirical findings.

The above review shows that there are many contributions studying the determinants of bank interconnectedness or bank leverage. However, most of these studies focus either on interconnectivity or leverage but not how they are related. In contracts, a central goal of this paper is to understand how interconnectedness and leverage are related to each other. In this respect our paper is related to Shin (2009) and Gennaioli et al (2013). These two papers also proposed theoretical mechanisms in which bank interconnectedness and leverage are linked but through different mechanisms. The contribution of our paper is also empirical as it uses data from a large sample of banks from OECD countries to explore the empirical significance of the theory.

2 The model

In order to show the key forces that determine the portfolio decisions of an individual bank, we start describing a simplified version of the model that abstracts from aggregate shocks. After characterizing the model without aggregate uncertainty we add a shock that affects the investment return of all banks. This will allow us to study the aggregate dynamics of the whole banking sector.

Consider a bank owned by an investor with utility

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \ln(c_t),$$

where c_t represents the dividends paid by the bank and $\beta < 1$ is the intertemporal discount factor. The concavity of the utility function (which for simplicity takes the log-form) is an important feature of the model.

There are different ways of thinking about the assumption that banks value dividends through a concave utility function. One interpretation is that the function represents the preferences of the major shareholders of the bank. Alternatively we can think of this function as representing the preferences of the top management who must hold some of the shares for incentive purposes, that is, to insure that the interests of managers are aligned with shareholders. It can also be interpreted as capturing, in reduced form, the possible costs associated with financial distress: even if shareholders and managers are risk-neutral, the convex nature of financial distress costs would make the objective of the bank concave.

Denote by a_t the net worth of the bank at time t. Given the net worth, the bank could sell liabilities l_t to the nonfinancial sector at the market price $1/R^l_t$ and make risky investments k_t (also in the nonfinancial sector) at the market price $1/R^k_t$. The investment return at the beginning of the next period is $z_{t+1}k_t$, where z_{t+1} is a stochastic variable observed at $t+1$. We assume that z_{t+1} is independently and identically distributed across banks (idiosyncratic) and over time with $\mathbb{E}_t z_{t+1} = 1$. Therefore, R^k_t is the expected return from the investment while $z_{t+1}R^k_t$ is the actual return realized at $t+1$. There is no uncertainty on the liability side. Therefore, R^l_t is the expected and actual return.

The investment risk generates a demand for insurance that can be obtained through interbank diversification. Each bank can sell a share α_t of its risky investments to other banks and purchase a *diversified* portfolio f_t of risky investments from other banks. For an individual bank, the term $\alpha_t k_t$ represents interbank liabilities while f_t represents interbank assets. The market price for interbank liabilities and assets is denoted by $1/R^f$.

Even if a fraction α_t of the risky investments are sold to other banks, the originating bank continues to manage the investments. The purchasing banks are only entitled to a share α_t of the return.[4] Agency problems, however, limit the degree of diversification. When a bank

[4]The sale of bank investments to other banks is not equivalent to the sale of its equity shares. The holder of equity shares is entitled to the profits of the bank which depend also on the cost of the bank liabilities. Instead, the holders of the fraction α_t of the bank investments are entitled to the return of the bank investments independently of the cost of the bank liabilities. Syndicated loans is perhaps the closer

sells part of the risky investments, it may be prone to opportunistic behavior that weakens the return for external investors. This is captured, parsimoniously, by the cost $\varphi(\alpha_t)k_t$, where the function $\varphi(\alpha_t)$ is strictly convex. We refer to this function as the 'diversification cost'.

Assumption 1. *The diversification cost takes the form* $\varphi(\alpha_t) = \chi\alpha_t^\gamma$, *with* $\gamma > 1$.

The specific functional form assumed here is not essential but it is analytically convenient because it allows us to study the importance of the diversification cost by changing a single parameter, χ.

The problem solved by the bank can be written recursively as

$$V_t(a_t) = \max_{c_t,l_t,k_t,\alpha_t,f_t} \Big\{ \ln(c_t) + \beta\mathbb{E}_t V_{t+1}(a_{t+1}) \Big\} \tag{1}$$

subject to:

$$c_t = a_t + \frac{l_t}{R_t^l} - \frac{k_t}{R_t^k} + \frac{[\alpha_t - \varphi(\alpha_t)]k_t}{R_t^f} - \frac{f_t}{R_t^i}$$

$$a_{t+1} = z_{t+1}(1-\alpha_t)k_t + f_t - l_t.$$

The bank maximizes the discounted expected utility of the owner given the initial net worth $a_t = z_t(1-\alpha_{t-1})k_{t-1} + f_{t-1} - l_{t-1}$. The problem is subject to the budget constraint and the law of motion for the next period net worth. The first order conditions imply

$$R_t^f = R_t^l,$$

$$R_t^f = R_t^k\Big[1 - \varphi(\alpha_t) - \varphi'(\alpha_t) + \alpha_t\varphi'(\alpha_t)\Big].$$

Notice that the return from the interbank diversified portfolio, R_t^f, must be equal to the cost of bank liabilities, R_t^l. This has a simple intuition. Since the investment in a diversified portfolio is not risky, if $R_t^f > R_t^l$ every bank could arbitrage this investment by financing it

example to this type of arrangements.

with debt without incurring any risk. This is not the case with risky investments because of the limited ability to diversify them (due to the diversification cost). Banks would then demand a risk premium over the cost of its liabilities. Later, when we introduce the aggregate banking shock, the investment f_t is no longer riskless and, therefore, R_t^f will no longer be equal to R_t^l.

Combining the above two conditions we can express the return spread between risky investments and liabilities as

$$\frac{R_t^k}{R_t^l} = \frac{1}{1 - \varphi(\alpha_t) - \varphi'(\alpha_t) + \alpha_t \varphi'(\alpha_t)}. \tag{2}$$

This condition determines the share of risky investments sold to other banks, α_t, as a function of the return spread R_t^k/R_t^l. The following lemma establishes how the return spread and the diversification cost affect α_t.

Lemma 2.1. *Diversification α_t is strictly increasing in $\frac{R_t^k}{R_t^l}$ and strictly decreasing in χ if $\alpha_t < 1$.*

Proof 2.1. *We compute the derivative of α_t with respect to the return spread R_t^k/R_t^l from condition (2) by applying the implicit function theorem. Denoting by $x_t = R_t^k/R_t^l$ the return spread we obtain $\partial\alpha_t/\partial x_t = 1/[(1-\alpha_t)\varphi''(\alpha_t)x_t^2]$. Given the functional form for the diversification cost (Assumption 1), $\varphi''(\alpha_t) > 0$. Next we compute the derivative of α_t with respect to χ. Again, applying the implicit function theorem to condition (2) we obtain $\partial\alpha_t/\partial\chi = -[\alpha_t^\gamma + \gamma(1-\alpha_t)\alpha_t^{\gamma-1}]/[\gamma(\gamma-1)\chi(1-\alpha_t)\alpha_t^{\gamma-2}]$, which is negative if $\alpha_t < 1$.* ■

The monotonicity with respect to the return spread and the diversification cost is conditional on having α_t smaller than 1. Although α_t could be bigger than 1 for an individual bank, this cannot be the case for the whole banking sector.

2.1 Reformulation of the bank problem

We now take advantage of one special property of the model. Since in equilibrium $R_t^f = R_t^l$, only $l_t - f_t$ is determined for an individual bank. It will then be convenient to define the net liabilities $\bar{l}_t = l_t - f_t$ (net of the interbank financial assets). We also define $\bar{k}_t = (1-\alpha_t)k_t$ the retained risky investments. Using these new variables, the optimization problem of the bank can be rewritten as

$$V_t(a_t) = \max_{c_t,\bar{l}_t,\bar{k}_t} \left\{ \ln(c_t) + \beta \mathbb{E}_t V_{t+1}(a_{t+1}) \right\} \tag{3}$$

subject to:

$$c_t = a_t + \frac{\bar{l}_t}{R_t^l} - \frac{\bar{k}_t}{\bar{R}_t^k}$$

$$a_{t+1} = z_{t+1}\bar{k}_t - \bar{l}_t,$$

where $\bar{R}_t^k$ is the *adjusted* return spread defined as

$$\bar{R}_t^k = \frac{1}{\frac{1}{(1-\alpha_t)R_t^k} - \frac{\alpha_t - \varphi(\alpha_t)}{(1-\alpha_t)R_t^l}}. \tag{4}$$

The adjusted return spread depends on the two exogenous returns R_t^l and R_t^k, and on the optimal diversification α_t which is determined by equation (2). Since α_t depends only on R_t^k and R_t^l, the adjusted return spread is only a function of these two exogenous returns.

The next lemma, which will be used later for the derivation of some of the key results of the paper, establishes that the adjusted return spread $\bar{R}_t^k/R_t^l$ increases in R_t^k/R_t^l.

Lemma 2.2. *The adjusted return spread $\bar{R}_t^k/R_t^l$ is strictly increasing in R_t^k/R_t^l.*

Proof 2.2. *Condition (16) can be rewritten as*

$$\frac{R_t^l}{\bar{R}_t^k} = \frac{1}{(1-\alpha_t)}\frac{R_t^l}{R_t^k} - \frac{\alpha_t - \varphi(\alpha_t)}{(1-\alpha_t)}.$$

Eliminating $\frac{R_t^l}{R_t^k}$ using (2) and re-arranging we obtain

$$\frac{\bar{R}_t^k}{R_t^l} = \frac{1}{1-\varphi'(\alpha_t)}.$$

Since α_t is strictly increasing in R_t^k/R_t^l (see Lemma 2.1) and $\varphi'(\alpha_t)$ is strictly increasing in α_t, the right-hand-side of the equation is strictly increasing in R_t^k/R_t^l. Therefore, $\bar{R}_t^k/R_t^l$ is strictly increasing in R_t^k/R_t^l. ■

Problem (3) is a standard portfolio choice problem with two assets: a risky asset $\bar{k}_t$ with return $z_{t+1}\bar{R}_t^k$ and a riskless asset $-\bar{l}_t$ with return R_t^l. The problem has a simple solution characterized by the following lemma.

Lemma 2.3. *The optimal policy of the bank takes the form*

$$c_t = (1-\beta)a_t, \tag{5}$$

$$\frac{\bar{k}_t}{\bar{R}_t^k} = \phi_t \beta a_t, \tag{6}$$

$$-\frac{\bar{l}_t}{R_t^l} = (1-\phi_t)\beta a_t, \tag{7}$$

where ϕ_t is implicitly defined by the condition $\mathbb{E}_t\left\{\frac{1}{1+[z_{t+1}(\bar{R}_t^k/R_t^l)-1]\phi_t}\right\} = 1$, and it is strictly increasing in the return spread R_t^k/R_t^l.

Proof 2.3. *See Appendix A.*

We now have all the elements to define a banking equilibrium. At any point in time there is a distribution of banks over the net worth a, which we denote by $M_t(a)$. This is the distribution after the realization of the idiosyncratic shock in period t. The formal definition of a banking equilibrium follows.

Definition 2.1. *Given the exogenous returns R_t^k and R_t^l, a banking equilibrium in period t is defined by banks' decision rules $\alpha_t = g_t^\alpha(a)$, $c_t = g_t^c(a)$, $k_t = g_t^k(a)$, $f_t = g_t^f(a)$, $l_t = g_t^l(a)$ and interbank return $R_t^f = R_t^l$ such that the decision rules satisfy condition (2) and Lemma 2.3, and the interbank market clears, that is, $\int_a g_t^f(a)M_t(a) = \int_a g_t^\alpha(a)g_t^k(a)M_t(a)$.*

Conditions (6) and (7) in Lemma 2.3 determine $\bar{k}_t$ and $\bar{l}_t$ and the first order condition (2) determines the share of investments sold to other banks, α_t. Given $\bar{k}_t$ we can then determine $k_t = \bar{k}_t/(1-\alpha_t)$. What is left to determine are the variables f_t and l_t. Even if we cannot determine both of these two variables for an individual bank (only the net liabilities $\bar{l}_t = l_t - f_t$ are determined at the individual level), in a banking equilibrium the aggregation of individual decisions must satisfy $\int_a f_t M_t(a) = \alpha_t \int_a k_t M_t(a)$, that is, the total purchases of diversified investments must be equal to the total sales of these investments. From this we can solve for $\int_a l_t M_t(a) = \int_a (\bar{l}_t + f_t) M_t(a)$. Therefore, given the returns R_t^l and R_t^k, we can solve for the aggregate values of l_t, k_t and f_t.

2.2 Interconnectivity and leverage

We now study how interconnectivity and leverage are related in the model. We will focus on the aggregate non-consolidated banking sector and denote with capital letters aggregate variables.

The aggregate leverage is defined as the ratio of (non-consolidated) total bank assets at the end of the period, $K_t/R_t^k + F_t/R_t^l$, and (non-consolidated) total bank equities, also at the end of the period, $K_t/R_t^k - L_t/R_t^l$,

$$LEVERAGE = \frac{K_t/R_t^k + F_t/R_t^l}{K_t/R_t^k - L_t/R_t^l}. \tag{8}$$

This is obtained by summing the balance sheets of all firms but without consolidation. Therefore, total assets include not only the investments made in the nonfinancial sector, K_t/R_t^k, but also the assets purchased from other banks, F_t/R_t^l. Of course, if we were to consolidate the balance sheets of all banks, the resulting assets would not include F_t/R_t^l. Similarly for aggregate liabilities. The aggregate number can be interpret as the leverage of a representative bank.[5]

Next we define bank interconnectivity. This is the ratio of aggregate non-core liabilities (approximately, assets sold to other financial institutions) over aggregate non-consolidated

[5] This is conceptually different from Shin (2009). This paper proposes an accounting framework to characterize the overall leverage of the financial sector, netting out claims within the financial sector.

assets, that is,

$$INTERCONNECTIVITY = \frac{\alpha_t K_t / R_t^l}{K_t/R_t^k + F_t/R_t^l}. \tag{9}$$

The next step is to characterize the properties of these two indicators with special attention to the dependence from the return spread R_t^k/R_t^l and the diversification cost $\varphi(\alpha_t)$.

Proposition 2.1. *For empirically relevant parameters, leverage and interconnectivity are*

(i) strictly decreasing in the diversification cost χ*;*

(ii) strictly increasing in the return spread R_t^k/R_t^l*.*

Proof 2.1. *See Appendix B*

The dependence of leverage and interconnectivity from the return spread and the diversification cost is one of the key theoretical results of this paper that will be explored further in the empirical section.

It is important to emphasize that, although the two indices are defined by similar variables, they are not perfectly dependent. More specifically, an increase in the leverage does not necessarily imply an increase in the interconnectivity index. To see this more clearly, suppose that banks increase L_t without changing K_t and F_t. Since in equilibrium $\alpha_t K_t = F_t$, from equation (9) we can see that interconnectivity does not change. However, equation (8) shows that leverage increases. If in addition to increasing L_t banks reduce F_t (but keep K_t unchanged) then interconnectivity will decrease but leverage could decrease (provided that the reduction in F_t is not too large). Therefore, the properties stated in Proposition 2.1 do not result from a simple identity that links interconnectivity and leverage. Instead, it follows from the endogenous properties of the model outlined above.

2.3 Bank return differential

It will be convenient at this time to define the return differential for a bank and to characterize its properties. The return differential is defined as the difference between the return on total assets (revenue) and the return on total liabilities (cost), that is,

$$DIFFERENTIAL = \frac{K_t + F_t}{K_t/R_t^k + F_t/R_t^f} - \frac{L_t + \alpha_t K_t}{L_t/R_t^l + \alpha_t K_t/R_t^f}. \tag{10}$$

The asset return is calculated by dividing the average value of all assets held by the representative bank at the beginning of $t+1$, which is equal to $K_t + F_t$, by the cost incurred to purchase these assets at time t, which is equal to $K_t/R_t^k + F_t/R_t^f$. The return on liabilities is defined in a similar fashion: the value of all liabilities held by the representative bank at the beginning of $t+1$, which is equal to $L_t + \alpha_t K_t$, by the revenue from issuing these liabilities at time t, which is equal to $L_t/R_t^l + \alpha_t K_t/R_t^f$.

Proposition 2.2. *The bank return differential is*

(i) strictly increasing in the diversification cost χ*;*

(ii) strictly increasing in the return spread R_t^k/R_t^l *if* χ *is sufficiently large.*

Proof 2.2. *See Appendix C*

We will use Proposition 2.2 later when we discuss the plausibility of different mechanisms for explaining the dynamics of interconnectivity and leverage.

3 Empirical evidence

In this section we provide evidence about the correlation between interconnectivity and leverage. We start with a brief description of the data.

3.1 Data

We use data from Bankscope, a proprietary database maintained by the Bureau van Dijk. Bankscope includes balance sheet information for a very large sample of financial institutions in several countries. The sample used in the analysis includes roughly 14,000 financial institutions from 32 OECD countries. We consider different types of financial institutions: commercial banks, investment banks, securities firms, cooperative banks and savings banks. The sample period is 1999-2014. In order to minimize the influence of outliers, we winsorized the main variables by replacing extreme observations with the values of the first and last percentiles of the distribution. Appendix E provides further details for the sample selection.

Table 1 reports some descriptive statistics for the whole sample and for some sub-samples that will be used in the analysis: (i) Mega Banks (banks with total assets exceeding 100 billions dollars); (ii) Commercial Banks; and (iii) Investment Banks. The total number of observations is 257,734 with an average value of total assets of 9 billion dollars. Mega Banks are only 0.8% of the total sample (2,107 observations), but they account for a large share of aggregate assets (an average of 607 billions). Commercial banks are more than half of the sample (139,616 observations representing 55% of the sample) with an average value of assets of 6.6 billion dollars. Investment banks represent 1.6% of the sample with an average value of assets of 28.9 billion dollars.

The analysis focuses on two main statistics: *interconnectivity* and *leverage*. We present the results for selected countries and for the world averages calculated using asset based weights.

3.2 Leverage

We measure leverage as the ratio of total assets over equity, that is,

$$LEVERAGE_{it} = \frac{ASSETS_{it}}{ASSETS_{it} - LIABILITIES_{it}}. \tag{11}$$

This measure is consistent with definition (8) used in the theoretical section of the paper.

The second panel of Figure 2 presented in the introduction showed the dynamics of an asset-weighted average of leverage for the US economy. Interestingly, the aggregate dynamics presented in this figure hides very heterogeneous dynamics across different groups of banks. In the online appendix we report the dynamics of leverage for commercial and investment banks. While the trend for commercial banks is downward sloping, with a sudden increase from 2005-2007, the leverage of investment banks increased substantially in the period 2003-2007. Table 1 reports the aggregate average. When calculated on the full sample, the average is 12.6. Commercial banks are characterized by lower leverages (10.8) than investment banks (16.5).

The online appendix also reports the evolution of the aggregate leverage for selected countries. Germany, France and the UK are characterized by a leverage cycle similar to the cycle observed in the US: an increase in leverage in the period 2003-2007, followed by de-leveraging after the crisis. In contrast, in Italy, Canada and Japan, leverage remains relatively stable over the whole sample period.

3.3 Interconnectivity

Within the balance sheet of a financial institution we define the variable $DEPOSITS_{it}$ as the deposits received from non-financial institutions. They are the *core liabilities* of the bank. Denoting by $LIABILITIES_{it}$ the total liabilities, interconnectivity is then measured as

$$INTERCONNECTIVITY_{it} = \frac{LIABILITIES_{it} - DEPOSITS_{it}}{ASSETS_{it}}. \tag{12}$$

Therefore, interconnectivity is the ratio of non-core liabilities over total assets, which is consistent with the definition (9) used in the theoretical section of the paper.[6]

As shown in Table 1, the aggregate average of interconnectivity is 0.16. Commercial banks are less interconnected than investment banks (0.10 versus 0.61).

In the online appendix we report the evolution of the interconnectivity measure for each of the G7 countries using asset based weights. We also report a world measure, calculated as the asset-weighted average of all countries in the sample. These graphs show a similar dynamics as the dynamics for the United Sates shown in Figure 2: Interconnectivity has increased in the period 2000-2007 and decreased after the crisis for the world average and,

[6]As shown in the online appendix, the results presented here are robust to measuring interconnectivity as the ratio of non-core liabilities over total liabilities. Non-core liabilities have been also used to measure banks' financial vulnerability. See Hahm et al (2013).

individually, in France, Germany, United Kingdom and the United States. In Japan, Canada and Italy, however, bank interconnectivity does not show a clear trend. This could be the consequence of a lower exposure of these countries to securitization practices.[7]

Validation. Our interconnectivity measure is only a proxy for the true concept of interconnectivity, that is, bank liabilities held by other banks. This is because our measure of non-core liabilities also includes liabilities that are held by other financial institutions besides banks (for example, mutual funds and pension funds which are not included in the Bankscope sample). Although we do not have access to a precise measure of interconnectivity for individual banks, we can use aggregate banking level measures of interconnectivity to validate the robustness of our proxy. For that purpose we use data from the US Flow of Funds which provides information for the aggregated US financial sector.

Using the Flow of Funds, we construct a more refined measure of interconnectivity for the US financial sector by dividing the share of net interbank liabilities and short-term loans (including repurchasing agreements) by total assets. Using the US Flow of Funds, we also compute the less refined interconnectivity index defined in equation (12), that is, non-core liabilities over total assets. The comparison of the two measures will then provide an assessment of the accuracy of the less refined interconnectivity index we computed for each individual bank using Bankscope data.

Figure 6 shows the scatter plot for the two (aggregate) measures of interconnectivity computed from the US Flow of Funds for the whole financial sector excluding the FED, over the period 1952.1-2015.4. As can be seen from the figure, the two measures of interconnectivity are strongly correlated with each other. At least for the United States, this gives us some confidence about the validity of our proxy for bank interconnectivity computed from Bankscope data.

Figure 7 proposes a second validation exercise for our measure of interconnectivity. It plots the yearly version of the refined measure from the US Flow of Funds against the less refined measure computed from Bankscope, also for the United States. Again, we see a

[7]See Sato (2009) for a discussion of this issue for Japan and Ratnovki and Huang (2009) for Canada.

strong positive correlation between the two measures. The exception is 2008. This is likely due to the fact that the US Flow of Funds includes a larger set of financial institutions than Bankscope which could have some implications for the timing of the peak in interconnectivity (in 2007 versus 2008). In the online appendix we propose a third validation exercise based only on the comparable subset of US Commercial Banks. Taking data from the weekly survey of assets and liabilities of US commercial banks, we compute an indicator of interconnectivity as the gross interbank loans over total assets and plot it against our measure of interconnectivity for only US commercial banks computed from Bankscope data. Once again, we find a strong positive correlation between these two measures.

3.4 Interconnectivity and Leverage

We analyze the relation between interconnectivity and leverage along three dimensions: at the country level over time, and across banks.

Country-level evidence. Figure 8 draws a scatter plot for the aggregate leverage ratio against our measure of interconnectivity across time. The first panel is for the world average while the other three panels are for the United States, Canada and Japan. The graph shows a strong positive correlation between interconnectivity and leverage. In some countries—like France, Germany and especially the UK—the positive correlation between leverage and interconnectivity is particularly strong. In the UK, as for the US, we see a contemporaneous rise in interconnectivity and leverage in the period 2003-2008 followed by a subsequent decline for both variables after the crisis. The similarity in the dynamics of interconnectivity and leverage for the US and the UK might reflect the similarity of the financial systems in these two countries. On the other hand, in Japan and Canada there is not a clear relation between interconnectivity and leverage over time.

Figure 9 draws scatter plots for the leverage ratio and interconnectivity at the country level for some sample years. Also in this case we observe a positive correlation, which seems particularly strong in 2007 at the peak of the boom. On the one hand, we have low-interconnected and low-leveraged financial systems in countries like Poland, Turkey, and Mexico. On the other, we have highly interconnected and highly leveraged financial systems in countries like Switzerland, the United Kingdom and France.

We estimate conditional correlations at the country level with a simple two way fixed effect estimators. The results are reported in Table 2. In the first column we use interconnectivity at the country level as the only regressor. Thus, the estimated coefficient represents the average slope for all years in the scatter plots presented in Figure 9. Interestingly, variations in interconnectivity alone account for 38 percent of the variance in the aggregate leverage. In the second and third columns we add country and time fixed effects. Apart from the fit of the regressions which increases substantially, the interconnectivity coefficient remains positive and highly statistically significant.

While this subsection provides strong evidence for a positive correlation between financial interconnectivity and leverage at the country level, the richness of micro data available allows us to go a step further and investigate the existence of a significant correlation also at the micro level, that is, across banks.

Bank-level Evidence. We provide first some evidence for the sub-sample of large banks and then for the whole sample. Large banks are defined as financial institutions with a total value of assets exceeding 100 billion dollars. There are roughly 60 of these institutions in our sample. The average share of total assets for all financial institutions included in the sample is roughly constant at 50% over the sample period. Figure 10 shows the scatter plot of the leverage ratio against the share of non-core liabilities in these 60 institutions in various years. Also in this case we see a clear positive association between interconnectivity and leverage.

Table 3 reports some conditional correlations. In the first column we just run a simple regression using size (log of total assets) as the only control. The coefficient on the measure of interconnectivity is positive and highly statistically significant. In the second column we add country, year and specialization fixed effects (commercial versus investment and other financial institutions). Again, the coefficient on interconnectivity is positive and strongly significant. The regression fit, unsurprisingly, increases significantly. Finally, in the third column, we include firm level and time fixed effects. We are hence now exploring whether there is a positive association between interconnectivity and leverage *within* banks. Again, we find a positive and strongly significant coefficient attached to interconnectivity. In this case, also the size coefficient becomes positive and statistically significant.

We repeat the same exercise for different time periods: 1999-2007 and 2003-2007. The results are displayed in the online appendix. While the point estimates change slightly, the qualitative results remain unchanged.

Having estimated a strong positive correlation between interconnectivity and leverage for large firms, we now explore whether the relation also holds for the full sample. We concentrate here on within firms relation, thus considering a two-way fixed effects estimator. The results are reported in Table 4. The three columns correspond to the three sample periods used earlier. Again, we also condition on size which has a positive and highly significant effect. As for the measure of interconnectivity, we continue to find a positive and strongly significant coefficient.

Finally, we explore whether the within firms result changes across countries. In the online appendix we report the results obtained using a two-way fixed effects estimator in each of the G-7 countries (conditioning on the size of banks). We find positive and statistically significant coefficients for all the G-7 countries with the only exception of Canada. In summary, we find empirical evidence of a strong association between interconnectivity and leverage across firms, across countries and across time.

4 Aggregate Implications

So far we have studied the relation between interconnectivity and leverage mostly from a cross-sectional prospective, that is, we have shown that interconnectivity and leverage are highly correlated across countries, times and banks. However, the data shows that there is also a dynamic pattern over time: both interconnectivity and leverage have been rising on average before the 2008 crisis and then it sharply contracted in response to the crisis. In order to capture this dynamic pattern we extend the model by adding an aggregate shock that affects the whole banking sector. We will then show how the model can replicate, at least qualitatively, the dynamics of interconnectivity and leverage observed in the data.

We consider a shock whose realization affects the investment return of all banks in period $t+1$. This is an aggregate, uninsurable shock for the entire banking sector. We denote this shock by η_{t+1} and assume that it can take two values, that is, $\eta_{t+1} \in \{\underline{\eta}, \overline{\eta}\}$, with probability p and $1-p$ respectively. The average value of this shock is normalized to 1, that is, $\mathbb{E}\eta_{t+1} = 1$. We think of the realization $\underline{\eta} < \overline{\eta}$ as a banking crisis that causes investment losses to all banks (for instance the panic that followed Lehman's bankruptcy in September 2008 after the collapse of the real estate market).

With the addition of this shock, the return from risky investments takes the form $\eta_{t+1} z_{t+1} k_t$, where z_{t+1} is the idiosyncratic shock considered before. The main difference between z_{t+1} and η_{t+1} is that the latter, being an aggregate shock, cannot be diversified. Therefore, the investment f_t is exposed to the aggregate risk and it is no longer a riskless asset. This implies that in equilibrium the expected return from purchasing the liabilities issued by other banks, R_t^f, is no longer equal to the return on the core liabilities of the bank R_t^l. Banks will require a risk premium for holding f_t.

The problem solved by the bank can be written as

$$V_t(a_t) = \max_{c_t, l_t, f_t, k_t, \alpha_t} \left\{ \ln(c_t) + \beta \mathbb{E}_t V_{t+1}(a_{t+1}) \right\} \tag{13}$$

subject to:

$$c_t = a_t + \frac{l_t}{R_t^l} - \frac{k_t}{R_t^k} + \frac{[\alpha_t - \varphi(\alpha_t)]k_t}{R_t^f} - \frac{f_t}{R_t^f}$$

$$a_{t+1} = \eta_{t+1} \Big[z_{t+1}(1-\alpha_t)k_t + f_t \Big] - l_t.$$

This problem differs from the previous problem only in the law of motion for next period assets which becomes $a_{t+1} = \eta_{t+1}[z_{t+1}(1-\alpha_t)k_t + f_t] - l_t$. The first order conditions for α_t

and k_t imply

$$R_t^f \;=\; R_t^k\Big[1-\varphi(\alpha_t)-\varphi'(\alpha_t)+\alpha_t\varphi'(\alpha_t)\Big]. \tag{14}$$

This condition determines the share of risky investments sold to other banks, α_t, as a function of the return spread R_t^k/R_t^f, This is equal to condition (2) derived earlier. What changes is that R_t^f is no longer equal to R_t^l in equilibrium.

4.1 Reformulation of the bank problem

As before, it will be convenient to define $\bar{k}_t=(1-\alpha_t)k_t$ the retained risky investments. The optimization problem of the bank can then be rewritten as

$$V_t(a_t) \;=\; \max_{c_t,l_t,f_t,\bar{k}_t}\Big\{\ln(c_t)+\beta\mathbb{E}_tV_{t+1}(a_{t+1})\Big\} \tag{15}$$

subject to:

$$c_t=a_t+\frac{l_t}{R_t^l}-\frac{\bar{k}_t}{\bar{R}_t^k}-\frac{f_t}{R_t^f}$$

$$a_{t+1}=\eta_{t+1}\Big[z_{t+1}\bar{k}_t+f_t\Big]-l_t.$$

The variable $\bar{R}_t^k$ is the *adjusted* investment return defined as

$$\bar{R}_t^k=\frac{1}{\frac{1}{(1-\alpha_t)R_t^k}-\frac{\alpha_t-\varphi(\alpha_t)}{(1-\alpha_t)R_t^f}}. \tag{16}$$

The adjusted return depends on the 'exogenous' return R_t^k, on the 'endogenous' return R_t^f, and on the optimal diversification α_t. Since α_t depends only on R_t^k and R_t^f (see condition (14)), the adjusted return is a function of R_t^k and R_t^f.

Problem (3) is a standard portfolio choice problem with three assets. The first asset is $-l_t$ with riskless return R_t^l. The second asset is f_t with risky return $\eta_{t+1}R_t^f$. The third asset is $\bar{k}_t$ with risky return $\eta_{t+1}z_{t+1}\bar{R}_t^k$. The solution is characterized by the following lemma.

Lemma 4.1. *The optimal policy of the bank takes the form*

$$
\begin{aligned}
c_t &= (1-\beta)a_t, && (17)\\
-\frac{l_t}{R^l_t} &= (1-\phi^k_t-\phi^f_t)\beta a_t, && (18)\\
\frac{f_t}{R^f_t} &= \phi^f_t \beta a_t, && (19)\\
\frac{\bar{k}_t}{\bar{R}^k_t} &= \phi^k_t \beta a_t, && (20)
\end{aligned}
$$

where ϕ^f_t and ϕ^k_t are defined implicitly by the conditions

$$\mathbb{E}_t\left\{\frac{1}{1+\left[\eta_{t+1}z_{t+1}\left(\frac{\bar{R}^k_t}{R^l_t}\right)-1\right]\phi^k_t+\left[\eta_{t+1}\left(\frac{R^f_t}{R^l_t}\right)-1\right]\phi^f_t}\right\}=1,$$

$$\mathbb{E}_t\left\{\frac{\eta_{t+1}\left(\frac{R^f_t}{R^l_t}\right)}{1+\left[\eta_{t+1}z_{t+1}\left(\frac{\bar{R}^k_t}{R^l_t}\right)-1\right]\phi^k_t+\left[\eta_{t+1}\left(\frac{R^f_t}{R^l_t}\right)-1\right]\phi^f_t}\right\}=1.$$

Proof 4.1. *See Appendix D.*

Conditions (21) and (21) determine the shares of savings, ϕ^f_t and ϕ^k_t, allocated to diversified and non-diversified investments. Since these conditions are independent of the bank initial assets a_t, all banks allocated the same shares of wealth to the three assets $-l_t/R^l_t$, f_t/R^f_t, and $\bar{k}_t/\bar{R}^k_t$.

The definition of a banking equilibrium is similar to the model without aggregate uncertainty. The only difference is that in equilibrium the return R^f_t, which is endogenous, is not equal to the return on core bank liabilities R^l_t. Denote by $M_t(a)$ the distribution of banks in period t over the net worth a_t after the realization of the idiosyncratic and aggregate shocks. Following is a formal definition of a banking equilibrium.

Definition 4.1. *Given the exogenous returns R^l_t and R^k_t, a banking equilibrium in period t is defined by banks' decision rules $\alpha_t = g^{\alpha}_t(a)$, $c_t = g^c_t(a)$, $k_t = g^k_t(a)$, $f_t = g^f_t(a)$, $l_t = g^l_t(a)$ and interbank return R^f_t such that the decision rules satisfy condition (14) and Lemma 2.3,* *and the interbank market clears, that is,* $\int_a g_t^f(a)M(a) = \int_a g_t^\alpha(a) g_t^k(a)M(a)$.

Conditions (18)-(20) determine l_t, f_t, $\bar{k}_t$, and the first order condition (14) determines the share of investments sold to other banks, α_t. Given $\bar{k}_t$ we can then determine $k_t = \bar{k}_t/(1-\alpha_t)$. With aggregate uncertainty, the variables f_t and l_t are both determined at the level of an individual bank. In the previous version of the model without aggregate uncertainty, instead, f_t and l_t were only determined for the aggregated banking sector.

4.2 Likelihood of crises and dynamics of interconnectivity and leverage

Since the aggregate shock is assumed to be i.i.d., the actual realization of this shock affects the ex-post profitability of banks but does not affect the optimal portfolio composition chosen by banks. This implies that interconnectivity and leverage do not change over time. Instead, if the aggregate shock were persistent, the portfolio composition would change in response to a shock but only when the realization reverses (that is, when $\eta_t = \overline{\eta}$ and $\eta_{t+1} = \underline{\eta}$, or viceversa). The model would display limited dynamics and would not generate the 'gradual' increase in interconectivity and leverage observed in the period that preceded the 2008 crisis. Therefore, in this section we introduce a different approach to generate the dynamics of interconnectivity and leverage observed in the data.

We assume that the probability of a crisis p is not observable and banks make portfolio decisions based on their 'belief' about this probability. The belief is then updated using Bayes rule as banks observe new realizations of the aggregate shock η_{t+1}. As we will see, this provides a mechanism for the endogenous evolution of interconnectivity and leverage that could generate, at least qualitatively, the dynamics observed in the data. Before, specifying the details of the environment with Bayesian learning, however, it will be useful to study how the likelihood of a bank crisis, captured by the probability p, affects interconnectivity and leverage in the model.

The role of the probability p. A reduction in p have two effects on the portfolio decisions of banks. The first effect works through an increase in the expected return from risky investments. In fact, as the probability of a bank crisis declines, the probability of the good outcome increases, which raises the expected return from risky investments. The impact of the higher expected return is similar to an increase in the return spread R^k_t/R^l_t analyzed earlier. Proposition 2.1 established that a higher return spread raises interconnectivity and leverage because banks are willing to take more risk. At the same time, because they take more risk, banks have a higher incentive to become interconnected. Therefore, the first effect of a reduction in p is to raise interconnectivity and leverage.

The second effect of a lower crisis probability p on the portfolio decisions of banks works through the reduction in aggregate risk (since the probability of the bad outcome $\eta_{t+1} = \underline{\eta}$ declines). The reduction in risk encourages investments k_t and reduces the incentive to diversify, that is, the variable α_t. This implies that the impact of a lower p on the supply of diversified investments $\alpha_t k_t$ is ambiguous: k_t increases but α_t declines. The demand for diversified investments f_t, instead, increases because they are less risky. This should lead to more diversification. Thus, the overall impact on interconnectivity induced by the lower risk is ambiguous.

Since the overall impact of a change in p on interconnectivity results from two effects—the first positive while the second ambiguous—it is not possible to prove whether the impact is always positive or negative. However, in all numerical simulations we conducted, we found that interconnectivity increases when we reduce p (negative relation). This is shown in Figure 4 for a particular parametrization of the model (we will describe the parametrization below).

Learning the probability p. The next step is to think about the evolution of p. During the last two decades the financial sector in many advanced economies has gone through a process of transformation driven by financial innovations. How these changes have affected the likelihood of a bank crisis was difficult to assess. Therefore, the assumption that the market perfectly knew the magnitude of the aggregate risk—formalized in the probability

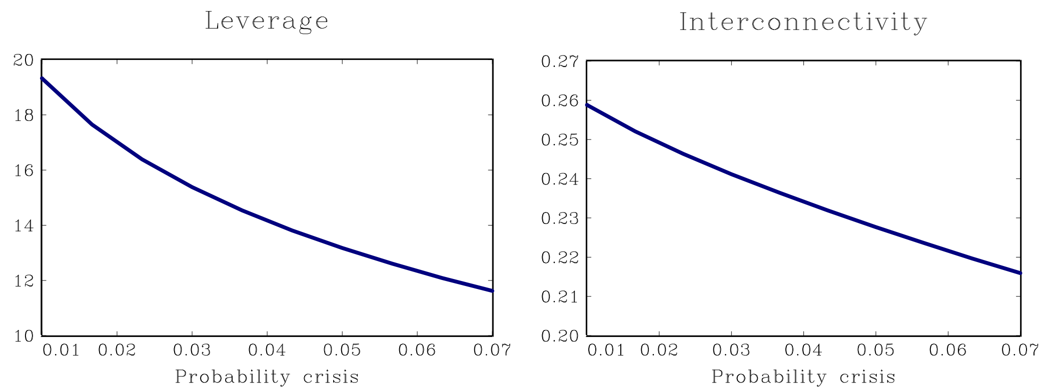

Figure 4: Dependence of leverage and interconnectivity on probability of crises.

p—may not be a plausible assumption. A more realistic assumption is that the market had some 'belief' about the aggregate risk which was then updated as new information became available.

To formalize this idea, we assume that the probability of a crisis (that is, the probability that $\eta_t = \underline{\eta}$) is itself a stochastic variable that can take two values, $p_t \in \{p_L, p_H\}$, and follows a first order Markov process with transition probability matrix $\Gamma(p_{t-1}, p_t)$. Banks do not observe p_t but they know its stochastic process, that is, they know p_L, p_H and $\Gamma(p_{t-1}, p_t)$. Thus, banks make decisions based on their 'belief' about p_t, not its true value. Technically, the belief is the probability assigned to the event $p_t = P_H$. We denote this belief probability by θ_t, that is,

$$\theta_t \equiv \text{Probability}\Big(\; p_t = p_H \;\Big).$$

Of course, the probability that $p_t = p_L$ is simply $1 - \theta_t$. Effectively, $theta_t$ represents the aggregate risk perceived by the market.

Banks start with a common prior belief θ_t. After observing the aggregate shock $\eta_t \in \{\underline{\eta}, \overline{\eta}\}$, they update the prior using Bayes rule. Since all banks start with the same belief and the updating is based on the observation of an aggregate shock, the new belief will also be the same across banks.

Denote by $g(\eta_t|p_t)$ the probability of a particular realization of the aggregate shock η_t, conditional on p_t. Formally,

$$g(\eta_t|p_L) = \begin{cases} p_L & \text{for } \eta_t = \underline{\eta} \\ 1-p_L & \text{for } \eta_t = \overline{\eta} \end{cases}, \qquad g(\eta_t|p_H) = \begin{cases} p_H & \text{for } \eta_t = \underline{\eta} \\ 1-p_H & \text{for } \eta_t = \overline{\eta} \end{cases}$$

Given the prior probability θ_t, the posterior probability conditional on the observation of η_t is equal to

$$\tilde{\theta}_t = \frac{g(\eta_t|p_H)\theta_t}{g(\eta_t|p_H)\theta_t + g(\eta_t|p_L)(1-\theta_t)}.$$

Given the posterior probability, the new prior belief becomes

$$\theta_{t+1} = \Gamma(p_H, p_H)\tilde{\theta}_t + \Gamma(p_L, p_H)(1-\tilde{\theta}_t).$$

The assumption that p_t is stochastic guarantees that learning is never complete, that is, the probability distribution never converges. This is guaranteed by the persistence of the stochastic process for p_t. If p_t were i.i.d., then the new belief will converge to 1/2 in only one period. In fact, we would have $\Gamma(p_H, p_H) = \Gamma(p_L, p_H) = 1/2$. We can then seen from the above equation that $\theta_{t+1} = 1/2$.

Model simulation. We conduct a numerical simulation starting with some prior belief θ_t. The model is simulated for N periods. In the first $N_1 < N$ periods there are no crises, that is, the realization of the aggregate shock is $\eta_t = \overline{\eta}$. Then in Period $N_1 + 1$ the economy experiences a crisis, that is, the realization of the aggregate shock is $\eta_t = \underline{\eta}$. Since the simulation is not meant to provide a full quantitative assessment of the model but only a numerical example to illustrate its qualitative properties, the parameters are not chosen according to precise calibration targets.

The diversification cost takes the form $\chi\alpha^{\nu}$ where $\chi = 0.06$ and $\nu = 1.5$. The return spread is $R^k/R^l = 1.05$. The idiosyncratic shock can take two values, $z_1 = 0.9$ and $z_2 = 1.1$ with equal probability. The aggregate shock takes the values $\underline{\eta} = 0.95$ and $\overline{\eta} = 1$. The probability of the low shock (crisis) takes the values $P_L = 0.01$ and $P_H = 0.07$. The transition probability for these two values is symmetric and highly persistent. The persistent probability is 0.99.

We start the simulation with the prior $\theta_t = 0.5$. Thus, banks assign the same probability to $p = p_L = 0.01$ (low aggregate risk) and $p = p_H = 0.07$ (high aggregate risk). The dynamics of the prior belief is shown in the second panel of Figure 5. Since in the first N_1 periods there are no negative realizations of the aggregate shock (no crises), Bayesian updating implies that the belief θ_t, that is, the probability that $p_{t+1} = p_H$, declines.

As banks revise downward the assessed probability of a crisis (which implies a higher perceived expected return from risky investments and lower risk), they chose higher leverage and interconnectivity. When the crisis materializes in period $N_1 + 1$, however, the prior probability θ_t increases drastically, which leads to a reversal in interconnectivity and leverage. The drastic change in prior belief induced by a single observation of the negative shock derives from the fact that $\eta_t = \underline{\eta}$ is a low probability event (calibrated to range between 1% and 7%). This implies that the realization of a crisis is very informative and leads to a significant revisions of its prior. The probability of a positive shock, instead, is high (between 93% and 99%). Thus, the observation of a positive shock is not very informative and leads to a moderate revision of the prior. In this way the model generates the gradual upward trend in leverage and interconnectivity before 2008 and the sharp reversal after 2008 (see Figure 2).

As we can see from Figure 5, the model also predicts that, in absence of further shocks, leverage and interconnectivity start rising again after their sharp declines. We did not observe this pattern in the data. It is important to realize, however, that the period following the crisis of 2007-2008, was characterized by the introduction of new regulations affecting both leverage (the beginning of the phase in of the Basel III capital requirements) and interconnectivity (the phase in the US of the Dodd-Frank act and the so-called 'Volcker Rule', aimed at limiting proprietary trading by banks). These new regulatory interventions (from which we abstract in the model) are likely to have played an important role in further reducing interconnectivity and leverage in the years that followed the 2007-2008 crisis.

The first panel at the bottom of Figure 5 plots the equilibrium return on diversified

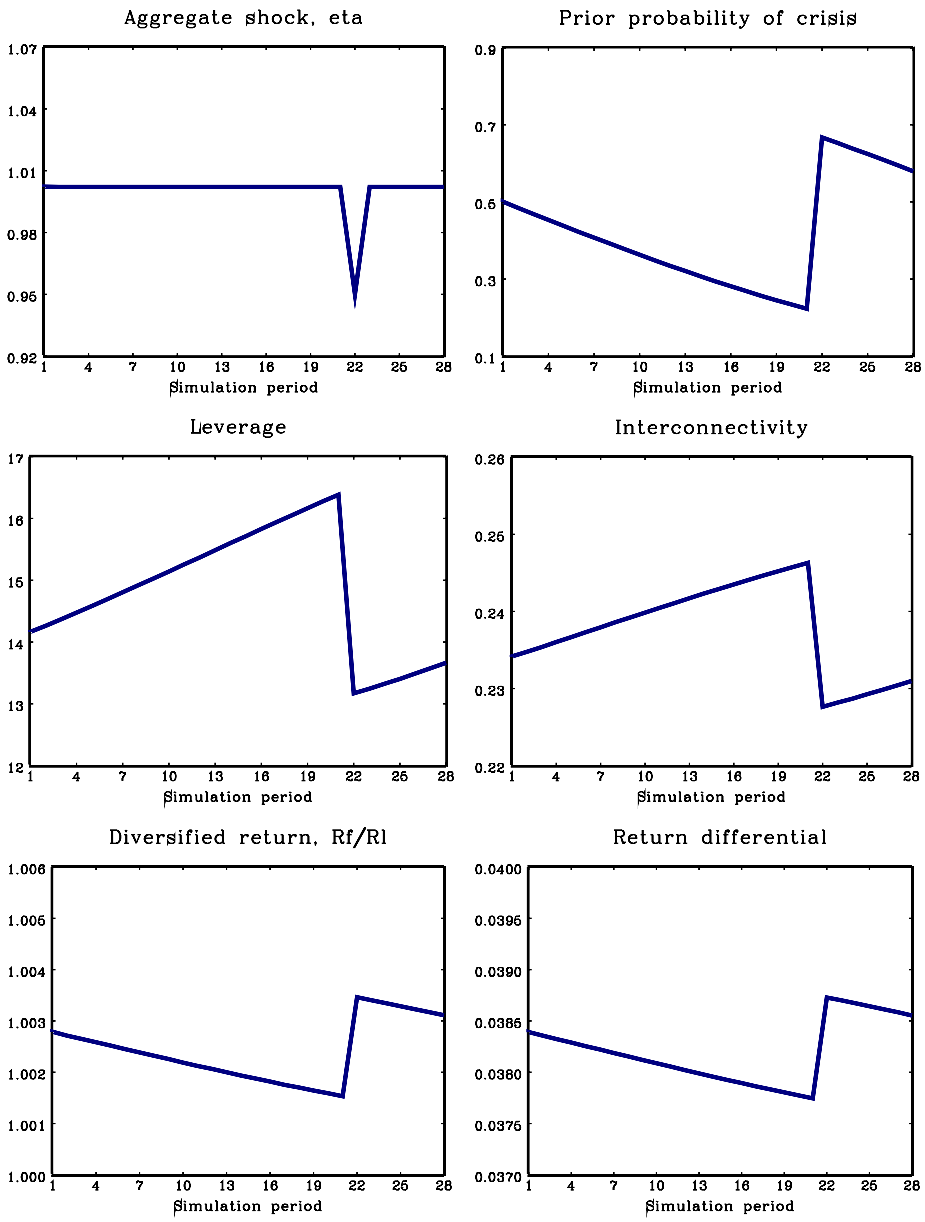

Figure 5: Dynamics of leverage and interconnectivity with learning.

investments f_t, relative to the return on bank liabilities, that is, R_t^f/R_t^l. While R_t^l is exogenously constant in the model, R_t^f is endogenously determined to clear the interbank market. Over the expansion period R_t^f declines as banks perceived these investment less risky. A reversal is then observed after the crisis.

Finally, the last panel of Figure 5 plots the bank return differential defined in equation

10. This is the difference between the return on total assets (revenue) and the return on total liabilities (cost). Even though banks perceived higher investment returns prior to the crisis, the 'actual' return differential declines until the crisis arrives. The significance of this prediction of the model will become clear in the next section.

4.3 Alternative mechanisms

Of course, learning about the aggregate risk is not the only mechanism that could have generated the dynamics of interconnectivity and leverage shown in Figure 2. In this subsection we discuss two additional mechanisms: increase in the return spread R_t^k/R_t^l and reduction in the cost of diversification captured by the parameter χ. The first change could be the result of an increase in the investment return R_t^k and/or a decline in cost of borrowing R_t^l. The second change could be the result of financial innovations that facilitated diversification.

Proposition 2.1 established that a higher return spread R_t^k/R_t^l and a lower diversification cost χ are associated with higher interconnectivity and leverage. Therefore, the pre-crisis increase in interconnectivity and leverage and the subsequent decline could have been the result of changes in the return spread and diversification cost. More specifically, an increase and subsequent decrease in the return spread (for a given cost of diversification) could have been the force underlying the observed dynamics of interconnectivity and leverage. Similarly, for a given return spread, a decrease and subsequent increase in the cost of diversification could have also generated similar dynamics.

In order to explore the empirical plausibility of the first mechanism (change in return spread), we compute an empirical proxy for the return differential of banks defined in equation (10). The empirical measure is the difference between two variables: (i) the interest income over the value of assets that earn interests; (ii) the interest expenditures over the average liabilities. More specifically,

$$DIFFERENTIAL_{it} = \frac{INT\_INCOME_{it}}{AV\_ASSETS_{it}} - \frac{INT\_EXP_{it}}{AV\_LIABILITIES_{it}}.$$

Although this measure does not reflect exactly the bank return differential defined in the model by equation (10), it is our closest empirical counterpart we can compute from the data.

Figure 11 reports the dynamics for the world asset-weighted average of the empirical measure. Interestingly, the figure shows a decline in the boom phase of 2003-2007 and a mild increase since then. This pattern is exactly the opposite of what we would see from an increase in the return spread R_t^k/R_t^l (see Proposition 2.2). Therefore, the hypothesis that the dynamics of interconnectivity and leverage were driven by an increase in return spread before the crisis and subequent decline after the crisis does not seem to be supported by the data. We should also emphasize that an increase in the value of the aggregate shock η_t before the crisis seems inconsistent with the data since it would have resulted in a higher measured return. In the learning mechanism described earlier, instead, the return differential declined prior to the crisis. In fact, the last panel of Figure 5 showed that the return differential predicted by the model declined before the crisis and then reversed after the crisis. What caused banks to take more leverage and become more interconnected was the increase in the 'perceived' return, not the 'actual' return.

Exploring the empirical plausibility of the second mechanism (reduction and subsequent increase in diversification cost) is more difficult. It would involve the construction of an empirical proxy for the diversification cost φ. In recent work, Philippon (2015) finds that the *cost of intermediation* has been rather stable over the last several decades. Although the cost of 'intermediation' is not the same object as the cost of 'diversification', nevertheless, it would be interesting to check whether a measure of the intermediation cost computed from our sample of banks shows a similar pattern as in Philippon (2015).

To do so, we compute an adjusted aggregate return on assets by summing up all the profits, assets and non-core liabilities for each financial firm i operating in country j at time t, that is,

$$ADJ\_ROA_{jt} = \frac{\sum_i PROFITS_{ijt}}{\sum_i ASSETS_{ijt} - \sum_i NON\_CORE\_LIAB_{ijt}}.$$

Subtracting the non-core liabilities is a way (admittedly crude) to net out activities taking place within the financial sector. In this way we concentrate on the intermediation activities between the ultimate lenders and the ultimate borrowers, which is closer in spirit to the exercise performed by Philippon (2015). Figure 12 reports the computed series for each of the G7 countries.

As can be seen, in most countries, the proxy for the intermediation cost is fairly stable over the period that preceded the crisis. In particular, for the United States we find a value close to 2%, in accordance to the findings of Philippon (2015). To the extent that the proxy captures our theoretical concept of diversification cost, the finding does not support the hypothesis that changes in the cost of diversification was a major factor underlying the observed dynamics of interconnectivity and leverage before and after the crisis. But even if we remain open to the view that the diversification cost has declined before the crisis, it is not obvious why it drastically increased after the crisis. If the lower diversification cost were the result of financial innovations, why would these innovations become useless after the crisis?

5 Heterogeneity and response to the aggregate shock

In the model presented so far, banks are ex-ante homogeneous and they all chose the same leverage and interconnectivity. In reality, banks could be different in several dimensions due to specialized business. For example, the core business of investment banks is different from the core business of commercial banks. It would then be useful to allow for some form of ex-ante heterogeneity and analyze how the heterogeneity affects the financial structure of banks and their response to aggregate shocks.

5.1 Heterogeneity in the model

We consider one particular form of ex-ante heterogeneity: differences in the diversification cost which in the model are captured by differences in the parameter χ. The following proposition establishes the importance of the diversification cost for inteconnectivity and leverage.

Lemma 5.1. *Banks with lower diversification cost χ are more interconnected and leveraged.*

Proof 5.1. *The leverage of banks defined as assets over equity is equal to $\phi_t^k/(1-\alpha_t)+\phi^f$. Since ϕ^f is the same for all banks while $\phi_t^k/(1-\alpha_t)$ decreases in χ, the leverage of banks with lower diversification cost is higher than for banks with higher diversification cost.*

The next step is to study how banks with different interconnectivity and leverage respond to an aggregate shock. To do so we first derive a dynamic expression for the growth rate of bank assets a_t which evolves according to

$$a_{t+1} = \eta_{t+1}(z_{t+1}\bar{k}_t + f_t) - l_t.$$

Using (18)-(19), the above equation can be rewritten as

$$\frac{a_{t+1}}{a_t} = \beta R_t^l \left\{ 1 + \left(\eta_{t+1} z_{t+1} \frac{\bar{R}_t^k}{R_t^l} - 1 \right) \phi_t^k + \left(\eta_{t+1} \frac{R_t^f}{R_t^l} - 1 \right) \phi_t^f \right\}. \tag{21}$$

Equation (21) defines the (gross) growth rate of bank assets from which we can characterize the dependence of this growth rate on the aggregate shock. Taking the derivative with respect to η_{t+1} and averaging over z_{t+1} we obtain

$$\frac{\partial \left(\frac{a_{t+1}}{a_t} \right)}{\partial \eta_{t+1}} = \beta R_t^l \left(\frac{\bar{R}_t^k}{R_t^l} \phi_t^k + \frac{R_t^f}{R_t^l} \phi_t^f \right).$$

Proposition 5.1. *The investment k_{t+1} of banks that are more interconnected is more sensitive to the aggregate shock η_{t+1}.*

Proof 5.1. *The term $\frac{\bar{R}_t^k}{R_t^l}\phi_t^k$ is decreasing in the cost of diversification χ. Thus, banks that are more interconnected are more sensitive to the aggregate shock η_{t+1}. Since investments k_{t+1} are proportional to a_{t+1}, a lower realization of η_{t+1} induces larger investment contractions for banks that are more interconnected.*

In the next subsection we investigate whether this property is supported by the data.

5.2 Empirical analysis

After the 2008 Lehman Brother bankruptcy which sparked the global financial crisis, the rate of growth of loans to the non financial sectors experienced a sharp decline. Of course, the decline in lending could have been the result of a contraction in demand and/or supply. However, the goal of this section is not to separate the causes of the lending contraction between demand and supply factors. Instead, our goal is to investigate whether the lending contraction of an individual bank was related to the degree of interconnectivity. More specifically, we investigate whether banks that at the beginning of the crisis were more interconnected experienced greater contractions in lending growth as predicted by our theoretical model (see Proposition 5.1).

We estimate the following regression equation:

$$\begin{aligned}\frac{Loans_{ikt}}{Loans_{ikt-1}} &= \alpha_0 + \alpha_1 POST\_LEHMAN + \alpha_2 POST\_LEHMAN * INTERCONN_{ik} \\ &+\alpha_3 INTERCONN_{ik} + \alpha_4 POST\_LEHMAN * LEVERAGE_{ik} \\ &+\alpha_5 LEVERAGE_{ik} + \alpha_6 Unempl_{kt-1} + \alpha_7 ln(Assets)_{ikt} + FE + \epsilon_{ijkt}\end{aligned} \tag{22}$$

The dependent variable is the growth rate of loans to non financial sectors for bank i in country k at time t. The variable $POST\_LEHMAN$ is a dummy for the 2009-2011 period.[8] $INTERCONN_{ik}$ and $LEVERAGE_{ik}$ are the averages of interconnectivity and leverage for bank i in the 2003-2006 period. $Unempl_{kt-1}$ is the unemployment rate prevailing at time $t-1$ in country k, which we use as a rough proxy for demand conditions. We control also for the size of banks (the log of total assets). FE is a set of fixed effects. We experiment with: i) country fixed effects, ii) Firm fixed effects (which make α_3 and α_5 not identifiable), iii) Firms and time fixed effects (leaving also α_1 unidentified). The residuals ϵ_{ikt} are assumed to be i.i.d normal variate with zero mean and variance σ_ϵ^2.

[8] Lehman bankruptcy happened on September 16, 2008. However, since we are using annual data, we defined the crisis as starting in 2009. For robustness we repeated the estimation using the post-Lehman dummy defined over the period 2008-2011 and the results were similar.

Equation (22) is estimated on the sub-sample of commercial banks since they are more involved in lending activities compared to investment banks or securities firms. The results are reported in Table 5.

The average drop in credit growth in the post Lehman period is substantial and significant. The coefficient for the interaction with interconnectivity has the negative sign and it is statistically significant. This implies that the drop in the growth of credit to the nonfinancial sector was larger for banks that were more interconnected before the crisis. This result is robust after controlling for country fixed effects, bank size, and country unemployment. Moving to the specifications that include banks fixed effects (columns 5 and 6), capturing within banks variation, we find a negative and significant interaction terms, consistent with our model.

In order to address the potential endogeneity of both leverage and interconnectivity, we match each bank to another bank (possibly in a different country) based on three characteristics in 2003: 1) size, 2) interest rate spreads, and 3) profitability (measured as return on average assets). We then instrument interconnectivity and leverage of each bank with the interconnectivity and the leverage of the matched bank. The logic for this identification strategy is that by belonging to a different bank, the instrument is immune from an endogeneity problem with respect to lending growth.[9] To check the goodness of the instrument we conduct a statistical test based on the Cragg-Donald statistics. We obtain very high value for the F-statistics that allow us to reject the hypothesis of weak instruments.[10] The results obtained using 2SLS are reported in Table 6. The results are broadly consistent to what we found with a simple OLS estimation.

While we are aware of the limits of the data at our disposal, the evidence presented in this section is consistent with our theoretical result: banks that were more interconnected experiences larger drops in lending growth during the crisis. This result is consistent with the findings of Ivashina and Scharfstein (2010).

[9]This method has been used in international trade to instrument trade restrictions with the restrictions of neighbouring countries. See for example Kee, Nicita and Olarreaga (2009).

[10]The appropriate critical values have been computed by Stock-Yogo (2005).

6 Conclusion

In this paper we have shown that there is a strong positive correlation between financial interconnectivity and leverage across countries, across financial institutions and over time. This is consistent with the theoretical results derived in the first part of the paper where we showed that interconnectivity and leverage are closely related: banks that are more interconnected have an incentive to leverage and banks that are more leveraged have an incentive to become more interconnected. We then extended the model to include an aggregate, uninsurable shock, that affects the whole banking sector. We interpret a negative realization of the aggregate shock as a banking crisis. The probability distribution of this shock is unknown. Banks make decisions based on their priors which are then updated over time according to Bayes rule (learning).

The model with learning can generate the dynamics of interconnectivity and leverage observed in data. The model also predicts that more interconnected banks experience sharper contractions in lending growth in response to an aggregate banking shock. We explored this prediction empirically using the "Lehman shock" as a proxy for a banking crisis. The empirical results show that more interconnected banks experienced larger contractions in lending growth during the 2008-2009 crisis.

The issue studied in the paper could open several avenues for future research. Although cross-bank diversification (interconnectivity) reduces the idiosyncratic risk for an individual bank, it does not eliminate the aggregate or 'systemic' risk which is likely to increase when the leverage of the whole financial sector increases. Our model provides a micro structure that can be embedded in a general equilibrium framework to study the issue of interconnectivity and macroeconomic stability. Moreover, this paper is relevant also for the policy discussion about financial stability that followed the 2008-2009 global financial crisis. The new Basel III accord, to be fully implemented by 2019, both includes new regulations on capital (leverage), as well as on liquidity (BIS 2011, 2014). In particular, the new "net stable funding ratio" aims at limiting the excessive usage of short term wholesale funding, a concept related to our measure of interconnectivity. Our model could be used to evaluate the impact of these two different policies, as well as the potential spillovers arising between them. We leave the study of these issues for future research.

A Proof of Lemma 2.3

The bank problem is a standard intertemporal portfolio choice between a safe and risky asset similar to the problem studied in Merton (1971). The solution takes the simple form thanks to the log-specification of the utility function together with constant return to scale investments.

We now show that ϕ_t is strictly increasing in the adjusted return spread. From Lemma 2.2 we know that the adjusted return differential $\bar{R}^k_t/R^l_t$ is strictly increasing in R^k_t/R^l_t. Therefore, we only need to prove that ϕ_t is strictly increasing in the adjusted differential $\bar{R}^k_t/R^l_t$. This can be proved by using the condition that determines ϕ_t from Lemma 2.3. For convenience we rewrite this condition here

$$\mathbb{E}_t\left\{\frac{1}{1+[z_{t+1}\bar{x}_t-1]\phi_t}\right\}=1, \tag{23}$$

where we have used the variable $\bar{x}_t = \bar{R}^k_t/R^l_t$ to denote the adjusted return differential.

Using the implicit function theorem we derive

$$\frac{\partial\phi_t}{\partial\bar{x}_t}=-\frac{\mathbb{E}_t\left\{\frac{z_{t+1}\phi_t}{[1+\phi_t[z_{t+1}\bar{x}_t-1]]^2}\right\}}{\mathbb{E}_t\left\{\frac{z_{t+1}\bar{x}_t-1}{[1+\phi_t[z_{t+1}\bar{x}_t-1]]^2}\right\}}$$

Since the numerator is positive, the sign of the derivative depends on the denominator which can be rewritten as

$$\begin{aligned}\mathbb{E}_t\left\{\frac{z_{t+1}\bar{x}_t-1}{[1+\phi_t[z_{t+1}\bar{x}_t-1]]^2}\right\} &= \mathbb{E}_t\left\{\frac{z_{t+1}\bar{x}_t-1}{1+\phi_t[z_{t+1}\bar{x}_t-1]}\right\}\left\{\frac{1}{1+\phi_t[z_{t+1}\bar{x}_t-1]}\right\}\\ &= \mathbb{E}_t\left\{\frac{z_{t+1}\bar{x}_t-1}{1+\phi_t[z_{t+1}\bar{x}_t-1]}\right\}\mathbb{E}_t\left\{\frac{1}{1+\phi_t[z_{t+1}\bar{x}_t-1]}\right\}+\\ &\quad COV\left\{\frac{z_{t+1}\bar{x}_t-1}{1+\phi_t[z_{t+1}\bar{x}_t-1]},\frac{1}{1+\phi_t[z_{t+1}\bar{x}_t-1]}\right\}\end{aligned}$$

By condition (23), the first term on the right-hand-side is equal to zero. To see this, by subtracting 1 on both sides of condition (23) we obtain

$$-\mathbb{E}_t\left\{\frac{[z_{t+1}\bar{x}_t-1]\phi_t}{1+[z_{t+1}\bar{x}_t-1]\phi_t}\right\}=0$$

Multiplying both sides by $-1/\phi_t$ we obtain

$$\mathbb{E}_t\left\{\frac{z_{t+1}\bar{x}_t-1}{1+[z_{t+1}\bar{x}_t-1]\phi_t}\right\}=0.$$

Therefore, we have

$$\mathbb{E}_t\left\{\frac{z_{t+1}\bar{x}_t-1}{[1+\phi_t[z_{t+1}\bar{x}_t-1]]^2}\right\} = COV\left\{\frac{z_{t+1}\bar{x}_t-1}{1+\phi_t[z_{t+1}\bar{x}_t-1]},\frac{1}{1+\phi_t[z_{t+1}\bar{x}_t-1]}\right\}$$

The covariance is clearly negative because the first term is strictly increasing in z_{t+1} while the second term is strictly decreasing in z_{t+1}. Therefore, $\partial\phi_t/\partial\bar{x}_t>0$. ■

B Proof of Proposition 2.1

Using $F_t=\alpha_t K_t$, the leverage ratio defined in equation (8) can be written as $\frac{1+\alpha_t\frac{R_t^k}{R_t^l}}{1-\frac{L_t/R_t^l}{K_t/R_t^k}}$. Since α_t is decreasing in χ and increasing in R_t^k/R_t^l (see Lemma 2.1), to show that the leverage is decreasing in the diversification cost and increasing in the return spread, it is sufficient to show that the term $\frac{L_t/R_t^l}{K_t/R_t^k}$ is strictly decreasing in χ and strictly increasing in R_t^k/R_t^l.

By definition $K_t=\bar{K}_t/(1-\alpha_t)$, $F_t=[\alpha_t/(1-\alpha_t)]\bar{K}_t$ and $L_t=F_t+\bar{L}_t$. From equations (6)-(7) we can derive $\bar{L}_t=-[(1-\phi_t)/\phi_t](R_t^l/\bar{R}_t^k)\bar{K}_t$. Using these terms, we have

$$\frac{L_t/R_t^l}{K_t/R_t^k}=\left[\alpha_t-(1-\alpha_t)\left(\frac{1-\phi_t}{\phi_t}\right)\frac{R_t^l}{\bar{R}_t^k}\right]\frac{R_t^k}{R_t^l}.$$

We now use equation (16) to replace $\bar{R}_t^k$. After re-arranging we obtain

$$\frac{L_t/R_t^l}{K_t/R_t^k}=\alpha_t\frac{R_t^k}{R_t^l}+\left(\frac{\phi_t-1}{\phi_t}\right)\left[1-\alpha_t\frac{R_t^k}{R_t^l}+\varphi(\alpha_t)\frac{R_t^k}{R_t^l}\right].$$

This can be written more compactly as

$$\frac{L_t/R_t^l}{K_t/R_t^k}=\alpha_t x_t+y_t\Big[1-\alpha_t x_t+\varphi(\alpha_t)x_t\Big], \tag{24}$$

where $x_t=\frac{R_t^k}{R_t^l}$ and $y_t=\left(\frac{\phi_t-1}{\phi_t}\right)$.

Differentiating the right-hand-side with respect to χ we obtain

$$\frac{\partial\left(\frac{L_t/R_t^l}{K_t/R_t^k}\right)}{\partial\chi}=\alpha_t'x_t(1-y_t)+\Big[\chi\gamma\alpha_t^{\gamma-1}\alpha_t'+\alpha_t^{\gamma}\Big]x_t y_t,$$

where α_t' is now the derivative of α_t with respect to χ.

Since $1-y_t=1/\phi_t>0$ and $\alpha_t'<0$ (see Lemma 2.1), the first term of the derivative is negative. Therefore, a sufficient condition for the derivative to be negative is that also the second term is negative. For empirically relevant parameters $\phi_t>1$ which implies $y_t=(\phi_t-1)/\phi_t>0$. In fact, if $\phi_t<1$, then banks would choose $\bar{L}_t=L_t-F_t<0$, that is, they would have less total liabilities than financial assets invested in other banks. Thus, the second term of the derivative is negative if

$$\chi\gamma\alpha_t^{\gamma-1}\alpha_t' + \alpha_t^{\gamma} < 0.$$

In Lemma 2.1 we have derived $\alpha_t' = -[\alpha_t^{\gamma} + \gamma(1-\alpha_t)\alpha_t^{\gamma-1}]/[\chi(1-\alpha_t)\gamma(\gamma-1)\alpha_t^{\gamma-2}]$. Substituting in the above expression and re-arranging we obtain

$$1 < \frac{\gamma}{\gamma-1} + \frac{\alpha_t}{(1-\alpha_t)(\gamma-1)}.$$

Both terms on the right-hand-side are positive. Furthermore, since $\gamma > 1$, the first term is bigger than 1. Therefore, the inequality is satisfied, proving that the derivative of the leverage decreases in the diversification cost.

To show that the leverage ratio is increasing in $x_t = R_t^k/R_t^l$, we need to show that $\frac{L_t/R_t^l}{K_t/R_t^k}$ is increasing in x_t. Differentiating the right-hand-side of (24) with respect to x_t we obtain

$$\frac{\partial\left(\frac{L_t/R_t^l}{K_t/R_t^k}\right)}{\partial x_t} = (\alpha_t' x_t + \alpha_t) + y_t'\Big[1 - \alpha_t x_t + \varphi(\alpha_t)x_t\Big] + y_t\Big[\varphi_t'(\alpha_t)\alpha_t' x_t + \varphi(\alpha_t)\Big],$$

where α_t' is now the derivative of α_t with respect to x_t.

Lemma 2.1 established that α_t is increasing in $x_t = R_t^k/R_t^l$, that is, $\alpha_t' > 0$. Furthermore, Lemma 2.3 established that ϕ_t is strictly increasing in $x_t = R_t^k/R_t^l$, which implies that $y_t = \left(\frac{\phi_t - 1}{\phi_t}\right)$ is also increasing in $x_t = R_t^k/R_t^l$, that is, $y_t' > 0$. Therefore, sufficient conditions for the derivative to be positive are

$$\begin{gathered}\phi_t > 1 \\ 1 - \alpha_t x_t + \varphi(\alpha_t)x_t > 0 \quad .\end{gathered}$$

As argued above, the first condition ($\phi_t > 1$) is satisfied for empirically relevant parameterizations. For the second condition it is sufficient that $\alpha_t x_t \leq 1$, which is also satisfied for empirically relevant parameterizations. In fact, since in the data x_t is not very different from 1 (for example it is not bigger than 1.1), the condition allows α_t to be close to 1 (about 90 percent if x_t is 1.1). Since α_t represents the relative size of the interbank market compared to the size of the whole banking sector, α_t is significantly smaller than 1 in the data. Therefore, for empirically relevant parameterizations, leverage increases with the return spread $x_t = R_t^k/R_t^l$.

The next step is to prove that the interconnectivity index is decreasing in χ and increasing in $x_t = R_t^k/R_t^l$. The index can be simplified to

$$\frac{\alpha_t x_t}{1 + \alpha_t x_t}.$$

Differentiating with respect to χ we obtain

$$\frac{\partial INTERCONNECTIVITY}{\partial \chi} = \frac{\alpha_t' x_t}{(1+\alpha_t x_t)^2},$$

where α_t' is the derivative of α_t with respect to χ. As shown in Lemma 2.1, this is negative. Therefore, bank connectivity decreases in the diversification cost.

We now compute the derivative of interconnectivity with respect to x_t and obtain

$$\frac{\partial INTERCONNECTIVITY}{\partial x_t} = \frac{\alpha_t' x_t + \alpha_t}{(1+\alpha_t x_t)^2},$$

where α_t' is the derivative of α_t with respect to x_t. As shown in Lemma 2.1, this is positive. Therefore, bank connectivity increases in the return spread. ■

C Proof of Proposition 2.2

Taking into account that in aggregate $F_t = \alpha_t K_t$, the bank differential return defined in equation (10) can be rewritten as

$$DIFFERENTIAL = \left(\frac{x_t - 1}{1+\alpha_t x_t}\right) R_t^l.$$

As in the previous proof, we have defined the variable $x_t = R_t^k / R_t^l$ to be the return spread.

Differentiating with respect to χ we obtain

$$\frac{\partial DIFFERENTIAL}{\partial \chi} = -\frac{\alpha_t' x_t (x_t - 1)}{(1+\alpha_t x_t)^2} R_t^l,$$

where α_t' is the derivative of α_t with respect to χ. We have shown in Lemma 2.1 that this derivative is negative. Therefore, the return differential increases in the differentiation cost.

Consider now the dependence of the bank return differential from the return spread. The derivative of the return differential with respect to x_t is

$$\frac{\partial DIFFERENTIAL}{\partial x_t} = \frac{1+\alpha_t + x_t(1-x_t)\alpha_t'}{(1+\alpha_t x_t)^2} R_t^l,$$

where α_t' is the derivative of α_t with respect to return spread x_t. For the derivative to be positive we need that the following condition is satisfied

$$1+\alpha_t + x_t(1-x_t)\alpha_t' > 0.$$

In Lemma 2.1 we have derived $\alpha_t' = 1/[(1-\alpha_t)\varphi''(\alpha_t)x_t^2]$. Substituting in the above expression and re-arranging we obtain

$$1-(1-\alpha_t^2)\varphi''(\alpha_t)<\frac{1}{x_t}.$$

We now use equation (2) to eliminate $1/x_t$ and rewrite the condition as

$$\varphi(\alpha_t)+\varphi'(\alpha_t)-\alpha_t\varphi'(\alpha_t)>(1-\alpha_t^2)\varphi''(\alpha_t).$$

Using the functional form for the diversification cost specified in Assumption 1, the condition can be rewritten as

$$\left(\frac{1}{\gamma-1}\right)\alpha+\left[\frac{1+\gamma^2-2\gamma}{\gamma(\gamma-1)}\right]\alpha^2>1,$$

which is satisfied if α_t is sufficiently small. Since α_t is decreasing in χ, a sufficiently high value of χ guarantees that the bank return differential is increasing in the return spread $x_t=R_t^k/R_t^l$. For example, when the diversification cost takes the quadratic form ($\gamma=2$), it is sufficient that $\alpha_t\leq 0.73$. This upper bound for α_t is significantly larger than the average value observed for the whole banking sector. (See Figure 2 for the US). ■

D Proof of Lemma 4.1

The first order conditions for Problem (15) with respect to l_t, f_t and $\bar{k}_t$ are, respectively

$$\frac{1}{c_tR_t^l}=\beta\mathbb{E}_t\frac{1}{c_{t+1}}\tag{25}$$

$$\frac{1}{c_tR_t^f}=\beta\mathbb{E}_t\frac{\eta_{t+1}}{c_{t+1}}\tag{26}$$

$$\frac{1}{c_t\bar{R}_t^k}=\beta\mathbb{E}_t\frac{\eta_{t+1}z_{t+1}}{c_{t+1}}\tag{27}$$

We now guess that the optimal consumption policy takes the form

$$(1-\gamma)a_t,\tag{28}$$

where γ is a constant parameter. We will later verify the guess. Thus γa_t is the saved wealth for the next period.

Define ϕ_t^f the fraction allocated to (partially) diversified investments, that is, $f_t/R_t^f=\phi_t^f\gamma a_t$; ϕ_t^k the fraction of savings allocated to risky investments, that is, $\bar{k}_t/\bar{R}_t^k=\phi_t^k\gamma a_t$. The remaining fraction $1-\phi_t^f-\phi_t^k$ will then be allocated to the safe investment, that is, $-l_t/R_t^l=(1-\phi_t^f-\phi_t^k)\gamma a_t$. Using these shares and the guess about the savings, the next period wealth will be

$$a_{t+1}=\left\{1+\left[\eta_{t+1}z_{t+1}\left(\frac{\bar{R}_t^k}{R_t^l}\right)-1\right]\phi_t^k+\left[\eta_{t+1}\left(\frac{R_t^l}{R_t^l}\right)-1\right]\phi_t^f\right\}\gamma a_tR_t^l\tag{29}$$

We now use (28) and (29) to replace c_t, c_{t+1}, a_{t+1} in the first order conditions (25)-(27) and obtain

$$\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{1}{1 + \left[\eta_{t+1} z_{t+1} \left(\frac{\bar{R}_t^k}{R_t^l}\right) - 1\right] \phi_t^k + \left[\eta_{t+1} \left(\frac{R_t^l}{R_t^l}\right) - 1\right] \phi_t^f} \right\} \tag{30}$$

$$\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{\eta_{t+1} z_{t+1} \left(\frac{\bar{R}_t^k}{R_t^l}\right)}{1 + \left[\eta_{t+1} z_{t+1} \left(\frac{\bar{R}_t^k}{R_t^l}\right) - 1\right] \phi_t^k + \left[\eta_{t+1} \left(\frac{R_t^l}{R_t^l}\right) - 1\right] \phi_t^f} \right\} \tag{31}$$

$$\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{\eta_{t+1} \left(\frac{R_t^f}{R_t^l}\right)}{1 + \left[\eta_{t+1} \left(\frac{\bar{R}_t^k}{R_t^l}\right) - 1\right] \phi_t^k + \left[\eta_{t+1} \left(\frac{R_t^l}{R_t^l}\right) - 1\right] \phi_t^f} \right\} \tag{32}$$

Next we can show that γ must be equal to β and, therefore, we obtain (21) and (21).

E Data Appendix

The data on bank balance sheets are taken from Bankscope, which is a comprehensive and global database containing information on 28,000 banks worldwide provided by Bureau van Djik. Each bank report contains detailed consolidated and/or unconsolidated balance sheet and income statement. Since the data are expressed in national currency, we converted the national figures in US dollars using the exchange rates provided by Bankscope.

An issue in the use of Bankscope data is the possibility of double counting of financial institutions. In fact, for a given Bureau van Djik id number (BVDIDNUM), which identifies uniquely a bank, in each given YEAR, it is possible to have several observations with various consolidation codes. There are eight different consolidation status in Bankscope: C1 (statement of a mother bank integrating the statements of its controlled subsidiaries or branches with no unconsolidated companion), C2 (statement of a mother bank integrating the statements of its controlled subsidiaries or branches with an unconsolidated companion), C* (additional consolidated statement), U1 (statement not integrating the statements of the possible controlled subsidiaries or branches of the concerned bank with no consolidated companion), U2 (statement not integrating the statements of the possible controlled subsidiaries or branches of the concerned bank with a consolidated companion), U* (additional unconsolidated statement) and A1 (aggregate statement with no companion).[11] We polished the data in order to avoid duplicate observations and to favor consolidated statements over unconsolidated ones.

[11]See Bankscope user guide and Duprey and Lé (2013) for additional details.

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Table 1: **Summary Statistics**

	Number Obs		Total Assets		Leverage		Interconnectivity	
	Total	%	mean	s.d.	mean	s.d.	mean	s.d.
ALL	257,734		9,090	82,080	12.6	9.0	0.16	0.20
of which:								
MEGA BANKS	2,107	0.8	607,370.5	576,543.4	25.6	15.2	0.57	0.24
Commercial Banks	139616	54	6,682	70,991	10.8	5.6	0.10	0.15
Investment Banks	4,205	1.6	28,985	97,320	16.5	19.0	0.61	0.30

Notes: Millions of USD.

Table 2: **Interconnectivity and Leverage: Cross-Country Evidence**

Dep Variable	A/E	A/E	A/E
INTERCONN	30.666***	28.305***	27.448***
	(1.574)	(2.141)	(2.159)
Country FE	No	Yes	Yes
Time FE	No	No	Yes
R-squared	0.427	0.832	0.866
N	512	512	512

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

Table 3: **Interconnectivity and Leverage, Very Large Financial Institutions (1999-2014)**

Dep Variable	A/E	A/E	A/E
INTERCONN	36.112***	34.246***	28.821***
	(1.735)	(3.006)	(7.937)
size	0.054	-0.860*	4.492*
	(0.377)	(0.456)	(2.361)
Specialisation FE	No	Yes	No
Country FE	No	Yes	No
Time FE	No	Yes	Yes
Banks FE	No	No	Yes
R-squared	0.349	0.500	0.191
N	1281	1281	1281

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

Table 4: **Interconnectivity and Leverage, All financial institutions**

Dep Variable	A/E	A/E	A/E
Time Period	1999-2014	1999-2007	2003-2007
INTERCONN	8.334***	6.657***	5.776***
	(0.453)	(0.683)	(0.776)
size	2.470***	2.660***	2.736***
	(0.100)	(0.134)	(0.181)
Banks FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R-squared	0.106	0.134	0.137
N	176649	125787	69563

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

Table 5: **2008 Crisis impact on Lending Growth - Sensitivity to Interconnectivity - 2003-2011- Commercial Banks**

	(1)	(2)	(3)	(4)	(5)	(6)
POST LEHMAN (2009-)	-0.110***	-0.066***	-0.122***	-0.107***	-0.164***	
	(0.002)	(0.005)	(0.007)	(0.007)	(0.008)	
LEHMAN*INTERCONN		-0.196***		-0.218***	-0.207***	-0.199***
		(0.015)		(0.016)	(0.015)	(0.015)
INTERCONN		-0.009		0.018*		
		(0.010)		(0.010)		
LEHMAN*LEVERAGE			0.002***	0.003***	0.008***	0.008***
			(0.000)	(0.000)	(0.000)	(0.000)
LEVERAGE			-0.007***	-0.007***		
			(0.000)	(0.000)		
log(Assets)		0.009***	0.012***	0.014***	-0.000	0.029***
		(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
Unempl		-0.011***	-0.006***	-0.010***	-0.008***	-0.003**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Country FE	No	Yes	Yes	Yes	No	No
Banks FE	No	No	No	No	Yes	Yes
Time FE	No	No	No	No	No	Yes
R-squared	0.032	0.065	0.071	0.074	0.072	0.080
N	76133	74199	74465	74194	74194	74194

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

Table 6: **2008 Crisis impact on Lending Growth - Sensitivity to Interconnectivity - 2003-2011- Commercial Banks - Instrumental Variables**

	(1)	(2)	(3)	(4)	(5)
POST LEHMAN (2009-)	-0.082***	-0.104***	-0.080***	-0.118***	
	(0.009)	(0.021)	(0.022)	(0.022)	
LEHMAN*INTERCONN	-0.173***		-0.193***	-0.137***	-0.191***
	(0.046)		(0.048)	(0.045)	(0.051)
INTERCONN	-0.594***		-0.630***		
	(0.068)		(0.070)		
LEHMAN*LEVERAGE		-0.000	-0.000	0.001	-0.000
		(0.002)	(0.002)	(0.002)	(0.002)
LEVERAGE		-0.011***	-0.010***		
		(0.002)	(0.002)		
log(Assets)	0.030***	0.020***	0.037***	0.063***	0.103***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.004)
Unempl	-0.003*	0.000	-0.003*	0.001	-0.008***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
Country FE	Yes	Yes	Yes	No	No
Banks FE	No	No	No	Yes	Yes
Time FE	No	No	No	No	Yes
R-squared	0.012	0.050	0.021	0.055	0.068
N	67791	67991	67791	67359	67359
Cragg-Donald Wald F	637.1426	717.2184	238.8	2976.199	2429.159

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

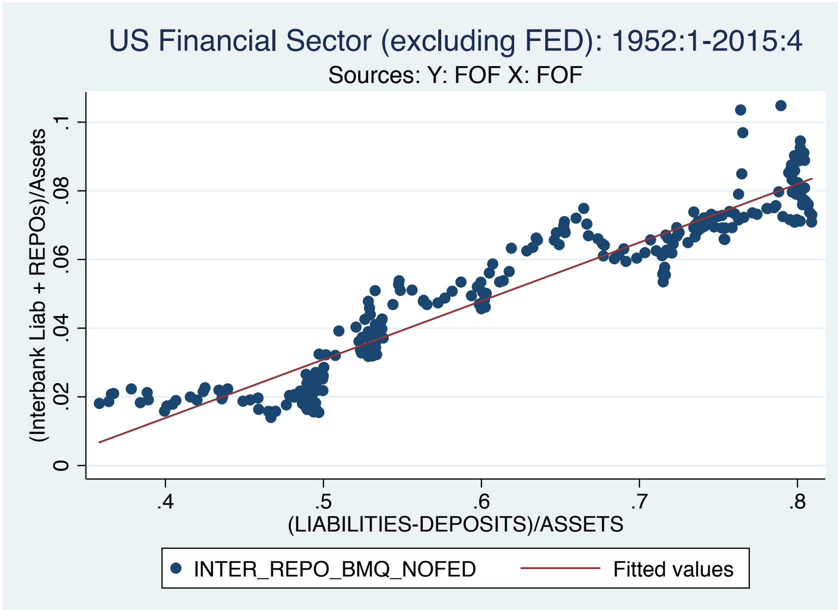

Figure 6: Alternative measures of interconnectivity, US Financial Sector, Flow of Funds

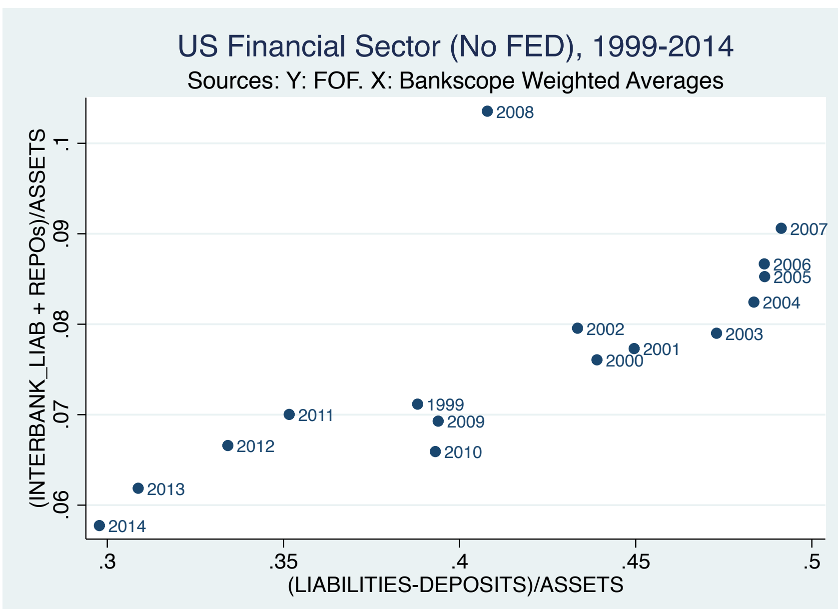

Figure 7: Alternative measures of interconnectivity, US Financial Sector, Flow of Funds and Bankscope

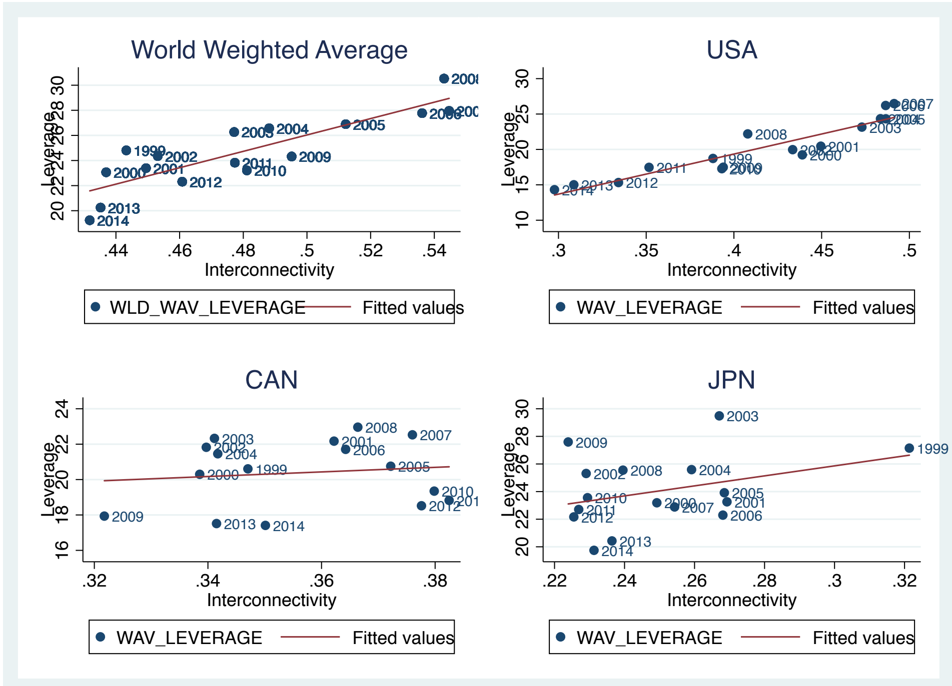

Figure 8: Leverage and Interconnectivity, Across Time, Within Selected Countries

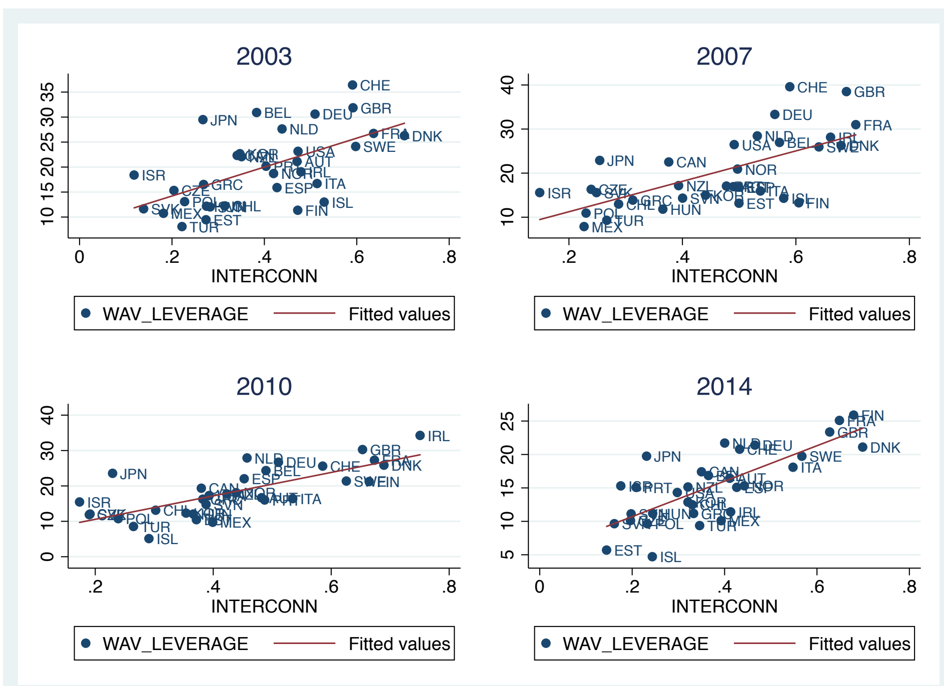

Figure 9: Leverage and Interconnectivity, Across countries, Selected Years

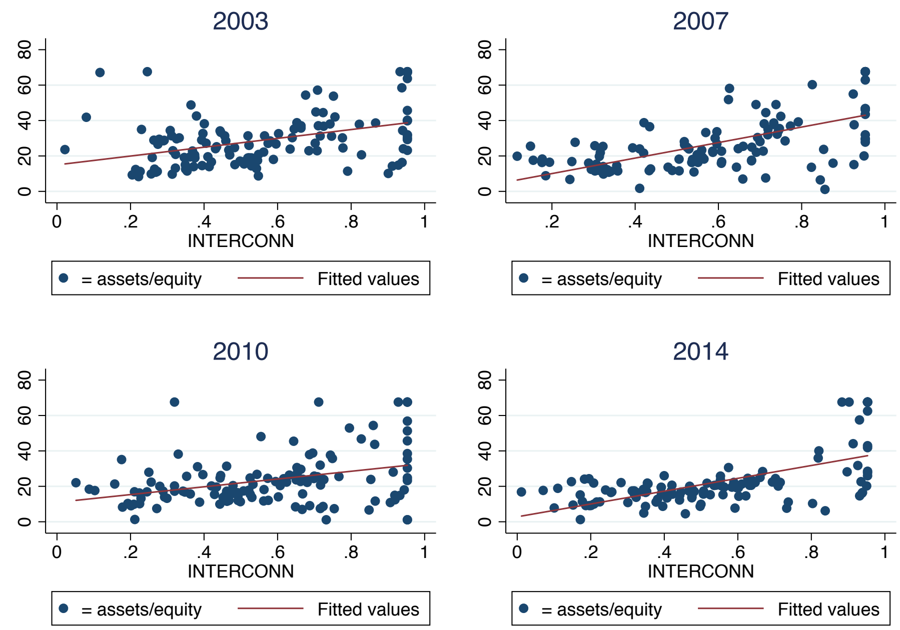

Figure 10: Leverage and Interconnectivity, Across Very Large Firms, Selected Years

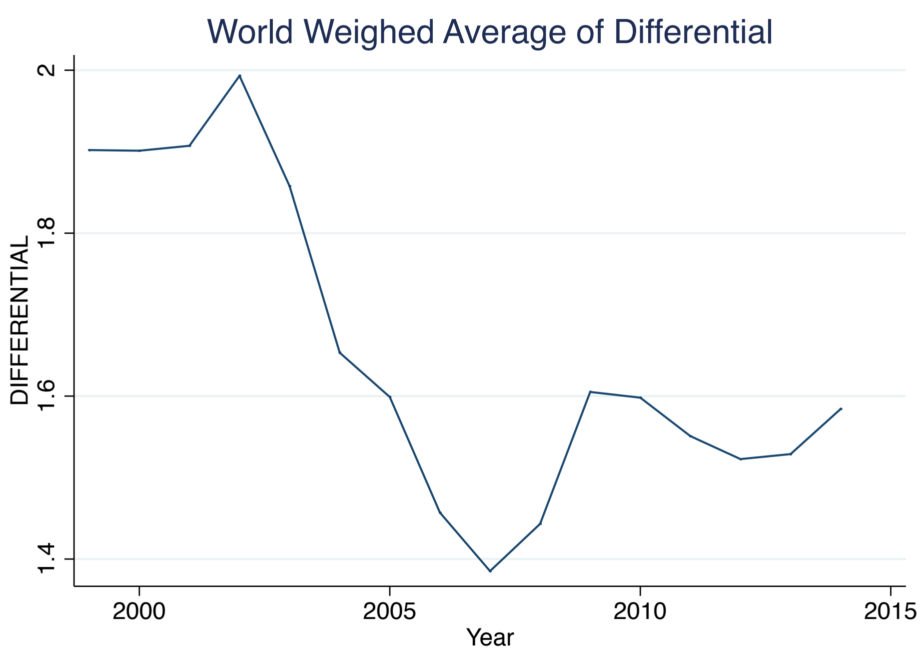

Figure 11: Return Differential over Time

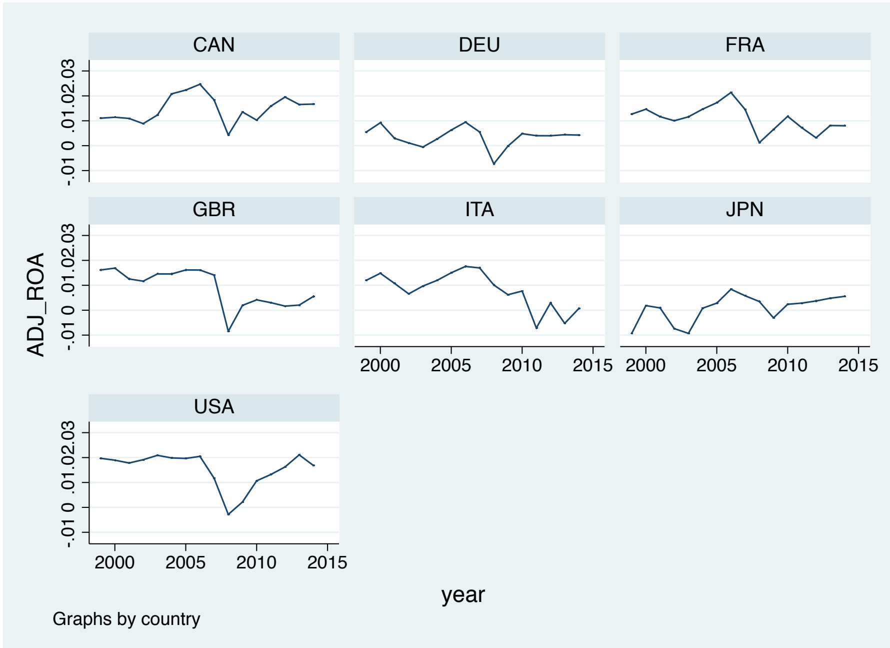

Figure 12: Estimate of Cost of Intermediation within our dataset.

Banks Interconnectivity and Leverage*

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Collegio Carlo Alberto and ESG UQAM

Laura Moretti
Central Bank of Ireland

Vincenzo Quadrini
University of Southern California

July 8 2016

ONLINE APPENDIX - NOT FOR PUBLICATION

1 Content

This appendix includes some supplementary material that we did not insert in the main text due to space constraints and the results obtained using an alternative measure for interconnectivity:

$$INTERCONNECTIVITY2 = \frac{LIABILITIES - DEPOSITS}{LIABILITIES} \tag{1}$$

The results obtained using this alternative measure of interconnectivity are very similar to those presented in the paper.

*The views expressed in this paper do not reflect the views of the Central Bank of Ireland or the European System of Central Banks. All errors are ours.

2 Supplementary Material

Table 1: **Composition of the sample by country**

Country	Obs.	Percent
AUT	4,143	1.61
BEL	1,314	0.51
CAN	1,357	0.53
CHE	6,965	2.7
CHL	565	0.22
CZE	545	0.21
DEU	28,729	11.15
DNK	1,786	0.69
ESP	2,830	1.1
EST	126	0.05
FIN	421	0.16
FRA	6,420	2.49
GBR	6,751	2.62
GRC	317	0.12
HUN	590	0.23
IRL	693	0.27
ISL	277	0.11
ISR	203	0.08
ITA	11,205	4.35
JPN	11,596	4.5
KOR	860	0.33
MEX	1,442	0.56
NLD	1,072	0.42
NOR	2,018	0.78
NZL	307	0.12
POL	763	0.3
PRT	1,007	0.39
SVK	307	0.12
SVN	310	0.12
SWE	1,680	0.65
TUR	1,055	0.41
USA	160,080	62.11
Total	257,734	100

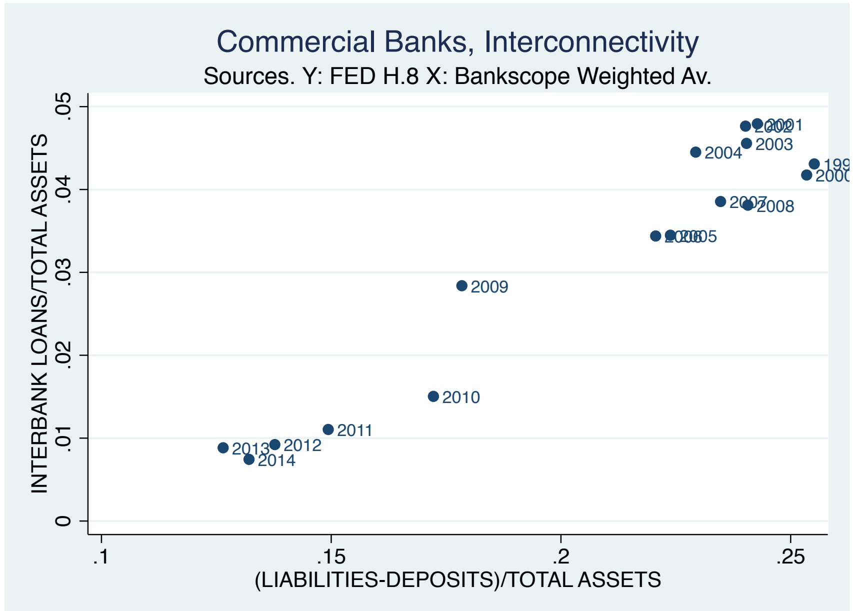

Figure 1: Alternative measures of interconnectivity, U.S. Financial Sector, Survey of Assets and Liabilities of Commercial Banks and Bankscope.

Table 2: **Interconnectivity and Leverage, Very Large Financial Institutions (1999-2007)**

Dep Variable	A/E	A/E	A/E
INTERCONN	38.593***	33.054***	15.711*
	(2.424)	(4.273)	(8.535)
size	0.994*	-0.823	6.988***
	(0.560)	(0.642)	(2.552)
Specialisation FE	No	Yes	No
Country FE	No	Yes	No
Time FE	No	Yes	Yes
Banks FE	No	No	Yes
R-squared	0.388	0.552	0.104
N	714	714	714

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

Table 3: **Interconnectivity and Leverage, Very Large Financial Institutions (2003-2007)**

Dep Variable	A/E	A/E	A/E
INTERCONN	42.942***	37.036***	17.867*
	(3.274)	(6.125)	(9.219)
size	0.240	-0.782	18.852***
	(0.828)	(0.813)	(4.721)
Specialisation FE	No	Yes	No
Country FE	No	Yes	No
Time FE	No	Yes	Yes
Banks FE	No	No	Yes
R-squared	0.403	0.588	0.203
N	403	403	403

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

Table 4: **Interconnectivity and Leverage: By Country, 1999-2011, FE**

Dep Var: A/E	USA	CAN	GBR	JPN	DEU	FRA	ITA
INTERCONN	5.300***	1.612	5.110**	-6.597	6.405***	10.584***	3.644***
	(0.368)	(1.788)	(2.292)	(4.993)	(1.441)	(3.275)	(1.186)
size	1.533***	3.249***	5.433***	6.880***	3.847***	8.443***	6.213***
	(0.073)	(0.647)	(0.620)	(0.960)	(0.542)	(0.987)	(0.778)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.056	0.189	0.297	0.074	0.534	0.293	0.221
N	132945	1055	3400	10699	26534	5071	10438

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

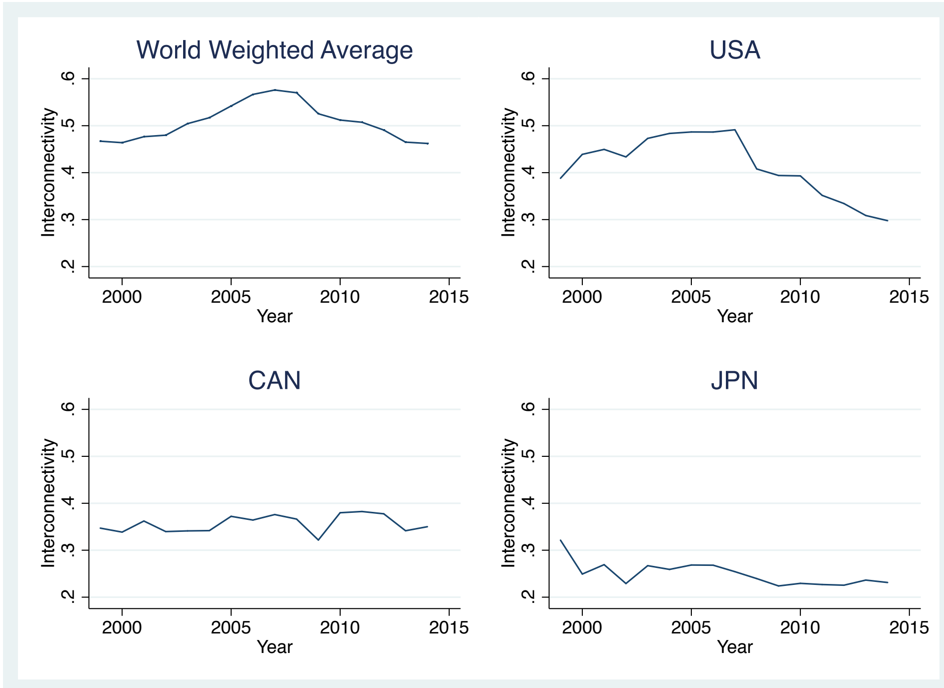

Figure 2: Interconnectivity over time, selected countries.

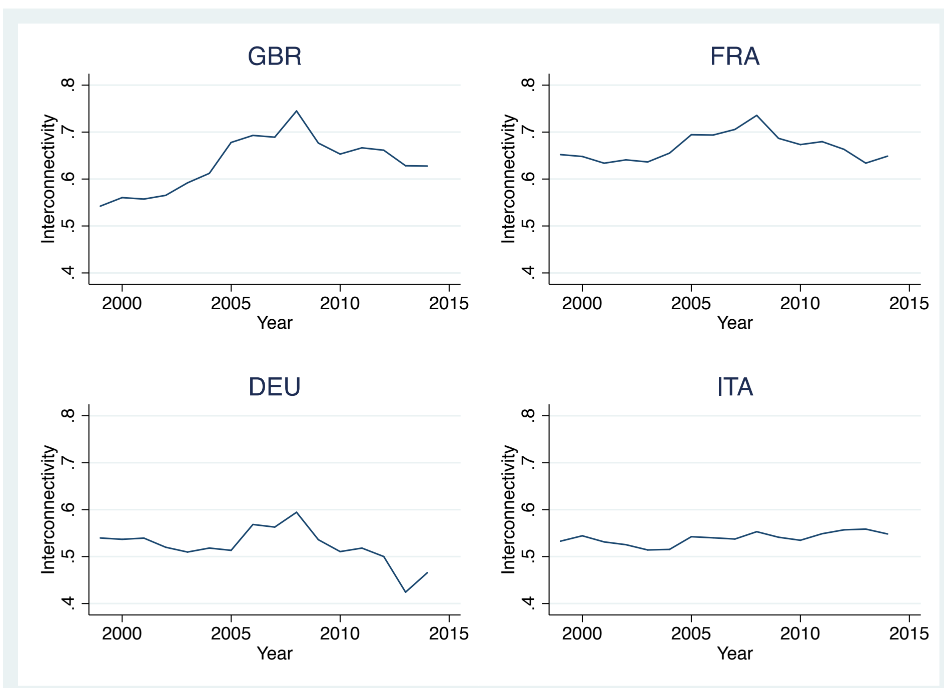

Figure 3: Interconnectivity over time, selected countries.

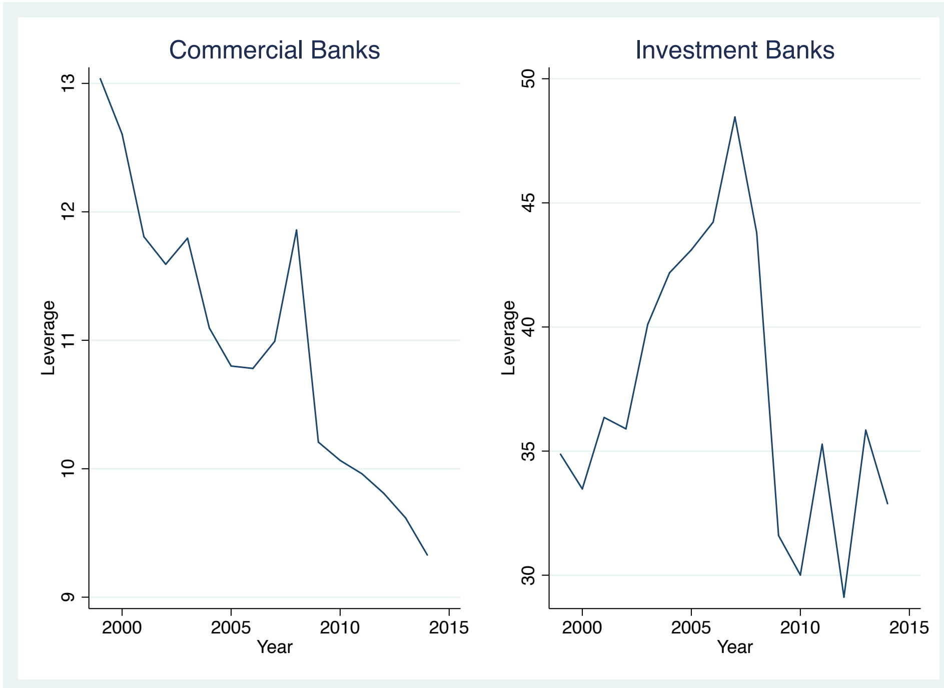

Figure 4: Leverage over time, USA, Commercial and Investment Banks

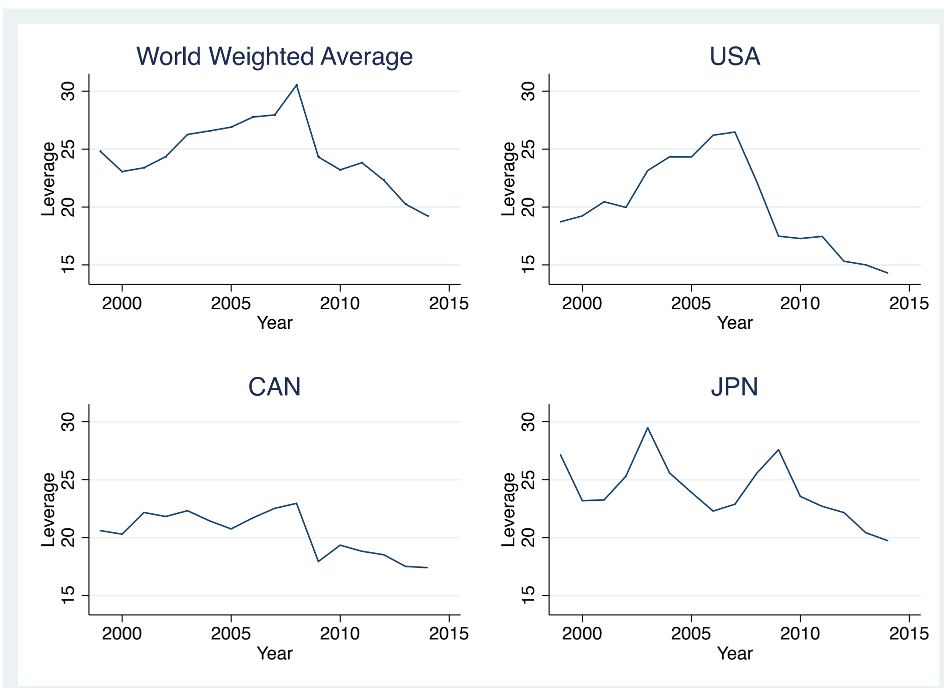

Figure 5: Leverage over time, selected countries

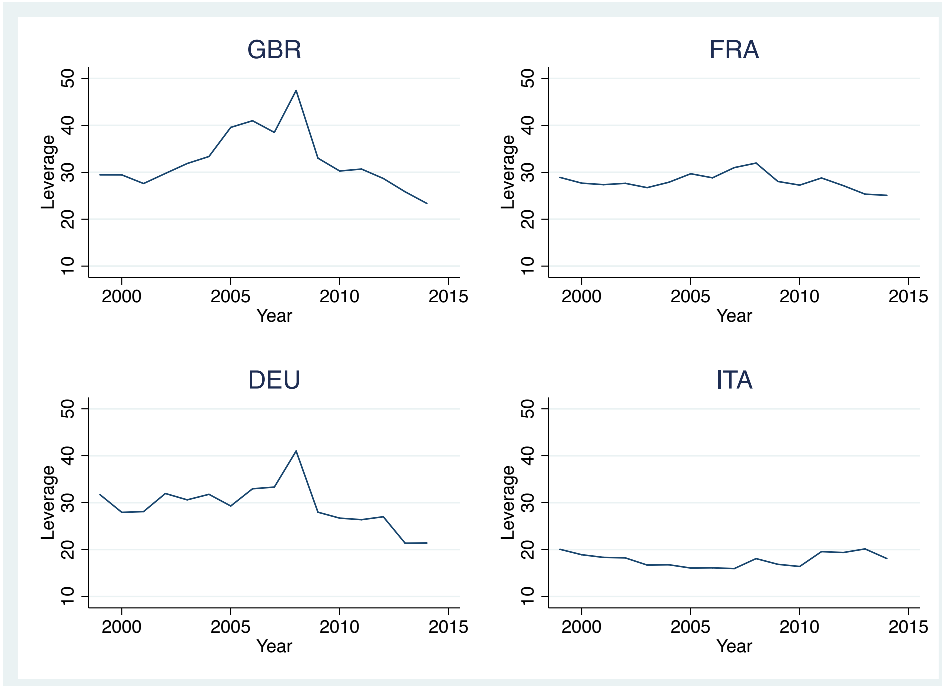

Figure 6: Leverage over time, selected countries

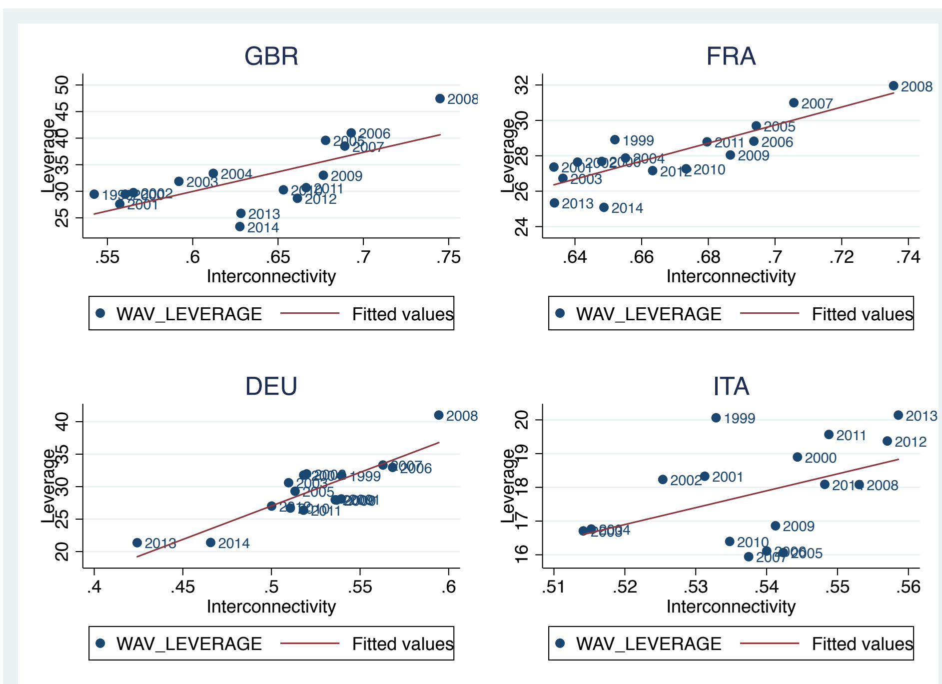

Figure 7: Leverage and Interconnectivity, Across Time, Within Selected Countries

3 Robustness: Non-core Liabilities over Total Liabilities (Intconn2)

Table 5: **Interconnectivity and Leverage: Cross-Country Evidence**

Dep Variable	A/E	A/E	A/E
INTCONN2	28.143***	24.591***	24.056***
	(1.595)	(2.139)	(2.161)
Country FE	No	Yes	Yes
Time FE	No	No	Yes
R-squared	0.379	0.821	0.857
N	512	512	512

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

Table 6: **Interconnectivity and Leverage, Very Large Financial Institutions (1999-2014)**

Dep Variable	A/E	A/E	A/E
INTCONN2	31.075***	21.190***	26.143***
	(1.776)	(2.933)	(6.275)
size	0.305	-0.728	5.085***
	(0.399)	(0.461)	(1.763)
Specialisation FE	No	Yes	No
Country FE	No	Yes	No
Time FE	No	Yes	Yes
Banks FE	No	No	Yes
R-squared	0.276	0.439	0.194
N	1281	1281	1281

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

Table 7: **Interconnectivity and Leverage, All financial institutions**

Dep Variable	A/E	A/E	A/E
Time Period	1999-2014	1999-2007	2003-2007
INTCONN2	3.005***	1.792***	1.404***
	(0.350)	(0.443)	(0.544)
size	2.867***	3.019***	3.215***
	(0.111)	(0.144)	(0.189)
Banks FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R-squared	0.085	0.108	0.108
N	213469	125785	69695

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

Table 8: **Interconnectivity and Leverage: By Country, 1999-2011, FE**

Dep Var: A/E	USA	CAN	GBR	JPN	DEU	FRA	ITA
IINTCONN2	1.190***	0.485	2.157	-5.609	3.660***	5.304**	-0.991
	(0.300)	(1.536)	(3.007)	(6.005)	(1.155)	(2.354)	(1.236)
size	1.639***	4.188***	5.680***	6.599***	3.986***	8.432***	6.050***
	(0.077)	(0.712)	(0.598)	(0.906)	(0.547)	(0.830)	(0.590)
hline Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.048	0.239	0.285	0.075	0.517	0.273	0.233
N	132446	1040	3335	10699	26529	5069	10438

Notes: Standard Errors in Parenthesis
*,**,*** Statistically Significant at 10%, 5% and 1%

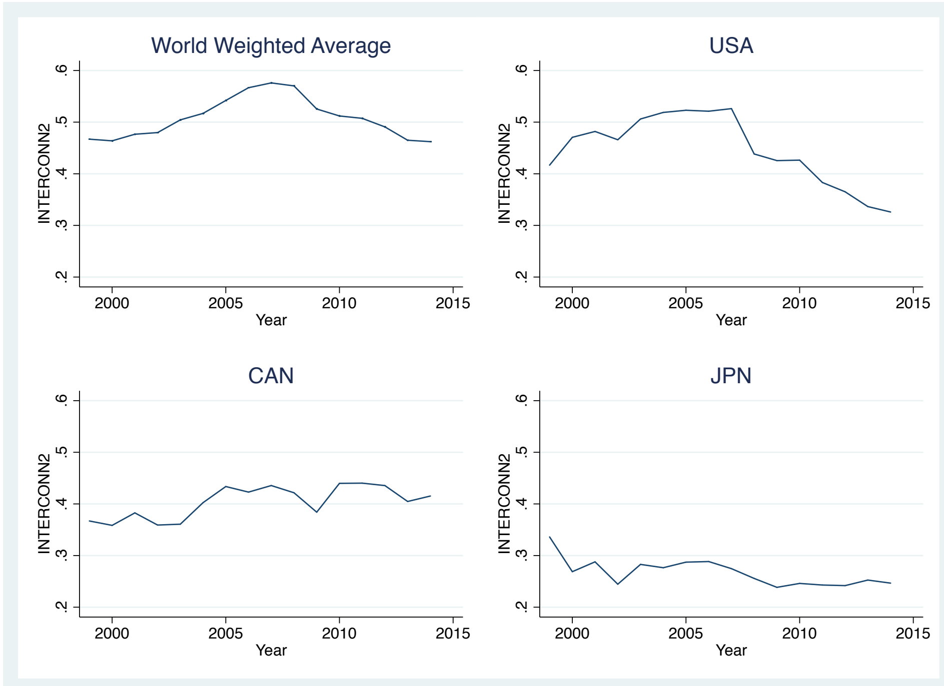

Figure 8: Interconnectivity over time, selected countries.

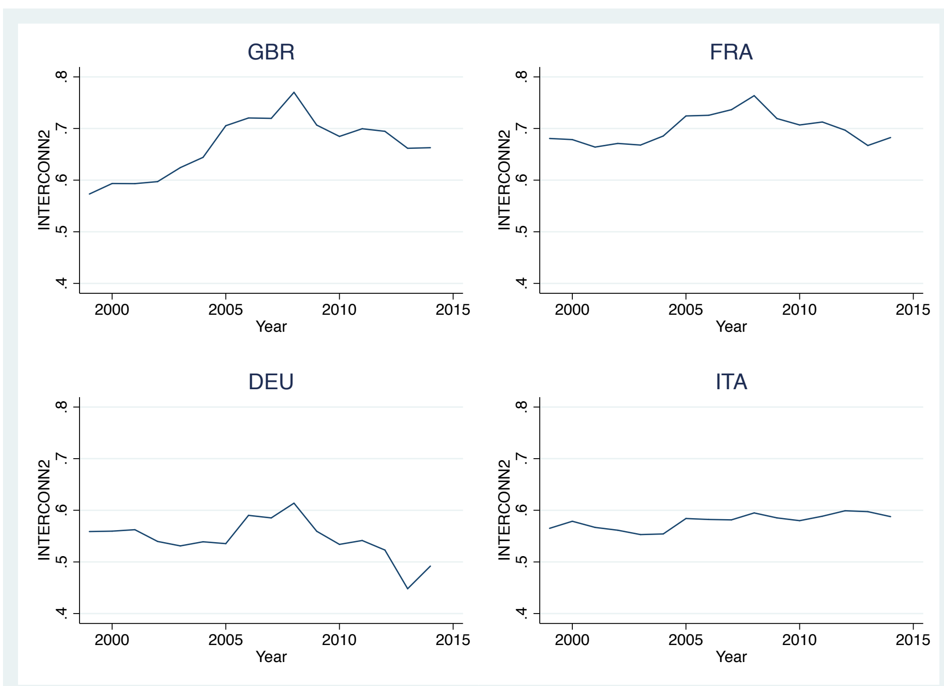

Figure 9: Interconnectivity over time, selected countries.

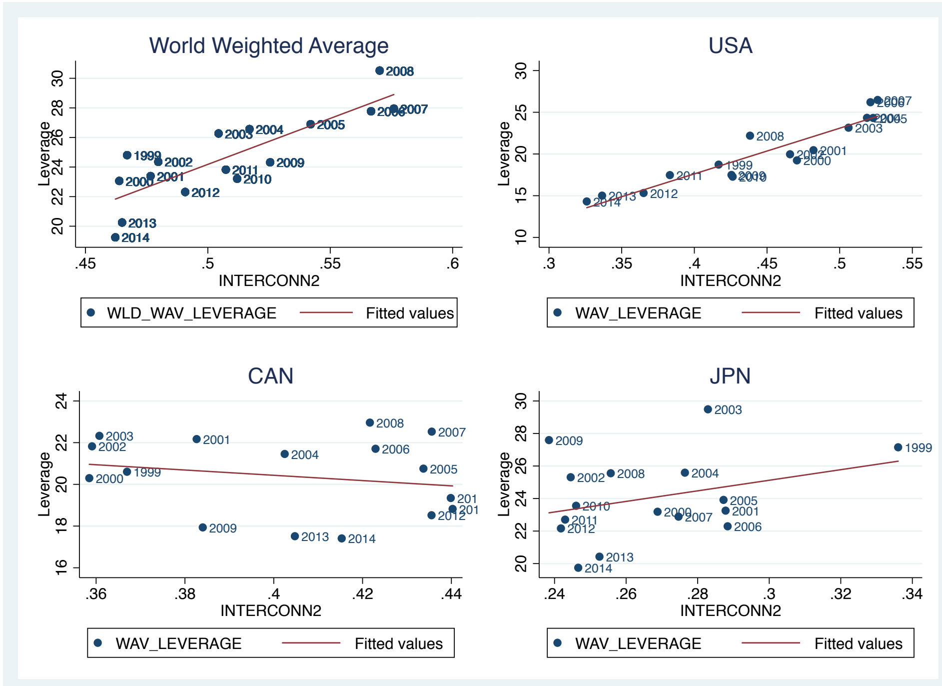

Figure 10: Leverage and Interconnectivity, Across Time, Within Selected Countries

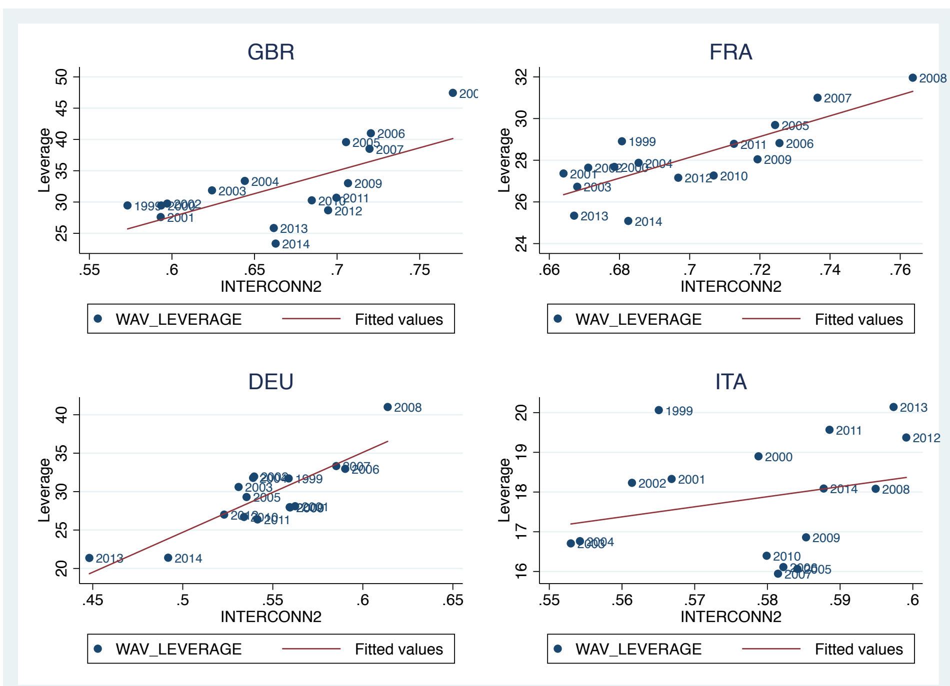

Figure 11: Leverage and Interconnectivity, Across Time, Within Selected Countries

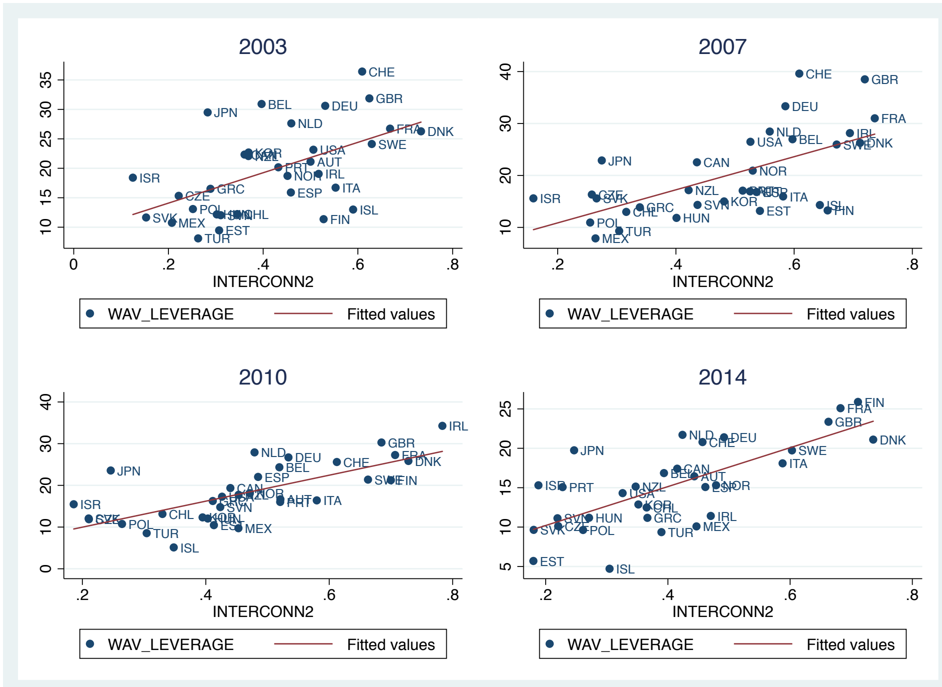

Figure 12: Leverage and Interconnectivity, Across countries, Selected Years

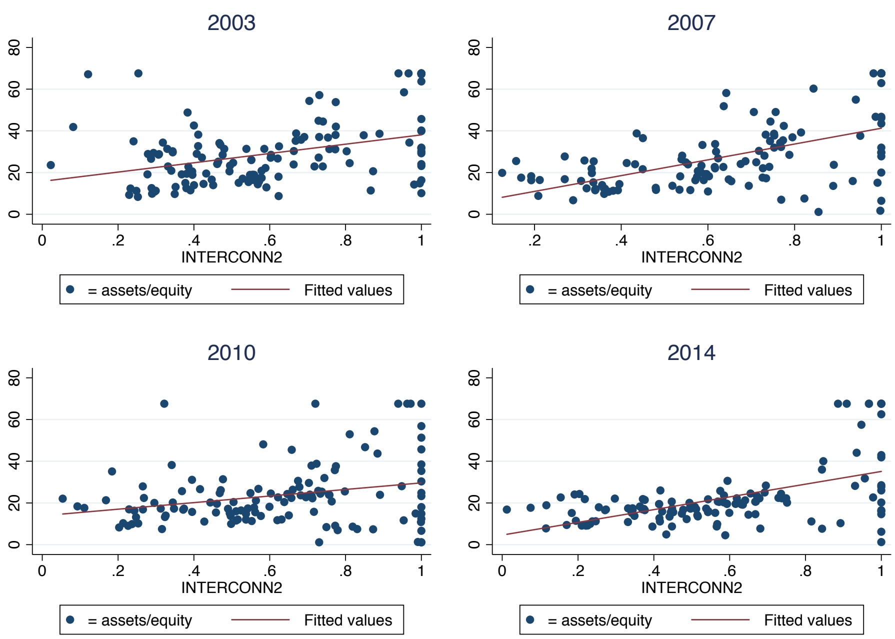

Figure 13: Leverage and Interconnectivity, Across Very Large Firms, Selected Years