

BANKS INTERCONNECTIVITY AND LEVERAGE*

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Abstract

We show that higher interconnectivity among financial intermediaries induces banks to choose more leverage. Although this leads to higher investment growth, the banking sector becomes more vulnerable to aggregate shocks (crises). We also show that learning about the likelihood of a crisis could have played an important role in generating the high interconnectivity and leverage before the 2008 crisis and the drastic reversal after the crisis. Using balance sheet data for over 14,000 financial intermediaries in 30 OECD countries we find that there is a strong positive correlation between our proxy for interconnectivity and leverage, consistent with the model.

JEL classification: E32, G11, G21

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1 Introduction

During the last three decades we have witnessed a significant expansion of the financial sector. The assets of US financial businesses have more than doubled as a fraction of the country GDP. Until the 2008 crisis, this trend has been associated with two features of the financial intermediation sector. The first feature is the high degree of cross-bank balance-sheet connectivity. The second feature is the high leverage of financial intermediaries. Differently from leverage, the concept of connectivity is not standard in the literature. In this paper we use the term interconnectivity to indicate the relative size of assets and liabilities issued by financial intermediaries and held by other financial intermediaries. Therefore, it relates to the cross-bank ownership of assets and liabilities within the financial intermediation sector.

Our concept of interconnectivity can be made more precise using a schematic balance sheet of banks as drawn in Figure 1. There are two types of assets and two types of liabilities. The first type of assets (core investments) refer to investments made in the nonfinancial sector, such as industrial loans and residential mortgages. The second type of assets (non-core investments) refers to securities issued by other financial firms, such as bonds. Similarly on the liabilities side. The first type of liabilities (core liabilities) are those held by the nonfinancial sector, such as households deposits. The second type of liabilities (non-core liabilities) are those held by other financial institutions, such as commercial papers purchased by other financial firms. Formally, we define the index of interconnectivity as the ratio of non-core liabilities over total assets.¹

Figure 1: Schematic balance sheet of a bank.

ASSETS	LIABILITIES
Investments in nonfinancial sector <i>(Core investments)</i>	Liabilities held by nonfinancial sector <i>(Core liabilities)</i>
Investments in financial sector <i>(Non-core investments)</i>	Liabilities held by financial sector <i>(Non-core liabilities)</i>
	Equities

$$\text{Interconnectivity} = \frac{\text{Non-core liabilities}}{\text{Core investments} + \text{Non-core investments}}$$

$$\text{Leverage} = \frac{\text{Core investments} + \text{Non-core investments}}{\text{Equities}}$$

¹In a banking equilibrium, the aggregate value of non-core liabilities are equal to the aggregate value of non-core investments. Therefore, whether we define the index as the ratio of non-core liabilities or non-core investment over assets does not matter. In the data, however, we need to use empirical proxies and the index could differ depending on whether we use non-core liabilities or non-core assets. More discussion about the empirical measure of interconnectivity is provided in Section 5.

The first panel of Figure 2 plots the empirical measure of interconnectivity for the US banking sector using data from Bankscope over the period 1999-2014. Since Bankscope does not specify the identity of the holders of bank liabilities, the empirical index is only a ‘proxy’ for interconnectivity. More specifically, we define non-core liabilities in the data as total liabilities minus core deposits. Although core deposits are mostly held by the nonfinancial sector, only part of the remaining liabilities are held by the financial sector. Nevertheless, the fraction of the residual liabilities held by financial institutions is certainly higher than for core deposits. A more detailed description of the data and the construction of the interconnectivity measure is provided in the empirical Section 5. It is also important to point out that the index plotted in Figure 2 is for the whole banking sector, not only depositary institutions. In fact, as we will show later, the dynamics is heavily affected by non-depositary institutions. The figure shows that interconnectivity reached a peak just before the 2008 financial crisis and then drastically declined during and after the crisis.

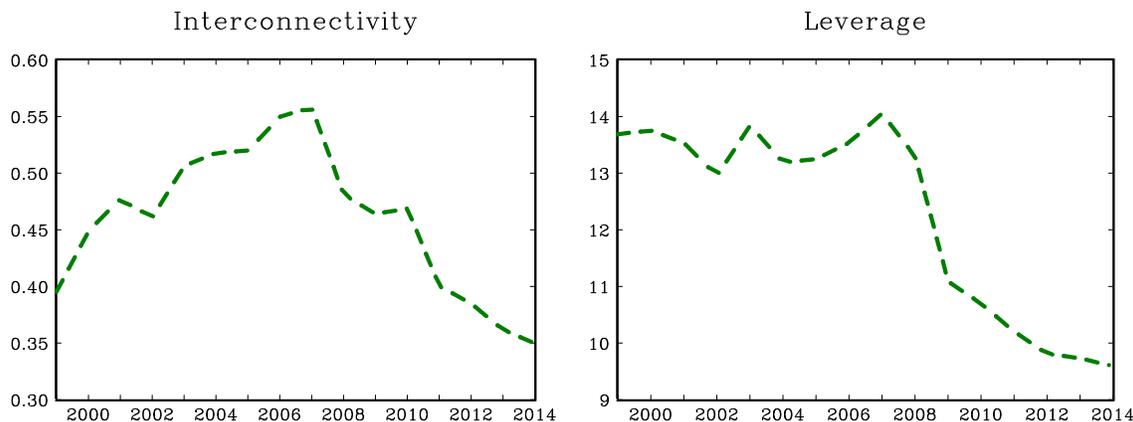


Figure 2: Banks interconnectivity (first panel) and leverage (second panel) in the United States, 1999-2014. *Interconnectivity* is measured as the ratio of aggregate non-core liabilities to aggregate assets and *Leverage* as the ratio of aggregate assets over aggregate equity. Aggregate assets, liabilities and equities are computed by summing the values of these variables for all Commercial and Savings Banks, Cooperative Banks, Investment Banks and Securities Firms, and Finance Companies in the US. Assets and liabilities are in book values.

The second panel of Figure 2 plots the leverage of the US banking sector. Leverage is computed as the ratio of total assets over equity. Also leverage reached a peak just before the financial crisis and declined drastically after the crisis. The two panels show that the indexes of interconnectivity and leverage tend to move together. In the empirical section we will show that these patterns are not limited to the United States but, with few exceptions, they are also observed in other countries over time. Furthermore, the positive correlation between interconnectivity and leverage is also observed across countries (countries in which the banking sector is more interconnected is also more leveraged) and across banks (banks that are more interconnected are also more leveraged).²

²It is important to point out that the positive relation between interconnectivity and leverage does not

Motivated by the empirical patterns, this paper addresses three questions. First, how are interconnectivity and leverage related at the bank level? More specifically, does interconnectivity affect the optimal leverage chosen by banks? Second, how does interconnectivity affect the stability of the whole banking sector? Third, what are the forces that induced banks to choose high levels of interconnectivity and leverage before the crisis and much lower levels after the crisis?

To address these questions we develop a dynamic model where banks make risky investments in the nonfinancial sector funded with equity and debt. To reduce the investment risk, banks sell part of the investments to other banks (diversification). However, the investment sales to other banks imply a 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. Higher diversification is achieved by selling part 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. Therefore, the linkage between interconnectivity and leverage is a two-way stream: factors that encourage more leverage also induce higher interconnectivity, and factors that encourage more interconnectivity also induce higher leverage.

To study the importance of interconnectivity for the volatility of the banking sector we consider an aggregate shock that affects all banks. A negative realization of this shock takes the form of a drop in the ex-post realized investment return of all banks, which we interpret as an economy-wide banking crisis. The sale of risky investments allows banks to reduce exposure to the idiosyncratic risk but not the aggregate risk. So the ‘relative’ exposure of banks to the aggregate risk increases and this makes the performance of individual banks more correlated to the performance of the industry. But since the overall risk (aggregate plus idiosyncratic) declines, banks are more willing to leverage. We then show that, by inducing banks to take more leverage, diversification (interconnectivity) amplifies the consequences of an aggregate shock. In other words, the aggregate shock would have had a much smaller effect on aggregate investments if banks were not allowed to be interconnected.

We also use the model to understand the possible factors that could have induced banks to be highly interconnected and leverage before the crisis but much less after the crisis (the third question addressed in this paper). In particular, we explore the role of Bayesian learning about the probability distribution of the aggregate shock. Bayesian learning has been used in aggregative model of debt by Boz and Mendoza (2014) and Hennessy and Radnaev (2016). They showed that this mechanism can generate financial and macroeconomic cycles. In this paper we show that learning is important not only for the leverage cycle but also for the

derive from an accounting identity. To show this, suppose that a bank increases core investments and core liabilities by the same amount. All other items (non core investments, non-core liabilities and equities) are left unchanged in the balance sheet. Effectively, the bank fully funds the increase in core investments with core deposits. It can be verified that this reduces interconnectivity but increases leverage. Therefore, the two indexes can move in opposite directions. See Figure 6 for a counterexample using the theoretical model developed in this paper.

interconnectivity cycle. More importantly, the leverage cycle of banks would be negligible in absence of the interconnectivity cycle. Thus, movements in interconnectivity create a powerful amplification mechanism for the leverage and macroeconomic cycles.

The learning mechanism works as follows: Since the probability distribution of the aggregate shock is unknown, banks make their portfolio decisions based on their ‘belief’ about the stochastic distribution of the shock (probability of a crisis). The belief is then updated over time through Bayesian learning. Learning implies that when a crisis (negative aggregate shock) does not realize, banks lower the assessed risk of the 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 perceived probability of crises is revised upward. Since 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, interconnectivity and investments. In this way, the model generates the dynamics of interconnectivity and leverage that resembles the dynamics observed in data. But, as observed above, the high leverage and subsequent decline would have been much smaller if banks were not allowed to become interconnected.

We provide empirical support for the co-movement of interconnectivity and leverage. First, we use data from Bankscope to explore the correlation between interconnectivity and leverage along three dimensions: across banks, across time and across countries. The empirical analysis shows that there is a strong positive association between banks interconnectivity and leverage, as predicted by the model. In particular, banks that are more interconnected are more leveraged; when an individual bank becomes more connected to other banks over time, it becomes 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.

The paper is organized as follows. After a brief review of the related literature, Section 2 describes the basic model and characterizes its properties. Section 3 explores the response to aggregate shocks and its dependency on interconnectivity. Section 4 presents the dynamics generated by the model with Bayesian learning. Section 5 conducts the empirical analysis and 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. Acemoglu et al. (2015) proposed a model where a more densely connected financial network attenuates the impact of small shocks but it amplifies large shocks. Bigio and La'O (2016) shows how sectoral financial shocks propagate through an input-output network. Also related is the literature that formalizes the interbank market as a source of liquidity for banks such as Bianchi and Bigio (2014).

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 (2017) presented evidence that banks who are more interconnected are characterized by higher measures of systemic risk.³ 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.⁴ Peltonen et al. (2015) analyzed the role of interconnectedness of the banking system as a source of vulnerability to crises.⁵

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. Geanakoplos (2010) and Simsek (2013) proposed some explanations for the pro-ciclicity of leverage. Nuno and Thomas (2017) 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. Begenau (2016) studies the importance of capital requirement for the optimal choice of leverage, investment and risk of banks in a business cycle model. Elenev et al. (2017) studies the quantitative effects of macro-prudential policies in a model with financially constrained producers and intermediaries.

Our paper is also related to the literature that studies the dynamics of leverage of non-financial firms over the business cycle as they face similar trade-offs over the choice of the optimal capital structure. For example, Covas and Den Haan (2011) and Begenau and Salomao (2016) study business cycle dynamics of debt and equity using Compustat Data. Devereux and Yetman (2010) showed that leverage constraints can also affect the nature of cross-countries business cycle co-movements. The work of Boz and Mendoza (2014) and Hennessy and Radnaev (2016) are especially related to our paper since they also consider Bayesian learning about the distribution of the aggregate shock in a model with endogenous leverage. Both papers can generate a leverage cycle but they do not study the importance of interconnectivity as we do in our paper.

The above review shows that there are many contributions studying either the determinants of interconnectivity or the determinants of leverage. However, most of them do not

³See 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.

⁴See also Liu et al., 2015 for an analysis of different sources of interconnectedness in the banking sector.

⁵Abad et al (2017) provide a snapshot (as of March 2015) of the interconnectedness between 184 European banks and entities belonging to the shadow banking systems of several countries.

study both interconnectivity and leverage and how they are related which, in contrast, is the goal of our paper. In this respect the theoretical contribution of our paper is related to Shin (2009) and Gennaioli et al. (2013). Gennaioli et al. (2013) propose a theory of securitization of bank investments which also predicts a positive relation between interconnectivity and leverage. The mechanism, however, is different. While in Gennaioli et al. (2013) securitization increases leverage because it relaxes the borrowing constraints of banks, in our model the central mechanism is based on risk aversion: risk-averse banks trade-off the lower cost of debt with the risk of leveraging. There are also some similarities between our explanation of the dynamics of interconnectivity and leverage based on learning and Gennaioli et al. (2013) explanation based on neglected risk (see also Gennaioli et al. (2012)). Neglected risk is based on some form of deviation from full rationality while our approach maintains that agents are fully rational. Still, our approach predicts that banks may (rationally) under-estimate the probability of a crisis after a sequence of good aggregate shocks.⁶ The contribution of our paper is also empirical as it uses data from a large sample of banks in OECD countries to explore the empirical significance of the theory. Kojien and Yogo (2016) shows that an increase in interconnectivity is also observed in the insurance industry where more companies resell their insurance policies to other companies in the industry. This suggests that a similar framework as the one developed in our paper could be used to study the changes observed in the insurance industry.

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

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 obtained by Ivashina and Scharfstein (2010) for the US and Abbassi et al. (2015) for Germany. Our paper provides a theoretical framework that rationalizes these empirical findings.

2 The model

We describe here an industry equilibrium model in which banks can raise funds from other sectors at the gross interest R^l and make investments also in other sectors of the economy with expected gross return R^k . In addition, banks can buy and sell liabilities from/to other banks at the market price $1/R_t^f$. While R^l and R^k are exogenous in the model (since these rates relate to transactions with other sectors of the economy not explicitly modelled in the

⁶Another difference is that in our model the equity of banks is not fixed—which is an assumption in both Gennaioli et al. (2013) and Shin (2009)—but it is optimally chosen by banks. With fixed equity, the only way for banks to expand investments outside the financial sector is by leveraging.

paper), the rate R_t^f is endogenously determined to clear the interbank market. This justifies the time subscript in R_t^f but not in R^l and R^k .

2.1 Banks' structure and optimization

The banking sector is populated by a measure 1 of atomistic banks each 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 utility function represents the preferences of the major shareholders of the bank. Alternatively we can think of the utility 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 $1/R^l$ and make risky investments k_t (also in the nonfinancial sector) at the market price $1/R^k$. The prices $1/R^l$ and $1/R^k$ are exogenous in the model. However, while the repayment of liabilities l_t in the next period is known today, the investment payout at the beginning of the next period is unknown. More specifically it takes the form $\eta_{t+1}z_{t+1}k_t$ where η_{t+1} is an aggregate stochastic variable (aggregate shock) affecting the return of all banks and z_{t+1} is an idiosyncratic stochastic variable (idiosyncratic shock) that affects only the return of the individual bank. Both variables are observed at $t + 1$ and, therefore, after the choice of k_t .

We assume that z_{t+1} is independently and identically distributed across banks (idiosyncratic) and over time with $\mathbb{E}_t z_{t+1} = 1$. For the aggregate shock we assume that it takes two values, that is, $\eta_{t+1} \in \{\underline{\eta}, \bar{\eta}\}$, with probability p and $1 - p$ respectively, and satisfy $\mathbb{E}_t \eta_{t+1} = 1$. Therefore, R^k is the 'expected' gross return from the risky investment while $\eta_{t+1}z_{t+1}R^k$ is the actual gross return realized at $t + 1$. Since there is no uncertainty on the liability side, R^l is both the expected and actual return.

We think of the realization $\eta < \bar{\eta}$ 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). Later we allow the probability p (the likelihood of a crisis) to change over time. For the moment however, we take p as a constant parameter.

Both aggregate and idiosyncratic shocks create a risk for the bank. The idiosyncratic risk, however, can be partially diversified with interbank activities. 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 made by 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 is $1/R_t^f$, which will be determined in equilibrium to clear the interbank market.

Even if a fraction α_t of the risky investments are sold to other banks, the originating bank continues to manage the investments and the purchasing banks are only entitled to a share α_t of the return.⁷

By pooling together the investments of many atomistic firms, the actual return from the diversified investment f_t is independent of the idiosyncratic shock z_t faced by an individual bank. However, the return from the diversified portfolio f_t still depends on the aggregate shock η_t because this affects the risky investments of all firms alike. Therefore, only the idiosyncratic risk can be diversified through the interbank market. Agency problems, however, limit the degree of diversification. When a bank 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 as

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

subject to:

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

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

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

$$\frac{R^k}{R_t^f} = \frac{1}{1 - \varphi(\alpha_t) - \varphi'(\alpha_t) + \alpha_t \varphi'(\alpha_t)}. \quad (2)$$

⁷This is different from the sale of equity shares. The holder of equity shares is entitled to the profits of the bank which depend also on the cost of 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 example of this type of arrangements. However, what we have in mind is more general capturing all types of financial arrangements with uncertain returns.

This condition determines the share of risky investments sold to other banks, α_t , as a function of ratio between the expected return on risky investments and interbank assets, R_t^k/R_t^f . The following lemma establishes how the return ratio and the diversification cost affect α_t .

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

Proof 2.1. *We compute the derivative of α_t with respect to the return ratio R_t^k/R_t^f from condition (2) by applying the implicit function theorem. Denoting by $r_t = R_t^k/R_t^f$ the return ratio we obtain $\partial\alpha_t/\partial r_t = 1/[(1 - \alpha_t)\varphi''(\alpha_t)r_t^2]$. 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 properties stated in the lemma have simple intuitions. The (endogenous) return R_t^f represents one of the costs of funding risky investments by reselling them in the interbank market (the other is the diversification cost). Therefore, lower is R_t^f relatively to the (exogenous) return R_t^k , and higher is the incentive to fund risky investment through this channel. It is then optimal for the bank to choose a higher value of α_t . The diversification cost plays a similar role since a lower value of χ implies a lower cost of funding risky investments with their resales to other banks. The monotonicity property stated in the lemma is conditional on α_t be 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. Therefore, the condition $\alpha_t < 1$ is always satisfied in the banking equilibrium which we will define below.

2.2 Reformulation of the bank problem and industry equilibrium

It will be convenient to define $\bar{k}_t = (1 - \alpha_t)k_t$ the retained risky investments. We can then rewrite the optimization problem of the bank as

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

subject to:

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

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

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

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

The adjusted return depends on the ‘exogenous’ return R^k , on the ‘endogenous’ return R_t^f , and on the optimal diversification α_t . Since α_t depends only on R^k and R_t^f (see condition (2)), the adjusted return is also a function of R^k and R_t^f .

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 ratio \bar{R}_t^k/R_t^f increases in R^k/R_t^f and decreases in the diversification cost.

Lemma 2.2. *The adjusted return ratio \bar{R}_t^k/R_t^f is strictly increasing in R^k/R_t^f and strictly decreasing in χ .*

Proof 2.2. *Condition (4) can be rewritten as*

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

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

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

Since α_t is strictly increasing in R^k/R_t^f (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^k/R_t^f . Therefore, \bar{R}_t^k/R_t^f is strictly increasing in R^k/R_t^f .

Using the above expression for $\frac{\bar{R}_t^k}{R_t^f}$ we derive

$$\frac{\partial \bar{R}_t^k/R_t^f}{\partial \chi} = \frac{\varphi''(\alpha_t) \frac{\partial \alpha_t}{\partial \chi}}{[1 - \varphi'(\alpha_t)]^2}.$$

We have already shown in the proof of Lemma 2.1 that $\frac{\partial \alpha_t}{\partial \chi} < 0$. Since the diversification cost function is concave, $\varphi''(\alpha_t) > 0$. This implies that the above derivative is negative and, therefore, \bar{R}_t^k/R_t^f is strictly decreasing in χ . ■

Problem (3) is a portfolio choice with three assets. The first asset is $-l_t$ with riskless return R^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 optimal portfolio choice is characterized by the following lemma.

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

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

$$-\frac{l_t}{R^l} = (1 - \phi_t^k - \phi_t^f)\beta a_t, \tag{6}$$

$$\frac{f_t}{R_t^f} = \phi_t^f \beta a_t, \tag{7}$$

$$\frac{\bar{k}_t}{\bar{R}_t^k} = \phi_t^k \beta a_t, \tag{8}$$

where ϕ_t^f and ϕ_t^k are defined implicitly by the conditions

$$\mathbb{E}_t \left\{ \frac{R^l}{R^l(1 - \phi^f - \phi^k) + \eta_{t+1}R_t^f\phi_t^f + \eta_{t+1}z_{t+1}\bar{R}_t^k\phi_t^k} \right\} = 1, \quad (9)$$

$$\mathbb{E}_t \left\{ \frac{\eta_{t+1}R_t^f}{R^l(1 - \phi^f - \phi^k) + \eta_{t+1}R_t^f\phi_t^f + \eta_{t+1}z_{t+1}\bar{R}_t^k\phi_t^k} \right\} = 1. \quad (10)$$

Proof 2.3. See Appendix C.

Conditions (9) and (10) determine the shares of savings, ϕ_t^f and ϕ_t^k , allocated to diversified (with respect to the idiosyncratic risk) and non-diversified investments. Since these conditions are independent of the bank initial assets a_t , banks allocate the same shares of wealth $1 - \phi^f = \phi^k$ to $-l_t/R^l$, the same share ϕ^f to f_t/R_t^f , and the same share ϕ^k to \bar{k}_t/\bar{R}_t^k .

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^l and R^k , and the distribution of banks over net worth $M_t(a)$, 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 such that the decision rules satisfy condition (2), (5), (6), (7), (8), 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 (5)-(8) determine c_t , l_t , f_t , \bar{k}_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 $k_t = \bar{k}_t/(1 - \alpha_t)$. The aggregation of the individual policies will then provide the equilibrium condition for the determination of the interbank market return R_t^f . The market clearing condition simply equalizes the aggregation of individual demands for diversified investments f_t , to the aggregation of individual supplies $\alpha_t k_t$.

2.3 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. Going back to the balance sheet presented in Figure 1, we can now associate the various items of the balance sheet to the specific variables in the model, as indicated in Figure 3.

The aggregate balance sheet for the whole banking sector is obtained by summing the balance sheets of all banks but without consolidation. Therefore, total assets include not only the investments made in the nonfinancial sector, K_t/R^k , but also the assets purchased from other banks, F_t/R_t^f . Of course, if we were to consolidate the balance sheets of all

Figure 3: Schematic balance sheet in the model.

ASSETS	LIABILITIES
Investments in nonfinancial sector, $\frac{K_t}{R^k}$ <i>(Core investments)</i>	Liabilities held by nonfinancial sector, $\frac{L_t}{R^l}$ <i>(Core liabilities)</i>
Investments in financial sector, $\frac{F_t}{R_t^f}$ <i>(Non-core investments)</i>	Liabilities held by financial sector, $\frac{\alpha_t K_t}{R_t^f}$ <i>(Non-core liabilities)</i>
	Equity, $A_t - D_t - \frac{\varphi(\alpha_t)K_t}{R_t^f}$

banks, the resulting assets would not include F_t/R_t^f . Similarly for aggregate liabilities. Interconnectivity and leverage are then equal to

$$INTERCONNECTIVITY = \frac{\frac{\alpha_t K_t}{R_t^f}}{\frac{K_t}{R^k} + \frac{F_t}{R_t^f}}, \quad (11)$$

$$LEVERAGE = \frac{\frac{K_t}{R^k} + \frac{F_t}{R_t^f}}{\frac{K_t}{R^k} - \frac{L_t}{R^l}}. \quad (12)$$

Our definition of leverage is conceptually different from Shin (2009). That paper proposes an accounting framework to characterize the overall leverage of the financial sector, netting out claims within the sector. In our framework, we do not net out the internal claims.

The next step is to characterize the properties of these two indexes with special attention to the dependence from the return spread R^k/R^l and the diversification cost $\varphi(\alpha_t)$. This can be done analytically in the special case without aggregate shocks, that is, $\underline{\eta} = \bar{\eta} = 1$. The reason being that, under the assumption $\underline{\eta} = \bar{\eta} = 1$, the equilibrium is characterized by $R_t^f = R^l$, that is, the endogenous interbank return is equal to cost of core liabilities. In fact we can see that conditions (9) and (10) cannot be both satisfied when $\underline{\eta} = \bar{\eta} = 1$ unless $R_t^f = R^l$. This has a simple intuition: In absence of aggregate shocks, diversified investments carry no risk. Therefore, if the return is bigger than the cost of core liabilities, l_t , banks have an incentive to buy an infinite amount of diversified investment f_t funded by core liabilities l_t . The high demand for f_t will drive its price $1/R_t^f$ up until it becomes equal to $1/R^l$.⁸

⁸In absence of aggregate shocks, we cannot determine separately l_t and f_t for an individual bank. Only $\bar{l}_t = l_t - f_t$ is determined at the individual level. However, we can separately determine the aggregate values of l_t and f_t since in equilibrium we have $\int_a f_t M_t(a) = \alpha_t \int_a k_t M_t(a)$. From this we can then solve for $\int_a l_t M_t(a) = \int_a (\bar{l}_t + f_t) M_t(a)$.

Proposition 2.1. *Suppose that $\underline{\eta} = \bar{\eta} = 1$. For empirically relevant parameters, leverage and interconnectivity are*

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

(i) strictly decreasing in the diversification cost χ .

Proof 2.1. *See Appendix B.*

It is important to emphasize that, although leverage and interconnectivity indices are defined by similar variables, they are not perfectly dependent. More specifically, an increase in leverage does not necessarily imply an increase in interconnectivity. To see this, suppose that banks increase L_t without changing K_t and F_t . Since in equilibrium $\alpha_t K_t = F_t$, from equation (11) we can see that interconnectivity does not change. However, equation (12) 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 increase (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 (optimality) of the model. In Section 4.2 we will show that the model could generate the opposite relation between interconnectivity and leverage. For example, in response to a change in the volatility of the idiosyncratic shock z_{t+1} .

With aggregate shocks it becomes more difficult to prove Proposition 2.1. The main difficulty derives from the fact that, as we change R^k/R^l or χ , the equilibrium return R_t^f also changes which in turn affects the optimal choice of leverage and interconnectivity. However, we conjecture that the properties stated in Proposition 2.1 also hold with aggregate shocks, as we now show for a calibrated version of the model.

Calibration: For the calibration of the exogenous returns R^l and R^k we use, respectively, the average return on bank assets and the average return on bank liabilities for the period 1999-2014. This is the period for which we have data from Bankscope. Based on these averages we set $R^l = 1.01883$ and $R^k = 1.04291$.

The discount factor β determines the expected equity return for the bank. During the period 1999-2014 the average return on equity was 9.4 percent. Therefore, we set $\beta = 1/1.094 = 0.914$.

We interpret the realization $\eta = \underline{\eta}$ as a financial crisis and we set the probability of a crisis to $p = 0.02$. Thus, on average, a crisis arises every 50 years. This is in the range of values used in the literature. To calibrate the value of $\underline{\eta}$, we used the drop in equity returns experienced by banks starting in 2007 (that is, when the crisis started). The cumulative drop in equity return in the period 2008-2010 from the average over the whole sample period 1999-2014, was about 25 percent. So every year from 2008 to 2010, the return on equity of banks was almost 7 percent lower (20%/3) than the average return over the sample period

1999-2014. By setting $\eta = 0.99$ the model generates a reduction in equity return in response to a crisis which is close to 20 percent.⁹

At this point there are three parameters that need to be calibrated: the elasticity of the diversification cost, γ , the scaling parameter for the diversification cost, χ , and the standard deviation of the idiosyncratic shock, σ_z . Unfortunately, we do not have direct evidence to pin down γ . We assume that the diversification cost is close to be linear and set it to 1.1. We will conduct a sensitivity analysis with respect to this parameter. Finally we set χ and σ_z to match the average leverage ratio and the average interconnectivity index during the sample period 1999-2014. However, we re-scale by half the empirical measure of interconnectivity in order to reconcile it with the one computed from the model. This is because our empirical data does not include all financial intermediaries. As a result, some of the liabilities issued by banks included in the sample are actually purchased by financial firms that are not in that sample, such as mutual funds. Because of this, our empirical measure of interconnectivity is higher than the actual interconnectivity for the whole financial intermediation sector. Flows of funds data suggest that 0.5 is a plausible re-scaling factor. Therefore, the calibration target is the average interconnectivity index divided by 2.¹⁰

The top panels of Figure 4 plots leverage and interconnectivity for different values of R^k and, therefore, R^k/R^l . The bottom panels plot the same variables but for different values of the diversification cost parameter χ . The parameters values are reported in the caption of the Figure.¹¹

The figure shows that a higher return spread between risky investments and liabilities is associated to higher interconnectivity and leverage. Furthermore, it increases the return on diversified investment R_t^f . This is because a higher R^k implies a higher incentive to invest and, therefore, a higher supply of risky investments to other banks. To induce other banks to buy these assets, they have to be sold at a lower price $1/R_t^f$. The increase in the diversification cost has the opposite effect on interconnectivity and leverage. Higher diversification cost implies a lower insurance of the idiosyncratic shock. Because of the higher risk, banks choose a smaller leverage. The last panel shows that the equilibrium return R_t^f decreases with the diversification cost. This is because, the supply of diversified assets decreases and this raises the price $1/R_t^f$.

To illustrate the importance of interconnectivity for the choice of leverage, we conduct the following exercise. We force banks to choose $\alpha_t = 0$ so that they do not become inter-

⁹Even if the realized return from k is only 1 percent smaller when the crisis hits, the percentage equity losses are much bigger because banks are heavily leveraged.

¹⁰We explore the market for repurchasing agreements (REPOs) from the Flow of Funds (FoF) to gauge the importance of the financial actors not captured by our model. REPOs constitute an important share of non-core liabilities both for depository institutions (commercial banks, savings banks, credit unions) and for investment banks and securities firms. We sum the holdings of REPOs reported in the asset side of Mutual funds, Insurance Companies, GSEs and Pension Funds, and we divide this figure by the total REPOs reported in the liabilities side of depository institutions and brokers and dealers. The average share we obtained for the period 1999-2014 is 0.50, from which we derive the re-scaling factor used in this exercise.

¹¹To find the equilibrium we simply need to solve the system of nonlinear equations (2), (5), (6), (7), (8), (9), (10) and the interbank market clearing condition $F_t = \alpha_t K_t$. The solution returns the values of $\alpha_t, C_t, L_t, F_t, K_t, \phi_t^f, \phi_t^k, R_t^f$.

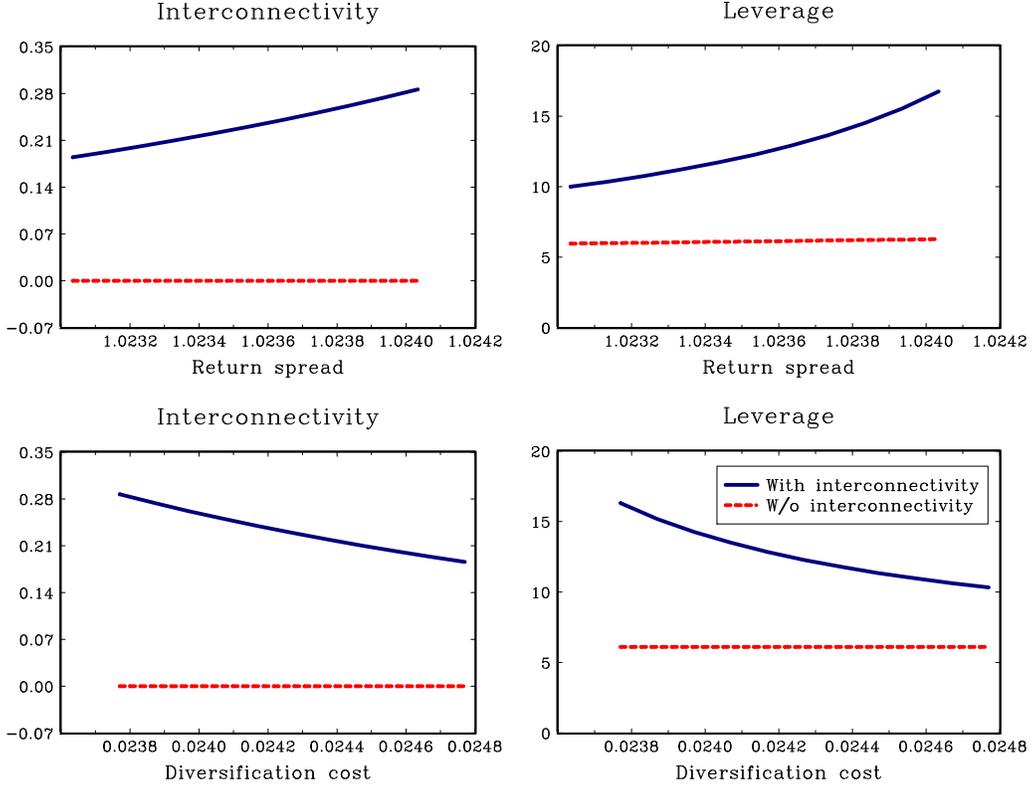


Figure 4: Sensitivity of interconnectivity and leverage to diversification cost and return spread. Baseline parameter values are: $\beta = 0.9139$, $R^l = 1.0189$, $R^k = 1.0429$, $\chi = 0.024$, $\gamma = 1.1$, $z \in \{0.932, 1.068\}$ with equal probabilities, $\eta \in \{0.9900, 1.0002\}$ with $p = 0.02$ the probability of $\eta = 0.99$. The sensitivity is performed by changing R^k or χ .

connected. We then recompute the optimal portfolio choices under this constraint. Figure 4 plots interconnectivity and leverage with and without this constraint. When banks are not allowed to become interconnected, they choose a much smaller leverage.

When the diversification cost declines, banks become more interconnected because it is less costly to diversify. Since diversification reduces the idiosyncratic risk, banks are more willing to take the aggregate risk and become more leveraged. Therefore, it is interconnectivity that induces banks to become more leveraged.

When the return spread increases, banks would become more leveraged even if they could not diversify. However, since leverage increases the risk faced by banks, the ability to become more interconnected reduces the risk of leveraging, which further encourages more leverage. Therefore, when the return spread increases, interconnectivity ‘amplifies’ the impact of the higher return spread on leverage.

Before moving to the next section we show how the elasticity of the diversification cost, captured by the parameter γ , affects the sensitivity of interconnectivity and leverage. We then show how interconnectivity and leverage are affected by the volatility of the idiosyncratic shock.

To show the sensitivity to the elasticity of the diversification cost, we increase the value of γ from 1.1 in the baseline model to 1.5. In doing so we also recalibrate χ and the standard deviation of the idiosyncratic shock so that the model match the same levels of interconnectivity and leverage as in the previous calibration. The results are shown in Figure 5.

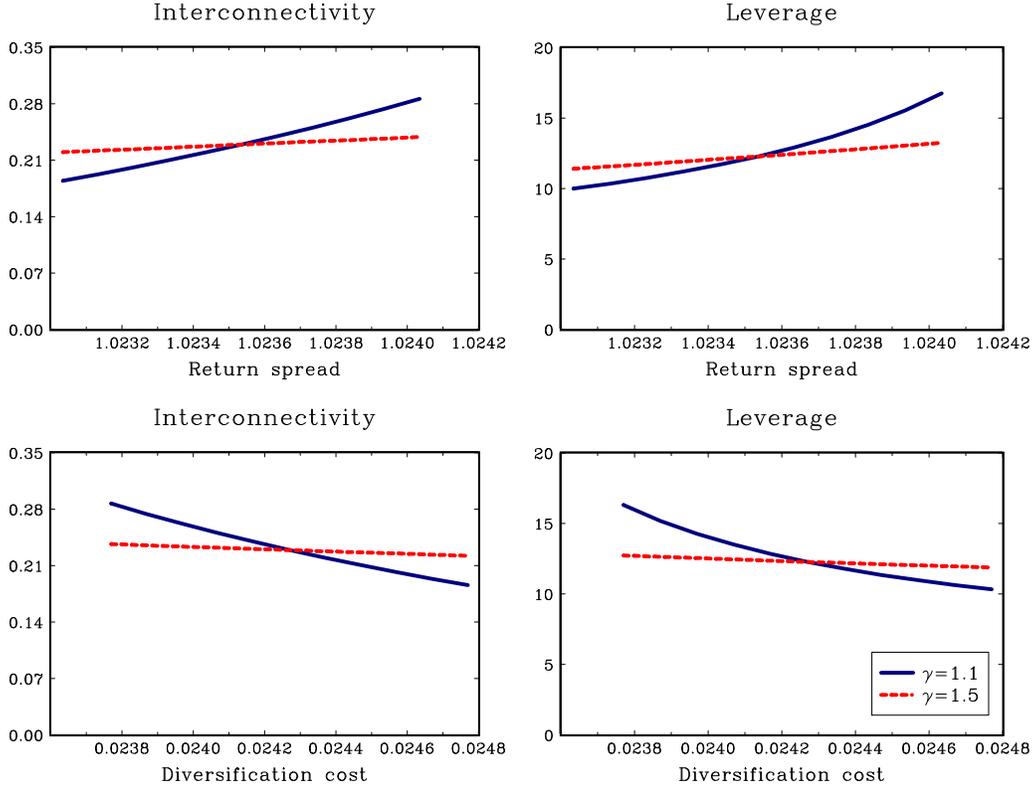


Figure 5: Sensitivity of interconnectivity and leverage for different values of γ . Baseline parameter values when $\gamma = 1.1$ are: $\beta = 0.9139$, $R^l = 1.0189$, $R^k = 1.0429$, $\chi = 0.024$, $z \in \{0.932, 1.068\}$ with equal probabilities, $\eta \in \{0.9900, 1.0002\}$ with $p = 0.02$ the probability of $\eta = 0.99$. Baseline parameter values when $\gamma = 1.5$ are: $\beta = 0.9139$, $R^l = 1.0189$, $R^k = 1.0429$, $\chi = 0.031$, $z \in \{0.933, 1.067\}$ with equal probabilities, $\eta \in \{0.9900, 1.0002\}$ with $p = 0.02$ the probability of $\eta = 0.99$. The sensitivity is performed by changing R^k or χ .

As expected, the sensitivity of interconnectivity and leverage to χ and R^k/R^l declines when the elasticity of the cost is higher, that is, γ is bigger. This implies that the results shown later will be quantitatively smaller when the elasticity of the diversification cost is higher.

We explore now how interconnectivity and leverage respond to a change in the volatility of the idiosyncratic shock, z_{t+1} . This relates to the recent literature on time-varying volatility. Higher idiosyncratic risk increases the incentive of banks to diversify (higher interconnectivity). However, since diversification does not completely offset the higher risk, banks choose to be less leveraged. This is shown in Figure 6.

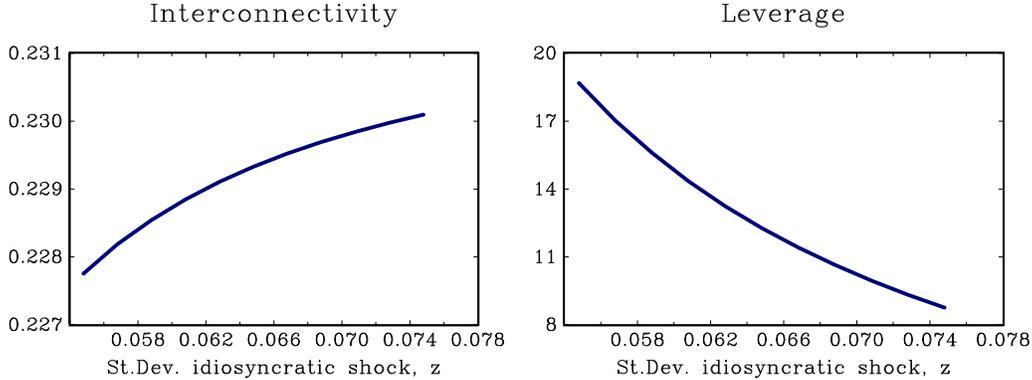


Figure 6: Sensitivity of interconnectivity and leverage to standard deviation of the idiosyncratic shock. Baseline parameter values are: $\beta = 0.9139$, $R^l = 1.0189$, $R^k = 1.0429$, $\chi = 0.024$, $\gamma = 1.1$, $z \in \{0.932, 1.068\}$ with equal probabilities, $\eta \in \{0.9900, 1.0002\}$ with $p = 0.02$ the probability of $\eta = 0.99$. The sensitivity is performed by changing the low and high values of z .

As can be seen from the figure, higher volatility of the idiosyncratic shock is associate to higher interconnectivity but lower leverage. This shows that the positive co-movement between interconnectivity and leverage is not simply the result of an accounting identity. The two indexes could be both positively or negatively correlated. It depends on the dominant forces underlying their movements.

3 Interconnectivity and the impact of aggregate shocks

In this section we show how the response of banks' investment to aggregate shocks is affected by the degree of banks' interconnectivity. Since investment is proportional to net worth a_t , we first need to derive an expression for the growth rate of net worth. We start with the equation that links the next period net worth to the portfolio choice of the bank and the realization of the shocks (idiosyncratic and aggregate), that is,

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

Using (6)-(8), the equation can be rewritten as

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

which defines the (gross) growth rate of net worth. From this expression we can characterize how the growth rate of net worth for the whole banking sector is affected by the aggregate shock. Averaging over the idiosyncratic shock z_{t+1} and taking the derivative with respect to η_{t+1} we obtain

$$\frac{\partial \left(\frac{a_{t+1}}{a_t} \right)}{\partial \eta_{t+1}} = \beta R^l \left(\frac{\bar{R}_t^k}{R^l} \phi_t^k + \frac{R_t^f}{R^l} \phi_t^f \right). \quad (13)$$

This shows that the growth rate of net worth for the banking sector is positively related to the aggregate shock. Since investment k_{t+1} is proportional to a_{t+1} , investment is also positively related to the aggregate shock. Therefore, a bank crisis (low realization of η_{t+1}) induces a contraction in investments.

The top panels of Figure 7 show the sensitivity of the growth rate of investments to a banking crisis (negative aggregate shock) for different return spreads R^k/R^l and diversification costs χ . The continuous lines show the overall decline in growth rate when the aggregate shock switches from $\eta_t = \bar{\eta}$ to $\eta_t = \underline{\eta}$. As we increase the return spread (left panel) and decrease the diversification cost (right panel), a banking crisis has a larger negative impact on the investment growth of banks. The numbers reported in the graph are quite large. For example, -0.10 means that the gross growth rate of investment contracts by 10% in response to a banking crisis (approximately from slightly above 1 to 0.9, which implies a drop in the ‘level’ of risky assets of slightly less than 10%).

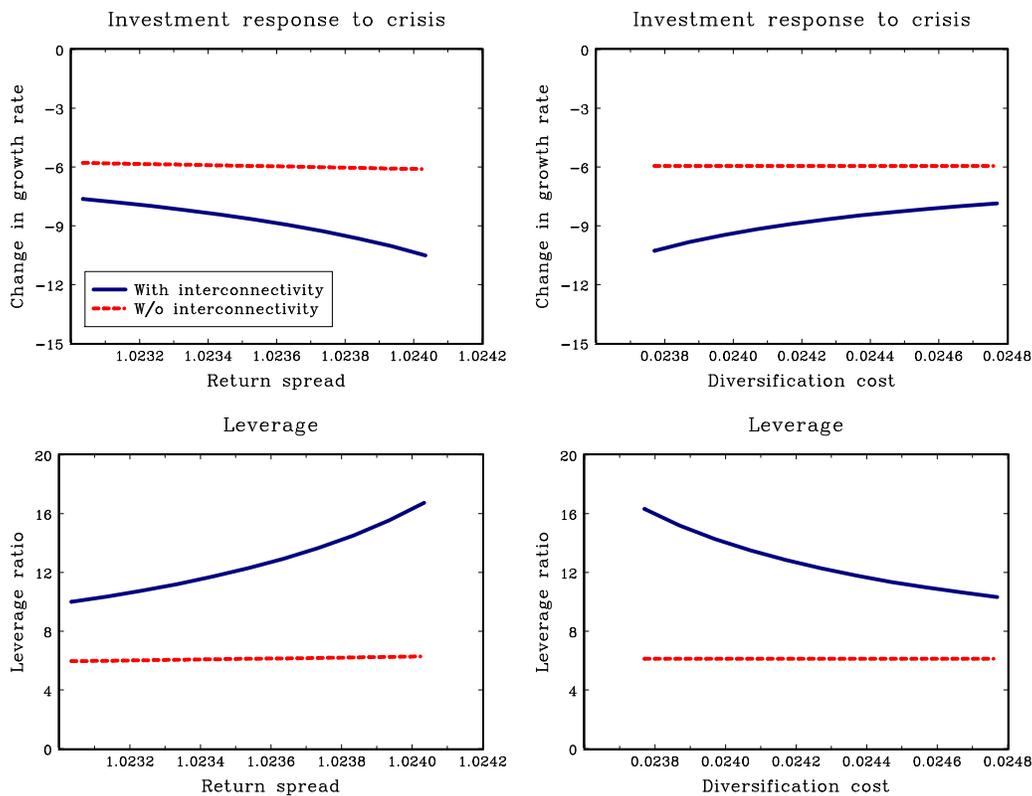


Figure 7: Sensitivity of investment growth to a banking crisis ($\eta_{t+1} = \underline{\eta}$). The negative shock realizes at time t and affects growth between t and $t + 1$. Baseline parameter values are: $\beta = 0.9139$, $R^l = 1.0189$, $R^k = 1.0429$, $\chi = 0.024$, $\gamma = 1.1$, $z \in \{0.932, 1.068\}$ with equal probabilities, $\eta \in \{0.9900, 1.0002\}$ with $p = 0.02$ the probability of $\eta = 0.99$. The sensitivity is performed by changing R^k or χ .

The sensitivity result is a direct consequence of how the changes in return spread and diversification cost affect interconnectivity and leverage. As shown by the continuous lines in the bottom panels of Figure 7, a higher return spread and a lower diversification cost induce

more leverage and interconnectivity. But higher leverage implies that a negative shock has a proportionally bigger impact on banks' net worth and, therefore, a bigger impact on investment.

The next step is to show the importance of interconnectivity. In the case of a diminished diversification cost, banks become more interconnected because it is less costly to diversify. Since diversification reduces the idiosyncratic risk, banks are more willing to take the aggregate risk and become more leveraged. Therefore, it is interconnectivity that induces banks to become more leveraged.

In the case of a higher return spread, banks would become more leveraged even if they could not become more interconnected (diversify). However, since leverage increases the risk faced by banks, the ability to become more interconnected makes the leverage less risky, which further encourages more leverage. Therefore, when the return spread increases, interconnectivity amplifies the impact of the higher return spread on leverage: if banks could not become more interconnected, the increase in leverage would be smaller and, as a result, an aggregate shock would have a smaller impact on investments.

To illustrate the importance of interconnectivity, we conduct the following counterfactual exercise. We force banks to choose $\alpha_t = 0$ so that they do not become interconnected. We then recompute the responses of investment growth to a negative aggregate shock under this assumption. The dashed lines reported in Figure 7 show the results.

When we do not allow banks to become interconnected (by artificially imposing that $\alpha_t = 0$), the response of investment growth to a crisis is significantly smaller. In some cases, the response drops by half. This is because, when banks cannot become interconnected, they choose lower leverage (as shown by the dashed lines in the bottom panels of Figure 7). Furthermore, the response is not very sensitive to the return spread because the sensitivity of leverage, without interconnectivity, is very small.

4 Dynamics of interconnectivity and leverage

We have shown in the introduction that the banking sector in the US has experienced significant changes in the degree of interconnectivity and leverage. Similar changes took place in other countries. What could be the driving forces underlying these changes? In the context of the model presented so far there are two candidates. The first candidate is an increase in the return spread, R_t^k/R_t^l . As shown in Subsection 2.3, a higher return spread between risky investments and core liabilities induces banks to become more interconnected and leveraged. The second candidate is a change in the diversification cost captured by the parameter χ . Subsection 2.3 also showed that a lower diversification cost implies higher interconnectivity and leverage. Before discussing these two mechanisms, we would like to explore first a third mechanism that allows for time-variation in the probability of crises.

One limitation of the model developed so far is the assumption that the probability distribution of the aggregate shock does not change over time. However, as the structure of the banking sector changes due to financial innovations, the risk of a banking crisis could also change, that is, p is time dependent. Furthermore, the probability of a crisis may not be publicly observed and banks make decisions based on their ‘prior’ belief about p . In this section we extend the model by allowing for Bayesian learning about the probability of crises.

To better understand the role of learning, it would be helpful to study first how the likelihood of a crisis, captured by the probability p , affects interconnectivity and leverage. Figure 8 plots the sensitivity of leverage and interconnectivity to the probability p . As can be seen, higher probabilities of crises are associated with lower interconnectivity and leverage.

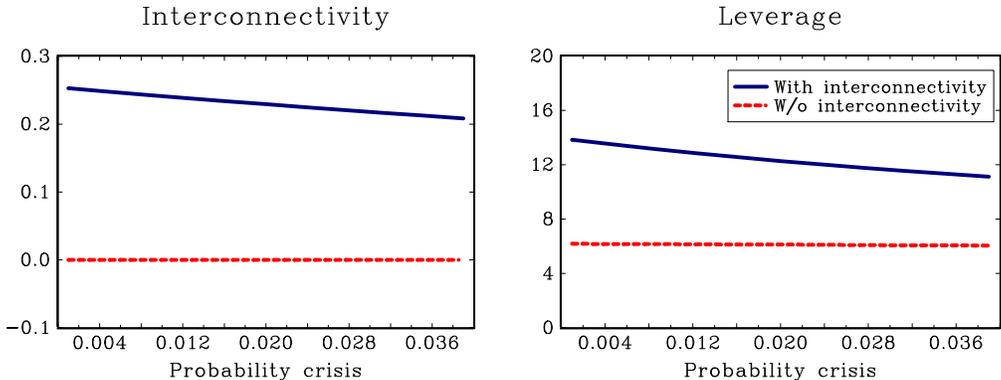


Figure 8: Sensitivity of interconnectivity and leverage to probability of banking crisis. Baseline parameter values are: $\beta = 0.9139$, $R^l = 1.0189$, $R^k = 1.0429$, $\chi = 0.024$, $\gamma = 1.1$, $z \in \{0.932, 1.068\}$ with equal probabilities, $\eta \in \{0.9900, 1.0002\}$ with $p = 0.02$ the probability of $\eta = 0.99$. The sensitivity is performed by changing p .

An increase in p has two effects on the portfolio decisions of banks. First, as the probability of a crisis rises (and the probability of the good outcome declines), the expected return from risky investments, $[p\underline{\eta} + (1 - p)\bar{\eta}]R_t^k$, decreases. Furthermore, the investment risk increases. This implies that, for a given interbank return R_t^f , the share of savings allo-

cated to risky investments declines. The demand for diversified investments F_t also declines (since, for given price $1/R_t^f$, the expected return of these investments falls). These are direct implications of the optimality conditions (9) and (10). The reduction in the demand for diversified investments then leads to a fall in its price $1/R_t^f$. Since α_t depends negatively on R_t^f , the sales of diversified investments also fall. This leads to lower interconnectivity and leverage as Figure 8 shows.

The learning mechanism introduced in the next section allows for an endogenous dynamics of the ‘perceived’ probability p used by banks when they make portfolio decisions.

4.1 Learning the likelihood of a crisis

During the last three decades the financial sector in many advanced economies has gone through a process of transformation driven by financial innovations. How these changes affected the likelihood of a crisis was difficult to assess. Thus, the assumption that the market perfectly knew the magnitude of the aggregate risk—formalized in the probability p —may not be a plausible assumption. A more realistic assumption is that the market formed and some ‘belief’ about the aggregate risk. The belief was then updated as new information became available (experimentation).

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 $\Gamma(p_{t-1}, p_t)$. Banks make decisions based on their ‘belief’ about p_t , not the true value of p_t which is unobservable. Technically, the belief is the probability assigned to the event $p_t = p_H$, which we denote by

$$\theta_t \equiv \text{Probability} \left(p_t = p_H \right).$$

The probability that $p_t = p_L$ is then $1 - \theta_t$. Effectively, θ_t represents the aggregate risk perceived by the market.

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

Denote by $\Pi(\eta_t|p_t)$ the probability of a particular (observed) realization of the aggregate shock $\eta_t \in \{\underline{\eta}, \bar{\eta}\}$, conditional on the true (unobserved) $p_t \in \{p_L, p_H\}$. Formally,

$$\Pi(\eta_t|p_L) = \begin{cases} p_L, & \text{for } \eta_t = \underline{\eta} \\ 1 - p_L, & \text{for } \eta_t = \bar{\eta} \end{cases}, \quad \Pi(\eta_t|p_H) = \begin{cases} p_H, & \text{for } \eta_t = \underline{\eta} \\ 1 - p_H, & \text{for } \eta_t = \bar{\eta} \end{cases}.$$

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

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

The new prior belief then 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 and persistent guarantees that learning is never complete, that is, the probability distribution never converges. If the stochastic process for p_t were i.i.d., the new belief would converge to 1/2 in only one period. In fact, we would have $\Gamma(p_H, p_H) = \Gamma(p_L, p_H) = 1/2$ and the above equation implies that $\theta_{t+1} = 1/2$.

Calibration and simulation. We simulate the model starting in 1999, which is the first year of our empirical sample from Bankscope, until 2014, which is the last year of the sample. In the first 9 years (until 2007) there are no crises, that is, the realization of the aggregate shock is $\eta_t = \bar{\eta}$. Then in 2008 the economy experiences a crisis, that is, the realization of the aggregate shock is $\eta_t = \underline{\eta}$ but it returns to the high value $\eta_t = \bar{\eta}$ in the remaining years (2009-2014).

Compared to the model without learning studied earlier, we also have the parameters associated with the unobserved probability of crises. This probability follows a symmetric first order Markov process with two states, p_L and p_H . We assume that the process is highly persistent and set $\Gamma(p_L, p_L) = \Gamma(p_H, p_H) = 0.99$. This implies that the unconditional average probability of a crisis is $(p_L + p_H)/2 = 0.02$. Therefore, as in the previous calibration we assume that the frequency of a crisis is 50 years. For the calibration of p_L (and p_H) we use information from the credit default swaps for banks plotted in Figure 9. To the extent that a crisis increases the likelihood of bank default, the credit swaps should capture the probability of crises perceived by the market. As can be seen from the figure, the credit default rates were very close to zero before the crisis. We interpret this as evidence that the low probability p_L should be very close to zero. Therefore, we set $p_L = 0.001$. Given the value of p_L , the condition $(p_L + p_H)/2 = 0.02$ then implies $p_H = 0.039$. Therefore, the true probability of a crisis fluctuates between 0.1% and 3.9%.

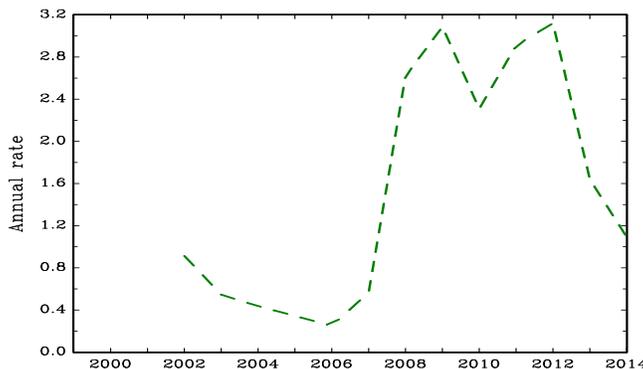


Figure 9: Credit default swaps for large US banks. We took a simple average of the 5-years CDS default spread for the following banks: Bank of America, Citigroup, Goldman Sachs, JP Morgan, Merrill Lynch, Morgan Stanley, and Wells Fargo. Data are annualized and available at monthly frequency from Bloomberg.

Before we can start the simulation we have to initialize the prior probability θ_t . In absence of direct empirical observations, we initialize its value in 1999 so that the expected probability of a crisis in 2007 is 0.5%, that is, $\theta_{2007}p_H + (1 - \theta_{2007})p_L = 0.005$, which is the value of the credit default swap in 2007. Although credit default swaps are not the ‘expected’ probability of a crisis, it is obviously affected by this probability.

Finally, given the 2007 prior, we recalibrate χ and σ_z so that interconnectivity and leverage in the model match the empirical measures of interconnectivity and leverage in 2007, that is, the year before the crisis. However, to reconcile the empirical measure of interconnectivity with the model, we re-scale the empirical measure by half as we did in the previous Section 2.3 (see, in particular, footnote 10).

The dynamics of the key variables are displayed in Figure 10. Let’s focus first on the continuous line. The second panel plots the prior probability θ_t and the third panel plots the (subjective) expected probability of a crisis, $\theta_t p_H + (1 - \theta_t)p_L$. Because during the first 9 years there are no negative realizations of the aggregate shock (no crises), Bayesian updating implies that θ_t —the prior probability of the high risk regime—declines. As a consequence of that also the expected probability of a crisis declines. However, the decline is relatively slow for two reasons. First, since the realization of $\eta_t = \bar{\eta}$ is a high probability event, its observation is not very informative about the unknown p . Thus, the prior is updated slowly. Second, the prior is already very close to zero, which is the lower bound for θ_t .

In the top-right panel, together with the probability of a crisis, we also plotted the credit default swap rates. As observed above, credit default swaps are not the probability of crisis. However, to the extent that a crisis increases the default probability of banks, an increase in the probability of crisis should lead to an increase in default swap rates. The plot seems to suggest that. However, we would like to emphasize that, even if the dynamics of the expected probability in the model captures the dynamics of credit default swaps quantitatively well, we should still interpret the match as qualitative rather than quantitative since the two variables do not measure the exact same things.

As banks revise downward the assessed probability of a crisis (which implies a higher perceived expected return from risky investments and lower risk), they choose higher leverage and interconnectivity. When the crisis materializes in 2008, 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 0.1% and 3.9%). This implies that, differently from the realization of $\eta_t = \bar{\eta}$, a crisis is very informative and leads to a significant revision of the prior. A positive shock, instead, is a high probability event (between 96.1% and 99.9%). Thus, the observation of $\eta_t = \bar{\eta}$ 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 in 2008. The figure also reports the dynamics of interconnectivity and leverage in the data. Although the match is not perfect, the model captures the overall dynamics.

The last panel of Figure 10 plots asset growth (that is, the growth rate of $K_t + F_t$) which, in response to the crisis drops roughly 20 percent. Even if the return on k_t drops by

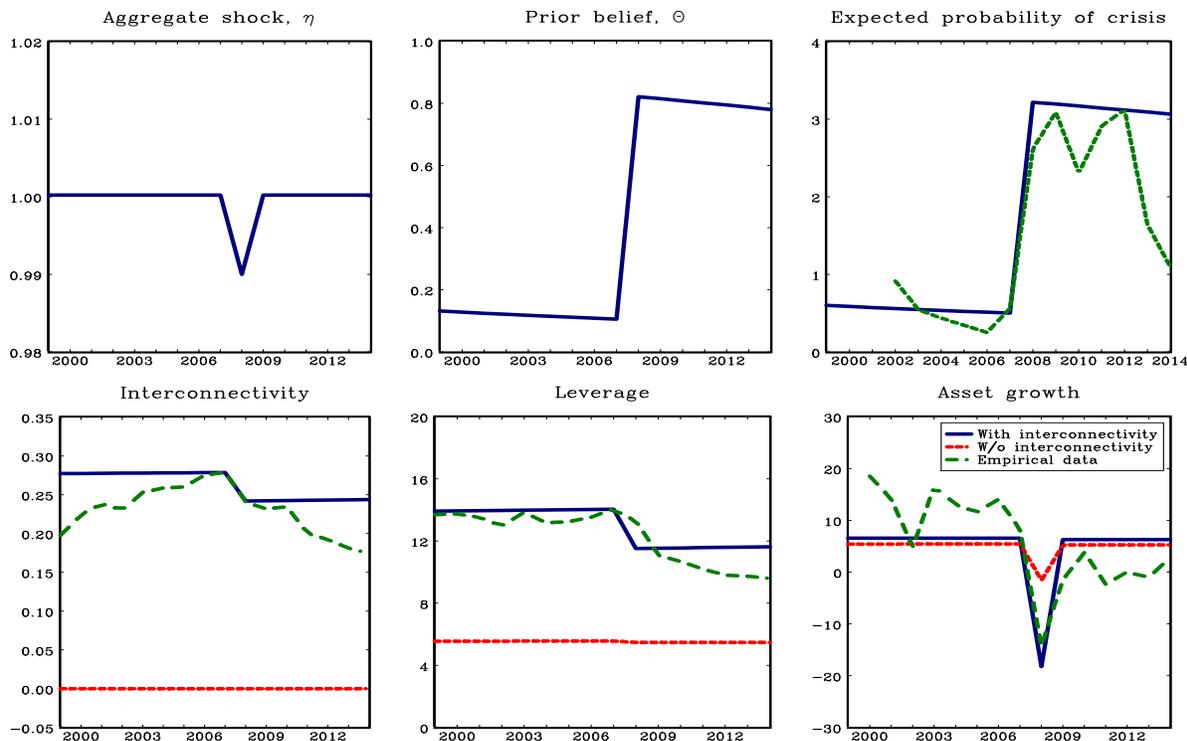


Figure 10: Dynamics with Bayesian learning initialized with prior $\theta_{1999} = 0.1315$. Parameter values are: $\beta = 0.9139$, $R^l = 1.0189$, $R^k = 1.0429$, $\chi = 0.024$, $\gamma = 1.1$, $z \in \{0.932, 1.068\}$ with equal probabilities, $\eta \in \{0.9900, 1.0002\}$ with two probability regimes for $\eta = 0.99$: $p_L = 0.001$ and $p_H = 0.039$.

only 1 percent from the mean, this causes a large drop in equity because banks are highly leveraged. Since investment is proportional to equity, large drops in equity involve large losses in investment. This captures the real consequences of a banking crisis.

We move now to the dynamics of the short-dashed lines shown in the bottom panels. These lines are generated under the counterfactual exercise in which we impose $\alpha = 0$. Essentially we prevent banks from becoming interconnected. As can be seen, the inability to diversify reduces significantly the leverage chosen by banks. Because banks are less leveraged, then a crisis has a much smaller impact on the growth of investment as shown in the last panel. However, the benefit of having milder contractions in investments comes at the cost of lower growth in good times. Overall, the average growth is smaller without interconnectivity. From a policy perspective, there is a trade-off: lower volatility at the expenses of slower growth. For a full analysis of policies, however, the model should be extended to specify the non-financial sector, which we leave for future research.

4.2 Alternative mechanisms

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 compare

this mechanism with other two mechanisms: an increase in the return spread R^k/R^l and a reduction in the cost of diversification captured by the parameter χ . The first change could have been the result of an increase in the investment return R_t^k and/or a decline in cost of borrowing R_t^l . For example, the increasing demand of financial securities from emerging countries could have led to a fall in R_t^l . The second change could have been the result of financial innovations that facilitated diversification. Although not explicitly modelled, the growth in securitization could be seen as a way to facilitate diversification as we will discuss in more details in Section 5.

Proposition 2.1 showed 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 trend could have been the result of changes in the return spread and/or diversification cost.

In order to explore the empirical plausibility of the first mechanism, we construct an empirical proxy for the return spread computed as the difference between two variables: (i) the interest income over the value of assets that earn interest; (ii) the interest expenditures over the average liabilities. More specifically,

$$SPREAD_{it} = \frac{INT_INCOME_{it}}{AV_ASSETS_{it}} - \frac{INT_EXP_{it}}{AV_LIABILITIES_{it}}.$$

Although this measure does not reflect exactly the return spread, it is our closest empirical counterpart.

The first panel of Figure 11 shows the dynamics of this empirical measure for the US. Interestingly, there is a decline in the boom phase of 2003-2007 and a mild increase since then. When we compare the average returns before the crisis (1999-2007) and after the crisis (2008-2014), we do not see much of a difference. This suggests that the high levels of interconnectivity and leverage before the crisis and the subsequent decline after the crisis was not driven by a change in return spread. An interesting feature of the learning mechanism described earlier is that it would generate a dynamics that resembles that in the data even if the return spread does not change. What matters is the return spread perceived by banks.

An exploration of the empirical plausibility of the second mechanism—that is, a reduction and subsequent increase in diversification cost—would require the construction of an empirical proxy for the diversification cost $\varphi(\alpha_t)$. 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’ proposed in this paper, 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 all profits, assets and non-core liabilities of each financial firm i , 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

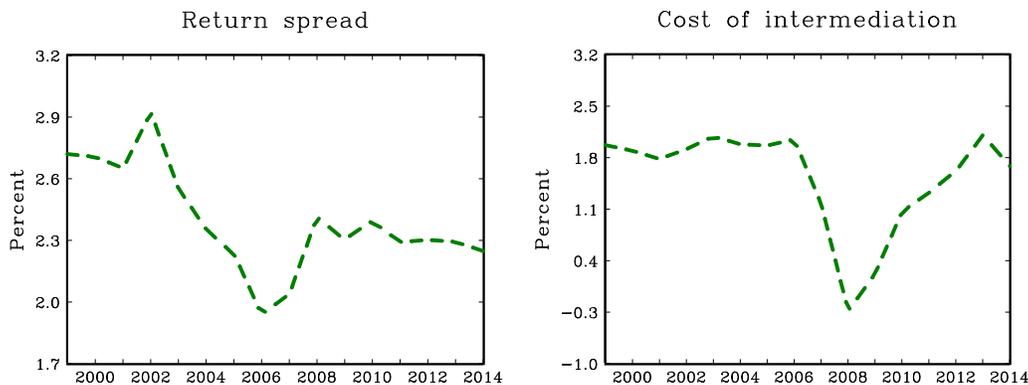


Figure 11: Return spread over time, US. Return spreads are obtained as aggregate return differentials summing up figures for Commercial and Savings Banks, Cooperative Banks, Investment Banks and Securities Firms, and Finance Companies.

between the ultimate lenders and the ultimate borrowers, which is closer in spirit to the exercise performed by Philippon (2015).

The second panel of Figure 11 plots the computed series for the US. For the period that precedes the crisis the value of the series is fairly stable and 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 data does not seem to support the hypothesis that changes in the cost of diversification were a major factor underlying the observed dynamics of interconnectivity and leverage before and after the crisis.

Although the learning mechanism could capture, at least qualitatively, the dynamics leading to the crisis and during the crisis, it does not explain why interconnectivity and leverage continued to fall after the crisis. The model predicts that after the crisis interconnectivity and leverage started to grow again, although at a very slow pace, as we can see from Figure 10. It is important to acknowledge, however, that after the 2007-2008 crisis there has been new regulations that affected 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 could have played an important role in further reducing interconnectivity and leverage in the years that followed the 2007-2008 crisis. The new regulations, however, were introduced after the crisis, and therefore, they cannot explain the initial collapse in interconnectivity and leverage. They seem more relevant for capturing the lack of recovery after the crisis.

5 Empirical analysis

In this section we provide evidence about the relation between interconnectivity and leverage. We start with a brief description of the micro data and how we construct the empirical proxy for the interconnectivity index.

5.1 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 30 OECD countries. We consider different types of financial institutions: commercial banks, investment banks, securities firms, cooperative banks, savings banks and finance companies. 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 D provides further details for the sample selection.

We use book values of assets and liabilities. 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 257,131 with an average value of total assets of 9 billion dollars. Mega Banks are only 0.8% of the total sample (2,108 observations), but they account for a large share of aggregate assets (an average of 609 billions). Commercial banks are more than half of the sample (139,325 observations representing 54% 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 29 billion dollars.

In order to construct the interconnectivity index, we need to classify bank liabilities in core and non-core liabilities. Conceptually, the core-liabilities of banks are those held by the nonfinancial sector while the non-core liabilities are those held by other banks. Unfortunately, Bankscope does not provide information about the holders of bank liabilities and, therefore, we have to rely on some approximation. Our approach is to use the empirical variable $DEPOSITS_{it}$ as a proxy for the core-liabilities of bank i at time t . The proxy for the non-core liabilities is then given by all other liabilities of the bank. The empirical measure of interconnectivity is then given by

$$INTERCONNECTIVITY_{it} = \frac{LIABILITIES_{it} - DEPOSITS_{it}}{ASSETS_{it}}, \quad (14)$$

where $LIABILITIES_{it}$ and $ASSETS_{it}$ are, respectively, the total liabilities and the total assets of bank i at period t .

As pointed out in the introduction, not all $DEPOSITS_{it}$ are held by the nonfinancial sector and not all other liabilities $LIABILITIES_{it} - DEPOSITS_{it}$ are held within the intermediation sector. However, $LIABILITIES_{it} - DEPOSITS_{it}$ are more likely to contain items held within the financial sector than $DEPOSITS_{it}$. Therefore, if we see in the data that $LIABILITIES_{it} - DEPOSITS_{it}$ expands more than $DEPOSITS_{it}$, we interpret it as an indication that cross-bank holdings has increased more than total liabilities.

The empirical leverage is more standard and it is equal to

$$LEVERAGE_{it} = \frac{ASSETS_{it}}{ASSETS_{it} - LIABILITIES_{it}}. \quad (15)$$

The second panel of Figure 2 presented in the introduction showed the dynamics of an asset-weighted average of leverage for the US economy. The aggregate dynamics presented in this figure hides 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 (16.7).

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.

5.1.1 Practical examples

As emphasized above, our measure of interconnectivity is only a proxy for the concept of interconnectivity developed in the theoretical framework. A natural question is whether the empirical proxy for non-core liabilities includes items that fit the idea of non-core liabilities in the model, that is, items that allow the financial intermediation sector to be more diversified. Although the our data does not provide enough information to answer this question, we can describe an example that illustrates how the empirical measure of interconnectivity captures diversification within the financial intermediation sector.

Consider an economy with three banks—*I*, *II* and *III*—and two scenarios—A and B. The balance sheets of the three banks in the two scenarios are shown in the figure below.

Scenario A

Bank I		Bank II		Bank III	
ASSETS	LIABIL	ASSETS	LIABIL	ASSETS	LIABIL
<i>Mortgages=100</i>	<i>Deposits=90</i> <i>Equity=10</i>	<i>Mortgages=100</i>	<i>Deposits=90</i> <i>Equity=10</i>		

Scenario B

Bank I		Bank II		Bank III	
ASSETS	LIABIL	ASSETS	LIABIL	ASSETS	LIABIL
<i>Mortgages=50</i> <i>Securities=45</i> <i>Cash=5</i>	<i>Deposits=90</i> <i>Equity=10</i>	<i>Mortgages=50</i> <i>Securities=45</i> <i>Cash=5</i>	<i>Deposits=90</i> <i>Equity=10</i>	<i>Mortgages=100</i>	<i>Securities=90</i> <i>Equity=10</i>

In the first scenario banks *I* and *II* are active while bank *III* is inactive. Banks *I* and *II* issue equity for 10, raise deposits for 90, and make mortgages for 100. Aggregating the balance sheets of the three banks, the aggregate leverage is 10 while interconnectivity is zero.

In the second scenario bank *III* becomes active. It purchases 50 mortgages from bank *I* and 50 mortgages from bank *II*. To fund these purchases, it raises equity for 10 and issues bonds for 90. Of the issued bonds, 45 are sold to bank *I* and 45 to bank *II*. In this new scenario, the leverage of the banking sector remains 10 since each bank has a leverage of 10. However, the banking sector is now interconnected according to our measure. In particular, the total assets (the sum of the assets of the three banks) are 300 while the non-core liabilities are 90 (the liabilities of bank *III*). The interconnectivity index is thus $90/300=0.3$.

An important difference is that the investment portfolio of banks *I* and *II* is less risky in the second scenario, that is, in the scenario where the banking sector is interconnected. Since banks face lower risk, they may choose higher leverage. This can be achieved by raising more deposits and using the revenues to pay shareholders. Alternatively, they can use the cash obtained through the sales of mortgages to pay dividends to shareholders. Whatever the mechanism, the banking system becomes more leveraged.

The above example is similar to securitization. Securitization is another example that fits the theoretical mechanism developed in the paper. With securitization, however, the assets and liabilities created by bank *III* may not be recorded in the balance sheet of this bank. In fact, once the securities representative of the pooled mortgages are sold to banks *I* and *II*, these securities are no longer liabilities for bank *III*. Therefore, our empirical index of interconnectivity may miss the growth of securitization that took place before the crisis and declined after the crisis. Financial derivatives traded between banks could also generate cross-bank diversification in the spirit of the theoretical model. However, since many financial derivatives may not be fully recorded in conventional balance sheets, they are not captured by our empirical measure of interconnectivity. Nevertheless, although securitization and financial derivatives may not be captured by our empirical index of interconnectivity, they provide examples of high cross-bank diversification in the spirit of our model. Their dynamics—high growth before the crisis and subsequent contraction after the crisis—is similar to dynamics of our empirical index.

5.1.2 Summary statistics and validation

Table 1 reports summary statistics for interconnectivity and leverage. The aggregate average of interconnectivity is 0.15. 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. 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 States shown in Figure 2: Interconnectivity has increased in the period 2000-2007 and decreased after the crisis for the world average and, 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.¹²

¹²See Sato (2009) for a discussion of this issue for Japan and Ratnovki and Huang (2009) for Canada.

Using the Flow of Funds, we can construct a more refined measure of interconnectivity for the US financial sector by dividing the share of net interbank liabilities and short-term borrowing (including repurchasing agreements) by total assets. We also compute the less refined interconnectivity index defined in equation (14), 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 and for different countries using Bankscope data.

In the online appendix, we report the scatter plot for the two (aggregate) measures of interconnectivity both computed from the US Flow of Funds for the whole financial sector excluding the FED, over the period 1952:Q1-2015:Q4. 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.

We propose a second validation exercise. In the online appendix, we report the yearly version of the refined measure from the US Flow of Funds against the less refined measure computed now directly from Bankscope (in both cases, focusing on the US). Again, we see a 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).

Finally, we propose a third validation exercises, only relying on Mega Banks, since for the majority of them we have information about the deposits held by other banks. We plot the ratio of interbank deposits over total assets against the measure of interconnectivity defined in equation (14) for different years. Again, there is a strong positive correlation between these two alternative measures.¹³

5.2 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 12 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, the UK and Germany. The graph shows a strong positive correlation between interconnectivity and leverage. In the online appendix, we report the same correlation for France, Italy, Canada and Japan, where the relation is less strong.

Figure 13 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

¹³In the online appendix we propose a fourth 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. We then plot it against our measure of interconnectivity computed from Bankscope data for the subset of US commercial banks. Once again, we find a strong positive correlation between these two measures.

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 13. Interestingly, variations in interconnectivity alone account for 37 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 14 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 banks, we now explore whether the relation also holds for the full sample. We concentrate here on within banks 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 banks 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 banks, across countries and across time.

In the online appendix, we show how these results are robust to the use of an alternative measure of interconnectivity, namely the ratio of non-core liabilities to total liabilities. Moreover, for the subsample of Mega Banks, for which data are available, we report also the results (similar to those of Table 3) obtained using the ratio of interbank deposits over total assets as a further alternative measure of interconnectivity.

5.3 Response to an aggregate shock

In our model, the response of lending to an aggregate banking crisis is magnified by the level of interconnectivity. In the model, 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. This heterogeneity, in turn, would generate different choices of interconnectivity and leverage, and hence heterogeneous responses of different banks to the same aggregate shock.

After the 2008 Lehman Brother bankruptcy, which sparked the global financial crisis, the rate of growth of bank 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. The goal of this section is not to separate the causes of the lending contraction between demand and supply factors. Instead, our goal is simply to investigate whether the lending contraction was related to the degree of interconnectivity, in the spirit of the results presented in Section 3. 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 model (see Figure 7).

In order to explore empirically this hypothesis, we estimate the regression equation:

$$\begin{aligned} \frac{Loans_{ikt}}{Loans_{ikt-1}} = & \alpha_1 POST_LEHMAN + \alpha_2 POST_LEHMAN * INTERCONN_{ik} + \\ & \alpha_3 INTERCONN_{ik} + \alpha_4 POST_LEHMAN * LEVERAGE_{ik} + \\ & \alpha_5 LEVERAGE_{ik} + \alpha_6 Unempl_{kt-1} + \alpha_7 \ln(Assets)_{ikt} + FE + \epsilon_{ijkt} \end{aligned} \quad (16)$$

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.¹⁴

¹⁴Lehman bankruptcy happened on September 16, 2008. However, since we are using annual data, we

$INTERCONN_{ik}$ 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 .

Equation (16) 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 non financial 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 term, consistent with the 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.¹⁵ 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.¹⁶ 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 confirms the findings of Ivashina and Scharfstein (2010) for the US and Abbassi et al. (2015) for Germany, and it extends them to a larger set of countries.¹⁷

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.

¹⁵This 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).

¹⁶The appropriate critical values have been computed by Stock-Yogo (2005).

¹⁷Although, compared to these studies, we have access to less detailed data.

6 Conclusion

In this paper we have shown that there is a strong positive correlation between financial connectivity of banks and their leverage across countries, across financial institutions and over time. This is consistent with the theoretical results derived in the paper where 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. Our model include also an aggregate, uninsurable shock, that affects the whole banking sector. We interpret a negative realization of this shock as a banking crisis. The probability distribution of this shock is assumed to be unknown and banks make decisions based on their prior beliefs, which are then updated over time using Bayes' rule (learning). This model can generate the aggregate dynamics of interconnectivity and leverage observed in data. It also predicts that systems in which banks are more interconnected experience sharper contractions in lending growth in response to an aggregate banking shock. We explored these predictions using both micro and aggregate data, and we found broad empirical support.

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 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 how interconnectivity affects macroeconomic stability. Our study is also relevant 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 first order conditions for Problem (3) with respect to l_t , f_t and \bar{k}_t are, respectively

$$\frac{1}{c_t R_t^l} = \beta \mathbb{E}_t \frac{1}{c_{t+1}} \quad (17)$$

$$\frac{1}{c_t R_t^f} = \beta \mathbb{E}_t \frac{\eta_{t+1}}{c_{t+1}} \quad (18)$$

$$\frac{1}{c_t \bar{R}_t^k} = \beta \mathbb{E}_t \frac{\eta_{t+1} z_{t+1}}{c_{t+1}} \quad (19)$$

We now guess that the optimal consumption policy takes the form

$$(1 - \gamma)a_t, \quad (20)$$

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

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

We now use (29) and (30) to replace c_t , c_{t+1} , a_{t+1} in the first order conditions (26)-(28) and obtain

$$\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{1}{1 + \left[\eta_{t+1} z_{t+1} \left(\frac{\bar{R}_t^k}{R_t^l} \right) - 1 \right] \phi_t^k + \left[\eta_{t+1} \left(\frac{R_t^l}{R_t^l} \right) - 1 \right] \phi_t^f} \right\} \quad (22)$$

$$\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{\eta_{t+1} z_{t+1} \left(\frac{\bar{R}_t^k}{R_t^l} \right)}{1 + \left[\eta_{t+1} z_{t+1} \left(\frac{\bar{R}_t^k}{R_t^l} \right) - 1 \right] \phi_t^k + \left[\eta_{t+1} \left(\frac{R_t^l}{R_t^l} \right) - 1 \right] \phi_t^f} \right\} \quad (23)$$

$$\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{\eta_{t+1} \left(\frac{R_t^l}{R_t^l} \right)}{1 + \left[\eta_{t+1} \left(\frac{\bar{R}_t^k}{R_t^l} \right) - 1 \right] \phi_t^k + \left[\eta_{t+1} \left(\frac{R_t^l}{R_t^l} \right) - 1 \right] \phi_t^f} \right\} \quad (24)$$

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

B Proof of Proposition 2.1

In absence of aggregate shocks, conditions (9) and (9) imply that $R_t^f = R_t^l$. Furthermore, only $\bar{l}_t = l_t - f_t$ is determined at the individual level. Using (6) and (7) this is equal to

$\bar{l}_t = (\phi^k - 1)R_t^l \beta a_t$. The separate values of l_t and f_t are determined only in aggregate by the equilibrium condition $F_t = \alpha_t K_t$ (where capital letters denote aggregate variables).

Using $F_t = \alpha_t K_t$ and $R_t^f = R_t^l$, the leverage ratio defined in equation (12) 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)-(8) we can derive $\bar{L}_t = [(\phi_t^k - 1)/\phi_t^k](R_t^l/\bar{R}_t^k)\bar{K}_t$. Using these terms, we have

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

We now use equation (4) to replace \bar{R}_t^k . After re-arranging we obtain

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

This can be written more compactly as

$$\frac{L_t/R_t^l}{K_t/R_t^k} = \alpha_t x_t + y_t \left[1 - \alpha_t x_t + \varphi(\alpha_t) x_t \right], \quad (25)$$

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

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

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

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

Since $1 - y_t = 1/\phi_t^k > 0$ 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 $\phi_t^k > 1$ which implies $y_t = (\phi_t^k - 1)/\phi_t^k > 0$. In fact, if $\phi_t^k < 1$, 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 (25) with respect to x_t we obtain

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

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^k is strictly increasing in $x_t = R_t^k/R_t^l$, which implies that $y_t = \left(\frac{\phi_t^k - 1}{\phi_t^k} \right)$ 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

$$\begin{aligned} \phi_t^k &> 1 \\ 1 - \alpha_t x_t + \varphi(\alpha_t) x_t &> 0 \quad . \end{aligned}$$

As argued above, the first condition ($\phi_t^k > 1$) 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 Lemma 2.3

The first order conditions for Problem (3) with respect to l_t , f_t and \bar{k}_t are, respectively

$$\frac{1}{c_t R_t^l} = \beta \mathbb{E}_t \frac{1}{c_{t+1}} \quad (26)$$

$$\frac{1}{c_t R_t^f} = \beta \mathbb{E}_t \frac{\eta_{t+1}}{c_{t+1}} \quad (27)$$

$$\frac{1}{c_t \bar{R}_t^k} = \beta \mathbb{E}_t \frac{\eta_{t+1} z_{t+1}}{c_{t+1}} \quad (28)$$

We now guess that the optimal consumption policy takes the form

$$(1 - \gamma)a_t, \quad (29)$$

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

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

We now use (29) and (30) to replace c_t , c_{t+1} , a_{t+1} in the first order conditions (26)-(28) and obtain

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

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

$$\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{\eta_{t+1} \left(\frac{R_t^l}{R_t^l} \right)}{1 + \left[\eta_{t+1} \left(\frac{\bar{R}_t^k}{R_t^l} \right) - 1 \right] \phi_t^k + \left[\eta_{t+1} \left(\frac{R_t^l}{R_t^l} \right) - 1 \right] \phi_t^f} \right\} \quad (33)$$

Next we can show that γ must be equal to β and, therefore, we obtain (9) and (10).

D 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).¹⁸ We polished the data in order to avoid duplicate observations and to favor consolidated statements over unconsolidated ones.

¹⁸See 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	257,131		9,078	82,160	12.5	9.0	0.15	0.20
of which:								
Mega Banks	2,108	0.8	609,211	577,079	25.7	15.1	0.57	0.24
Commercial Banks	139,325	54	6,651	71,044	10.8	5.7	0.10	0.15
Investment Banks	4,139	1.6	29,038	97,790	16.7	19.4	0.61	0.31

Notes: assets are in millions of USD. Leverage is measured as total assets over total equity. Interconnectivity is measured as the ratio between non-core liabilities and total assets. Mega banks are defined as financial institution with balance sheet never smaller than 100 USD billions.

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

Dep Variable	A/E	A/E	A/E
INTERCONN	22.689*** (1.353)	19.098*** (2.220)	20.929*** (2.229)
Country FE	No	Yes	Yes
Time FE	No	No	Yes
R-squared	0.370	0.788	0.850
N	480	480	480

Notes: unconditional and conditional correlations between leverage and interconnectivity at country level. Interconnectivity is measured as the ratio of aggregate non-core liabilities to aggregate assets and Leverage as the ratio of aggregate assets over aggregate equity. Aggregate assets, liabilities and equities are computed by summing the values of these variables for all Commercial and Savings Banks, Cooperative Banks, Investment Banks and Securities Firms, and Finance Companies. Assets and liabilities are in book values. 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	35.597***	28.802***	30.066***
	(1.735)	(3.070)	(8.040)
size	-0.134	-1.029**	4.445*
	(0.376)	(0.449)	(2.360)
Specialisation FE	No	Yes	No
Country FE	No	Yes	No
Time FE	No	Yes	Yes
Banks FE	No	No	Yes
R-squared	0.343	0.513	0.194
N	1272	1272	1272

Notes: unconditional and conditional correlations between leverage and interconnectivity for financial institutions with balance sheets larger than 100 USD billions. Leverage is measured as total assets over total equity for each financial institution. Interconnectivity is measured as the ratio between non-core liabilities and total assets. Assets and liabilities are in book values. 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	8.284***	6.684***	5.785***
	(0.454)	(0.686)	(0.779)
size	2.476***	2.658***	2.742***
	(0.101)	(0.135)	(0.182)
Banks FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R-squared	0.094	0.118	0.116
N	213576	125883	69705

Notes: conditional correlations between leverage and interconnectivity for all financial institutions (two way fixed effect estimator). Leverage is measured as total assets over total equity for each financial institution. Interconnectivity is measured as the ratio between non-core liabilities and total assets. Size is measured as the log of total assets. Assets and liabilities are in book values. 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)
POST LEHMAN (2009-)	-0.067*** (0.005)	-0.124*** (0.007)	-0.109*** (0.007)	-0.165*** (0.008)	
LEHMAN*INTERCONN	-0.190*** (0.015)		-0.212*** (0.016)	-0.206*** (0.015)	-0.196*** (0.015)
INTERCONN	-0.010 (0.010)		0.016 (0.010)		
LEHMAN*LEVERAGE		0.002*** (0.000)	0.003*** (0.000)	0.008*** (0.000)	0.008*** (0.000)
LEVERAGE		-0.007*** (0.000)	-0.007*** (0.000)		
log(Assets)	0.009*** (0.001)	0.012*** (0.001)	0.014*** (0.001)	-0.000 (0.004)	0.028*** (0.004)
Unempl	-0.011*** (0.001)	-0.006*** (0.001)	-0.009*** (0.001)	-0.008*** (0.001)	-0.003* (0.001)
Country FE	Yes	Yes	Yes	No	No
Banks FE	No	No	No	Yes	Yes
Time FE	No	No	No	No	Yes
R-squared-adj	0.064	0.069	0.073	0.072	0.080
N	74051	74314	74046	74046	74046

Notes: impact of interconnectivity on the reduction of the growth of lending following Lehman Brothers bankruptcy. OLS estimates. *INTERCONN* is the average interconnectivity for the period 2003-2006. *LEVERAGE* is the average leverage for the period 2003-2006. *Unempl* if the unemployment rate (a time $t - 1$). 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-)	-0.084*** (0.009)	-0.104*** (0.021)	-0.082*** (0.022)	-0.119*** (0.021)	
LEHMAN*INTERCONN	-0.163*** (0.047)		-0.181*** (0.049)	-0.131*** (0.046)	-0.183*** (0.051)
INTERCONN	-0.639*** (0.069)		-0.676*** (0.071)		
LEHMAN*LEVERAGE		-0.000 (0.002)	-0.000 (0.002)	0.001 (0.002)	-0.000 (0.002)
LEVERAGE		-0.010*** (0.002)	-0.009*** (0.002)		
log(Assets)	0.032*** (0.002)	0.020*** (0.001)	0.038*** (0.002)	0.063*** (0.003)	0.103*** (0.004)
Unempl	-0.003 (0.002)	0.000 (0.001)	-0.002 (0.002)	0.001 (0.002)	-0.008*** (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-adj	0.000	0.049	-0.033	0.055	0.068
N	67753	67953	67753	67333	67333
Cragg-Donald Wald F	616.2122	730.9893	237.1676	3024.929	2463.496

Notes: impact of interconnectivity on the reduction of the growth of lending following Lehman Brothers bankruptcy. IV estimates. *INTERCONN* is the average interconnectivity for the period 2003-2006. *LEVERAGE* is the average leverage for the period 2003-2006. *Unempl* is the unemployment rate (a time $t - 1$). Standard Errors in Parenthesis. *, **, *** Statistically Significant at 10%, 5% and 1%.

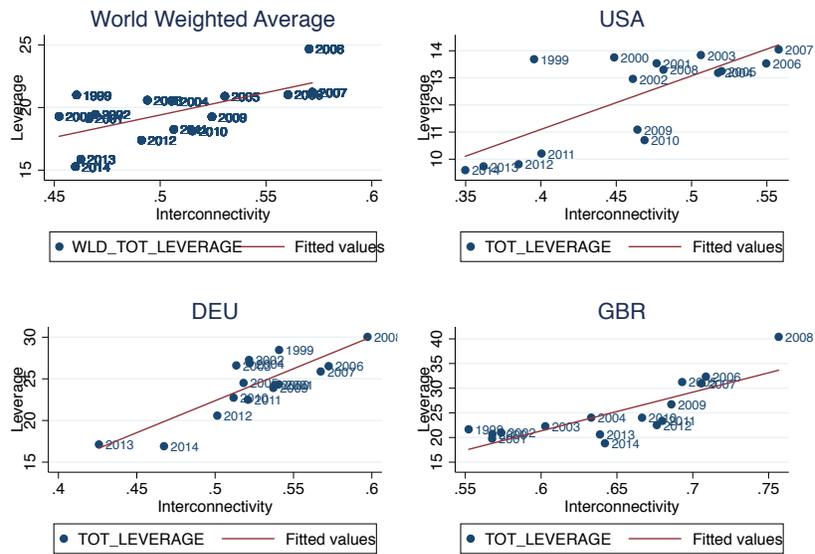


Figure 12: Leverage and Interconnectivity, Across Time, Within Selected Countries. Leverage is measured as total assets over total equity for each financial institution. Interconnectivity is measured as the ratio between non-core liabilities and total assets. Aggregate assets, non-core liabilities and equities are computed by summing the values of these variables for all Commercial and Savings Banks, Cooperative Banks, Investment Banks and Securities Firms, and Finance Companies. Assets and liabilities are in book values.

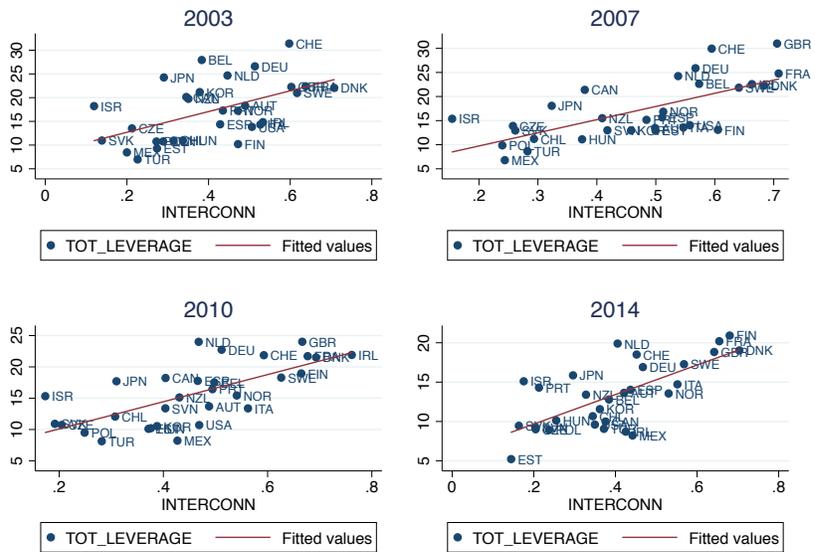


Figure 13: Leverage and Interconnectivity, Across countries, Selected Years. Leverage is measured as total assets over total equity for each financial institution. Interconnectivity is measured as the ratio between non-core liabilities and total assets. Aggregate assets, non-core liabilities and equities are computed by summing the values of these variables for all Commercial and Savings Banks, Cooperative Banks, Investment Banks and Securities Firms, and Finance Companies. Assets and liabilities are in book values.

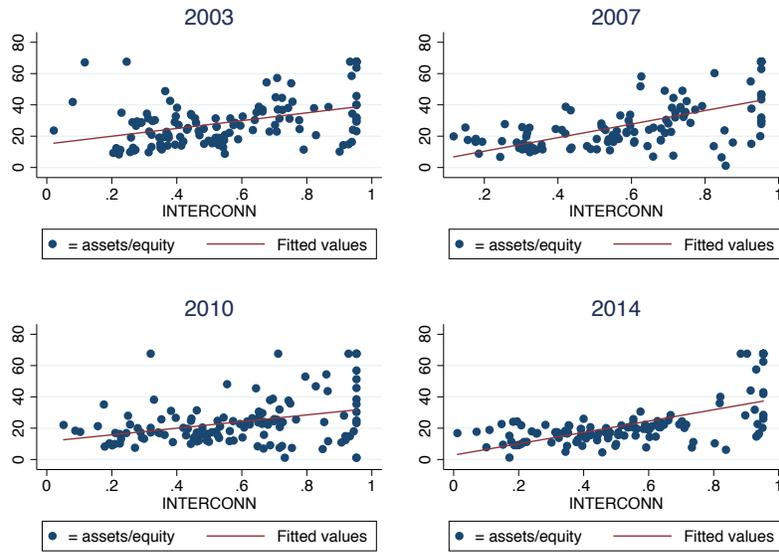


Figure 14: Leverage and Interconnectivity, Mega Banks, Selected Years. Leverage is measured as total assets over total equity for each financial institution. Interconnectivity is measured as the ratio between non-core liabilities and total assets. Mega banks are financial institutions with balance sheets larger than 100 USD billions.