BANKS FUNDING, LEVERAGE, AND INVESTMENT*

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10th January 2019

Abstract

The sources of funding for the banking sector have changed significantly during the last two decades. The share of non-core liabilities over total assets was very high before the 2008 crisis but declined significantly after the crisis. Bank leverage also declined during this period. To understand these patterns we propose a model where a higher share of non-core funding makes leverage more attractive to banks. Although this leads to higher investment growth, the banking sector becomes more vulnerable to crises. We also show that learning about the likelihood of a crisis could have played an important role in generating high shares of non-core funding and high leverages 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 the size of non-core funding and leverage, consistent with the model. We also find that banks with higher reliance on non-core funding experienced stronger decline in investment after the crisis, which is also consistent with the model.

JEL classification: E32, G11, G21

Keywords: Market Funding, Leverage, Bank Crises

*We would like to thank Juliana Begenau, Tobias Broer, Ester Faia, Matej Marinč for discussing the paper in various conference. We would also like to thank Matija Lozej and participants to several conferences and seminars for useful comments and suggestions. Alessandro Barattieri acknowledges financial support from the Einaudi Institute for Economics and Finance (EIEF) Research Grants 2016, Vincenzo Quadrini from NSF Grant 1460013. An earlier version of this paper has circulated under the title ‘Bank Interconnectivity and Leverage’. The views expressed in this paper do not reflect the views of the ECB, the Central Bank of Ireland or the European System of Central Banks. All errors are ours.
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, the expansion of the financial sector has been associated with two related trends. The first trend is the growing importance of non-core funding. Generally speaking, non-core funding consists of liabilities issued by financial intermediaries that are different from the typical bank deposits. A significant portion of these liabilities are held by other financial intermediaries and this generates important balance sheet interconnectedness across banks. The second trend is the increase in the leverage of financial intermediaries.

Figure 1 plots a schematic balance sheet of banks, with two types of assets and two types of liabilities. The first type of assets (core investments) include investments made by banks in the non-financial sector, such as industrial loans and residential mortgages. The second type of assets (non-core investments) include securities issued by other financial firms, such as bonds and mortgage-backed securities. Similarly, on the other side of the balance sheet we have liabilities held by the non-financial sector, such as households deposits (core liabilities). The second type of liabilities (non-core liabilities) are those held by other financial institutions, such as commercial papers issued by financial firms and purchased by other financial firms. Formally, we define non-core-funding (NCF) as the ratio of non-core liabilities over total assets.\(^1\)

The first panel of Figure 2 plots the empirical measure of NCF using data from the US

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\(^1\)In a banking equilibrium, the aggregate value of non-core liabilities are equal to the aggregate value of non-core investments. Therefore, whether we define NCF 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 NCF is provided in Section 5.
Flow of Funds over the period 1999-2013. We concentrate on three categories of financial intermediaries: depository institutions, securities brokers and dealers, and finance companies. Since the Flow of Funds do not specify the identity of the holders of liabilities, the empirical index is only a ‘proxy’ for NCF. More specifically, the empirical measure of non-core liabilities is the sum of repurchasing agreements (REPOs), commercial papers and loans from other financial institutions. More details are provided in the Data Appendix. The NCF measure reached a peak just before the 2008 financial crisis and then declined drastically during and after the crisis.

\[ \text{NCF} = \text{sum of REPOs, commercial papers and loans from other financial institutions} \]

The second panel of Figure 2 plots the leverage of the US financial sector also focusing on the three main categories of financial intermediaries. Leverage is computed as the ratio of total assets over equity. Leverage was also very high before the financial crisis but declined drastically after the crisis. Therefore, at least over this period, NCF and leverage for the whole banking sector moved together.

In the empirical section of the paper (Section 5) we use firm-level data from Bankscope for over 14,000 financial institutions located in 30 OECD countries. We show that the patterns displayed in Figure 2 are not limited to the United States but, with few exceptions, are also observed in other countries. More generally, in the empirical section we explore the correlation between NCF and leverage along three dimensions: across banks, across time and across countries. We show that there is a strong positive association between the banks’ NCF and leverage. In particular, banks that have higher NCF are more leveraged; when an individual bank increases its NCF, it becomes also more leveraged; countries in which the banking sector uses more NCF exhibit higher leverage.\(^2\)

\(^2\)It is important to point out that the positive relation between the NCF and leverage does not derive from
Motivated by these empirical patterns, we address three questions. First, how are NCF and leverage related at the level of an individual bank? More specifically, how does non-core funding affect the optimal leverage chosen by a bank? Second, how does non-core funding affect the stability of the whole banking sector? Third, what are the forces that induced banks to increase NCF and leverage before the crisis and reduce them after the crisis?

To address these questions we develop a dynamic model where banks make investments in the non-financial sector (core investments) and in the financial sector (non-core investments) funded with equity, liabilities sold to the non-financial sector (core liabilities) and liabilities sold to other banks (non-core liabilities). A key difference between core and non-core liabilities is that the latter provide insurance against the idiosyncratic risk associated with core investments. We formalize this idea by assuming that banks issue securities whose payout depends on the return from its core investments and sell them to other banks. The cross-ownership of bank liabilities, however, creates a systemic risk for the whole banking sector since the default of some banks could trigger the default of other banks, resulting in an economy-wide banking crisis. Therefore, the expansion of non-core funding for the whole banking sector implies a trade-off between risk-sharing and systemic risk: higher NCF allows for better insurance of the idiosyncratic risk but it increases the aggregate (systemic) risk.

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 the idiosyncratic risk through the issuance of non-core liabilities. At the same time, when banks are more diversified (as a result of higher NCF), they face lower idiosyncratic risk and are more willing to leverage. Therefore, the linkage between NCF and leverage is a two-way stream: factors that encourage more leverage also induce higher NCF, and factors that encourage NCF also induce higher leverage. But there are also factors that affect simultaneously NCF and leverage and not necessarily in the same direction. For example, an increase in idiosyncratic risk increases the incentive to issue non-core liabilities while reducing the incentive to leverage.

Regarding the second question addressed in this paper (how non-core funding affects the stability of the banking sector) we show that higher NCF increases the aggregate volatility of the whole banking sector through two channels. First, the issuance of non-core liabilities and their cross-bank holdings create the conditions for systemic risk as the default of some banks induces the default of other banks, leading to an economy-wide banking crisis. The losses incurred by banks in a crisis increase with the size of NCF which in turn induces higher contraction in core investments. The second channel operates through leverage. Since non-core liabilities reduces the idiosyncratic risk, banks are more willing to leverage. But higher leverage implies that the losses incurred in a crisis have a proportionally stronger effect on the equity of banks. This in turn has a stronger negative effect on investments.

We also use the model to understand the possible factors that could have induced banks to increase 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 the NCF but increases leverage. See Figure 6 for a counterexample based on the theoretical model.
to increase non-core funding and leverage before the crisis but to reduce them after the crisis (the third question addressed in this paper). In particular, we explore the role of Bayesian learning about the probability of a crisis. Bayesian learning has been formalized in aggregate models of debt by Boz and Mendoza (2014) and Hennessy and Radnaev (2016). They showed that this mechanism can generate financial and macroeconomic cycles in the non-financial sector (since there are no banks in these models). In this paper we show that learning is important not only for the leverage cycle but also for the NCF cycle of banks. More importantly, the leverage cycle of banks would be negligible in absence of the NCF cycle. Thus, movements in NCF create a powerful amplification mechanism for the leverage of the banking sector and, more generally, for the macroeconomic cycle.

The learning mechanism works as follows: Since the probability of a banking crisis is unknown, banks make their portfolio decisions based on their ‘belief’ about this probability. The belief is then updated over time through Bayesian learning. Learning implies that when a crisis does not materialize, banks lower the assessed probability of the crisis, that is, they perceive a lower systemic risk. But a lower systemic risk increases the attractiveness of non-core investments which in equilibrium increases the issuance of non-core liabilities. As banks issue more non-core liabilities, they face lower idiosyncratic risks which, together with the lower perceived systemic risk, makes it optimal to take more leverage.

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 (the probability of future crises). This causes a drastic reduction in NCF, leverage and investments. In this way, the model generates a dynamics of NCF and leverage that resembles the dynamics observed in the data. Importantly, as we observed above, the increase in leverage and subsequent decline would be much smaller if banks were not able to issue non-core liabilities. The model also predicts that banks with higher reliance on non-core funding are more vulnerable to a crisis. The empirical section of the paper shows that this property is consistent with the data.

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 of investments to a banking crisis and its dependency on NCF. Section 4 presents the extended model with Bayesian learning. Section 5 conducts the empirical analysis and Section 6 concludes.

1.1 Related literature

The main contribution of our paper is to study the interplay between non-core funding and leverage of banks. There is a large body of literature that studies either the role played by non-core funding or the role of leverage for the operation of banks. However, papers that study simultaneously the interaction between non-core funding and leverage are limited.

Two of the early contributions that studied the role of non-core funding as a way to create interconnectedness among banks are Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000). They develop formal models illustrating how interconnectedness within the financial sector can be a source of propagation of shocks. These contributions led to the
development of a large literature.\textsuperscript{3}

The trade-off between risk-sharing and contagion—which is one of the features of our model—is also emphasized in the financial network model of Cabrales, Gottardi and Vega Redondo (2017). Also related to our paper is Foley-Fisher, Narajabad and Verani (2018). They document how the liability structure of banks creates the conditions for self-fulfilling runs in shadow banking, which is also a feature of our model.

Studies of shadow banking are related to our paper since shadow banks rely more on non-core funding. Begenau and Landvoigt (2017) study how capital regulation for commercial banks affects shadow banking activity. Chen and Zha (2018) show that monetary policy in China has been less effective due to the presence of shadow banks. Dubois and Lambertini (2018) investigates the role of wholesale funding in a macroeconomic setting.

There is also a literature that models the interbank market as a source of liquidity for banks, such as Bianchi and Bigio (2014). Our study emphasizes the insurance function (as opposed to the liquidity function) played by interbank activities and, for that purpose, it looks at a broader set of interbank transactions.

On the empirical side there are several studies that look at the importance of bank interconnectedness for systemic risk. Billio et al. (2012) propose empirical measures of systemic risk in finance and insurance sectors based on principal components analysis and Granger-causality tests. Cai, Saunders and Steffen (2017) propose a measure of bank interconnectedness using syndicated corporate loan portfolios and find evidence that more interconnected banks are characterized by higher measures of systemic risk.\textsuperscript{4}

The second strand of literature related to our paper is on bank leverage. In a series of papers, Adrian and Shin (2010, 2011, 2014) document that leverage is pro-cyclical and there is a strong positive relationship between leverage and the size of the balance sheet. They also show that, at the aggregate level, changes in balance sheets impact asset prices via changes in risk appetite. Nuno and Thomas (2017) document the presence of a bank leverage cycle in the post-war US data. Geanakoplos (2010) and Simsek (2013) propose theoretical explanations for the pro-cyclicality of leverage while Begenau (2016) studies the importance of bank capital requirement for the optimal choice of leverage, investment and risk. 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 for

\textsuperscript{3}For example, David and Lear (2011) developed a model in which bank 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. Gennaioli et al. (2013) proposed a model of securitization where interconnectedness can lead to financial crises in presence of bounded rationality in the form of ‘neglected risk’. Eisert and Eufinger (2014) showed that banks could have an incentive to become interconnected to exploit their implicit government guarantee.

\textsuperscript{4}See also Drehmann and Tarashev (2013) for an empirical analysis of banks interconnectedness and systemic risk based on Shapley values, as well as Peltonen et al. (2018) who analyze the role of the aggregate interconnectedness of the banking sector as a mechanism that increases vulnerability to crises. Hale et al. (2016) study the transmission of financial crises via interbank exposures based on deal-level data for interbank syndicated loans. Cetorelli and Goldberg (2012) show the importance of international bank linkages for the cross-country transmission of (monetary) shocks.
non-financial firms over the business cycle. For example, Covas and Den Haan (2011) and Begenau and Salomao (2018) 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 study the importance of Bayesian learning in models with endogenous leverage. The scope of these studies, however, is limited to the non-financial sector. They do not explore the role of non-core funding for banks and its interaction with bank leverage, as we do in our paper.

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. 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 the 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, Koijen and Yogo (2016) shows that an increase in interconnectedness is also a feature of the insurance industry where companies resell their insurance policies to other companies. This suggests that a similar theoretical framework as the one developed in our paper could be used to study the insurance industry.

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 \( 1/R^f_t \). 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), the rate \( R^f_t \) is endogenously determined to clear the interbank market. This justifies the time subscript in \( R^f_t \) but not in \( R^l \) and \( R^k \). Notice that \( R^l \) also reflects the possibility of deposit insurance: in practice, deposit insurance reduces the effective cost of liabilities and creates a risk-taking incentive for banks as in many other banking models.

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 assumption that banks are atomistic is obviously an abstraction but it facilitates the tractability of the model.
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 concavity of the utility function for banks. One interpretation is that this function represents the preference of the major shareholders of the bank. Alternatively, we can think of the utility function as representing the preferences of top managers 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 convexity of the financial distress cost would make the objective of the bank concave. An alternative approach would be to assume that dividends enter the objective of the bank linearly together with a convex cost of default. This alternative model would have similar properties to the model proposed here.

Denote by $a_t$ the net worth of the bank at time $t$. Given the net worth, the bank could sell (core) liabilities $l_t$ to the non-financial sector at the market price $1/R^l_t$ and make risky (core) investments $k_t$, also in the non-financial sector, at the market price $1/R^k_t$. As observed above, prices $1/R^l_t$ and $1/R^k_t$ 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 $z_{t+1}k_t$ where $z_{t+1}$ is an iid idiosyncratic stochastic variable (shock) that affects only the return of the individual bank. The shock is observed at $t + 1$ and, therefore, after the choice of $k_t$, and satisfies $E_t z_{t+1} = 1$. Therefore, $R^k_t$ is the ‘expected’ gross return from the risky investment while $z_{t+1}R^k_t$ is the actual gross return realized at $t + 1$. Since there is no uncertainty on the liability side, $R^l_t$ is both the expected and actual return.

The risk generated by the idiosyncratic shock can be diversified with the sale of securities $m_t$ with payout conditional on the return of the risky investment. More specifically, $m_t$ securities issued at time $t$ pay $z_{t+1}m_t$ at time $t + 1$. The price for these securities, which will be determined in equilibrium, is $1/R^m_t$. Banks can also buy a diversified portfolio of liabilities issued by other banks which we denote by $f_t$. Thus, by issuing $m_t$ and purchasing $f_t$, both at price $1/R^m_t$, a bank is able to diversify the investment risk associate to the risky investment $k_t$. We refer to $m_t$ and $f_t$, respectively, as non-core liabilities and non-core investments.

The ability to insure the investment risk, however, is limited by the cost of issuing non-core liabilities $m_t$. The cost takes the form $\varphi(m_t/k_t)k_t$, where $\varphi(.)$ is strictly increasing and convex. To simplify the notation we will use the variable $\alpha_t = m_t/k_t$, which represents the share of core investments funded with non-core liabilities.

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

The specific functional form assumed is not essential but it is analytically convenient because it allows us to study the importance of the issuance cost with the parameter $\chi$.

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5 The sale of non-core liabilities 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 $f_t$ are entitled to the return of the bank core 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.
Given the net worth \( a_t \), the budget constraint of a bank at the beginning of the period is

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

where \( c_t \) denotes the dividends paid by the bank.

**Systemic banking crisis:** Although the market for non-core liabilities allows banks to insure the idiosyncratic risk, the cross ownership of these liabilities creates the conditions for a systemic banking crisis. To see why, consider the balance-sheet of a bank at end of period \( t \), after the portfolio choice and the payment of dividends. This is illustrated in Figure 3.

Figure 3: Schematic balance sheet in the model.

<table>
<thead>
<tr>
<th>ASSETS</th>
<th>LIABILITIES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investments in non-financial sector, ( \frac{k_t}{R^k} ) (Core investments)</td>
<td>Liabilities held by non-financial sector, ( \frac{l_t}{R^l} ) (Core liabilities)</td>
</tr>
<tr>
<td>Investments in financial sector, ( \frac{f_t}{R^f} ) (Non-core investments)</td>
<td>Liabilities held by financial sector, ( \frac{m_t}{R^f} ) (Non-core liabilities)</td>
</tr>
<tr>
<td>Equity, ( e_t )</td>
<td></td>
</tr>
</tbody>
</table>

On the asset side the bank holds core investment \( k_t/R^k \) and non-core investment \( f_t/R^f \). On the funding side there are core liabilities \( l_t/R^l \) and non-core liabilities \( m_t/R^f \). The difference between assets and liabilities is the equity of the bank \( e_t \). Figure 3 is the model equivalent of the empirical balance sheet presented in Figure 1. We will see that in equilibrium all banks choose the same portfolio composition. Therefore, Figure 3 can also be interpreted as the aggregation of the unconsolidated banking sector.

The end-of-period balance sheet illustrates why non-core assets and liabilities create the conditions for systemic risk through bank default. Suppose that the market believes that all banks are going to default on their non-core liabilities \( m_t/R^f \). Since non-core investments \( f_t/R^f \) are a diversified portfolio of non-core liabilities issued by all banks, their value drops to zero. Each single bank could then become insolvent, meaning that the value of assets becomes smaller than the value of its liabilities, that is, \( k_t/R^k < l_t/R^l + m_t/R^f \). This induce all banks to default, validating the market expectation of economy-wide default. Instead, if the market believes that banks are not going to default, each single bank remains solvent (since in equilibrium \( k_t/R^k + f_t/R^f > l_t/R^l + m_t/R^f \)) and will not default. This could generate self-fulfilling banking crises, that is, it is the market expectation of a crisis (banks’ default) that causes the crisis.

In case of economy-wide default, banks enter a process of renegotiation and incur the renegotiation cost \( \mu f_t \). Thus, in the event of default, the net recovery of non-core investments is \((1 - \mu)f_t\) instead of \( f_t \).
Since banking crises are self-fulfilling when all banks make portfolio decision that satisfy
\[ \frac{k_t}{R^k} < \frac{l_t}{R^l} + \frac{m_t}{R^l}, \]
that is, there are multiple equilibria, we assume that the crisis equilibrium is selected through the random draw of a non-fundamental variable (sunspot). This is stated formally in the following assumption.

**Assumption 2.** Denote by \( s_t \) a stochastic variable that takes the value of 1 with probability \( p \) and zero with probability \( 1 - p \). If \( \frac{k_t}{R^k} < \frac{l_t}{R^l} + \frac{m_t}{R^l} \) for all banks, the crisis equilibrium arises if the random draw of \( s_t \) is 1. If \( \frac{k_t}{R^k} \geq \frac{l_t}{R^l} + \frac{m_t}{R^l} \) for all banks, a crisis equilibrium never arises.

We will see that in equilibrium, if the condition for multiplicity \( \frac{k_t}{R^k} < \frac{l_t}{R^l} + \frac{m_t}{R^l} \) is satisfied for one bank, it will be satisfied for all banks. This is because banks make portfolio decision characterized by the same ratios \( \frac{l_t}{k_t}, \frac{m_t}{k_t} \) and \( \frac{f_t}{k_t} \).

For the analysis that follows it would be convenient to define the variable \( \eta_t \) as a dummy that takes the value of \( 1 - \mu \) in the event of a banking crisis and 1 without a crisis. Given Assumption 2, the probability that \( \eta_t = 1 - \mu \), denoted by \( p_t \), is given by

\[
p_t = \begin{cases} 
p, & \text{if } \frac{k_t}{R^k} < \frac{l_t}{R^l} + \frac{m_t}{R^l} \\
0, & \text{otherwise} \end{cases}
\]

(1)

The variable \( p_t \) is the probability of a crisis and it is positive and equal to \( p \) only if the self-fulfilling equilibrium is feasible, that is, \( \frac{k_t}{R^k} < \frac{l_t}{R^l} + \frac{m_t}{R^l} \).

**Optimization problem:** A bank solves the following optimization problem

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

(2)

subject to:

\[
c_t = a_t + \frac{l_t}{R^l} - \frac{k_t}{R^k} + \frac{[\alpha_t - \varphi(\alpha_t)]k_t}{R^l} - \frac{f_t}{R^f} \\
a_{t+1} = z_{t+1}(1 - \alpha_t)k_t + \eta_t f_t - l_t.
\]

It maximizes the discounted expected utility of the owner, given the net worth \( a_t \), subject to the budget constraint and the law of motion for the next period net worth. By combining the first order conditions for \( \alpha_t \) and \( k_t \) we derive

\[
\frac{R^k}{R^l} = \frac{1}{1 - \varphi(\alpha_t) - \varphi'(\alpha_t) + \alpha_t \varphi'(\alpha_t)}.
\]

(3)

This condition determines \( \alpha_t \) as a function of the return ratio between core and non-core investments, \( \frac{R^k}{R^l} \). The next lemma characterizes the dependence of \( \alpha_t \) from the return ratio and the issuance cost.
Lemma 2.1. The share of non-core funding $\alpha_t$ is strictly increasing in $\frac{R_k}{R_f}$ and strictly decreasing in $\chi$ if $\alpha_t < 1$.

Proof 2.1. We compute the derivative of $\alpha_t$ with respect to the return ratio $R_k/R_f$ from condition (3) by applying the implicit function theorem. Denoting by $r_t = R_k/R_f$ 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 $\alpha_t$ with respect to $\chi$. Again, applying the implicit function theorem to condition (3) 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 $\alpha_t < 1$. ■

These properties have simple intuitions. The (endogenous) return $R_f$ is part of the cost of funding risky investments with non-core liabilities (the other part is the issuance cost). Therefore, lower is $R_f$ relatively to the (exogenous) expected return $R_k$, and higher is the incentive to fund core investments with non-core liabilities. It is then optimal to choose a higher $\alpha_t$. The issuance cost plays a similar role since a lower value of $\chi$ implies a lower cost of funding core investments through non-core liabilities. The monotonicity property stated in the lemma is conditional on $\alpha_t$ be smaller than 1. Although $\alpha_t$ could be bigger than 1 for an individual bank, this cannot be the case for the whole banking sector. Therefore, this condition is always satisfied in the banking equilibrium.

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

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

subject to:

$$c_t = a_t + l_t - \frac{\bar{k}_t}{R_k} - \frac{f_t}{R_f}$$

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

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

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

The adjusted return depends on the ‘exogenous’ expected return $R_k$, on the ‘endogenous’ return $R_f$, and on the optimal $\alpha_t$. Since $\alpha_t$ is itself a function of $R_k$ and $R_f$ (see condition (3)), the adjusted return can be expressed as a function of $R_k$ and $R_f$ only.

The next lemma, which will be used later, establishes that the adjusted return ratio $\bar{R}_t^k/R_f$ increases in $R_k/R_f$ and decreases in the issuance cost.
Lemma 2.2. The ratio $\frac{\bar{R}_k}{R_f^t}$ is strictly increasing in $\frac{R_k^t}{R_f^t}$ and strictly decreasing in $\chi$.

Proof 2.2. Condition (5) can be rewritten as

$$\frac{R_f^t}{\bar{R}_k^t} = \frac{1}{(1-\alpha^t)} \left( 1 - \varphi(\alpha^t) \right) \cdot (1 - \alpha^t).$$

Eliminating $\frac{R_f^t}{\bar{R}_k^t}$ using (3) and re-arranging we obtain

$$\frac{\bar{R}_k^t}{R_f^t} = \frac{1}{1 - \varphi'(\alpha^t)}.$$

Since $\alpha^t$ is strictly increasing in $\frac{R_k^t}{R_f^t}$ (see Lemma 2.1) and $\varphi'(\alpha^t)$ is strictly increasing in $\alpha^t$, the right-hand-side is strictly increasing in $\frac{R_k^t}{R_f^t}$ and, therefore, $\frac{\bar{R}_k^t}{R_f^t}$ is also strictly increasing in $\frac{R_k^t}{R_f^t}$. Using the above expression for $\frac{\bar{R}_k^t}{R_f^t}$ we derive

$$\frac{\partial \bar{R}_k^t}{\partial \chi} = \frac{\varphi''(\alpha^t) \frac{\partial \alpha^t}{\partial \chi}}{(1 - \varphi'(\alpha^t))^2}.$$

We have already shown in the proof of Lemma 2.1 that $\frac{\partial \alpha^t}{\partial \chi} < 0$. Since the issuance cost function is concave, $\varphi''(\alpha^t) > 0$. This implies that the above derivative is negative and, therefore, $\frac{\bar{R}_k^t}{R_f^t}$ is strictly decreasing in $\chi$. \[\Box\]

Problem (4) is a portfolio choice with three assets. The first asset is $-l_t$ with riskless return $R_l^t$. The second asset is $f_t$ with risky return $\eta_{t+1} R_f^t$. The third asset is $\bar{k}_t$ with risky return $z_{t+1} R_k^t$. Notice that, while the risk associated with $f_t$ derives from an aggregate sunspot shock that affects all banks, the risk associated with $k_t$ is purely idiosyncratic. The optimal portfolio choice is characterized by the following lemma.

Lemma 2.3. The optimal policy of the bank is

$$c_t = (1 - \beta) a_t,$$

$$-\frac{l_t}{R_l^t} = (1 - \phi^l - \phi^f_t) \beta a_t,$$

$$\frac{f_t}{R_f^t} = \phi^f_t \beta a_t,$$

$$\frac{\bar{k}_t}{R_k^t} = \phi^k_t \beta a_t,$$

where $\phi^f_t$ and $\phi^k_t$ are determined by the conditions

$$\mathbb{E}_t \left\{ \frac{R_l^t}{R_l^t(1 - \phi^f - \phi^k) + \eta_{t+1} R_f^t \phi^f_t + z_{t+1} R_k^t \phi^k_t} \right\} = 1,$$

$$\mathbb{E}_t \left\{ \frac{\eta_{t+1} R_f^t}{R_f^t(1 - \phi^f - \phi^k) + \eta_{t+1} R_f^t \phi^f_t + z_{t+1} R_k^t \phi^k_t} \right\} = 1.$$
Proof 2.3. See Appendix A.

Conditions (10) and (11) determine the shares of savings, \( \phi^f_t \) and \( \phi^k_t \), allocated to diversified (with respect to the idiosyncratic risk) and non-diversified investments. Since these conditions are independent of the initial assets \( a_t \), banks allocate the same shares of wealth \( 1 - \phi^f - \phi^k \) and \( \phi^f \) to the three assets \( -l_t/R^f, f_t/R^f_t \) and \( k_t/R^k_t \).

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

**Definition 2.1.** Given the exogenous returns \( R^f \) 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 \( \alpha_t = g^\alpha_t(a), c_t = g^c_t(a), l_t = g^l_t(a), f_t = g^f_t(a) \), price for non-core funding \( 1/R^f_t \) and probability of crisis \( p_t \), such that the decision rules satisfy condition (3), (6), (7), (8), (9), the market for non-core funding clears, that is, \( \int_a g^f_t(a) M_t(a) = \int_a g^\alpha_t(a) g^k_t(a) M_t(a) \), and the crisis probability is defined in (1).

Conditions (6)-(9) determine \( c_t, l_t, f_t, k_t \), and the first order condition (3) determines the share of investments sold to other banks, \( \alpha_t \). Given \( k_t \), we can determine the original core investment \( k_t = k_t/(1 - \alpha_t) \). The aggregation of the individual policies will then provide the equilibrium condition for the determination of the price for non-core liabilities \( 1/R^f_t \). 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 Non-core funding and leverage

We now study how non-core funding and leverage are related in the model. We will focus on the aggregate non-consolidated banking sector. This is obtained by summing the balance sheets of all banks. We will then denote with capital letters aggregate variables. Since the aggregation of individual balance sheets is without consolidation, total assets include not only the investments made in the non-financial sector, \( K_t/R^k \), but also the assets purchased from other banks, \( F_t/R^f_t \). Similarly for aggregate liabilities. The aggregate non-consolidated balance sheet takes the same form as an individual balance sheet displayed in Figure 1.

The aggregate indices of non-core funding and leverage in the model are given by

\[
NCF = \frac{\alpha_t K_t}{R^k_t} + \frac{F_t}{R^f_t}, \quad (12)
\]

\[
LEVERAGE = \frac{\alpha_t K_t}{R^k_t} + \frac{F_t}{R^f_t} - \frac{L_t}{R^l_t}. \quad (13)
\]
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 analysis, instead, we do not net out internal claims.

The next step is to characterize the properties of these two indices with special attention to the dependence from the return spread $R^k/R^l$ and the issuance cost $\varphi(\alpha_t)$. This can be done analytically only for the special case without crises, that is, $p_t = 0$. Without crises, in equilibrium we have that $R^f_t = R^l_t$, that is, the endogenous return from non-core investments is equal to the cost core liabilities. This can be easily seen from conditions (10) and (11): when $\eta_t = 1$ with certainty, these two conditions cannot be both satisfied unless $R^f_t = R^l_t$.

Intuitively, without aggregate shocks, non-core investments carry no risk. Therefore, if the return is bigger than the cost of funding it, banks have an incentive to buy an infinite amount of diversified investment $f_t$ funded with core liabilities $l_t$. The high demand for $f_t$ will drive its price $1/R^f_t$ up until it becomes equal to $1/R^l_t$.

**Proposition 2.1.** If $p = 0$, the indices of leverage and non-core funding are

(ii) strictly increasing in the return spread $R^k_t/R^l_t$;

(i) strictly decreasing in the issuance cost $\chi$.

**Proof 2.1.** See Appendix B.

It is important to emphasize that, although leverage and non-core funding indices are defined by similar variables, they are not perfectly dependent. More specifically, an increase in leverage does not necessarily imply an increase in NCF. 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 (12) we can see that the NCF does not change. However, equation (13) shows that leverage increases. If in addition to increasing $L_t$ banks reduce $F_t$ (but keep $K_t$ unchanged) the NCF index decreases 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 accounting identity that links, uniquely, the NCF and leverage indices. Instead, it follows from the endogenous properties of the model. We will show below that the model could generate the opposite relation between NCF and leverage in response to other changes. For example, in response to a change in the volatility of the idiosyncratic shock $z_{t+1}$.

With a positive probability of crises (aggregate shock), 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 $\chi$, the equilibrium return $R^f_t$ also changes which in turn affects the optimal choice of leverage and NCF. However, we conjecture that the properties stated in Proposition 2.1 also hold with aggregate shocks, as we will show with the calibrated model.

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6In 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 level of an individual bank. However, we can separately determine the aggregate values of $l_t$ and $f_t$ since in equilibrium we have $\int_a f_t M_t(a) = \alpha_t \int_a k_t M_t(a)$. We can then solve for $\int_a l_t M_t(a) = \int_a (\bar{l}_t + f_t) M_t(a)$. 

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Calibration: For the calibration of the exogenous returns $R^l$ and $R^k$ we use, respectively, the average bank prime loan rates and the average 3-months certificate of deposits rate for the period 1999-2013. Based on these averages we set $R^l = 1.0256$ and $R^k = 1.0538$.

The discount factor $\beta$ determines the expected equity return for the bank. During the period 1999-2013 the average return on equity was 10.9 percent. Therefore, we set $\beta = 1/1.109 = 0.906$. See the Data Appendix for details.

We set the probability of a negative sunspot $p = 0.02$. Thus, provided that the condition for self-fulfilling equilibria is satisfied, a financial crisis arises on average every 50 years. This is in the range of values used in the literature. To calibrate the value of $\mu$, the cost of renegotiating non-core liabilities, 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 1999-2013, was about 24 percent. So every year from 2008 to 2010, the equity return of banks was almost 8 percent lower ($24\% \div 3$) than the average return over the sample period 1999-2013. By setting $\mu = 0.05$ the model generates a reduction in equity return in response to the crisis of about 24 percent.7

There are three parameters left to be calibrated: the elasticity of the issuance cost, $\gamma$, the scaling parameter for the issuance cost, $\chi$, and the standard deviation of the idiosyncratic shock, $\sigma_z$. Unfortunately, we do not have direct evidence to pin down $\gamma$. We assume that the diversification cost is close to be linear and set it to 1.1. The sensitivity analysis will clarify the role played by this parameter. Finally, we set $\chi$ and $\sigma_z$ to match the average leverage and NCF indices during the sample period 1999-2013.

Properties The top panels of Figure 4 plots the indices of leverage and NCF 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 issuance cost parameter $\chi$. The parameter values are reported in the caption of the Figure.8

The continuous lines show that a higher return spread between core investments and core liabilities is associated to higher NCF and leverage. Although not shown, a higher return spread decreases the price of non-core liabilities $1/R^l_t$. This is because a higher $R^k$ implies a higher incentive to invest and, therefore, a higher supply of non-core liabilities to other banks. To induce banks to purchase these liabilities, the price has to fall. The increase in the issuance cost has the opposite effect on the NCF and leverage. With a higher cost, banks have less incentive to insurance the idiosyncratic shock. Since they face higher risk, it is then optimal for banks to leverage less. This implies that the supply of non-core liabilities declines which leads to an increase in their price $1/R^l_t$.

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

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7Even if the renegotiation cost is only 5% the value of non-core investments, the percent equity losses are larger because banks are heavily leveraged.

8To compute the equilibrium, we simply need to solve the system of nonlinear equations (3), (6), (7), (8), (9), (10), (11) and the non-core clearing condition $F_t = \alpha_t K_t$. The solution returns the values of $\alpha_t$, $C_t$, $L_t$, $F_t$, $K_t$, $\phi^l_t$, $\phi^k_t$, $R^l_t$. 

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We then recompute the optimal portfolio choice under this constraint. The dashed lines in Figure 4 plots the NCF and leverage when banks cannot diversify. As can been seen, in absence of the non-core financial market, the equilibrium is characterized by much smaller leverage.

The importance of non-core funding for the choice of leverage can be explained as follows. When the return spread increases, banks would choose to become more leveraged even if they could not diversify through the issuance of non-core liabilities. However, since leverage increases the risk faced by banks\(^9\), the ability to issue non-core liabilities reduces the risk, which further encourages leverage. Therefore, when the return spread increases, non-core funding ‘amplifies’ the impact of the higher return spread on leverage. When the issuance cost declines, banks expands non-core funding because it is less costly. Since non-core funding reduces the idiosyncratic risk, banks are more willing to leverage. Therefore, it is the non-core funding that induces banks to become more leveraged.

Before moving to the next section, we show how the elasticity of the diversification cost,

\(^9\)higher leverage means that a negative realization of \(z_{t+1}\) has a larger percentage effect on the equity of the bank and, therefore, on dividends

---

Figure 4: Sensitivity of NCF and leverage to return spread and issuance cost. Parameters: \(\beta = 0.9017, R^d = 1.0256, R^k = 1.0538, \chi = 0.02952, \gamma = 1.1, z \in \{0.93176, 1.06824\}\) with equal probabilities, \(\eta \in \{0.95, 1.00\}\) with probabilities \(\{0.02, 0.98\}\). The sensitivity is performed by changing \(R^k\) or \(\chi\).
captured by the parameter $\gamma$, affects the sensitivity of NCF and leverage. We increase the value of $\gamma$ from 1.1 in the baseline model to 1.5. In doing so we also recalculate $\chi$ and the standard deviation of the idiosyncratic shock so that the model matches the same levels NCF and leverage as in the previous calibration. The results are shown in Figure 5. As expected, the sensitivity of NCF and leverage to $\chi$ and $R^k/R^l$ declines when the elasticity of the cost is higher, that is, $\gamma$ is bigger.

![Graphs showing sensitivity of NCF and leverage to different values of $\gamma$.](image)

**Figure 5:** Sensitivity of NCF and leverage to different values of $\gamma$. Parameters when $\gamma = 1.1$: $\beta = 0.9017$, $R^l = 1.0256$, $R^k = 1.0538$, $\chi = 0.02952$, $z \in \{0.93176, 1.06824\}$ with equal probabilities, $\eta \in \{0.99, 1.0002\}$ with $p = 0.02$ the probability of $\eta = 0.99$. Parameters when $\gamma = 1.5$: $\beta = 0.9017$, $R^l = 1.0256$, $R^k = 1.0538$, $\chi = 0.04223$, $z \in \{0.92996, 1.07004\}$ with equal probabilities, $\eta \in \{0.95, 1.00\}$ with probabilities $\{0.02, 0.98\}$. The sensitivity is performed by changing $R^k$ or $\chi$.

We also explore how NCF and leverage respond to a change in the volatility of the idiosyncratic shock, $z_{t+1}$. This is related to the recent literature on time-varying volatility. As Figure 6 shows, higher idiosyncratic risk increases the incentive of banks to diversify (higher NCF). However, since diversification does not completely offset the higher risk, banks choose to be less leveraged. This shows that the positive co-movement between the NCF and leverage is not simply the result of an accounting identity. The two indices could be both positively or negatively correlated. It depends on the dominant forces underlying their change.
Figure 6: Sensitivity of NCF and leverage to standard deviation of the idiosyncratic shock. Parameters: \( \beta = 0.9017, R^l = 1.0256, R^k = 1.0538, \chi = 0.02952, \gamma = 1.1, z \in \{0.93176, 1.06824\} \) with equal probabilities, \( \eta \in \{0.95, 1.00\} \) with probabilities \{0.02, 0.98\}. The sensitivity is performed by changing the low and high values of \( z \).

3 Non-core funding and the impact of aggregate shocks

In this section we show how the response of banks’ investment to aggregate shocks is affected by the size of non-core funding. Since investment is proportional to net worth \( a_t \), we first need to derive an expression for the growth rate of \( a_t \). 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,

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

Using (7)-(9), the equation can be rewritten as

\[
\frac{a_{t+1}}{a_t} = \beta R^l \left\{ 1 + \left( z_{t+1} \frac{\bar{R}^k}{R^l} - 1 \right) \phi^k_t + \left( \eta_{t+1} \frac{R^f_t}{R^l} - 1 \right) \phi^f_t \right\}.
\]

This defines the (gross) growth rate of net worth. We can use this expression to characterize how the growth rate of net worth for the whole banking sector is affected by a crisis. Averaging over the idiosyncratic shock \( z_{t+1} \) and taking the derivative with respect to \( \eta_{t+1} \) we obtain

\[
\frac{\partial \left( \frac{a_{t+1}}{a_t} \right)}{\partial \eta_{t+1}} = \beta R^l \phi^f_t.
\]

This expression shows that the impact of a crisis on the growth rate of net worth for the banking sector increases with \( \phi^f \), which captures the importance of non-core funding. Since \( k_{t+1} \) is proportional to \( a_{t+1} \), investment is also positively related to the aggregate shock, the impact of a crisis on investment also increases with the size of non-core funding.

The top panels of Figure 7 show the sensitivity of the growth rate of \( k_t \) to a crisis for different return spreads \( R^k/R^l \) and issuance costs \( \chi \). The continuous lines show the overall
decline in growth rate when η_t switches from 1 to 1 − μ. As we increase the return spread (left panel) and decrease the issuance cost (right panel), the impact of a banking crisis on investment growth increases. 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 (η_t+1 = 1 − μ). The negative shock realizes at time t and affects growth between t and t + 1. Parameters: β = 0.9017, R^l = 1.0256, R^k = 1.0538, χ = 0.02952, γ = 1.1, z ∈ {0.93176, 1.06824} with equal probabilities, η ∈ {0.95, 1.00} with probabilities {0.02, 0.98}. The sensitivity is performed by changing R^k or χ.

The sensitivity result is a direct consequence of how the return spread and the issuance cost affect NCF 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 higher NCF and leverage. But higher NCF and leverage implies that a crisis has a proportionally stronger impact on banks’ net worth and, therefore, on core investments.

The next step is to show the importance of non-core funding. In the case of a diminished issuance cost, banks become more diversified because it is less costly. Since diversification reduces the idiosyncratic risk, banks are more willing to take the risk associated with a crisis and become more leveraged. Therefore, it is non-core funding 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 diversify. However, since leverage increases the risk faced by banks, the ability to issue non-core liabilities makes leverage less risky, which encourages more leverage. Therefore, when the return spread increases, NCF amplifies the impact of the higher return spread on leverage: if banks could not issue non-core liabilities, the increase in leverage would be smaller and, consequently, a crisis would have a smaller impact on investments.

To illustrate the importance of the NCF, we conduct the following counterfactual exercise. We force banks to choose $\alpha_t = 0$ so that they cannot diversify. We then recompute the response of investment growth to a negative aggregate shock under this assumption. The dashed lines reported in Figure 7 show the results. As can be seen, in absence of non-core funding, the response of investment growth to a crisis is significantly smaller. In some cases, the response drops by half. Furthermore, the response is not very sensitive to the return spread because the sensitivity of leverage, without NCF, is very small.

4 Dynamics of non-core funding and leverage

As shown in the introduction, the US banking sector has experienced significant changes in the degree of non-core funding and leverage. Similar changes took place in other countries. One goal of this paper is to understand 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, $R^{k}_t/R^{l}_t$. 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 the change in the issuance cost captured by the parameter $\chi$. Subsection 2.3 also showed that a smaller cost for issuing non-core liabilities implies higher NCF and leverage. Before discussing these two mechanisms, however, explore a third mechanism that allows for time-variations in the probability of crises.

One limitation of the model studied so far is the assumption that the probability distribution of the aggregate shock does not change over time. However, the risk of a banking crisis, captured by the probability $p$, could also change. Furthermore, the actual probability may not be known. As a result, banks make decisions based on their ‘prior’ belief about $p$, not the actual $p$. In this section we extend the model by allowing for Bayesian learning about $p$ which in the model corresponds to the probability of that the sunspot shock takes the value $s_t = 1$.

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 the NCF and leverage. Figure 8 plots the sensitivity of NCF and leverage to the probability $p$. As can be seen, higher probabilities of crises are associated with lower NCF and leverage.

An increase in $p$ has two effects on the portfolio decisions of banks. First, as the probability of a crisis rises, the expected return from non-core funding decreases. This decreases the demand for non-core liabilities which lowers their price $1/R^{f}_t$. As a result, banks reduce the issuance of these liabilities and, therefore, the insurance of the idiosyncratic risk associated with core investments. Because banks are less insured, they have lower incentive to
leverage. Therefore, a higher probability of crises lowers both NCF and leverage as Figure 8 shows. With the learning mechanism introduced in the next section, the model will generate an endogenous dynamics of the ‘perceived’ probability $p$ which is used by banks to 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 know 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 forms some ‘belief’ about the aggregate risk, which is then updated as new information becomes available (experimentation).

To formalize this idea, we assume that the probability of a crisis (that is, the probability that $\eta_t = \eta$) 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 its true value, 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 $1 - \theta_t$. Effectively, $\theta_t$ represents the aggregate risk perceived by the market.

Banks start with a common prior belief $\theta_t$. After observing the aggregate shock $\eta_t \in \{\eta, \bar{\eta}\}$, 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, all banks maintain a common belief over time.

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

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

Given the prior probability \( \theta_t \), the posterior probability conditional on the observation of \( \eta_t \) 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.\(^{10}\)

**Simulation.** We simulate the model starting in 1999 until 2013. In the first 9 years (until 2007) there are no crises. In terms of the model this means that for the pre-crisis simulation the realization of the aggregate shock is \( \eta_t = \bar{\eta} \). Then in 2008 the economy experiences a crisis, that is, \( \eta_t = \bar{\eta} \) but it returns to the high value \( \eta_t = \bar{\eta} \) in the remaining years (2009-2013).

Compared to the model without learning, 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 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%.

Before we can start the simulation we have to initialize the prior probability \( \theta_t \). 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

\(^{10}\)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 \( \Gamma(p_H, p_H) = \Gamma(p_L, p_H) = 1/2 \), which implies \( \theta_{t+1} = 1/2 \).
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 $\chi$ and $\sigma_z$ so that the NCF and leverage in the model match the corresponding empirical measures in 2007, that is, the year before the crisis.

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 $\theta_t$ 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 nine years there are no crises, Bayesian updating implies that $\theta_t$—the prior probability of the high risk regime—declines. As a consequence of this, 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 $p$ and the prior is updated slowly. Second, the prior is already very close to zero, which is the lower bound for $\theta_t$.

In the top-right panel, together with the probability of a crisis, we also plotted the credit default swap rates. As we already observed, 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 this probability should lead to an increase in the default swap rate. 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 are directly comparable quantitatively.

As banks revise downward the assessed probability of a crisis (which implies a higher perceived expected return from non-core investments and lower aggregate risk), they choose higher NCF and leverage. When the crisis materializes in 2008, however, the prior probability $\theta_t$ increases drastically, which leads to a reversal in the NCF and leverage. The drastic change in prior belief induced by a single observation of the negative shock derives from the fact that $\eta_t = 0.95$ is a low probability event (calibrated to range between 0.1% and 3.9%). This
Figure 10: Dynamics with Bayesian learning initialized with prior $\theta_{1999} = 0.1315$. Parameters: $\beta = 0.9017$, $R^l = 1.0256$, $R^k = 1.0538$, $\chi = 0.028008$, $\gamma = 1.1$, $z \in \{0.9322, 1.0678\}$ with equal probabilities, $\eta \in \{0.95, 1.00\}$ with two probability regimes for $\eta = 0.95$: $p_L = 0.001$ and $p_H = 0.039$.

implies that, differently from the realization of $\eta_t = 1$, 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 $\eta_t = 1$ is not very informative and leads to a moderate revision of the prior. In this way the model generates the gradual upward trend in NCF and leverage before 2008 and the sharp reversal in 2008. The figure also plots the empirical measures of NCF and leverage. 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 $f_t$ drops by only 5 percent, this causes a large percentage drop in equity because banks are highly leverage. Since investment is proportional to equity, large drops in equity involve large losses in investment.

We move now to the dynamics illustrated with short-dashed lines in the bottom panels. These lines are generated under the counterfactual exercise in which we impose $\alpha_t = 0$. In this counterfactual exercise, we prevent banks from issuing non-core liabilities. As can be seen, the inability to diversify reduces significantly the leverage chosen by banks. Because banks are less leveraged, a crisis has a much smaller impact on the growth of investment (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 non-core funding. From a policy prospective, there is a trade-off: lower volatility at the expenses of slower growth. For a comprehensive analysis of policies, however, the model should be extended to specify the non-financial sector, which we leave for future research.

4.2 Bank heterogeneity

The theoretical analysis has been conducted using a model in which banks differ only in the amount of equity $a_t$ which, at any point in time, results from the whole history of idiosyncratic and aggregate shocks. However, even if banks differ in equity, they all make the same portfolio choices and they have the same financial structure (same leverage and non-core funding). In this way the model admits aggregation and, effectively, it is as if there is a representative bank. The data, however, shows that the financial structure of banks is very heterogeneous. For example, investment banks are much more leveraged and fund investments with non-core liabilities more than commercial banks. Also, the dynamics shown in Figure 2 is driven more by investment banks than commercial banks.

One way to think about heterogeneous financial institutions is in terms of access to non-core funding. Either as a result of stricter regulations or perhaps because of specialization, some banks may find more difficult to issue non-core liabilities. Within our model this is captured by a higher issuance cost $\phi(a_t) = \chi a_t^\gamma$. For example, commercial banks may be characterized by a higher $\chi$ than investment banks. We are then interested in understanding how differences in the issuance cost differentiate the optimal portfolio choice of banks and their responses to crises.

Figure 11 shows the portfolio composition and leverage chosen by banks with different cost parameter $\chi$. The graph is constructed under the assumption that the price of non-core liabilities, $1/R_t^f$, is the equilibrium price for the baseline model. This is different from the sensitivity analysis conducted in Section 2.3 and shown in Figure 4. In that section, the change in $\chi$ was for all banks. Since banks change their policies when they face a different $\chi$, the equilibrium price $1/R_t^f$ would also change. Here, instead, we consider a single bank that faces a $\chi$ different from all other banks. Since banks are atomistic, the presence of a single heterogeneous bank does not affect the equilibrium price. Another way to think about this exercise is that $1/R_t^f$ is the equilibrium price that would prevail when all banks are heterogeneous once we aggregate them.

As can be seen from the figure, banks with lower issuance cost $\chi$ choose to fund investments with a higher share of non-core liabilities and a lower share of core liabilities. They also use less equity and, as a result, they are more leveraged. On the asset side they hold less non-core investments and, therefore, higher share of core investments. Thus, banks with lower issuance cost are net suppliers of non-core liabilities while banks with higher cost are net buyers of these liabilities. Broadly speaking, the financial structure of banks with higher issuance cost resembles the financial structure of commercial banks while the financial structure of banks with lower issuance cost resembles that of investment banks.

We show next how the different financial structure of banks (induced by different issuance costs) affects their dynamics in response to a crisis. To do so we repeat the simulation of
the model with learning conducted in Section 4.1. We consider two atomistic banks with different issuance costs. The first bank has a cost parameter $\chi$ that is 6% higher than the cost of all other banks. The second bank has a $\chi$ that is 6% lower than the cost of all other banks. By considering only two atomistic banks that differ from all other banks we are able to maintain the aggregate equilibrium dynamics (in particular the dynamics of the price for non-core assets and liabilities $1/R^f_t$).

Figure 12 plots the dynamics for the high-cost bank, the low-cost bank and for the aggregate economy. The response to a crisis of the low-cost bank is much larger. Especially noticeable is the higher drop in investment growth (for both total and core investments). Even if the drop in investment growth is very large in only one period, the level is very persistent. So the crisis generates a large and persistent contraction in financial intermediation, especially for low-cost banks. Notice also that the growth rate continues to be lower after the crisis even if the decline is not as big as ad impact.

The key mechanism leading to the larger investment drop for low-cost banks can be described as follows. After the crisis, the perceived risk of holding non-core assets $f_t$ increases. This follows from the upward Bayesian updating of the probability of a banking crisis, which reduces the demand for non-core liabilities. The consequent drop in price $1/R^f_t$ induces banks to issue less non-core liabilities. This is especially important for banks that rely more on this source of funding, that is, banks with lower issuance cost. But as they cut more non-core funding, their core investments are much less insured and, as a result, they choose to downside more core investments.

In the empirical Subsection 5.3 we show that the higher investment sensitivity to the crisis of banks that are more dependent on non-core funding finds support in the data.
Figure 12: Dynamics with Bayesian learning initialized with prior $\theta_{1999} = 0.1315$. Parameters: $\beta = 0.9017$, $R_l = 1.0256$, $R_k = 1.0538$, $\chi = 0.028008$, $\gamma = 1.1$, $z \in \{0.9322, 1.0678\}$ with equal probabilities, $\eta \in \{0.95, 1.00\}$ with two probability regimes for $\eta = 0.95$: $p_L = 0.001$ and $p_H = 0.039$. High-cost bank has $\chi = 0.03$; low-cost bank has $\chi = 0.0266$.

4.3 Alternative mechanisms

Learning about the aggregate risk is not the only mechanism that could have generated the dynamics of the NCF 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 issuance cost captured by the parameter $\chi$. The first change could have been the result of an increase in the investment return $R_k^t$ and/or a decline in cost of borrowing $R_l^t$. For example, the increasing demand for financial securities from emerging countries could have led to a fall in $R_l^t$. The second change could have been the result of financial innovations that facilitated the issuance of non-core liabilities. 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 $R_k^t/R_l^t$ and a lower diversification cost $\chi$ are associated with higher NCF and leverage. Therefore, the pre-crisis trend could have been the result of changes in the return spread and/or issuance cost.

The first panel of Figure 13 shows the dynamics of the difference between the US prime lending rate and the 3-month US certificate of deposits rate that we used to calibrate $R_k^t$ and $R_l^t$. Interestingly, when we compare the average returns before the crisis and after the crisis,
we do not see much of a difference. This suggests that the high levels of NCF and leverage before the crisis and the subsequent decline after the crisis were not driven by a change in return spread.

\[ a) \text{Return Spread} \quad \text{b) Cost of Intermediation} \]

Figure 13: Return Spreads (first panel) and Cost of intermediation (second panel) in the United States, 1999-2013. Return Spread as the difference between the US prime lending rate and the 3-month US certificate of deposits. Cost of intermediation is measured as an adjusted aggregate return on assets by summing all profits and assets (net of non-core liabilities) for Commercial and Savings Banks, Cooperative Banks, Investment Banks and Securities Firms, and Finance Companies. Assets and liabilities are in book values.

An exploration of the empirical plausibility of the second mechanism—decrease and subsequent increase in issuance cost—would require the construction of an empirical proxy for the issuance cost \( \varphi(\alpha_t) \). In recent work, Philippon (2015) finds that the cost of intermediation has been rather stable over the last few decades. Although the cost of ‘intermediation’ is not the same object as the cost of issuing non-core liabilities proposed in this paper, we checked whether a measure of the intermediation cost computed from our micro data shows a similar pattern as in Philippon (2015). Data details are provided in Section 5.

We computed 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,

\[
ADJ\text{ROA}_{jt} = \frac{\sum_i PROFITS_{ijt}}{\sum_i \text{ASSETS}_{ijt} - \sum_i \text{NON\_CORE\_LIAB}_{ijt}}.
\]

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

The second panel of Figure 13 plots the computed series for the US. For the period that proceeded 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 issuance 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 NCF 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 NCF and leverage continued to fall after the crisis. The model predicts that after the crisis the NCF and leverage started to grow again even though at a very slow pace (see Figure 10). It is important to point out, however, that after the 2008 crisis the introduction of new regulations may have affected both leverage (for example, the starting phase of the Basel III capital requirements) and NCF (for example, 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 non-core funding and leverage in the years that followed the 2008 crisis. The new regulations, however, were introduced after the crisis and, therefore, they cannot explain the initial collapse in NCF and leverage. They could be more relevant for capturing the persistence after the crisis.

5 Empirical analysis

In this section we start with a brief description of the micro data and the construction of the empirical proxy for the NCF index. We then provide evidence about the relation between non-core funding and leverage. Finally, we explore whether the degree of use of non-core funding before the 2008 crisis is associated to different responses in asset growth of banks.

5.1 Data

Data is from Bankscope, a proprietary database maintained by the Bureau van Dijk. The database contains 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 C provides further details for the sample selection.

We use book values of assets and liabilities. Table 2 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 NCF, we need to classify bank liabilities in core and non-core liabilities. Conceptually, the core-liabilities of banks are those held by the non-financial 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 given by all other liabilities of the bank, that is, $LIABILITIES_{it} - DEPOSITS_{it}$. The empirical measure of the NCF index is then given by

$$NCF_{it} = \frac{LIABILITIES_{it} - DEPOSITS_{it}}{ASSETS_{it}}, \quad (15)$$

where $ASSETS_{it}$ are the total assets of bank $i$ in year $t$.

Clearly, not all $DEPOSITS_{it}$ are held by the non-financial sector and not all the other liabilities are held within the intermediation sector. However, the empirical variable $LIABILITIES_{it} - DEPOSITS_{it}$ is more likely to contain items held within the financial sector than the variable $DEPOSITS_{it}$. 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 have increased more than total liabilities.

The empirical measure of the leverage index is more standard and it is given by

$$LEVERAGE_{it} = \frac{ASSETS_{it}}{ASSETS_{it} - LIABILITIES_{it}}. \quad (16)$$

### 5.1.1 Practical examples

As emphasized above, our empirical measure of NCF is a proxy for the concept of non-core funding formalized in the theoretical model. A natural question is whether the empirical proxy for non-core funding includes items that fit the structure of non-core liabilities formalized in the model, that is, items that allow the financial intermediation sector to be more diversified. Although the data does not provide specific information to answer this question, we provide an example that illustrates how the empirical measure of NCF could capture 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.
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 aggregate NCF 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. Half of the issued bonds are sold to bank I and the other half 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 has now created non-core assets and liabilities. 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). Thus, the NCF index is \( \frac{90}{300} = 0.3 \).

An important difference between the two scenarios is that, abstracting from the aggregate risk, the investment portfolio of banks I and II is less risky after the creation of non-core funding. 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. 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 NCF 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. Still, since many financial derivatives may not be fully recorded in official balance sheets, they are not captured by our empirical measure of NCF. Nevertheless, our empirical index of NCF captures, although imperfectly, the cross-bank diversification conceptualized in the theoretical model.
5.1.2 Summary statistics

Table 2 reports summary statistics for NCF and leverage. The average leverage in aggregate is 12.6. Commercial banks are characterized by lower leverages (10.8) than investment banks (16.7). The NCF average is 0.15. Commercial banks have lower NCF than investment banks (0.10 versus 0.61).

For the US, the series for aggregate leverage and NCF obtained using Bankscope data are highly correlated to those computed using the Flow of Funds (data we used in the previous section to calibrate the model). The correlation between the two series for leverage is 0.93 and the correlation for NCF is 0.70.

The online appendix reports the evolution of the aggregate leverage and NCF for selected countries. Germany, France and the UK are characterized by a leverage cycle similar to the one 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. Interestingly, the aggregate dynamics of leverage presented for the US hides heterogeneous dynamics across different groups of banks: While the trend for commercial banks is downward sloping with a sudden increase in 2005-2007, the leverage of investment banks increased substantially in the period 2003-2007 and declined thereafter.

Also for NCF, many countries display a similar dynamics as in the United States. The NCF index has increased during 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, the NCF index does not show a clear trend. This could reflect the lower exposure of these countries to securitization practices.11

5.2 Non-core funding and leverage

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

Country-level evidence. Figure 14 draws a scatter plot for the aggregate leverage ratio against our measure of NCF 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 NCF and leverage. The online appendix plots the same variables for France, Italy, Canada and Japan.

Figure 15 draws scatter plots for the leverage ratio and NCF at the country level for some sample years. Also in this case we observe a positive correlation, which seems particularly strong in 2007 at the peak of the boom. On the one hand, we have low-NCF and low-leveraged financial systems in countries like Poland, Turkey, and Mexico. On the other, we have highly non-core funding 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 3. In the first column we use NCF 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 15. Interestingly, variations in NCF 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 coefficient for NCF remains positive and highly statistically significant.

**Bank-level evidence.** So far we have provided strong evidence of a positive correlation between the NCF and leverage at the country level. The richness of micro data allows us to go a step further and investigate this correlation also at the micro level, that is, across banks.

We first look at a sub-sample of large banks and then to 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 16 shows the scatter plot of the leverage ratio against the share of non-core liabilities for these 60 institutions in various years. Also across banks we see a clear positive association between NCF and leverage.

Table 4 reports some conditional correlations. In the first column we run a simple regression using size (log of total assets) as the only control. The coefficient on the measure of NCF 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 NCF 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 NCF and leverage within banks. Again, we find a positive and strongly significant coefficient attached to the NCF index. 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 the NCF 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 5. 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 NCF, 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, there is empirical evidence for a strong association between the NCF and leverage across banks, across countries and across time.

The online appendix shows that these results are robust to the use of an alternative measure of NCF, namely the ratio of non-core liabilities to total liabilities. Moreover, for the subsample of Mega Banks (the sample for which data is available), we report also the results (similar to those reported in Table 3) obtained using the ratio of interbank deposits over total assets as an alternative measure of NCF.

5.3 Bank heterogeneity and response to the crisis

In Subsection 4.1 we have shown that the model predicts a sharp decline in the asset growth of banks after a crisis. Furthermore, in Subsection 4.2 we have shown that the model predicts a stronger decline for banks that rely more on non-core funding, that is, they have a higher NCF. In this section we provides evidence in support of these properties.

Indeed, after the 2008 Lehman Brother bankruptcy, which sparked the global financial crisis, the rate of growth of bank assets experienced a sharp decline. Of course, in the data, the decline could have been the result of a contraction in either demand or supply. In this section we will not try to separate the causes of the contraction. Instead, we investigate whether the degree of non-core funding that prevailed before the crisis is associated to different responses in asset growth of banks. More specifically, we investigate whether banks characterized by higher levels of non-core funding before the crisis experienced greater contractions in asset growth as predicted by model (see Figure 12).

It is important to emphasize that our goal here is not to establish a specific causal relationship. Instead, we only want to investigate the existence of statistical correlations. We do that by estimating the following regression equation

\[
\Delta \text{Assets}_{i,k,t} = \alpha_0 + \alpha_1 \text{CRISIS} + \delta_j \text{CRISIS} \times NCF_{Q_j} + \gamma_j \text{CRISIS} \times LEV_{Q_j} + \alpha_2 \text{Unempl}_{k,t-1} + \alpha_3 \log(\text{Assets})_{i,k,t} + FE + \epsilon_{i,j,k,t} \tag{17}
\]

The dependent variable is the growth rate of assets for bank \(i\) in country \(k\) at time \(t\). The variable \(\text{CRISIS}\) is a dummy for the 2009-2011 period.\(^{12}\) We then compute the average levels of non-core funding and leverage for each bank \(i\) in the 2003-2006 period and, based on that, we construct the quartiles of the distributions. \(NCF_{Q_j}\) and \(LEV_{Q_j}\) are dummy variables equals to 1 if the bank belongs to the \(j^{th}\) quartile of the distribution of, respectively, average non-core funding and leverage over the period 2003-2006. This is the pre-crisis period. \(\text{Unempl}_{k,t-1}\) is the Unemployment rate prevailing at time \(t-1\) in country

\(^{12}\)Lehman bankruptcy happened on September 16, 2008. However, since we are using annual data, we defined the crisis as starting in 2009. For robustness we repeated the estimation using a CRISIS dummy defined over the period 2008-2011 and the results were similar.
which we use as a rough proxy for macroeconomic 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) bank specialization fixed effects, ii) country fixed effects, and iii) time fixed effects (which prevents us from identifying $\alpha_1$). The residuals $\epsilon_{i,k,t}$ are assumed to be i.i.d normal variate with zero mean and variance $\sigma^2_t$.

The main coefficients of interest are $\delta_j$, reflecting the sensitivity of the drop in the average asset growth during the crisis to the level of non-core funding before the crisis. The results are reported in Table 6. The average drop in credit growth in the post Lehman period is substantial and significant. The coefficients on both $\delta_2$, $\delta_3$ and $\delta_4$ are negative and statistically significant across all specifications. Moreover, $\delta_4$ is always larger (in absolute value) than $\delta_3$ which in turn is larger than $\delta_2$. Therefore, the drop in the growth of investment increases with the non-core funding of banks. This result is robust to the addition of several controls: bank size, unemployment, and different combinations of fixed effects.

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 with higher levels of non-core funding experienced larger contractions in asset growth in the aftermath of the crisis. This confirms the findings of Ivashina and Scharfstein (2010) for the US and Abbassi et al. (2016) for Germany. Our study extends the empirical analysis beyond the US and Germany and considers a larger set of countries, although our data is less detailed.

6 Conclusion

In this paper we have shown that there is a strong positive correlation between the non-core funding 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 non-core funding 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 allows for banking crises that could be generated by the cross-ownership of bank assets and liabilities, that is, with the expansion of non-core funding.

The probability of a banking crisis is assumed to be unknown and banks make decisions based on their prior beliefs, which are then updated over time using Bayes’ rule (learning). With Bayesian learning, the model can generate the aggregate pattern of non-core funding and leverage observed in data in the 2000s. It also predicts that systems with higher non-core funding experience sharper contractions of investment (lending) growth in response to a banking crisis. We explored these predictions using both aggregate and micro data, and found broad empirical support for the theoretical prediction of the model.

The issue studied in the paper could open several avenues for future research. Although cross-bank diversification (interconnectedness) reduces the idiosyncratic risk for an individual bank, it increases the aggregate risk. The model provides a micro structure that can be embedded in a general equilibrium framework to study how non-core funding 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 closely related to our measure of non-core funding. 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 (4) with respect to $l_t$, $f_t$ and $k_t$ are, respectively,

\[
\frac{1}{c_t R^l} = \beta\mathbb{E}_t \frac{1}{c_{t+1}} \tag{18}
\]
\[
\frac{1}{c_t R^k} = \beta\mathbb{E}_t \frac{\eta_{t+1}}{c_{t+1}} \tag{19}
\]
\[
\frac{1}{c_t R^f} = \beta\mathbb{E}_t \frac{\eta_{t+1} z_{t+1}}{c_{t+1}} \tag{20}
\]

We guess that the optimal consumption policy takes the form

\[
(1 - \gamma)a_t, \tag{21}
\]

where $\gamma$ is a constant parameter. We will later verify that the guess is indeed correct. Thus $\gamma a_t$ is the saved wealth for the next period.

Define \( \phi^k_t \) the fraction of wealth allocated to non-core investments, that is, \( f_t/R^l_t = \phi^k_t \gamma a_t \); \( \phi^k_t \) the fraction allocated to risky investments, that is, \( k_t/R^k_t = \phi^k_t \gamma a_t \); the remaining fraction \( 1 - \phi^k_t - \phi^k_t \) is allocated to the safe investment, that is, \( -l_t/R^l_t = (1 - \phi^f_t - \phi^k_t) \gamma a_t \). Using these shares and the guess about savings, the next period wealth is

\[
a_{t+1} = \left\{ 1 + \left[ z_{t+1} \left( \frac{R^k_t}{R^l_t} \right) - 1 \right] \phi^k_t + \left[ \eta_{t+1} \left( \frac{R^f_t}{R^l_t} \right) - 1 \right] \phi^f_t \right\} \gamma a_t R^l \tag{22}
\]

Using (21) and (22) to replace $c_t, c_{t+1}, a_{t+1}$ in (18)-(20) we obtain

\[
\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{1}{1 + \left[ z_{t+1} \left( \frac{R^k_t}{R^l_t} \right) - 1 \right] \phi^k_t + \left[ \eta_{t+1} \left( \frac{R^f_t}{R^l_t} \right) - 1 \right] \phi^f_t} \right\} \tag{23}
\]
\[
\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{z_{t+1} \left( \frac{R^k_t}{R^l_t} \right)}{1 + \left[ z_{t+1} \left( \frac{R^k_t}{R^l_t} \right) - 1 \right] \phi^k_t + \left[ \eta_{t+1} \left( \frac{R^f_t}{R^l_t} \right) - 1 \right] \phi^f_t} \right\} \tag{24}
\]
\[
\frac{\gamma}{\beta} = \mathbb{E}_t \left\{ \frac{\eta_{t+1} \left( \frac{R^f_t}{R^l_t} \right)}{1 + \left[ z_{t+1} \left( \frac{R^k_t}{R^l_t} \right) - 1 \right] \phi^k_t + \left[ \eta_{t+1} \left( \frac{R^f_t}{R^l_t} \right) - 1 \right] \phi^f_t} \right\} \tag{25}
\]

Next we can show that $\gamma$ must be equal to $\beta$ and, therefore, we obtain (10) and (11). After multiplying equation (24) by $\phi^k_t$ and equation (25) by $\phi^f_t$, we sum equations (23)-(25) to obtain

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

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We now subtract 1 from both sides and obtain

\[
\left(1 + \phi_t^k + \phi_t^f\right)\frac{\gamma}{\beta} - 1 = (\phi_t^k + \phi_t^f)\mathbb{E}_t \left\{ \frac{1}{1 + \left(z_{t+1} \left(\frac{R_{k_{t+1}}}{R_{k_t}}\right) - 1\right) \phi_t^k + \left[\eta_{t+1} \left(\frac{R_{l_{t+1}}}{R_{l_t}}\right) - 1\right] \phi_t^f} \right\}
\]

Equation (23) tells us that the expectation term of the right-hand-side must be equal to \(\gamma/\beta\). Therefore, the condition simplifies to

\[
\left(1 + \phi_t^k + \phi_t^f\right)\frac{\gamma}{\beta} - 1 = (\phi_t^k + \phi_t^f)\frac{\gamma}{\beta},
\]

which is satisfied only if \(\gamma = \beta\). 

\[\blacksquare\]

### B Proof of Proposition 2.1

In absence of aggregate shocks, conditions (10) and (11) imply that \(R_{l_{t+1}} = R_{l_t}\). Furthermore, only \(\bar{l}_t = l_t - f_t\) is determined at the individual level. Using (7) and (8) this is equal to \(\bar{l}_t = (\phi_t^k - 1)R_{l_t}\beta\). 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 \(R_{l_{t+1}} = R_{l_t}\), the leverage ratio defined in equation (13) can be written as \(\frac{1 + \alpha_t R_{k_{t+1}}}{1 - \frac{\bar{l}_t}{R_{l_{t+1}}}}\). Since \(\alpha_t\) is decreasing in \(\chi\) and increasing in \(R_{k_t}/R_{l_t}\) (see Lemma 2.1), to show that the leverage is decreasing in the issuance cost and increasing in the return spread, it is sufficient to show that the term \(\frac{\bar{l}_t}{R_{l_{t+1}}}\) is strictly decreasing in \(\chi\) and strictly increasing in \(R_{k_t}/R_{l_t}\).

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 (7)-(9) we can derive \(\bar{l}_t = [(\phi_t^k - 1)/\phi_t^k](R_{l_{t+1}}/\bar{R}_{k_{t+1}})\bar{K}_t\). Using these terms, we have

\[
\frac{L_t}{R_{l_{t+1}}} = \frac{F_t}{K_t/R_{k_{t+1}}} = \left[\frac{\alpha_t}{1 - \alpha_t} \left(\frac{1 - \phi_t^k}{\phi_t^k}\right) \frac{R_{l_{t+1}}}{\bar{R}_{k_{t+1}}} \right] \frac{R_{k_{t+1}}}{R_{l_{t+1}}}.
\]

We now use equation (5) to replace \(\bar{R}_{k_{t+1}}\). After re-arranging we obtain

\[
\frac{L_t}{R_{l_{t+1}}} = \frac{\alpha_t R_{k_{t+1}}}{R_{l_{t+1}}} + \left(\frac{\phi_t^k - 1}{\phi_t^k}\right) \left[1 - \alpha_t \frac{R_{k_{t+1}}}{R_{l_{t+1}}} + \varphi(\alpha_t) \frac{R_{k_{t+1}}}{R_{l_{t+1}}}\right].
\]

This can be written more compactly as

\[
\frac{L_t}{R_{l_{t+1}}} = \alpha_t x + y_t \left[1 - \alpha_t x + \varphi(\alpha_t) x\right],
\]

where \(x = \frac{R_{k_{t+1}}}{R_{l_{t+1}}}\) and \(y_t = \left(\frac{\phi_t^k - 1}{\phi_t^k}\right)\).
Differentiating the right-hand-side with respect to $\chi$ we obtain

$$
\frac{\partial \left( \frac{L_t}{K_t/R^t} \right)}{\partial \chi} = \alpha'_t x(1 - y_t) + \left[ \chi \gamma \alpha_t^{-1} \alpha_t' + \alpha_t^\gamma \right] y_t,
$$

where $\alpha_t'$ is the derivative of $\alpha_t$ with respect to $\chi$.

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 we have that $\phi_t^k > 1$, which implies $y_t = (\phi_t^k - 1)/\phi_t^k > 0$. If $\phi_t^k < 1$, banks would choose $L_t = L_t - F_t < 0$, that is, they would have lower total liabilities than non-core investments. Thus, the second term of the derivative is negative if

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

In Lemma 2.1 we have derived $\alpha_t' = -[\alpha_t^\gamma + \gamma (1 - \alpha_t) \alpha_t^{-1}]/[\chi (1 - \alpha_t) \gamma (\gamma - 1) \alpha_t^{-2}]$. 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 issuance cost.

To show that the leverage ratio is increasing in $x = R^k/R^l$, we need to show that $\frac{L_t/R^l}{K_t/R^l}$ is increasing in $x$. Differentiating the right-hand-side of (26) with respect to $x$ we obtain

$$
\frac{\partial \left( \frac{L_t}{K_t/R^l} \right)}{\partial x} = \alpha'_t x + \alpha_t + y_t \left[ 1 - \alpha_t x + \phi(\alpha_t) x \right] + y_t \left[ \phi'_t(\alpha_t) \alpha_t' x + \phi(\alpha_t) \right],
$$

where $\alpha_t'$ is now the derivative of $\alpha_t$ with respect to $x_t$.

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

$$
\phi_t^k > 1,
$$

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

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

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The next step is to prove that the NCF is decreasing in \( \chi \) and increasing in \( x = R^k/R^l \).
The index can be simplified to
\[
\frac{\alpha_t x}{1 + \alpha_t x}.
\]
Differentiating with respect to \( \chi \) we obtain
\[
\frac{\partial NCF}{\partial \chi} = \frac{\alpha'_t x}{(1 + \alpha_t x)^2},
\]
where \( \alpha'_t \) is the derivative of \( \alpha_t \) with respect to \( \chi \). As shown in Lemma 2.1, this is negative. Therefore, NCF decreases in the issuance cost.

We now compute the derivative of NCF with respect to \( x \) and obtain
\[
\frac{\partial NCF}{\partial x} = \frac{\alpha'_t x + \alpha_t}{(1 + \alpha_t x)^2},
\]
where \( \alpha'_t \) is the derivative of \( \alpha_t \) with respect to \( x \). As shown in Lemma 2.1, this is positive. Therefore, NCF increases in the return spread.

\[\square\]

C Data Appendix

Aggregate Data for the US. We build the series for leverage and NCF using data from the Flow of Funds for the U.S. depository institutions, securities brokers and dealers, and finance companies. Following Nuno and Thomas (2017) we use the series in level (coded FL) for the first period while the levels for the subsequent periods are obtained by using the series for the changes (FU). This procedure avoids structural breaks in the series. The results however are very similar if we use directly the series in levels. We retrieve quarterly series and then use quarter 4 for the annual analysis. The series are listed in Table 1.

We compute the growth of real assets by deflating nominal assets with the implicit GDP deflator for the US available from the FRED Database. We use 2013 as the base year. The exogenous returns \( R^l \), \( R^k \) and the discount rate \( \beta \) are calibrated using data for the bank prime loan rate, the average 3-months certificate of deposits rate and the return on bank equity, averaged over the period 1999-2013. These three series are also available in the FRED database. Data on banks’ CDS are from Bloomberg.

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

We focus on Commercial and Savings Banks, Cooperative Banks, Investment Banks and Securities Firms, and Finance Companies. The information provided covers over 14,000 financial institutions located in the following 30 OECD countries (ISO-3 codes): Austria,
Table 1: Data series from the US Flows of Funds.

<table>
<thead>
<tr>
<th>US Depository Institutions</th>
<th>Securities Brokers and Dealers</th>
<th>Finance Companies</th>
</tr>
</thead>
<tbody>
<tr>
<td>764090760 Total Assets (Call report)</td>
<td>664090663 Total Assets</td>
<td>614090610 Total Assets</td>
</tr>
<tr>
<td>765080003 Equity Capital (Call report)</td>
<td>665080003 Equity Capital</td>
<td>615080003 Equity Capital</td>
</tr>
<tr>
<td>762150005 Federal Funds and Security Repurchase Agreements (REPOs), liability</td>
<td>662151003 Security Repurchase Agreements (REPOs), liability</td>
<td>613169100 Commercial Papers, liability</td>
</tr>
<tr>
<td>763169175 Open Market Papers, liability</td>
<td>663168005 Loans from Depository Institutions, liability</td>
<td>613168003 Loans from Depository Institutions, liability</td>
</tr>
<tr>
<td>764112205 Interbank transactions due to U.S. banks, liability</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: i) the Flow of Funds reports separately the fed funds and REPOs liabilities holding for US depository institutions only from 2012Q1. After this date, it is possible to verify that the weights of REPOs in the total figures for the series 762150005 is above 80%. ii) From 2010Q1, the Flow of Funds include also estimates of asset-backed commercial papers within the series 763169175, introducing a structural break not addressable with our cumulation of the series in changes. In the series used to compute the NCF index, we therefore simply subtract the series FL763169103 (asset backed commercial papers) in levels from the series FL763169175 (open market papers) for the US depository institutions.

Belgium, Canada, Switzerland, Chile, Check Republic, Germany, Denmark, Spain, Estonia, Finland, France, Great Britain, Hungary, Ireland, Israel, Italy, Japan, South Korea, Mexico, Netherlands, Norway, New Zealand, Poland, Portugal, Slovakia, Slovenia, Sweden, Turkey, United States.

An issue with the use of Bankscope data is the possibility of double counting of financial institutions. In fact, for a given Bureau van Djik id number (BVIDNUM), 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). See Bankscope user guide and Duprey and Lé (2013) for additional details. We polished the data in order to avoid duplicate observations and favor consolidated statements over unconsolidated ones.
References


Table 2: **Summary Statistics**

<table>
<thead>
<tr>
<th></th>
<th>Number Obs</th>
<th>Total Assets</th>
<th>Leverage</th>
<th>NCF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>mean s.d.</td>
<td>mean s.d.</td>
<td>mean s.d.</td>
</tr>
<tr>
<td>ALL</td>
<td>257,131</td>
<td>9,078 82,160</td>
<td>12.5 9.0</td>
<td>0.15 0.20</td>
</tr>
<tr>
<td>of which:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mega Banks</td>
<td>2,108</td>
<td>0.8 609,211 577,079</td>
<td>25.7 15.1</td>
<td>0.57 0.24</td>
</tr>
<tr>
<td>Commercial Banks</td>
<td>139,325</td>
<td>54 6,651 71,044</td>
<td>10.8 5.7</td>
<td>0.10 0.15</td>
</tr>
<tr>
<td>Investment Banks</td>
<td>4,139</td>
<td>1.6 29,038 97,790</td>
<td>16.7 19.4</td>
<td>0.61 0.31</td>
</tr>
</tbody>
</table>

Notes: assets are in millions of USD. Leverage is measured as total assets over total equity. NCF 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 3: **Market funding and Leverage: Country-level Evidence**

<table>
<thead>
<tr>
<th>Dep Variable</th>
<th>A/E</th>
<th>A/E</th>
<th>A/E</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCF</td>
<td>22.689***</td>
<td>19.098***</td>
<td>20.929***</td>
</tr>
<tr>
<td>(1.353)</td>
<td>(2.220)</td>
<td>(2.229)</td>
<td></td>
</tr>
<tr>
<td>Country FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time FE</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.370</td>
<td>0.788</td>
<td>0.850</td>
</tr>
<tr>
<td>N</td>
<td>480</td>
<td>480</td>
<td>480</td>
</tr>
</tbody>
</table>

Notes: unconditional and conditional correlations between leverage and NCF at country level. NCF 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 4: Market Funding and Leverage, Very Large Financial Institutions (1999-2014)

<table>
<thead>
<tr>
<th>Dep Variable</th>
<th>A/E</th>
<th>A/E</th>
<th>A/E</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCF</td>
<td>35.597***</td>
<td>28.802***</td>
<td>30.066***</td>
</tr>
<tr>
<td>size</td>
<td>-0.134</td>
<td>-1.029**</td>
<td>4.445*</td>
</tr>
<tr>
<td>Specialisation FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Country FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Time FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Banks FE</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.343</td>
<td>0.513</td>
<td>0.194</td>
</tr>
<tr>
<td>N</td>
<td>1272</td>
<td>1272</td>
<td>1272</td>
</tr>
</tbody>
</table>

Notes: unconditional and conditional correlations between leverage and NCF for financial institutions with balance sheets larger than 100 USD billions. Leverage is measured as total assets over total equity for each financial institution. NCF 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 5: Marker Funding and Leverage, All financial institutions

<table>
<thead>
<tr>
<th>Dep Variable</th>
<th>A/E</th>
<th>A/E</th>
<th>A/E</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCF</td>
<td>8.284***</td>
<td>6.684***</td>
<td>5.785***</td>
</tr>
<tr>
<td>size</td>
<td>2.476***</td>
<td>2.658***</td>
<td>2.742***</td>
</tr>
<tr>
<td>Banks FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.094</td>
<td>0.118</td>
<td>0.116</td>
</tr>
<tr>
<td>N</td>
<td>213576</td>
<td>125883</td>
<td>69705</td>
</tr>
</tbody>
</table>

Notes: conditional correlations between leverage and NCF for all financial institutions (two way fixed effect estimator). Leverage is measured as total assets over total equity for each financial institution. NCF 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>
<thead>
<tr>
<th>Dep Var: $\Delta \text{Assets}_{i,k,t}$</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRISIS (2009-)</td>
<td>-0.050***</td>
<td>-0.029***</td>
<td>-0.004*</td>
<td>-0.004*</td>
<td>0.007***</td>
<td></td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRISIS*$NCF_{Q2}$</td>
<td>-0.017***</td>
<td>-0.018***</td>
<td>-0.018***</td>
<td>-0.024***</td>
<td>-0.024***</td>
<td></td>
</tr>
<tr>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRISIS*$NCF_{Q3}$</td>
<td>-0.029***</td>
<td>-0.033***</td>
<td>-0.032***</td>
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<td>-0.044***</td>
<td></td>
</tr>
<tr>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRISIS*$NCF_{Q4}$</td>
<td>-0.038***</td>
<td>-0.056***</td>
<td>-0.054***</td>
<td>-0.084***</td>
<td>-0.085***</td>
<td></td>
</tr>
<tr>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRISIS*$LEV_{Q2}$</td>
<td>-0.018***</td>
<td>-0.018***</td>
<td>-0.015***</td>
<td>-0.015***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>CRISIS*$LEV_{Q3}$</td>
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<td>-0.024***</td>
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<td>-0.019***</td>
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<td></td>
</tr>
<tr>
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<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRISIS*$LEV_{Q4}$</td>
<td>-0.035***</td>
<td>-0.035***</td>
<td>-0.021***</td>
<td>-0.024***</td>
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<td>(0.003)</td>
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<tr>
<td>Log(Assets)</td>
<td>0.011***</td>
<td>0.011***</td>
<td>0.011***</td>
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<td>(0.000)</td>
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<tr>
<td>$Unempl_{k,t-1}$</td>
<td>-0.001***</td>
<td>-0.001***</td>
<td>-0.003***</td>
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Notes: impact of NCF on the reduction of the growth of assets during the financial crisis. OLS estimates. $NCF_{Qj}$ and $LEV_{Qj}$ are dummy variables that takes value one if the bank belongs to the $j^{th}$ quartile of the distribution of, respectively, average non-core funding and leverage over the period 2003-2006. $Unempl_{k,t-1}$ is the Unemployment rate prevailing at time $t - 1$. Standard Errors in Parenthesis. *,**,*** Statistically Significant at 10%, 5% and 1%.
Figure 14: Leverage and Market Funding, Across Time, Within Selected Countries. Leverage is measured as total assets over total equity for each financial institution. NCF 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 15: Leverage and Market Funding, Across countries, Selected Years. Leverage is measured as total assets over total equity for each financial institution. NCF 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 16: Leverage and Market Funding, Mega Banks, Selected Years. Leverage is measured as total assets over total equity for each financial institution. NCF 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.