Banking crises, R&D investments and slow recoveries

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Abstract

This paper studies how banking crises affect the composition of corporate investments and economic growth. Theoretically, it builds a partial equilibrium endogenous growth model with a banking sector and aggregate shocks. In the model, entrepreneurs can invest in two types of technologies: a safe, short-term one and an innovative, long-term one. Long-term projects are growth-enhancing but subject to a liquidity cost which credit constrained entrepreneurs cover by borrowing from the banking sector. When bank creditors are sufficiently pessimistic about the aggregate liquidity needs of the real sector, they will run on the bank and cause a credit freeze. This liquidity crisis disrupts real sector investments which reduces returns and tightens credits constraints in the next period. Furthermore, tighter credit constraints after the crisis decrease the share of entrepreneurs' investments in innovative projects, which slows down growth. Industry-level data on R&D investments following 13 recent banking crises episodes support this hypothesis. I show that industries that depend more on the banking sector reduce their R&D spending disproportionately more following episodes of banking distress, confirming the hypothesis that at least part of this effect is caused by a credit supply channel.

JEL Classification: G01, G21, E22

Keywords: banking crises, R&D investments, economic growth, global games

1 Introduction

Banking crises are generally associated with large and persistent economic disruptions (Cerra and Saxena, 2008; Laeven and Valencia, 2008; Furceri and Mourougane, 2012; Ball, 2014). Looking at 100 systemic banking crises, Reinhart and Rogoff (2014) find that it takes, on average, eight years

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for countries to reach their pre-crisis levels of GDP per capita. Figure 1 plots the evolution of the average real GDP per capita following 13 recent banking crises episodes as compared to other non-banking crisis recessions in the same set of countries[1]. Clearly, economic recovery following banking crises tends to be slower. This paper proposes a new channel which can explain this medium-to long-term effect of banking crises on real economic growth. In an endogenous growth model in the spirit of Aghion, Angeletos, Banerjee and Manova (2010), I show that financial sector distress impacts not only the volume, but also the composition of real sector investment. By decreasing the share of investments in innovation, banking crises can have a long-lasting effect on growth as documented by recent empirical evidence. Industry-level data for 13 recent banking crises episodes support this theoretical prediction.

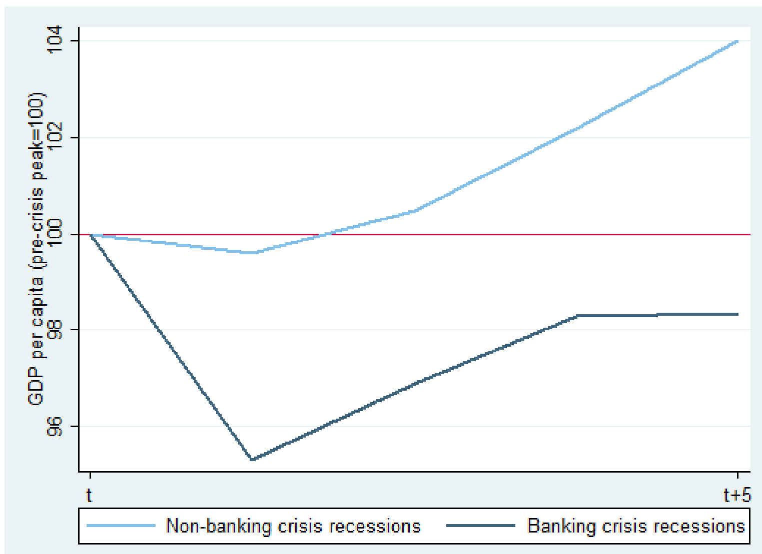

Figure 1: Recovery from banking/non-banking crises recessions

The magnitude of the 2007-2009 global financial crisis has emphasized the importance of negative shocks to banks' supply of external finance. The main trigger of the liquidity dry-up that singled out this crisis was a run on the repo market by short-term bank creditors (see Brunnermeier, 2009; Gorton and Metrick, 2012; Adrian, Colla and Shin, 2012; Acharya and Mora, 2013). This papers models a banking sector that captures some of these stylized facts. In the theoretical model, crises are triggered by a coordination failure among banks' short-term creditors. These creditors observe noisy signals about the liquidity needs of the real sector and run on the bank when they are sufficiently pessimistic about the probability that real sector projects survive the liquidity shock. Employing a recent global games methodology, the probability that such banking crisis occurs is

[1]The countries included are: Austria (2008;2001), Belgium (2008;2001), France (2008; 2001), Germany (2008;2001), Italy (2008;2001), Japan (1997;2008), Korea (1997;2008), Portugal (2008;2001), Slovenia (2008), Spain (2008;1992), Turkey (2000;2007), United Kingdom (2007;1989) and United States (2007; 2000), where the first date is a banking crises episode identified in Laeven and Valencia (2012), while the second is a recession date from the FRED Economic Data of St.Louis Federal Reserve Bank.

pinned down by bad economic fundamentals, but is still the result of investors' self-fulfilling beliefs (Morris and Shin, 1998; Goldstein and Pauzner, 2005).

This static bank run model is then embedded in an over-lapping generations model of entrepreneurs who can invest in two different technologies: a safe, low return short-term technology and a high return long-term technology. Long-term technologies can be seen as investments in innovation, which are more productive but risky since they are subject to a random liquidity shock which entrepreneurs cover by borrowing from the bank. One key element is that credit markets are imperfect and entrepreneurs face credit constraints when borrowing. As in Aghion et al. (2010), entrepreneurs will invest more in the long-term technology when they face lower credit constraints.

Given these real sector investment patterns, it can be shown that credit constraints evolve over the financial cycle. The mechanism through which this happens is as follows: as long as banking crises do not occur, entrepreneurs will invest more in the long-term, innovative technology which yields higher returns. Given that input markets are perfectly competitive, higher returns on capital cause banks to relax credit constraints which results in even more investment in the long-term technology. This higher share of long-term investments explains the high growth prior to the crisis. Once a banking crisis occurs, credit to the real sector is frozen and long-term investments fail. At the same time, returns in the next period are lower which tightens credit constraints and further depresses investments in long-term technologies. The lower share of investment in long-term technologies explains why growth following an episode of banking distress tends to be slower. The focus on project heterogeneity in this paper is inspired by Matsuyama (2007) and Aghion et al. (2010) who also emphasize a shift in the composition of investment over the business cycle. The new insight here is to show that banking crises can trigger a similar effect as a result of changes in credit constraints.

The main empirical conjecture of this model is that recovery from banking crises is slowed down by the shift in the composition of real sector investments. This happens because, following periods of banking distress, firms reduce investments in productivity-enhancing projects which will, in turn, have long-term effects on economic growth. I test this hypothesis empirically using industry-level data on R&D spending as a proxy for long-term, growth-enhancing investments.

The identification strategy used to disentangle the "exogenous" effect of financial conditions on the growth in R&D investments is the "difference-in-difference" methodology proposed by Rajan and Zingales (1998). The main argument is that if companies rely on external funds to finance investments in R&D, a tightening of credit conditions following banking crises should disproportionately affect the industries that generally depend more on the banking sector to obtain funds. This approach has been previously used to study the impact of banking crises on industrial growth in value added (Kroszner, Laeven and Klingebiel, 2007; Dell'Ariccia, Detragiache and Rajan, 2008). This study complements this work by looking at a potential channel through which banking crises can have long-lasting effects on growth. Using data on R&D investments around 13 recent banking crises, I show that industries more dependent on external finance will disproportionately reduce their investments in R&D following periods of bank distress. At the same time, this impact appears stronger in countries that have a more developed banking sector as compared to stock markets, suggesting that bank-dependent borrowers cannot substitute bank finance with other types of external financing during banking crises. These results are robust to an array of robustness tests, in particular with regards to different proxies for dependence on external finance. By disproportionally impacting borrowers who depend more on the banking sector, this documented drop in R&D spending following banking crises is, at least partially, caused by a "credit channel" or supply-side conditions and not simply a consequence of the business cycle.

Next, I show that not only the size, but also the share of R&D investment in total investment is, on average, lower in industries more dependent on external finance. The lower share of investments in innovation can provide an explanation for why growth following episodes of bank distress tends to be slower as compared to other recessions.

The remainder of the paper is organized as follows. The next section discusses previous research and the motivation of the paper. Section 3 presents the theoretical model and the dynamics it suggests. Section 4 lays out the empirical strategies employed, while section 5 presents the main results. Finally, section 6 concludes.

2 Relation to literature

This work is related and contributes to several branches of literature. Theoretically, there is a large literature modeling financial crises which focuses mainly on the how financial crises occur and can be mitigated (for a review, see Goldstein, 2010). The two main views of financial crises are that they occur as a result of panic and coordination failures (Diamond and Dybvig, 1983) or a deterioration of bank fundamentals (Allen and Gale, 1998). Recent developments in global games bring together these two views by modeling crises pinned down by bad fundamentals, which are still self-fulfilling as they would not have occurred if agents did not expect them to occur (Carlsson and Van Damme, 1993; Morris and Shin, 1998; Morris and Shin, 2001; Morris and Shin, 2004; Goldstein and Pauzner, 2005). The introduction of information asymmetries in this framework eliminates the multiplicity of equilibria which generally characterizes bank run models and allows agents to coordinate around a unique threshold equilibrium.[2] In a framework close to mine, Rochet and Vives (2004) model a "modern" form of bank runs, where large-well informed investors refuse to renew their credit. Their interest, however, is understanding how different bank regulation policies can help mitigate the coordination problem and eliminate runs on otherwise solvent banks. In this paper, I embed a static bank run model in a dynamic framework, to study how the probability of

[2] By and large, this methodology has remained static and is primarily concerned with understanding the triggers of crises and how they can be mitigated. One exception is Angeletos, Hellwig and Pavan (2007) who build a dynamic model of currency attacks in which agents learn from previous actions.

a crisis occurring evolves as a result of decisions of real economic agents.

Second, my model provides a theoretical micro-foundation for a growing empirical literature that studies the real consequences of banking crises. The immediate consequences of financial crises are, by now, well understood. For example, 2007-08 liquidity dry-up in the banking sector has been followed by a sizable squeeze in bank lending amounting to a 47% drop in new loans during the peak of the crisis (Ivashina and Scharfstein, 2010). This credit crunch has been followed by significant drops in corporate investments on new technologies, employment and capital spending (Duchin, Ozbas and Sensoy, 2010; Campello, Graham and Harvey, 2010). Moreover, these effects of banking crises on the real economic outputs seem not only large, but also long-lasting (Reinhart and Rogoff, 2014; Ball, 2014).

Theoretical literature, however, generally treats separately the analysis of long-run growth and short-term instability. A large literature on the effects of financial intermediaries and markets on growth generally overlooks shocks and crises (see Levine, 2005, for an overview). Real business cycles literature, on the other hand, emphasizes the role of credit market constraints in propagating productivity shocks, but largely treats financial intermediaries as a veil (Bernanke, Gertler and Gilchrist, 1999; Gertler and Kiyotaki, 2010).[3]

One potential link between short- and long-run dynamics are investments that drive productivity growth such as investments in innovation or Research and Development (R&D). Investments in innovation have been shown to be strongly pro-cyclical despite the neoclassical growth argument that R&D investments should be concentrated in periods of recessions when the opportunity costs in terms of foregone output are lower (Aghion and Howitt, 1998). The leading explanation for this cyclicality of R&D is the presence of credit constraints (Aghion et al., 2010; Ouyang, 2011). The idea is that the pro-cyclicality of profits makes financial constraints more biding in recessions which affects firms' ability to borrow and discourages investments in innovation. Aghion et al. (2010) formalize this idea in a partial equilibrium model in which investments in innovation have higher liquidity risks which makes them pro-cyclical in the presence of credit constraints. They show that this pro-cyclicality highlights a new propagation mechanism through which credit market imperfections can explain both the lower mean growth and the higher volatility of economies with tighter credit conditions. They confirm these results empirically by showing that countries with a better access to credit, i.e. more financially developed, have a lower sensitivity of growth to productivity shocks. Subsequent evidence is brought by Aghion, Askenazy, Berman, Cette and Eymard (2012) who use a sample a French firms and find that the share of R&D investment, as a natural measure of long-term investment- is more procyclical in firms that face tighter credit

[3]Recent contributions model the role of financial sectors as a source of business cycles rather than just a propagator of shocks that originate in other sectors of the economy. Kiyotaki and Moore (2012), Jermann and Quadrini (2012) and Brunnermeier and Sannikov (2014), among others, have studied how shocks to financial conditions can induce a crisis that affects real activity. These models however, do not explicitly model the financial sector or the source of the disruptions that trigger the crisis.

constraints.[4] This paper builds on the idea that credit constraints impact the composition of investment to study of the evolution of investments in R&D around banking crises. In particular, it is concerned with highlighting the *exogenous* impact of credit supply conditions on investments in innovation. The basic argument is that changes in credit standards or credit supply can cause a shift in the composition of investment by discouraging investment in innovation and this effect is independent of the pro-cyclicality implied by balance-sheet effects in economic downturns.

Yet, disentangling the effects of demand from supply shocks following financial crises is empirically challenging given that crises are usually followed by economic recessions (Demirgüç-Kunt and Detragiache, 1998; Kahle and Stulz, 2013). One empirical strategy used to identify the causal effect of banking crises looks at the differential effect of the crisis on bank dependent borrowers. For example, Dell'Ariccia et al. (2008) and Kroszner et al. (2007) show how banking crises exogenously hinder real activity by disproportionately affecting industries that are more dependent on external finance. Chava and Purnanandam (2011) uses the 1998 Russian crisis as an exogenous capital shock to the US banking sector and show how capital losses suffered by banks adversely affected their ability to make loans which resulted in significant drops in capital expenditures in bank-dependent firms. Chodorow-Reich (2014) shows that pre-crisis clients of banks in worse financial conditions had a fifty percent lower likelihood of receiving a new loan. At the same time, he shows that borrowers of weaker banks could not simply switch to healthier banks during the crisis.

I use a framework similar to Kroszner et al. (2007) to document a new channel through which banking crises can have an "exogeneous" impact on the real economy.

3 Theoretical model

3.1 Set-up

3.1.1 Agents, preferences and goods

The economy consists of three risk-neutral agents: entrepreneurs, bank, and investors. The real sector of the economy comprises an infinite sequence of overlapping generations of entrepreneurs who live three periods [0,1,2]. The financial sector is represented by a bank which obtains funding from investors and lends to entrepreneurs. There is a continuum [0,1] of investors, each endowed with one unit of wealth at the beginning of each period. Entrepreneurs are born with an endowment of H units of labor (stock of human capital), but no wealth. There are two types of capital goods in the economy, which in combination with labor, produce a consumption good. All agents consume in the last period of their lives (t=2) after which they die.[5]

[4] Barlevy (2007) provides an alternative explanation to the prc-cyclicality of R&D investments in a model in which the gains from innovation are immediate for the innovator, but lost if imitated. This can explain why it is more profitable to innovate in booms when the gains from new ideas are larger.

[5] A zero discount factor between periods is assumed.

3.1.2 Final good production

The final good is produced by means of a new-classical production function of the form:

$$Y_t = A_t K_t^{\alpha} H_t^{1-\alpha}$$

with capital K_t and human capital H_t as inputs. I assume that the scale parameter A_t, which measures aggregate productivity, depends on the aggregate capital stock (as in Romer, 1986): $A_t = aK_t^{\gamma}$, with $\gamma = 1-\alpha$. This assumption, together with the fact that the stock of human capital is fixed throughout the lifetime of an entrepreneur, $H_t = \overline{H}$, yields a standard AK model:[6]

$$Y_t = \sigma K_t \text{ with } \sigma = a\overline{H}^{1-\alpha}$$

Input markets are competitive, and capital and labor are remunerated at their marginal productivity, such that their shares of final output are given by the usual formulas:

$$\frac{\partial Y}{\partial K}K = \alpha\sigma K \text{ and } \frac{\partial Y}{\partial H}H = (1-\alpha)\sigma K \tag{1}$$

3.1.3 Technologies and investment opportunities

There is a continuum of entrepreneurs (firms) with unit mass. Because of constant returns to scale, there is no loss in assuming that firms have identical endowments of human capital. The representative firm is endowed with H_t units of human capital at each of the three dates [0,1,2]. Entrepreneurs have access to two types of capital goods, which use two technologies of the form described above to produce the final good. A short-term capital good, denoted by K_1, takes one period to produce using technology, Y_1:

$$Y_{1,t} = (a_1 K_{1,t}^{\gamma}) K_{1,t}^{\alpha} \overline{H}^{1-\alpha} \equiv \sigma_1 K_{1,t} \tag{2}$$

The long-term capital good, denoted by $K_{2,t}$ on the other hand, takes two periods to become productive and generates an output:

$$Y_{2,t} = (a_2 K_{2,t}^{\gamma} K_{2,t}^{\alpha}) H_t^{1-\alpha} \equiv \sigma_2 K_{2,t} \tag{3}$$

We assume that $a_2 > a_1$, which assures that the total productivity of the long-term investment is higher than the one of the short-term technology, or $\sigma_2 > \sigma_1$. Moreover, for any value of the capital-labor ratio the marginal returns of capital and labor are higher in the case of the long-term technology. One can think of these long-term investments as research and development, fixed

[6] Aghion, Banerjee and Piketty (1999) use a similar production function to study endogenous investment cycles. However, instead of introducing an aggregate capital accumulation externality a la Romer (1986), they assume an unlimited labor supply at a constant real wage which generates a similar AK technology.

investments or spending on new technologies which are more conducive to long-term growth. Short-term investments, on the other hand, can be seen as investments in working capital.

Moreover, long-term investments are subject to a liquidity shock in the form of a random expense, C_1 which occurs in period one. If the entrepreneur is successful in covering the liquidity shock, then production in period 2 will take place and yield output $Y_2 + C_1$. This means that, if the liquidity shock is fully covered and production of the long-term technology takes place, the entrepreneur will receive an extra benefit C_1 in the last period such that the value of the long-term investment remains unaffected by the liquidity shock. This assumption guarantees that long-term investments, when they survive the liquidity costs, are still more productive than short-term investments.[7] If, on the other hand, the entrepreneur fails to fully cover the random liquidity cost, production of the long-term technology is scrapped, the long-term capital good becomes obsolete and $Y_2 = 0$.

The liquidity shock specific to long-term technologies modeled in this paper resembles the *aggregate* liquidity shock in Holmstrom and Tirole (1998). In their seminal work, Holmstrom and Tirole (1998) show that, when firms face *idiosyncratic* liquidity needs, the private sector is self-sufficient and a Pareto allocation can be implemented where banks offer insurance against liquidity needs by pooling firm risks. In the presence of *aggregate* liquidity needs, however, the real sector is no longer able to insure itself. They show that governments can improve liquidity and achieve a Pareto optimal equilibrium by issuing bonds. In their model, however, financial intermediaries play a rather passive role and runs do not happen as investors cannot claim assets in the intermediate period. In this paper, *aggregate* liquidity shocks also make the real sector unable to insure itself against liquidity shocks by issuing claims in financial market. However, there is not need for government intervention since the interest here rests in modeling the impact that banking crises have on firms that depend on the banking sector for obtaining liquidity. This assumption is also justified empirically. While some big firms can circumvention the banking sector and raise outside fund directly in capital markets in times of banking distress, most firms do not, if fact, have this option (see, Adrian et al., 2012).

The second motivation for modeling aggregate liquidity shocks comes the empirical literature on banking crises. For example, in documenting the impact of the 2008-2009 financial crisis, Ivashina and Scharfstein (2010) shows that together with the liquidity freeze in the banking sector, firms also demanded massively liquidity by drawing down their bank credit lines. This suggests a spike in liquidity demand by the real sector which is what the aggregate liquidity shock assumed in this model tries to capture.

The timing of the events is presented in Figure 2 below. At the beginning of their life entrepreneurs borrow and decide how much to invest in the short-term capital, K_1, or the long-term

[7] As it will become clear later on this assumption does not affect the equilibrium composition of investment. For tractability, I will ignore the possibility that the net present value of the long-term investment is diminished by the liquidity cost.

one, K_2. In period 1, short-term capital becomes productive and Y_1 is realized. The long-term investment is subject to a liquidity shock. Entrepreneurs will use their own funds, Y_1 as well as borrow from the banking sector to cover the additional cost. In the last period, $t = 2$, long-term investments become productive only if the liquidity shock is covered and entrepreneurs consume their total life-time income after which they die.

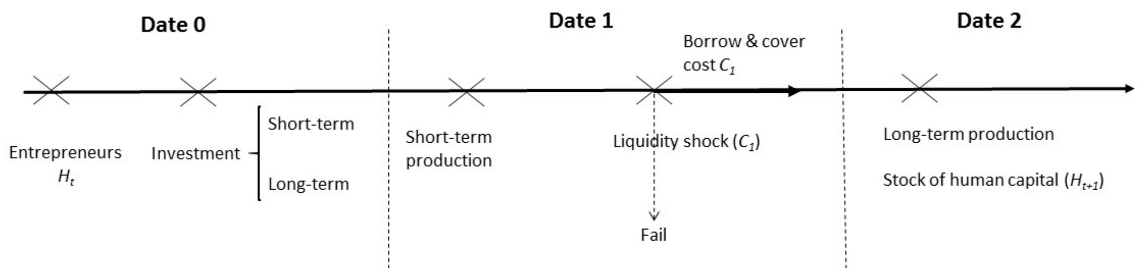

Figure 2: Timing of the real sector

3.1.4 Credit markets

An essential ingredient of the model are credit market imperfections. I assume entrepreneurs borrow from the bank to make initial investments K_1 and K_2, as well as to cover the liquidity shock. Entrepreneurs cannot borrow more than a share $\mu \leq 1$ of their current income. The micro-foundations of this credit multiplier rest in the usual information asymmetries between borrowers and lenders and are not formally modeled here (see Holmstrom and Tirole, 1997; Aghion et al., 1999). For example, Aghion et al. (1999) derive a micro-economic model of lending in which ex-post moral hazard and costly state verification generate a credit multiplier similar to the one assumed here. They show that whenever an increase in interest rates leads to increased benefits from monitoring, the maximum amount which lenders are willing to lend also increases, i.e. the credit multiplier is an increasing function of interest rates. For the time being, I take this credit multiplier as given and solve the entrepreneur's maximization problem. I will later endogeneize it and show how credit constraints evolve over the business cycle.

3.1.5 Growth

The interpretation of the two types of investments and the liquidity shock follows Aghion et al. (2010). In particular, short-term investments can be seen as investments in working capital or maintaining the current business, while long-term investments are investments in R&D, learning about new technologies or new businesses. These latter investments are more risky, since unexpected extra-cost for adopting the new technology or setting up a new business can always occur. At the same time, investing in these long-term technologies is more likely to be more conducive to productivity growth as usually assumed in endogenous-growth models (see, for example, Aghion and Howitt, 1998). I thus assume that the stock of knowledge or human capital available in the economy in the next period will increase proportionally to the investments in long-term technology. Similarly, since these long-term investments are largely intangible, it is also reasonable to consider that they may be lost (partially or completely) when the liquidity shock is not covered. Formally, the growth rate of the stock of human capital (H_t), will follow the law of motion:

$$H_{t+1} = F(K_{2,t}, H_t),$$

where F is continuous, increasing in all its arguments and homogeneous of degree one. This stylized endogenous growth model allows me to understand how frictions in the banking sector impact growth without going deeper into the micro-foundations of productivity growth.

3.2 Entrepreneurs' maximization problem

Entrepreneurs borrow and produce a consumption good in order to maximize their end of life (period 2) consumption as outlined below. In the first period (period 0), they borrow in order to invest in short- and long-term capital. Since entrepreneurs have no wealth at the beginning of their life, I assume that their $t = 0$ borrowing is a share μ of the "market value" of the entrepreneur's capital, ϕH: $B_0 = \mu\phi H$, where ϕ is a multiplier for the value of human capital endowment.[8] I further assume that entrepreneurs can only borrow based on the market value of his human capital the first period, prior to investing. Thus, in $t = 0$ entrepreneurs borrow and invest in K_1 and K_2, subject to the borrowing constraint:

$$K_1 + K_2 \leq \mu\phi H. \tag{4}$$

In the second period ($t = 1$), the short-term investment yields Y_1 and entrepreneurs are hit by the liquidity shock, C_1 . The shock is covered using period one income and, if needed, by borrowing from the bank up to the credit multiplier:

$$B_1 = e(C_1 - Y_1) \text{ and } B_1 \leq \mu Y_1, \tag{5}$$

where e is an indicator function taking value 1 if the entrepreneur covers the liquidity shock and 0 otherwise and B_1 is the borrowing in period 1. Credit constraints thus prevent firms from fully insuring against the liquidity shock. Finally, in the last period, long-term investment produces $Y_2 + C_1$ if entrepreneurs are successful in covering the liquidity shock. Total production in $t = 2$

[8] An alternative way to think about this transformation would be that entrepreneurs are employed in a real sector prior to investing in the two technologies and ϕ is the return on labor they will obtain.

after the extra debt in the intermediate period is payed off is:

$$(Y_2 + C_1)e + (1-e)Y_1 - B_1 = eY_2 + Y_1. \tag{6}$$

Thus, final production is simply the short-term technology output, as well as the long-term investment outcome, granted that the liquidity cost is covered. At the same time, the probability that entrepreneurs are able to cover the liquidity shock depends on both their own funds in the intermediate period, Y_1, as well as the credit constraints they face, μ. Denote by λ this probability, it follows from Eq. (5) that $\lambda(\mu, Y_1)$=Prob$[C_1 < (1+\mu)Y_1]$. That is, entrepreneurs will use their own funds, as well as, the maximum amount of borrowing they can obtain from the bank, μY_1 to cover the extra investment in the intermediate period. This is always ex-ante optimal since I have assumed that, if long-term investments survive their net value is unaffected by the extra liquidity cost.[9]

3.2.1 Equilibrium investment

Under the assumption of competitive markets for inputs, the share of final output obtained by the entrepreneur given productions in Eq. (2) and (3) represents his end of life-utility. Given Eq. (6) and initial period borrowing constraint in Eq. (4), the entrepreneur's utility maximization problem becomes:

$$\begin{aligned} &\underset{K_1,K_2}{\text{Max}}\ E[U_2] = \lambda(\mu, K_1)(1-\alpha)\sigma_2 K_2 + (1-\alpha)\sigma_1 K_1 \\ &\text{subject to} \\ &K_1 + K_2 = \mu\phi H. \end{aligned}$$

The maximization problem yields the following optimal levels of long- and short-term investment:

$$K_2(\mu, K_1) = \frac{\lambda\sigma_2 - \sigma_1}{(\partial\lambda/\partial K_1)\sigma_2} \qquad \text{and} \qquad K_1 = \mu\phi H - K_2(\mu, K_1) \tag{7}$$

I further assume that the liquidity cost is drawn from a uniform distribution, with support [0, C_{max}] and, as a result, $\lambda(\mu, K_1) = (1+\mu)\sigma_1 K_1/C_{max}$. The parameter C_{max} thus reflects the extent to which the firm depends on obtaining external financing: the higher C_{max} the less likely that the firm will be able to cover the liquidity shock using its retained earnings, $\sigma_1 K_1$. Replacing λ in Eq. (7) above yields the equilibrium level of long-term investment:

$$K_2(\mu) = \frac{\phi\mu H}{2} - \frac{C_{max}}{2(1+\mu)\sigma_2} \tag{8}$$

[9] Assuming otherwise, will not change the analysis as long as the productivity of the long-term technology is high enough compared to the short-term one ($a_2 \gg a_1$), however it will make the exercise less tractable.

It can be easily checked that $K_2(\mu)$ is increasing in μ: $\partial K_2/\partial\mu = \phi\mu H/2 + C_{max}/(2\sigma_2(1+\mu)^2) > 0$.

Lemma 1 follows directly:

Lemma 1 An equilibrium composition of investment exists and is given by $K_1 = \phi\mu H - K_2(\mu)$ and $K_2 = K_2(\mu)$, where $K_2(\mu)$ is increasing in μ.

Thus, laxer credit constraints (higher μ) lead to a higher share of investment in long-term capital. This result is also present in the model of Aghion et al. (2010). In their model, however, liquidity shocks are idiosyncratic and projects are subject to productivity shocks which impact the probability that the long-term investment is disrupted (by decreasing or increasing the funds available in the intermediate period). They show that credit constraints induce a "liquidity risk effect" which motivates entrepreneurs to invest relatively more in long-term projects during periods of positive productivity shocks. This provides an explanation for why more productivity-enhancing investments such as R&D investments take place during booms, despite the fact that their opportunity cost would be lower during downturns. By contrast, in my model, I look at how credit constraints impact the composition of investment following periods of banking distress. I turn to the characterization of the financial sector next.

3.3 The financial sector

The financial sector is formed of a representative, infinitively-lived bank and its short-term creditors. In each period, the bank raises outside capital from a mass [0,1] of investors each endowed with a unit of wealth. This structure of the banking sector captures a "modern" organizational structure of banks that fund themselves in the short-term, from, for example, large collective funds who place uninsured wholesale deposits (CDs) with the bank. As a consequence, these instruments can usually be withdrawn in any period (for a similar approach, see Rochet and Vives, 2004). This short-term funding structure is thus prone to runs since investors can decide not to renew their deposit to the bank in the intermediate period and deprive the financial institution of funds.

The bank invests its funds partly in risky assets (loans to entrepreneurs), with the rest being stored as cash. In the first period ($t = 0$), the balance sheet of the bank can be represented as:

Assets	Liabilities
I(loans)	$D_0 = 1$
M	

In this representation, I is the volume of loans granted to entrepreneurs and M is the amount of cash reserves held by the bank. For the time being, I consider M as exogenous (for example, it can a regulatory requirement). $D_0(=1)$ represents the volume of short-term loans (CDs) that investors make to the bank. Under normal circumstances, since returns on the assets I are collected in the last period, $t=2$ and cannot be liquidated earlier, bank creditors are repaid the nominal value of their deposits $D \geq 1$ in the last period. However, early withdrawals can also occur as investors can decide not to renew the loan to the bank and withdraw at date $t=1$. Regardless of the date of withdrawal, investors are entitled to receive D, as long as the bank has funds to repay them. The bank uses its liquid assets to repay investors who withdraw in the first period, given that risky assets cannot be liquidated.

Although stylized, this representation of the banking sector captures some key aspects of modern forms of bank runs. Indeed, the increased use of shorter-term maturity instruments was one of the main trends in the banking sector which significantly contributed to the lending boom that laid the foundations for the 2007-08 financial crisis (Brunnermeier, 2009). In my model, early withdrawals can cause a collapse of the bank if a sufficiently large number of investors refuse to renew their short-term loans, draining the banking sector of funds. At the same time, entrepreneurs who face an exogenous liquidity shock seek to raise financing from the banking sector implying a further demand for funds that the bank need to cover. This liquidity dry-up coming from both sides of the balance sheet is another well documented feature of the 2007-08 banking panic[10].

Thus at $t=1$ the bank faces two types of liquidity needs. On the one hand, investors can withdraw their deposits demanding repayment of the nominal value of their investment, D. On the other hand, entrepreneurs seek to raise $C_1 - Y_1$ funds from the bank to cover the extra funds required by the long-term technology to become productive at $t=2$. By denoting the proportion of investors who demand early withdrawal by ℓ, the demand for funds the bank faces in the intermediate period is:

$$\ell D + C_1 - Y_1 > M \tag{9}$$

Equation (9) above implies that the bank fails if the liquid funds, M, it has available cannot cover the demand of funds coming from *both* the investors and the entrepreneurs. The equilibrium in the financial sector can be split in two parts. First, I solve for the equilibrium of the investors' problem employing a global games methodology. Then, I solve for the bank's optimization problem considering the equilibrium outcomes of the entrepreneurs and investors.

3.3.1 Investors' coordination problem

Equation (9) characterizes the run threshold of the bank which depends on the proportion of investors who withdraw and the size of the random liquidity shock: $\ell D + C_1 > M + Y_1$. Note,

[10] Ivashina and Scharfstein (2010) show how, together with the run by short-term creditors, there was a simultaneous run by borrowers who drew down their credit lines, squeezing the banking sector of liquidity from the assets part of the balance sheet as well.

however, that the space of liquidity costs can be partitioned in three intervals. First, when $C \geq M + Y_1$, firms' liquidity needs are so high that investment projects will always fail, even if no investor withdraws, $\ell = 0$. Thus all investors have a dominant strategy to foreclose on their loans when $C_1 \geq M + Y_1$. In the second region, when $C_1 < Y_1 + M - D$ liquidity needs are sufficiently low that long-term investments will always survive, even if all investors withdraw, $\ell = 0$. Is thus optimal for everyone to leave their money in the bank. Finally, in the intermediate range $[Y_1 + M - D, M + Y_1]$, panic-based runs can occur depending on investors' self-fulfilling beliefs. This brings about a classical coordination problem in the spirit of Diamond and Dybvig (1983) which is known to have multiple equilibria. For every level of C_1 in the range $[Y_1 + M - D, M + Y_1]$ a bank run can occur or not solely on the basis of the expectations that investors have about the actions of others. However, a recent literature in global games has shown how introducing imperfect information can eliminate this multiplicity of equilibria (Morris and Shin, 1998; Morris and Shin, 2004; Goldstein and Pauzner, 2005). I follow this approach and assume that investors have imperfect information about the size of the liquidity shock and, as a result, about the liquidity demands entrepreneurs need to cover in order for long-term projects to be successful. More specifically, I assume that in $t = 1$ investors observe the true liquidity shock which a noise:

$$x_i = C_1 + \epsilon_i,$$

where x_i is investor's i noisy signal and ϵ_i is an idiosyncratic noise which is independent of C_1 and uniformly distributed over $[-\epsilon, \epsilon]$.

Using this global games approach, I model a banking crisis which is the result of investor "panic", but is still linked to the fundamentals in the real economy, which represent the liquidity needs of entrepreneurs. Proposition 1 states the basic equilibrium result.

Proposition 1 There exists a unique Bayesian Nash Equilibrium in which all investors roll-over their short-term debt when they observe a signal higher than x^* and withdraw their funds in $t = 1$ when they observe a signal lower than x^*. That is, the bank will be in a liquidity squeeze, whenever the random shock C_1 is lower than a threshold value, C^*, which is characterized by the following equation:

$$C^* = M + Y_1 - 1 \tag{10}$$

Proof *See Appendix*

Given this unique threshold, the probability of bank runs, which is also the probability that long-term investments fail, is given by $Prob[C_1 > C^*]$. Given the characterization of the equilibrium critical cost in Equation (10), this probability is decreasing in Y_1, M and D. The intuition behind this result is straightforward. As entrepreneurs invest more in the long-term technology, the income available to cover the liquidity shock decreases, which means the bank has to service a higher liquidity need in the interim period. This will increase the probability that short-term creditors panic and refuse to roll over their loans. Similarly, if the bank hold more liquid assets, higher M, this decreases the probability the long-term investments fail. Finally, higher returns demanded by investors facilitates their coordination and decreases the probability of runs.

3.4 Model dynamics and empirical predictions

The dynamics of the economy are summarized in Proposition 3.

Proposition 3 (i) As long as a bank run does not occur, the credit multiplier μ increases, leading to a lending boom in the long-term technology.

(ii) A credit crunch leads to a drop in H_t in the next period, which lowers the bank's expected return and increases credit constraints.

(iii) Tighter credit constraints after the banking crisis, lead to a lower share of investment in the long-term technology, which slows down the recovery.

Part (i) follows from the assumption of a procyclical credit constraint and Lemma 1. Part (ii) follow from the the fact that the ex-ante expected return of the bank is $\alpha\sigma_1 K_1 + \lambda\alpha\sigma_2 K_2$, which given (8) is increasing in H_t and μ. Finally, part (iii) follows from part (i) and Lemma 1.

The main empirical conjecture of this simple model is that one channel through which banking crisis can have a long-lasting effect on growth is through affecting investments in long-term productivity-enhancing projects. The remainder of this paper tests empirically this prediction.

4 Empirical evidence

This section provides an indirect test of the theoretical prediction in the previous section by providing causal evidence of the impact of banking crises on long-term investments. One common proxy of investments in productivity-enhancing projects is Research and Development expenditures (R&D) across sectors. The importance of R&D investments in driving productivity growth is well-recognized in the endogenous growth literature. At the same time, recent research has shown that R&D spending also reacts systematically to business cycle fluctuations (Barlevy, 2007; Ouyang, 2011). As such, R&D investments represent an ideal proxy to create the link between short- and long-run dynamics as suggested by the theoretical model in the previous section. Yet, given this strong procyclicality of R&D, one needs an identification strategy to disentangle whether banking crises have an "exogenous" effect on R&D spending which cannot be explained by business cycle fluctuations.

4.1 Econometric strategy

I use the classical Rajan and Zingales (1998) "difference-in-difference" approach to estimate the differential effect of banking crises on R&D spending across sectors and countries. Rajan and Zingales (1998) argue that there is a "technological reason" why some industries depend more on obtaining external financing, which is related to, for example, the initial project scale, the cash cycle, size of upfront investments. They then show that these sectors which dependent more on external finance tend to grow disproportionately faster in countries where the financial sector is more developed. The companion argument is shown in Kroszner et al. (2007) and Dell'Ariccia et al. (2008) who find that sectors more dependent on external finance perform relatively worse than industries less dependent during periods of banking crises. The rationale is that if the banking sector is the key institution allowing credit constraints to be relaxed, then a negative shock to these intermediaries should have a disproportionately contractionary effect on those sectors which depend the most on bank financing (Kroszner et al., 2007). This differential impact suggests that banking crises exogenously hinder real activity and the drop in industry value added is, at least partially, caused by supply side effects and not simply a consequence of a low aggregate demand or lack of investment opportunities.

I use a similar identification strategy by focusing on cross-industry, cross-country effects to disentangle a causal link from banking distress and R&D investments. The main hypothesis tested is that, following a banking crisis, firms in industries more dependent on bank finance will decrease their investments in research and development disproportionately more than firms in less dependent industries. Finding evidence of these sectoral differences in the data would therefore provide indirect but strong support for the presence of a causal effect of banking crises on R&D investments. The baseline specification follows closely Kroszner et al. (2007) and implements and event study analysis. More specifically, the model tested is as follows:

$$\Delta R\&D_{ic} = \alpha_i + \mu_c + \beta_1 ExtDep_i + \beta_2 Share_{ic} + \epsilon_{ic}, \tag{11}$$

where α_i are industry dummies, μ_c are country dummies and $\Delta R\&D_{cit}$ is the difference in average growth of R&D investments between pre-crisis and crisis periods of sector i in country c. In other words, $\Delta R\&D_{ic} = R\&D_{ic,crisis} - R\&D_{ic,pre-crisis}$, where $R\&D_{ci}$ is the average real growth in research and development investment during the pre- and crisis periods. I use different definitions for these pre- and crisis time frames which are detailed later on. $ExtDep_i$ is an industry-level measure of dependence on external financing, while $Share_{ic}$ is the share of industry i in country c in total R&D spending. The inclusion of the latter is meant to capture industry "convergence" effects, i.e. the tendency of larger industries to experience a slower growth in general and in investment, in particular (see also Rajan and Zingales, 1998; Kroszner et al., 2007; Dell'Ariccia et al., 2008). To avoid any potential endogeneity problems, pre-crisis levels of the industry share of R&D are used.[11] This first empirical strategy focuses on cross-industry effects to capture the differential effect of banking crises. The coefficient of interest is β_1 and I expect $\beta_1 < 0$, that is, the growth rate of R&D after the crisis is lower in more financially dependent industries.

In a second specification, I consider a more rich model which focuses on cross-industry, cross-country interaction effects. Towards that end, I interact a country-level measure of bank development with industry-level measures of external finance dependence to estimate the following model:

$$\Delta R\&D_{ic} = \alpha_i + \mu_c + \beta_1 ExtDep_i * BB_c + \beta_2 Share_{ic} + \epsilon_{ic}, \tag{12}$$

where BB_c is a country-level measure of bank development. This model follows closely Kroszner et al. (2007), however at difference with their model I used a measure of a country's dependence on the banking sector relative to the stock markets as opposed to their measure of private credit to GDP. This is justified in several ways. First, a large percentage of the countries in my sample are developed economies which have relatively similar levels of bank development traditionally measured by the ratio of private credit to GDP. By contrast, these countries are rather different with respect to the development of the banking sector as compared to financial markets in the sense that some countries are more "bank-based", while others more "stock markets-based". This distinction is particular important in this case given that previous research has stressed the importance of equity funding to finance R&D investments. If firms have easy access to capital markets, then the effects of a credit crunch would be diminished. As a result, the disproportionate effect of banking crises on bank-dependent borrowers should be stronger in countries that reply more on the banking sector to obtain funding, i.e. more bank-based economies. This cross-industry, cross-country effect is captured by the interaction term $ExtDep_i * BB_c$. Again, I expect this interaction term to be negative, meaning that industries more dependent on external finance invest less in R&D following periods of bank distress and the more so in countries that are obtain more funds through banks as compared to stock markets. In other words, the reduction in the growth rate of R&D is greater for financially dependent firms in more bank-based economies.

Finally, all specifications allow for country and industry fixed effects. Industry fixed effects capture all sector-specific omitted characteristics, while country fixed effects should control for country-specific characteristics that might affect investments in all industries. This array of fixed effects reduces concerns of omitted variable bias or model mis-specification and allows us to focus on within country, between industries variations.

[11] One concern with the inclusion of an industry's share of R&D spending in total research and development spending in a country is that more R&D intensive industries might also be the ones that generally depend more on external finance (Rajan and Zingales, 1998). This is not generally the case, since the two indexes of external dependence and the share of R&D have a very low positive correlation. Moreover, results are generally robust with the exclusion of the share variable from the model.

4.2 Data and descriptive statistics

Research and Development data comes for OECD's ANBERD database which collects annual data on R&D expenditures by industry for up to 100 manufacturing and service sectors in 34 (OECD member and a few non-members) countries since 1987. I focus on manufacturing industries only for several reasons. First, the year-industry coverage for manufacturing industries in ANBERD is much more wide. Second, R&D is heavily concentrated in manufacturing. For example, Barlevy (2007) documents that the share of R&D expenditure in manufacturing firms in the US ranged between 70-80% of total R&D expenditure since 1990. Similarly, for the countries covered in the ANBERD database manufacturing industries' average share of R&D spending between 1987-2013 represents 69.5% of total R&D investment.

To date banking crisis years, I use the Laeven and Valencia (2012) dataset. The timing of the banking crises and the availability of R&D data from ANBERD limits the sample to 13 country-crisis years and 29 two- and three-digit ISIC level manufacturing sectors.[12]

To compute the share of R&D investment in total investment, I use data on Gross Fixed Investment from the OECD Structural Statistics of Industry and Services database. Gross investment in tangible goods (GITG) captures the investments in land, existing buildings and structures, plant, machinery and equipment and new buildings and structures. Total investment is then calculated as the sum of *R&D* spending and gross investment in an industry since at the time of the analysis most countries have not implemented the System of National Accounts (SNA) 2008 guidelines that require countries to account the R&D expenses as an investment, rather than consumption. As a result the data on Gross investment at industry level does not include R&D investment.[13]

Finally, I also use the World Bank Economic Data to compute the ratio of Private Credit to Stock Market Capitalization which captures the degree to which an economy is bank-based as opposed to stock-market based (Levine, 2002).

4.2.1 Measures of external dependence

I use two measures of external dependence to capture an industry's reliance an external finance. First, I follow Rajan and Zingales (1998) and define external dependence ($ExtDep$) as the share of capital expenditure not financed with cash-flow from operations. Rajan and Zingales (1998) build their measure based on a sample of US Compustat manufacturing firms for the 1980s.[14] To preserve my sample size, I re-compute their index for 29 two- and three-digit ISIC level manufacturing

[12] The 13 banking crises covered are: Austria (2008), Belgium (2008), France (2008), Germany (2008), Italy (2008), Japan (1997), Korea (1997), Portugal (2008), Slovenia (2008), Spain (2008), Turkey (2000), United Kingdom (2007) and United States (2007). The 29 industries covered are presented in Appendix B.

[13] The date of implementation of the SNA framework differs across OECD countries, however for the sample of countries considered the USA has implemented the standard in 2013, while all EU countries in 2014.

[14] Rajan and Zingales (1998) compute a firm's dependence on external finance as Capital expenditures (*Compustat item* CAPX) plus Acquisitions (*Compustat item* AQC) minus Cash Flow from Operation divided by Capital Expenditures. Cash flow from operations is the sum of *Compustat items*: IBC, DPC, TXDC, ESUBC, SSPIV, FOPO, RECCH, INVCH, APALCH.

Table 1: R&D investments around a banking crisis

Table reports country averages of R&D growth around a crisis year. The pre-crisis period is $[t-3, t-1]$, while the post-crisis period is $[t+1,\ t{+}3]$ for a crisis year t. Crisis years represent the first year of a systemic banking crisis reported in Laeven and Valencia (2012). External dependence is measured using the Rajan and Zingales (1998) (RZ) and Calderon and Liu (2003) (CM) indexes based on a two- or three- digit ISIC. Low (High) external dependent industries are industries with an index below (above) the median.

		R&D growth Low ED			R&D growth High ED		
Country	Crisis year	# Ind	before	after	# Ind	before	after
External Dependence (RZ)							
AUSTRIA	2008	17	0.07	-0.01	11	0.00	0.03
BELGIUM	2008	17	0.01	0.04	6	0.04	0.41
FRANCE	2008	17	0.08	0.00	6	0.09	-0.01
GERMANY	2008	17	0.02	0.01	6	0.07	0.01
ITALY	2008	17	0.12	0.01	6	0.09	0.01
JAPAN	1997	10	0.00	-0.01	3	0.01	0.03
KOREA	1997	17	0.04	-0.03	6	0.25	-0.13
PORTUGAL	2008	10	0.24	0.02	5	0.15	-0.03
SLOVENIA	2008	13	0.23	0.11	5	0.13	0.08
SPAIN	2008	17	0.03	-0.01	6	0.07	-0.12
TURKEY	2000	11	0.19	0.06	3	0.47	0.03
UK	2008	8	0.02	0.00	5	0.12	0.08
USA	2008	13	0.02	0.01	8	0.06	0.02
Median			4.1%	0.7%		8.9%	2.0%
Difference				**-3.4%***			**-6.9%****
Bank Dependence (CM)							
AUSTRIA	2008	11	0.05	0.04	15	0.11	-0.02
BELGIUM	2008	9	-0.02	0.35	13	0.03	0.08
FRANCE	2008	9	0.02	0.03	13	0.24	-0.01
GERMANY	2008	9	0.03	0.04	13	0.05	0.01
ITALY	2008	9	0.11	0.02	13	0.28	0.03
JAPAN	1997	5	0.00	-0.02	6	0.00	-0.02
KOREA	1997	9	0.19	-0.18	13	0.08	-0.01
PORTUGAL	2008	9	0.51	-0.02	6	0.30	0.08
SLOVENIA	2008	7	0.15	0.12	9	0.58	0.23
SPAIN	2008	9	0.02	-0.04	13	0.08	-0.03
TURKEY	2000	5	0.40	0.13	7	0.33	0.08
UK	2008	7	0.08	0.06	5	0.05	0.00
USA	2008	9	0.03	-0.02	10	0.07	0.06
Median			5.1%	2.7%		8.2%	0.8%
Difference				**-2.4%**			**-7.4%***

*/** represent significance at the 5%/1% for the Pearson's chi-squared (MOOD) test under the null hypothesis that the medians of the samples are identical.

industries for which I have data on R&D investments from ANBERD. I compute the external dependence measure for US firms as the industry median for the period 1990-1999 (see Appendix A). Two important assumptions underlie this approach: (i) this measure of external dependence reflects technological characteristics of an industry which are stable over time and (ii) constructing the industry measure for US data is motivated by the fact that the use of finance by US Compustat firms is less likely to be skewed by constraints on the supply side and should reflect more their demand for external finance as compared to companies in countries with less advanced financial systems. The index presented in Appendix B is comparable to the ones in Rajan and Zingales (1998) or Raddatz (2006). It labels, for example, industries like Pharmaceuticals (ISIC level 21), Electronics (ISIC level 264) or Medical supplies (ISIC level 325) as being highly dependent on external finance, while Leather (ISIC level 15), Wearing apparel (ISIC level 14) and Textiles (ISIC level 13) among the least dependent.

While Rajan and Zingales's (1998) approach offers a valid and exogenous way to identify the extent of an industry's external dependence, this measure, by construction, does not differentiate whether the external finance is obtained from the banking sector or financial markets. This distinction is important when looking at investments in R&D in particular, since previous research has underlined the importance of equity in financing innovation, in particular in countries with highly developed financial markets (Brown, Fazzari and Petersen, 2009; Brown, Martinsson and Petersen, 2012). As a result, I used a second measure of external dependence based on Carlin and Mayer (2003). They propose a measure of bank dependence ($BankDep$), computed as the ratio of bank loans to investment for a large sample of Japanese firms over the period 1981-1990. Since it considers directly firms' reliance on bank finance, this second measure represents a better proxy of an industry's dependence on the banking sector. A measure of external capital dependence that explicitly looks at bank loans might be able to capture more accurately a potential effect of banking crises on R&D spending.

Since Carlin and Mayer's (2003) measure is constructed for only a limited number of two- and three-industry codes, I recompute their measure using a sample of both listed and non-listed firms from two of the most bank-based economies in my sample, i.e. Japan and Germany. I collected balance sheet data from the Orbis Database for a sample of 50,000 firms for the period 2004-2007 and derived industry averages using the same approach as for the ExtDep measure.[15] This alternative measure of dependence is also presented in Appendix B. The correlation between the two proxies is 22.7%.

[15]The time span is dictated by the availability of data in Orbis. Investment in year t is computed as the difference between Total Assets$_t$ and Total Assets$_{t-1}$ less the Depreciation in year t.

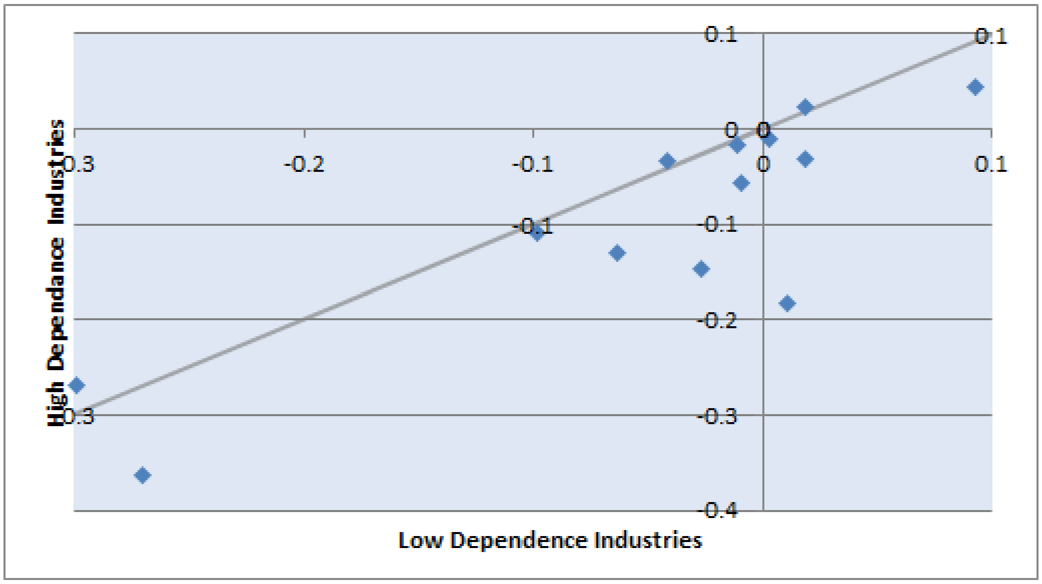

Figure 3: Change in average growth rates around a banking crisis

4.2.2 Descriptive statistics

As a first glance at the data, I perform a simple split-sample analysis by looking at the investments in research and development around a banking crisis. In particular, I compute the average R&D growth in the periods $[t-3, t-1]$ and $[t+1,\ t{+}3]$ around a crisis occurring in year t for each of the 13 crises episodes covered in my sample. I then split the sample in industries that have a financial dependence index below/above the median. The statistics are presented in Table 1. In most countries, growth in R&D investment drops in the years following a banking crisis and, more importantly, this drop appears greater in sectors that rely more on external funds. Overall, looking at the Rajan and Zingales (1998) proxy for external dependence (upper panel), the difference in median growth in R&D around a crisis year is -3.4% in low dependent industries versus -6.9% in highly dependent ones. The growth differential is even stronger when looking at the bank dependence proxy in the lower panel of Table 1. Here, the drop in growth in R&D is -2.4% in industries low dependent on bank finance and -7.4% for those that rely extensively on the banking sector.

Another way of looking at the data is to graph the changes in R&D growth around a crisis episode. Figure 3 plots for each country the difference between the average growth around a crisis episode in the low versus high dependence industries. The change in growth in low dependent industries is plotted on the horizontal line and high dependent on the vertical, such that each dot represents one country. For example, in the case of Spain, high dependent industries saw a drop in average growth of -13% in the three years after as compared to before the crisis. Conversely, the drop in low dependent industries was only -6%. In Figure 3 data points cluster in the lower quadrants below the 45 degree line. This shows that the growth differential tends to be negative in both types of industries, i.e. all industries tend to have a lower growth after the banking crisis. However, the higher absolute values are in the industries highly dependent on external finance. In other words, the average drop in growth around a crisis episode tends to be higher in industries that rely more on external finance.

The patterns in the descriptive statistics above suggest that industries highly dependent on external finance tend to reduce investments in R&D more in the three years following a financial crisis and thus support the hypothesis put forward in the theoretical model. In the next section, I analyze these results in a more rigorous way.

4.3 Empirical results

Estimates from the benchmark models in Eq. (11) and (12) are presented in Table 2. These estimations look at the difference in real growth in R&D investments around a crisis event. They thus require taking a stance on the horizon over which the effects of the crisis are expected to materialize. I consider several time frames. In columns (1)-(4), the baseline results consider the average growth in R&D between $[t+1, t+3]$ and $[t-1, t-3]$ for a crisis in year t.

Overall, the results support the hypothesis that banking crises have an exogenous impact on investments in research and development. The proxy of financial dependence is always negative and statistically significant, indicating that the reduction in R&D investments is relatively higher in industries that are more dependent on external finance. Thus, the effect of the banking crisis manifests itself, at least partly, through the lending channel. Furthermore, this effect is economically significant: on average, in a country experiencing a banking crisis, a sector in the 75th percentile of external dependence measured by the $ExtDep$ index experiences a 13% greater contraction in real growth in R&D spending than a sector in the 25th percentile of external dependence. Similarly, a sector in the 75th percentile of external dependence measured by the $BankDep$ index experiences a 15% greater contraction in real growth in R&D spending than a sector in the 25th percentile of bank dependence.[16]

Turning to the interaction between the two proxies of external dependence and a country's relative dependence on the banking sector, the results obtained are consistent with the baseline estimation. The coefficient of the interaction term is negative and statistically significant across most specifications.

[16]This economic effect was computed by setting the industry's share in total R&D spending at its sample mean.

Table 2: Effects of banking crisis: event study

The dependent variable in columns (1)-(4) is the difference between the average real growth in R&D in the three years following a banking crisis as compared to the three years preceding one. The dependent variable in columns (5)-(8) is difference between the average real growth in R&D in the crisis period, $[t,\ t+2]$ and the pre-crisis period, $[t_1,\ t-3]$, where t is the crisis year in Laeven and Valencia (2012) and t_1 is $t-8$ in most cases, or the first year for which R&D data is available. ExtDep is the external dependence measure following Rajan and Zingales (1998) based on a two- or three- digit ISIC. BankDep is a measure of dependence on bank finance following Carlin and Mayer (2003). ExtDep*BB and BankDep*BB are interaction terms between the two proxies of financial dependence and a country's reliance on the banking sector measured as Private Credit to Market Capitalization in the year $t-8$ or the first year for which I have data. Share$_{t-3}$ is the share of the sector's R&D investment in total R&D investment lagged by three periods. Growth observations are winsorized at +100% and -100%. Robust standard errors are reported in parentheses. *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

	$\Delta R\&D = (R\&D_{[t+1,t+3]}$ - $R\&D_{[t-1,t-3]})$				$\Delta R\&D = (R\&D_{[t,t+2]}$ - $R\&D_{[t1,t-3]})$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ExtDep	-0.355***				-0.491***			
	(0.0690)				(0.0551)			
BankDep		-0.0581**				-0.101***		
		(0.0240)				(0.0158)		
ExtDep*BB			-0.0167***				-0.0187***	
			(0.00570)				(0.00508)	
BankDep*BB				-0.00839***				-0.000992
				(0.00270)				(0.00343)
Share$_{t-3}$	0.567	0.253	0.410	0.198	-1.153***	-0.661**	-1.314***	-0.686**
	(0.521)	(0.406)	(0.540)	(0.399)	(0.357)	(0.296)	(0.346)	(0.291)
Constant	-0.0160	-0.366***	-0.00485	-0.266***	0.0233	-0.425***	0.0288	-0.148***
	(0.0553)	(0.0501)	(0.0513)	(0.0609)	(0.0416)	(0.0411)	(0.0390)	(0.0417)
Observations	342	329	316	303	342	329	325	312
R-squared	0.318	0.304	0.291	0.279	0.288	0.272	0.250	0.221
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

This confirms the hypothesis that banking crises impact disproportionately more R&D investments in industries more dependent on external finance in countries with more developed banking sectors as compared to the financial markets.[17]

I check the robustness of these results along several lines. First, I use different time horizons over which the effects of the crisis episodes are expected to materialize. In columns (5)-(8) of Table 2 the baseline results are confirmed using the interval $[t, t+2]$ for the crisis period, that is including the crisis year. Moreover, the pre-crisis period considers a longer time frame i.e. $[t_1, t-3]$, where t_1 is $t-8$ in most cases, or the first year for which R&D data is available (see also, Kroszner et al., 2007). In unreported results, I also check whether the main results hold when considering the difference in average R&D growth over the periods $[t+1, t+4]$ and $[t-1, t-4]$, as well $[t+1, t+3]$ and $[t-8, t-3]$. The results are qualitatively similar and support the main hypothesis of a differential effect of external finance dependence on R&D growth.

Second, following a specification in Kroszner et al. (2007), I investigate the link between external dependence and real R&D growth during crisis and non-crisis periods separately. The descriptive statistics in Table 1 suggest that pre-crisis growth in R&D is higher in more externally dependent industries. This is also in line with the argument that R&D intensive sectors usually need more external capital to finance their investments, and consequently would benefit more from higher access to finance (Rajan and Zingales, 1998). Previous empirical evidence looking at the growth in R&D investments, however, generally finds little support for this claim. For example, Kroszner et al. (2007) find that more R&D intensive industries do not necessarily grow less (more) during (non) crisis periods. Similarly, Calderon and Liu (2003) find no correlation between the degree of bank dependence of industries and investments in research and development.

To test the hypothesis that dependence on external finance has a differential impact on the real growth in R&D during non- and crisis periods, I estimate the following model:

$$R\&D_{ic} = \alpha_i + \mu_c + \beta_1 ExtDep_i * BB_c + \beta_2 IndustryShare_{ic} + \epsilon_{ic}, \tag{13}$$

where $R\&D_{ci}$ represents the average investments in R&D during crisis and non-crisis period. Results are presented in columns (1)-(4) of Table 3. Overall, results point to a disproportionate effect of financial dependence on R&D growth. During non-crisis periods, the coefficients of the interaction term between external dependence and financial development are positive and statistically significant in the case of *BankDep*. This suggests that, during normal times, industries more dependent on the banking sector in more bank-based economies, tend to invest more in research and development.

[17] Estimating Eq. (12) with Private Credit to GDP as opposed to Private Credit to Stock Market Capitalization to capture the level of financial development does not yield statistically significant results. This is to be expected since the levels of Private Credit to GDP do not differ significantly in the sample of 13 developed economies. It also confirms the hypothesis that the effect of the credit crunch that follows banking crises tends to be stronger in countries that rely more on bank finance.

Table 3: Financial dependence and R&D growth: before and during banking crises periods

The dependent variable in columns (1)-(4) is the average real growth of R&D during pre- and crisis periods. Crisis period represents the period $[t, t+3]$ for a banking crisis starting in year t. Non-crisis period represents all observations outsie the crisis period. The dependent variable in columns (5)-(10) is the year-on-year growth in R&D spending. Columns (5)-(8) refer to countries experiencing a crisis, while columns (9)-(10) contain the full sample. ExtDep is the external dependence measure following Rajan and Zingales (1998) based on a two- or three- digit ISIC. BankDep is a measure of dependence on bank finance following Carlin and Mayer (2003). ExtDep*BB and BankDep*BB are interaction terms between the two proxies of financial dependence and a country's reliance on the banking sector measured as Private Credit to Market Capitalization in the year $t-8$ or the first year for which I have data on R&D. ExtDep*Recession is an interaction term between the measure of external depedence and a recession dummy built in line with Braun and Larrain (2005). Share$_{t-3}$ is the share of the sector's R&D investment in total R&D investment lagged by three periods. Growth observations are winsorized at +100% and -100%. Robust standard errors are reported in parentheses. *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

	Period averages				Panel Estimation				Full sample	
	Pre-crisis period		Crisis period		Pre-crisis period		Crisis period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ExtDep*BB	0.00474		-0.00690*		0.00590*		-0.00747**			
	(0.00421)		(0.00417)		(0.00350)		(0.00374)			
BankDep*BB		0.00680***		0.00318		0.00363*		0.00300		
		(0.00222)		(0.00198)		(0.00191)		(0.00206)		
ExtDep*Crisis									-0.0205**	-0.0198*
									(0.0103)	(0.0119)
ExtDep*Recession										-0.0121
										(0.00930)
Share$_{t-3}$	0.334*	0.221	-0.329	-0.258	-0.483***	-0.439***	-0.784***	-0.558***	-0.404***	-0.522***
	(0.176)	(0.135)	(0.244)	(0.183)	(0.153)	(0.124)	(0.254)	(0.182)	(0.0813)	(0.123)
Constant	0.0447**	0.115***	0.0385	-0.0568**	0.0190	0.0891**	0.0898**	-0.0176	0.113***	0.0566**
	(0.0180)	(0.0367)	(0.0251)	(0.0277)	(0.0315)	(0.0427)	(0.0450)	(0.0591)	(0.0248)	(0.0264)
Observations	332	319	352	338	3,516	3,370	1,413	1,356	8,296	8,047
R-squared	0.160	0.181	0.213	0.216	0.039	0.038	0.084	0.089	0.031	0.037
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES

The coefficient of the interaction $ExtDep * BB$ using the measure proposed by Rajan and Zingales (1998) is also positive but less precise. The opposite occurs during periods of bank distress when the coefficients of the interaction term become negative or lose statistical significance. Estimations in columns (1)-(4) use period averages. I re-estimate the model in Eq. (15) in a more econometrically demanding setting by looking at the year on year real growth of R&D spending in panel framework. Results presented in columns (5)-(8) of Table 3 confirm the previous finding: externally dependent industries tend to invest more in R&D during non-crisis periods, in particular in more bank-based economies, while the opposite is true during periods of bank distress.

Finally, I compare these results to a related literature that focuses on the impact of economic distress on financially dependent sectors. Braun and Larrain (2005), for example, show that industries more dependent on external finance tend to grow less during economic recessions. They investigate the growth in industrial value over economic business cycles as opposed to banking crises. I recheck the robustness of my baseline results by looking at whether the differential impact of banking crises on R&D spending still holds when controlling for the effect of economic recessions. In particular, the model specification tested is:

$$R\&D_{ict} = \alpha_i + \mu_c + \lambda_t + \beta_1 ExtDep_i * Crisis_{ct} + \beta_2 ExtDep_i * Recession_{ct} + \beta_3 Share_{ic} + \epsilon_{ict}, \quad (14)$$

where $R\&D_{cit}$ is the annual real growth in research and development spending in sector i of country c in year t, α_i is a industry fixed effects, μ_c are country fixed effects and λ_t time fixed effects. $Crisis_{ct}$ is a banking crisis dummy that takes the value 1 in the first three years following a banking crisis and 0 otherwise.[18]. $Recession_{ct}$ is a recession dummy which takes the value 1 in the years between the peak and the trough of the cyclical component of real GDP following the methodology proposed by Braun and Larrain (2005).[19] At the same time, at difference with the other model specifications, Eq. 14 is estimated on the full sample of countries in the ANBERD database. This empirical strategy is more effective since it includes also countries that have not experienced banking crises, but may have experienced recessions during the period considered.

Column (9) in Table 3 show that the differential impact of banking crises on R&D investment in more externally dependent industries holds even in a panel setting in the full sample of countries. Moreover, this effect is still present, albeit less precise in Column (10) which includes the interaction term between a measure of external dependence and the recession dummy. Thus, the banking crises effects dominates the recession effect on externally dependent sectors. Specifically, the coefficient of the interaction of $ExtDep$ with the recession indicator is negative but not statistically significant, while the interaction of $ExtDep$ with the crisis dummy is still negative and statistically significant.

[18]Results are robust when considering two years after the crisis and available upon request

[19]More precisely, for each country, troughs are identified as years when the current logarithm of real local currency GDP (from World Bank) deviates by more than one standard deviation from its trend level (computed using the Hodrick-Prescott filter with a smoothing parameter of 100). For each trough, a local peak is defined as the closest preceding year for which cyclical GDP (the difference between actual and trend values) is higher than during the previous and posterior years (see also Braun and Larrain, 2005).

4.3.1 Effect of banking crises on the composition of investment

Having established the importance of financial constraints for the growth in R&D spending, I now investigate whether this drop in research and development investments is also associated with a shift in the corporate investment. More specifically, I test the hypothesis that the share of R&D investment in total investment also drops disproportionately more in externally dependent industries. The theoretical model in the previous section shows that this lower share of investments in innovation as compared to the total investment can explain the weak recovery following episodes of bank distress. To test this prediction, an modified version of Eq. (12) that takes into account the composition of investment is used:

$$\Delta \frac{R\&D_{ic}}{TI_{ic}} = \alpha_i + \mu_c + \beta_1 ExtDep_i * BB_c + \beta_2 Share_{ic} + \epsilon_{ic}, \tag{15}$$

where TI_{ic} is the total investment in sector i in country c. Total investment is computed as the sum of $R\&D$ spending and Gross investment in fixed goods, since the gross investment data from the OECD does not include R&D spending. Similar to previous estimations, I look at the average share in R&D in the three years before and after the crisis.[20] Results are presented in columns (1)-(4) of Table 4 and confirm the shift in the composition of corporate investment around a crisis event. Regardless of the measure of financial dependence used the average share of R&D investment in total investment is lower after the banking crisis in industries more reliant of external finance. Moreover, the results are also confirmed when looking at the interaction between external dependence and a measure of country-level dependence on the banking sector, albeit less precise in the case of *BankDep*. Thus, not only the size of R&D investments, but also their share in total investment drops as a result of tighter credit conditions following episodes of bank distress. Coupled these two empirical results suggest a potential new channel through which banking crises can have long-lasting consequences on the real economy.

Moreover, columns (5)-(8) in Table 4 provide further evidence of the robustness of this shift in the composition of corporate investment. Here, I re-estimate the models in Eq. 11 and 12 to show that gross investment also drops disproportionately more in industries more dependent on external finance following banking crises. The coefficients of the two measures of dependence on external finance, as well as the of the interaction terms are negative and highly significant. Read together the evidence in columns (1)-(4) and (5)-(8) suggests that while both gross fixed investment and R&D seems to grow less in highly dependent industries following crises, the reduction in R&D is higher implying that a lower share of investment is dedicated to R&D. This is provides strong support for the theoretical argument that tighter credit constraint following crises discourages in particular investments in more innovative and riskier technologies.

[20] The results are qualitatively similar when using the averages over $[t, t+2]$ and $[t-8, t-3]$ as in Table 2.

Table 4: Share of R&D investments in Total Investment around a crisis event

The dependent variable in columns (1)-(4) is difference between the average share of R&D in Total Investment in the three years following a banking crisis as compared to the three preceding years. The dependent variable in columns (5)-(8) is difference between the average real growth in Gross Investment in Tangible Goods in the three years following a banking crisis as compared to the three preceding years. ExtDep is the external dependence measure following Rajan and Zingales (1998) based on a two- or three- digit ISIC. BankDep is a measure of dependence on bank finance following Carlin and Mayer (2003). ExtDep*BB and BankDep*BB are interaction terms between the two proxies of financial dependence and a country's reliance on the banking sector measured as Private Credit to Market Capitalization in the year $t-8$ or the first year for which I have data. Share$_{t-3}$ is the share of the sector's R&D investment in total R&D investment lagged by three periods in columns (1)-(4) and the share of an industry's total investment in column (5)-(8), respectively. Robust standard errors are reported in parentheses. *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

	$\Delta(R\&D/TI)$= $(R\&D/TI)_{[t+1,t+3]}$ - $(R\&D/TI)_{[t-1,t-3]})$				$\Delta GITG$= $(GITG_{[t+1,t+3]}$ - $GITG_{[t-1,t-3]})$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ExtDep	-0.424***				-0.395***			
	(0.0173)				(0.0674)			
BankDep		-0.135***				-0.124***		
		(0.00783)				(0.0268)		
ExtDep*BB			-0.00992**				-0.0317***	
			(0.00470)				(0.00550)	
BankDep*BB				0.0113				-0.00537*
				(0.00736)				(0.00310)
Share$_{t-3}$	-0.371*	-0.292*	-0.433**	-0.268	0.567	0.156	0.336	0.153
	(0.214)	(0.168)	(0.205)	(0.167)	(0.575)	(0.456)	(0.559)	(0.453)
Constant	0.0114	-0.385***	0.0194	0.0195	-0.127**	-0.517***	-0.0906**	-0.210***
	(0.0200)	(0.0172)	(0.0188)	(0.0308)	(0.0496)	(0.0657)	(0.0441)	(0.0616)
Observations	245	234	232	197	255	244	245	234
R-squared	0.467	0.465	0.417	0.427	0.453	0.448	0.457	0.437
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

5 Conclusions

The 2007-08 global financial crisis has given renewed impetus to the study of the causes and consequences of financial crises. A large empirical literature looks at how the funding constraints faced by banks at the onset of the crisis have led to a credit freeze to the real sector, and how, in turn, this affected corporate investment and performance (Ivashina and Scharfstein, 2010; Duchin et al., 2010; Campello et al., 2010). Yet, this literature is generally concerned with the short-run effects of such credit crunches. In this paper, I try to build a bridge between static models of financial crises and studies of long-term growth. I do so by integrating a bank run model into a long-run growth model, which allows me to study the growth implications of credit market freezes. My modeling approach is motivated by two key facts. First, I build on recent theoretical contributions that stress the importance of credit constraints not only on the volume of real sector investments but also on their composition (Matsuyama, 2007; Aghion et al., 2010; Favara, 2012). Second, I model a "modern" banking system in which coordination failures of bank creditors to rollover their short-term debts can deprive a financial institution of its funding.

In the theoretical model, bank crises, when they occur, cause entrepreneurs to shift their investments from long-term, risky technologies, to short-term, safe projects. I show that, by impacting the investment in productivity enhancing projects, financial crises can have a long-lasting effect on economic activity as documented by recent empirical evidence.

I test these theoretical predictions on a sample of 13 recent banking crises. Using data on Research and Development spending as a proxy for long-term investments, I show that industries more dependent on external finance, invest disproportionally less in R&D following a banking crisis. Since decreases in R&D slow down productivity, the consequences of this drop in investments on economic growth may last longer than the actual financial crisis, which can explain the slow recovery following such crises.

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Appendix

A Proof of Proposition 1

The proof of Proposition 1 follows closely Morris and Shin (1998). They prove the uniqueness of equilibrium in a model of self-fulfilling currency attacks with imperfect information about macroeconomic fundamentals. The main argument of their proof is to show that a unique equilibrium switching point and a threshold state exist, such that agents attack the currency if their signal is smaller than a threshold signal and that successful speculative attacks occur if the state variable is below the threshold state.

I present a sketch of the proof here. First, denote by $\pi(x)$ the proportion of investors who demand early withdrawal in $t = 1$ upon observing a signal x, for any given strategy profile. The realized proportion of investors who end up foreclosing depends on the state C_1 drawn by nature and is denoted by $\ell(\pi, C_1)$. Given the fact that C_1 and ϵ are uniformly distributed over [0, C_{max}] and [-ϵ, ϵ], respectively, signals x_i are also uniformly distributed over $[C_1 - \epsilon, C_1 + \epsilon]$. We have that[21]:

$$\ell(\pi, C_1) = \frac{1}{2\epsilon} \int_{C_1-\epsilon}^{C_1+\epsilon} \pi(x)dx \tag{16}$$

Denote by $\ell^*(C_1)$ the threshold number of investors who need to run on the bank to trigger the liquidity freeze. From Equation (9) it follows that:

$$\ell^*(C_1) = \frac{M + Y_1 - C_1}{D} \tag{17}$$

Thus a liquidity freeze will occur if more that $\ell^*(C_1)$ investors withdraw. Consequently, if less than $\ell^*(C_1)$ investors foreclose, long-term projects survive and investors obtain the nominal value of their deposits, D. Denote this event by $A(\pi)$:

$$A(\pi) = \{C_1 | \ell(\pi, C_1) \leq \ell^*(C_1)\} \tag{18}$$

Thus the payoff of investors, given the strategy π they follow, is D if $C_1 \in A(\pi)$ and zero otherwise. The actual payoff of investors depends on the realization of C_1. So the *expected* utility from leaving the money in the bank conditional on the signal x and the true C_1 is:

$$u(x, \pi) = \frac{1}{2\epsilon} \int_{A(\pi) \cap [x-\epsilon, x+\epsilon]} DdC_1, \tag{19}$$

where I have used the fact that posterior distribution of C_1 is uniform over $[x - \epsilon, x + \epsilon]$.[22]

[21] Following Morris and Shin (1998), I assume that $2\epsilon < \min[Y_1 + M - D, C_{max} - Y_1 - M]$. This condition assure us that the critical levels $Y_1 + M - D$ and $Y_1 + M$ are at least 2ϵ away from the margins of the interval [0, C_{max}]. This sufficient condition assures that when $C_1 = 0$, the agent with the highest expectation about C_1 which is 2ϵ will have no incentive to run since he believe that C_1 is in the "safe" region where long-term investments always survive.

[22] The actual posterior distribution of C_1 is [max(0, x-ϵ), min(1, x+ϵ)]. To avoid carrying around the min, max

Given this information structure and payoffs, the first step in Morris and Shin's (1998) proof rests in showing that investors decisions are strategic complements, i.e. the more investors leave their funds in the bank, the higher the incentives of others to do so. This implies that given two strategy profiles π and π', if $\pi(x) \geq \pi'(x)$ for every x, than the payoff of leaving the money in the bank is higher when more investors leave their money in the bank, i.e., $u(x,\pi) \geq u(x,\pi')$ for all x. To show this, note that if $\pi(x) \geq \pi'(x)$ then $\ell(\pi, C_1) \geq \ell(\pi', C_1)$ from the definition of ℓ in (16). Furthermore, from (18), $A(\pi) \supseteq A(\pi')$, which implies that:

$$u(x,\pi) = \frac{1}{2\epsilon}\int_{A(\pi)\cap[x-\epsilon,x+\epsilon]} DdC_1 \geq \frac{1}{2\epsilon}\int_{A(\pi')\cap[x-\epsilon,x+\epsilon]} DdC_1 = u(x,\pi'). \tag{20}$$

Next, assume that investors follow a simple rule where they withdraw if $u(x,\pi) < 1$ and leave their money in the bank if $u(x,\pi) \geq 1$. Thus the proportion of investors who run on the bank, π, is given by an indicator function I_{x^*} of the form:

$$I_{x^*} = \begin{cases} 1 & \text{if } x \geq x^* \\ 0 & \text{if } x < x^* \end{cases}$$

The second step of proof of equilibrium is to show that there exists a unique x^* for which:

$$u(x^*, I_{x^*}) = 0, \tag{21}$$

where $u(x^*, I_{x^*})$ is the expected payoff from rolling over a loan, when all the others follow a switching strategy around x^*. To show this, Morris and Shin (1998) first prove that $u(x^*, I_{x^*})$ is continuous and strictly decreasing in x^* (Lemma 2, in their paper)[23] Given this these properties, the goal is to show that when an equilibrium in switching strategies exists, i.e. an x^* for which $u(x^*, I_{x^*}) = 0$, it is also unique.

To see this, consider first a very low signal, say $\underline{x}_1$, for which leaving the money in the bank is an optimal strategy no matter what the others do. The marginal investor with signal, $\underline{x}_1$, knows that the liquidity costs must be below the lower limit $Y_1 + M - D$ where investment projects always succeed. In this region, the payoff from leaving the money in the bank is always greater than 1, the outside option of investors, i.e., $u(\underline{x}_1, I_{\underline{x}_1}) > 1$. Similarly, for a sufficiently large signal, $\overline{x}_1$, the marginal speculator knows that investment projects always fail, such that $u(\overline{x}_1, I_{\overline{x}_1}) < 1$. Given the monotonicity of $u(x, I_x)$, there exists a unique value of x for which, $u(x, I_x) = 1$, and this is defined by x^*.

Given the existence of this unique threshold, the equilibrium values of x^* and C^* are given by

operators we restrict our analysis to the states that are at least ϵ distance away from the bounds of prior belief. In other words, $x \in [\epsilon, 1-\epsilon]$.

[23]This proof is similar to Morris and Shin (1998) and I do not repeat it here (see the Appendix of their paper).

the two equations:

$$\ell(I_{x^*}, C^*) = \ell^*(C^*)$$
$$u(x^*, I_{x^*}) = 0,$$

where the proportion of investors who run is given by those investors receiving a signal above the threshold x^*:

$$\ell(I_{x^*}, C^*)) = Prob(x_i > x^*|C^*) = Prob(C_1 + \epsilon_i > x^*|C^*) = 1 - \frac{1}{2\epsilon}(x^* - C^* + \epsilon), \qquad (22)$$

since x_i is uniformly distributed over $[C_1 - \epsilon, C_1 + \epsilon]$. Given (17), the first equation that defines the threshold signal x^* as a function of C^* is:

$$x^* = C^* - \epsilon - \frac{2\epsilon}{D}(M + Y_1 - C^*) \qquad (23)$$

The second equation is the indifference condition of an investor who receives the threshold signal, x^*. The expected utility of this marginal investors is given by[24]:

$$\frac{1}{2\epsilon}\int_{x^*-\epsilon}^{C^*} D dC_1 - 1 = 0,$$

where the investors' outside option is to 1. This indifference equation is equivalent to:

$$C^* = x^* + \frac{2\epsilon}{D} - \epsilon$$

Plunging this into equation (23) gives us the equation in Proposition 1:

$$C^* = M + Y_1 - 1.$$

QED

[24]Since, conditional on $x_i = x^*$, $C_1 \sim$ unif$[x^* - \epsilon, x^* + \epsilon]$, the upper bound the integral should be $min(C^*, x^* + \epsilon)$. However, Morris and Shin (1998) as long as $D > 1$, $min(C^*, x^* + \epsilon) = C^*$. Suppose the opposite. If, $x^* + \epsilon < C^*$, then $Prob[C_1 < C^*|x^*]$=1, i.e. the indifferent depositor always knows that a everyone renews their investment for any realization of C_1. Then x^* cannot be the signal of the indifferent depositor. This contradicts out initial assumption.

B Measures of dependence on external finance

ISIC Rev 4	Description	ED (RZ)	BD (CM)
D10T12	Food products, beverages and tobacco	0.05	-
D13	Textiles	0.06	-2.83
D14	Wearing apparel	-0.28	-0.83
D15	Leather and related products, footwear	-0.48	-5.11
D16	Wood and products of wood and cork, except furniture	0.06	-1.80
D17	Paper and paper products	0.05	-2.78
D18	Printing and reproduction of recorded media	0.39	-3.96
D19	Coke and refined petroleum products	0.02	0.25
D20	Chemicals and chemical products	0.16	0.79
D21	Pharmaceuticals, medicinal chemical and botanical products	3.06	0.06
D22	Rubber and plastic products	0.30	0.01
D23	Other non-metallic mineral products	0.17	-2.27
D24	Basic metals	0.22	1.76
D25	Fabricated metal products, except machinery and equipment	0.24	0.22
D26	Computer, electronic and optical products	0.37	0.32
D262	Computers and peripheral equipment	0.45	0.03
D263	Communication equipment	0.51	-0.54
D264	Consumer electronics	1.03	0.32
D266	Irradiation, electromedical equipment	0.93	-0.05
D268	Magnetic and optical media	0.30	-
D27	Electrical equipment	0.22	0.70
D28	Machinery and equipment n.e.c.	0.04	1.13
D29	Motor vehicles, trailers and semi-trailers	0.29	1.22
D30	Other transport equipment	0.25	1.27
D301	Building of ships and boats	0.25	1.28
D303	Air and spacecraft and related machinery	0.13	2.34
D31T33	Furniture, other manufacturing machinery	0.74	-2.59
D32	Other manufacturing	0.90	-1.75
D325	Medical and dental instruments and supplies	0.94	0.35

ED index in the second column presents the Rajan and Zingales (1998) measure of dependence of external finance computed for a sample of US Compustat for the period 1990-1999. The BD index in the last column is the measure of bank dependence proposed by Calderon and Liu (2003).