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Authors(s)	Peia, Oana
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Banking Crises and Investments in Innovation

Oana Peia, University College Dublin

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Banking crises and investments in innovation*

Oana Peia†

University College Dublin

Abstract

This paper proposes a new channel to explain the medium- to long-term effects of banking crises on the real economy. It embeds a banking sector prone to runs in a stylized growth model to show that episodes of bank distress affect not only the volume, but also the composition of firm investment, by disproportionally decreasing investments in innovation. This hypothesis is confirmed empirically employing industry-level data on R&D spending around 13 recent banking crises episodes. Using difference-in-difference identification strategies, I show that industries that depend more on external finance, in more bank-based economies, invest disproportionally less in R&D following systemic banking crises. These industries also have a lower share of R&D spending in total investment, suggesting a shift in the composition of investment that is specific to recessions following banking crises and not other business cycle recessions.

JEL Classification: G01, G21, E22

Keywords: banking crises, R&D investment, financial dependence, global games

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†Email: oana.peia@ucd.ie. Address: School of Economics, University College Dublin, Dublin, Ireland.

1 Introduction

Banking crises are generally associated with large and persistent economic disruptions (Cerra and Saxena, 2008; Ball, 2014; Boissay et al., 2016). Looking at 100 systemic banking crises, Reinhart and Rogoff (2014) find that it takes, on average, eight years to recover and reach pre-crisis levels of GDP per capita. Yet, despite this medium to long-term effect of financial sector distress on the real economy, economics literature largely treats separately the role of financial intermediaries in long-run growth versus short-run volatility.[1]

This paper proposes a new channel that can explain this longer-term effect of banking crises on real economic growth. In a simple theoretical framework, I show that episodes of financial distress can have long-lasting effects on the real economy by disproportionately reducing investments in high productivity projects. This channel is then supported empirically, by providing causal evidence of the impact of banking crises on Research and Development (R&D) spending as a proxy for investments in innovation.

The theoretical framework is a growth model with a banking sector prone to bank runs. In the model, firms can invest in two different projects: a low return, short-term technology and a high return, long-term technology. As in Aghion et al. (2010), long-term technologies can be seen as investments in innovation, which are more productive but risky, as random liquidity shocks that hit the firm can disrupt their completion. Firms borrow from the banking sector to cover these liquidity costs. Banking crises are the result of coordination failures among depositors who run on the banking sector when they observe pessimistic signals about the liquidity needs of the real sector. Thus, liquidity tensions on both sides of banks' balance sheet trigger the crisis in the model.[2] I employ a global games framework to characterize the unique equilibrium of depositors' coordination problem, which pins down the equilibrium probability of bank runs and optimal credit supply (Morris and Shin, 1998). I show that an increase in credit supply results in a higher share of investment in the long-term technology, as more access to credit increases the probability that this investment survives the liquidity shock. This role of credit constraints on the composition of investments has also been suggested in Matsuyama (2007) and Aghion et al. (2010) as a consequence of classical balance sheet effects during economic downturns. However, balance sheet effects alone cannot explain the

[1] A large finance and growth literature acknowledges the positive role of financial development on long-run growth rates, but generally overlooks crises (see Beck et al., 2000; Levine, 2005). Business cycle literature emphasizes the role of credit market imperfections in propagating productivity shocks, but takes the productivity process as exogenous and does not explicitly model the behavior of financial intermediaries (Bernanke et al., 1999; Gertler and Kiyotaki, 2010). Recent macroeconomic models with financial frictions generally employ random financial shocks as the source of disruptions that trigger the crisis (see, among others, Bianchi and Mendoza, 2011; Kiyotaki and Moore, 2012; Jermann and Quadrini, 2012; Brunnermeier and Sannikov, 2014). One exception is Boissay et al. (2016) in which adverse selection in the interbank market, and not binding collateral constraints, causes financial market runs. In their model, crises arise endogenously and are followed by severe "financial" recessions. At difference, the focus in this paper is on the effects of the crisis on the real side of the economy.

[2] Empirical evidence suggests banks experienced a similar liquidity drain on both sides of their balance sheets at the onset of the 2007-08 Global Financial Crisis: as short-term bank creditors ran on the repo market (Gorton and Metrick, 2012), deposits inflow froze (Acharya and Mora, 2015) and firms massively drew down their credit lines (Ivashina and Scharfstein, 2010; Ippolito et al., 2016).

slower recovery following banking crises, so this paper takes a different perspective by focusing on a supply-side channel.

The new insight here is to model the evolution of credit supply around banking crises and study how this impacts real sector investment patterns. The mechanism through which this happens is as follows. As long as banking crises do not occur, higher aggregate wealth results in an increased deposit inflow, which allows the banking sector to become more leveraged. More leveraged banks will lend a higher share of their total assets to the real sector, i.e. increase credit supply. The intuition behind this mechanism is a simple risk and return trade-off, since more lending increases the bank's returns, while the downside risk that real sector investments fail is largely borne by bank creditors. Once a banking crisis occurs, credit to the real sector freezes and long-term investments fail. Lower aggregate income after the crisis means banks are less leveraged and will decrease their loan-to-assets ratios.[3] This tighter credit supply leads to a lower share of investment in the long-term technology, which explains the lower growth rates following the crisis as compared to the pre-crisis period.

The main testable prediction of the model is that banking crises have a disproportionally larger effect on investments in growth-enhancing projects, such as investments in Research and Development. This channel is tested empirically using data on R&D investment in 13 countries that have experienced a systemic banking crisis during 1987-2012, across 29 two- and three-digit ISIC level manufacturing industries. In order to identify a causal effect of banking crises on R&D investment, I employ a difference-in-difference methodology following Rajan and Zingales (1998). The main argument is that tight credit conditions following banking crises have a greater impact on bank-dependent borrowers. To build an exogenous measure of bank dependence, I interact the Rajan and Zingales (1998) industry-level measure of dependence on external finance with a country-level measure of dependence on the banking sector, measured as private credit to stock market capitalization. This identification strategy is motivated by the idea that, during banking crises, borrowers in more bank-based economies cannot circumvent the banking sector and raise outside funds in capital markets. Figure 1 summarizes the main finding by plotting the evolution of R&D investments following a banking crisis in year t. It shows that industries more dependent on external finance (dashed line) invest less in R&D as compared to less dependent industries and this difference appears larger in countries that rely more on the banking sector to obtain funding, i.e. those with an above the median level of bank dependence (right-hand panel).

Empirical estimations in both a cross-sectional, as well as a panel setting, confirm that industries more dependent on external finance, in more bank-based economies, invest disproportionally less in R&D following banking crises. This effect is also economically significant: a sector in the 75th percentile of external dependence, in a country in the 75th percentile of banking sector dependence,

[3] This procyclical evolution of credit supply is another well-documented empirical pattern across the financial cycle (Asea and Blomberg, 1998; Lown and Morgan, 2006; Kahle and Stulz, 2013; Becker and Ivashina, 2014).

Figure 1: R&D investments following banking crises

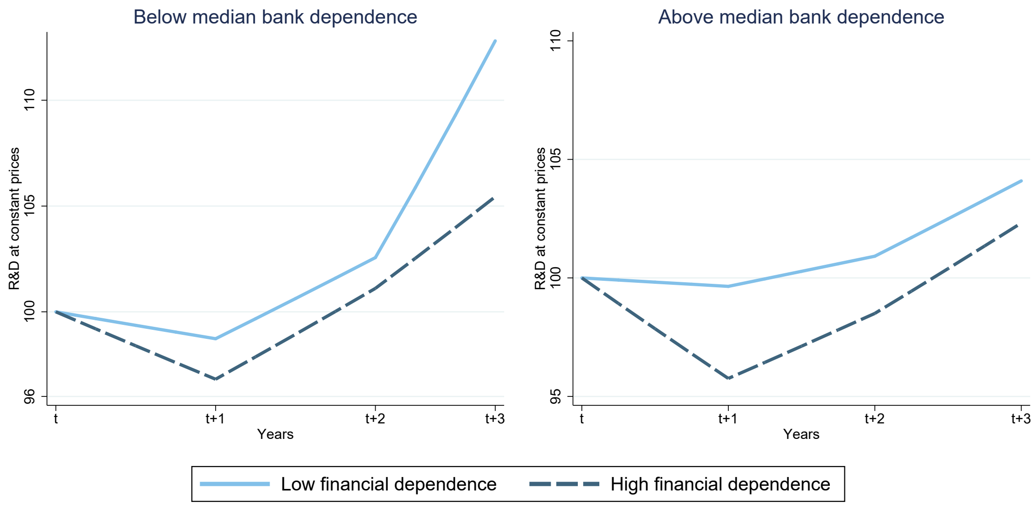


Figure compares the evolution of R&D spending following a banking crisis in year t in industries below (Low financial dependence) and above (High financial dependence) the median external dependence index based on Rajan and Zingales (1998). R&D spending is set to 100 in year t. The average of this index is computed for the sample of countries below the median level of bank dependence in the left-hand panel and above the median in the right-hand panel, respectively. Bank dependence is measured as the ratio of private credit to stock market capitalization.

experiences a 4.2 percentage points lower real R&D growth following a banking crisis as compared to a sector in the 25th percentile of external dependence, in a country in the 25th percentile of bank dependence.

Moreover, this paper also documents a novel effect of banking crises on investment patterns. In particular, I show that not only the volume of R&D investment, but also its *share* in total investment is relatively lower in industries more dependent on external finance, in more bank-based economies. Given the importance of investments in innovation for long-term productivity growth, this shift in the composition of investment can provide a potential explanation for the slower growth following banking crises as compared to other recessions.

These results not only document an important real effect of banking crises, but also draw attention to the importance of bank funding for R&D investment. Finance literature generally argues that other sources of funding matter for these investments (Brown et al., 2009; Brown et al., 2012; Hsu et al., 2014). The results in this paper suggest that contractions in credit supply matter, even if firms are not funding R&D spending through bank debt. The argument is that the disruption in credit supply that follows banking crises will cause firms to divert internal cash flows away from R&D towards more "essential" investments, especially in bank-based economies where they have less access to other types of external finance (see also Nanda and Nicholas, 2014).

The sensitivity of these findings is subjected to a variety of robustness checks. First, the effect of the crisis is robust to different pre- and post-crisis time horizons, as well as different measures of financial dependence at the industry and country level. Importantly, results are not sensitive to the inclusion of a proxy for "regular" economic recessions. This suggests that the effect captured is specific to recessions that follow banking crises and are driven by the contraction in credit supply specific to these episodes. Next, I control for other industry-level characteristics such as asset tangibility or predominance of small firms to confirm that the differential effects captured are the result of differences in financial dependence and not other industry characteristics. Finally, I employ a wide array of fixed effects to mitigate omitted variable bias and perform different falsification strategies. The main results continue to hold under these alternative assumptions and suggest that the disproportionate drop in R&D investment following banking crises is, at least partially, caused by a "credit channel" or supply-side conditions and not simply a consequence of demand-side factors specific to the business cycle.

The remainder of this paper is organized as follows. The next section discusses previous research and the motivation of the paper. Section 3 sketches a theoretical framework and derives the main testable implications. Section 4 presents the empirical strategies and results. Finally, section 5 concludes.

2 Relation to literature

This paper relates to several strands of literature. From a theoretical point of view, it is related to a large literature modelling banking crises (for a review, see Goldstein, 2010). The two main views of financial crises in this literature are that they occur as a result of panic (Diamond and Dybvig, 1983) or a deterioration of bank fundamentals (Allen and Gale, 1998). An equilibrium selection refinement called "global games" brings together these two views by modelling crises pinned down by bad fundamentals, but which are still self-fulfilling (Carlsson and Van Damme, 1993; Morris and Shin 1998, 2004; Goldstein and Pauzner, 2005, Rochet and Vives, 2004). The introduction in this framework of imperfect information eliminates the multiplicity of equilibria that generally characterizes bank run models and allows agents to coordinate around a unique threshold equilibrium.

While this literature is mainly concerned with how crises occur and can be mitigated, this paper embeds a static bank run model in a dynamic framework, to study how the probability of crises affects the decisions of agents in the real economy. The theoretical framework builds on Aghion et al. (2010) to sketch a mechanism that can explain the long-lasting effects of banking crises on the real economy (Laeven and Valencia, 2008; Furceri and Mourougane, 2012; Reinhart and Rogoff, 2014; Ball, 2014; Boissay et al., 2016). One potential link between short-run financial distress and long-run economic dynamics is represented by investments that drive productivity growth, such as investments in innovation or Research and Development. Investment in R&D is not only the main driver of productivity growth in a large endogenous growth literature (Aghion and Howitt, 2009), but its importance is also widely acknowledged empirically (Hall et al., 2010).[4] At the same time, recent empirical findings show that R&D spending tends to be strongly pro-cyclical, despite the classical argument that investment in innovation should be concentrated in periods of recessions, when the opportunity costs in terms of foregone output are lower (Aghion and Howitt, 1998).

The leading theoretical argument for this pro-cyclicality of R&D is the presence of credit constraints (Comin and Gertler, 2006; Aghion et al., 2010). The idea is that pro-cyclical profits make financial constraints more biding in recessions, which affects firms' ability to borrow and discourages investments in innovation.[5] 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 mechanism that can explain both the lower mean growth and the higher volatility of economies with tighter credit conditions. They confirm this empirically by showing that countries with better access to credit, i.e. more financially developed, have a lower sensitivity of growth to productivity shocks. Subsequent evidence is brought by Aghion et al. (2012) who use a sample of French firms and find that the share of R&D investments is more pro-cyclical in firms that face tighter credit constraints.

This paper builds on the idea that financial constraints matter for investments in innovation by focusing on periods in which these constraints are likely to be more biding, i.e. following banking crises. In particular, it investigates the *exogenous* effect of a bank lending channel on investments in innovation. The basic argument is that changes in credit standards or credit supply will have a disproportionate effect on investments in innovation and this effect is independent from the pro-cyclicality of R&D implied by balance-sheet conditions during economic downturns. Disentangling the effects of demand from supply shocks following financial crises is, nonetheless, 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 borrowers that depend more on external finance. Kroszner et al. (2007) and Dell'Ariccia et al. (2008) use this approach to show that more financially dependent industries have a lower growth in value added following episodes of bank distress. This paper employs a similar identification strategy to document a new channel through which banking crises can have long-lasting effects on growth, by relating credit-supply shocks to investments in innovation. It also extends the difference-in-difference methodology proposed in Rajan and Zingales (1998) by focusing on bank-dependent borrowers and not dependence on external

[4] Measuring the returns to investments in innovation in standard growth accounting yields an elasticity of output to R&D between 0.05 to 0.12, which is somewhat higher than for ordinary capital investment (see Hall et al., 2010). Furthermore, the time frame over which we expect the effects of business R&D investment on output growth to materialize is around two years in cross-country regressions (Guellec and van Pottelsberghe de la Potterie, 2001), and between one to four years for firms-level studies (Hall et al., 2010).

[5] Barlevy (2007) provides an alternative explanation 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.

finance in general.

The link between crises, the composition of investment and slow recoveries is also suggested in several recent works. For example, Garicano and Steinwender (2015) employ a sample of Spanish firms to show that after the 2008 Global Financial Crisis, firms shifted investments away from long-term to short-term ones. Schmitz (2017) shows that smaller firms exhibit a greater contraction in R&D following financial shocks and since these firms also have a higher innovative capacity, the effect of financial shocks on productivity growth tends to be persistent over time. Fernández et al. (2013) document that industries more dependent on external finance have a lower share of intangible assets during periods of bank distress.

Finally, this paper is also related to a growing literature that links financial conditions to R&D investments and innovation. Studies employing Euler investment equations generally find mixed evidence on the importance of liquidity constraints for R&D spending (Bond et al., 2005; Brown et al., 2012). Moreover, access to equity finance matters more for this type of investment in countries like the US (Brown et al., 2009). Hsu et al. (2014) look at a cross-section of public firms and find a stronger impact of equity and not credit markets on R&D spending. Similarly, Acharya and Xu (2017) find that public firms in externally dependent industries are more innovative than their private counterparts, suggesting that increased access to finance boosts innovation. However, in bank-based economies, access to credit matters as Benfratello et al. (2008) show that local bank development increases the probability that Italian firms invest in innovation, in particular among smaller firms. Finally, this paper is also related to Nanda and Nicholas (2014) who employ a difference-in-difference methodology to show that private firms operating in US counties with higher bank distress during the 1930's Great Depression were less innovative than public ones.

3 A simple theoretical framework

To understand how banking crises can affect real sector investment decisions, this section presents a stylized bank run model as a three-period game between entrepreneurs, investors and a bank. I then embed this static model in an overlapping generations framework and derive the main implications of the model for real sector investment cycles.

3.1 The static model

The economy consists of three agents: entrepreneurs, investors and a bank. All agents are risk-neutral. The real sector of the economy is represented by a continuum of homogeneous entrepreneurs with unit mass who live three periods [0,1,2].[6] The financial sector is represented by a bank that borrows from a continuum [0,1] of investors and lends to entrepreneurs. Entrepreneurs have no

[6]We assume a zero discount factor between periods.

wealth and borrow from the bank to invest.

A. The real sector

A representative entrepreneur has access to two types of investment projects: a short-term, safe technology, which takes one period to produce output Y_1, and a long-term, risky technology that generates Y_2 after two periods. Denote by I the total amount of funds an entrepreneur can borrow in $t = 0$ and by k the share of these funds invested in the long-term project. Assuming linear technologies, the output generated by the firm in periods 1 and 2 is given by:

$$Y_1 = \sigma_1(1-k)I \quad \text{and} \quad Y_2 = \sigma_2 kI, \tag{1}$$

where σ_1 and σ_2 are the productivity parameters of the short- and long-term technology, with $\sigma_2 \gg \sigma_1$ such that the productivity of the long-term investment is higher. Long-term investments are risky, as in $t = 1$ a random liquidity shock, denoted by C, hits the firm. If the entrepreneur is successful in covering this liquidity shock, then period 2 production yields output Y_2, otherwise the long-term investment becomes obsolete and is scrapped, i.e. $Y_2 = 0$.

The distinction between these two types of investment projects follows Aghion et al. (2010), who interpret long-term investments as spending on Research and Development, an inherently risky investment that, when successful, yields a significantly higher output. Short-term investments, on the other hand, can be seen as investments in working capital or maintenance of existing equipment. Thus, it is long-term investments that will tend to be more conducive to growth. Furthermore, the liquidity shock that disrupts the long-term technology captures a salient feature of investments in innovation, i.e. the high uncertainty associated with their output (Hall and Lerner, 2010). Note also that this shock is *aggregate*, as Holmstrom and Tirole (1998) show that, in the presence of idiosyncratic shocks, banks can offer insurance against the liquidity needs of the private sector by pooling firm risks. In their model, however, banking crises are ruled out, as investors cannot claim assets in the intermediate period. By contrast, the focus here is on cases in which bank runs occur.[7]

Under perfectly competitive input markets, the outputs of the two technologies are divided between the bank and the entrepreneur in fixed proportions, with a share α going to the bank.[8] The entrepreneur's expected profit over the three periods can be written as follows:

$$\Pi_E(k) = (1-\alpha)\left[\sigma_1(1-k)I + e\sigma_2 kI\right], \tag{2}$$

where $(1-\alpha)$ is fraction of output going to the entrepreneur, k is the share of borrowed funds

[7] Moreover, because we are concerned with episodes of bank runs, the possibility of government-injected liquidity in the banking sector, as in Holmstrom and Tirole (1998), is ignored. While government bailouts or central bank liquidity would naturally dampen the effects of the crisis in the model, empirical evidence suggests that only a limited amount of this liquidity is channeled towards the real sector (see Cornett et al., 2011).

[8] This is a standard result that follows from the assumption of no information asymmetries between the bank and the real sector and it implies that capital is remunerated at its marginal productivity. See Aghion and Howitt (2009) for a rationalization of this result under the assumption of a fixed labor supply (see also Aghion et al., 1999).

invested in the risky technology and e is an indicator function taking value 1 if the entrepreneur covers the liquidity shock and 0 otherwise. Entrepreneurs' borrowing capacity depends on the credit supply in the banking sector, which is determined next.

B. The financial sector

The financial sector comprises a bank and its creditors. A mass [0,1] of investors place their funds in the bank in $t = 0$.[9] The bank can invest these funds in risky assets (loans to entrepreneurs) or store them in a liquid asset (cash) and promises to pay investors a return $R > 1$ per unit of investment in period $t = 2$. The balance sheet of the bank at $t = 0$ can be represented as follows:

Figure 2: Balance sheet of the bank

Assets	Liabilities
I	D
M	E

where I is the volume of loans granted to entrepreneurs, M is the size of cash reserves held by the bank, D represents the volume of deposits investors place with the bank and E is the bank's equity. It is convenient to express the liabilities side of the bank as a function of the level of deposits, namely: $D + E = \left(1 + \frac{E}{D}\right) D \equiv \phi D$, where, $\phi \equiv 1 + \frac{E}{D}$, can be interpreted as a measure of leverage. Specifically, a lower ϕ, implies a higher level of deposits as compared to equity and a more leveraged bank. Given the size of its balance sheet, the bank decides how much funds to place in risky assets or store as cash. This is tantamount to deciding a loan-to-assets ratio, denoted by μ, such that a proportion $\mu\phi D$ of its total assets is invested in the real sector. This ratio will also pin-point the optimal credit supply to the real economy.

The return promised to investors in $t = 2$ is risky, as it depends on the outcome of the investment projects in the real sector. Specifically, investors receive R only if long-term investments do not fail.[10] As a result, investors can also decide to withdraw their deposit at $t = 1$ and get back their initial investment. This possibility makes the banking sector prone to runs if enough investors withdraw and drain the banking sector of funding.

[9] The terms investors, bank creditors and depositors are used interchangeably throughout the model. The external funds obtained by the bank can be equally thought of as uninsured deposits or short-term interbank debt obligations. For example, in a set-up close to the one in this paper, Rochet and Vives (2004) model a "modern" form of bank runs, where investors refuse to renew their credit to a bank. They study how regulation can mitigate this coordination problem and eliminate runs on otherwise solvent banks.

[10] This assumption implies limited liability for the bank as failure of long-term investments is equivalent to a bank failure in the model. This implies that the residual, i.e. the short-term production, is split only between the entrepreneur and the bank. Assuming investors receive this residual does not change the results, but makes the model less tractable.

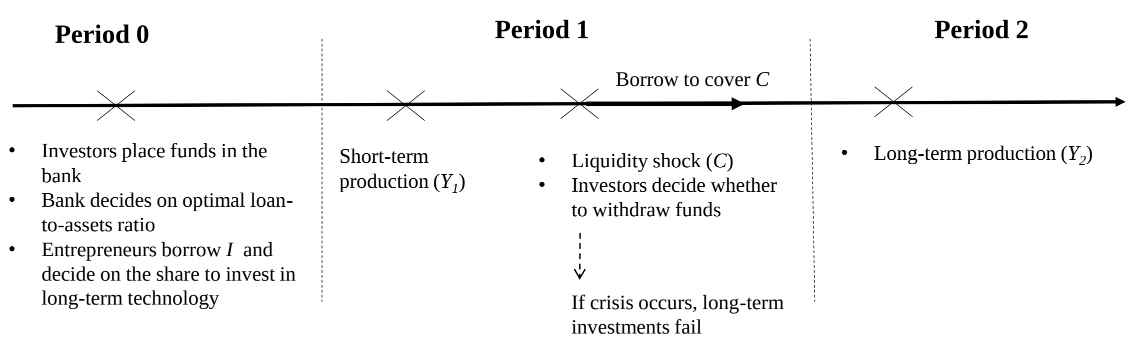
Hence, at $t = 1$, the bank faces two types of liquidity needs. On the one hand, a proportion of investors, denoted by ℓ, withdraws its initial investment, D. On the other hand, entrepreneurs, who face an exogenous liquidity shock, will seek to borrow from the bank. The bank is said to be in a liquidity crunch whenever the demand for funds is greater than the liquid assets available, M (assuming no fire sales) or:

$$\ell D + (C - Y_1) > M, \tag{3}$$

where ℓD is the liquidity demanded by bank creditors and $C - Y_1$ is the liquidity need coming from the real economy, given the shock C and entrepreneurs' retained earnings at $t = 1$, i.e., the production of the short-term technology, Y_1. Eq. (3) implies that a bank failure occurs as a result of a drain of liquidity coming from both sides of the bank's balance sheet.[11]

The timing of the model is presented in Figure 3. In the first period, investors place funds D with the bank, the bank decides the optimal loan-to-asset ratio, μ, entrepreneurs borrow I and decide the share of capital to invest in the long-term technology. In period 1, short-term production, Y_1, is realized and the firm is hit by the liquidity shock. Entrepreneurs use their own funds, Y_1, and, if necessary, borrow from the banking sector to cover this additional cost. In the last period, long-term investments become productive only if the liquidity shock is covered.[12]

Figure 3: Timing



The equilibrium of the model is solved by backward induction. First, I solve for the equilibrium of investors' coordination problem, who need to decide at $t = 1$ whether to withdraw or keep their funds in the bank. This pins down the equilibrium probability of a bank run. Given this probability, entrepreneurs decide the optimal share of borrowed funds to invest in the long-term technology. Finally, I solve for the bank's maximization problem considering the equilibrium outcomes of en-

[11] Ivashina and Scharfstein (2010) document that this type of liquidity crunch unfolded in the US around the 2007-08 financial crisis. They show that together with a freeze in interbank lending, firms also massively demanded liquidity by drawing down their bank credit lines. This suggests a spike in liquidity demand by the real sector, which is captured here by the aggregate liquidity shock.

[12] Following Aghion et al. (2010), I assume that the value of the long-term investment is unaffected by the liquidity shock and, if this shock is covered, the entrepreneur receives an extra benefit C in the last period. This guarantees that long-term investments, when they survive the liquidity shock, are still more productive than short-term ones. While this assumption does not affect the equilibrium composition of investment, the model is more tractable if we ignore the possibility that the net value of long-term investments is diminished by the liquidity cost.

trepreneurs' and investors' optimization problems.

C. Equilibrium

Investors face a coordination problem when they decide to withdraw their funds from the bank in the intermediate period. Note that Eq. (3) implies that the "crisis" threshold of the bank is: $\ell D + C^* = M + Y_1$. For liquidity shocks below C^*, the demand for funds the bank faces in $t = 1$ can be covered by its liquid funds M and long-term investments survive. However, when $C > C^*$, the bank cannot satisfy the demand for liquidity and, as a result, entrepreneurs cannot borrow and long-term investments fail.

Clearly, this run threshold depends on the proportion of investors who decide to withdraw. Their actions exhibit strategic complementarities: the more investors withdraw, the higher the incentives of others to do so, since real sector investments are more likely to fail. As a result, 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) that is known to have multiple equilibria. However, a global games equilibrium refinement eliminates this multiplicity of equilibria by introducing a certain type of imperfect information in the model (Morris and Shin, 1998; Goldstein and Pauzner, 2005). I follow this global games approach and assume that investors have imperfect information about the size of the liquidity shock entrepreneurs need to cover in order for long-term investments to succeed. More specifically, at $t = 1$, investors can only observe the liquidity shock with a small noise:

$$x_i = C + \epsilon_i,$$

where x_i is investor's i signal, C is the liquidity shock drawn from an uniform distribution and ϵ_i is an idiosyncratic noise uniformly distributed and independent of C.

In this global games framework, the model is characterized by a unique threshold equilibrium. Moreover, the occurrence of a bank run is the result of coordination failures among investors, but still linked to the fundamentals in the real economy, represented here by the liquidity shock, C. Proposition 1 states the equilibrium result of investors' coordination problem.

Proposition 1 There exists a unique Bayesian Nash Equilibrium in which all depositors run on the bank when they observe a signal higher than x^* and leave their funds in the bank in $t = 1$ when they observe a signal lower than x^*. The bank will then be in a liquidity crunch, whenever the random shock C is higher than a threshold value, C^*, which is characterized by the following equation:

$$C^* = M + Y_1 - \frac{D}{R}. \tag{4}$$

Proof *See Appendix.*

The probability of bank runs given this unique threshold is simply $Prob[C > C^*]$. Based on the characterization of the equilibrium critical cost in Eq. (4) and the fact that C is uniformly distributed, this probability is decreasing in Y_1, M and R. The intuition is straightforward. The lower the income available to entrepreneurs at $t = 1$, Y_1, the higher the demand for liquidity the bank needs to service in the interim period when the liquidity shock occurs. This will increase the probability that depositors panic and withdraw. Similarly, if the bank holds more liquid assets, M, this decreases the probability of a bank run. Finally, a higher return on deposits, R, facilitates coordination and makes runs less likely.

Given this equilibrium probability of bank runs, the bank chooses the optimal loan-to-assets ratio, μ, in order to maximize its profits as follows:

$$\begin{aligned}&\underset{\mu}{\text{Max}} \quad \lambda[\alpha\sigma_2 k\mu\phi D + \alpha\sigma_1(1-k)\mu\phi D - RD] + (1-\lambda)[\alpha\sigma_1(1-k)\mu\phi D] + (1-\mu)\phi D \\ &\text{given } \; k \text{ and } \lambda,\end{aligned}$$

where $\lambda = Prob[C < C^*]$ is the probability that long-term investments survive, $\alpha\sigma_2 k\mu\phi D$ and $\alpha\sigma_1(1-k)\mu\phi D$ are the bank's return from the long- and short-term investments, respectively and $(1-\mu)\phi D$ is the share of bank assets stored in cash. Thus, with probability λ, the bank receives its share of the two investment projects and repays its creditors, while with probability $1-\lambda$, there is a bank run and the bank receives a residual value, which is the share of the short-term investment.[13] Before solving the bank's optimization problem, two additional results are established in Lemma 1.

Lemma 1 The probability of survival of investments in innovation, λ, and the share of these investments in total investment, k, are monotonically increasing in the loan-to-assets ratio, μ, for $\phi < \overline{\phi}$.

Proof *See Appendix.*

From Eq. (4), it is clear that there are two opposing effects of an increase in μ on the probability of bank runs. First, higher lending to the real sector means the bank has less liquid assets (M), making it less likely to cover depositors who withdraw, which increases the probability of runs. The second effect is that more real sector investment (higher I) also means that entrepreneurs need to borrow less from the bank in the intermediate period, since they can use their (higher) $t = 1$ income (Y_1) to cover the liquidity shock. This second effect dominates the first as long as $\phi < \overline{\phi}$, i.e. when banks are sufficiently leveraged. The second part of Lemma 1 states that the share of investment in innovation increases in μ. This result follows directly from the first one, since higher μ increases the probability of success of long-term investments. This second result is similar to Aghion et al. (2010) where tighter credit constraints also decrease the share of long-term investments. However, the mechanism through which this happens is different. In Aghion et al. (2010), credit constraints introduce a wedge between the short- and long-term investment

[13] An alternative approach would be to assume that, in case of failure, the bank recovers none or all of the short-term production. This does not change the intuition of the model.

because they decrease the probability that entrepreneurs can borrow in the intermediate period, when liquidity costs occur. Yet, in their model, the credit multiplier does not impact the amount of initial borrowing, since, in equilibrium, entrepreneurs do not borrow in period $t = 0$. Here, a higher μ means that more funds are borrowed by firms in the initial period. This higher access to finance implies firms rely less on bank borrowing in the intermediate period, as Y_1 is higher as a result of the increase in lending. This decreases the equilibrium probability of bank runs and favors investment in the long-term technology. Given these trade-offs, solving the bank's maximization problem yields the following result:

Proposition 2 The optimal loan-to-assets ratio, μ, is monotonically increasing in bank leverage, whenever $\phi < \overline{\phi}$.

Proof *See Appendix.*

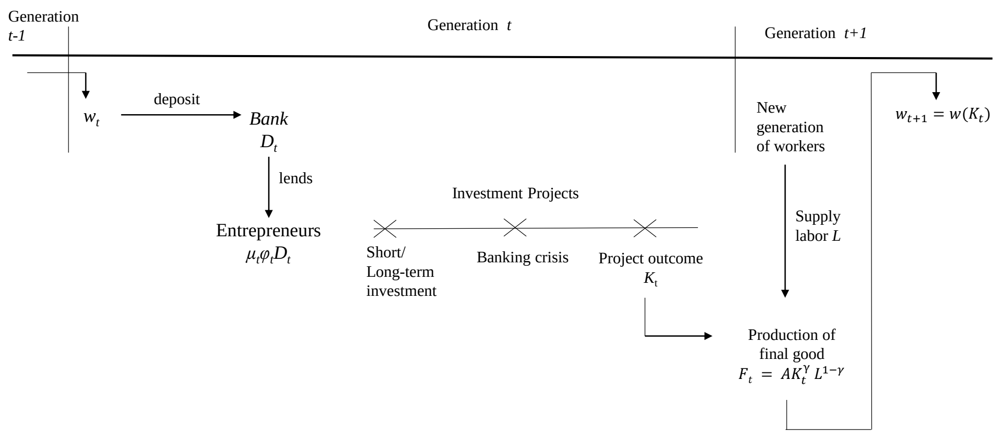
The mechanism behind Proposition 2 is easy to state. More leveraged banks find it optimal to place a higher share of their assets into risky real sector investments. This happens because more lending increases the probability of survival of long-term investments and, as a result, the expected return of the bank. This mechanism is observed for banks with a sufficiently high level of leverage ($\phi < \overline{\phi}$), beyond which bank creditors disproportionally bear the risk that long-term investments fail. Banks with high levels of equity compared to deposits find it optimal to undertake less risk in equilibrium and place more funds in the safe asset. The mechanism of the model is, thus, a simple risk and return trade-off. The more leveraged the bank, the higher the upside gain from investing in risky real sector assets, while the downside risk of project failure is born by investors who provide funds to the bank. This trade-off between leverage and credit supply is also responsible for the key dynamics of the model. The next section extends this three period model into a simple dynamic framework to study its implications for real sector investment patterns around banking crises.

3.2 The dynamic model

This section embeds the static model in the previous section in an overlapping generations framework to study the investment cycles arising from the endogenous selection of the two types of projects available to entrepreneurs. In the OLG model, the wealth in the economy is endogenously determined by the share of investment directed towards the long-term technology. However, the coordination game between investors, as well as the entrepreneur-bank relationship remain static, in the sense that these agents continue to be related by a financial contract that lasts three periods, i.e. the life span of entrepreneurs and investors.

The OLG model is summarized in Figure 4. In each overlapping generation, two types of agents are born: workers and entrepreneurs. There is a continuum of each type of agents with a unit mass. Workers supply their labor inelastically in the first part of their lives and earn a wage w_t, which they deposit in the bank. Wages become the pool of bank deposits, D_t, and represent the

Figure 4: Timing of the OLG model



aggregate wealth in the economy. Thus, workers are introduced in the model to simply enable the transmission of wealth between generations. Entrepreneurs, on the other hand, have access to the two types of investment projects described in the previous section. Projects take one or two periods to become productive during which bank runs may or may not occur, as depicted in Figure 4. The output from the two investments represents the accumulated capital of entrepreneurs at the end of their lives, which is simply:

$$K_t = (1-\alpha)\sigma_1(1-k_t)\mu_t\phi_t D_t + e_t(1-\alpha)\sigma_2 k_t \mu_t \phi_t D_t, \tag{5}$$

where: $e_t = \begin{cases} 1, & \text{if} \quad C_t \leq C_t^* \\ 0, & \text{if} \quad C_t > C_t^*. \end{cases}$

Thus, the level of capital at the end of time t depends on the wealth of the economy, D_t, the share of investment in innovation chosen by the entrepreneur, k_t, and the outcome of the coordination game between bank creditors, e_t. In the last period of their lives, entrepreneurs use this capital to produce a final consumption good by means of a Cobb-Douglas production function:

$$F_t = AK_t^{\gamma} L^{1-\gamma},$$

with capital K_t and labor L as inputs. Entrepreneurs hire the new generations of workers born in $t+1$, who supply labor inelastically and are paid at their marginal productivity, such that the economy-wide labor income at the beginning of $t = 1$ is:

$$w_{t+1}L = (1-\gamma)F_t \equiv w(K_t). \tag{6}$$

The remaining proceeds of this final good production, F_t, are consumed by entrepreneurs after which they die. Generation t workers also consume their income deposited in the bank and die. Furthermore, capital, K_t, once combined with labor to produce F_t, fully depreciates. As a result, at the beginning of time $t+1$, the aggregate wealth in the economy is represented by the aggregate wages of the young generation of workers who save by placing deposits in the banking sector in the first period of their lives:

$$D_{t+1} = w_{t+1}L = w(K_t). \tag{7}$$

To fully characterize the dynamics of the economy, we also need to study the evolution of the bank's balance sheet. At time t, the pool of deposits, D_t, available to the bank is just the aggregate wealth in the economy, as per Eq. (7). Given the assumption that capital fully depreciates at the end of each period, the equity of the bank stays constant over time.[14] Thus, an increase in D_t, which corresponds to a lower $\phi_t \equiv 1 + E/D_t$, is tantamount to an increase in the leverage of the bank.

Given the pool of deposits and the probability of survival of long-term investments, the bank chooses in each generation an optimal loan-to-assets ratio, μ_t, which is increasing in the leverage of the bank (see Proposition 2). Since the level of μ_t impacts the share of investments in innovation undertaken by entrepreneurs and the probability of runs, this has obvious implications for the wealth and investment dynamics in period $t+1$. Proposition 3 summarizes the dynamics of the economy.

Proposition 3 (i) As long as a bank run does not occur, higher aggregate income increases the pool of bank deposits, its leverage and loan-to-assets ratio μ_t. This results in a higher share of investment in the long-term technology.

(ii) A bank run decreases the aggregate wealth in the economy in the next period and results in a lower deposits-to-assets ratio and a less leveraged banking sector. This causes banks to tighten credit supply by decreasing their loan-to-assets ratio.

(iii) Tighter credit conditions after the banking crisis, lead to a lower share of investment in the long-term technology, which results in a lower growth as compared to the pre-crisis period.

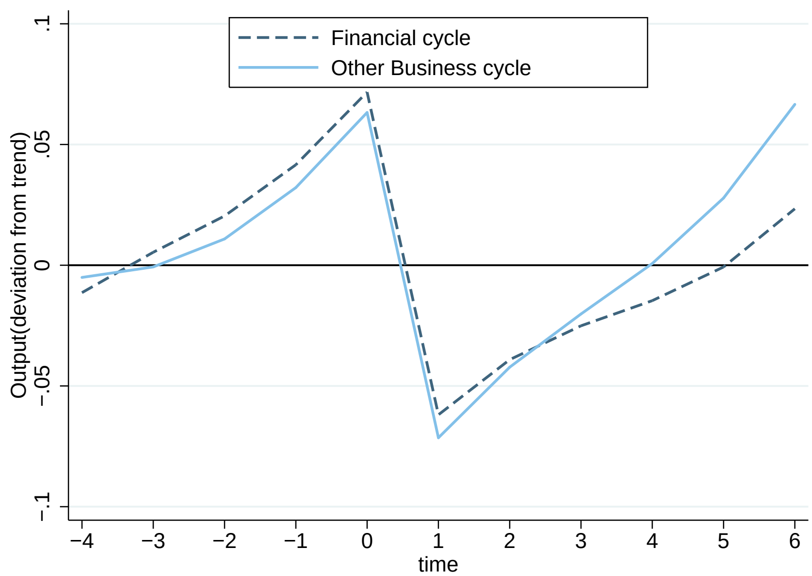
Proof *See Appendix.*

Figure 5 plots the simulation of the financial cycle described in Proposition 3, based on the structural parameter values in Appendix Table 9. This is represented by the dashed line which shows the deviation of output (F_t) from its long-run trend around a banking crisis occurring in time

[14]An alternative modeling approach would be to allow the bank to accumulate the returns in each generation as retained profits. This would imply a pro-cyclical evolution of the equity of the bank. The key results of the model would still hold under this alternative assumption as long as wealth in future periods, D_{t+1}, grows faster than the size of the bank equity. This is the case under innocuous assumptions that ensure a sufficiently high marginal productivity of labor in the final good production function, $(1-\gamma)$, in Eq. (6). However, to avoid notational clutter, bank equity is kept constant. This assumption is nonetheless consistent with empirical evidence that shows that bank equity levels tend to be rather stable over time. For example, Adrian et al. (2012) show that equity levels are "sticky" and bank lending changes are driven by the bank's debt levels. Thus, credit supply is the consequence of changes in bank leverage, which is consistent with the model presented in this paper.

0. A counter-factual economy is represented by the full line. In this economy, bank leverage and credit conditions are fixed at their initial period values and are kept constant. This counter-factual economy would be one in which banks are required to keep a constant leverage ratio, which, in the model, implies that μ and k are also constant. As depicted in Figure 5, this economy has a lower growth prior to the crisis, but a faster recovery afterwards. By contrast, the economy experiencing the financial cycle described in this paper has a higher growth prior to the crisis, captured by the higher deviation of output from its long-run trend in Figure 5 (dashed line). However, the opposite occurs after the crisis, since it takes five periods for output to recover and reach its long-run trend, whereas in the counter-factual economy, recovery takes only four periods. Tighter credit constraints which discourage the investment in innovation after the crisis are responsible for this slower recovery.

Figure 5: Dynamics of output around a banking crisis



Although stylized, the model presented in this section captures some central features of financial cycles (Borio, 2014). Empirically, such cycles are characterized by periods of credit boom ended by episodes of bank distress (Jordà et al., 2011; Boissay et al., 2016). Moreover, following the crisis, credit supply drops as documented in Asea and Blomberg (1998), Lown and Morgan (2006) and Becker and Ivashina (2014). In the model, this is the result of a pro-cyclical evolution of bank leverage, which is another well-documented empirical pattern across the financial cycle (Adrian et al., 2012; Kahle and Stulz, 2013).

The main testable implication of this simple model is that the evolution of credit supply around banking crises affects the composition of real sector investment patterns, by disproportionally discouraging long-term investments. The remainder of this paper tests empirically this prediction.

4 Empirical evidence

This section provides an empirical test of the theoretical predictions in the previous section by providing causal evidence of the impact of banking crises on the composition of investment. Specifically, it investigates the disproportional impact of such crises on long-term, productivity-enhancing projects, which are commonly proxied by investments in Research and Development. As this type of investment tends to be highly pro-cyclical (Comin and Gertler, 2006; Barlevy, 2007; Ouyang, 2011), one needs to disentangle empirically between the impact due to the contraction in credit supply following banking crises, as opposed to that explained by regular demand-side factors that lower overall investment opportunities during economic downturns. In doing so, the empirical strategy is split in two parts. I first investigate whether the observed drop in R&D investments following banking crises is explained by supply-side effects. I then investigate whether the crisis affects disproportionally more this type of investment, but looking at the share of investment in innovation in total investment.

4.1 Identification strategy

This paper employs 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 etc. At the same time, these differences tend to be persistent over time and across countries, offering a valid and exogenous way to identify the extent of an industry's dependence on external finance (Kroszner et al., 2007). Rajan and Zingales (1998) show that these industries tend to grow disproportionately faster in countries where the financial sector is more developed. However, the opposite occurs during financial crises, when industries more dependent on external finance perform relatively worse as compared to less dependent industries, as documented in Kroszner et al. (2007) and Dell'Ariccia et al. (2008). 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 that depend the most on obtaining external financing (Kroszner et al., 2007).

This paper uses a similar identification strategy by focusing on between-industry, within-country effects, to disentangle a causal link from banking distress to the composition of investment. The hypothesis tested is that, following a banking crisis, firms in industries more dependent on bank credit will decrease their investments in R&D disproportionately more than firms in less dependent industries. However, as the measure of dependence on external finance in Rajan and Zingales (1998) does not distinguish between the source of external finance, I interact this industry characteristic with a country-level measure that captures the importance of banking sector finance. Identification is then obtained from industries that depend more on external finance, in countries that rely more on the banking sector to obtain these funds.

This identification strategy differs from previous studies that focus on an interaction between industry external dependence and country financial development, measured by the ratio of private credit to GDP (see Rajan and Zingales, 1998; Kroszner et al., 2007; Dell'Ariccia et al., 2008; Hsu et al., 2014). There are several reasons for taking this new approach. First, most countries in my sample are advanced economies with relatively similar levels of private credit to GDP. By contrast, these countries are rather different with respect to the development of their banking sector as compared to capital markets, in the sense that some of them are more "bank-based", while others are more "capital markets-based". This distinction is particularly important in our case, given that previous research has stressed the importance of equity funding to finance R&D investments (Brown et al., 2009). If firms have easy access to capital markets, then the effects of a credit crunch would be diminished. As a result, the identification comes from industries in countries that generally rely more on banks as compared to equity markets to obtain their external financing, which are less likely to be able to switch to other forms of financing during crises.

Second, even if some firms are not directly financing their R&D investments with bank debt, their inability to access external finance for other "essential" activities during banking crises means that internal cash flows should be diverted away from investments in innovation (see also Nanda and Nicholas, 2014). Again, this effect should be stronger for borrowers that rely mostly on the banking sector to obtain external finance, i.e., in more bank-based economies. Finding evidence of these cross-country, cross-industry differences in the data would therefore provide indirect, but strong support for the presence of a causal effect of financial conditions (banking crises) on investments in innovation.

The baseline econometric specification follows Kroszner et al. (2007) and implements an event study analysis as follows:

$$\Delta R\&D_{ic} = \alpha_i + \mu_c + \beta_1 ExtDep_i \times Bank_c + \beta_2 Size_{ic} + \epsilon_{ic}, \tag{8}$$

where $\Delta R\&D_{ic} = R\&D_{ic,crisis} - R\&D_{ic,precrisis}$ is the difference in average real R&D growth rate between a crisis and pre-crisis period in industry i of country c. $ExtDep_i$ is an industry-level measure of dependence on external finance, $Bank_c$ is a country-level measure that captures the reliance on banking sector financing as opposed to capital markets, while $Size_{ic}$ is the share of industry i's R&D spending in total R&D of country c. Finally, the baseline model controls for country and industry dummies captured by μ_c and α_i, respectively. Eq. (8) is estimated cross-sectionally, since it uses one observation per country-sector: the change in average R&D growth around a banking crisis.

The coefficient of interest is β_1 and we expect $\beta_1 < 0$, meaning the growth rate of R&D investment after the crisis as compared to the pre-crisis period is significantly lower in more financially dependent industries, in countries with bigger banking sectors as compared to stock markets. This disproportionally lower investment in innovation suggests that contractions in credit supply that follow banking crises matter for investments in innovation and balance sheet effects alone cannot explain the drop in R&D investments following episodes of bank distress.

Model (8) also controls for the share of an industry's R&D in total research and development spending in a country to capture any size 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 endogeneity, pre-crisis levels of this industry size measure are used.[15] Finally, the inclusion of industry and country fixed effects controls for all sector-specific omitted characteristics, as well as country-specific characteristics that might affect investments in all industries such as institutional or legal environment. These fixed effects reduce concerns of omitted variable bias or model mis-specification and allows us to focus on within country, between industries variations.

4.2 Data and descriptive statistics

Research and Development data comes for OECD's ANBERD database, which collects annual data on R&D expenditures for up to 100 manufacturing and service industries in 34 countries. I focus on manufacturing industries only for several reasons. First, the ANBERD database has a considerably wider industry-year coverage for the manufacturing sector. Second, R&D is heavily concentrated in manufacturing. In the ANBERD database, manufacturing industries' share of R&D spending during the period 1987-2013 represents 69.5% of total R&D investment. Barlevy (2007) documents similar shares for US manufacturing firms that account for 70-80% of total R&D spending.

Banking crises episodes are obtained from the Laeven and Valencia (2012) dataset. The timing of crises and availability of R&D data from ANBERD limits the sample to 13 country-crisis episodes over the period 1990-2013 and 29 two- and three-digit ISIC level manufacturing sectors. The crisis years and countries are presented in Table 1, while the 29 industries covered in Appendix E.

To construct a measure of total investment, I use the Gross Investment in Tangible Goods (GITG) data series from OECD Structural Statistics of Industry and Services database, which captures 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 fixed investment in industry i in year t since, at the time of data collection, most countries have not implemented the System of National Accounts (SNA) 2008 guidelines that require R&D expenses to be accounted as an investment, rather than consumption. As a result, the data on gross

[15]One concern with the inclusion of the share of R&D is that more R&D intensive industries might also be the ones that systematically depend more on external finance. However, this is not the case here, as the two variables have a positive but rather low correlation. Moreover, the results (not presented) are robust to the exclusion of the size variable from the model. I also control for industry R&D intensity in the robustness section.

investment at industry level does not incorporate R&D expenditure.[16]

Table 1: R&D investment growth around a banking crisis

Table shows country-level median R&D growth around a crisis year in industries above/below the median of the external dependence index. The pre-crisis period is $[t-4, t-1]$, while the post-crisis period is $[t+1,\ t{+}3]$ for a crisis year t. Crisis year is the first year of a systemic banking crisis reported in Laeven and Valencia (2012). External dependence is the Rajan and Zingales (1998) measure based on a two- or three-digit ISIC level.

		Below median financial dependence		Above median financial dependence	
Country	Crisis year	before crisis	after crisis	before crisis	after crisis
Austria	2008	4.5%	2.7%	10.5%	-1.7%
Belgium	2008	2.6%	6.5%	3.1%	7.5%
Germany	2008	2.4%	0.9%	1.3%	1.5%
Spain	2008	6.4%	-4.7%	4.2%	-3.0%
France	2008	2.9%	1.5%	0.5%	0.6%
Italy	2008	9.6%	-1.5%	3.2%	1.1%
Japan	1997	0.5%	-2.7%	1.0%	1.0%
South Korea	1997	1.1%	-21.9%	8.8%	-17.5%
Portugal	2008	13.4%	-1.7%	15.5%	-4.5%
Slovenia	2008	8.1%	14.9%	6.4%	5.9%
Turkey	2000	6.0%	-1.8%	17.0%	-1.8%
UK	2008	3.0%	1.4%	1.7%	2.2%
USA	2008	2.1%	-2.9%	6.8%	-2.8%
Average		4.81%	-0.71%	6.16%	-0.88%
Difference		**-5.52%***		**-7.04%*****	

*/*** represent significance at the 10%/1% of a t-test for equality of means across the two samples.

The industry level measure of external dependence (*ExtDep*) follows Rajan and Zingales (1998) and is defined as the share of capital expenditure not financed with cash-flow from operations. Rajan and Zingales (1998) build their measure using a sample of US firms from Compustat during the 1980s under the assumption that the use of finance by US public 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.[17] To maximize my sample size, I re-compute their index for the 29 two- and three-digit ISIC level manufacturing industries for which matching R&D data is available in ANBERD, using a Compustat sample of 106,000 US firm-year observations over the period 1990-1999. I then aggregate the firm-level data at the industry level by computing the median of each two- and three-digit ISIC industry for the entire period. The time-invariant, industry-level index of external finance dependence is presented

[16]The date of implementation of the SNA framework differs across OECD countries, however among the 13 countries considered only the United States had implemented the standard in 2013, while all EU member countries in 2014.

[17]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.

in Appendix E and is comparable to the one constructed in Rajan and Zingales (1998) and Raddatz (2006). It labels, for example, Pharmaceuticals (ISIC 21), Electronics (ISIC 264) or Medical supplies (ISIC 325) as industries highly dependent on external finance, while Leather (ISIC 15) and Wearing apparel (ISIC 14) are among the least dependent.

Finally, to create a country-level measure of dependence on banking sector finance, I follow Levine (2002) and use data from the World Bank 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.

As a first glance of the data, Table 1 shows a simple split-sample analysis by looking at investments in R&D around a banking crisis. In particular, I compute the average R&D growth in the periods $[t-4, t-1]$ and $[t+1,\ t{+}3]$ around a crisis occurring in year t for each industry. I then split the sample in industries that have a financial dependence index below/above the median and report the median growth in this subsample for each country. The statistics presented in Table 1 show that, in most countries, growth in R&D investment drops in the years following a banking crisis. A cross-country average shows that pre-crisis growth rates tend to be slightly higher in industries above the median of financial dependence and, more importantly, these industries also see a larger drop in the growth rate after the crisis. The average drop in R&D growth in the post-crisis period is 5.52 percentage points in low dependent industries, versus 7.04 percentage points in highly dependent ones.

These descriptive statistics suggest that industries highly dependent on external finance tend to reduce investments in R&D more in the period following a financial crisis and thus support the hypothesis put forward in the theoretical model.

4.3 The effect of banking crises on R&D investment

The first set of results investigate the effect of banking sector distress on the growth in R&D spending. Columns (1)-(5) in Table 2 present the estimates of model (8), which is a cross-sectional event study with one observation per country-industry, i.e. the difference in real growth in R&D investment 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 (see also Kroszner et al., 2007; Manova, 2008). Column (1) looks at the average growth in R&D between $[t+1, t+3]$ and $[t-3, t-1]$ for a crisis in year t. Column (2) considers a longer time frame, particularly for the pre-crisis period, to mitigate any concerns regarding investment booms occurring before the banking crisis: $[t+1, t+4]$ and $[t-8, t-1]$. Finally, in column (3), I also include the crisis year in the average and compare the periods: $[t, t+2]$ and $[t-4, t-1]$.

The baseline results in columns (1)-(3) support the hypothesis that banking crises have an exogenous impact on investments in innovation. The interaction term, $ExtDep{*}Bank$, is always negative and statistically significant at a 1% level. This confirms that the average growth in R&D

Table 2: Banking crises and R&D investment

The dependent variable in columns (1)-(5) is the difference between the average real growth in R&D in the years following a banking crisis as compared to the average in the years preceding the crisis. The crisis and pre-crisis intervals are: $[t+1, t+3]$, $[t-3, t-1]$ in column (1); $[t+1, t+4]$, $[t-8, t-1]$ in column (2); and $[t, t+2]$, $[t-4, t-1]$ in column (3), for a banking crisis starting in year t. In column (4), standard errors are clustered at the country level. Column (5) estimates the model in column (1) for the 2008 Global Financial Crisis only. The dependent variable in columns (6)-(10) is the real growth rate of R&D investment in year t. ExtDep×Bank is the interaction term of the Rajan and Zingales (1998) industry-level measure of external dependence and a country-level measure of bank-dependence computed as the ratio of Private Credit to Stock Market Capitalization in year $t-8$ or the first year available. ExtDep×Bank×Crisis is a triple interaction term between the industry-level measure of external dependence, the country-level measure of bank dependence and a crisis dummy that takes the value 1 in the 3 years following a banking crisis. ExtDep×Crisis is an interaction term between external dependence and the crisis dummy. Size_{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. Constant term included, but not reported. *** represents significance at 1% level, ** at 5% level and * at 10% level.

	$\Delta R\&D$= ($R\&D_{crisis}$ - $R\&D_{precrisis}$)					Panel estimations: R&D growth				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ExtDep × Bank	-0.0187***	-0.0152***	-0.0259***	-0.0187**	-0.0152***					
	(0.00580)	(0.00528)	(0.00641)	(0.00633)	(0.00541)					
ExtDep × Bank × Crisis						-0.0104***	-0.0115***	-0.0113***	-0.00875***	
						(0.00284)	(0.00336)	(0.00367)	(0.00287)	
ExtDep × Crisis										-0.0202*
										(0.0108)
Size_{t-3}	0.274	-0.346	-0.0694	0.274	0.632	-0.368***	-0.658***	-0.446***	-0.596***	-0.372***
	(0.600)	(0.389)	(0.519)	(0.680)	(0.499)	(0.101)	(0.230)	(0.0956)	(0.143)	(0.100)
Observations	244	248	248	244	226	4,387	4,387	4,387	4,387	4,592
R-squared	0.289	0.279	0.287	0.289	0.340	0.045	0.082	0.165	0.166	0.046
Country FE	YES	YES	YES	YES	YES	YES		YES		YES
Industry FE	YES	YES	YES	YES	YES	YES			YES	YES
Year FE						YES	YES			YES
Country-year FE									YES	
Industry-year FE								YES		
Country-industry FE							YES			

in the crisis period compared to the pre-crisis one is lower in industries that are more dependent on external finance, in countries with relatively larger banking sectors as compared to financial markets. In other words, industries that depend more on bank credit experience a greater reduction of investment in R&D following a banking crisis. Estimations in columns (1)-(3) include country and industry dummies and standard errors are corrected for heteroskedasticity using the White (1980) correction. The results also hold when correcting for any correlation between industries in the same country, by clustering errors at the country level in column (4) (see Petersen, 2009). In column (5), model (8) is estimated for a restricted sample of countries that were hit by the 2008 Global Financial Crisis. This assures us that results are consistent with more recent banking crises episodes, as well.

The aggregation strategy in Eq. (8), which collapses the time dimension, has been shown to be an effective methodology to account for any serial correlation in the dependent variable that can bias standard errors in difference-in-difference models (see Bertrand et al., 2004). Nonetheless, given the panel structure of the data, I also perform a more standard difference-in-difference estimation by looking at the year-on-year real growth of R&D spending during crisis periods. More specifically, the model tested is:

$$R\&D_{ict} = \alpha_i + \mu_c + \lambda_t + \beta_1 ExtDep_i \times Bank_c \times Crisis_{ct} + \beta_2 Size_{ic} + \epsilon_{ict}, \tag{9}$$

where $R\&D_{ict}$ is the annual real growth in R&D in sector i of country c, in year t; α_i, μ_c and λ_t are industry, country and 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] The triple interaction term captures the differential impact of dependence on bank finance during periods of bank distress.

The results presented in column (6) of Table 2 confirm the findings from the event study. The negative and strongly significant coefficient of the triple interaction term suggests that investment patterns in financially dependent firms are different following banking crises, as they invest disproportionately less on R&D, all the more so in countries that rely more on the banking sector. These results are comparable to those in Dell'Ariccia et al. (2008) and Kroszner et al. (2007), who use similar triple interactions to document the effect of banking crises on value added growth in industries more dependent on external finance, in countries with deeper financial systems. This study extends their findings in two ways. First, I investigate a potential channel that can explain this lower growth in value added, i.e., through investments in productivity-enhancing projects. Second, since my sample is concentrated on countries with relatively high levels of financial development, I propose a different identification strategy. As such, the differential effect of banking crises on R&D investment is stronger in countries with a relatively larger banking sector as opposed to stock markets. This implies that identification is obtained from industries that are generally more dependent

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

on obtaining finance *from* the banking sector.

The estimations in column (6) allow for country, industry and year fixed effects. These should control for any country and industry specific time-invariant factors, as well as time-specific changes that affect all countries and industries equally, such as technological improvements or price shifts. To further safeguard against omitted variable bias, I condition the panel estimation on other two-way fixed effects. Column (7) in Table 2 controls for country-industry fixed effects that can account for time-invariant factors that can influence R&D investments in a particular industry and country, such as tax incentives or resource specificity. Similarly, column (8) controls for industry-year effects to account for industry-specific fluctuations in, for example, demand or technological advancements. Column (9) controls also for country-year fixed effects that can account for correlations between countries in the same year such as banking crises that affect several countries in the same year. The results obtained under these more econometrically demanding settings are highly robust.

Finally, a reduced form of Eq. (9), considering just an interaction between $ExtDep_i$ and the crisis dummy is presented in column (10). This estimation confirms that industries more dependent on external finance tend to grow less during banking crises, across all countries. However, the statistical significance of this interaction term is much weaker, confirming that the differential effect captured comes from financially dependent industries in countries with a predominant banking sector financing.

In sum, the results in Table 2 provide strong support for the importance of credit market conditions for investments in innovations, by showing that more bank dependent borrowers invest disproportionally less in R&D after banking crises. Furthermore, this differential effect is economically significant. Looking at column (6) estimates, a sector in the 75th percentile of external dependence, in a country in the 75th percentile of banking sector dependence, experiences a 4.2 percentage points lower real R&D growth following a banking crisis as compared to a sector in the 25th percentile of external dependence, in a country in the 25th percentile of bank dependence.

4.4 Effects of banking crises on the composition of investment

Having established the importance of changes in financial constraints for investments in innovation, I now investigate whether this drop in R& D spending is also associated with a shift in the composition of investment. More specifically, the hypothesis tested is that the *share* of R&D in total investment is significantly lower in industries more dependent on the banking sector. Since both total investment and R&D spending are expected to drop following banking crises, a drop in the share of R&D in total investment would imply that investments in innovation are affected disproportionally more by changes in financial conditions. In other words, banking crises discourage significantly more investments in innovation, as compared to other types of investment.

Table 3: Banking crises and the composition of investment

The dependent variable in columns (1)-(5) is the difference between the average share of R&D in Total Investment in the years following a banking crisis as compared to the average in the years preceding the crisis. The crisis and pre-crisis intervals for which these averages are computed, are $[t+1, t+3]$, $[t-3, t-1]$ in column (1); $[t+1, t+4]$, $[t-8, t-1]$ in column (2); and $[t, t+2]$, $[t-4, t-1]$ in column (3), for a banking crisis starting in year t. The dependent variable in columns (6)-(9) is the share of R&D in Total Investment in industry i of country c at time t. ExtDep×Bank is the interaction term of the Rajan and Zingales (1998) industry-level measure of external dependence and a country-level measure of bank-dependence computed as the ratio of Private Credit to Stock Market Capitalization in year $t-8$ or the first year available. ExtDep×Bank×Crisis is a triple interaction term between the industry-level measure of external dependence, the country-level measure of bank dependence and a crisis dummy that takes the value 1 in the 3 years following a banking crisis. Size_{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. Errors are clustered at country level in column (4). Column (5) replicates the model in column (1) for the 2008 Global Financial Crisis only. Constant term included, but not reported. *** represents significance at 1% level, ** at 5% level and * at 10% level.

	$\Delta(R\&D/TI)$= $(R\&D/TI)_{crisis}$ - $(R\&D/TI)_{precrisis}$					Panel regressions: $R\&D/TI$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ExtDep×Bank	-0.0104***	-0.0057	-0.0278***	-0.0104**	-0.0107***				
	(0.0033)	(0.0035)	(0.0082)	(0.0039)	(0.0034)				
ExtDep×Bank×Crisis						-0.0056**	-0.0047*	-0.0031	-0.0059**
						(0.0025)	(0.0024)	(0.0032)	(0.0030)
Size_{t-3}	-0.0962	0.0354	0.0916	-0.0962	-0.106	0.263**	0.0243	0.404***	0.616***
	(0.153)	(0.179)	(0.510)	(0.127)	(0.171)	(0.105)	(0.0243)	(0.0960)	(0.113)
Observations	234	234	234	234	216	4,415	4,415	4,415	4,415
R-squared	0.333	0.320	0.304	0.333	0.338	0.712	0.888	0.736	0.751
Country FE	YES	YES	YES	YES	YES	YES		YES	
Industry FE	YES	YES	YES	YES	YES	YES			YES
Year FE						YES	YES		
Country-year FE									YES
Industry-year FE								YES	
Country-industry FE							YES		

To test this prediction, a modified version of the cross-sectional model in Eq.(8) is used:

$$\Delta(R\&D/TI)_{ic} = \alpha_i + \mu_c + \beta_1 ExtDep_i \times Bank_c + \beta_2 Size_{ic} + \epsilon_{ic}, \tag{10}$$

where $\Delta(R\&D/TI)_{ic} = (R\&D/TI)_{crisis} - (R\&D/TI)_{precrisis}$ and $(R\&D/TI)_{ic}$ is the average share of R&D investment in Total investment in industry i of country c during the period considered.

Results are presented in Table 3 and confirm the shift in the composition of corporate investment around a crisis event. Regardless of the time frame employed to compute the pre- and crisis periods in columns (1)-(3), the average share of R&D investment in total investment is lower after a banking crisis in industries more reliant on external finance, in more bank-based economies. Thus, banking crises are not only followed by a drop in spending on R&D, but also in its share in total investment. Coupled, these two empirical results suggest a potential new channel through which banking crises can have long-lasting consequences on the real economy and lend broad support to the qualitative implications of the theoretical model presented in the previous section.

The remaining columns in Table 3 propose the same empirical exercises as the ones in Table 2. Specifically, column (4) allows for clustering of error terms at the country level, while column (5) looks at a restricted sample of countries hit by the 2008 Global Financial Crisis. Finally, columns (6)-(9) in Table 3 extend the event analysis to a panel setting. Thus, a modified version of model (9) is run using the share of R&D in total investment, rather than the growth rate of R&D as dependent variable. The negative coefficient of the triple interaction term $ExtDep_i \times Bank_c \times Crisis_{ct}$ is still significant at a 5% level in column (6), which controls for country, industry and time fixed effects. This shows that industries more reliant on external finance, in more bank-based economies, invest a lower share of their total investment in innovation during periods of bank distress. Columns (7)-(9) control for an array of fixed effects including country-industry, industry-year and country-year. Result are consistent across these alternative specifications, with the exception of column (8), where the triple interaction term is less precisely estimated, owing, most likely, to the lost degrees of freedom due to the large number of industry-year dummy variables included.

Finally, the effect of banking crises on the composition of investment is also economically significant. Looking at Table 3, column (1) estimates, a sector in the 75th percentile of external dependence, in a country in the 75th percentile of banking sector dependence, has a 2.2 percentage points lower share of R&D in total investment following a banking crisis as compared to a sector in the 25th percentile of external dependence, in a country in the 25th percentile of bank dependence.

4.5 Banking crises or balance sheet effects?

One concern with the interpretation of the results obtained thus far is that the differential effect documented may simply reflect balance sheet effects, which result in a low investment demand in economic downturns, in general. For example, Braun and Larrain (2005) show that industries more dependent on external finance tend to have a lower growth in value added during regular business cycle recessions as well. Thus, it might be the case that R&D investment simply responds to these business cycle fluctuations and, to a lesser extent, to the credit supply conditions around banking crises. I check the robustness of the 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 tested is:

$$\begin{aligned} R\&D_{ict} &= \alpha_i + \mu_c + \lambda_t + \beta_1 ExtDep_i \times Bank_c \times Crisis_{ct} + \\ &\quad \beta_2 ExtDep_i \times Bank_c \times Recession_{ct} + \beta_3 Size_{ic} + \epsilon_{ict}, \end{aligned} \tag{11}$$

where $R\&D_{ict}$ is the annual real growth in R&D in sector i of country c in year t and α_i, μ_c and λ_t are industry, country and 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. $Recession_{ct}$ is a dummy that takes the value 1 in the years between the peak and trough of the cyclical component of real GDP following the methodology proposed by Braun and Larrain (2005).[19] The coefficient of interest is still β_1 and the hypothesis is that the negative effect of banking crises it captures is still statistically significant once the effect of economic recessions is taken into account.

The results in Table 4 confirm that the differential impact of banking crises on R&D investment holds even when controlling for recessions. Specifically, the coefficient of the interaction of $ExtDep \times Bank \times Recession$, which captures recession periods, is mostly negative but statistically significant only in a few cases. On the other hand, triple interaction $ExtDep \times Bank \times Crisis$, which captures banking crisis periods, is still negative and strongly significant across all specifications. More precisely, columns (1)-(4) pertain to the regressions related to the real growth rate of R&D investments and control for the usual one- and two-level fixed effects. These estimations are performed only on the sample of 13 countries that have experienced a banking crisis. As some of the recession and crisis periods overlap (although not perfectly), I check the robustness of the model by including the full set of countries for which R&D data is available in the ANBERD database and not just countries that have experienced a banking crisis over the period considered. This increases the number of observations and includes other countries that have experienced only economic recessions over the period 1987-2013.[20] The results obtained for this extended sample are presented in column (5) and confirm the strongly significant effect of banking crises on investments in innovation, and, to a lesser extent, that of balance sheet conditions during economic recessions.

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

[20]More precisely, the new countries included are Australia, Canada, China, Czech Republic, Finland, Mexico, Norway, Romania, Slovak Republic and Singapore. The data availability for some of these countries is however restricted to more recent years.

Table 4: Banking crises versus balance sheet effects

The dependent variable in columns (1)-(5) is the real growth rate of R&D investment, while in columns (6)-(9) is the share of R&D in Total Investment. ExtDep×Bank×Crisis is a triple interaction term between the industry-level measure of external dependence, the country-level measure of bank dependence and a crisis dummy that takes the value 1 in the 3 years following a banking crisis. ExtDep×Bank×Recession is a triple interaction term with a dummy taking value 1 in the years in which a recession occurred in country c. Size$_{t-3}$ is the share of the sector's R&D investment in total R&D investment in the three years prior to the crisis. Growth observations are winsorized at +100% and -100%. Robust standard errors are reported in parentheses. Column (5) includes the full sample of countries for which industry-level data on R&D is available in ANBERD and not just crisis countries. Constant term included, but not reported. *** represents significance at 1% level, ** at 5% level and * at 10% level.

	R&D growth					*R&D/TI*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ExtDep×Bank×Crisis	-0.0094***	-0.0112***	-0.0107***	-0.0074***	-0.0102***	-0.0062**	-0.0044**	-0.0086**	-0.0056*
	(0.0026)	(0.0033)	(0.0039)	(0.0028)	(0.0034)	(0.0029)	(0.0021)	(0.0042)	(0.0028)
ExtDep×Bank×Recession	-0.0025	0.0018	0.0014	-0.0081	-0.0038	-0.0242***	-0.0041	-0.0353***	-0.0298***
	(0.0063)	(0.0074)	(0.0093)	(0.0080)	(0.0055)	(0.0077)	(0.0058)	(0.0123)	(0.0083)
Size$_{t-3}$	-0.359***	-0.631***	-0.430***	-0.623***	-0.380***	0.465***	0.0250	0.682***	1.189***
	(0.103)	(0.222)	(0.0992)	(0.164)	(0.107)	(0.162)	(0.0247)	(0.144)	(0.114)
Observations	4,080	4,080	4,080	4,080	4,580	4,103	4,103	4,103	4,103
R-squared	0.049	0.089	0.179	0.183	0.041	0.730	0.881	0.756	0.776
Country FE	YES		YES		YES	YES		YES	
Industry FE	YES			YES	YES	YES			YES
Year FE	YES	YES			YES	YES	YES		
Country-industry FE		YES					YES		
Country-Year FE				YES					YES
Industry-year FE			YES					YES	

Finally, columns (6)-(9) in Table 4 estimate model (11) considering the share of R&D in total investment as a dependent variable. When considering this model, the coefficient of the interaction term $ExtDep \times Bank \times Recession$ is now statistically significant in two of the three specifications. Nonetheless, the effect of financial conditions on the composition of investment is still significant across all fixed effects identification strategies in columns (6)-(9). Moreover, as crisis and recession periods sometimes overlap, it is the explanatory power and not the size of the coefficient that is of interest in this econometric specification.

Overall, the results in this section support the interpretation that, it is not necessarily balance sheet effects that matter for investments in innovation, but contractions in credit supply due to the banking crisis.

4.6 Differential effects during crises and non-crises periods

This section investigates the link between dependence on the banking sector and R&D investment 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 consistent 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). However, previous empirical evidence looking at the growth in R&D investments, 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, while Hsu et al. (2014) find that neither equity nor credit market development spurs investments in R&D during non-crisis periods. These results, however, are generally based on smaller samples or use listed company data. Research that looks at non-listed firms as well, does confirm the importance of financial constraints on R&D investments. For example, Nanda and Nicholas (2014) find that non-listed US firms did reduce disproportionately their R&D spending during the Great Depression in the 1930s. Acharya and Xu (2017) show that, within financially dependent industries, public firms spend more on R&D as compared to private ones, as the latter are more likely to be financially constrained.

This section tests the hypothesis that financially dependent industries have different investment rates in innovation during non-crisis versus crisis periods. Specifically, the model tested is as follows:

$$R\&D_{avg,ic} = \alpha_i + \mu_c + \beta_1 ExtDep_i * Bank_c + \beta_2 Size_{avg,ic} + \epsilon_{ic}, \tag{12}$$

where $R\&D_{avg,ic}$ represents the average investment in R&D during a crisis or non-crisis period, while $Size_{avg,ic}$ is the average share of R&D of industry i in total country c's R&D investment, over the two separate periods, as well.

Table 5: Innovation during banking crises versus non-crises periods

The dependent variable in columns (1)-(2) is the average growth in R&D in years not classified as a crisis period, while in columns (3)-(4) this average is computed in years classified as crisis years, namely the three years following a banking crisis. Columns (2) and (4) refer to a balanced sample that includes the same country-industries in the non- and crisis periods. The dependent variable in columns (5) and (7) is the real growth in R&D, while in columns (6) and (8) is the share of R&D in total investment. Size_{avg} is the average share of a sector's R&D investment in total R&D investment over the period considered. Size_{t-3} is the lagged share of the sector's R&D investment in total R&D investment. Growth observations are winsorized at +100% and -100%. Robust standard errors are reported in parentheses. Constant term included, but not reported. *** represents significance at 1% level, ** at 5% level and * at 10% level.

	Period averages				Panel estimations			
	Non-crisis		Crisis		Non-crisis		Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ExtDep×Bank	0.0061*	0.0046*	-0.0074*	-0.008*	0.0043	0.0007	-0.012***	-0.0046*
	(0.0035)	(0.0026)	(0.0043)	(0.004)	(0.0034)	(0.0025)	(0.003)	(0.0025)
Size_{avg}	0.402**	0.395**	-0.216	0.0028				
	(0.183)	(0.183)	(0.228)	(0.289)				
Size_{t-3}					-0.513**	0.303*	-0.447**	0.85***
					(0.220)	(0.177)	(0.203)	(0.22)
Observations	273	270	288	270	2,662	2,684	973	975
R-squared	0.148	0.151	0.135	0.137	0.043	0.709	0.112	0.731
	Industry and country FE				*Industry, country, year FE*			

Results pertaining to Eq. (12) are presented in columns (1)-(4) of Table 5. Overall, they point to a disproportionate effect of financial dependence on R&D growth. During non-crisis periods (columns (1)-(2)), the coefficients of the interaction terms are positive and statistically significant. This suggests that, during normal times, industries more dependent on external finance, in more bank-based economies, tend to invest more in research and development. The opposite, however, occurs during periods of bank distress (columns (3)-(4)), when the coefficients of the interaction term become negative, but are still significant at a 10% level. One concern with this approach is that the averages over the two samples might include different country-industry observations in the non- versus the crisis periods. This was not the case in the event-study regressions in Tables 2 and Table 3 that included, by construction, only industries that had data for the entire pre- and crisis time intervals considered. To mitigate this concern, columns (2) and (4) are estimated by looking at a balanced sample, where the same number of country-industry observations is included in both the non-crisis and crisis period averages. Results are consistent in this restricted sample.

Next, this split sample analysis is replicated in a panel setting in columns (5)-(8). Columns (5) and (7) refer to the growth in R&D, while columns (6) and (8) to the share of R&D in total investment. Similarly to the aggregated estimations, the positive, albeit less precisely estimated, impact of $ExtDep \times Bank$ during non-crisis periods (columns (5)-(6)) is reversed after banking crises. These split sample results provide evidence of the importance of financial conditions for investments in innovation. They also suggest an explanation for the mixed results in previous literature as bank financing seems to matter for investment in innovation, however this effect is mainly present in countries in which firms do not have easy access to alternative funding through capital markets, i.e., more bank-based economies.

4.7 Alternative industry characteristics

Banking crises may have a differential impact on investments in innovation depending on other industry characteristics likely to also be related to their ability to obtain external finance. For example, firms that have more tangible assets should find it easier to obtain external finance and their investment in innovation should be less affected by the contraction in credit supply. Firms in sectors that produce more durable goods have been shown to have a more procyclical behavior and could be more adversely affected by banking crises (Caballero and Hammour, 1994). As a result, the observed drop in R&D spending might simply reflect the more procyclical swings in demand specific to these industries. Similarly, small firms are also more financially constrained, so industries dominated by smaller establishments should be more severely affected by disruptions in the credit supply (Beck et al., 2008).

I thus construct a series of alternative industry characteristics and control whether the effect of dependence on external finance is still present once these other structural differences are taken into account. Specifically, I construct a measure of asset tangibility following Braun and Larrain (2005) as the ratio of net property, plant and equipment to total assets of US Compustat firms over the period 1990-1999. The median of this ratio at the two- and three digit industry level results in a measure of asset tangibility that, similar to the proxy for external dependence, is assumed fixed across countries and time. Next, a classification of sectors producing durables and non-durable goods is obtained from the US Bureau of Economic Analysis. The measure constructed is a dummy variable assigning 1 to an industry classified as a durable goods producer. This measure is also identical across countries.

To build a proxy for industries dominated by small firms, I follow Dell'Ariccia et al. (2008) and use the total number of employees at the industry-level from the OECD STAN database over the period over 2000-2015. To avoid endogeneity concerns, I compute the median number of employees in each industry, in each country over the entire period. Industries are then classified according to this average size by assigning a dummy variable, called $Small$, equal to 1 if an industry has a below the median number of employees in a given country. This proxy will thus be country-specific to reflect potential differences in technology and product mix across countries.

Table 6 shows the results of an augmented model (9) that includes alongside the triple interaction term, $ExtDep_i \times Bank_c \times Crisis_{ct}$, another triple interaction term, where $ExtDep_i$ is replaced by an alternative industry characteristic. Results in Table 6 confirm the key role of financial dependence in explaining the differential investment in R&D during crises. The triple interaction term that includes $ExtDep_i$ is still significant across most specification once the other industry characteristics

Table 6: Alternative industry characteristics

The dependent variable in columns (1)-(4) is the average growth in R&D, while in columns (5)-(8) is the share of R&D in Total investment. Independent variables are triple interaction terms between the industry-level characteristics shown in the table, the country-level measure of bank dependence and a crisis dummy that takes the value 1 in the 3 years following a banking crisis. The industry-level measures are (i) ExtDep, the Rajan and Zingales (1998) measure of external dependence; (ii) Tangible, a measure of asset tangibility; (iii) Small, a dummy for industries dominated by small firms; (iv) Durables, a dummy for industries producing durable goods; (v) Intensity, a measure of the industry's intensity of R&D investment. Size_{t-3} is the share of the sector's R&D investment in total R&D investment in the three years prior to the crisis. Growth observations are winsorized at +100% and -100%. Robust standard errors are reported in parentheses. All regressions include industry, country and year fixed effects. Constant term included, but not reported. *** represents significance at 1% level, ** at 5% level and * at 10% level.

	R&D growth				*R&D/TI*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ExtDep	-0.014***	-0.0096***	-0.0088***	-0.0044	-0.0064**	-0.0096***	-0.011***	-0.0096**
	(0.0039)	(0.0030)	(0.0029)	(0.0034)	(0.0027)	(0.0029)	(0.0032)	(0.0039)
Tangible	-0.0001				-0.0000			
	(0.0005)				(0.0002)			
Small		-0.0091**				0.0047		
		(0.0036)				(0.003)		
Durable			-0.0103*				0.0002	
			(0.0059)				(0.0055)	
Intensity				-0.0113*				0.0078
				(0.0066)				(0.0057)
$Size_{t-3}$	-0.948***	-0.364***	-0.676***	-0.891***	0.637***	0.469***	0.467*	0.572***
	(0.207)	(0.0996)	(0.217)	(0.208)	(0.162)	(0.179)	(0.272)	(0.143)
Observations	3,082	3,545	2,354	2,247	3,103	3,558	2,368	2,262
R-squared	0.028	0.020	0.041	0.055	0.706	0.748	0.433	0.709

are taken into account. Columns (1)-(4) look at the growth in R&D, while columns (5)-(8) look at the share of R&D in total investment. Interestingly, while smaller industries and those producing durable goods, do seem to have a lower growth in R&D during crisis periods, the same does not hold for the ratio R&D/TI in columns (5)-(8). Specifically, none of the alternative industry characteristics considered seems to explain the change in the composition of investment following banking crises. This suggests that some industry characteristics might explain a drop in overall investment spending during crises, but not the relatively larger drop in R&D, which is most robustly related to external finance dependence.

Finally, Table 6 also includes a measure of R&D intensity at the industry level. R&D intensity is computed as the ratio of R&D expenses to sales for US Compustat firms over the period 1990-1999 (see also Hsu et al., 2014). Aggregation at the industry level is done in a similar manner as the measure of industry asset tangibility. The triple interaction term using R&D intensity in column (5) does suggest that industry that generally invest more in R&D, in more bank-based economies, have a lower R&D growth during crisis periods. At the same time, the explanatory power of the interaction term using external dependence is lost. However, when looking at the share of innovative investment in total investment, this is no longer the case, and it is still financial constraints that explain the cross-country, within industry differences in the composition of investment.

The identification strategy employed is thus robust to these alternative industry characteristics and suggests the important role of bank credit in explaining industry-level investment patterns around banking crises.

4.8 Alternative measures of financial dependence

This section tests the robustness of the results obtained when employing alternative measures of financial dependence. First, an alternative measure of dependence on external finance at the industry-level is considered. While Rajan and Zingales's (1998) approach offers a valid and exogenous way to identify the extent of an industry's dependence on external funding, this measure does not differentiate between the sources of finance. This distinction might be important when looking at investments in R&D in particular, since previous research has underlined the importance of equity in financing innovation, specifically in countries with highly developed capital markets (Brown et al., 2009; Brown et al., 2012). The identification strategy proposed in this paper, which uses an interaction term with a country's banking sector dependence, should generally mitigate this concern. Nonetheless, a robustness is proposed using a more direct measure of dependence on bank credit constructed following Carlin and Mayer (2003). They look explicitly at firm dependence on banking sector finance, by calculating a ratio of bank loans to investment for a large sample of Japanese firms, over the period 1981-1990. Since Carlin and Mayer's (2003) index is constructed for a smaller number of industry codes, I recompute their measure using a sample of both listed and non-listed firms in two bank-based economies in my sample, i.e., Japan and Germany. Data on total investment and bank credit is obtained from the ORBIS Database of Bureau van Dijk for a sample of 50,000 firms for the period 2004-2007.[21] Using an approach similar the one employed to construct the *ExtDep* measure, an industry index is obtained as the median value of firm-level observations for each industry code across the entire period.

This alternative measure of dependence, denoted by *BankDep*, is presented in Appendix E. Columns (1)-(4) of Table 7 show the results estimating Eq. (8) with this alternative measure of bank dependence. The dependent variable in columns (1)-(2) is the change in average R&D growth between two crisis windows $[t+1, t+3]$ $[t-3, t-1]$ in column (1) and $[t, t+2]$, $[t-4, t-1]$ in column (2), for a banking crisis starting in year t. The results are consistent with previous estimations and show that industries more dependent on bank finance experience a lower growth of R&D after banking crises, in particular in more bank-based economies. Results pertaining to the difference in the share of R&D in total investment around a banking crisis are shown in columns (3)-(4). These results are, however, less precise. This might be due to the fact that this new index is constructed using a smaller time-frame and sample of companies as compared to the Rajan and Zingales (1998) index, making it a less precise measure of external dependence.

A second robustness refers to an alternative measure of the country-level index of reliance on

[21] 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.

Table 7: Alternative measures of financial dependence

The dependent variable in columns (1)-(2) and (5)-(6) is the difference between the average real growth in R&D in the years following a banking crisis as compared to the average in the years preceding the crisis. The dependent variable in columns (3)-(4) and (7)-(8) is the difference between the average share of R&D in Total investment (TI) in the years following a banking crisis as compared to the average prior to the crisis. The crisis and pre-crisis intervals for which these averages are computed, are $[t+1, t+3]$, $[t-3, t-1]$ in column (1), (3), (5) and (7); and $[t, t+2]$, $[t-4, t-1]$ in columns (2), (4), (6) and (8), for a banking crisis starting in year t. BankDep×Bank is the interaction term of the industry-level measure of dependence on bank credit computed following Calderon and Liu (2003) and a country-level measure of bank-dependence computed as the ratio of Private Credit to Stock Market Capitalization in year $t-8$ or the first year available. ExtDep×Credit is an interaction between external dependence and a country level measure of bank dependence computed as the ratio of Private Credit to Stock Market Capitalization plus Domestic Bond Market size in year $t-8$ or the first year available. Size$_{t-3}$ is the share of a sector's R&D investment in total R&D investment in the three years prior to the crisis. Growth observations are winsorized at +100% and -100%. Country and industry fixed effects are included. Robust standard errors are reported in parentheses. Constant term included, but not reported. *** represents significance at 1% level, ** at 5% level and * at 10% level.

	$\Delta R\&D$		$\Delta(R\&D/TI)$		$\Delta R\&D$		$\Delta(R\&D/TI)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BankDep*Bank	-0.007**	-0.006*	0.001	-0.005				
	(0.003)	(0.003)	(0.001)	(0.004)				
ExtDep*Credit					-0.041**	-0.072***	-0.032**	-0.081***
					(0.018)	(0.023)	(0.012)	(0.024)
Size$_{t-3}$	0.105	0.0453	0.119	0.0411	-0.251	0.388	0.182	0.484
	(0.599)	(0.489)	(0.178)	(0.517)	(0.395)	(0.649)	(0.208)	(0.639)
Observations	226	227	216	216	191	190	187	187
R-squared	0.268	0.250	0.323	0.284	0.335	0.280	0.319	0.267

banking sector funding. The main estimations employed the ratio of Private Credit to Stock Market Capitalization to classify countries as more bank-based. However, in many countries bond markets represent nowadays an important alternative source of external funding. Thus, to gauge a country's dependence on bank credit, an alternative measure of banking sector dependence can be computed as the ratio of Private Credit to Stock Market Capitalization *plus* Bond Market Size. I use the World Bank data on Domestic Private Debt Securities as a measure of a country's bond market size. Results pertaining to this alternative measure of bank dependence, denoted $ExtDep \times Credit$, are presented in Table 6, columns (5)-(8). The model estimated is the event study analysis in Eq. (8) with R&D growth in columns (5)-(6) and the share of R&D in total investment in columns (7)-(8). Regardless of the time frame for the pre- and post-crisis periods considered, the results are strongly significant employing this alternative measure.

4.9 Robustness check: falsification strategies

A final robustness check is a falsification strategy commonly employed in difference-in-difference estimations (see Bertrand et al., 2004). In particular, I repeat the analysis in Table 2 by changing

Table 8: Falsification strategies: hypothetical crisis dates

The dependent variable is the difference between the average real growth in R&D in the years following a hypothetical banking crisis date as compared to the average in the previous years. The crisis and pre-crisis intervals used to compute averages are: $[t+1, t+3]$, $[t-3, t-1]$ in columns (1) and (4); $[t+1, t+4]$, $[t-8, t-1]$ in columns (2) and (5); and $[t, t+2]$, $[t-4, t-1]$ in columns (3) and (6), for a hypothetical banking crisis starting in year t. Columns (4)-(6) repeat the same empirical exercise for a set of countries that have not experienced a banking crisis and for which the year 2008 is assigned as the hypothetical crisis year. Country and industry fixed effects are included. * denotes significance at a 10% level.

	Randomized crisis date			Crisis date 2008		
	(1)	(2)	(3)	(4)	(5)	(6)
ExtDep*Bank	0.0421*	0.0252	0.0157	-0.0208	-0.0251	0.00479
	(0.0241)	(0.0176)	(0.0175)	(0.0273)	(0.0200)	(0.0364)
Size_{t-3}	0.184	0.0188	-0.323	0.111	-0.459	-0.187
	(0.653)	(0.321)	(0.775)	(0.474)	(0.468)	(0.488)
Observations	210	215	215	189	199	198
R-squared	0.208	0.144	0.178	0.267	0.284	0.291

the crisis year to a hypothetical crisis date. Table 8 looks at the difference in average real growth in R&D between the crisis and pre-crisis periods, where the crisis and pre-crisis periods are $[t+1, t+3]$ and $[t-3, t-1]$ in columns (1) and (4), $[t+1, t+4]$ and $[t-8, t-1]$ in columns (2) and (5) and $[t, t+2]$ and $[t-4, t-1]$ in columns (3) and (6), but now t is the hypothetical crisis year. Columns (1)-(3) consider the same set of 13 banking crisis countries employed so far, but change the crisis year to a random hypothetical date. The negative effect of $ExtDep \times Bank$ is no longer present or turns even positive, confirming that the disproportionate drop in R&D is specific to the years around an actual banking crisis. Columns (4)-(6) consider an alternative sample of countries that have not experienced a banking crisis over the period for which R&D data is available in the ANBERD database. For this new set of countries (presented in Footnote 27), the hypothetical crisis year is set to 2008, as this is the most common banking crisis year in the original dataset. Again, the coefficient of interest is no longer significant. As most of the countries in this alternative sample have, in fact, experienced a recession in 2008-2009, the lack of a statistically significant effect reinforces the argument that the differential drop in R&D is specific to recessions that follow banking crises. Overall, the lack of negative effects for the hypothetical crisis dates performed in this subsection suggests that the results obtained are specific to banking crises and not an artifact of the data.

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 this credit crunch 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 banking crises. This paper aims to build a bridge between static models of financial crises and models of long-term growth. In a stylized growth model with a banking sector, I show that contractions in credit supply that follow banking crises cause firms to shift their investments from long-term, high productivity investments, to short-term, low-productivity ones. By impacting the type of investment undertaken, banking crises affect not only on the volume of real sector investments, but also on their composition.

This theoretical prediction is confirmed empirically, employing a sample of 13 recent systemic banking crises and industry-level data on Research and Development spending as a proxy for long-term, productivity-enhancing investments. To highlight the exogenous impact of financial conditions on investments in innovation, I propose a new identification strategy that looks at the differential impact of the crisis on industries more dependent on external finance, in countries that generally rely more on banking sector financing. Empirical estimations consider both the size of R&D and the share of R&D in total investment as a dependent variable, in order to highlight a shift in the composition of investment around banking crises. Employing both cross-sectional and panel estimations, the results show a strong support for a differential impact of banking crises on investments in innovation, as industries more dependent on external finance, in more bank-based economies, have a disproportionally lower R&D spending following episodes of bank distress. Such differential effects across sectors imply that the drop in R&D spending is, at least partially, the result of the contraction in credit supply that follows banking crises and not simply demand-side factors that worsen overall borrowing ability and investment.

Since less investment in R&D can slow down productivity, the consequences of this shift in investment patterns on economic growth may last longer than the actual crisis and could explain the slow recovery following episodes of systemic banking crises. These results can hold policy implications as well. First, they are in line with the view that bank dependent borrowers cannot circumvent the banking sector in crisis times. Hence policy measures that provide alternative sources of funding for these borrowers are warranted to ensure that the negative real sector effects of crises are minimized. Second, they highlight the importance of financial constraints for investments in innovation and call for policy interventions that support R&D spending, in particular in periods of tight credit supply.

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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 (which, for brevity, is not repeated here) is to show that a unique threshold equilibrium exists, such that depositors withdraw if their signal is above a threshold signal, x^* and a liquidity crisis occurs for values of the liquidity shock higher than a threshold, C^*. Given this result, the proof of Proposition 1 consists of characterizing this unique threshold.

First, given the signal:

$$x_i = C + \epsilon_i, \tag{13}$$

we assume that C is uniformly distributed over the interval $[0,\, \bar{c}D]$ and ϵ over $[-\epsilon,\, \epsilon]$. Denote by $\ell^*(C)$ the threshold number of investors who need to run on the bank to trigger the liquidity freeze. From Eq. (3) it follows that:

$$\ell(C^*) = \frac{M + Y_1 - C^*}{D} \tag{14}$$

Thus, a liquidity freeze will occur if more that $\ell(C^*)$ investors withdraw. Consequently, if less than $\ell(C^*)$ investors withdraw, long-term projects survive and investors obtain a gross return, RD. Note then that the space of liquidity costs $[0, \bar{c}D]$ can be partitioned in three intervals. More specifically, for a sufficiently high liquidity cost, long-term investment projects will always fail, even if no investor withdraws, $\ell = 0$. This is the case if $C \geq M + Y_1 \equiv C_{max}$. In this region, all investors have a dominant strategy to withdraw. In the second region, when $C \leq M - D \equiv C_{min}$, liquidity needs are sufficiently low such that long-term investments will always survive, even if all investors withdraw, $\ell = 1$ and no investment in the short-term production takes place, $k = 1$.[22] Then whenever, $C \leq C_{min}$, it is optimal for everyone to leave their money in the bank. In the intermediate range, $[C_{min}, C_{max}]$, panic-based runs can occur depending on investors' self-fulfilling beliefs. In this region, though, investors' decisions about whether to withdraw no longer depend only on the information conveyed by the signal about the fundamental, but also on what the signal conveys about other agents' signals. Consider an investor receiving a signal sightly above the lower threshold, C_{min}. This investor infers that others might have received signals equal to or below this threshold, and thus have a dominant strategy to leave their funds in the bank. Then it is also optimal for him/her to stay. Applying the same logic several times, one can establish a boundary well above zero below which investors find it optimal not withdraw. At the same time, investors receiving a signal slightly below C_{max} is pessimistic about the probability of survival of the long-term investment projects and prefers to withdraw. Again, we can apply a backward reasoning argument and establish a boundary well below C_{max} above which investors withdraw. Morris and Shin (1998) show that these two boundaries coincide.[23]

Given this unique cut-off cost, the proportion of investors who withdraw is that receiving a signal above the threshold signal x^*:

$$\ell(C^*) = Prob(x_i > x^*|C^*) = Prob(C + \epsilon_i > x^*|C^*) = 1 - \frac{1}{2\epsilon}(x^* - C^* + \epsilon), \tag{15}$$

where we have used the fact that signals $x_i = C + \epsilon_i$ are also uniformly distributed over $[C - \epsilon, C + \epsilon]$, given that C and ϵ are drawn from uniform distributions over $[0,\, \bar{c}D]$ and $[-\epsilon,\, \epsilon]$. Combining this equation with the characterization of the equilibrium threshold in Eq. (14), we obtain a first

[22]These lower and upper dominance regions are within the bounds of the interval $[0, \bar{c}H]$ as long as $\mu < \frac{\phi - 1}{\phi}$ and $\phi > \sigma_1 - 1$. These restrictions are always valid under the parameter values chosen in numerical simulations. See Table 9.

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

equation that defines the threshold signal x^* as a function of C^* is:

$$x^* = C^* + \epsilon - \frac{2\epsilon}{D}(M + Y_1 - C^*) \tag{16}$$

A second equation in x^* and C^* is given by the indifference condition of an investor who receives the threshold signal, x^*, who is indifferent between withdrawing and leaving its funds D in the bank:

$$Prob[C < C^*|x^*]RD = D, \tag{17}$$

where an investors receives gross payoff RD if long-term investments survive, i.e., $Prob[C < C^*]$ and can recover the original investment D if he/she withdraws. Given the posterior distribution of $C \sim [x^* - \epsilon, x^* + \epsilon]$, this indifference condition is simply:

$$\frac{C^* - x^* + \epsilon}{2\epsilon} = \frac{1}{R} \tag{18}$$

Plunging this into equation (16) gives us the equation in Proposition 1:

$$C^* = M + Y_1 - \frac{D}{R}.$$

QED

B Proof of Lemma 1

Given the equilibrium of investors' coordination problem in Eq. (4), we have that the probability that long-term investments survive is:

$$\lambda(k, \mu) \equiv Prob[C < C^*| = \frac{(1-\mu)\phi + \sigma_1(1-k)\mu\phi}{\bar{c}} - \frac{1}{\bar{c}R}. \tag{19}$$

From the first order condition of the entrepreneur's maximization problem in Eq. (2) we have that:

$$-\sigma_1 + \frac{\partial\lambda(k,\mu)}{\partial k}\sigma_2 k + \lambda(k,\mu)\sigma_2 = 0. \tag{20}$$

Replacing $\lambda(k, \mu)$ with its equilibrium value in (19) yields:

$$k_{opt} = \frac{\sigma_1 - 1}{2\sigma_1} - \frac{(\bar{c}\sigma_1 - \phi\sigma_2)R + \sigma_2}{2\mu\sigma_1\sigma_2\phi R} \tag{21}$$

Thus $\frac{\partial k_{opt}}{\partial\mu} = \frac{(\bar{c}\sigma_1 - \phi\sigma_2)R + \sigma_2}{2\mu^2\sigma_1\sigma_2\phi R}$, is positive if and only if $\phi < \frac{\bar{c}\sigma_1}{\sigma_2} + \frac{1}{R} \equiv \overline{\phi}$. This proves one of the results in Lemma 1.

The sensitivity of the equilibrium probability with respect to the loans-to-assets ratio, μ is:

$$\frac{\partial\lambda(\mu)}{\partial\mu} = \frac{\phi}{\bar{c}}\left[-1 - \sigma_1\frac{\partial k(\mu)}{\partial\mu}\mu + \sigma_1(1-k)\right]. \tag{22}$$

Substituting Eq. (21) in (22) yields:

$$\frac{\partial\lambda(\mu)}{\partial\mu} = \frac{\phi}{\bar{c}}\left[-1 - \sigma_1\frac{(\bar{c}\sigma_1 - \phi\sigma_2)R + \sigma_2}{2\mu\sigma_1\sigma_2\phi R} + \sigma_1\left(1 - \frac{\sigma_1 - 1}{2\sigma_1} + \frac{(\bar{c}\sigma_1 - \phi\sigma_2)R + \sigma_2}{2\mu\sigma_1\sigma_2\phi R}\right)\right],$$

which can be simplified to:

$$\frac{\partial\lambda(\mu)}{\partial\mu} = \frac{\phi(\sigma_1 - 1)}{2\bar{c}} > 0,$$

given that $\sigma_1 > 1$. This proves the second result in Lemma 1. *QED*

Table 9: Structural parameters for numerical simulations

Description	Model's notation	Parameterization
Share of capital	α	0.3
Unit return short-term investment (bank)	$\alpha\sigma_1$	1.25
Unit return long-term investment (bank)	$\alpha\sigma_2$	2.5
Total Assets to Deposits Ratio	ϕ	1.3
Distribution of C	uniform over [0, $\bar{c}$D]	[0, 2D]
Investors' unit return	R	1.1

C Proof of Proposition 2

Having established the two results in Lemma 1, the proof of Proposition 2 follows directly from the bank maximization problem:

$$\underset{\mu}{\text{Max}}\, \lambda(\alpha\sigma_2 k\mu\phi D + \alpha\sigma_1(1-k)\mu\phi D - RD) + (1-\lambda)\alpha\sigma_1(1-k)\mu\phi D + (1-\mu)\phi D, \tag{23}$$

which yields the following FOC:

$$\begin{aligned}
&\frac{\partial\lambda}{\partial\mu}\left(\alpha\,\sigma_2\,k\mu\,\phi\,D + \alpha\,\sigma_1\,(1-k)\,\mu\,\phi\,D - R\,D\right) \\
&+\lambda\left(\alpha\,\sigma_2\,\frac{\partial k}{\partial\mu}\mu\,\phi\,D + \alpha\,\sigma_2\,k\phi\,D - \alpha\,\sigma_1\,\frac{\partial k}{\partial\mu}\mu\,\phi\,D + \alpha\,\sigma_1\,(1-k)\,\phi\,D\right) \\
&-\frac{\partial\lambda}{\partial\mu}\alpha\,\sigma_1(1-k)\mu\,\phi\,D - (1-\lambda)\,\alpha\sigma_1\frac{\partial k}{\partial\mu}\mu\,\phi\,D + (1-\lambda)\,\alpha\sigma_1\,(1-k)\,\phi\,D - \phi\,D = 0
\end{aligned}$$

This is equivalent to:

$$J \equiv \frac{\partial\lambda}{\partial\mu}\left(\alpha\,\sigma_2\,k\mu - \frac{R}{\phi}\right) + \lambda\left(\alpha\,\sigma_2\,\frac{\partial k}{\partial\mu}\mu + \alpha\,\sigma_2\,k\right) - \alpha\sigma_1\frac{\partial k}{\partial\mu}\mu + \alpha\sigma_1\,(1-k) - 1 = 0$$

Applying the implicit function theorem to function J above, we can show that:

$$\frac{d\mu}{d\phi} = -\frac{\partial J/\partial\phi}{\partial J/\partial\mu} < 0 \tag{24}$$

To show this consider:

$$\frac{\partial J}{\partial\mu} = \frac{\partial^2\lambda}{\partial^2\mu}(k\alpha\,\mu\,\sigma_2 - \frac{R}{\phi}) + 2\,\frac{\partial\lambda}{\partial\mu}\frac{\partial k}{\partial\mu}\alpha\,\mu\sigma_2 + 2\,k\frac{\partial\lambda}{\partial\mu}\alpha\sigma_2 + \underbrace{\frac{\partial^2 k}{\partial^2\mu}\alpha\,\mu(\lambda\sigma_2 - \sigma_1) + 2\,\frac{\partial k}{\partial\mu}\alpha(\lambda\sigma_2 - \sigma_1)}_{0}$$

Note that the last two terms in the expression above add up to zero since $\frac{\partial^2 k}{\partial\mu^2} = -\mu\frac{\partial k}{\partial\mu}$. Similarly, $\frac{\partial^2\lambda}{\partial\mu^2} = 0$, given Lemma 1 above. Moreover, also from Lemma 1, we also know that $\frac{\partial\lambda}{\partial\mu} > 0$ and $\frac{\partial k}{\partial\mu} > 0$. As a result $\frac{\partial J}{\partial\mu} > 0$. Similarly, consider:

$$\begin{aligned}
\frac{\partial J}{\partial\phi} \;=\;& \frac{R}{\phi}\underbrace{\left(-\frac{\partial^2\lambda}{\partial\phi\partial\mu} + \frac{1}{\phi}\frac{\partial\lambda}{\partial\mu}\right)}_{0} + \frac{\partial^2\lambda}{\partial\phi\partial\mu}\alpha\sigma_2 k\mu + \frac{\partial\lambda}{\partial\mu}\frac{\partial k}{\partial\phi}\alpha\sigma_2\mu + \frac{\partial\lambda}{\partial\phi}\frac{\partial k}{\partial\mu}\alpha\sigma_2\mu + \frac{\partial\lambda}{\partial\phi}\alpha\sigma_2 k + \\
&+\alpha\,(\lambda\sigma_2 - \sigma_1)\underbrace{\left(\mu\frac{\partial^2 k}{\partial\phi\partial\mu} + \frac{\partial k}{\partial\phi}\right)}_{0}
\end{aligned}$$

Again the first and last terms of the expression above are equal to zero since $\frac{\partial^2 \lambda}{\partial \phi \partial \mu} = \frac{1}{\phi}\frac{\partial \lambda}{\partial \mu}$ and $\mu \frac{\partial^2 k}{\partial \phi \partial \mu} = -\frac{\partial k}{\partial \phi}$. Moreover, given Lemma 1 and the equilibrium probability of survival of the long-term technology, λ, in Eq. (19), it can be easily shown that: $\frac{\partial^2 \lambda}{\partial \phi \partial \mu} > 0$, $\frac{\partial k}{\partial \phi} > 0$ and $\frac{\partial \lambda}{\partial \phi} > 0$. More specifically, $\frac{\partial^2 \lambda}{\partial \phi \partial \mu} = \frac{\sigma_1 - 1}{2\bar{c}} > 0$, $\frac{\partial k}{\partial \phi} = \frac{\bar{c}\sigma_1 r + \sigma_2}{2\mu\sigma_1\sigma_2\phi^2 r} > 0$ and $\frac{\partial \lambda}{\partial \phi} = \frac{1+\mu(\sigma_1 - 1)}{2\bar{c}} > 0$, given than, by definition, $\sigma_1 > 1$. This proves that $\frac{\partial J}{\partial \phi} > 0$ and thus $\frac{\partial \mu}{\partial \phi} < 0$.

D Proof of Proposition 3

Part (i) of of Proposition 3 follows from Proposition 2 and Lemma 1. Given the constant bank equity levels, increases in aggregate wealth lead to a more leveraged banking sector which will set a higher loan-to-assets ratio. From Lemma 1, this higher credit supply will also result in a higher share of investment in innovation. Part (ii) follows directly from Equations (5) and (7) presenting the dynamics of K_t and D_t. A banking crisis results in a drop in K_t and hence lower wages and savings for the generation born in $t+1$. Finally, Part (iii) follows from Part (i) and Lemma 1. Since investments in innovation are more productive and entrepreneurs invest a lower share of funds in this type of projects after bank runs, growth rates in the aftermath of crises will be lower compared to the pre-crisis ones.

E Measures of dependence on external finance

ISIC Rev 4	Description	ExtDep	BankDep
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

ExtDep 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. BankDep index in the last column is the measure of bank dependence proposed by Calderon and Liu (2003).

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